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

Text as Data Methods for Discovery

Text as Data Methods for Discovery Goal: Automatically Discover Organization (Similar Groups)

Texts and Geometry

Consider a document-term matrix

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- Provides a geometry $\rightsquigarrow$ modify with word weighting
- Natural notions of distance
- Building block for clustering, supervised learning, and scaling

Texts in Space

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$$\text{Doc1} \quad = \quad (1, 1, 3, \ldots, 5)$$

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\text{Doc1} &= (1, 1, 3, \ldots, 5) \\
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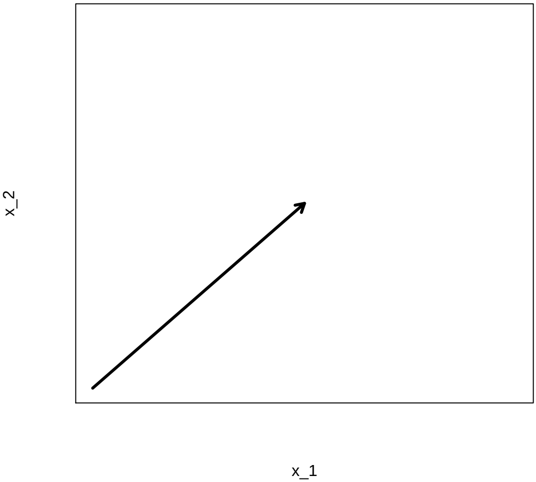
Vector Length



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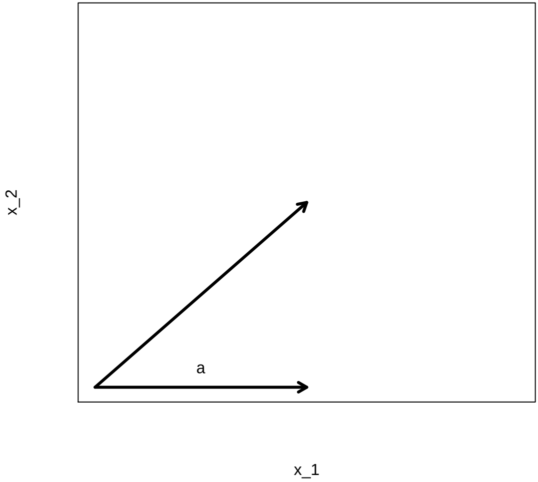
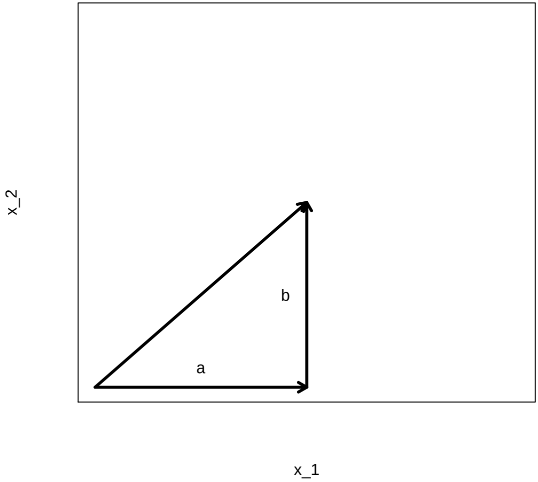


- Pythogorean Theorem: Side with length a

Vector Length



- Pythogorean Theorem: Side with length *a*
- Side with length *b* and right triangle

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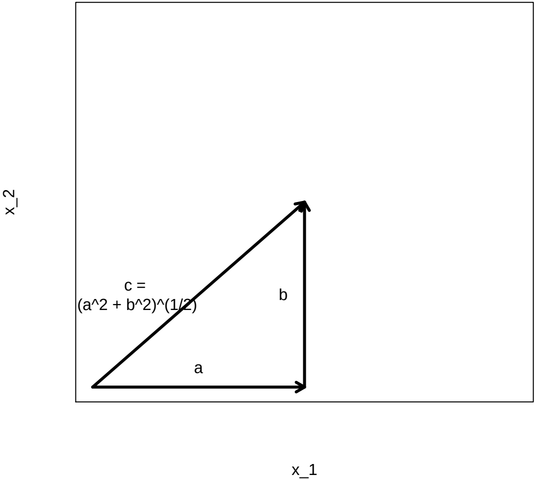

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- $c = \sqrt{a^2 + b^2}$

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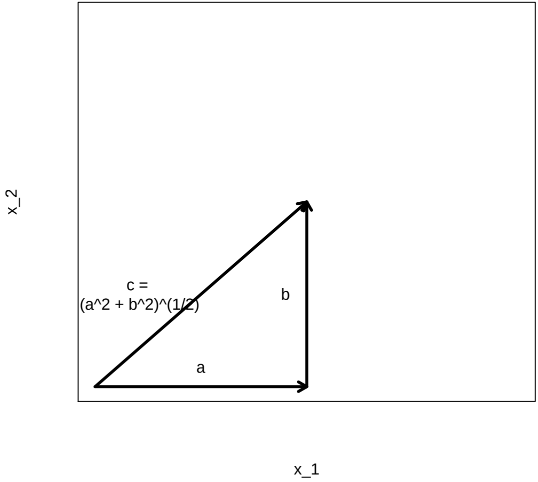

- Pythogorean Theorem: Side with length a
- Side with length b and right triangle
- $c = \sqrt{a^2 + b^2}$
- This is generally true

Vector (Euclidean) Length

Definition

Suppose $\boldsymbol{v} \in \Re^J$. *Then, we will define its length as*

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

Measures of Dissimilarity

Initial guess$\rightsquigarrow$ Distance metrics
Properties of a metric: (distance function) $d(\cdot, \cdot)$. Consider arbitrary documents $\boldsymbol{X}_i$, $\boldsymbol{X}_j$, $\boldsymbol{X}_k$

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Measures of Dissimilarity

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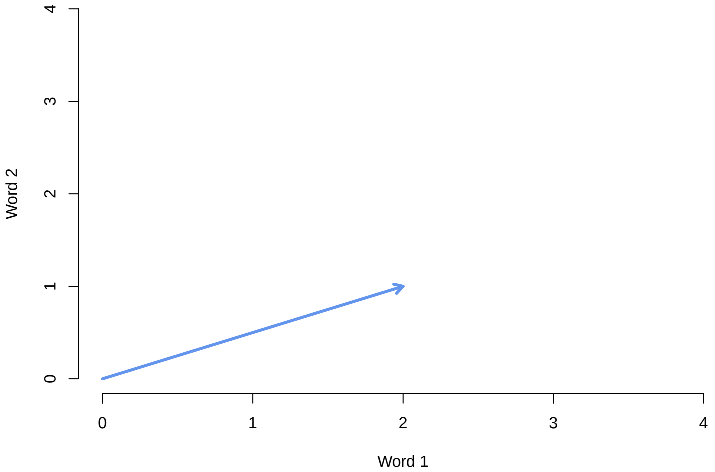
Explore distance functions to compare documents$\leadsto$Do we want additional assumptions/properties?

