Political Science 452: Text as Data

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Where We've Been, Where We're Going

- Class 1: Finding Text Data
- Class 2: Representing Texts Quantitatively
- Class 3: Dictionary Methods for Classification
- Class 4: Comparing Language Across Groups
- Class 5: Texts in Space
- Class 6: Clustering
- Class 7: Topic models
- Class 8: Supervised methods for classification
- Class 9: Ensemble methods for classification
- Class 10: Scaling Speech

Entropy Explanation (Hanna Wallach Slides)

- Probability and Information are intimately related
- Less probable events $\rightarrow$ more information
- More certain something will occur, less information you gain knowing it occurred
- Focus on the occurrence of binary event A

Basic unit of information built around event A for which we are maximally uncertain:

$$\mathrm{P}[A] \quad = \quad P[\neg A] = 1/2$$

Entropy Explanation (Hanna Wallach Slides)

Desired properties

- Information, Probability: Inversely related
- Certain event will occur and it does: no information gained
- Certain event will not occur and it does: infinite information gained
- Maximally uncertain: we should gain one unit of information by learning that A or $\neg A$ occurred

Entropy Explanation (Hanna Wallach Slides)

Information in event A is then,

$$I(A) = \log_2 \frac{1}{\mathrm{P}[A]}$$

And for a series of disjoint events, the entropy is

$$H(A_1, \ldots, A_n) = \sum_{i=1}^{N} \mathrm{P}[A_i] \log_2 \frac{1}{\mathrm{P}[A_i]}$$

Recall: use entropy to describe how well words separate classes (Week 4):
Conditional entropy(w): Information that remains after condition on w

$$\text{Mutual information}(w) = \text{Entropy} - \text{Conditional Entropy}(w)$$

Measures the reduction in information$\rightsquigarrow$ greater reduction, less information, w is a better predictor.

Clustering

Last week: measures of similarity between documents.

- Place documents in space
- Measure similarity, dissimilarity of documents

This week: identify groups of similar documents

Fully Automated Clustering Algorithms:

- Task: partition documents
  - Mutual exclusive
  - Exhaustive
  - Set of Groupings
- Task name: Clustering
  - Estimate: categories
  - Estimate: each document's category
- Label Clusters in Clustering (Week 4 Methods!)
- How to use clustering methods: (THINK!)
  - Tune clustering methods to problem (Discuss more next week, virtue of statistical models)

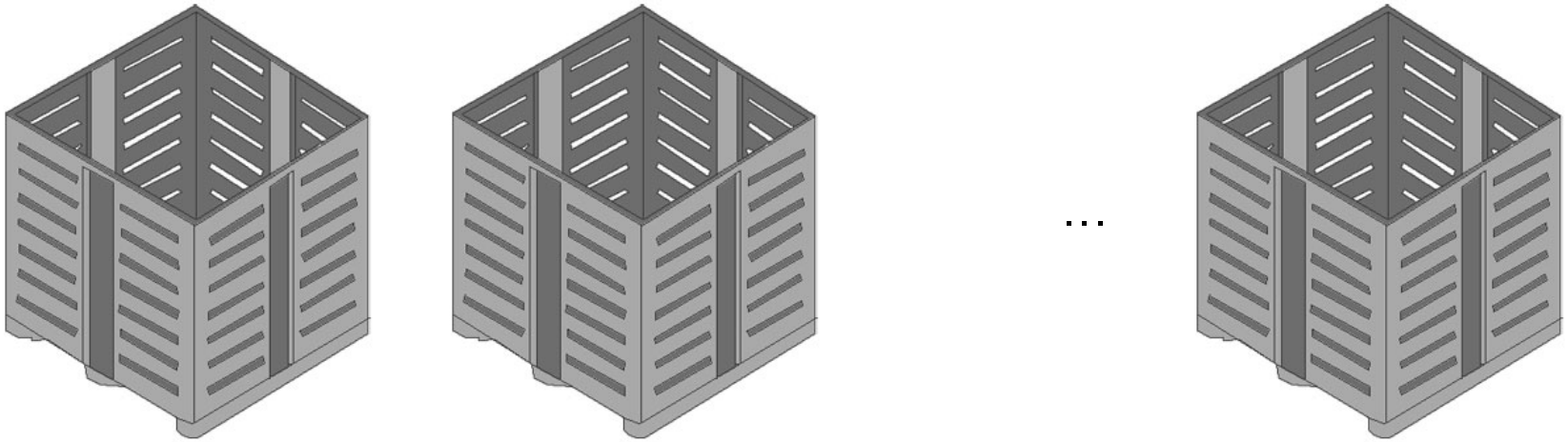
Computer Assisted Clustering Algorithms (Grimmer and King 2011)

Perspective 1: Supervised Methods

Document 1 Document 2 $\cdots$ Document N

Perspective 1: Supervised Methods

Document 1 Document 2 ··· Document N



Bins Known, Bin Assignment Estimated

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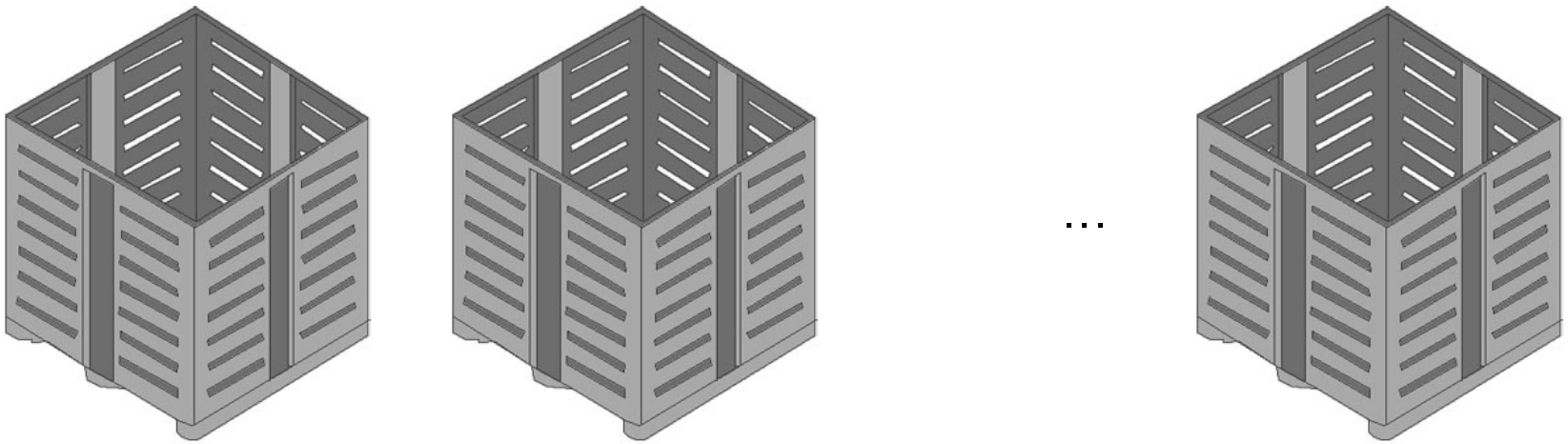

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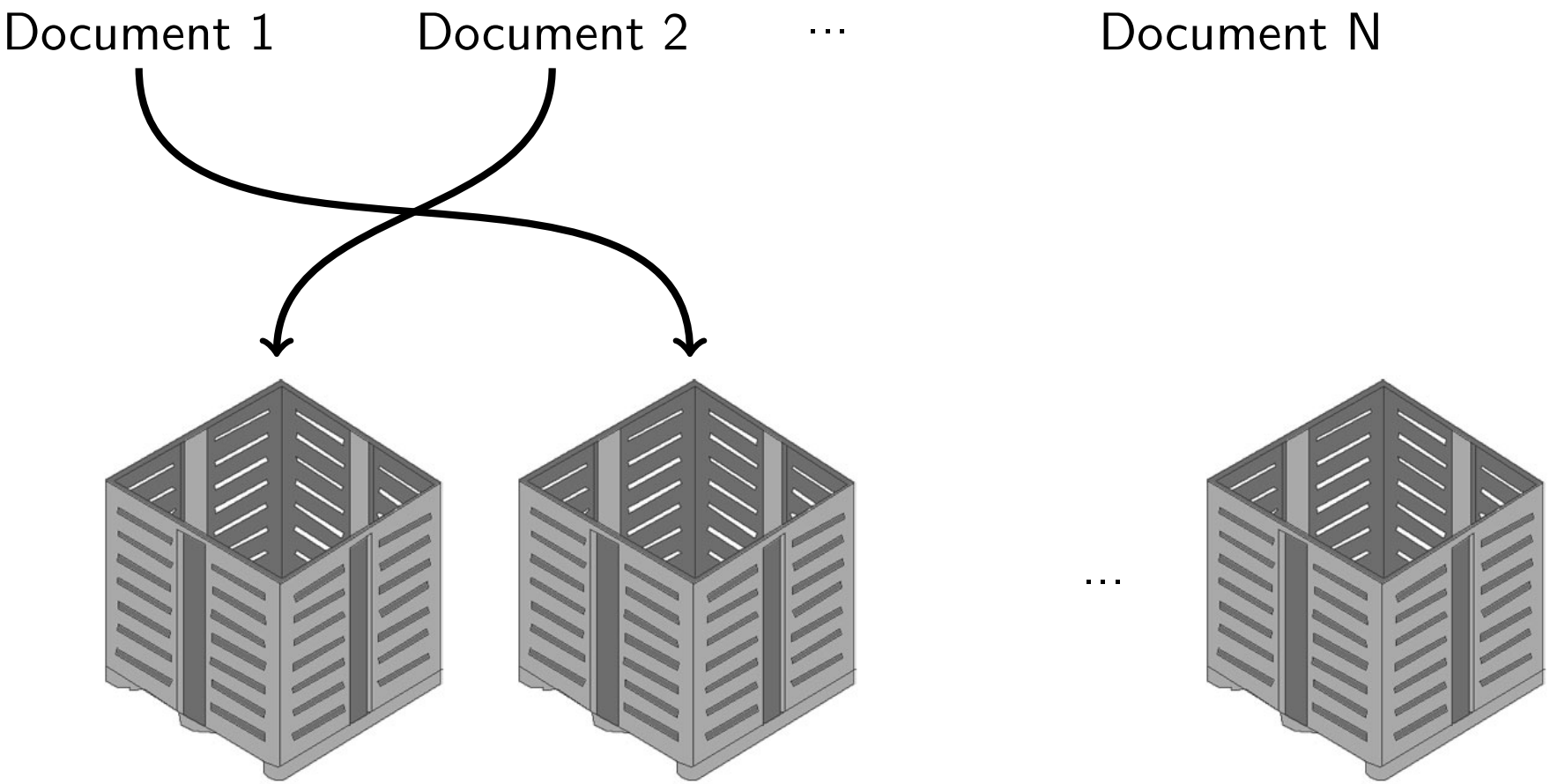

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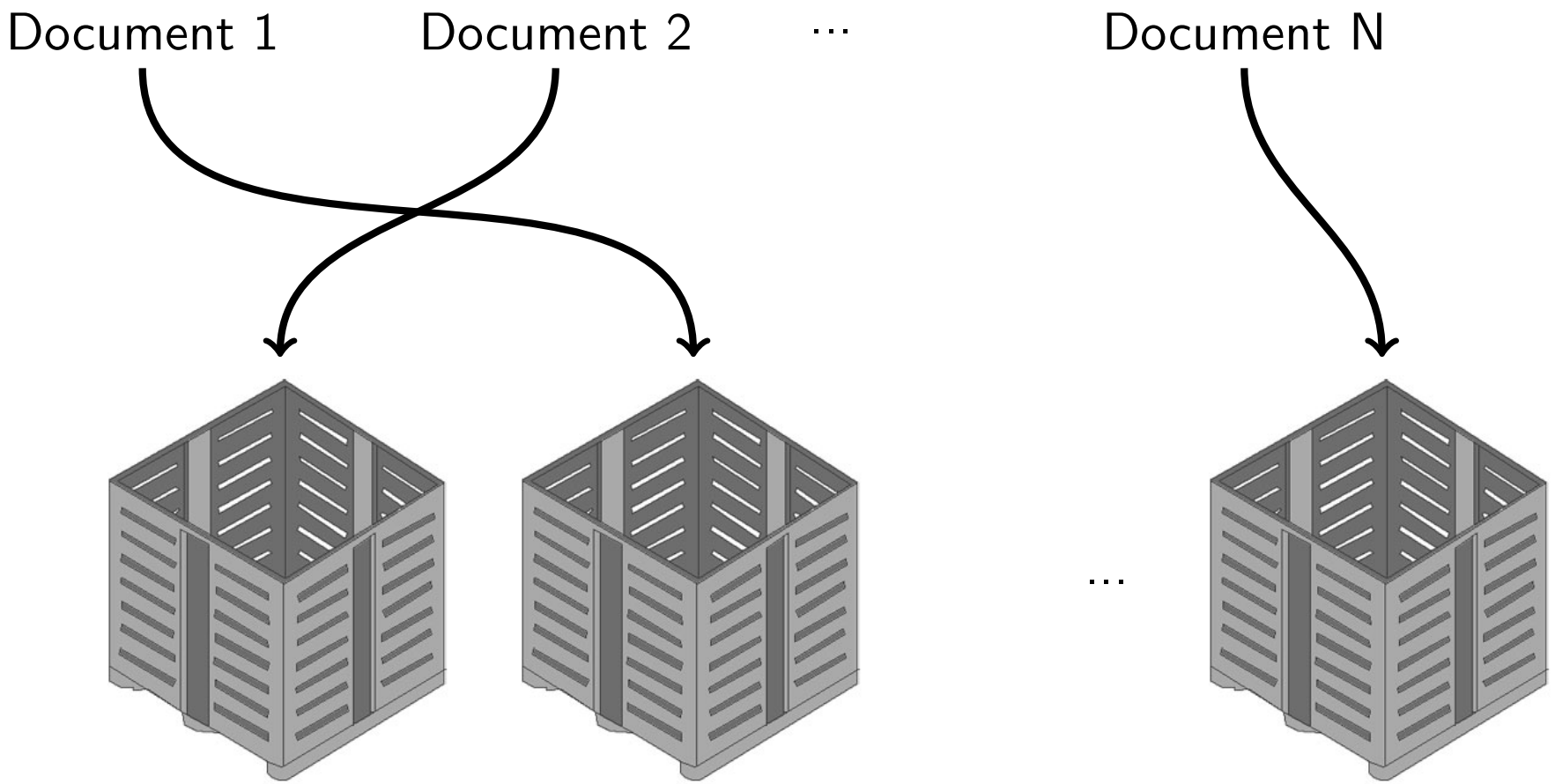

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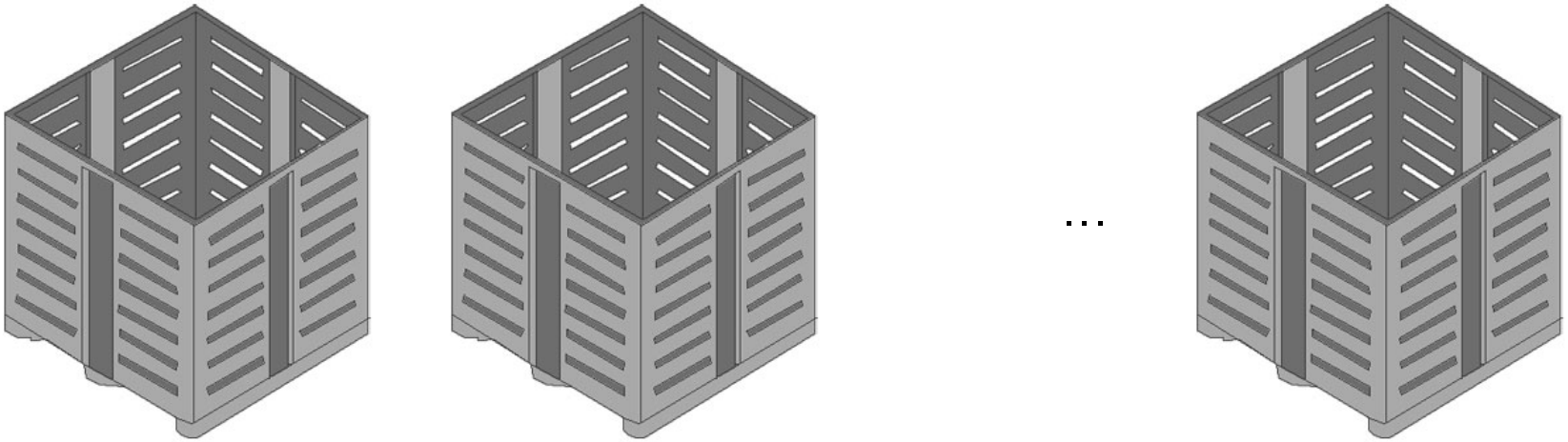

