Text as Data

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Stylometry $\rightsquigarrow$ Who Wrote Disputed Federalist Papers?

Federalist papers $\rightsquigarrow$ 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

- $\boldsymbol{Y} = (Y_1, Y_2, \ldots, Y_N) = (\text{Hamilton}, \text{Hamilton}, \text{Madison}, ..., \text{Hamilton})$
  $N \times 1$ matrix with author labels
- Define the number of words in federalist paper i as num_i

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

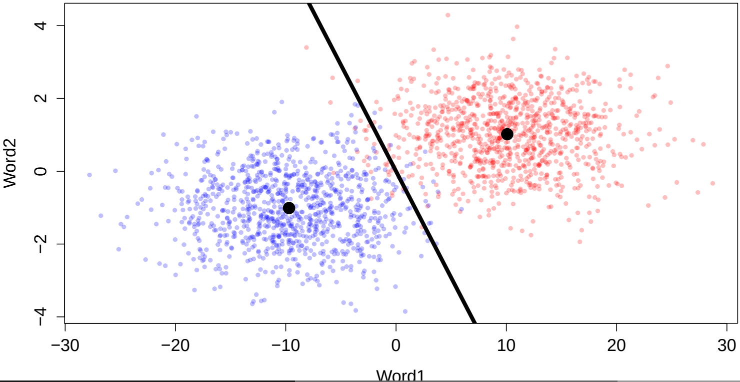
  $N \times J$ counting stop word usage rate
- $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_J)$
  Word weights.

Objective Function

Heuristically: find $\boldsymbol{\theta}^* = (\theta_1^*, \theta_2^*, \ldots, \theta_J^*)$ used to create score

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

that maximally discriminates between categories



Objective Function

Define:

$$
\begin{aligned}
\boldsymbol{\mu}_{\text{Madison}} &= \frac{1}{N_{\text{Madison}}} \sum_{i=1}^{N} I(Y_i = \text{Madison}) \boldsymbol{X}_i \\
\boldsymbol{\mu}_{\text{Hamilton}} &= \frac{1}{N_{\text{Hamilton}}} \sum_{i=1}^{N} I(Y_i = \text{Hamilton}) \boldsymbol{X}_i
\end{aligned}
$$

Objective Function

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

$$
\begin{aligned}
g(\boldsymbol{\theta}, \boldsymbol{X}, \boldsymbol{Y}, \text{Madison}) &= \frac{1}{N_{\text{Madison}}} \sum_{i=1}^{N} I(Y_i = \text{Madison}) \boldsymbol{\theta}^{'} \boldsymbol{X}_i = \boldsymbol{\theta}^{'} \boldsymbol{\mu}_{\text{Madison}} \\
g(\boldsymbol{\theta}, \boldsymbol{X}, \boldsymbol{Y}, \text{Hamilton}) &= \frac{1}{N_{\text{Hamilton}}} \sum_{i=1}^{N} I(Y_i = \text{Hamilton}) \boldsymbol{\theta}^{'} \boldsymbol{X}_i = \boldsymbol{\theta}^{'} \boldsymbol{\mu}_{\text{Hamilton}} \\
s(\boldsymbol{\theta}, \boldsymbol{X}, \boldsymbol{Y}, \text{Madison}) &= \sum_{i=1}^{N} I(Y_i = \text{Madison}) (\boldsymbol{\theta}^{'} \boldsymbol{X}_i - \boldsymbol{\theta}^{'} \boldsymbol{\mu}_{\text{Madison}})^2 \\
s(\boldsymbol{\theta}, \boldsymbol{X}, \boldsymbol{Y}, \text{Hamilton}) &= \sum_{i=1}^{N} I(Y_i = \text{Hamilton}) (\boldsymbol{\theta}^{'} \boldsymbol{X}_i - \boldsymbol{\theta}^{'} \boldsymbol{\mu}_{\text{Hamilton}})^2
\end{aligned}
$$

