Text as Data: Statistical Text Analysis for the Social Sciences, Discovery

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UC San Diego

September 7, 2022

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- Content analysis: discovering concepts and categorizing texts

Example: Conceptualizing U.S. Congress

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- Example: DW-Nominate

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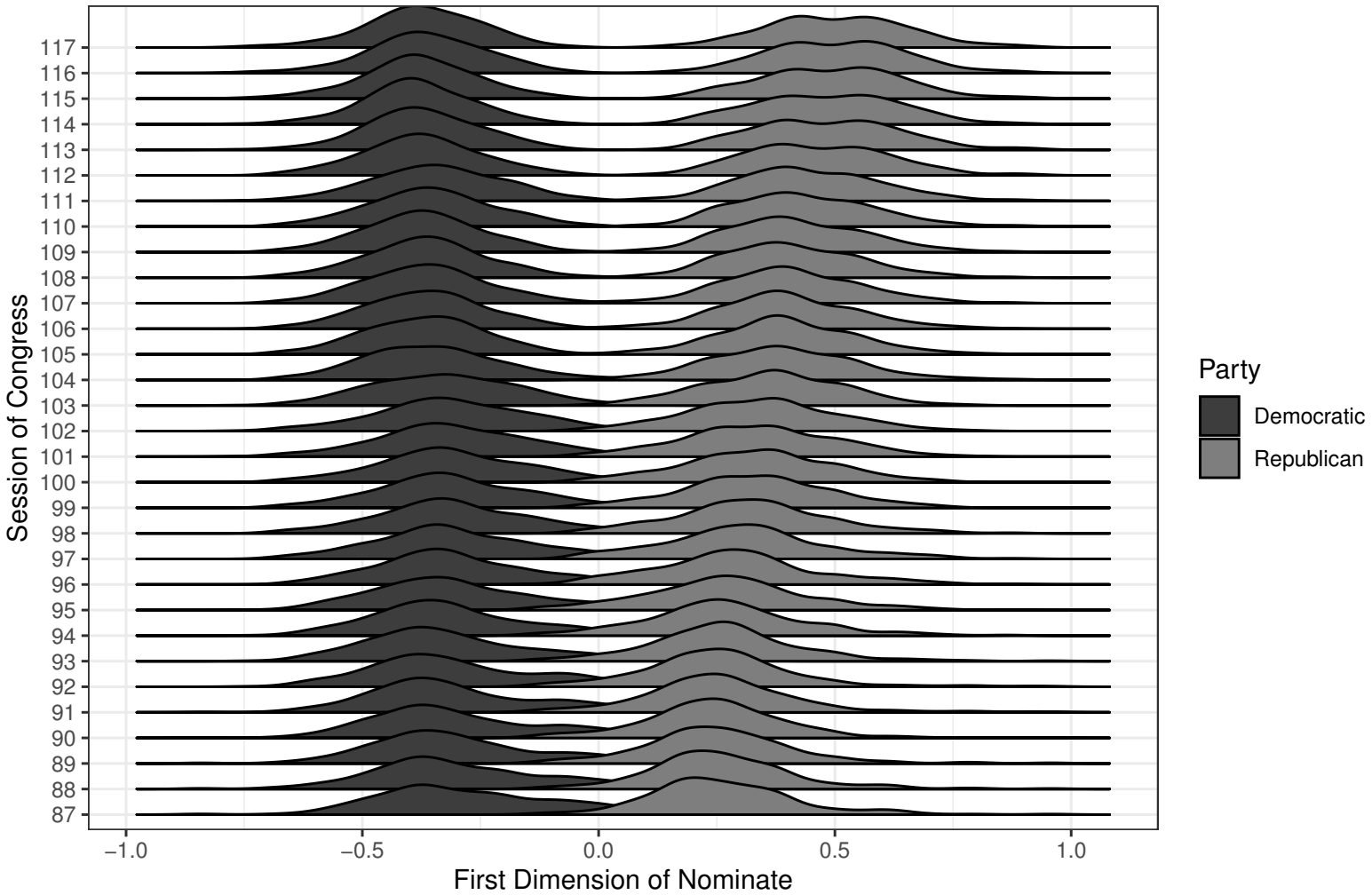

Is this the "right" conceptualization?

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- Problem: requires lots of reading, many judgement calls, difficult to reproduce

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  - Reproducability

Proposed Steps

1. Pattern detection with computational exploratory analysis
2. Hypothesis refinement using human-centered interpretation
3. Pattern confirmation

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  - Chicago vs. New York
  - Different philosophies

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Table 2. Most Distinctive Words, Difference of Proportions.

First Wave[a]		Second Wave[b]	
Hull House (Chicago)	Heterodoxy (New York City)	CWLU (Chicago)	Redstockings (New York City)
hullhouse	woman	chicago	movement
club	man	children	women
miss	women	center	men
school	life	union	radical
given	know	school	feminist
year	world	work	male
members	like	cwlu	political
chicago	sanger	vietnam	history
mr	men	nixon	womens
classes	said	people	feminism
house	home	office	revolution
boys	just	day	love
work	say	health	feminists
years	don't	city	left
social	little	working	power
held	way	vietnamese	oppression
clubs	think	legal	class
mrs	things	war	female
residents	want	care	personal
room	sex	womankind	woman
children	right	government	really

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Table 5. Sample of Structured Dataframe Sorted by *Movement History* Topic Weights.

File Name	Text (Head)	Mo Histo W
nyc.redstockings.1973.sarachild.powerofhistory-28.txt	THE ARCS OF HISTORY tific and fearless writers of her day" and Elizabeth Cady Stanton, too, "the matchless writer." [. . .]	0.96
nyc.redstockings.1973.sarachild.powerofhistory-27.txt	Ten any idea of what that work was all about "it's purpose and the breadth of its contents and even its method- we [. . .]	0.96
nyc.redstockings.1973.sarachild.powerofhistory-29.txt	Paraging depiction of the History in the bibliography, it suddenly struck m_e that Stanton, Anthony and Gage's [. . .]	0.94
nyc.redstockings.1973.sarachild.powerofhistory-30.txt	Said it was. And those who did take action in the area of history "especially for the present record"did not [. . .]	0.94
nyc.redstockings.1973.sarachild.powerofhistory-26.txt	And so their absence from history books meant there weren't any. We had to discover the problem of [. . .]	0.91
nyc.redstockings.1973.sarachild.powerofhistory-18.txt	Opposite of Beauvoir's book which was disappearing from the lists. I soon learned, even without reading it, [. . .]	0.86
nyc.redstockings.1973.sarachild.powerofhistory-31.txt	POSTSCRIPT The history question had a lot to do with the leadership question. History, after all, is all about [. . .]	0.86
nyc.redstockings.1973.sarachild.powerofhistory-25.txt	Most of the theories citing history that we encountered from both the right and the left essentially counseled [. . .]	0.81
nyc.redstockings.1973.sarachild.powerofhistory-02.txt	The Power Of History I am obnoxious to each carping tongue Who says my hand a needle better fits, A poet's [. . .]	0.75
nyc.redstockings.1973.sarachild.powerofhistory-17.txt	Of the key elements of Beauvoir's analysis upon which the WLM later built its work included: 1. Women have [. . .]	0.70

Note: This is a sample of a structured dataframe (see Figures 1 and 2) structured via a 40-topic Structural Topic Model. The topic weights indicate the perce each document related to each topic (e.g., 97 percent of the total words in the first document are related to the *movement history* topic, as indicated by the Weight" column, while close to 0 are related to the *antiwar* topic). Doing a descending sort by the *movement history* topic quickly indicates which documents this topic. As the text is included in the dataframe, the researcher can quickly read these documents to better understand the content of each topic. In this pa

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Validation:

- Chicago organizations used more concrete words (dictionary)
- Chicago organizations named more organizations, NY more individuals (NER)

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- Topic Models (A form of clustering)
- Embedding Methods
  - Placing documents or words in a low-dimensional space

Clustering

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  - Clustering methods suggest new (model and data driven) ways to organize texts
  - Using new method, new lens to look at social interaction

Perspective 1: Clustering

Document 1 Document 2 ⋯ Document N

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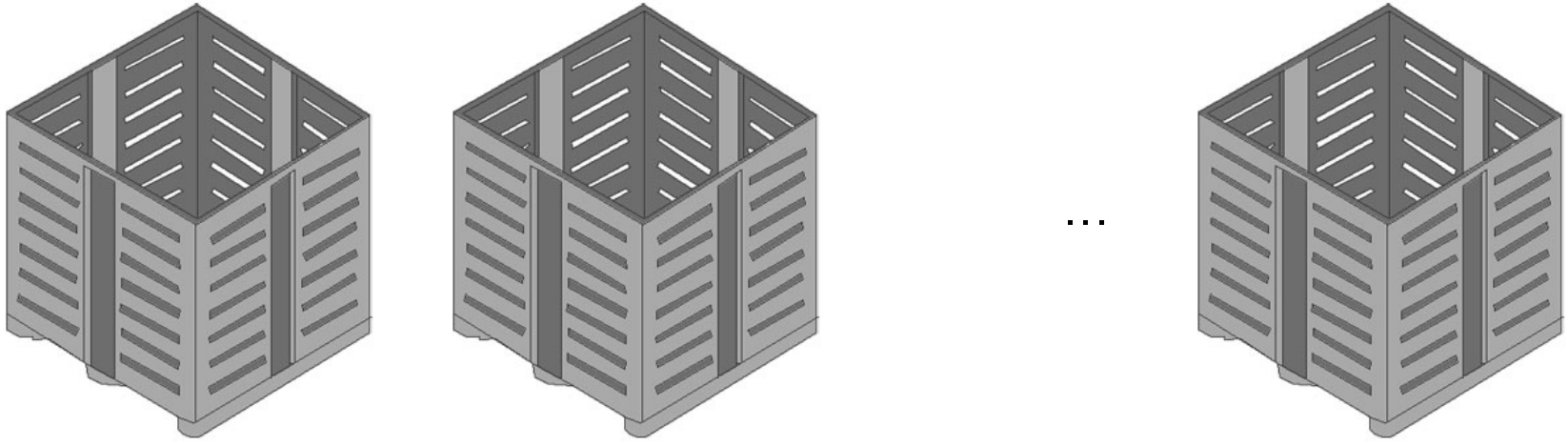

Bins and Bin Assignments Estimated

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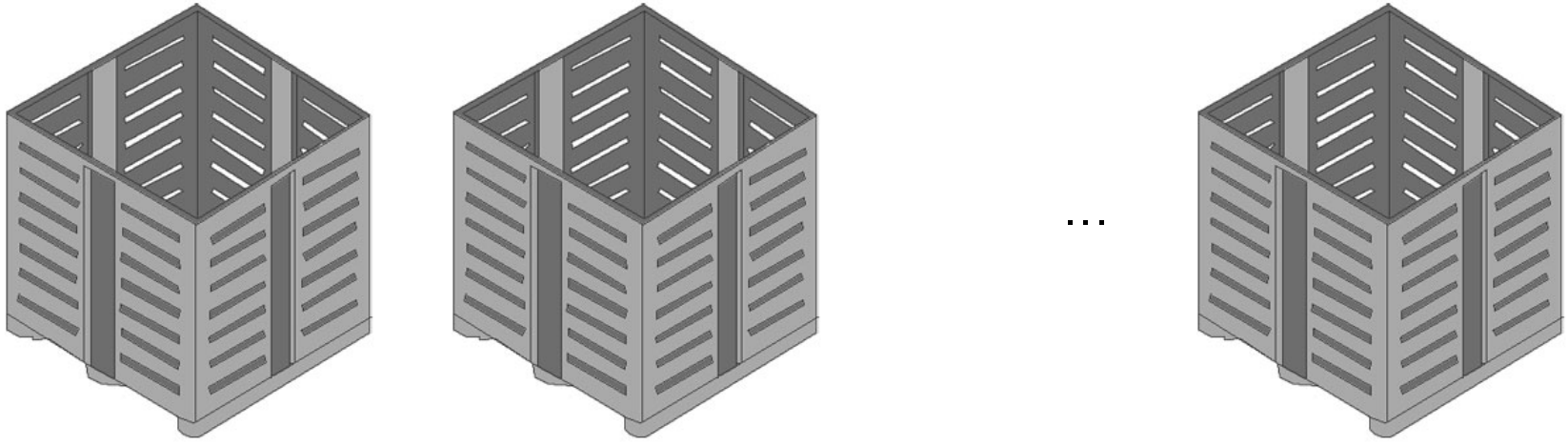