Bins and Bin Assignments Estimated

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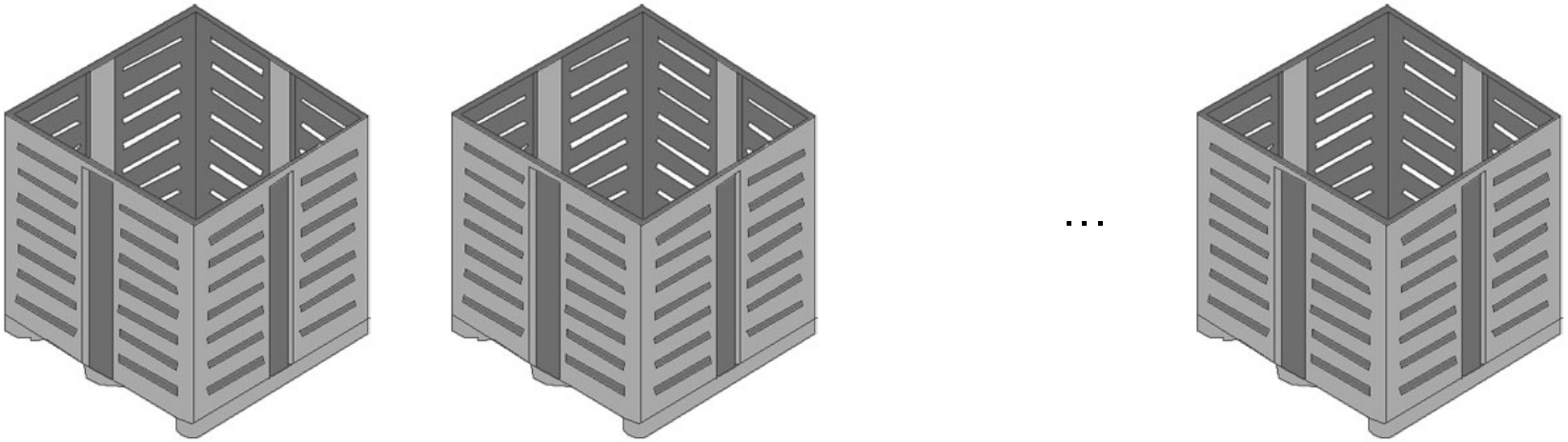

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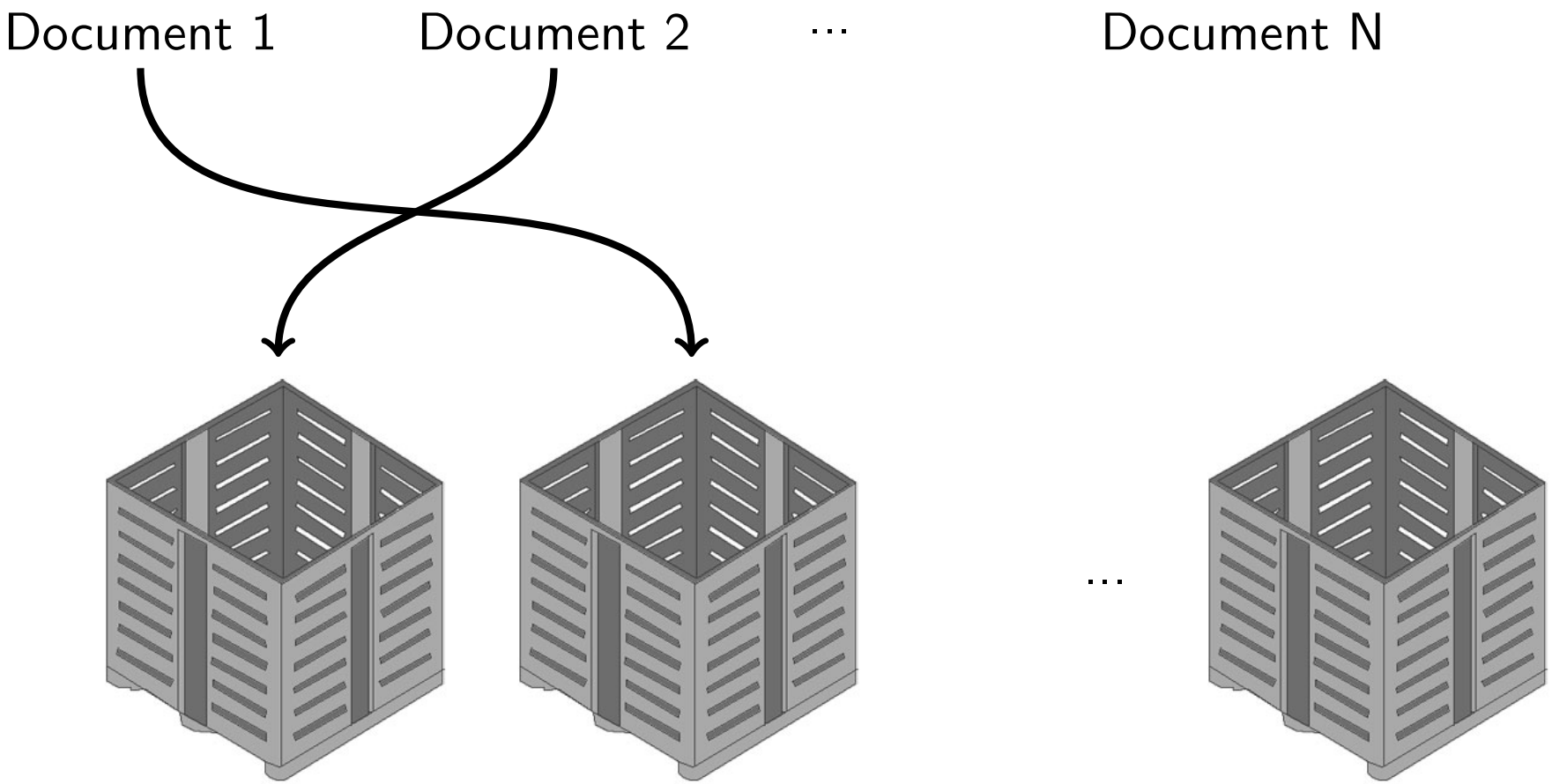

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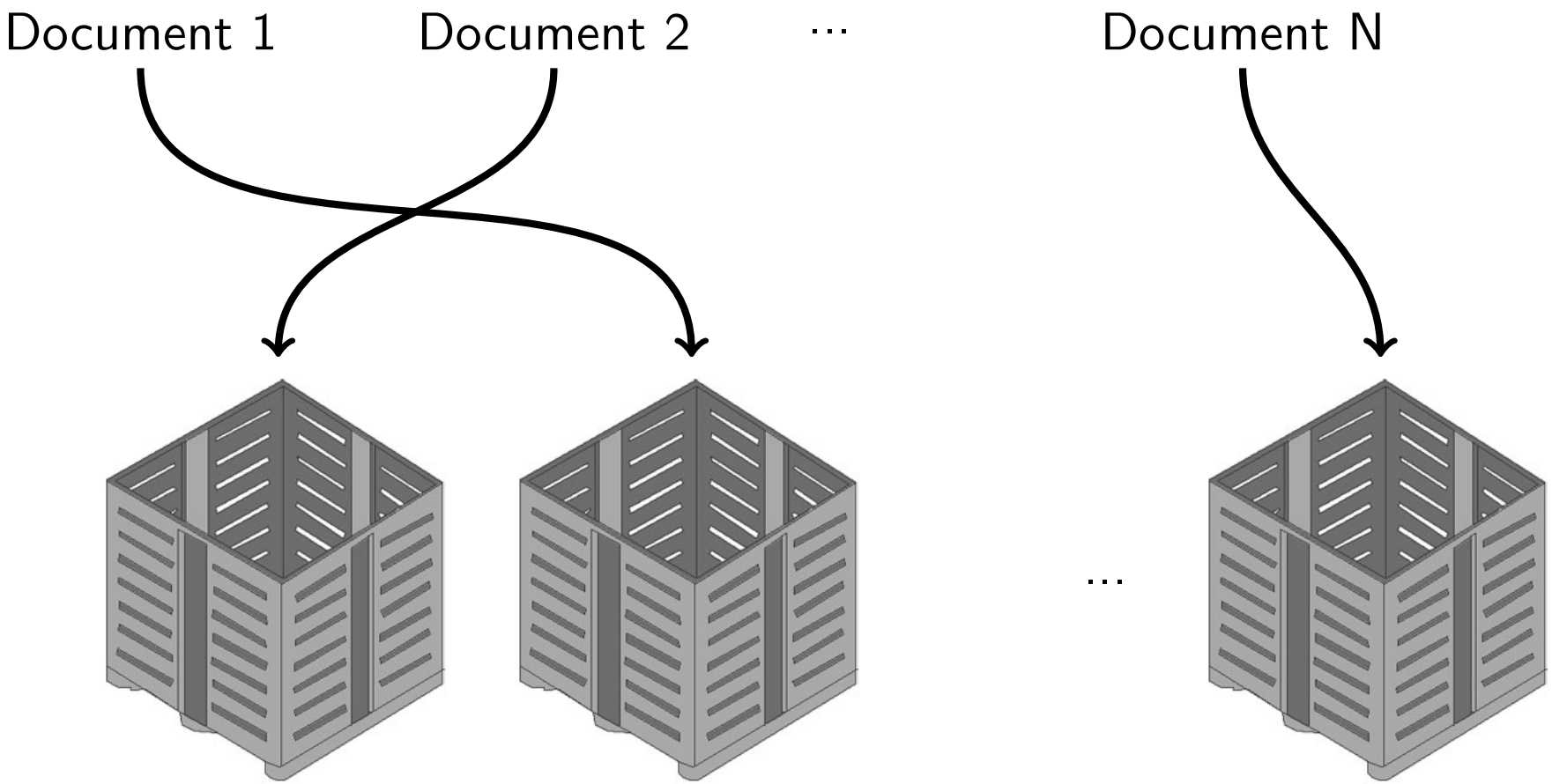

Bins and Bin Assignments Estimated

Perspective 2: Clustering

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|Doc1, Doc3, Doc6, Doc7|

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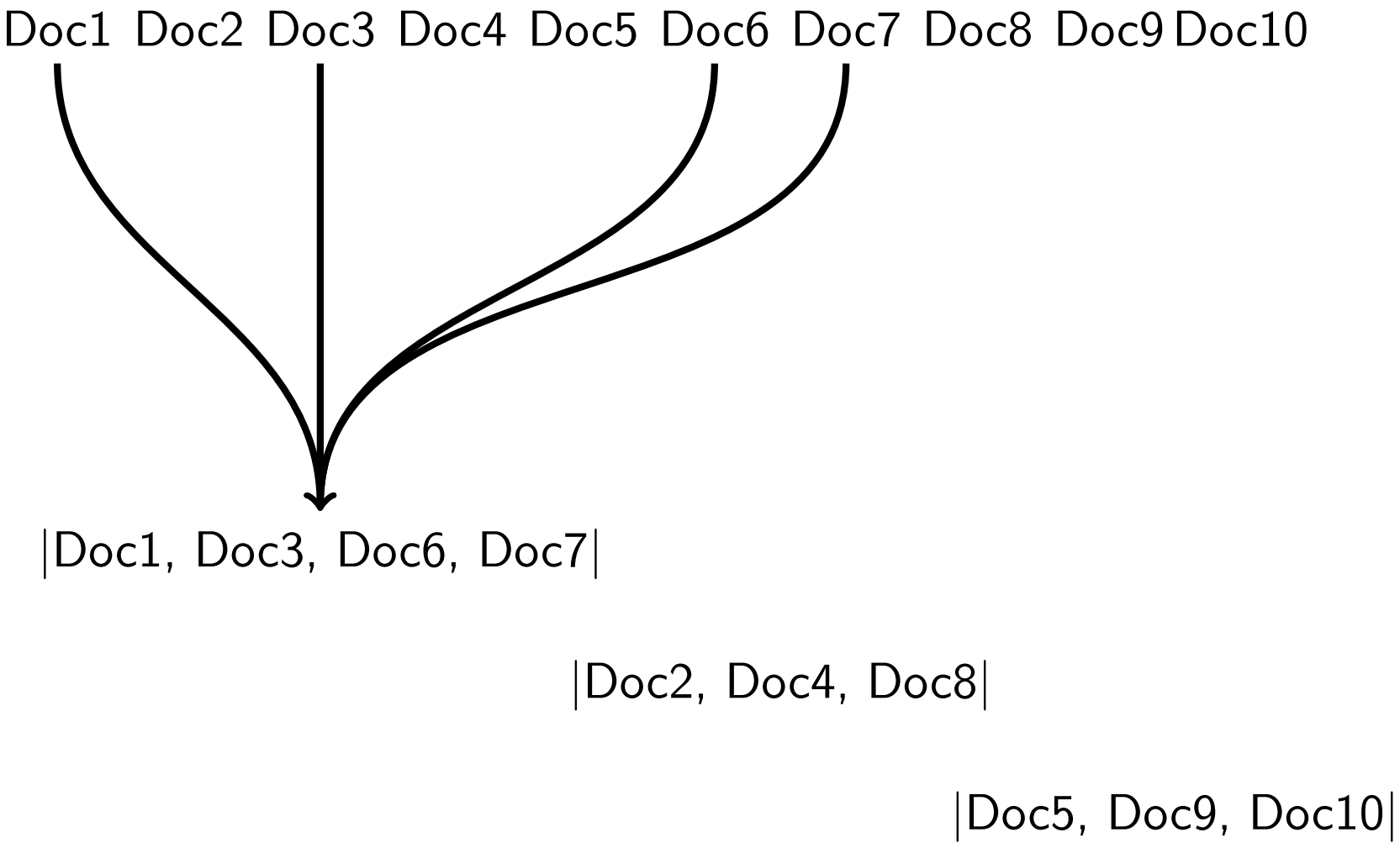

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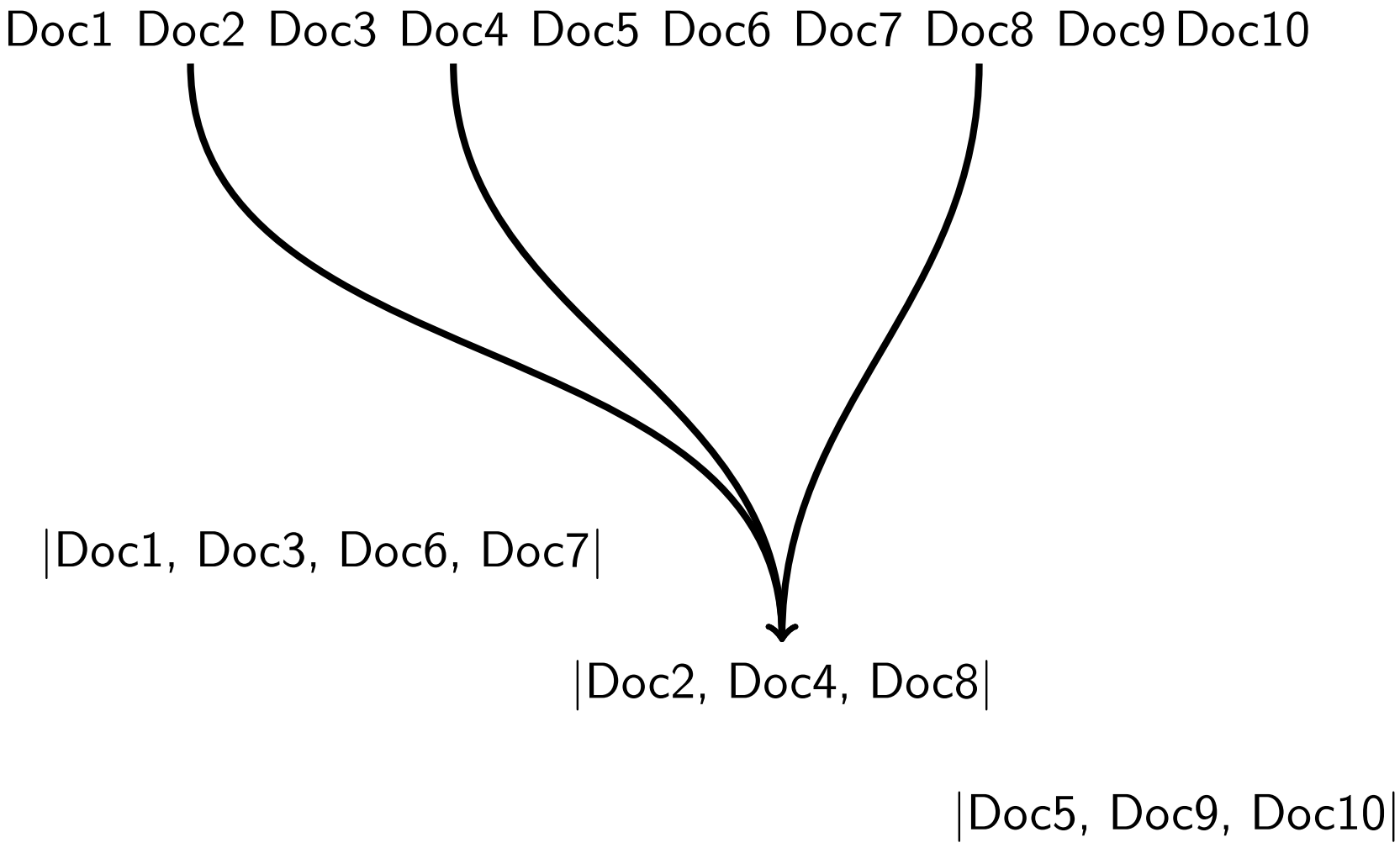