Measuring the Distance Between Documents

Euclidean Distance



Measuring the Distance Between Documents

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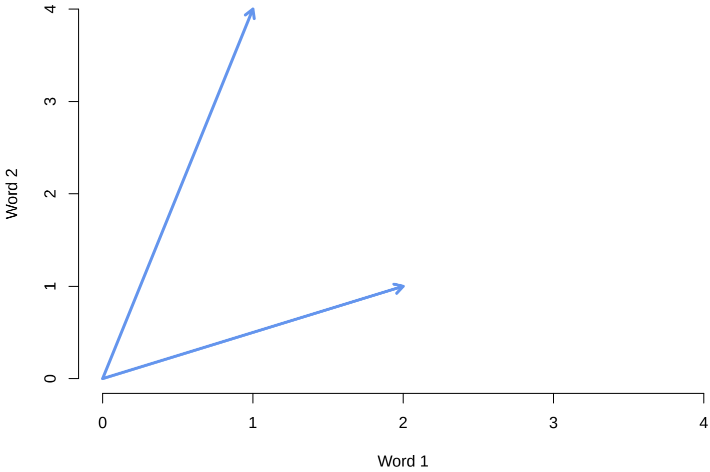

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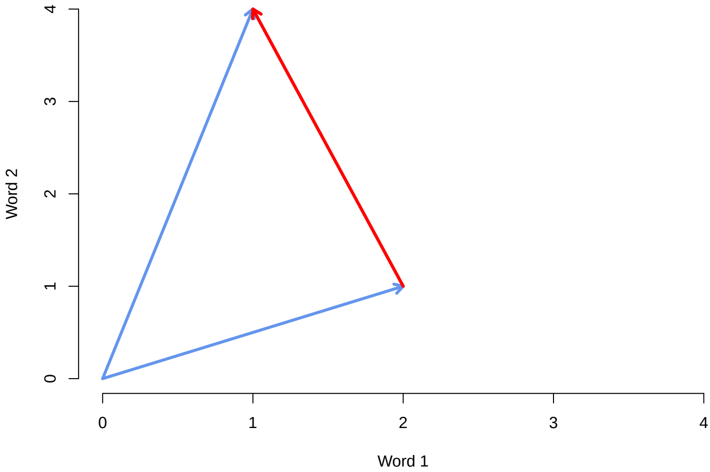

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Definition

The Euclidean distance between documents $\boldsymbol{X}_i$ and $\boldsymbol{X}_j$ as

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

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

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

Measuring Similarity (and removing document length)

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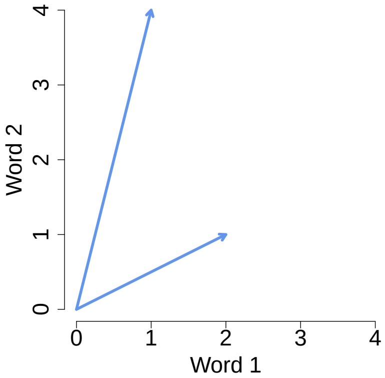
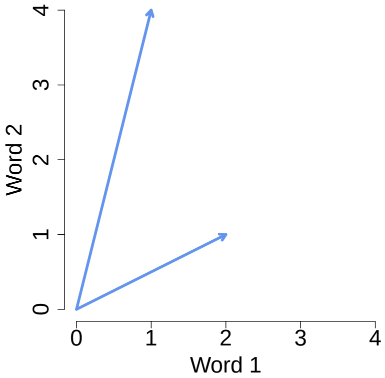
How should additional words be treated?

Measuring Similarity



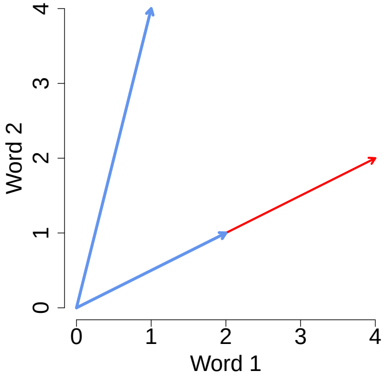
Measure 1: Inner product

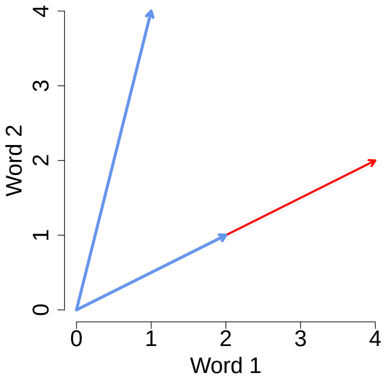
Measuring Similarity



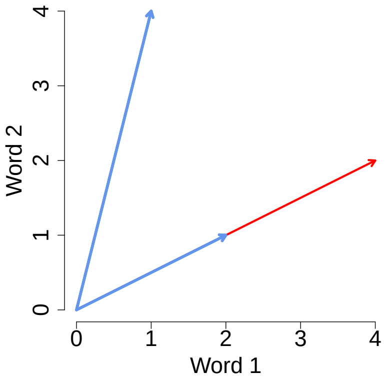
Measure 1: Inner product

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


Word 2
0
1
2
3
4
0
1
2
3
4
Word 1



Problem(?): length dependent



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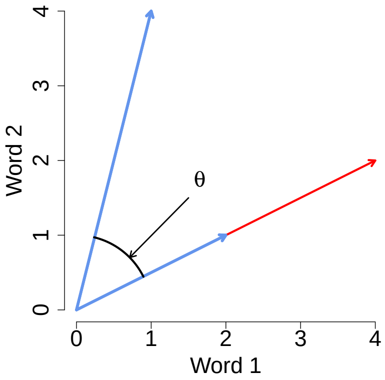
$$(4,2)^{'}(1,4) \quad = \quad 12$$



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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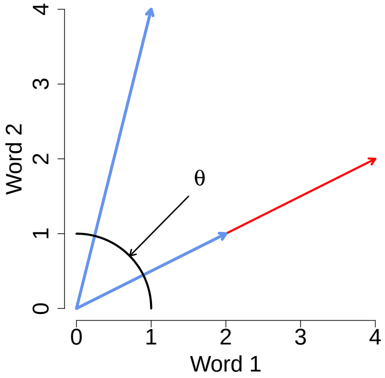

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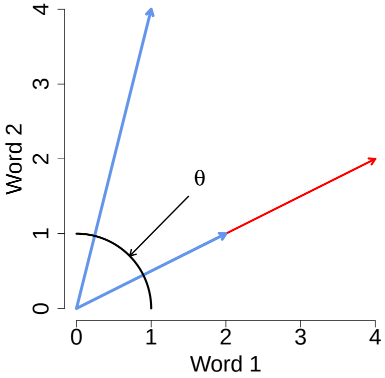

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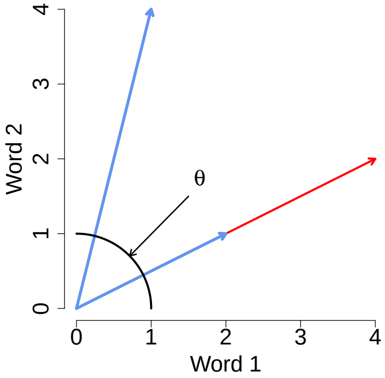

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- Use training set to identify separating words (Monroe, Ideology measurement)

Weighting Words: TF-IDF Weighting

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Why log ?

- Maximum at $n_j = 1$
- Decreases at rate $\frac{1}{n_j} \Rightarrow$ diminishing "penalty" for more common use
- Other functional forms are fine, embed assumptions about penalization of common use

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How Does This Matter For Measuring Similarity/Dissimilarity?
Inner Product

Weighting Words: TF-IDF

$$\mathbf{X}_{i,\text{idf}} \equiv \underbrace{\mathbf{X}_i}_{\text{tf}} \times \textbf{idf} = (X_{i1} \times \text{idf}_1, X_{i2} \times \text{idf}_2, \ldots, X_{iJ} \times \text{idf}_J)$$

$$\mathbf{X}_{j,\text{idf}} \equiv \mathbf{X}_j \times \textbf{idf} = (X_{j1} \times \text{idf}_1, X_{j2} \times \text{idf}_2, \ldots, X_{jJ} \times \text{idf}_J)$$

How Does This Matter For Measuring Similarity/Dissimilarity?
Inner Product

$$\mathbf{X}_{i,\text{idf}} \cdot \mathbf{X}_{j,\text{idf}} = (\mathbf{X}_i \times \textbf{idf})'(\mathbf{X}_j \times \textbf{idf})$$

Weighting Words: TF-IDF

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How Does This Matter For Measuring Similarity/Dissimilarity?