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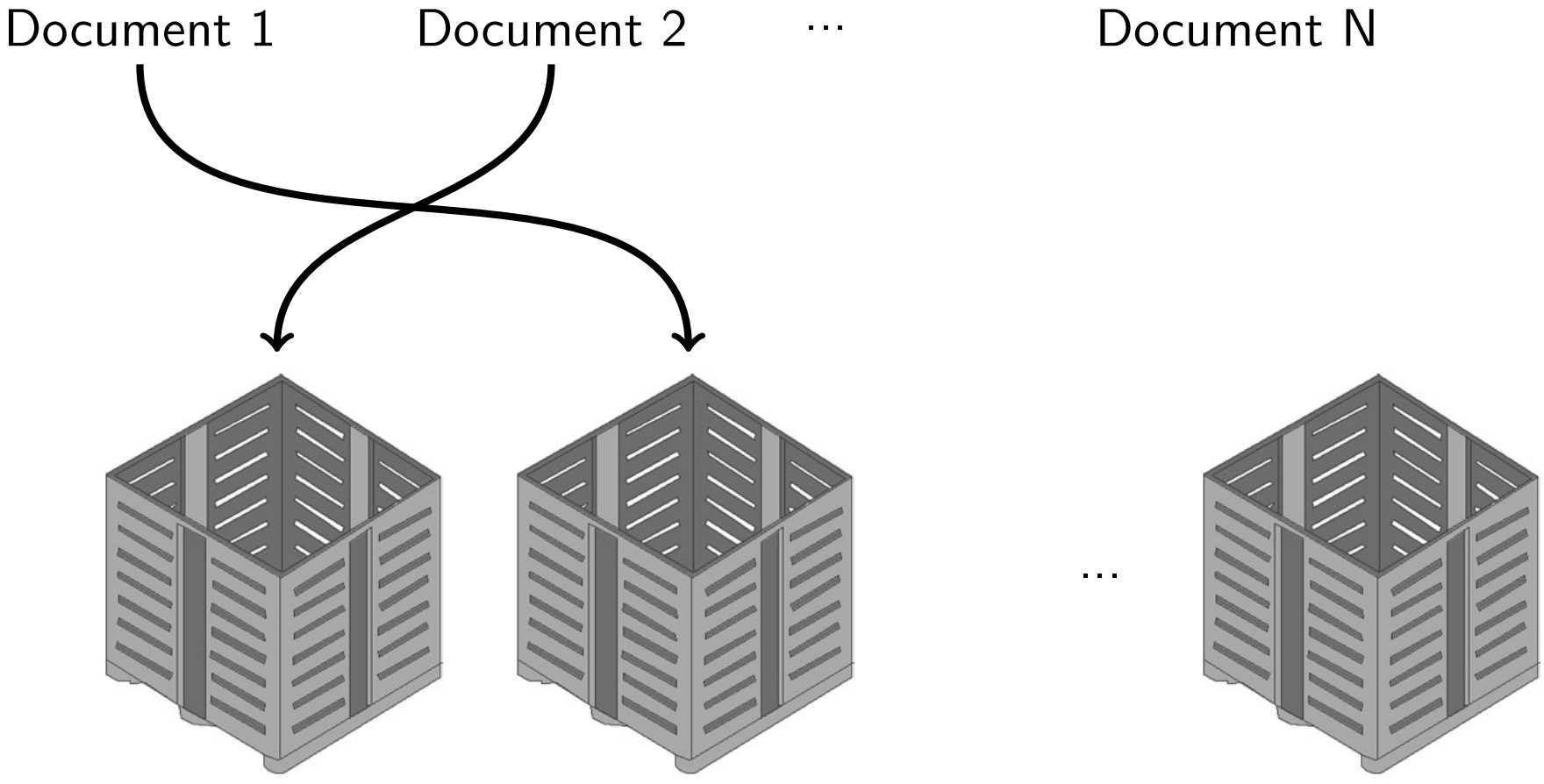

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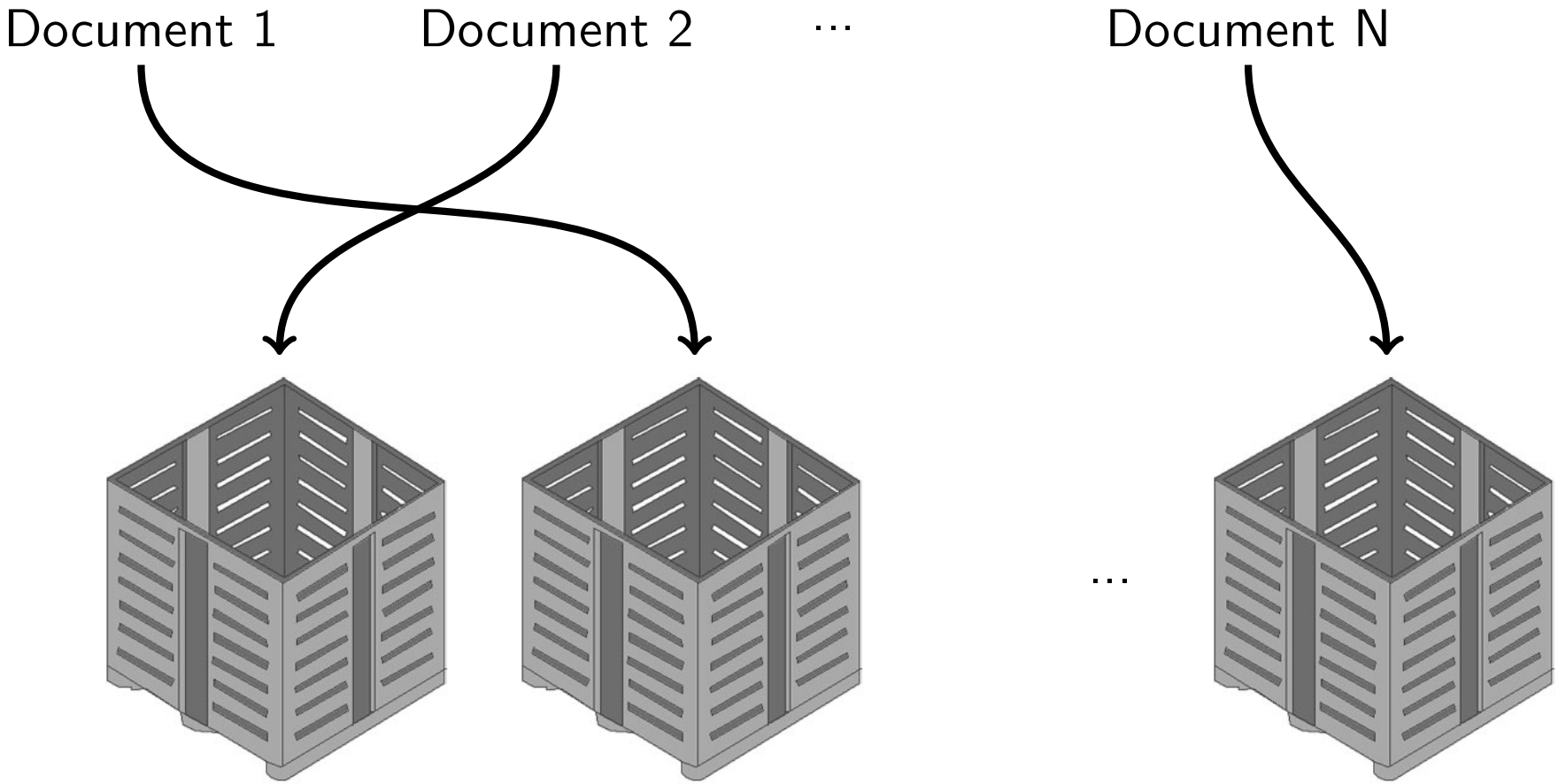

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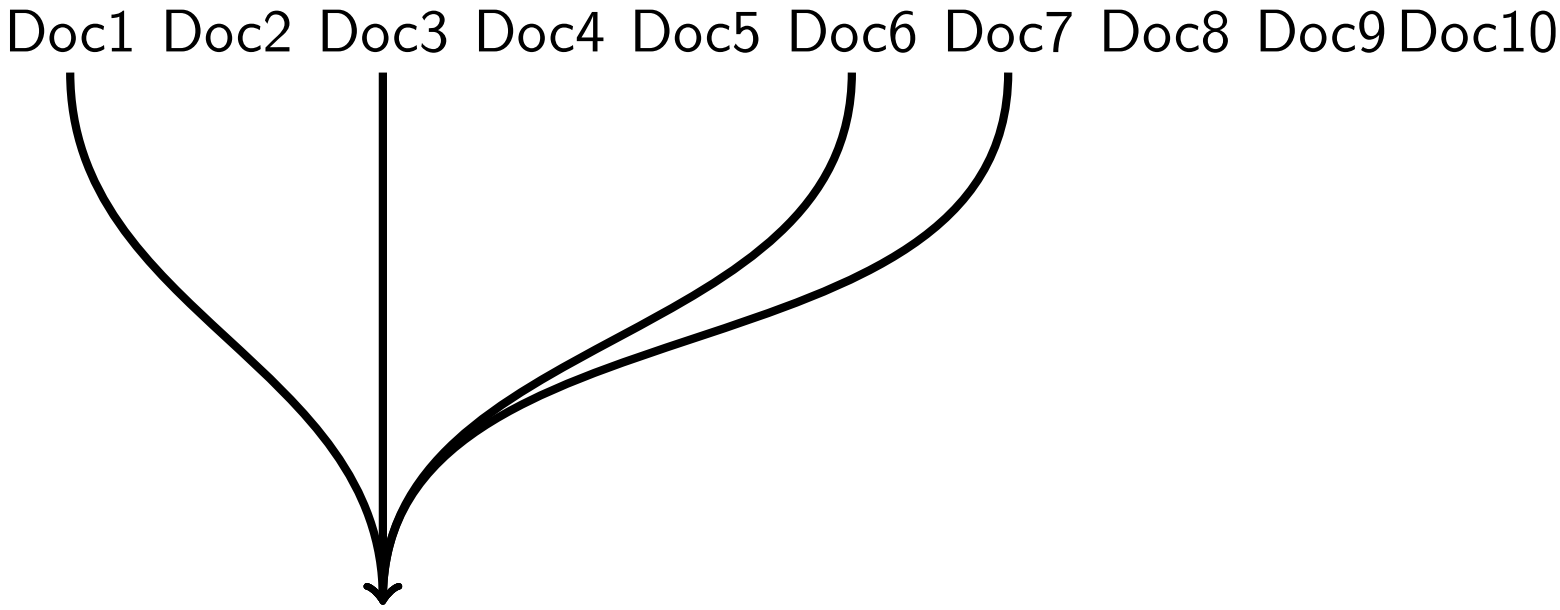