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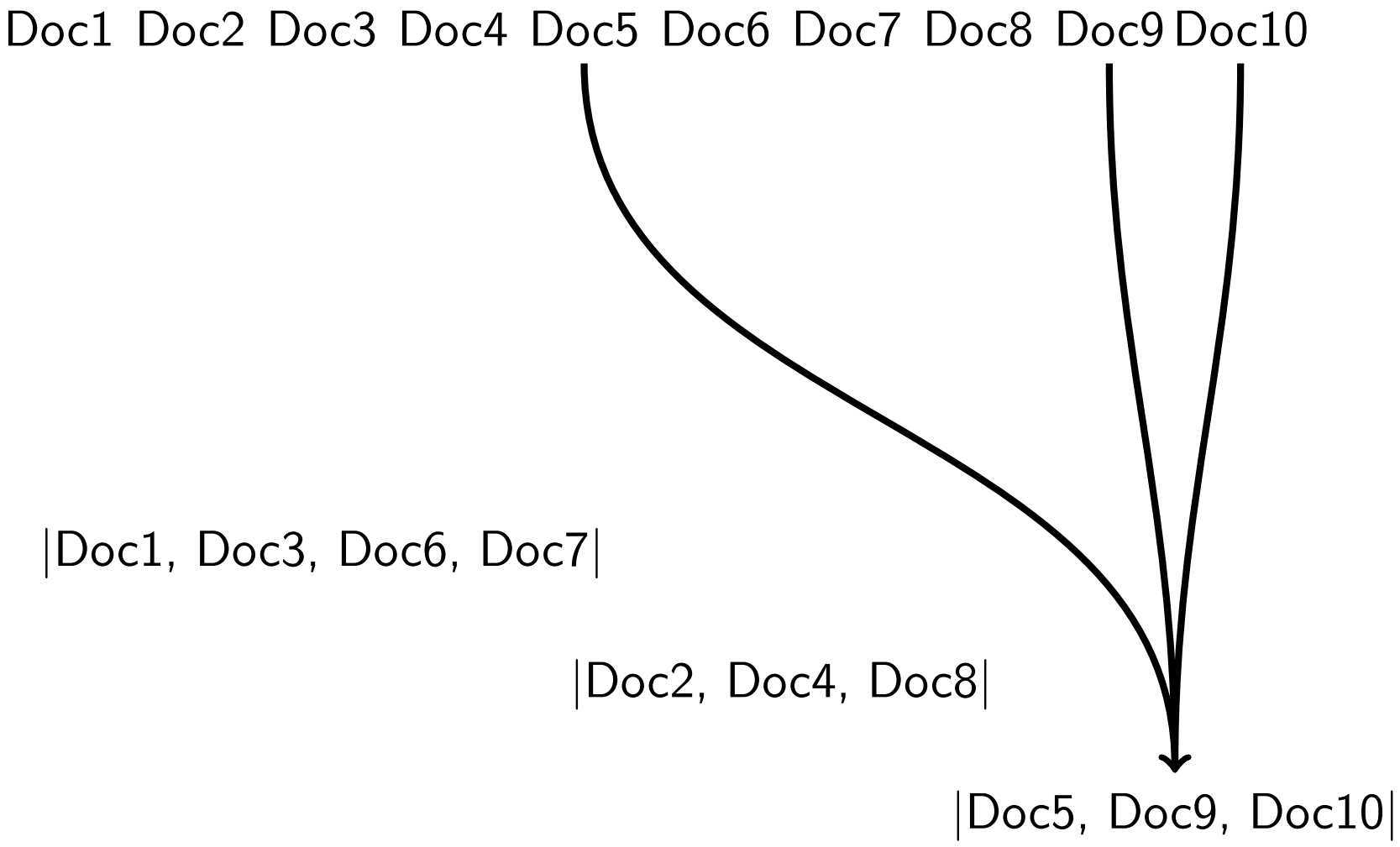

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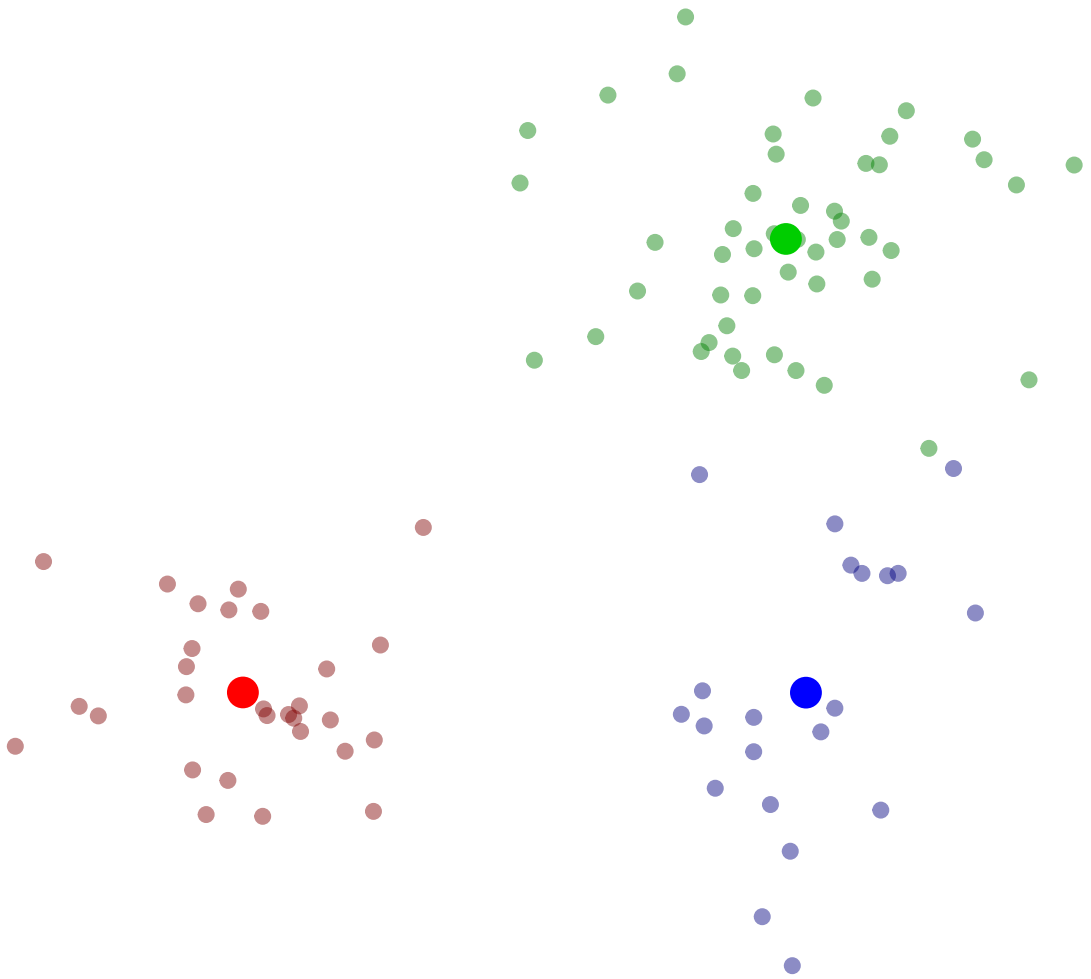

Perspective 4

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Compression: Retain only cluster label for documents in same group

Perspective 5

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  - Clustering methods suggest new (model and data driven) ways to organize texts

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- How do we formulate new ways to organize texts?
  - Clustering methods suggest new (model and data driven) ways to organize texts
  - Using new method, new lens to look at politics

Clustering: Terms and Notation

Set of documents $i = 1, 2, \ldots, N$.
Partition documents into $j = 1, \ldots, K$ clusters
Call c_i document i's cluster assignment

- $c_i = 2 \rightsquigarrow$ Document i assigned to second cluster
- $c_{10} = 4 \rightsquigarrow$ Document 10 assigned to fourth cluster

Define clustering as a partition of observations. Mathematically:

$$\mathbf{c} = (c_1, c_2, \ldots, c_N)$$

$\mathbf{c}$ constitutes the clustering.
Two trivial clusterings

$$\begin{aligned} \mathbf{c} &= (1, 2, \ldots, N) \\ \mathbf{c} &= (1, 1, \ldots, 1) \end{aligned}$$

Estimating Clustering: Data and Assumptions

Steps common across Fully Automated Clustering methods

- Assume similarity/dissimilarity between objects (Some methods assume implicitly)
- Define objective function
  - Domain (things you put in the function): space of clusterings
  - Range (thing that comes out of function): measure of clustering's performance
- Use approximate inference/optimization algorithm to identify optimal solution

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- Use approximate inference/optimization algorithm to identify optimal solution $\leftarrow$ Huge search space, very difficult (and interesting!) problem, only hinted at here

An Example FAC Method

K-means: most commonly used clustering algorithm.

Story: Data are grouped in K clusters and each cluster has a center or mean.

$\rightarrow$ Two types of parameters to estimate

1) For each cluster j, $(j = 1, \ldots, K)$

   r_{ij} =Indicator, Document i assigned to cluster j

   $\mathbf{r}_j = (r_{1j}, r_{2j}, \ldots, r_{Nj})$

   $\mathbf{r} = (\mathbf{r}_1^{'}, \mathbf{r}_2^{'}, \ldots, \mathbf{r}_K^{'})$ ($N \times K$ matrix)

   Note: Same information in $\mathbf{r}$ and $\mathbf{c}$

2) For each cluster j

   $\boldsymbol{\mu}_j$ a cluster center for cluster j.

   $\boldsymbol{\mu}_j = (\mu_{1j}, \mu_{2j}, \ldots, \mu_{Mj})$

Notation. Representation of document i:

$$\mathbf{y}_i = (y_{i1}, y_{i2}, \ldots, y_{iM})$$

Specifying the Method

1) Assume Euclidean distance between objects.
2) Objective function

$$f(\mathbf{r}, \boldsymbol{\mu}, \mathbf{y}) = \sum_{i=1}^{N} \sum_{j=1}^{K} r_{ij} \left(\sum_{m=1}^{M} (y_{im} - \mu_{km})^2 \right)$$

Goal:
Choose $\mathbf{r}^*$ and $\boldsymbol{\mu}^*$ to minimize $f(\cdot, \cdot, \mathbf{y})$
Two observations:

- If $K = N$ $f(r^*, \boldsymbol{\mu}^*, \mathbf{y}) = 0$ (Minimum)
  - Each observation in own cluster
  - $\boldsymbol{\mu}_i = \mathbf{y}_i$
- If $K = 1$, $f(r^*, \boldsymbol{\mu}^*, \mathbf{y}) = N \times \sigma^2$
  - Each observation in one cluster
  - Center: average of documents

Specifying the Method

1) Assume Euclidean distance between objects
2) Objective function
3) Algorithm for optimization

Iterative algorithm, Each Iteration t

- Conditional on $\boldsymbol{\mu}^{t-1}$ (from previous iteration), choose $\mathbf{r}^t$
- Conditional on $\mathbf{r}^t$, choose $\boldsymbol{\mu}^t$

Repeat until convergence, measured as change in f.

$$\text{Change} \quad = \quad f(\boldsymbol{\mu}^t, \mathbf{r}^t, \mathbf{y}) - f(\boldsymbol{\mu}^{t-1}, \mathbf{r}^{t-1}, \mathbf{y})$$

Specifying the Method

$$f(\mathbf{r}, \boldsymbol{\mu}, \mathbf{y}) \quad = \quad \sum_{i=1}^{N} \sum_{j=1}^{K} r_{ij} \left(\sum_{m=1}^{M} (y_{im} - \mu_{km})^2 \right)$$

Algorithm for estimation:
Begin: initialize $\boldsymbol{\mu}_1^{t-1}, \boldsymbol{\mu}_2^{t-1}, \ldots, \boldsymbol{\mu}_K^{t-1}$
Choose $\mathbf{r}^t$

$$r_{ij}^t = \begin{cases} 1 \text{ if } j = \arg\min_k \sum_{m=1}^{M} (y_{im} - \mu_{km})^2 \\ 0 \text{ otherwise ,} \end{cases} .$$

In words: Assign each document $\mathbf{y}_i$ to the closest center $\boldsymbol{\mu}_k$

$$f(\mathbf{r}, \boldsymbol{\mu}, \mathbf{y}) = \sum_{i=1}^{N} \sum_{j=1}^{K} r_{ij} \left(\sum_{m=1}^{M} (y_{im} - \mu_{km})^2 \right)$$

Conditional on $\mathbf{r}^t$, choose $\boldsymbol{\mu}^t$
Let's focus on $\boldsymbol{\mu}_k$

$$f(\mathbf{r}, \boldsymbol{\mu}_k, \mathbf{y})_k = \sum_{i=1}^{N} r_{ik} \left(\sum_{m=1}^{M} (y_{im} - \mu_{km})^2 \right)$$

Focus on just μ_{km}

$$f(\mathbf{r}, \mu_{km}, \mathbf{y})_{km} = \sum_{i=1}^{N} r_{ik}(y_{im} - \mu_{km})^2$$

Quadratic: take derivative, set equal to zero (second derivative test works)

$$\begin{aligned}
\frac{\partial f(\mathbf{r}, \mu_{km}, \mathbf{y})_{km}}{\partial \mu_{km}} &= -2\sum_{i=1}^{N} r_{ik}(y_{im} - \mu_{km}) \\
2\sum_{i=1}^{N} r_{ik}(y_{im} - \mu_{km}^t) &= 0 \\
\sum_{i=1}^{N} r_{ik} y_{im} - \mu_{km}^t \sum_{i=1}^{N} r_{ik} &= 0 \\
\frac{\sum_{i=1}^{N} r_{ik} y_{im}}{\sum_{i=1}^{N} r_{ik}} &= \mu_{km}^t
\end{aligned}$$

$$\boldsymbol{\mu}_k^t = \frac{\sum_{i=1}^N r_{ik}\mathbf{y}_i}{\sum_{i=1}^N r_{ik}}$$

In words:

- $\boldsymbol{\mu}_k^t$ is the average of documents assigned to the kth cluster

Algorithm, In Words

- Conditional on center estimates, assign documents to closest cluster centers
- Conditional on document assignments, cluster centers are averages of documents assigned to the cluster

Expectation-Maximization (EM) [connection guarantees convergence]

- Estimation of $r \rightsquigarrow$ Expectation step (data augmentation)
- Estimation of $\boldsymbol{\mu}_k \rightsquigarrow$ Maximization Step