Inner Product

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

Weighting Words: Inner Product

Define:

Weighting Words: Inner Product

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

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If we use tf-idf for our documents, then

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If we use tf-idf for our documents, then

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

Final Product

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

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

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 $\boldsymbol{x}_i = (x_{i1}, x_{i2}, \ldots, x_{iJ})$ (normalized)

K-Means$\rightsquigarrow$ Objective Function

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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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$$f(\boldsymbol{X}, \boldsymbol{T}, \boldsymbol{\Theta}) = \sum_{i=1}^{N} \sum_{k=1}^{K} \overbrace{\tau_{ik}}^{\text{cluster indicator}} \underbrace{\left(\sum_{j=1}^{J} (x_{ij} - \theta_{kj})^2 \right)}_{\text{Squared Euclidean Distance}}$$

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- Calculate squared euclidean distance from center

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- Calculate squared euclidean distance from center
- Only for the assigned cluster

K-Means$\leadsto$ Objective Function

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- Calculate squared euclidean distance from center
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- Two trivial solutions

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- Calculate squared euclidean distance from center
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  - If $K = N$ then $f(\boldsymbol{X}, \boldsymbol{T}, \boldsymbol{\Theta}) = 0$ (Minimum)

K-Means$\rightsquigarrow$ Objective Function

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$$f(\boldsymbol{X}, \boldsymbol{T}, \boldsymbol{\Theta}) \quad = \quad \sum_{i=1}^{N} \sum_{k=1}^{K} \overbrace{\tau_{ik}}^{\text{cluster indicator}} \underbrace{\left(\sum_{j=1}^{J} (x_{ij} - \theta_{kj})^2 \right)}_{\text{Squared Euclidean Distance}}$$

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    - $\boldsymbol{\theta}_i = \boldsymbol{x}_i$

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  - If $K = 1$, $f(\boldsymbol{X}, \boldsymbol{T}, \boldsymbol{\Theta}) = N \times \sigma^2$
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    - Each observation in same cluster
    - $\boldsymbol{\theta}_1 =$ Average across documents

K-Means$\rightsquigarrow$ Optimization

Coordinate descent

K-Means $\rightsquigarrow$ Optimization

Coordinate descent $\rightsquigarrow$ iterate between labels and centers.

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Iterative algorithm: each iteration t

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- Conditional on $\boldsymbol{\Theta}^{t-1}$ (from previous iteration), choose $\boldsymbol{T}^{t}$

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Repeat until convergence$\rightsquigarrow$ as measured as change in f dropping below threshold ϵ

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

K-Means $\rightsquigarrow$ Optimization

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1) initialize K cluster centers $\boldsymbol{\theta}_1^t, \boldsymbol{\theta}_2^t, \ldots, \boldsymbol{\theta}_K^t$.

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K-Means$\leadsto$ Optimization

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2) Choose $\boldsymbol{T}^t$

$$\tau_{im}^t = \begin{cases} 1 \text{ if } m = \arg\min_k \sum_{j=1}^{J} (x_{ij} - \theta_{kj}^t)^2 \\ 0 \text{ otherwise }, \end{cases} \quad .$$

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1) initialize K cluster centers $\boldsymbol{\theta}_1^t, \boldsymbol{\theta}_2^t, \ldots, \boldsymbol{\theta}_K^t$.

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In words: Assign each document $\boldsymbol{x}_i$ to the closest center $\boldsymbol{\theta}_m^t$

K-Means$\rightsquigarrow$ Optimization

K-Means$\rightsquigarrow$ Optimization

3) Choose $\Theta^t \rightsquigarrow$ Focus on the center for cluster k

K-Means$\rightsquigarrow$ Optimization

3) Choose Θ^t $\rightsquigarrow$ Focus on the center for cluster k

$$f(\boldsymbol{X}, \boldsymbol{T}^t, \boldsymbol{\Theta})_k \quad = \quad \sum_{i=1}^{N} \tau_{ik}^t \left(\sum_{j=1}^{J} (x_{ij} - \theta_{jk})^2 \right)$$

K-Means$\rightsquigarrow$ Optimization

3) Choose $\Theta^t \rightsquigarrow$ Focus on the center for cluster k

$$
\begin{aligned}
f(\boldsymbol{X}, \boldsymbol{T}^t, \boldsymbol{\Theta})_k &= \sum_{i=1}^{N} \tau_{ik}^{t} \left(\sum_{j=1}^{J} (x_{ij} - \theta_{jk})^2 \right) \\
\frac{\partial f(\boldsymbol{X}, \boldsymbol{T}^t, \boldsymbol{\Theta})_k}{\partial \theta_{kj}} &= -2 \sum_{i=1}^{N} \tau_{ij}^{t} \left(x_{ij} - \theta_{jk} \right)
\end{aligned}
$$

K-Means$\rightsquigarrow$ Optimization

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\frac{\partial f(\boldsymbol{X}, \boldsymbol{T}^t, \boldsymbol{\Theta})_k}{\partial \theta_{kj}} &= -2 \sum_{i=1}^{N} \tau_{ij}^t \left(x_{ij} - \theta_{jk} \right) \\
0 &= -2 \sum_{i=1}^{N} \tau_{ij}^t \left(x_{ij} - \theta_{jk}^* \right)
\end{aligned}
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K-Means$\rightsquigarrow$ Optimization

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&= \sum_{i=1}^{N} \tau_{ij}^t x_{ij} - \theta_{jk}^* \sum_{i=1}^{N} \tau_{ij}^t
\end{aligned}$$

K-Means$\rightsquigarrow$ Optimization

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\frac{\sum_{i=1}^{N} \tau_{ik}^t x_{ij}}{\sum_{i=1}^{N} \tau_{ik}^t} &= \theta_{jk}^*
\end{aligned}
$$

K-Means $\rightsquigarrow$ Optimization

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

K-Means$\rightsquigarrow$ Optimization

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

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In words: $\boldsymbol{\theta}^{t+1}$ is the average of the documents assigned to k.