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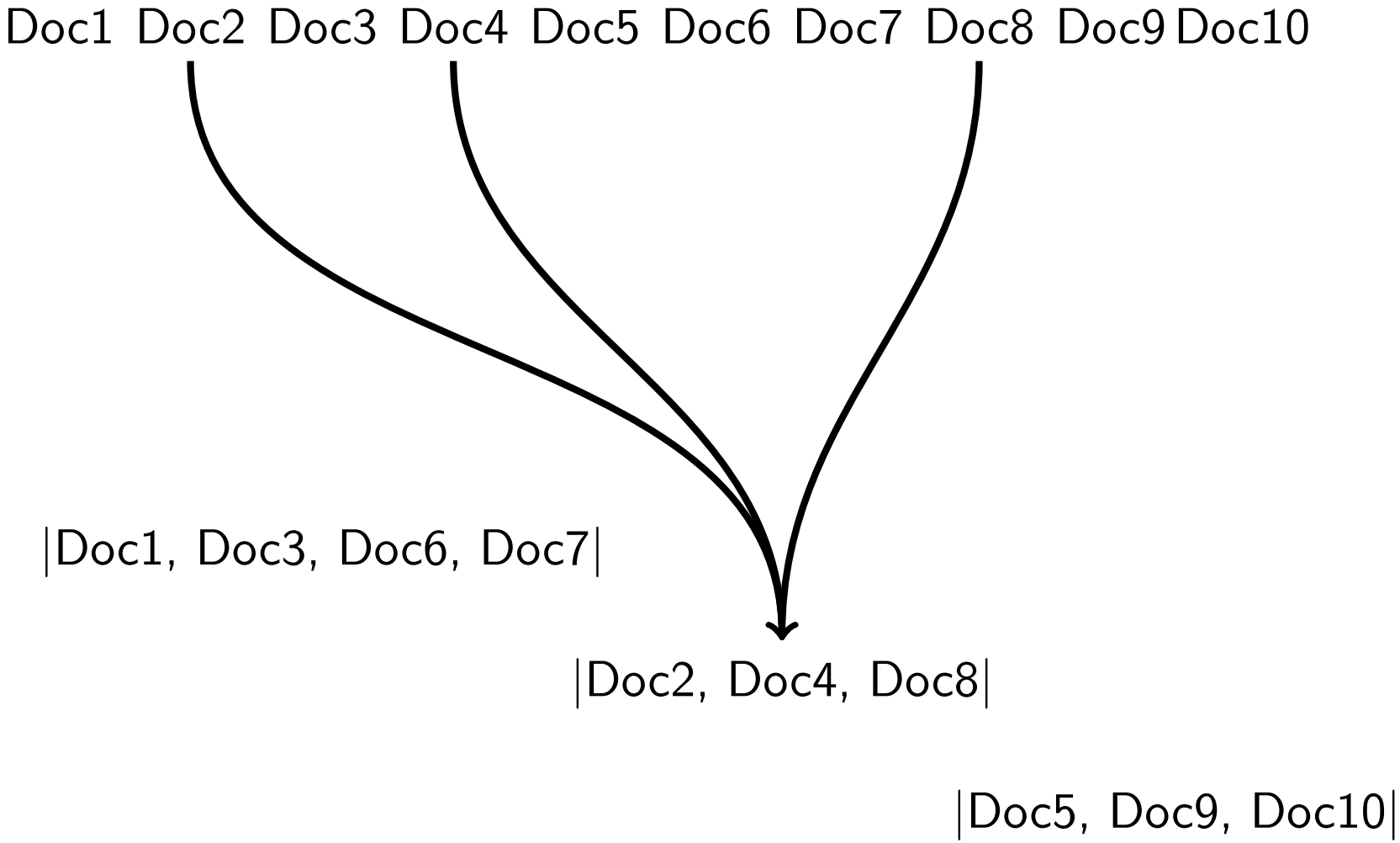

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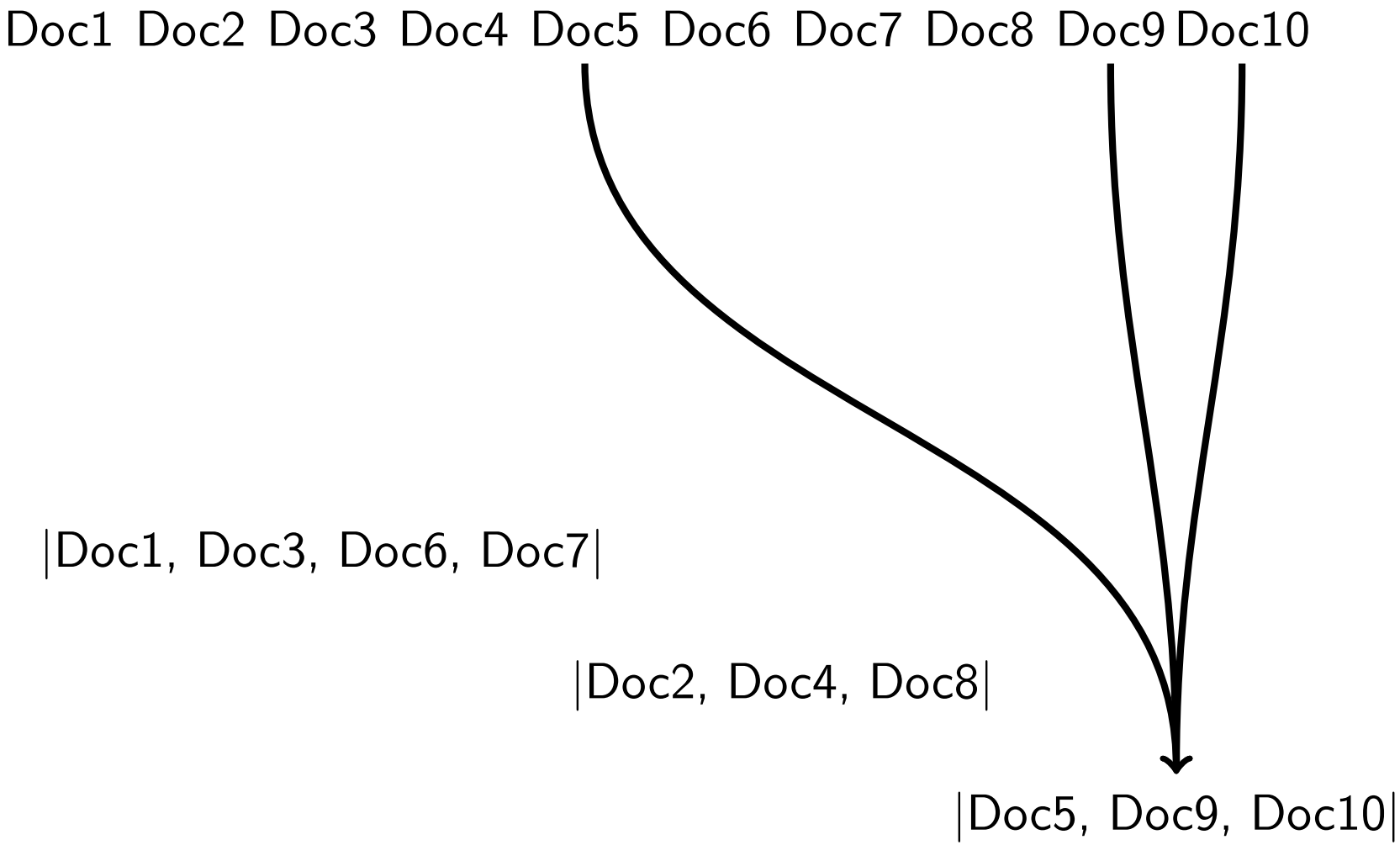

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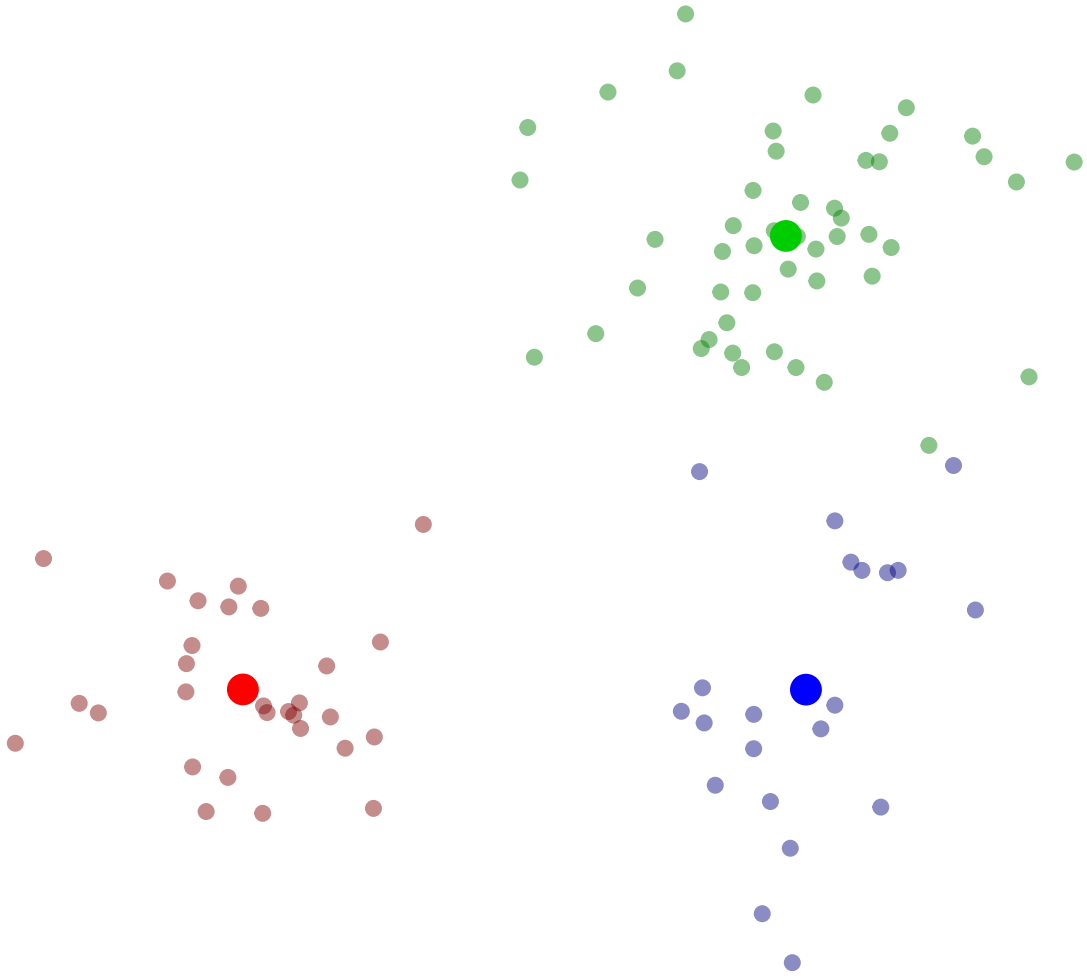

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Two trivial clusterings

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

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

Goal:
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Repeat until convergence, measured as change in f.

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

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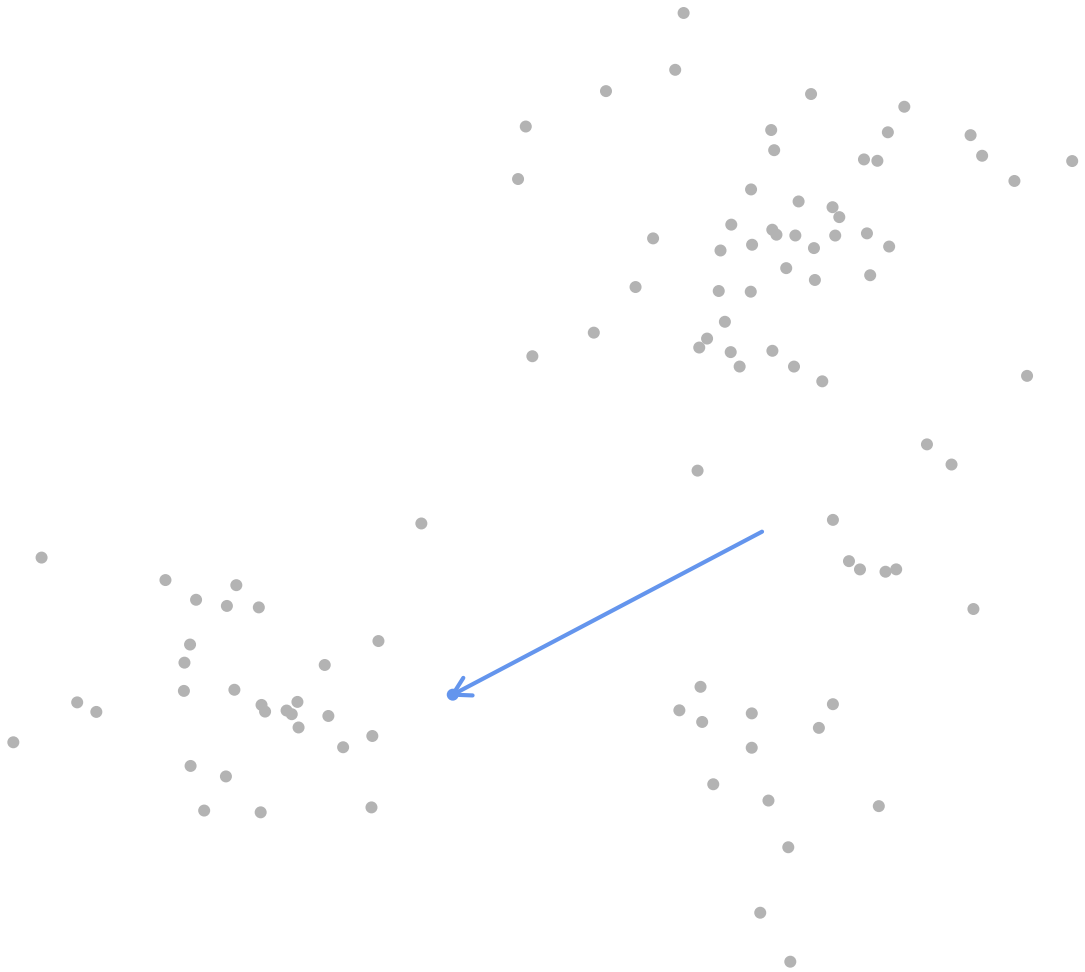