Visual Example

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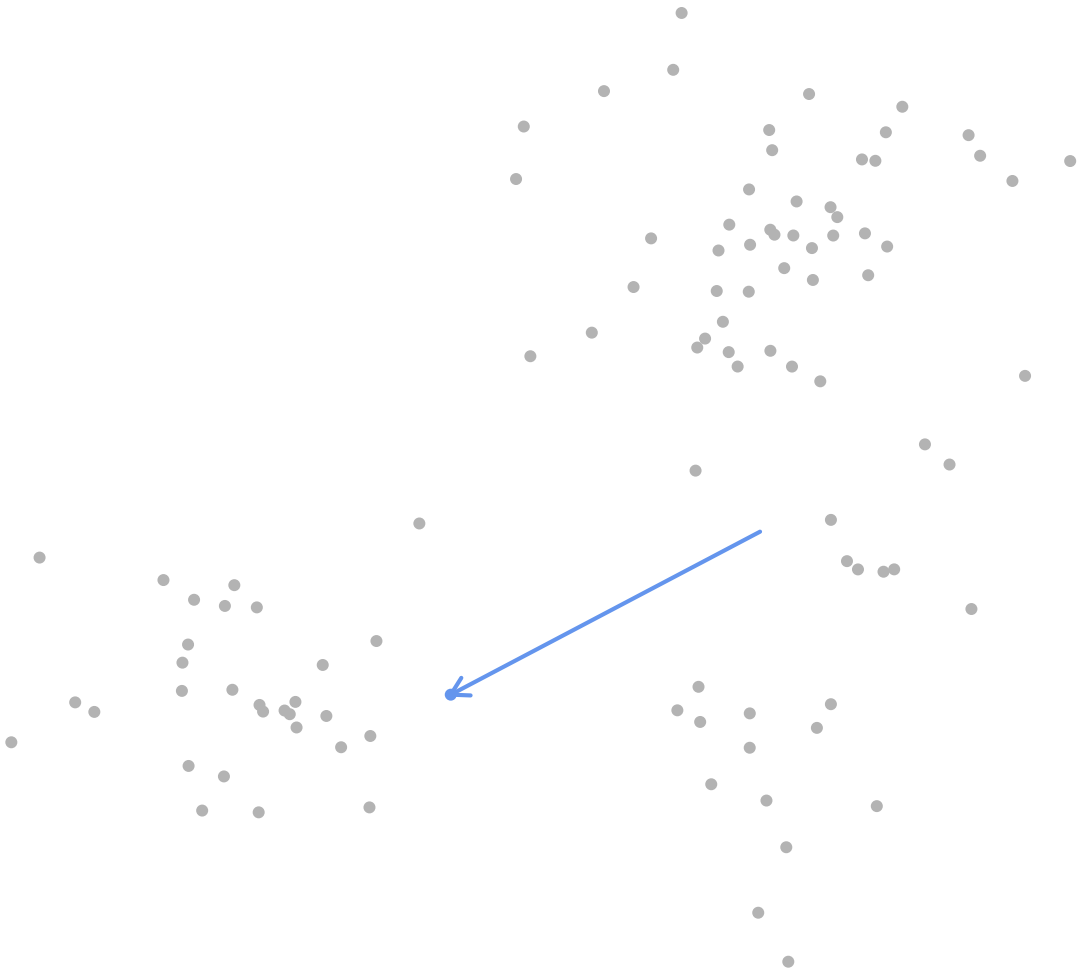

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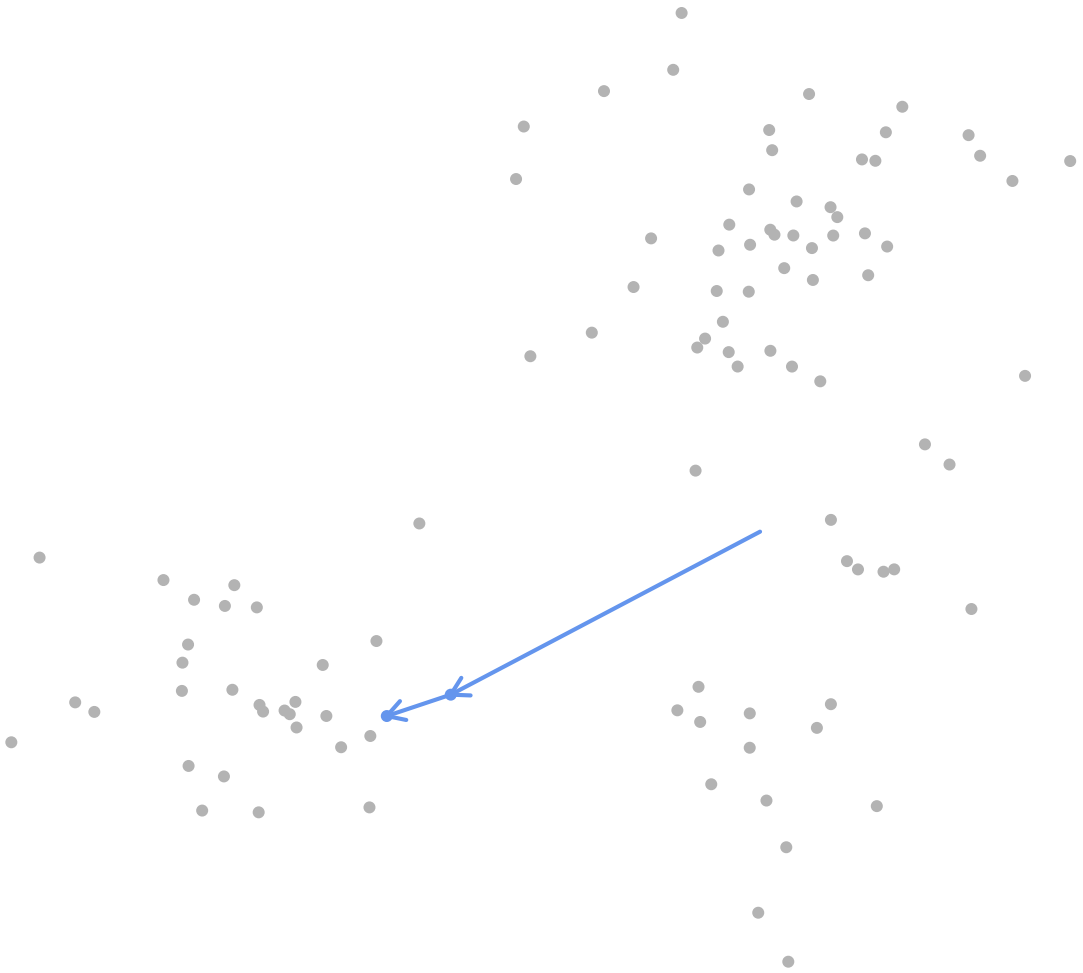

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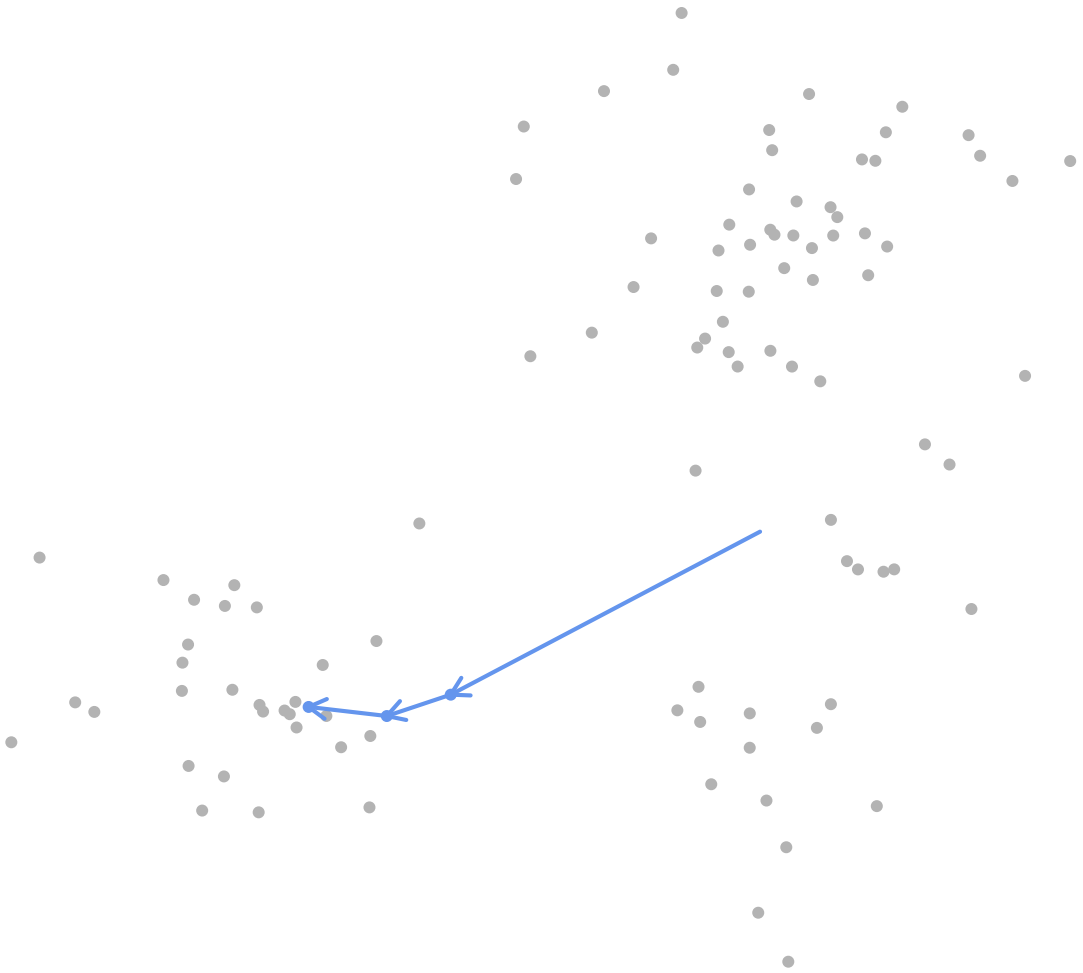

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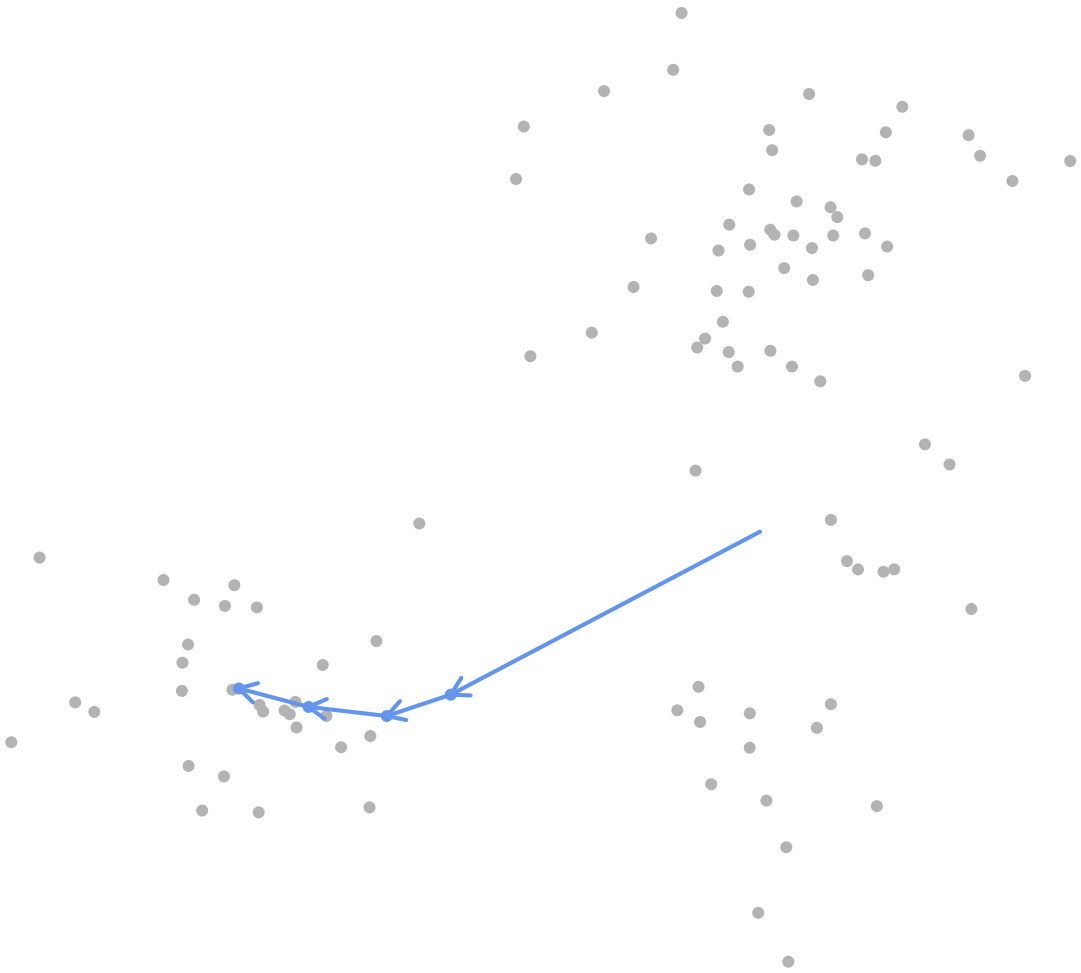

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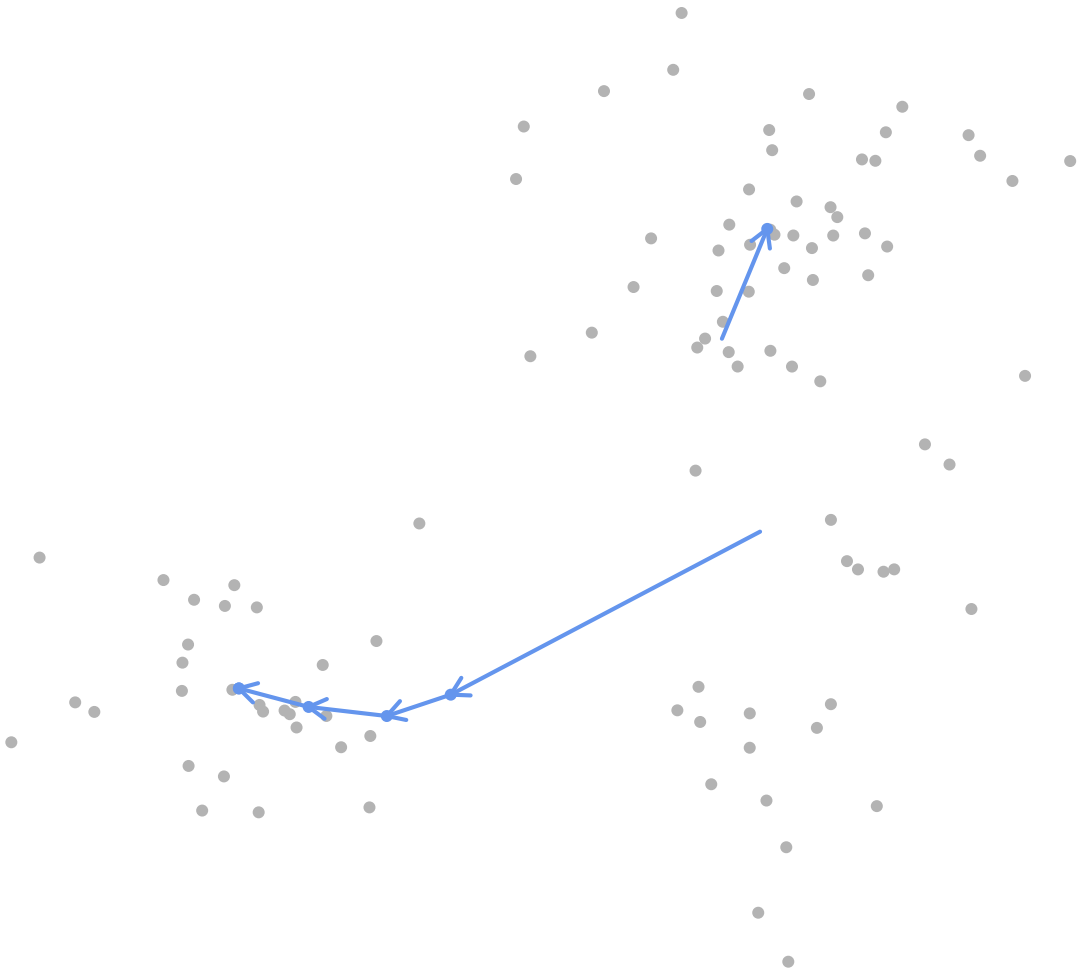