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Optimization algorithm:

- Initialize centers
- Do until converged:

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  - For each center, take average of assigned documents$\leadsto$ $\boldsymbol{\theta}_k^t$

K-Means$\rightsquigarrow$ Optimization

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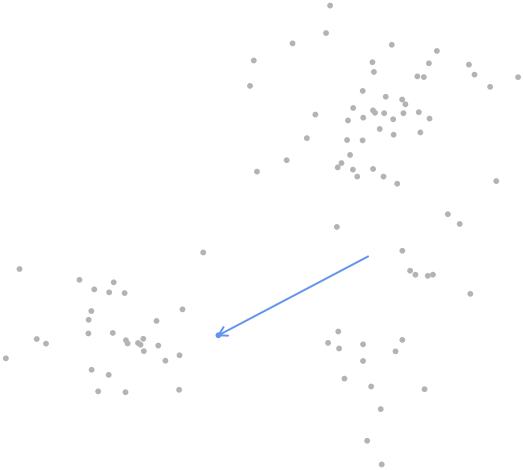
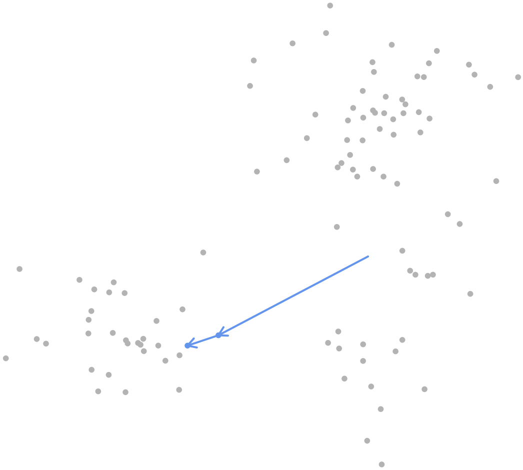
- Do until converged:
  - For each document, find closest center$\rightsquigarrow$ $\boldsymbol{\tau}_i^t$
  - For each center, take average of assigned documents$\rightsquigarrow$ $\boldsymbol{\theta}_k^t$
  - Update change $f(\boldsymbol{X}, \boldsymbol{T}^t, \boldsymbol{\Theta}^t) - f(\boldsymbol{X}, \boldsymbol{T}^{t-1}, \boldsymbol{\Theta}^{t-1})$

Visual Example

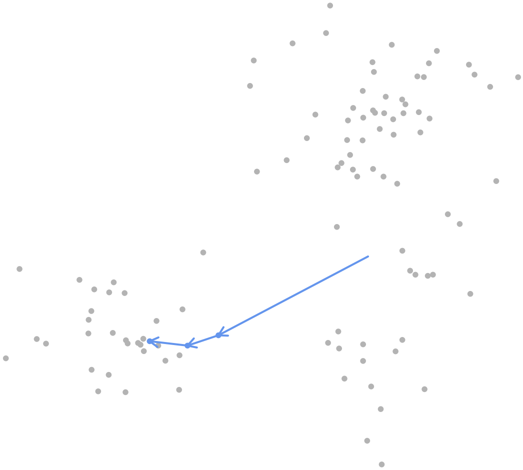
Visual Example



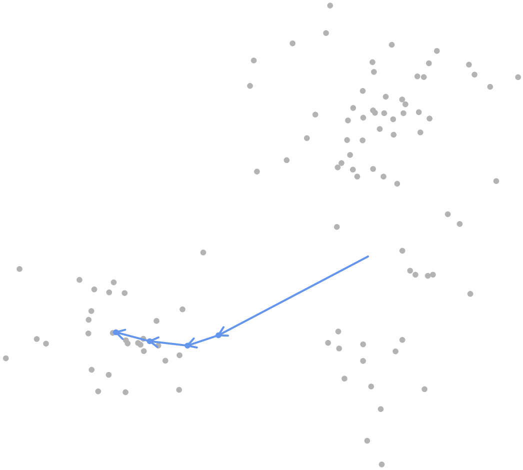
Visual Example



Visual Example



Visual Example



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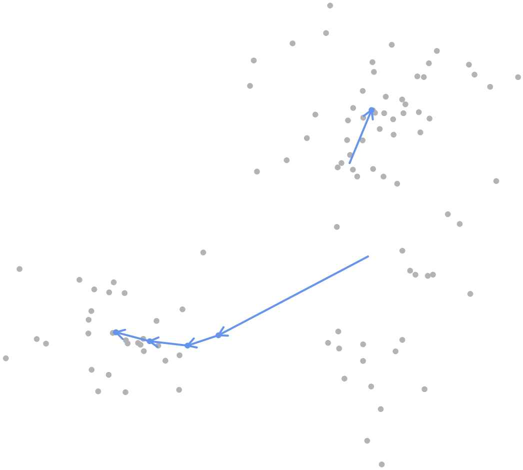

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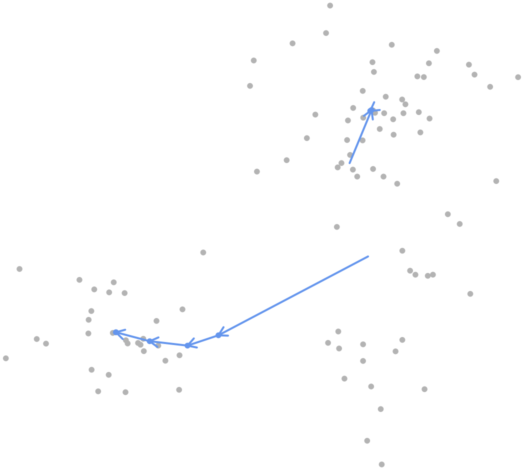

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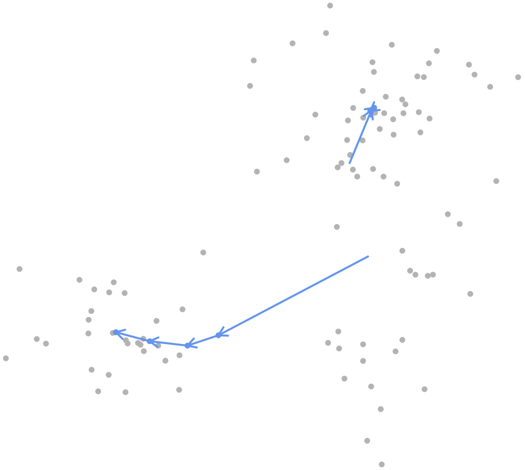

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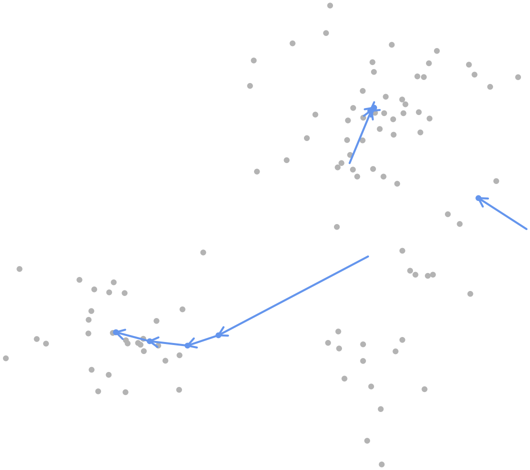

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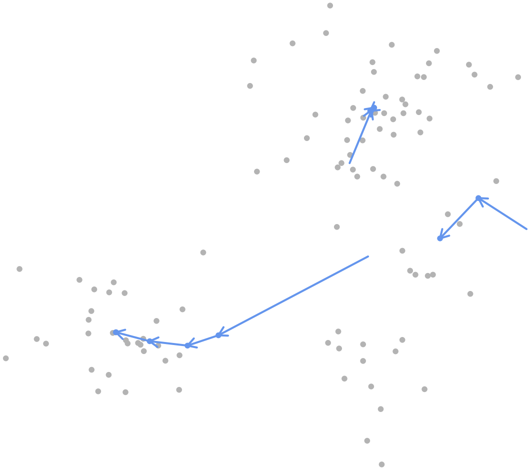

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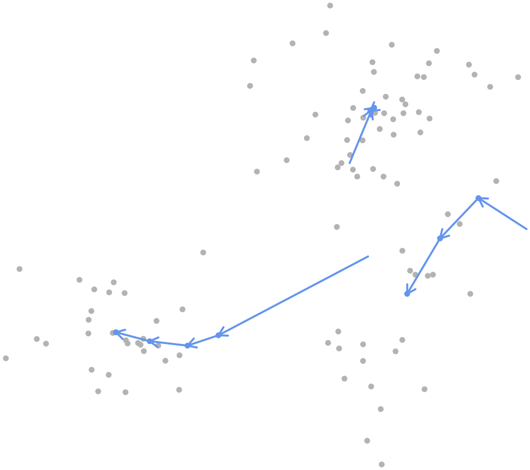