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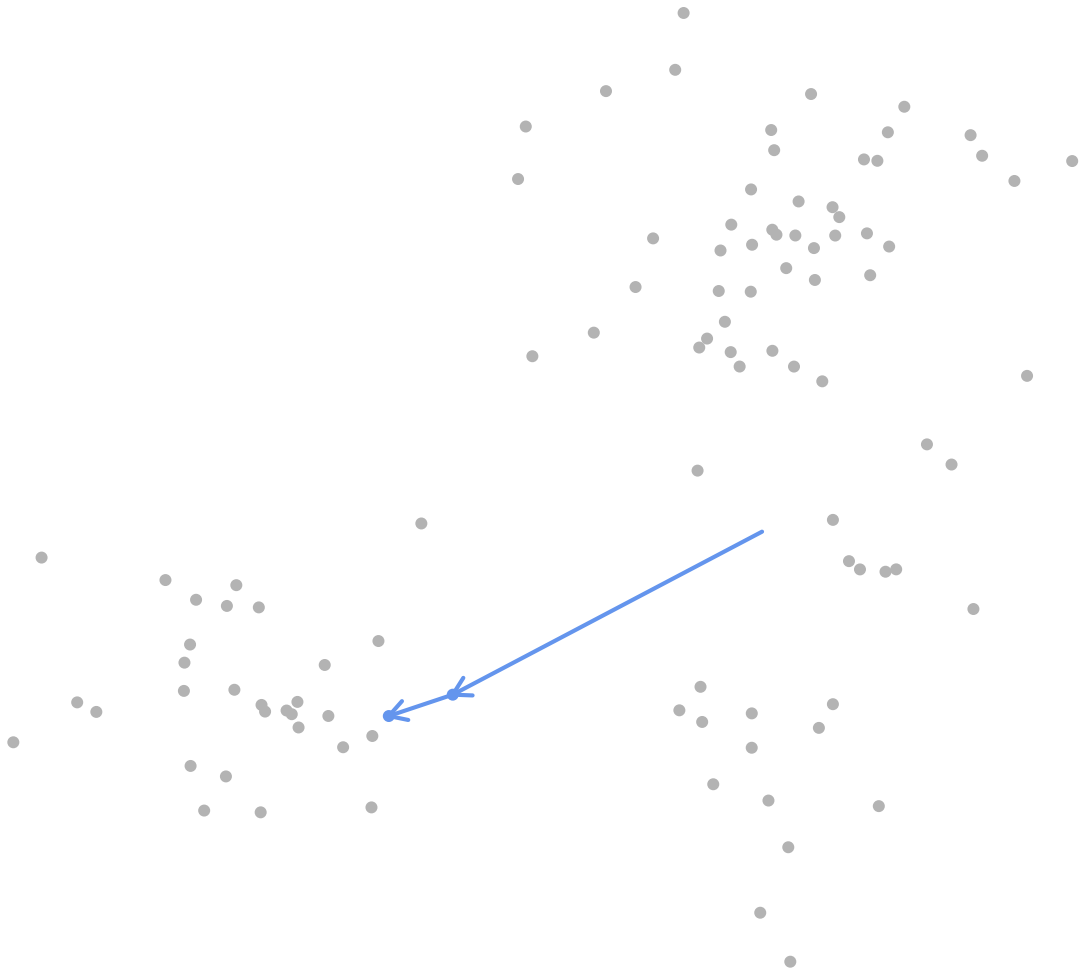

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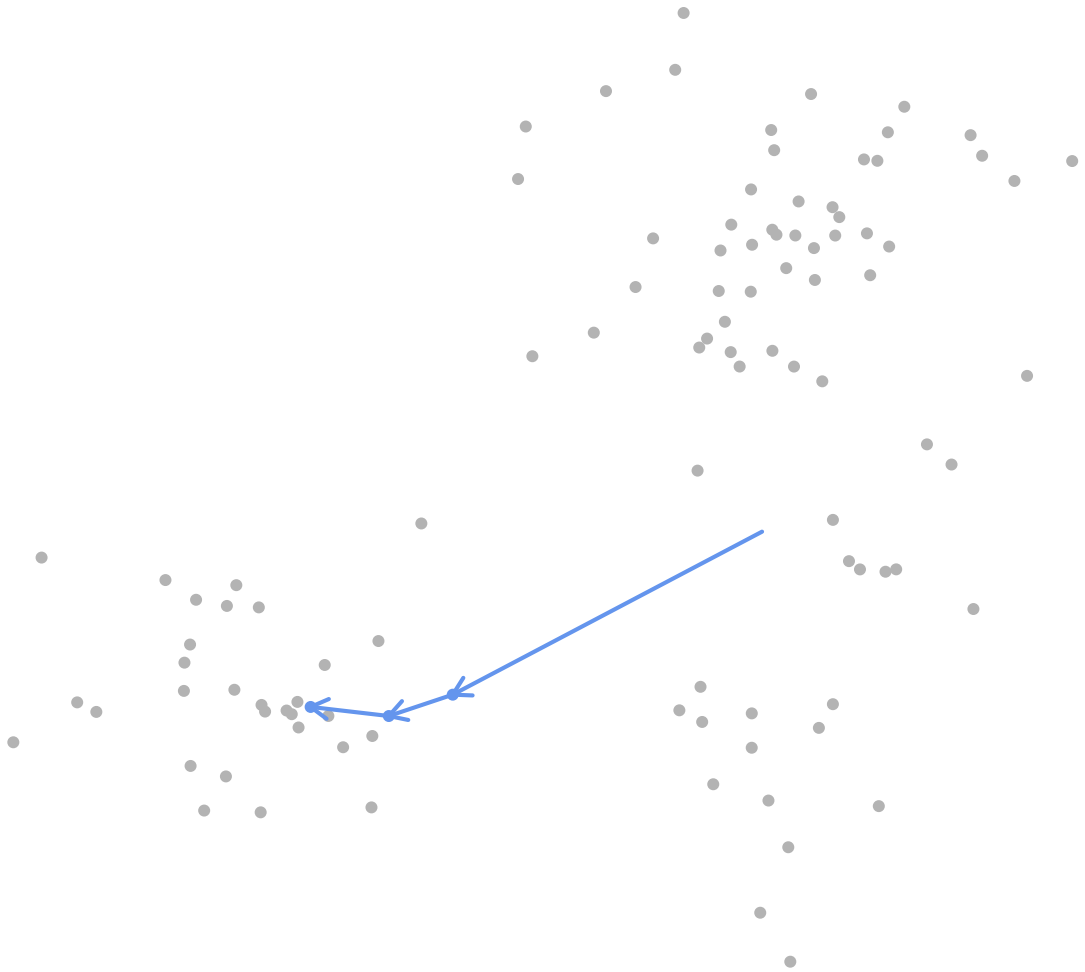

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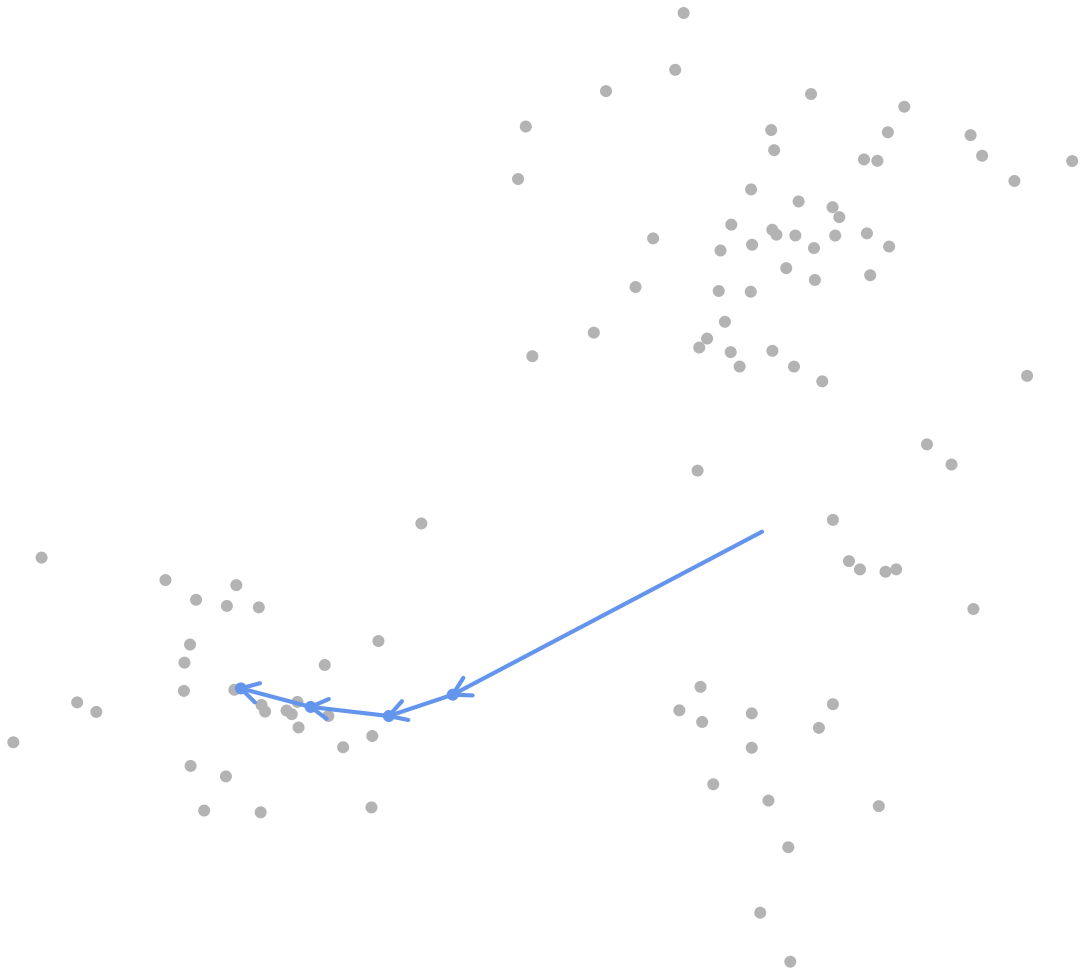