Objective Function $\rightsquigarrow$ Optimization

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

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

(Fisher's) Linear Discriminant Analysis

Optimization$\rightsquigarrow$ Word Weights

For each word j, construct weight θ_j^*,

$$\begin{aligned}
\mu_{j,\text{Hamilton}} &= \frac{\sum_{i=1}^{N} I(Y_i = \text{Hamilton})X_{ij}}{\sum_{j=1}^{J}\sum_{i=1}^{N} I(Y_i = \text{Hamilton})X_{ij}} \\
\mu_{j,\text{Madison}} &= \frac{\sum_{i=1}^{N} I(Y_i = \text{Madison})X_{ij}}{\sum_{j=1}^{J}\sum_{i=1}^{N} I(Y_i = \text{Madison})X_{ij}} \\
\sigma^2_{j,\text{Hamilton}} &= \text{Var}(X_{i,j}|\text{Hamilton}) \\
\sigma^2_{j,\text{Madison}} &= \text{Var}(X_{i,j}|\text{Madison})
\end{aligned}$$

We can then generate weight θ_j^* as

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

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.

Inferring Separating Words

Classification $\rightsquigarrow$ Custom Dictionaries

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- Difference in Secret/Not Secret Language $\rightsquigarrow$ Secretive Language (Gill and Spirling 2014)

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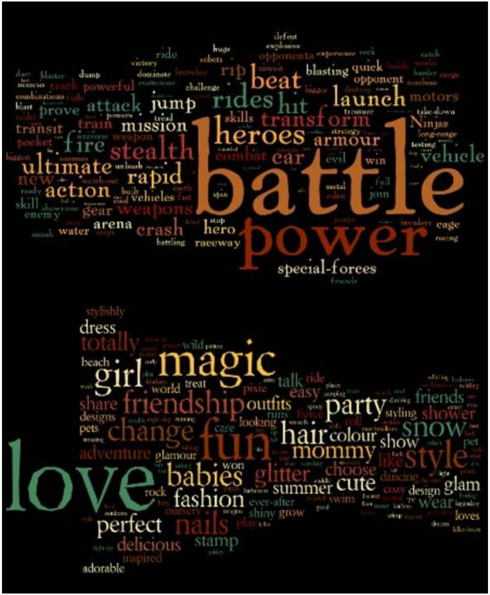

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Vague and Difficult to derive before hand

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Congressional Press Releases and Floor Speeches

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- Deeper question: what does it mean for two text collections to be different?

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- One Answer: texts used for different purposes

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- Problem: are they distinct from floor statements (approx. 52,000 during same time)?
  - Yes: press releases have different purposes, targets, and need not relate to official business
  - No: press releases are just reactive to floor activity, will follow floor statements
- Deeper question: what does it mean for two text collections to be different?
- One Answer: texts used for different purposes
- 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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- Pr(Press) $\equiv$ Probability selected document press release
- Pr(Speech) $\equiv$ Probability selected document speech

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- Minimum: $\Pr(\text{Press}) \rightarrow 0$ (or $\Pr(\text{Press}) \rightarrow 1$)

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

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Formula for mutual information
(based on ML estimates of probabilities)

$$
\begin{aligned}
n_p &= \text{Number Press Releases} \\
n_s &= \text{Number of Speeches} \\
D &= n_p + n_s \\
n_j &= \sum_{i=1}^{D} X_{i,j} \qquad \text{(No. docs } X_j \text{ appears)} \\
n_{-j} &= \text{ No. docs } X_j \text{ does not appear} \\
n_{j,p} &= \text{No. press and } X_j \\
n_{j,s} &= \text{No. speech and } X_j \\
n_{-j,p} &= \text{No. press and not } X_j \\
n_{-j,s} &= \text{No. speech and not } X_j
\end{aligned}
$$