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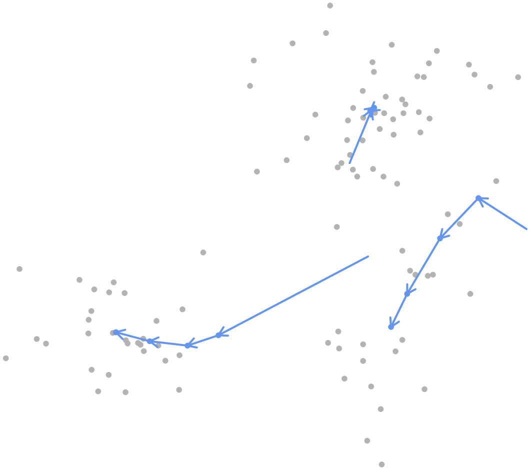

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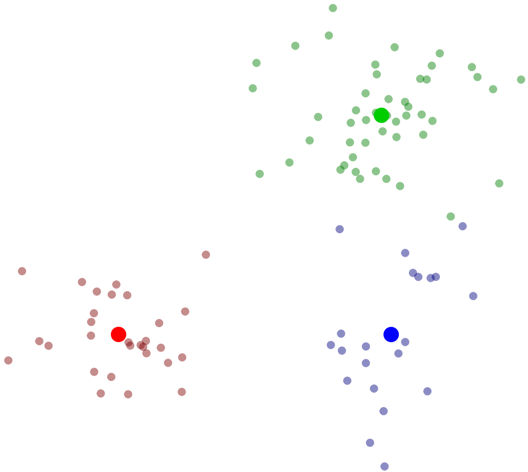

An Example: Jeff Flake

```
To the R Code!
```

Interpreting Cluster Components

Unsupervised methods

Interpreting Cluster Components

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

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`back to the R code!`

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J element long unit-length vector

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

Measuring Cluster Performance: Out of Sample Prediction

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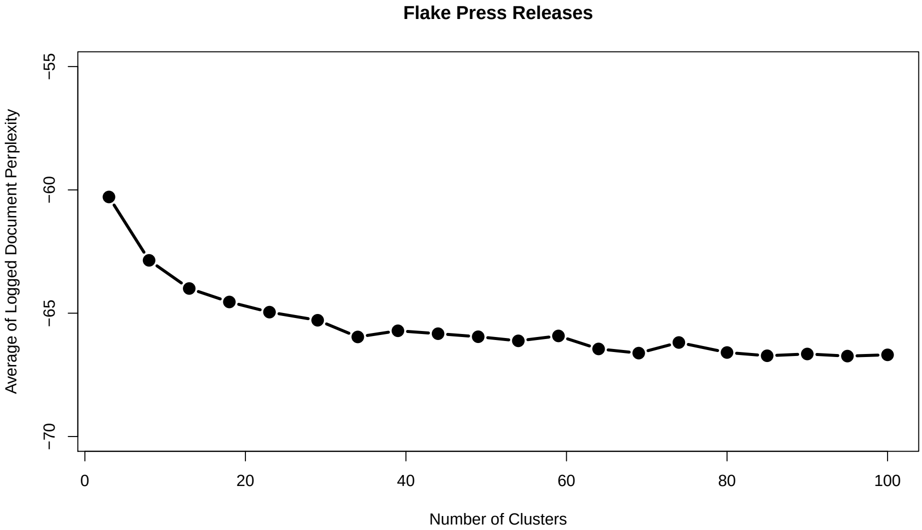
&= \log \sum_{k=1}^{K} \left[\pi_k \exp(\kappa \boldsymbol{\mu}_k^{'} \boldsymbol{x}^{*}_{\text{out}})\right] \\
\text{Perplexity}_{\text{word}} &= \exp\left(-\log p(\boldsymbol{x}^{*}_{\text{out}}|\boldsymbol{\mu},\boldsymbol{\pi})\right)
\end{aligned}$$


Flake Press Releases
Average of Logged Document Perplexity
−55
−60
−65
−70
0
20
40
60
80
100
Number of Clusters

What's Prediction Got to Do With It?

- Prediction $\rightsquigarrow$ One Task

(Roberts, et al 2017 Forthcoming)

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

Experimental Approaches

Mathematical 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)

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Higher rate of intruder identification $\rightsquigarrow$ more exclusive/cohesive topics

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Deploy on Mechanical Turk

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- 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

There are a lot of different clustering models (and many variations within each):
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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)

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- Apply our method (relying on many clustering algorithms)

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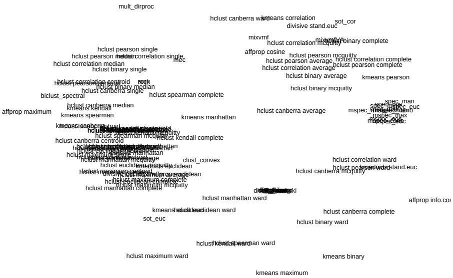

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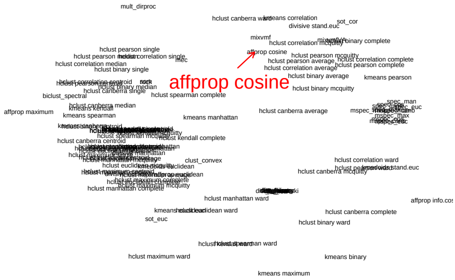

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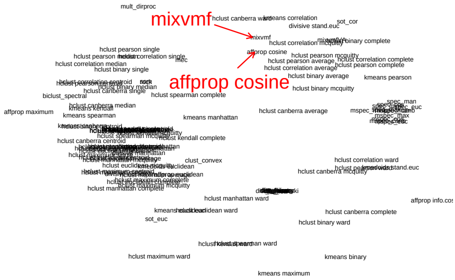

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Close to:

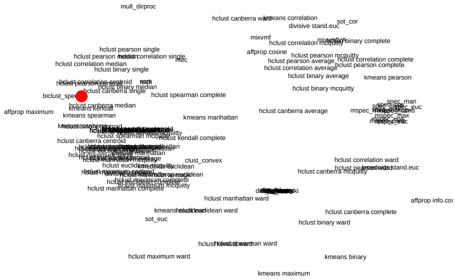
Mixture of von Mises-Fisher distributions (Banerjee et. al. 2005)

$\Rightarrow$ Similar clustering of documents

Example Discovery

Space between methods:

Example Discovery



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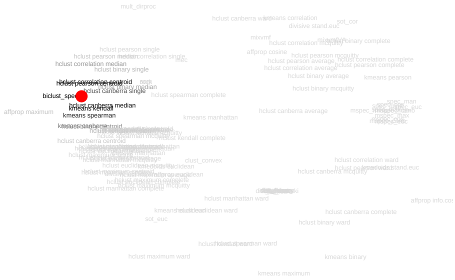

Space between methods:
local cluster ensemble

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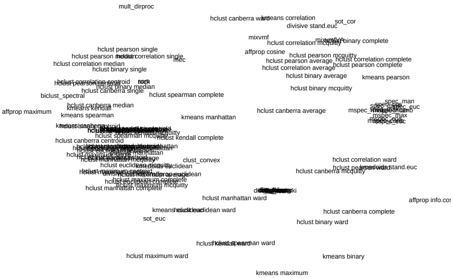