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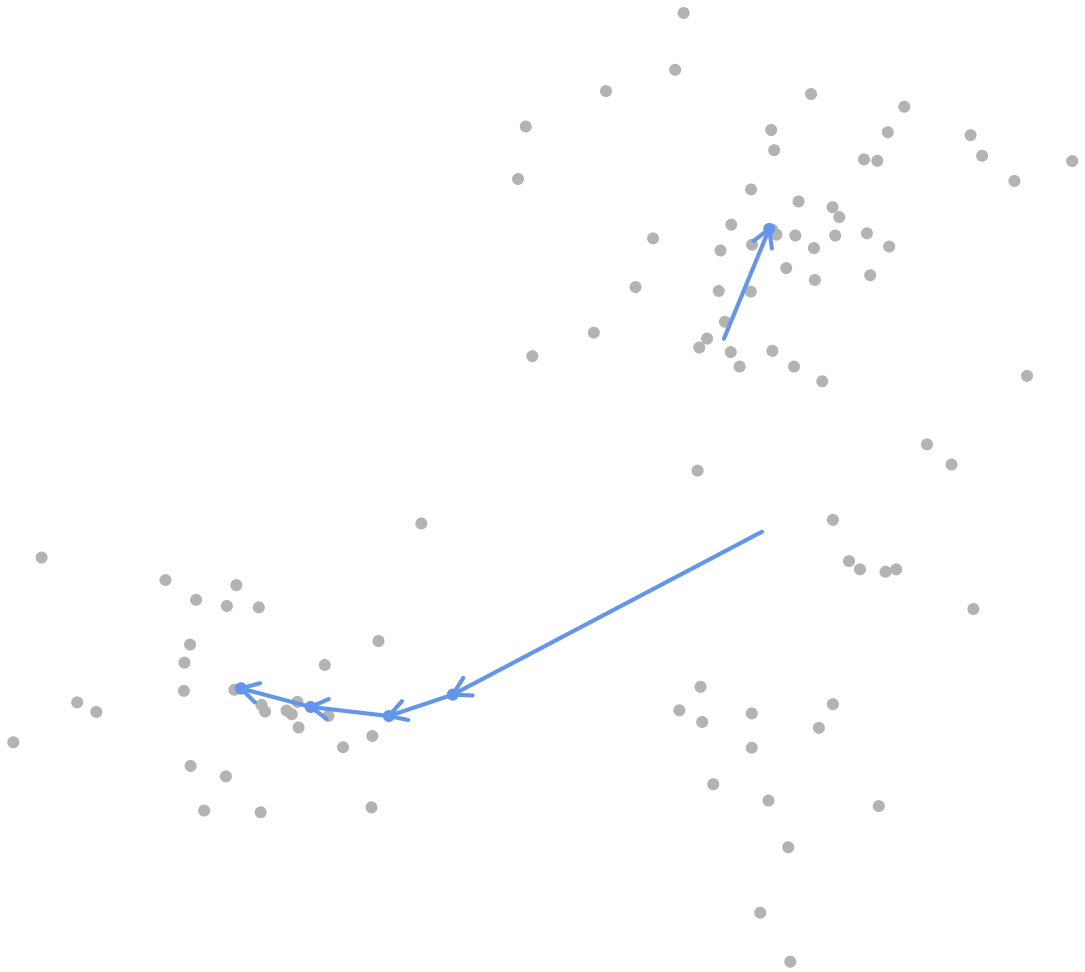

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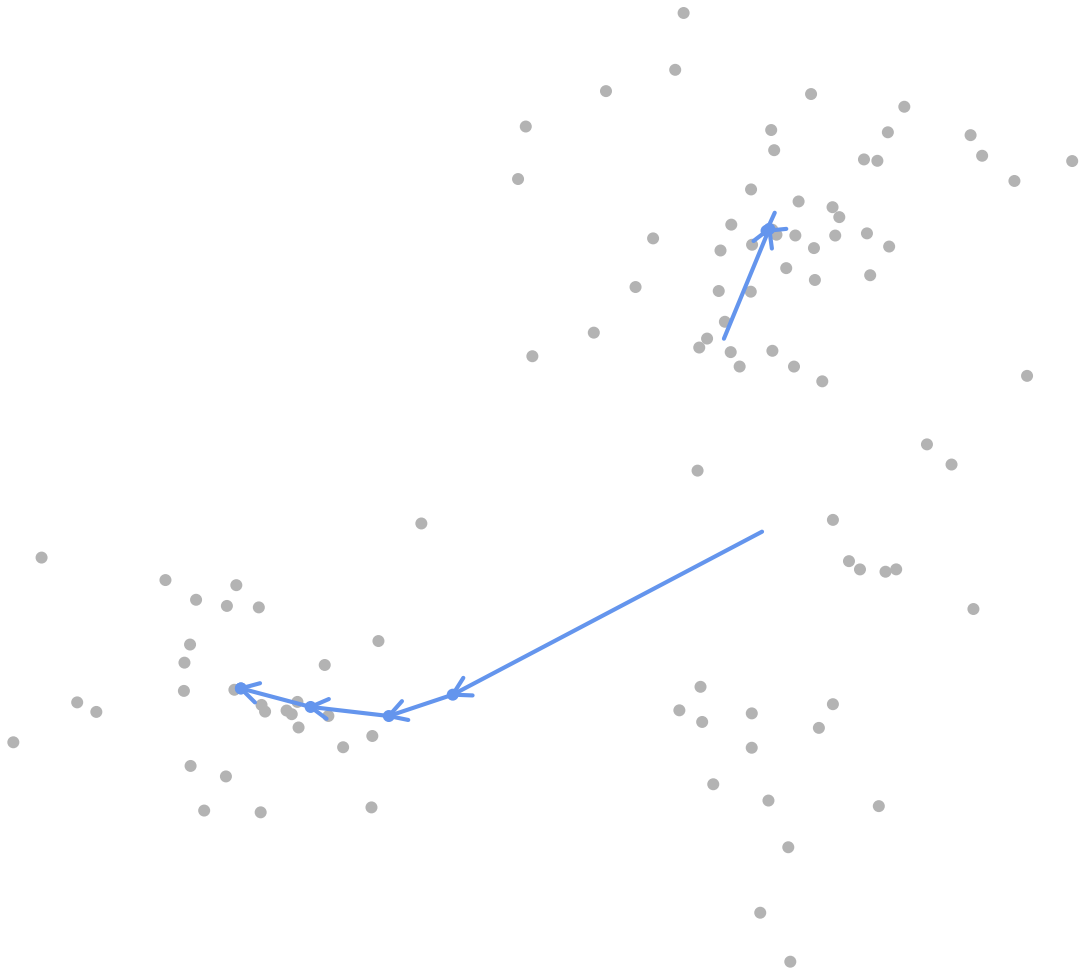

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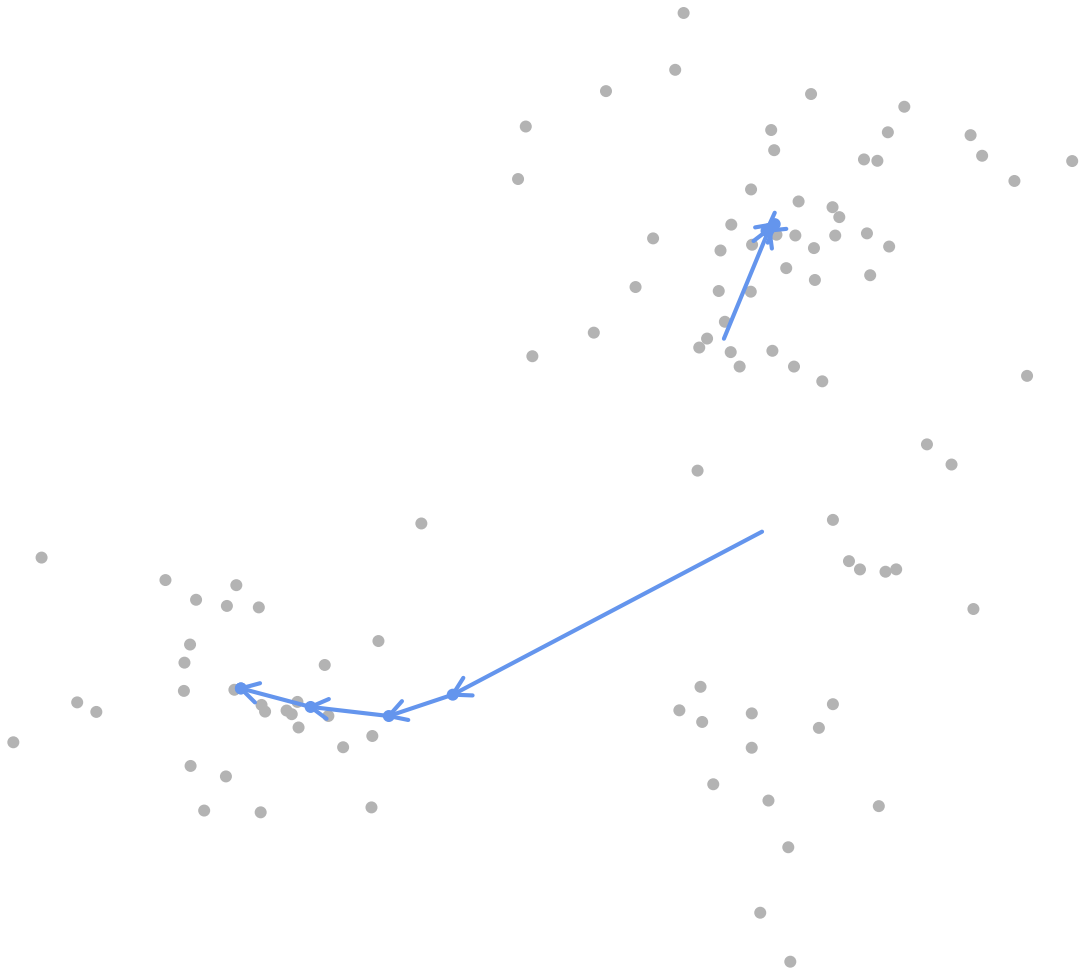

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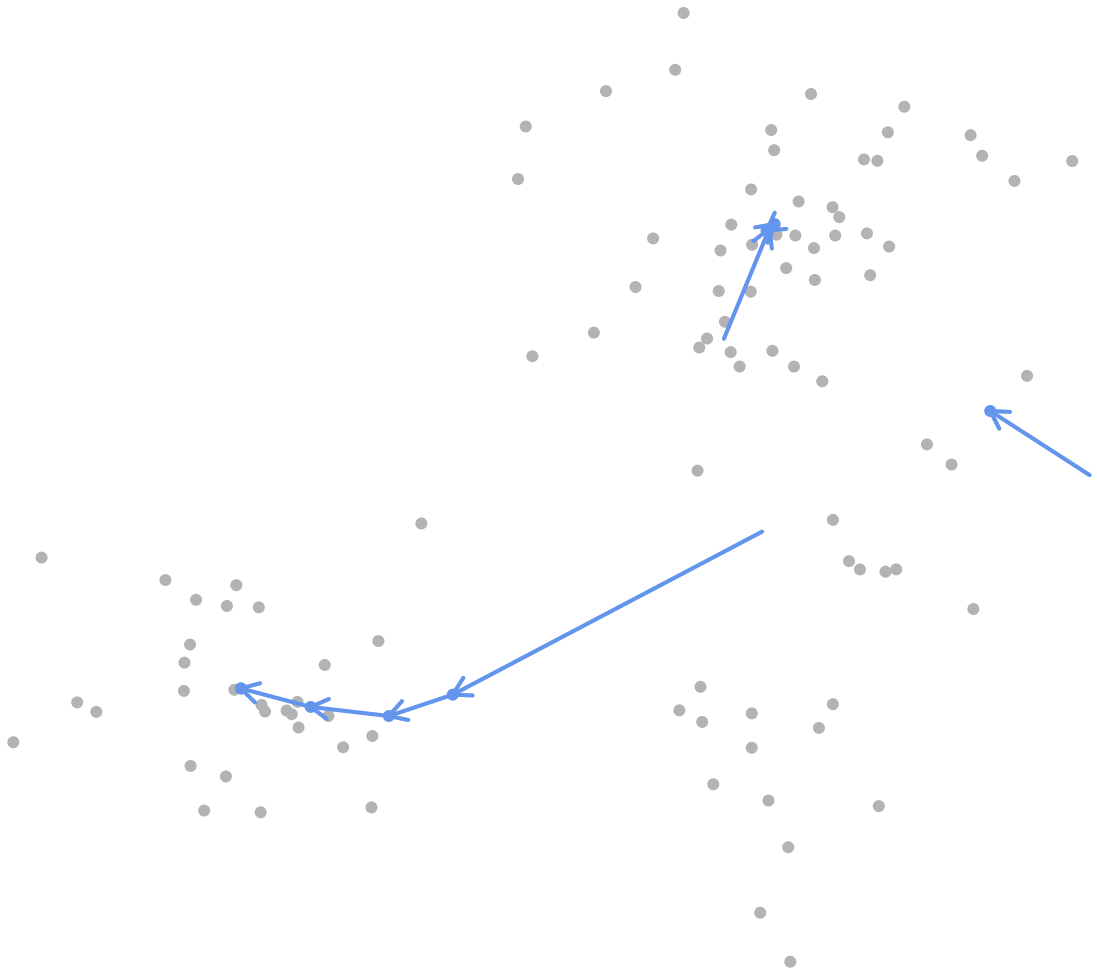