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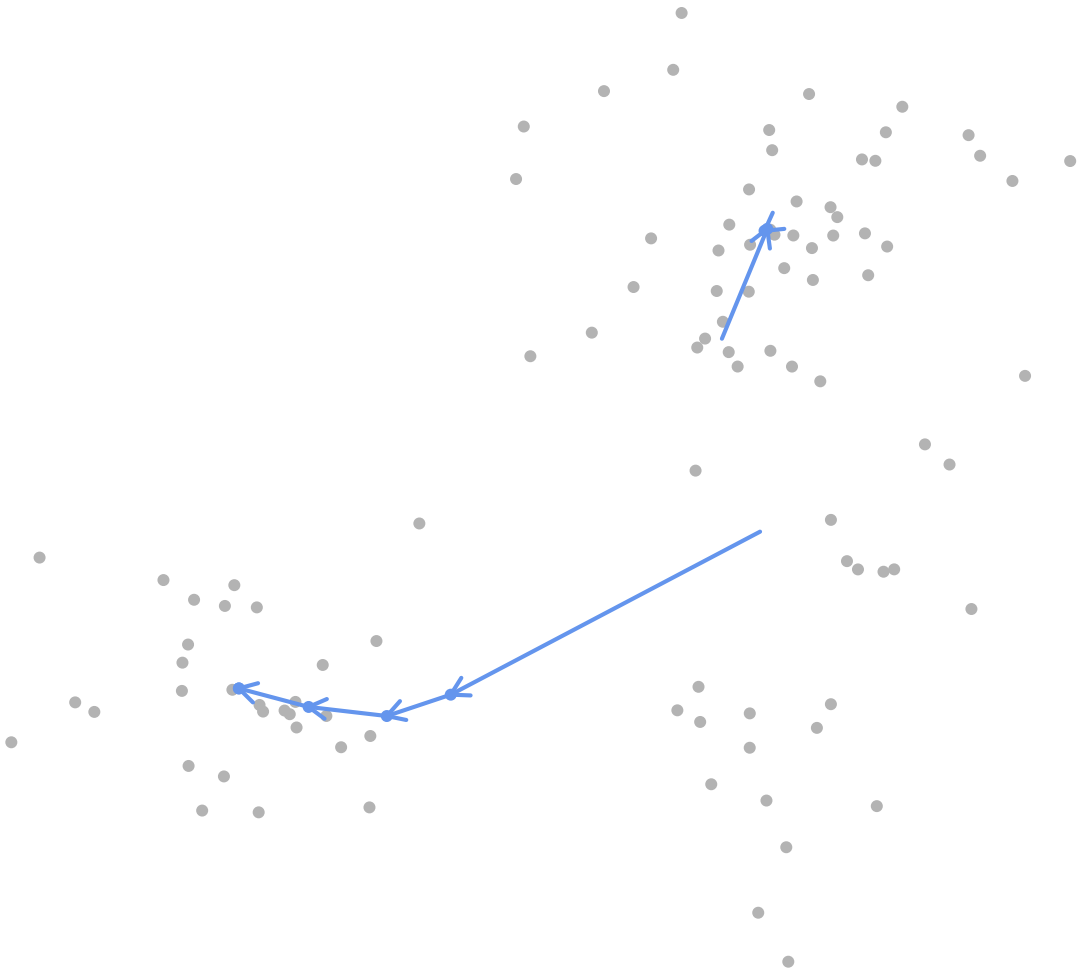

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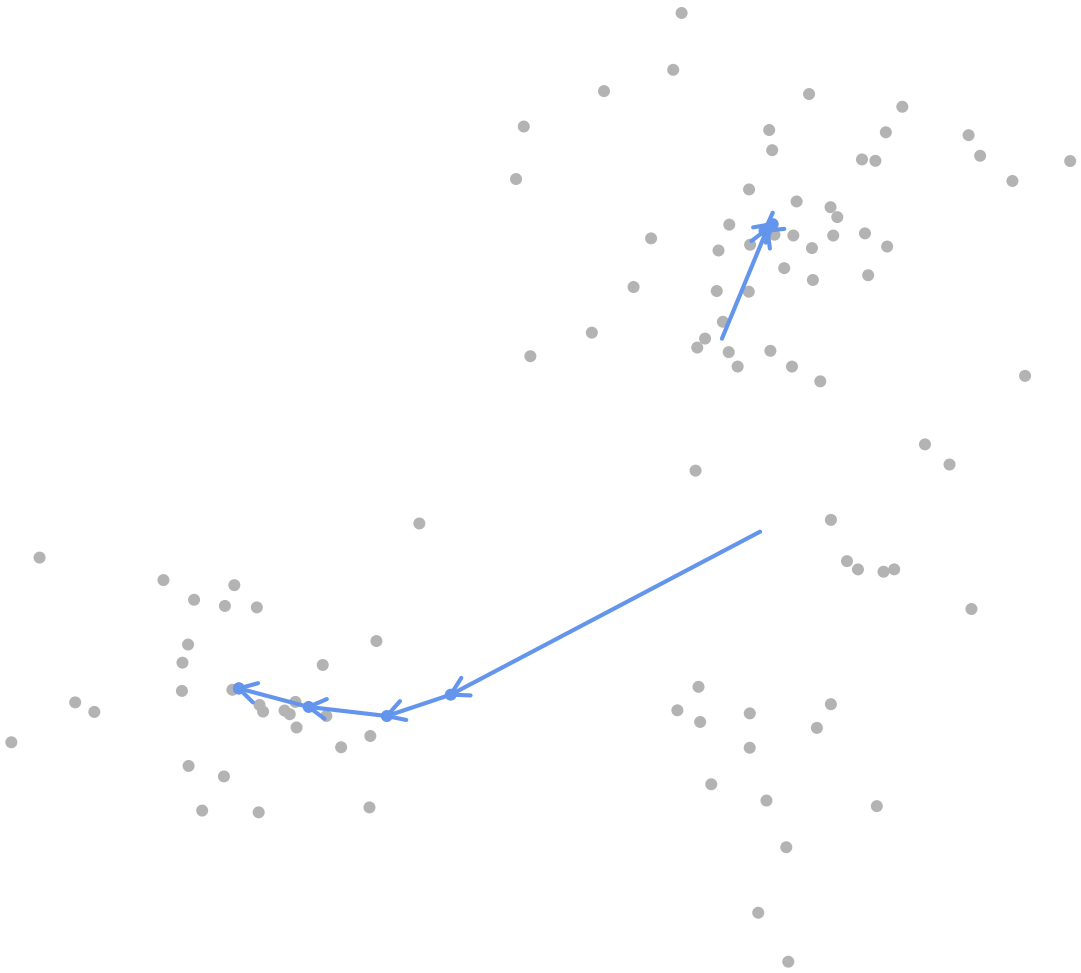

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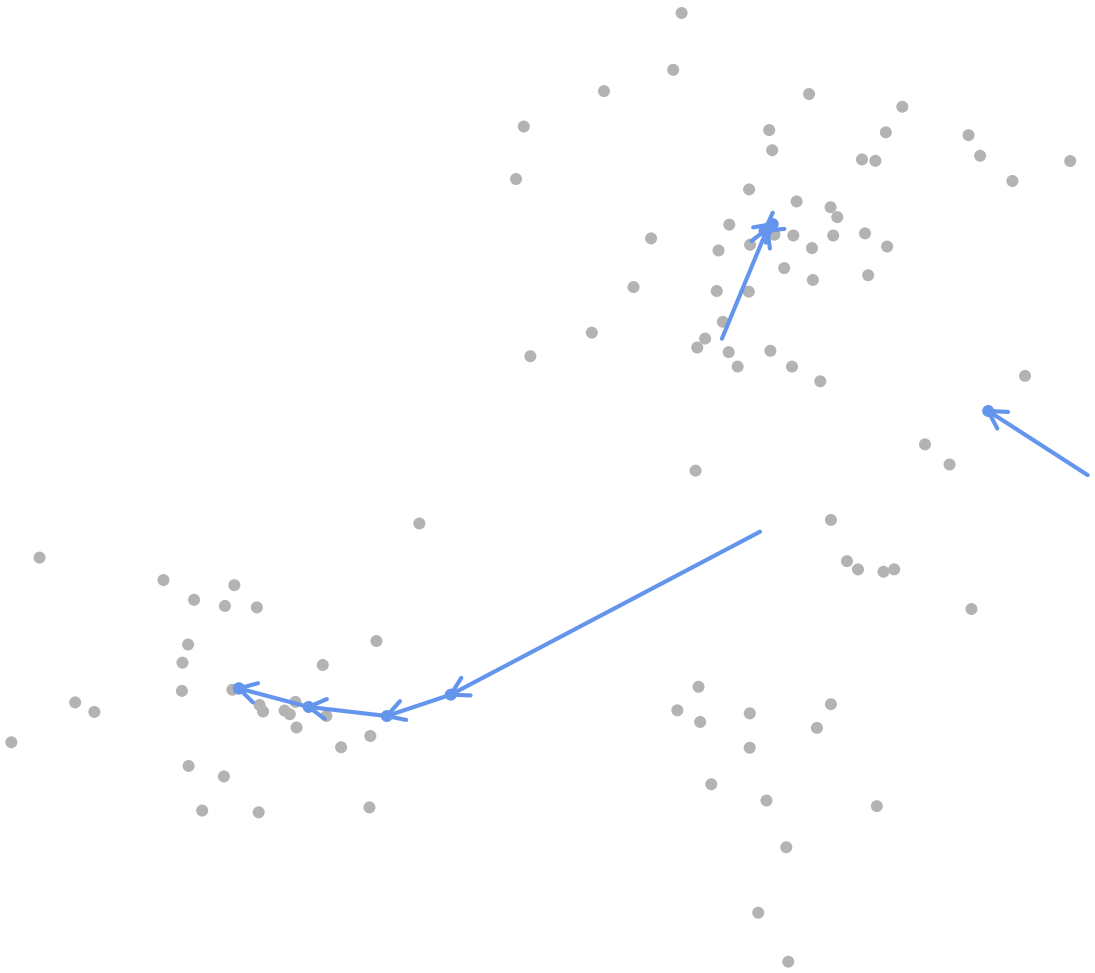

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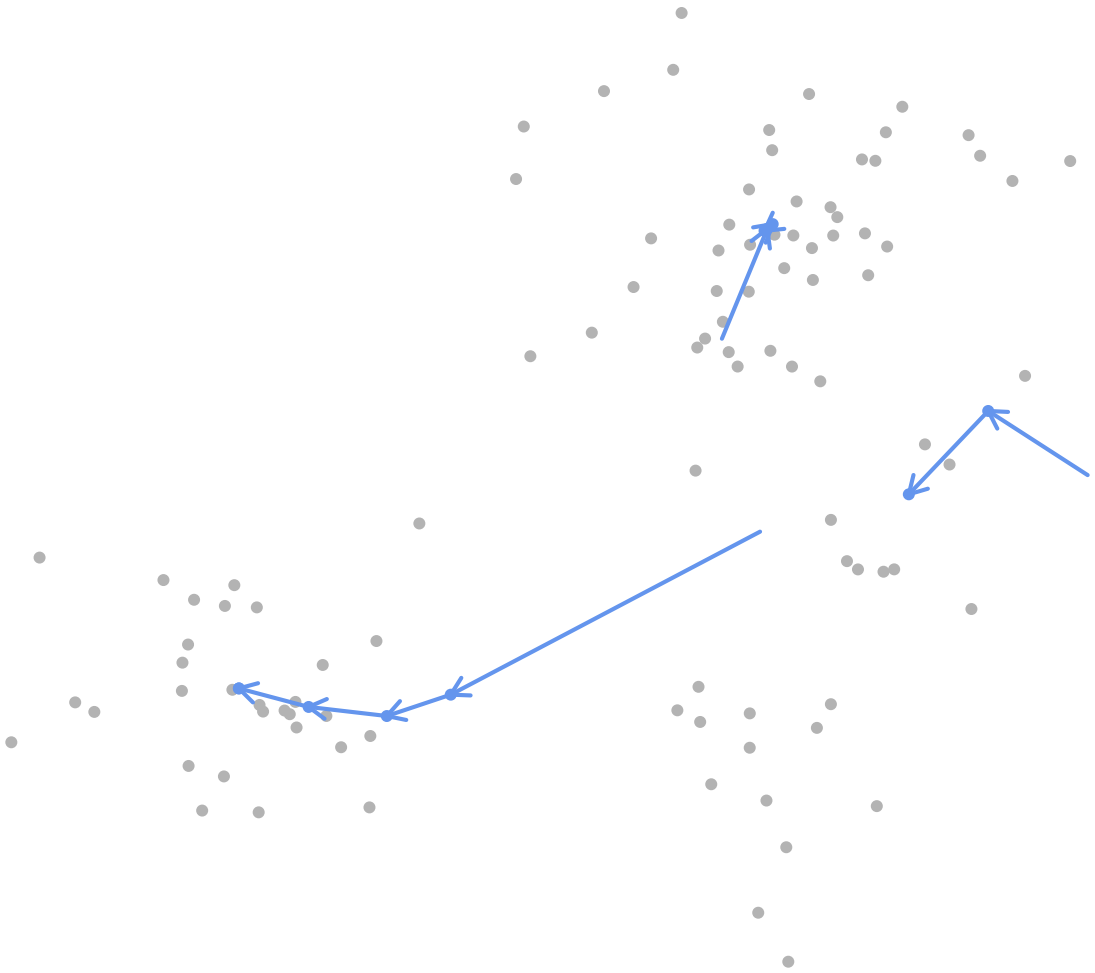

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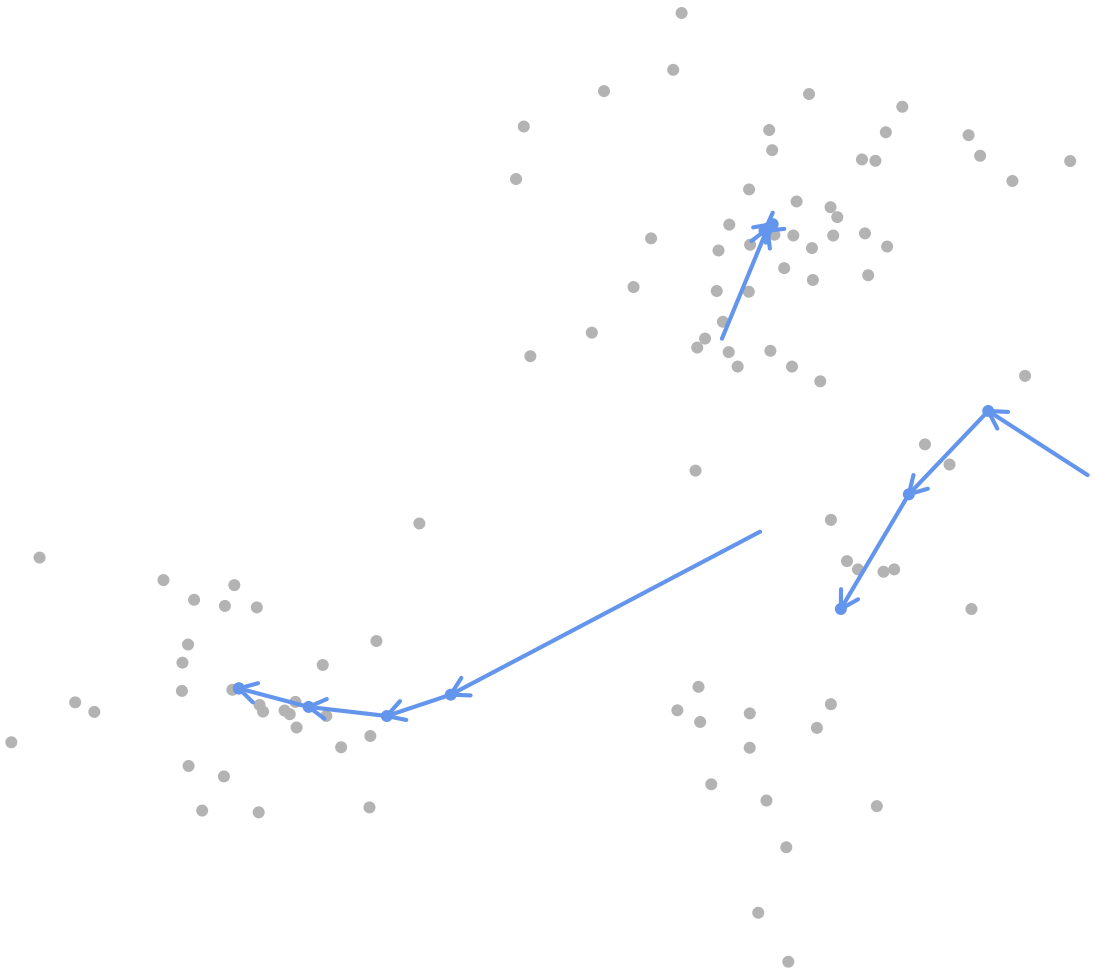