Example Discovery

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

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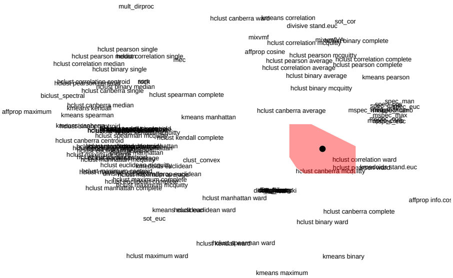
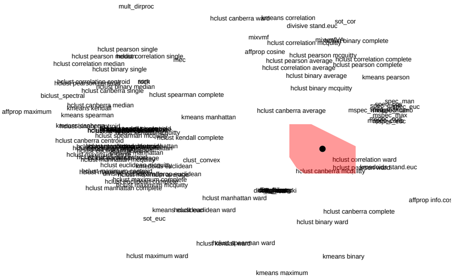


Mixture:

Example Discovery



Mixture:

0.39 Hclust-Canberra-McQuitty

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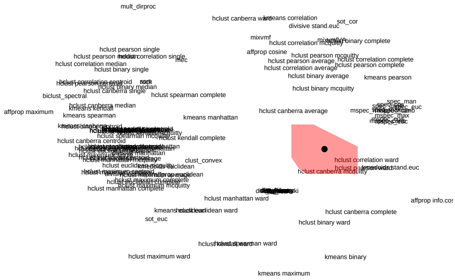

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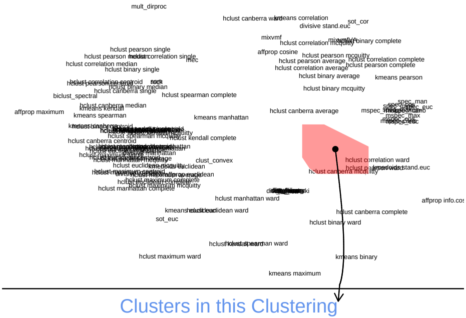
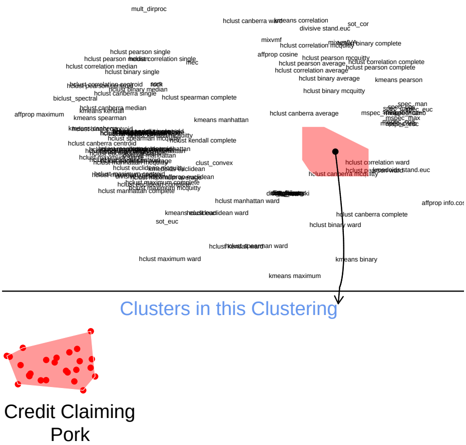


Mayhew

Example Discovery

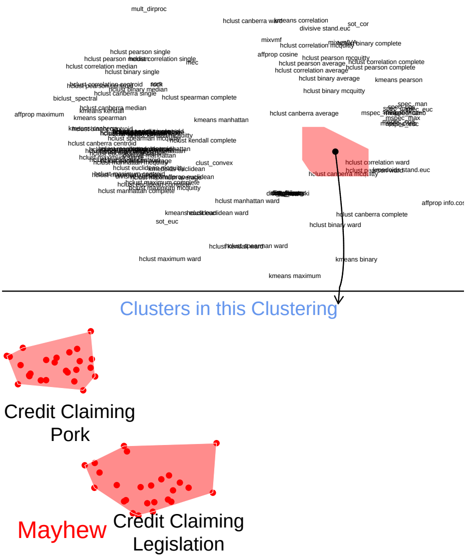


Credit Claiming, Pork:

"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"

Mayhew

Example Discovery

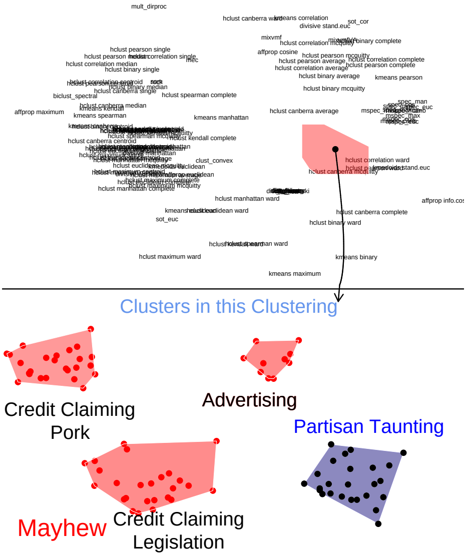


Credit Claiming, Legislation:
"As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period"

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

Sen. Lautenberg
on Senate Floor
4/29/04

- "Senator Lautenberg Blasts Republicans as 'Chicken Hawks' " [Government Oversight]

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Consequences for representation: Deliberative, Polarization, Policy

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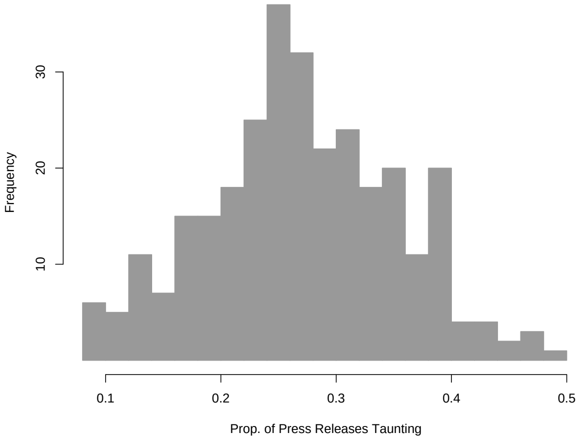

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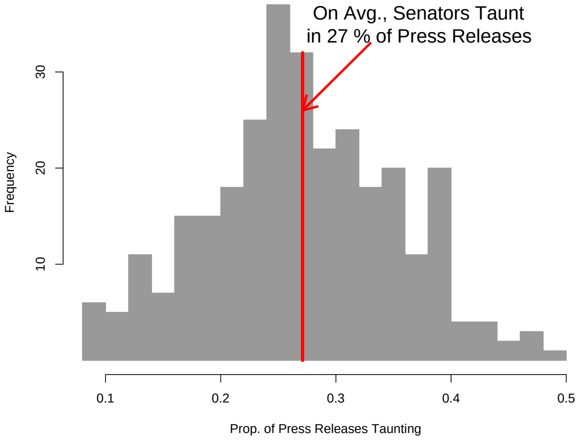
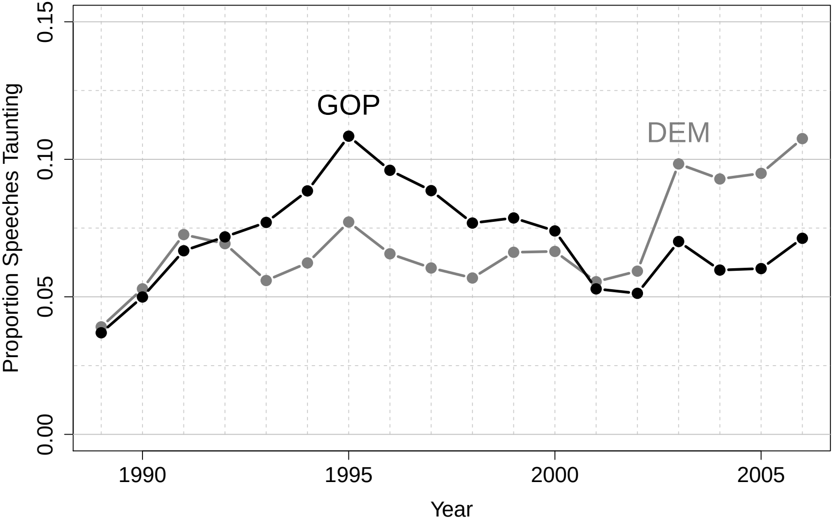