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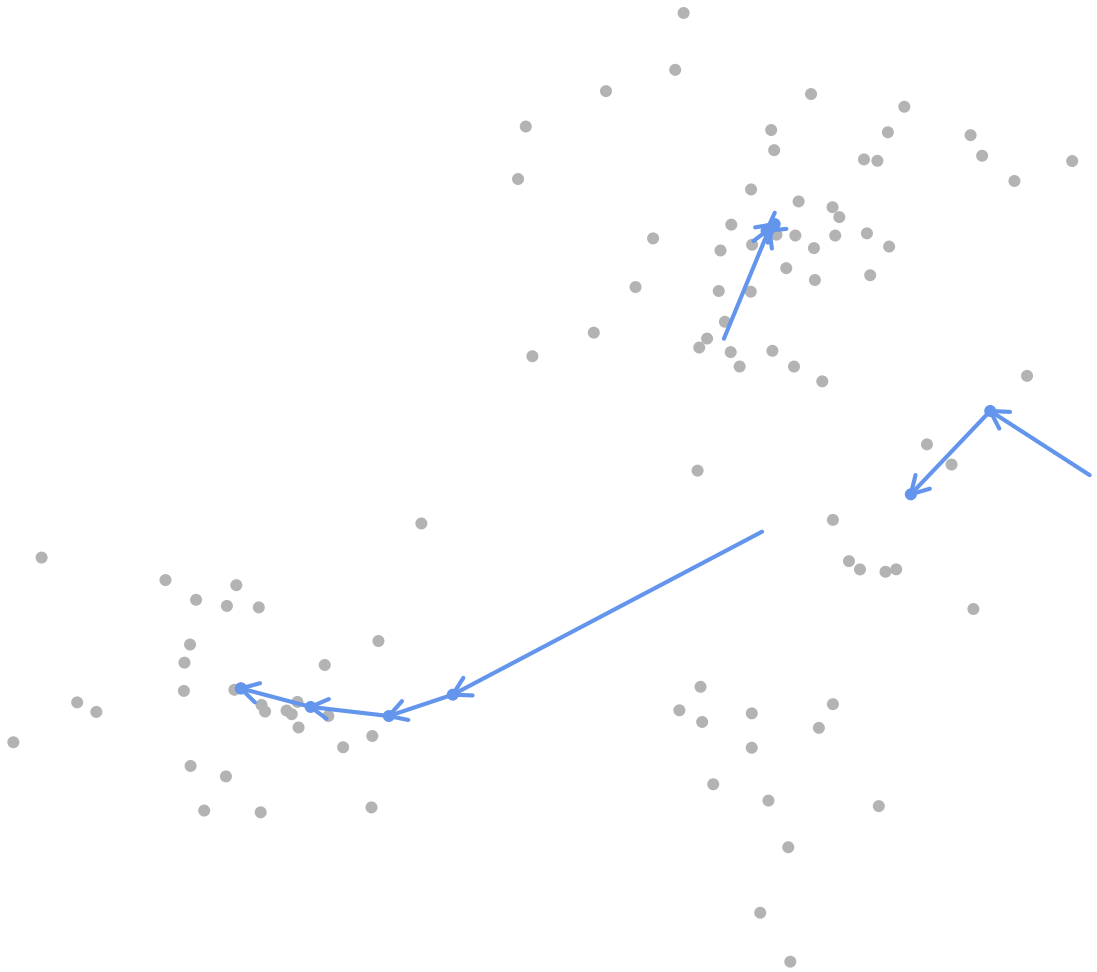
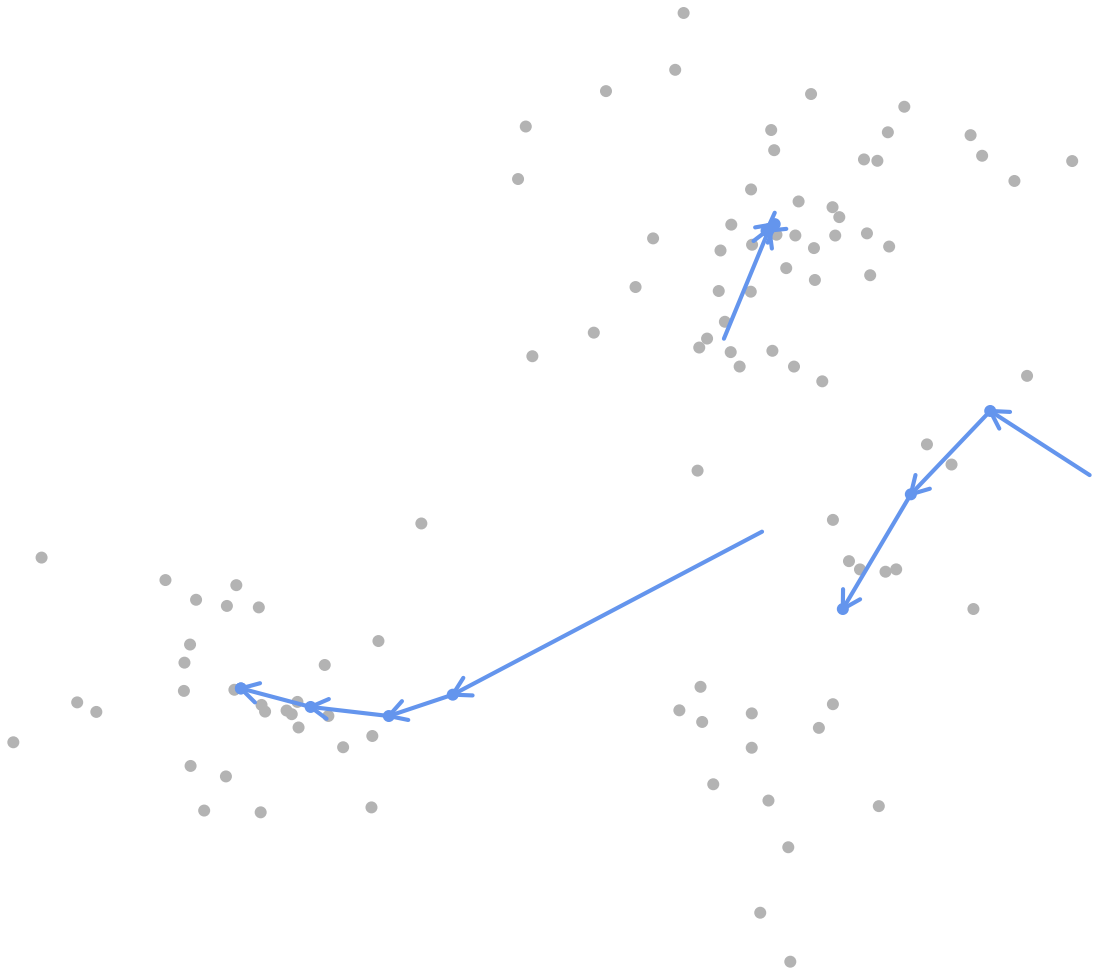
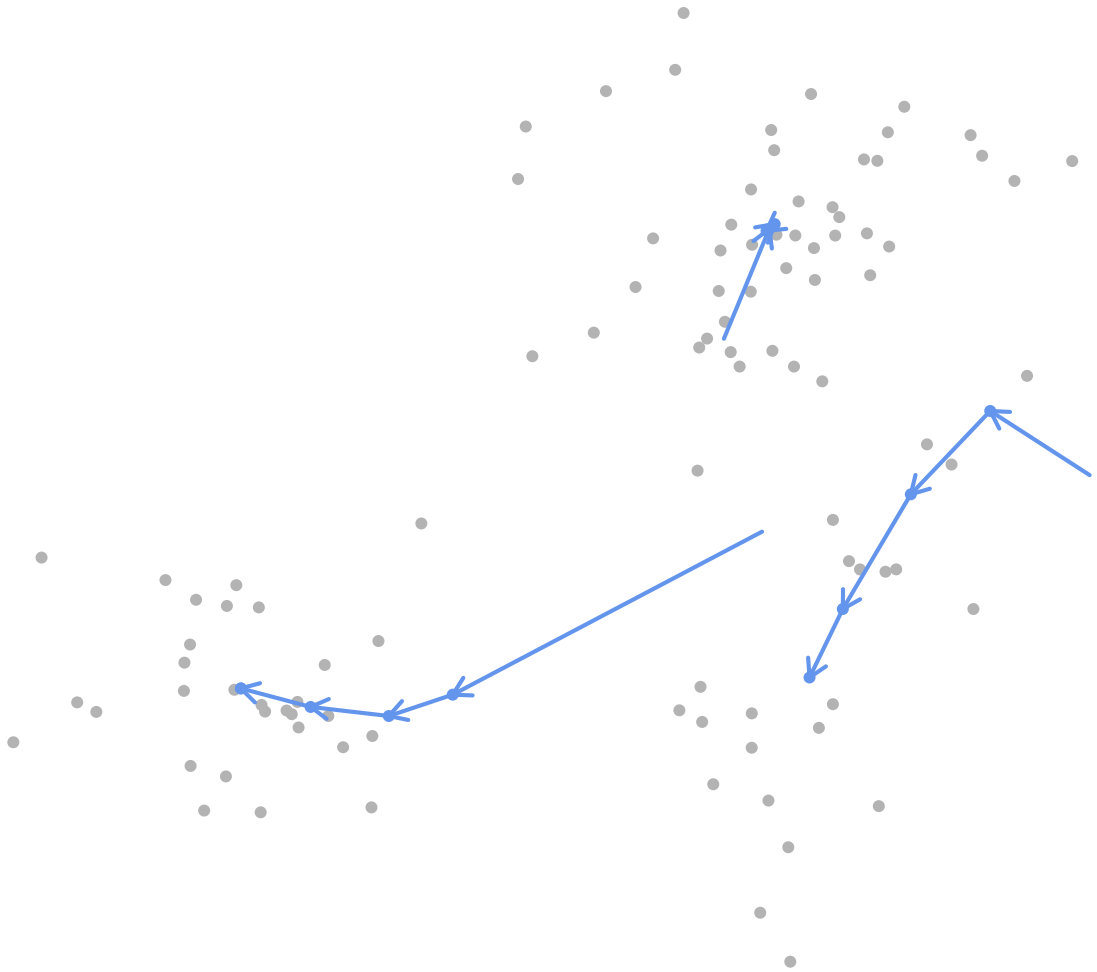