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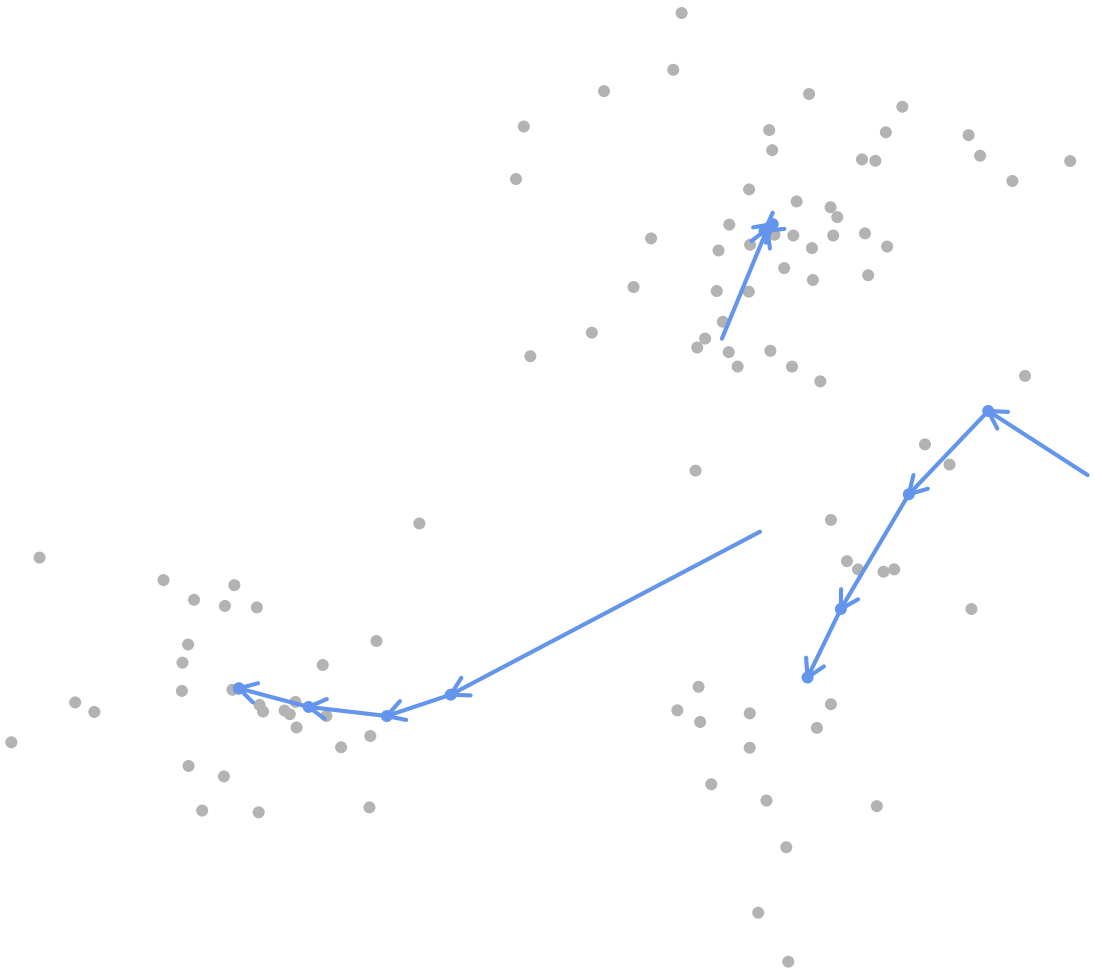

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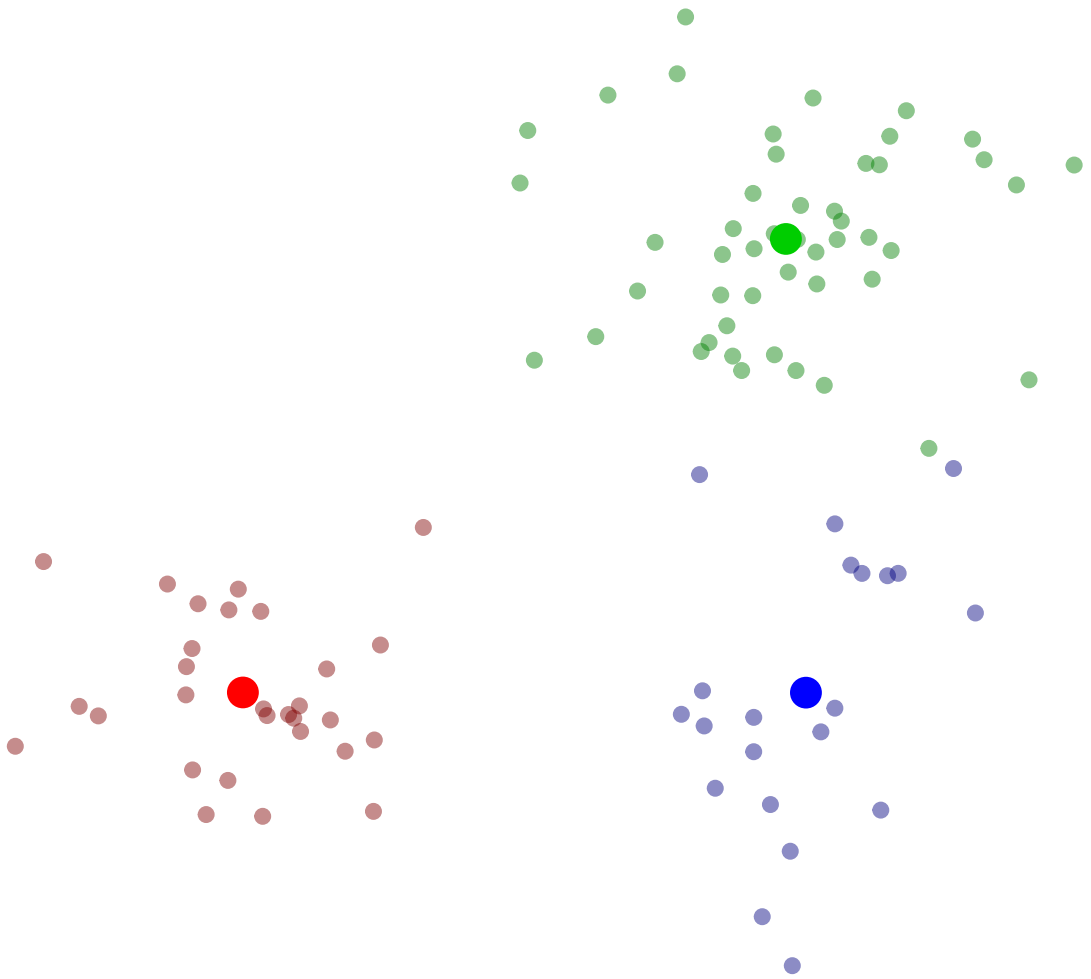

Interpreting Cluster Components

- Apply clustering methods, we have groups of documents
- How to interpret groups?
- Two (broad) methods:
  - Manual identification (Quinn et al 2010)
    - Sample set of documents from same cluster
    - Read documents
    - Assign cluster label
  - Automatic identification (Week 4 methods)
    - Know label classes
    - Use methods to identify separating words
    - Use these to help infer differences across clusters
- Best Validation:
  - Clustering methods suggest organization structure
  - Conditional on output, write coding rules
  - Humans code some documents
  - Use Week 8, 9 methods to classify
  - Correlation: strong evidence that grouping captures meaning you think

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- But, can help guide your selection
- Combination statistic + manual search
- Humans should be the final judge

Cluster Quality (Grimmer and King 2011)

More general problem: model selection through humans

What Are Humans Good For?

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What Are Humans Good For?

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More general problem: model selection through humans

What Are Humans Good For?

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- They can: compare two documents at a time

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

Mixture Models

- Statistical models: make extensions/generalizations easier
- Mixture models: workhorse model for statistical clustering of data

Single distribution DGP:

$$\mathbf{y}_i \sim \text{Distribution(parameters)}$$

Mixture model DGP:

$$\begin{aligned} \mathbf{r}_i|\boldsymbol{\pi} &\sim \text{Multinomial}(1, \boldsymbol{\pi}) \\ \mathbf{y}_i|r_{ik} = 1 &\sim \text{Distribution}(\text{param}_k) \end{aligned}$$

DGP in Words

- Draw a cluster label
- Go to distribution, draw contents

A Mixture of Multinomial Distributions

Recall Multinomial Distribution:

$$\mathbf{y}_i|\boldsymbol{\theta} \sim \text{Multinomial}(\overbrace{n_i}^{\text{Number of Words}}, \underbrace{\boldsymbol{\theta}}_{\text{Rate Words are Used}})$$

$$p(\mathbf{y}_i|\boldsymbol{\theta}) \propto \prod_{m=1}^{M} \theta_m^{y_{im}}$$

A Mixture of Multinomial Distributions

$$\begin{aligned} \mathbf{r}_i|\boldsymbol{\pi} &\sim \text{Multinomial}(1, \boldsymbol{\pi}) \\ \mathbf{y}_i|r_{ij} = k, \boldsymbol{\theta}_k &\sim \text{Multinomial}(n_i, \boldsymbol{\theta}_k) \end{aligned}$$

where θ_{km} describes the rate word m is used in topic k.
Note: $\sum_{m=1}^{M} \theta_{km} = 1$.

A Mixture of Multinomial Distributions: Specifying Model

- Distance metric: Implicit, normalized Euclidean distance
- Objective function
- Optimization: EM Algorithm

$$p(\mathbf{r}, \boldsymbol{\theta}, \boldsymbol{\pi} | \mathbf{y}) \quad \propto \quad \prod_{i=1}^{N} \prod_{j=1}^{K} \left[\pi_j \prod_{m=1}^{M} \theta_{km}^{y_{im}} \right]^{r_{ij}}$$

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\theta_k &\propto \sum_{i=1}^{N} r_{ik} \mathbf{y}_i
\end{aligned}
$$

(Non-parametric) Clustering of Press Releases (Grimmer 2011)

Apply version of mixture of multinomials to 64,033 Senate press releases
Model fit with approximately 45 topics

Label	Identifying Stems	% Press Rele
Appropriations/Grants	fund,project,000,million,water	8.6
Honorary	honor,servic,school,serv,american	8.2
Iraq War	iraq,troop,war,iraqi,american	6.6
Health Grants	health,program,educ,children,school	6.3
Homeland Security	secur,homeland,port,border,depart	5.3
Judicial Nominations	court,vote,justic,american,judg	4.8
Hurricanes/Disasters	disast,assist,hurrican,fema,flood	4.5
Taxes	tax,american,budget,social,secur	4.4
Defense Projects	million,defens,fund,air,militari	4.2
Health Policy	health,care,drug,medicar,senior	3.8

An Overview of Clustering Models

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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 mulitinomial, Chinese Restaurant Distance Dirichlet process multinomial, Pitmann-Yor Process multinomial, LSA, ...

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- Large quantitative literature on cluster analysis

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

Fully Automated → Computer Assisted (Grimmer and King 2011)

- Fully Automated Clustering may succeed, fails in general. Too hard to know when to apply models
- An alternative: Computer Assisted Clustering
  - Easy (if you don't think about it): list all clustering, choose best
  - Impossible in Practice
  - Solution: Organized list
  - Insight: Many clusterings are perceptually identical
  - Consider two clusterings of 10,000 documents, we move one document from 5 to 6.
- How to organize clusterings so humans can undestand?
- 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)

Grimmer, King, and Stewart, In Progress

A brief live demonstration of α software (time permitting)

Example Discovery: What Do Members of Congress Do?

- Paper (Grimmer and King 2011): introduce new evaluation methods (like Cluster Quality)

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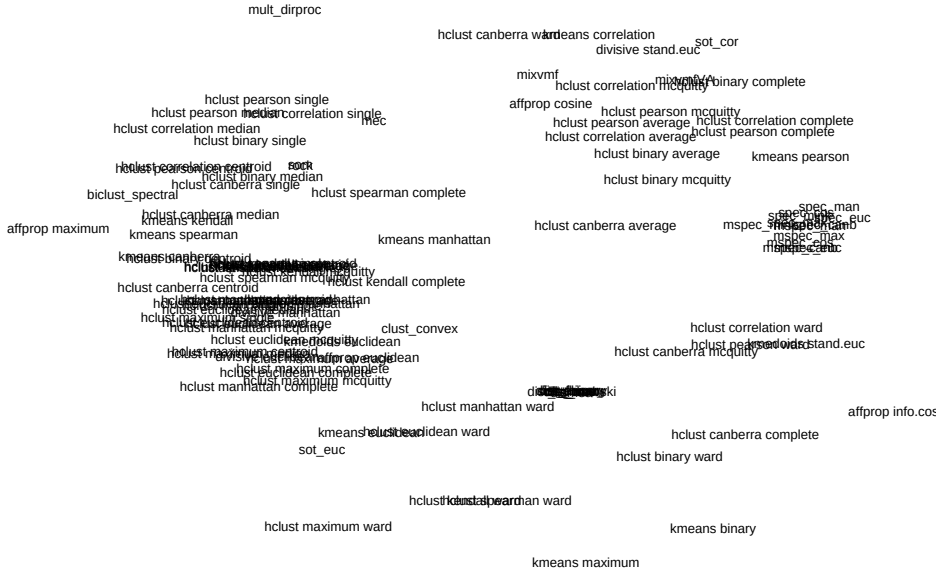
  - Advertising
  - Credit Claiming
  - Position Taking
- Data: 200 press releases from Frank Lautenberg's office (D-NJ)
- Apply our method (relying on many clustering algorithms)

Example Discovery



Example Discovery

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

Example Discovery

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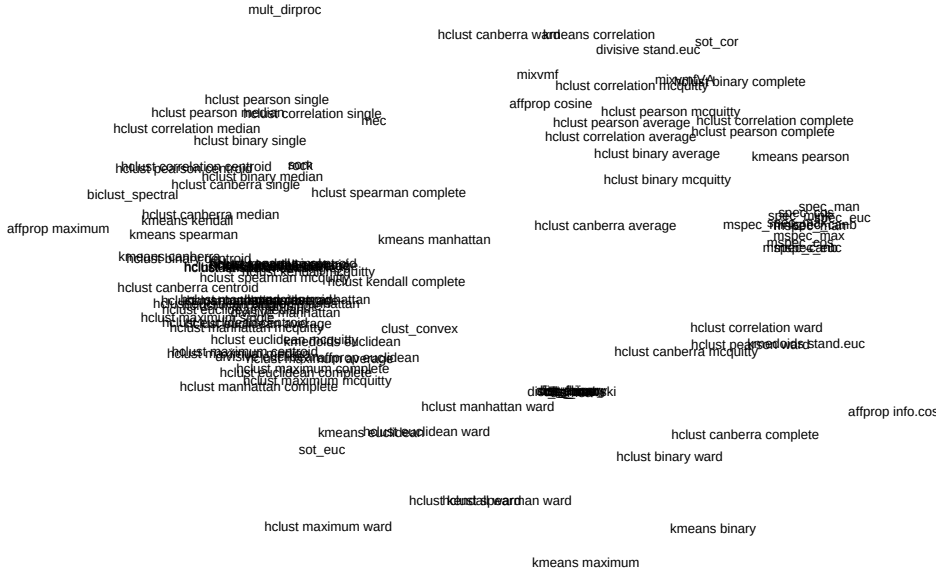
Close to:

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

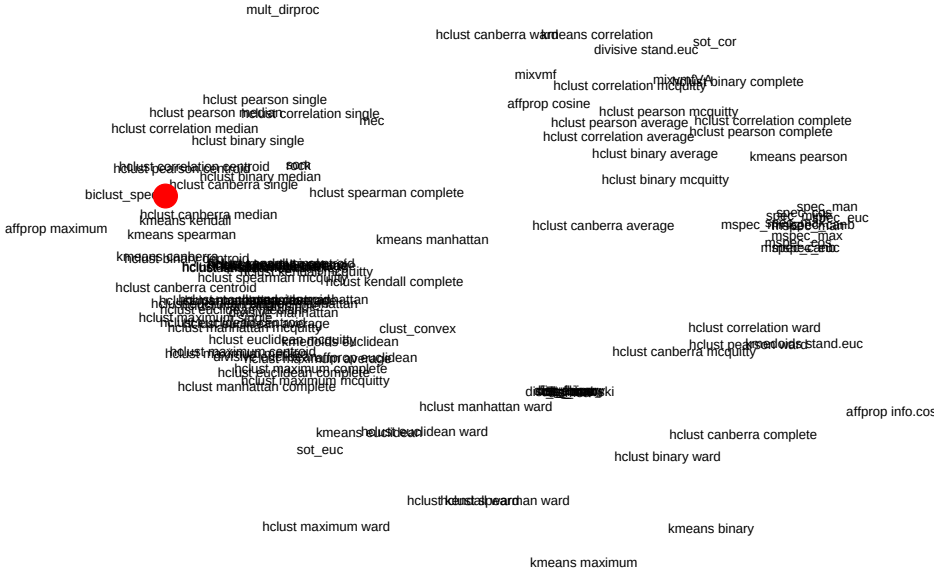
$\Rightarrow$ Similar clustering of documents

Example Discovery



Space between methods:

Example Discovery



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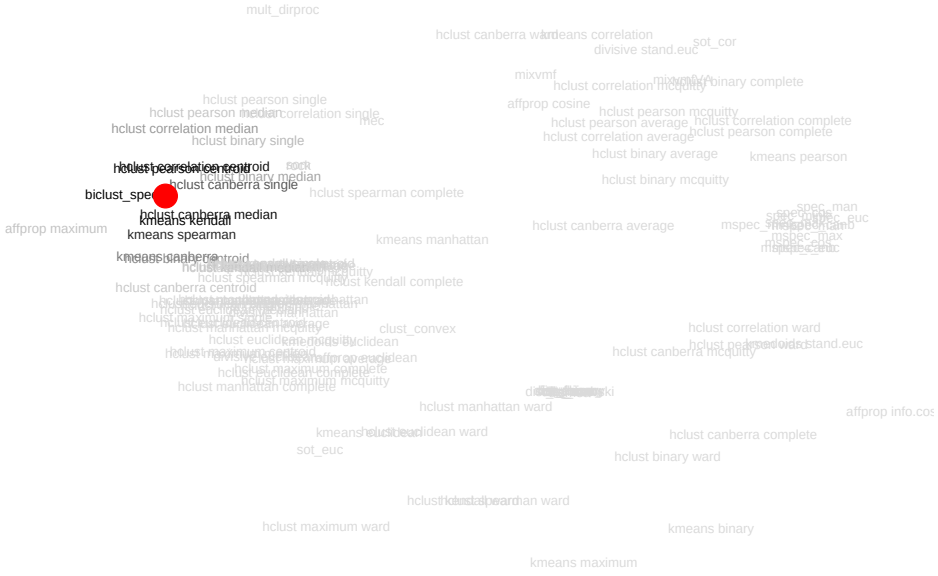
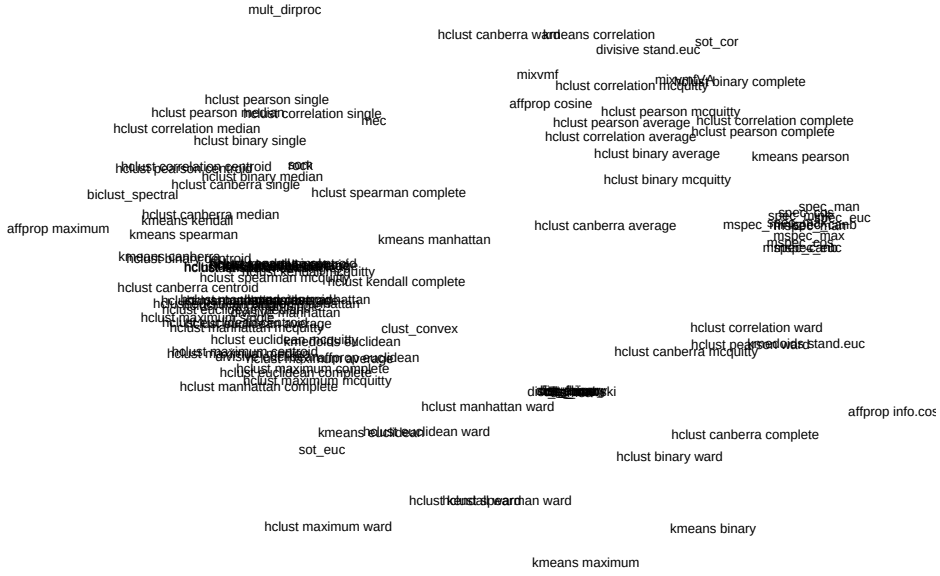


Space between methods:
local cluster ensemble

Example Discovery



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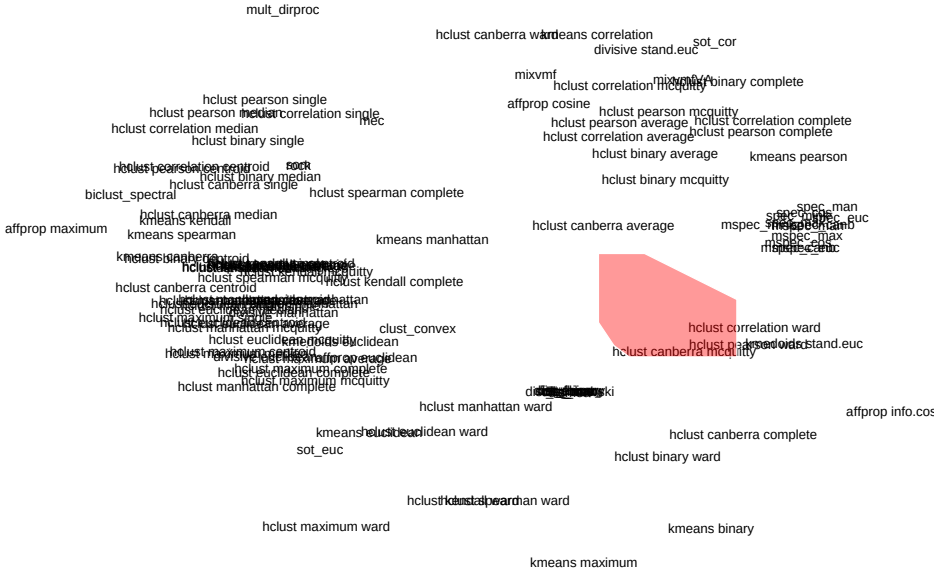
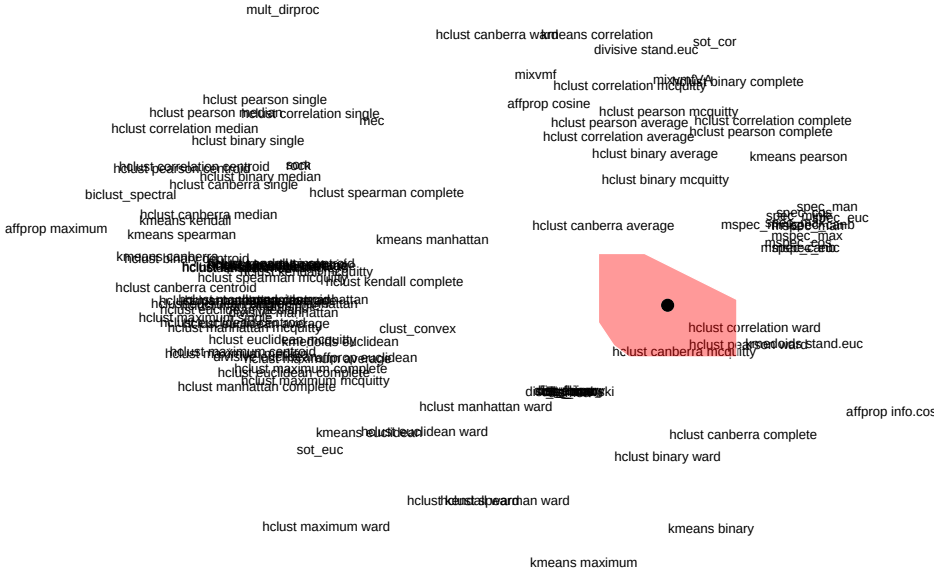


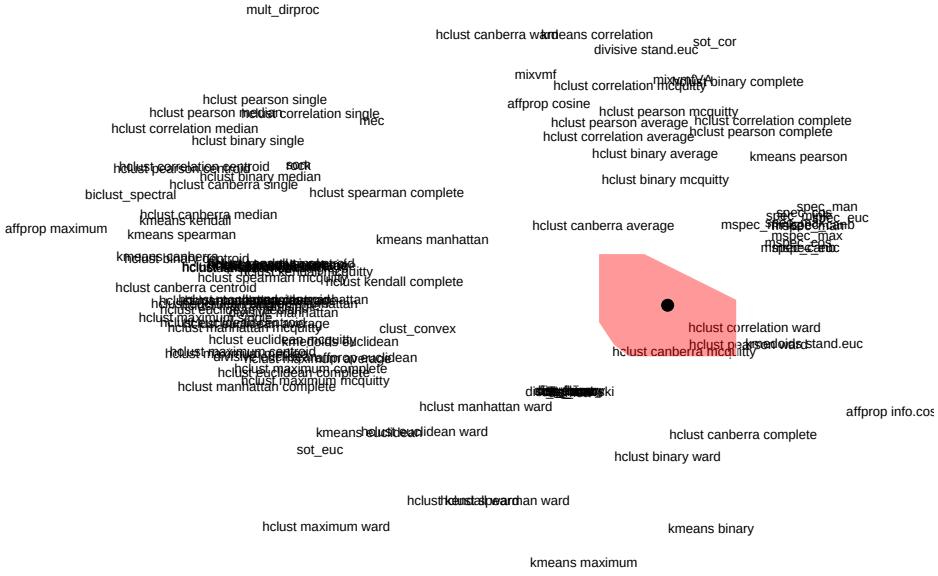
Found a region with clusterings that all reveal the same important insight

Example Discovery



Mixture:

Example Discovery



Mixture:

0.39 Hclust-Canberra-McQuitty

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0.09 Hclust-Pearson-Ward

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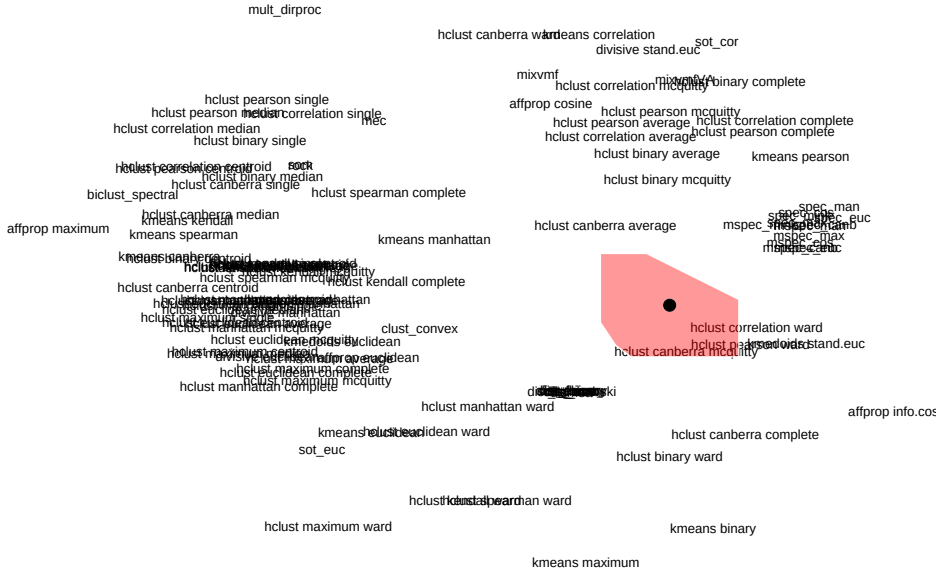

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Random Walk
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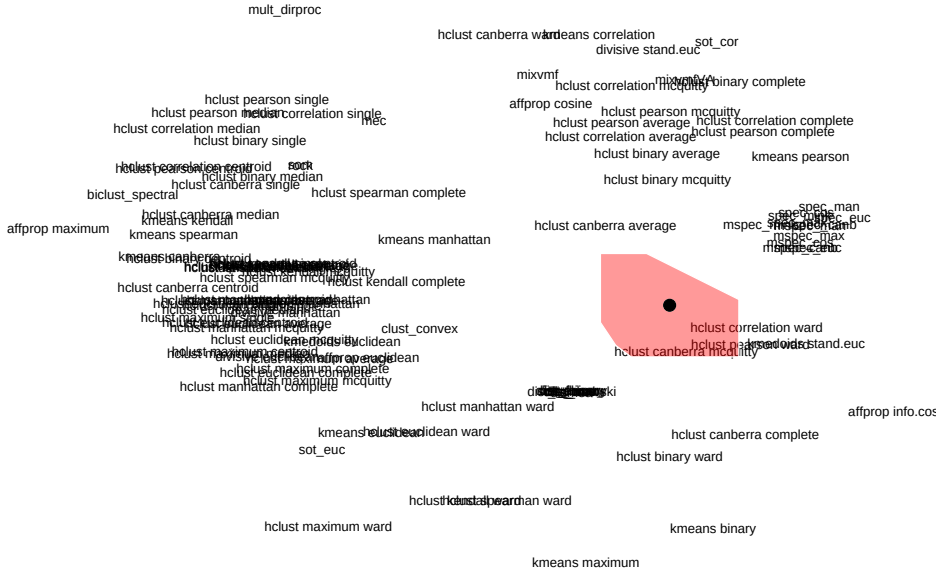

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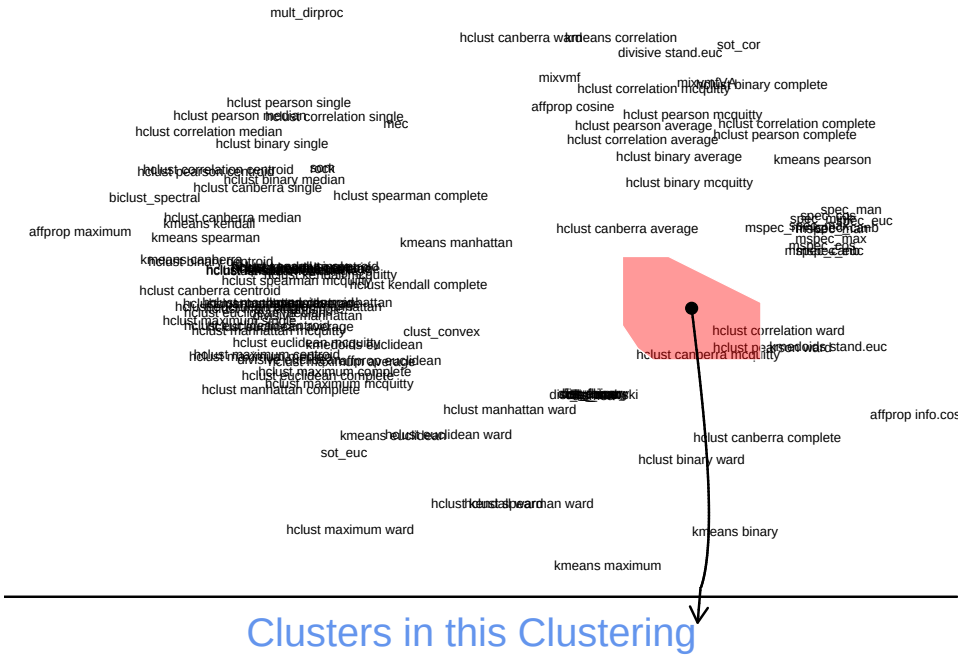
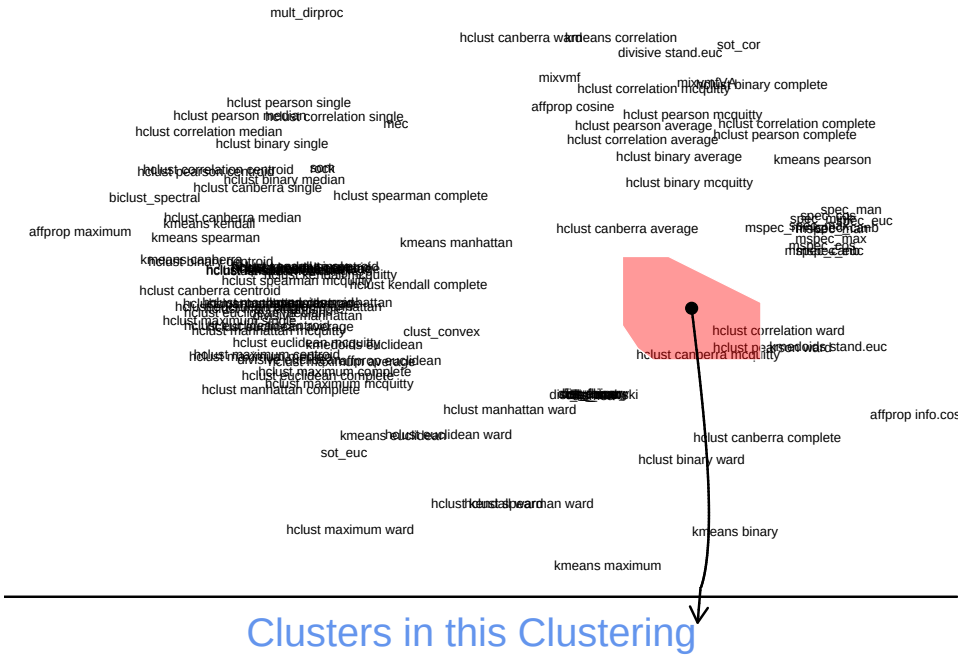
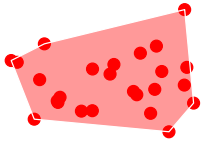