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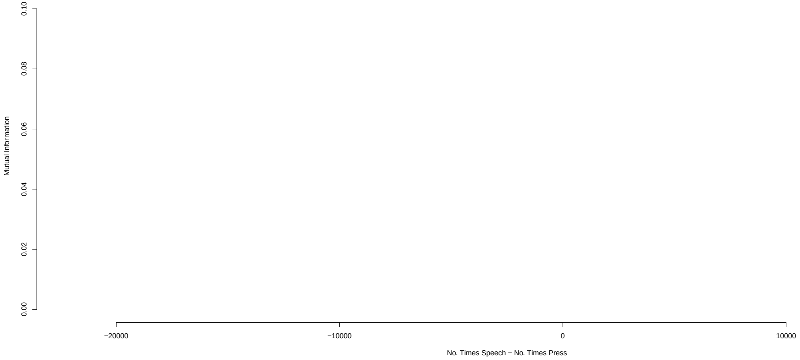
Formula for Mutual Information

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

What's Different About Press Releases



What's Different?

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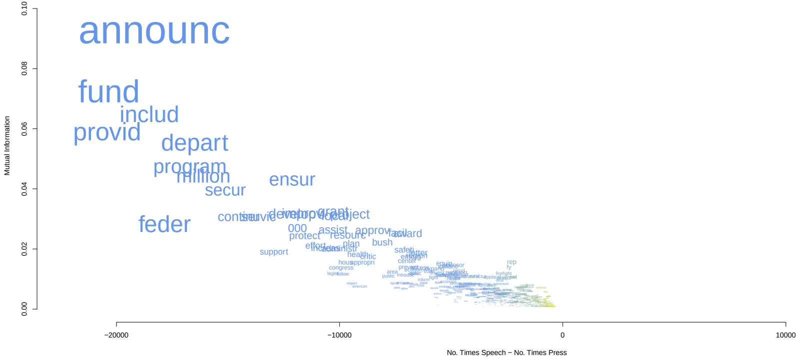

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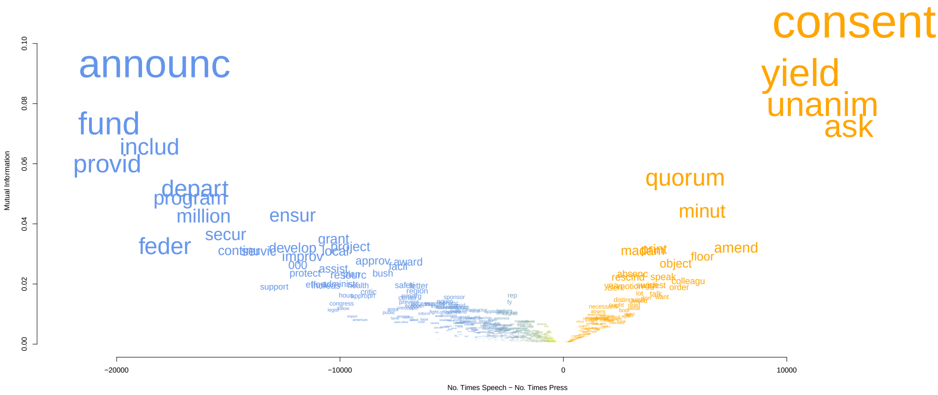

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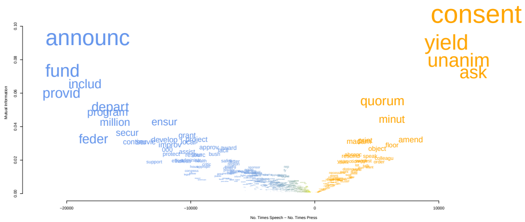

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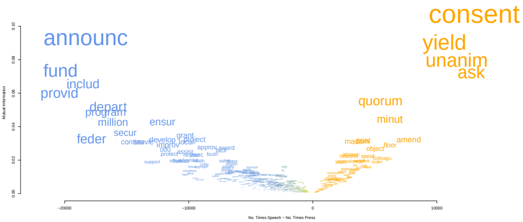

What's Different?