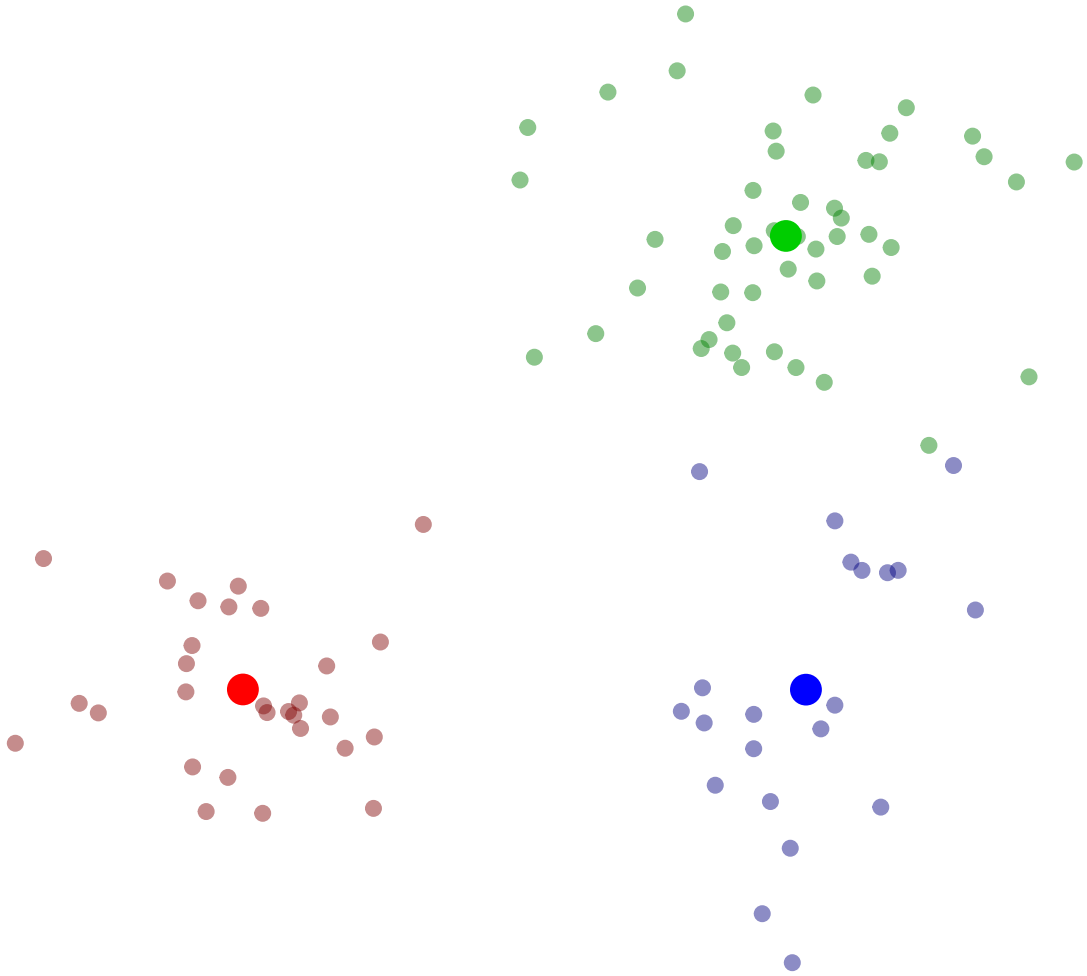
Visual Example



Visual Example



Visual Example



Example: Kmeans on Lautenberg Press Releases

Table 12.1: Applying k-means to the Press Releases

	Proportion	Words
1	0.17	s, presid, bush, administr, u, elect, compani, opec, tax, mr
2	0.16	senat, lautenberg, frank, r, statement, press, washington, comment, d, question
3	0.28	new, jersey, menendez, secur, million, fund, grant, chemic, nj, feder
4	0.39	sen, epa, bill, act, legisl, safeti, famili, protect, requir, victim

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	Proportion	Words
1	0.28	new, jersey, menendez, fund, project, feder, million, program, counti, nj
2	0.21	senat, lautenberg, frank, r, statement, s, presid, comment, press, follow
3	0.42	american, famili, victim, legisl, epa, act, libya, terror, sponsor, report
4	0.08	secur, chemic, homeland, port, law, risk, protect, administr, dhs, bill

Table 12.3: Applying k-means to the press releases, with different starting values than Table 12.1.

Example: New Representation

Cluster	Words
1	passenger, amtrak, rail, security, gas, lott, stronger, preempt, approved, billion
2	court, she, demint, burr, mi, nc, nomination, r, was, medal
3	iraq, dc, american, president, united, taxpayer, issued, following, statement, senator
4	funds, for, announce, county, million, will, river, grants, project, hudson
5	income, care, drug, children, health, coverage, programs, beneficiaries, medicare, deductibles
6	epa, pollution, residents, dangerous, near, environmental, data, safety, agency, chemicals

Table 12.2: k-means clusters using word embeddings representation.

Example: Mixtures of von Mises-Fisher Distributions

Table 12.4: Applying Mixtures of von Mises-Fisher Distributions to Lautenberg Press Releases

Cluster	Top Words
1	sen, d, bill, victim, famili, terror, militari, libya, r, american
2	secur, chemic, homeland, port, risk, law, dhs, protect, tsa, rail
3	new, jersey, fund, menendez, feder, project, nj, million, program, counti
4	senat, s, lautenberg, presid, bush, frank, releas, statement, unit, iraq

Example: Hierarchical Clustering

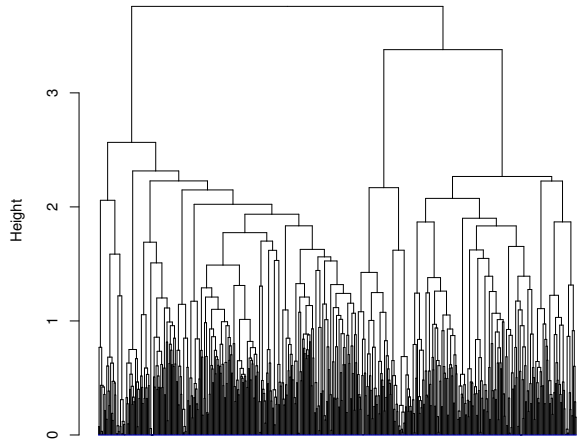

Figure 12.3: Hierarchical Clustering of the Lautenberg Press Releases using Ward's Minimum Variance Method.

Cluster	Top Words
1	american, dc, kill, unit, compens, bipartisan, john, legal, r, md
2	jersey, menendez, new, nj, robert, resid, communiti, project, garden, contact
3	secur, chemic, homeland, stronger, dhs, preempt, port, adopt, deem, attack

Table 12.6: Applying Hierarchical Clustering to the Lautenberg Press Releases

Description from Wikipedia

Back in the Senate, Lautenberg was once again considered one of the chamber's most liberal members. He was pro-choice, supported gun control, introduced many bills increasing penalti and car theft, and criticized the Bush administration on national security issues.[10] He was heavily involved in various anti-smoking and airline safety legislation. He also co-sponsored legisl drunk driving penalties. He was probably best known as the author of the legislation that banned smoking from most commercial airline flights.[19] He also is known for authoring the Ryan W which provides services to AIDS patients. **Upon his return to the Senate, Lautenberg was the first U.S. senator to introduce legislation calling for homeland security funds to be distributed so of risk and vulnerability.**[20]

In 2005, he became a leading voice within the Senate in calling for an investigation into the Bush administration payment of columnists.[21]

When Jon Corzine resigned from the Senate to become Governor of New Jersey, Lautenberg became the senior senator again in 2006. This also made him the only person to have been b senior senator from New Jersey twice each.[*citation needed*] Lautenberg received an "A" on the Drum Major Institute's 2005 Congressional Scorecard on middle-class issues.[22]

In 2007, Lautenberg proposed the Denying Firearms and Explosives to Dangerous Terrorists Act of 2007, designed to deny weapons purchases by persons that the government has placed watchlist. On June 21, 2007, Lautenberg passed Clifford Case for the most votes on the Senate floor of any United States Senator in New Jersey history.[23]

Interpreting Cluster Components

Unsupervised methods

Interpreting Cluster Components

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

Interpreting Cluster Components

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

- Apply clustering methods, we have groups of documents

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- Apply clustering methods, we have groups of documents
- How to interpret the groups?

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    - Read documents

Interpreting Cluster Components

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- Two (broad) methods:
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    - Read documents
    - Assign cluster label

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    - Assign cluster label
  - Automatic identification

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    - Assign cluster label
  - Automatic identification
    - Know label classes

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- No one statistic captures how you want to use your data
- But, can help guide your selection
- Combination statistics + manual search
- Humans should be the final judge

Lautenberg Press Releases with Many Clusters

Cluster	Top Words
1	hous, author, deadlin, system, manag, asset, new, hud, public, extend
2	epa, children, librari, test, mercuri, protect, agenc, chemic, product, health
3	s, u, compani, iran, foreign, busi, halliburton, control, airlin, sanction
4	secur, million, fund, grant, jersey, nj, homeland, port, new, dhs
5	program, educ, food, gang, train, youth, provid, job, abstin, fund
6	new, jersey, state, declar, menendez, feder, counti, disast, faa, administr
7	militari, increas, sen, famili, tricar, d, afghanistan, co, retire, fee
8	budget, new, million, cut, jersey, presid, highland, s, bush, educ
9	fire, safeti, grant, depart, firefight, colleg, campus, assist, nj, student
10	airport, grant, receiv, feder, jersey, menendez, fund, improv, announc, new
11	site, epa, ringwood, superfund, contamin, cleanup, report, resid, environment, agenc
12	presid, bush, s, senat, iraq, statement, administr, white, social, iraqi
13	rang, safeti, guard, grove, warren, air, fire, resid, communiti, account
14	senat, lautenberg, committe, monmouth, iraq, frank, commiss, fort, republican, r
15	american, women, honor, gao, iraq, news, live, mr, vaccin, propaganda
16	cigarett, tobacco, light, tar, compani, nicotin, market, smoker, low, d
17	broadband, municip, access, offer, provid, communiti, state, afford, public, prohibit
18	corp, park, armi, natur, beach, palmyra, cove, engin, dredg, munit
19	build, energi, emiss, bill, global, govern, warm, greenhous, green, feder
20	fund, new, jersey, project, menendez, transport, million, program, counti, tunnel
21	contract, presid, t, said, secretari, hud, get, jackson, select, don
22	ocean, water, state, protect, bill, pet, beach, whistleblow, legisl, nation
23	secur, port, homeland, risk, tsa, screener, rail, senat, chertoff, cap
24	safeti, airport, flight, faa, delay, truck, administr, runway, new, transport
25	judg, court, s, suprem, right, nomin, decis, senat, wigenton, attorney
26	lautenberg, press, statement, ambassador, sen, farm, issu, frank, offic, d
27	senat, lautenberg, statement, frank, r, follow, issu, unit, question, press

Example Discovery: Congressional Communication to Constituents

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

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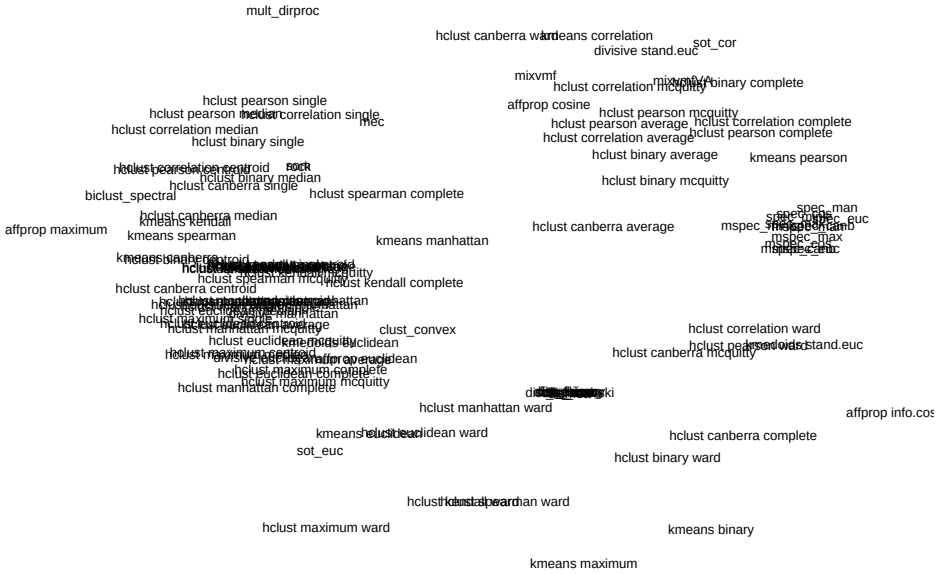
- Data: 200 press releases from Frank Lautenberg's office (D-NJ)

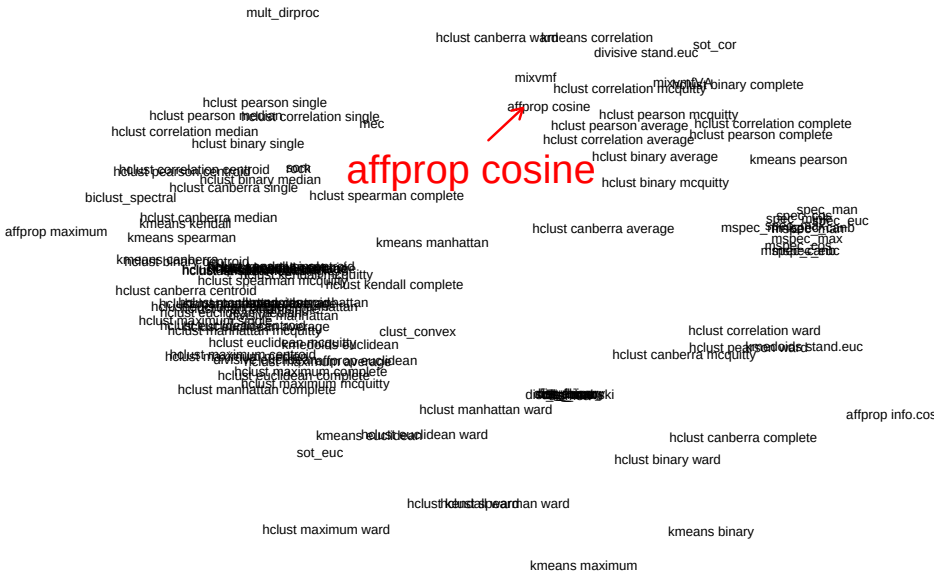
Example Discovery: Congressional Communication to Constituents