Over Time Tauting Rates in Speeches



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- 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

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

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

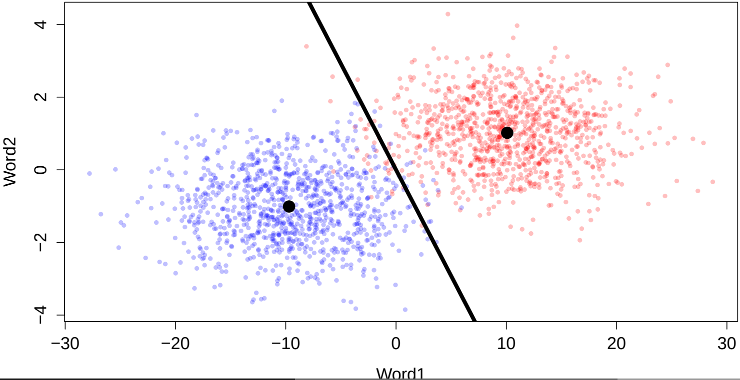
  $N \times J$ counting stop word usage rate
- $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_J)$
  Word weights.

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

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

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.

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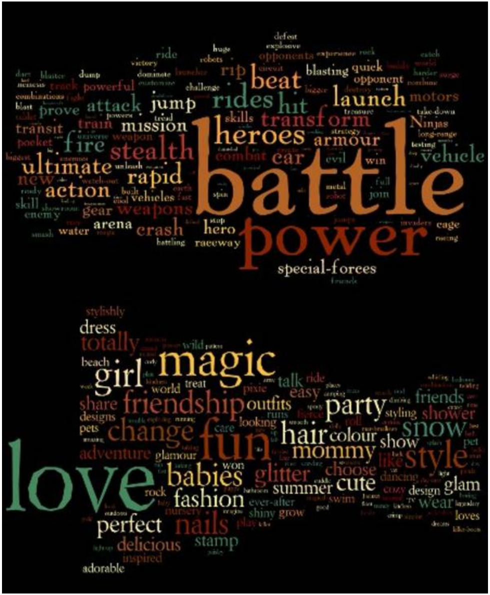

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Vague and Difficult to derive before hand

Congregational Language Across Sources

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Congressional Press Releases and Floor Speeches

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

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  - Randomly sample a press release
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  - Uncertainty about guess
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    - Minimum : All documents in one category

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- Maximum: $\Pr(\text{Press}) = \Pr(\text{Speech}) = 0.5$
- Minimum: $\Pr(\text{Press}) \to 0$ (or $\Pr(\text{Press}) \to 1$)

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Bigger mutual information $\Rightarrow$ better discrimination

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Bigger mutual information $\Rightarrow$ better discrimination

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)

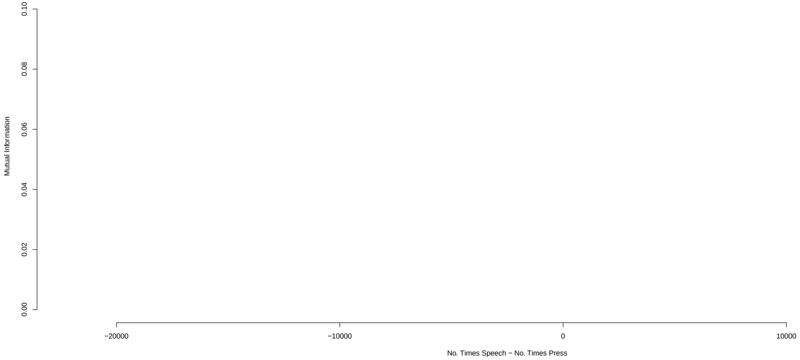
$$
\begin{aligned}
n_p &= \text{Number Press Releases} \\
n_s &= \text{Number of Speeches} \\
D &= n_p + n_s \\
n_j &= \sum_{i=1}^{D} X_{i,j} \qquad \text{(No. docs } X_j \text{ appears)} \\
n_{-j} &= \text{ No. docs } X_j \text{ does not appear} \\
n_{j,p} &= \text{No. press and } X_j \\
n_{j,s} &=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

A Method for Identifying Distinguishing Words

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



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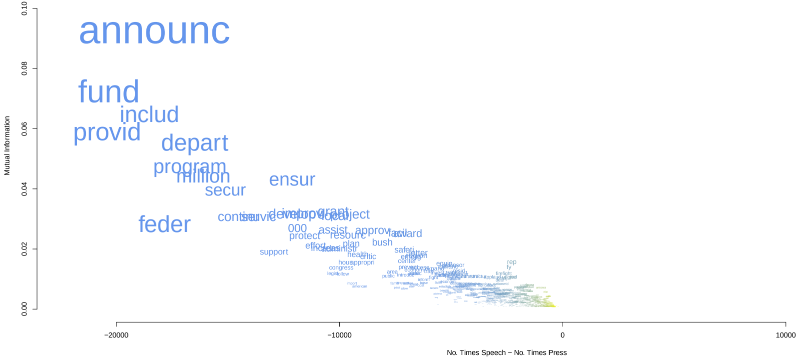

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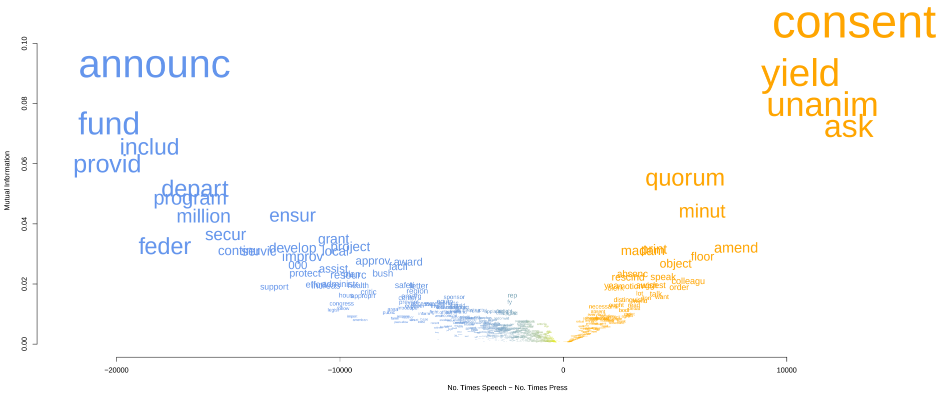

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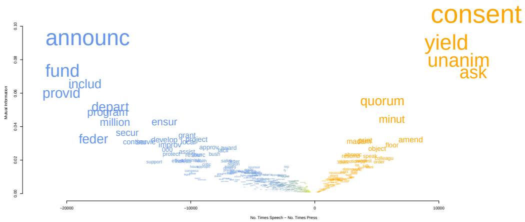

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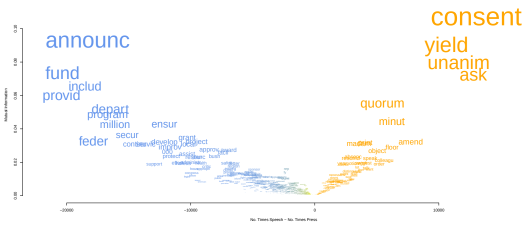
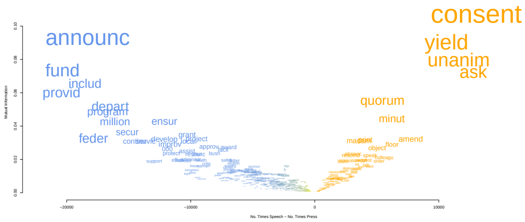


What's Different?