- Press Releases: Credit Claiming

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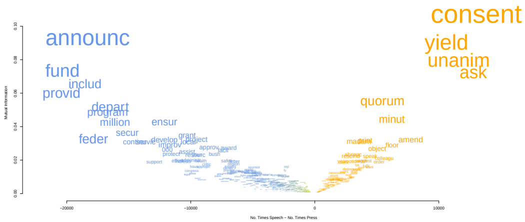

What's Different?

- Press Releases: Credit Claiming
- Floor Speeches: Procedural Words

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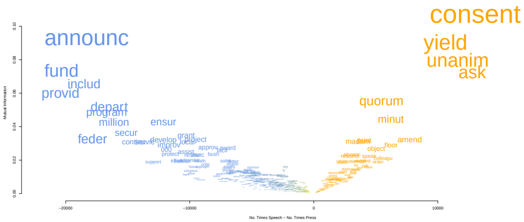

What's Different?

- Press Releases: Credit Claiming
- Floor Speeches: Procedural Words
- Validate: Manual Classification

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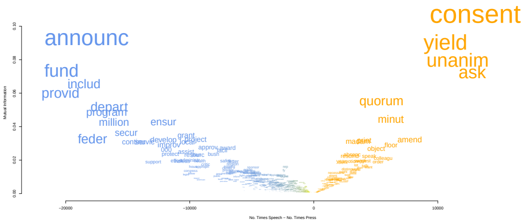

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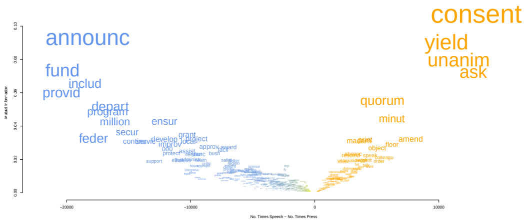

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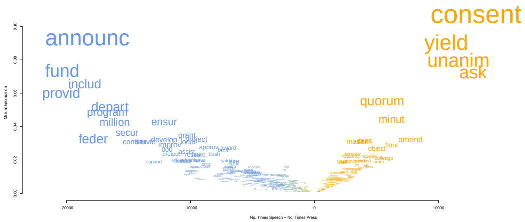

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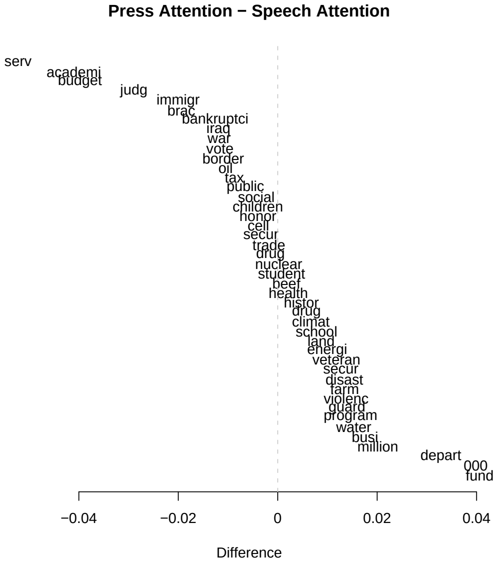

Fightin' Words $\rightsquigarrow$ An Introduction to Regularization

Monroe, Colaresi, and Quinn (2009) $\rightsquigarrow$ what makes a word partisan?

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Strategy $\leadsto$ Construct objective function on *proportions* (and then calculate log-odds)

Objective Function

Suppose we're interested in how a word separates partisan speech.
$\boldsymbol{Y} = (\text{Republican}, \text{Republican}, \text{Democrat}, \ldots, \text{Republican})$
$\boldsymbol{X} =$ Unnormalized matrix of word counts $N \times J$
Define

$$\begin{aligned}
\boldsymbol{x}_{\text{Republican}} &= (\sum_{i=1}^{N} I(Y_i = \text{Republican})X_{i1}, \sum_{i=1}^{N} I(Y_i = \text{Republican})X_{i2}, \\
&\quad \ldots, \sum_{i=1}^{N} I(Y_i = \text{Republican})X_{iJ})
\end{aligned}$$