Clusters in this Clustering

Mayhew

Example Discovery





Credit Claiming
Pork

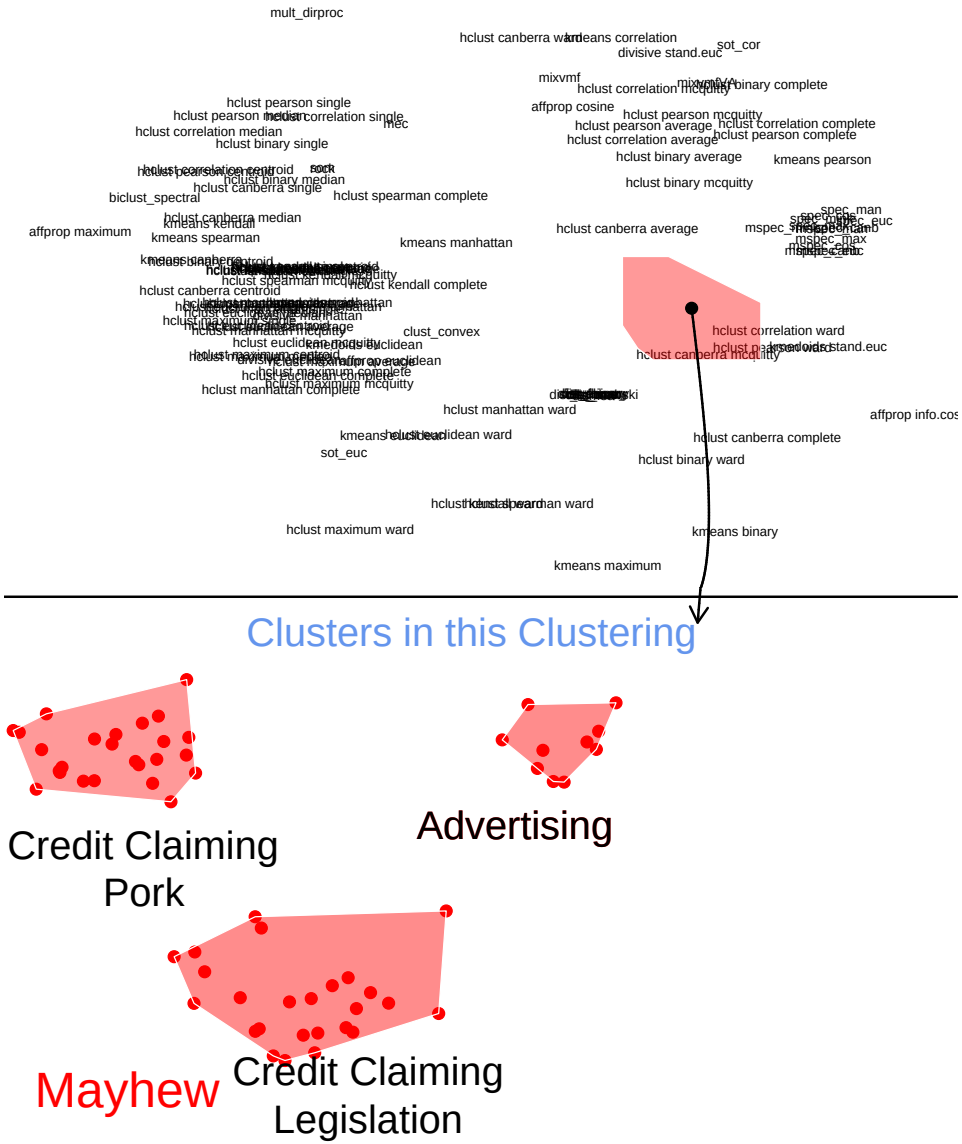
Credit Claiming, Pork:
"Sens. Frank R. Lautenberg (D-NJ) and Robert Menendez (D-NJ) announced that the U.S. Department of Commerce has awarded a $100,000 grant to the South Jersey Economic Development District"

Mayhew

Example Discovery

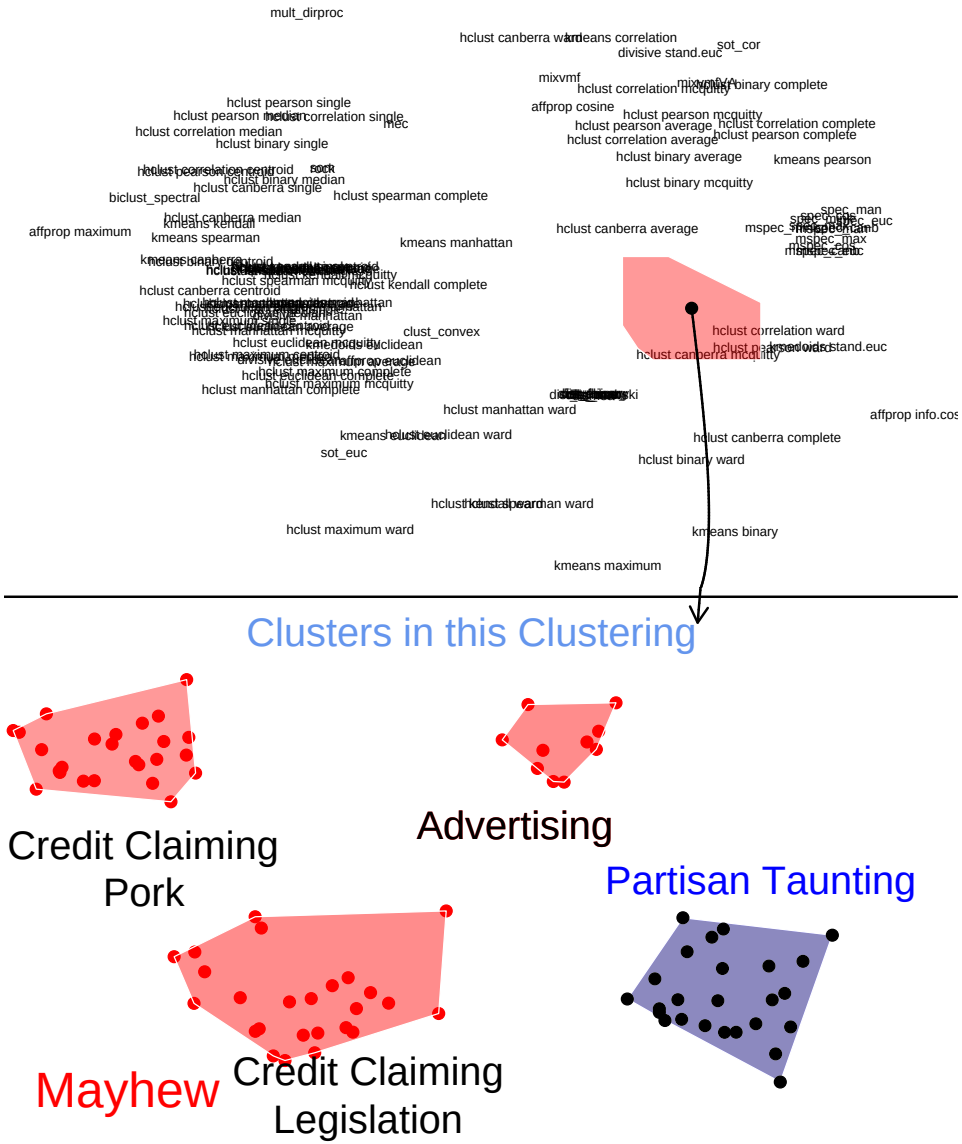
Credit Claiming, Legislation:
"As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period"

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

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on Senate Floor
4/29/04

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Consequences for representation: Deliberative, Polarization, Policy

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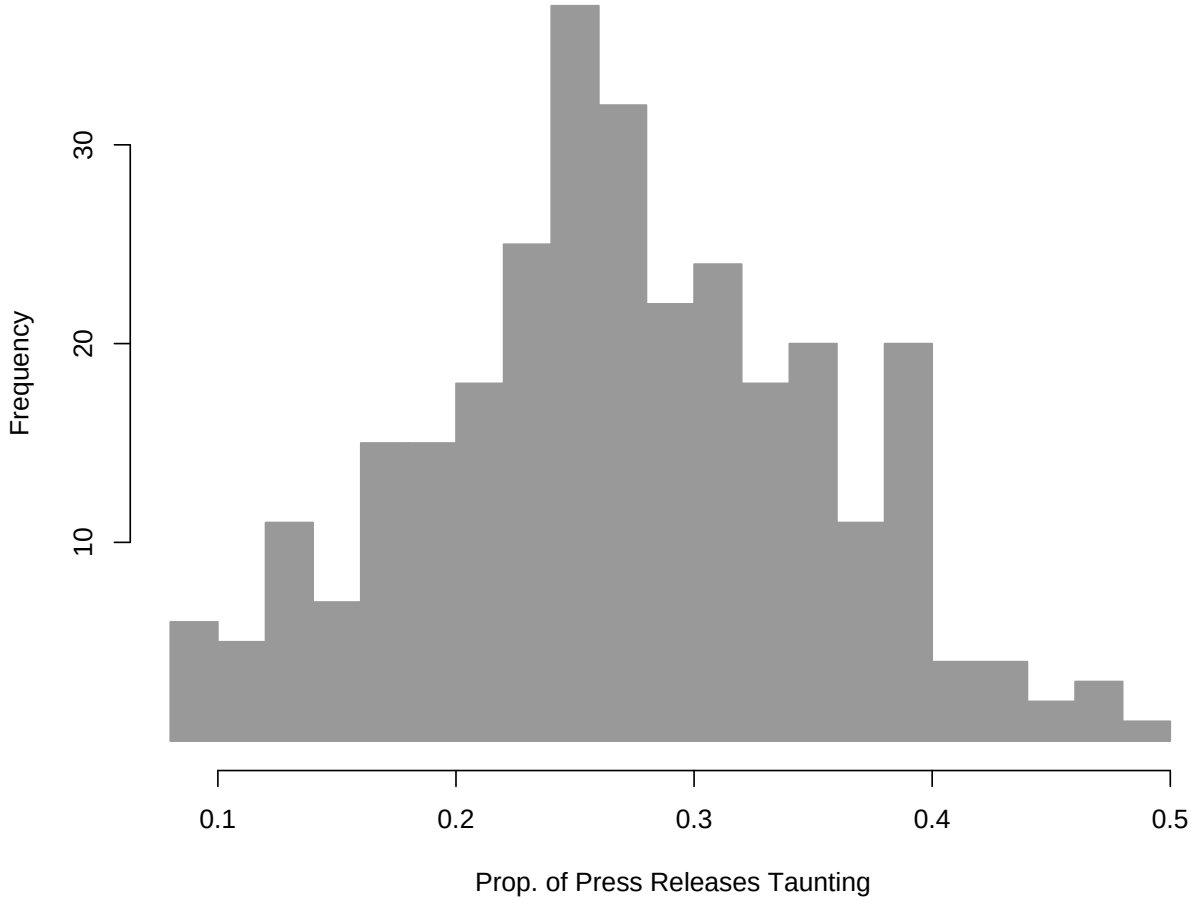

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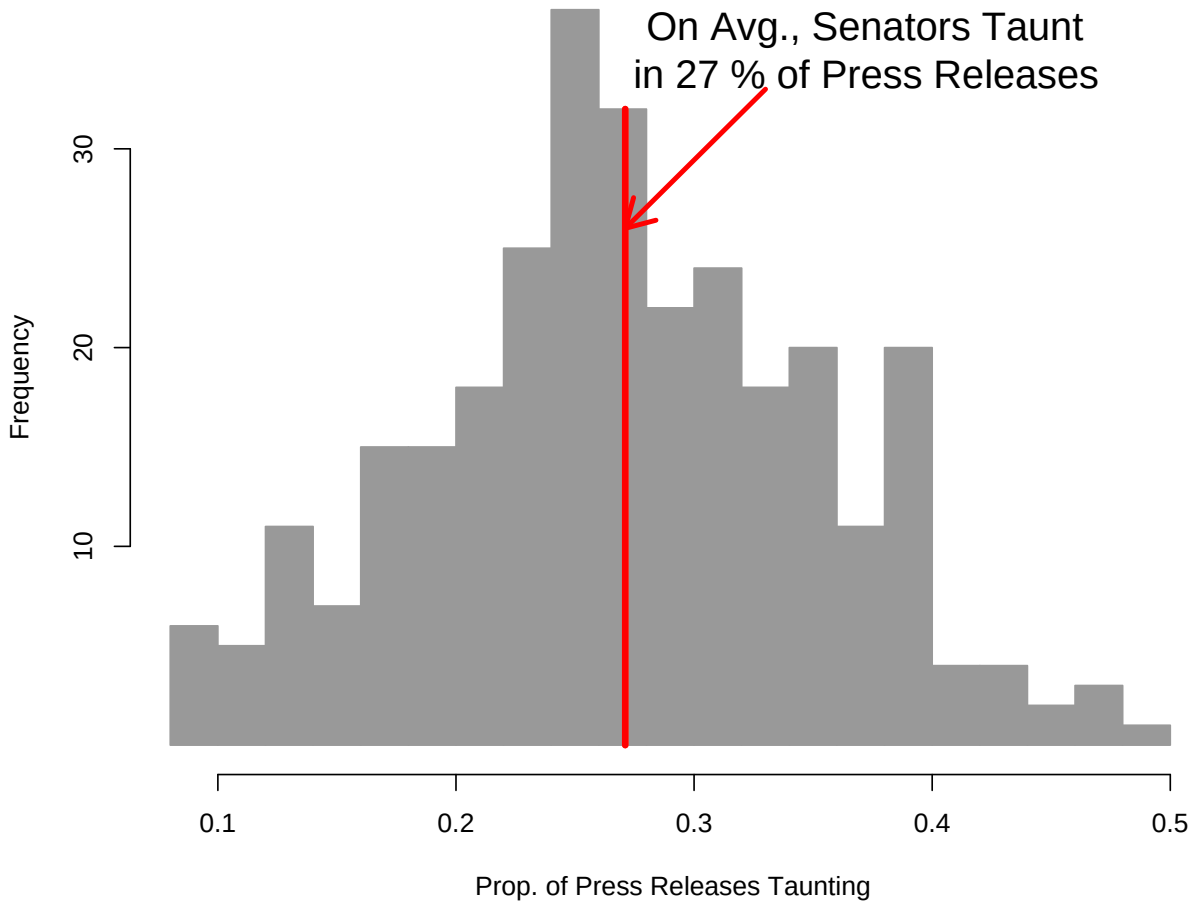

Clustering, FAC and CAC

This week

- Introduction to clustering
- Fully automated clustering algorithms
- Introduction to computer assisted clustering

Next week:

- Topic models
- Discover underlying issues in texts