- Press Releases: Credit Claiming

What's Different About Press Releases



What's Different?

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

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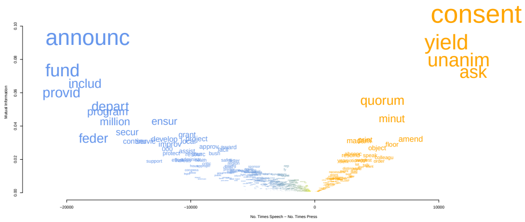

What's Different?

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

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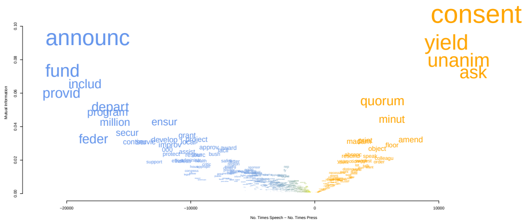

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- Sample 500 Press Releases, 500 Floor Speeches

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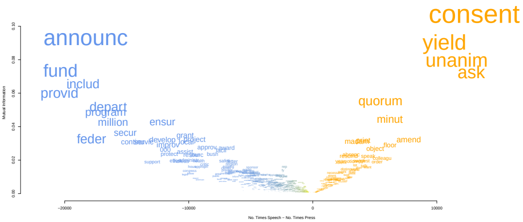

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- Press Releases: Credit Claiming
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- Sample 500 Press Releases, 500 Floor Speeches
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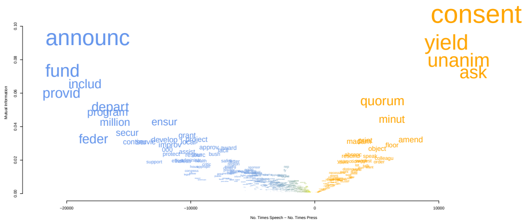

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- Procedural: 0% Press Releases, 44% Floor Speeches

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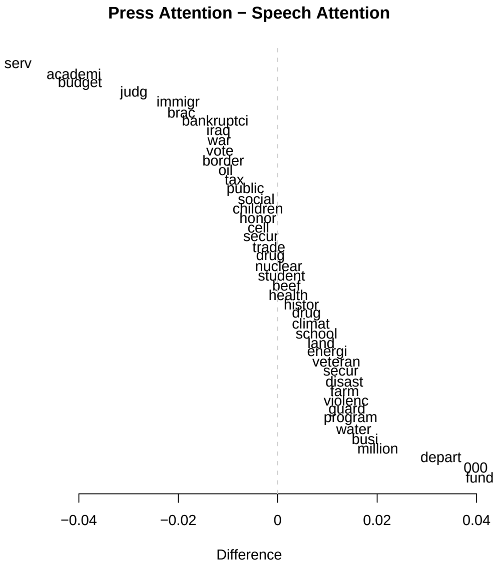

Fightin' Words $\rightsquigarrow$ An Introduction to Regularization

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

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Strategy⇝ Construct objective function on *proportions* (and then calculate log-odds)

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

Objective Function

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

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

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

Objective Function

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

Objective Function

$$\begin{aligned}\boldsymbol{\pi}_{\text{Republican}} &\sim \text{Dirichlet}(\boldsymbol{\alpha}) \\ \boldsymbol{x}_{\text{Republican}}|\boldsymbol{\pi}_{\text{Republican}} &\sim \text{Multinomial}(N_{\text{Republican}}, \boldsymbol{\pi}_{\text{Republican}})\end{aligned}$$

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

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

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p(\boldsymbol{\pi}|\boldsymbol{\alpha}, \boldsymbol{X}, \boldsymbol{Y}) &\propto p(\boldsymbol{\pi}|\boldsymbol{\alpha})p(\boldsymbol{x}_{\text{Republican}}|\boldsymbol{\pi}\boldsymbol{\alpha}, \boldsymbol{Y}) \\
&\propto \frac{\Gamma(\sum_{j=1}^{J}\alpha_j)}{\prod_j \Gamma(\alpha_j)} \prod_{j=1}^{J} \pi_j^{\alpha_j - 1} \pi_j^{x_{\text{Republican},j}}
\end{aligned}
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$$\pi^*_{\text{Republican},j} = \frac{x_{\text{Republican},j} + \alpha_j}{N_{\text{Republican}} + \sum_{j=1}^{J} \alpha_j}$$

Objective Function

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Calculating Log Odds Ratio

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

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

$$\begin{aligned}
\text{Var}(\log \text{Odds Ratio}_j) &\approx \frac{1}{x_{jD}+\alpha_j} + \frac{1}{x_{jR}+\alpha_j} \\
\text{Std. Log Odds}_j &= \frac{\log \text{Odds Ratio}_j}{\sqrt{\text{Var}(\log \text{Odds Ratio}_j)}}
\end{aligned}$$

Applying the Model

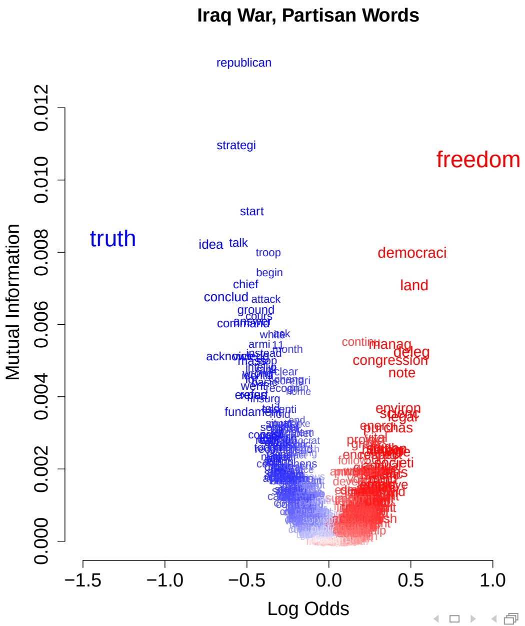
https://gist.github.com/thiagomarzagao/5851207

How do Republicans and Democrats differ in debate?

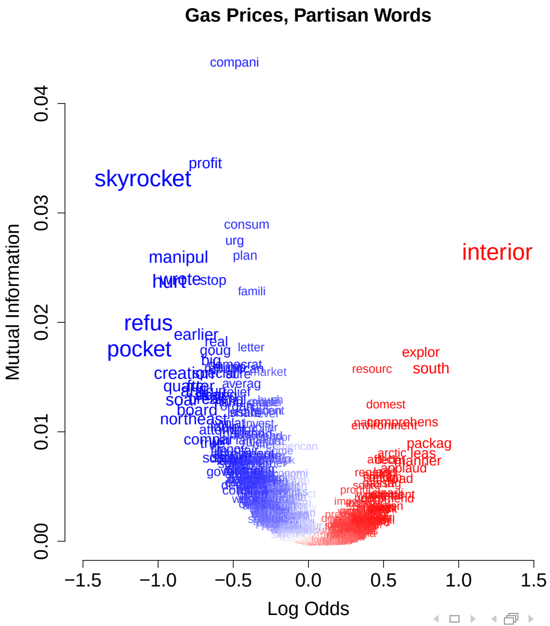
Condition on topic and examine word usage

- 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



Mutual Information, Standardized Log Odds



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

Figure 3: Average partisanship of speech, penalized estimates