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

Objective Function

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$$\boldsymbol{\pi}_{\text{Republican}} \sim \text{Dirichlet}(\boldsymbol{\alpha})$$

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\begin{aligned}
\boldsymbol{\pi}_{\text{Republican}} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\
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Objective Function

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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 $\log \text{Odds Ratio}_j$ as

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

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

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

Applying the Model

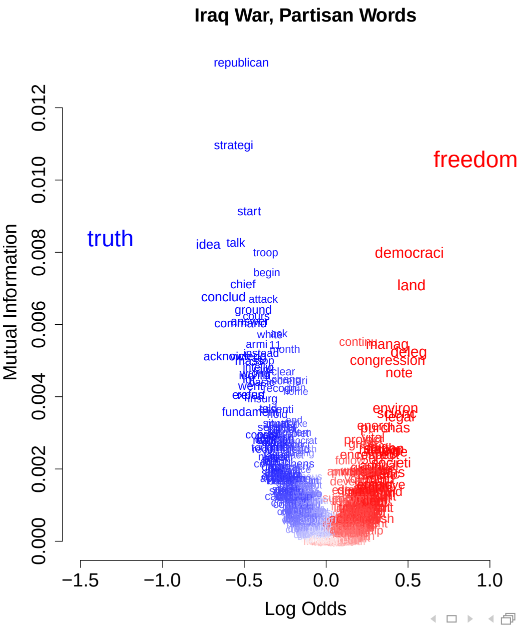
`https://gist.github.com/thiagomarzagao/5851207`

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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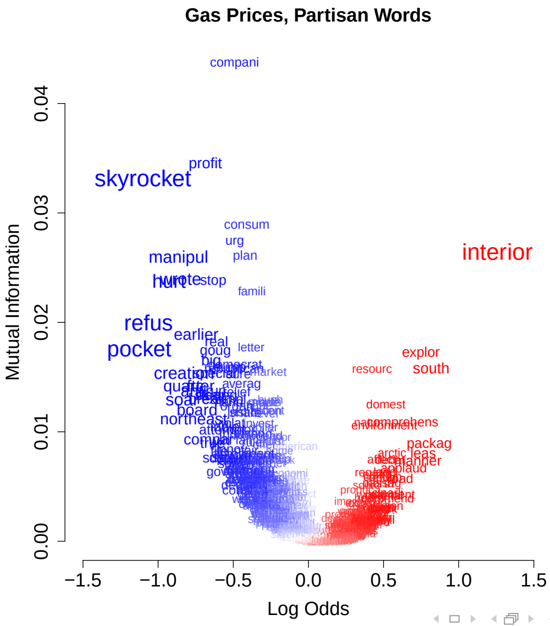
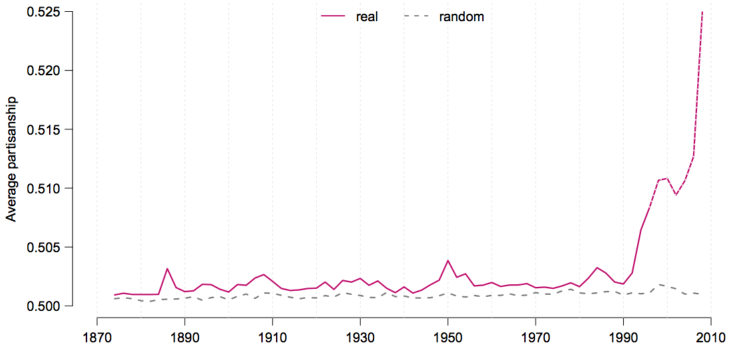


Gentzkow, Shapiro, and Taddy (2017): Rhetorical Polarization

Figure 3: Average partisanship of speech, penalized estimates

Panel A: Preferred specification



Discovery

Where do concepts/ideas/questions come from?

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