- Paper (Grimmer and King 2011): introduce new evaluation methods (like Cluster Quality)
- David Mayhew's (1974) famous typology
  - Advertising
  - Credit Claiming
  - Position Taking
- Data: 200 press releases from Frank Lautenberg's office (D-NJ)
- Apply method (relying on many clustering algorithms)

Example Discovery



Example Discovery



Each point is a clustering
Affinity Propagation-Cosine
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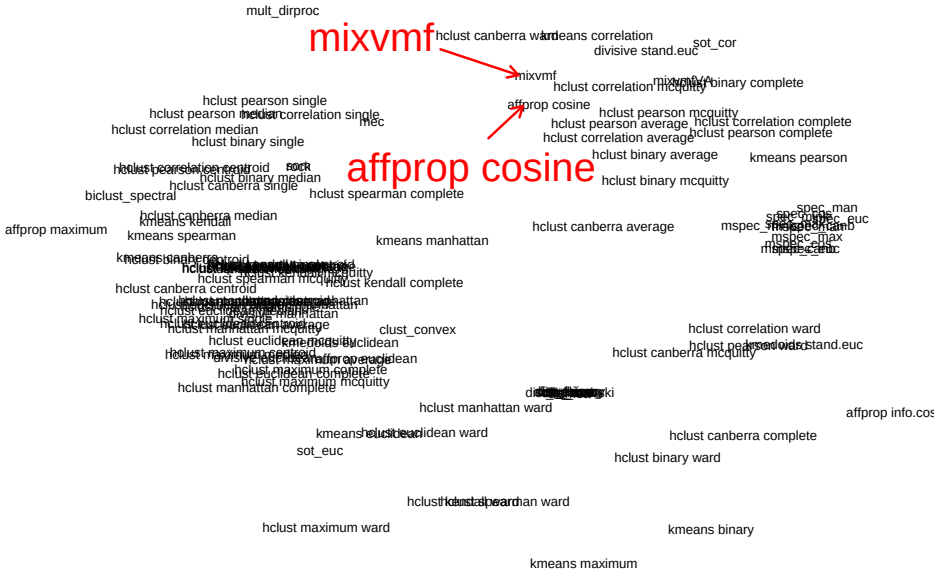
Example Discovery



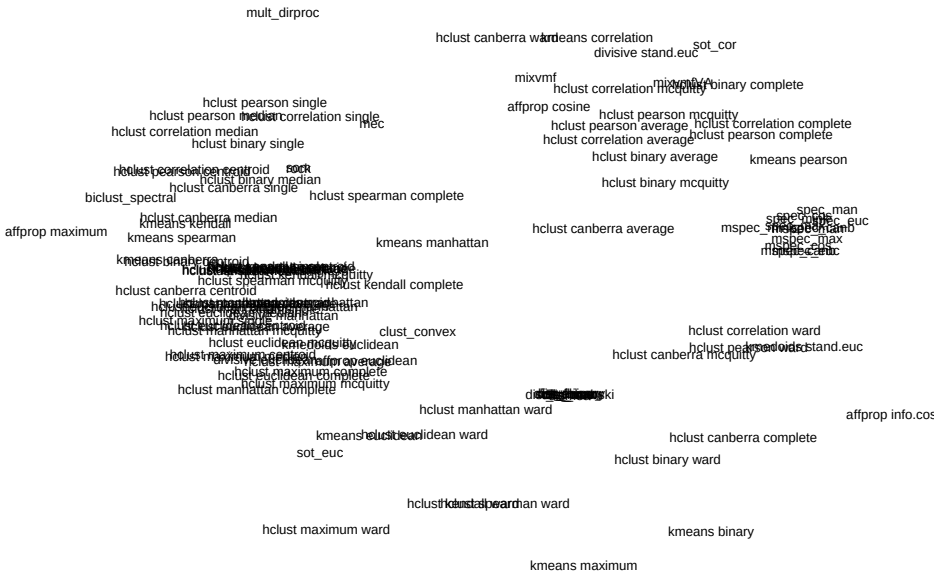
Each point is a clustering Affinity Propagation-Cosine (Dueck and Frey 2007)

Close to:

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

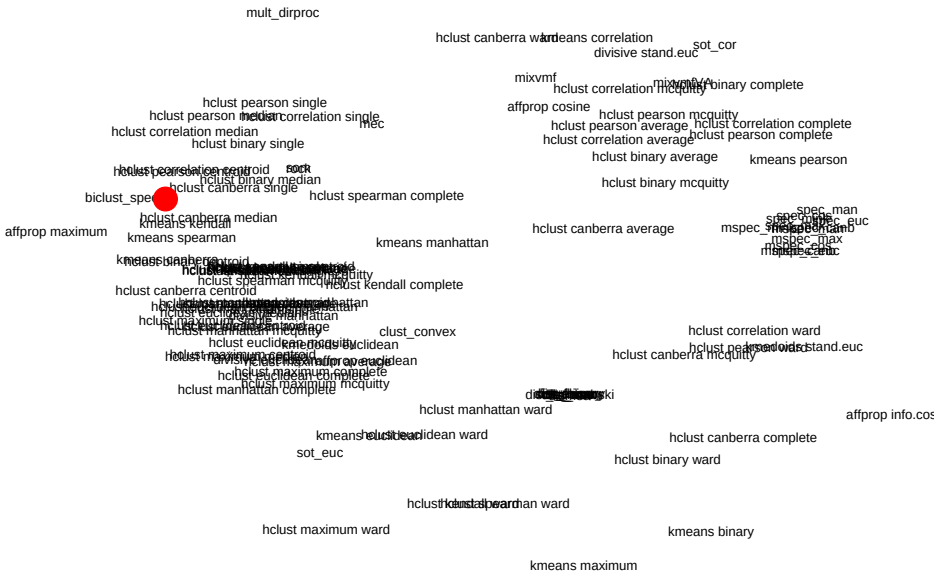
$\Rightarrow$ Similar clustering of documents

Example Discovery



Space between methods:

Example Discovery



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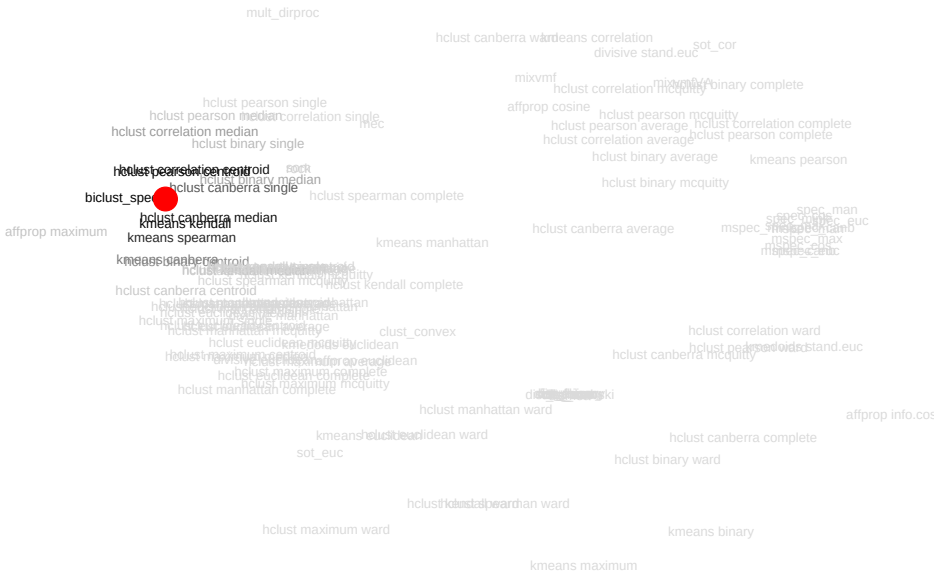
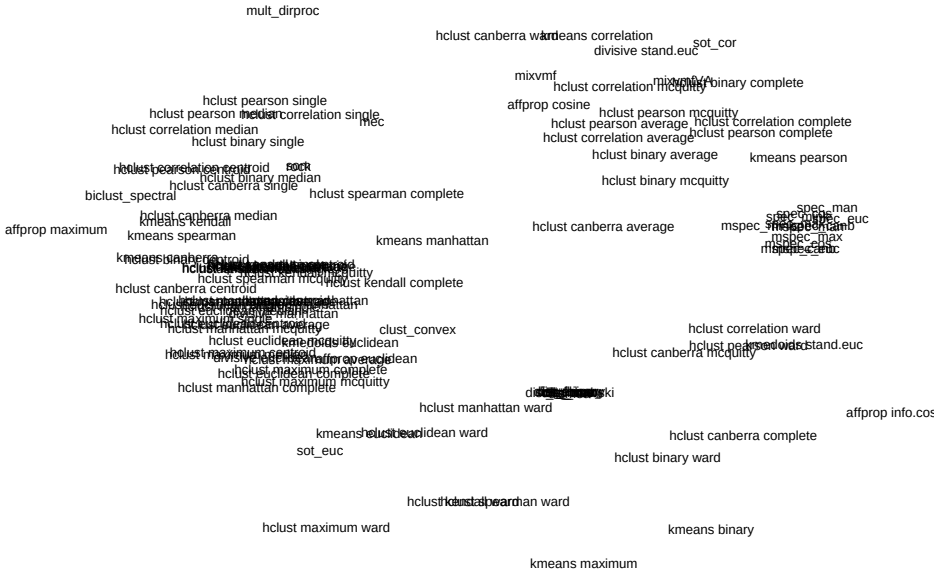


Space between methods:

local cluster ensemble

Example Discovery



Example Discovery

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

Example Discovery

Mixture:

Example Discovery

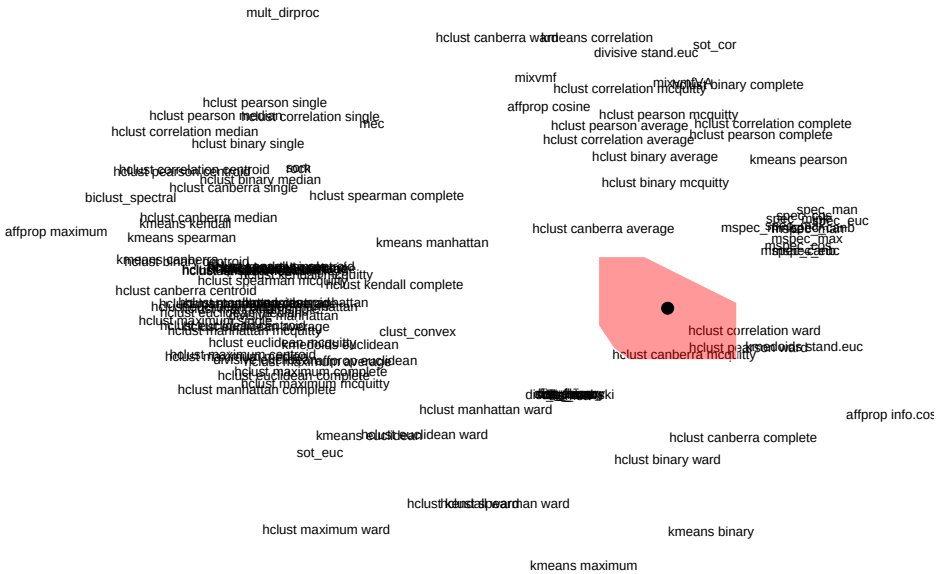
Mixture:

0.39 Hclust-Canberra-McQuitty

0.13 Hclust-Correlation-Ward

0.09 Hclust-Pearson-Ward

Example Discovery



Mixture:

0.39 Hclust-Canberra-McQuitty

0.30 Spectral clustering
Random Walk
(Metrics 1-6)

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0.09 Hclust-Pearson-Ward

0.04 Spectral clustering
Symmetric
(Metrics 1-6)

Example Discovery

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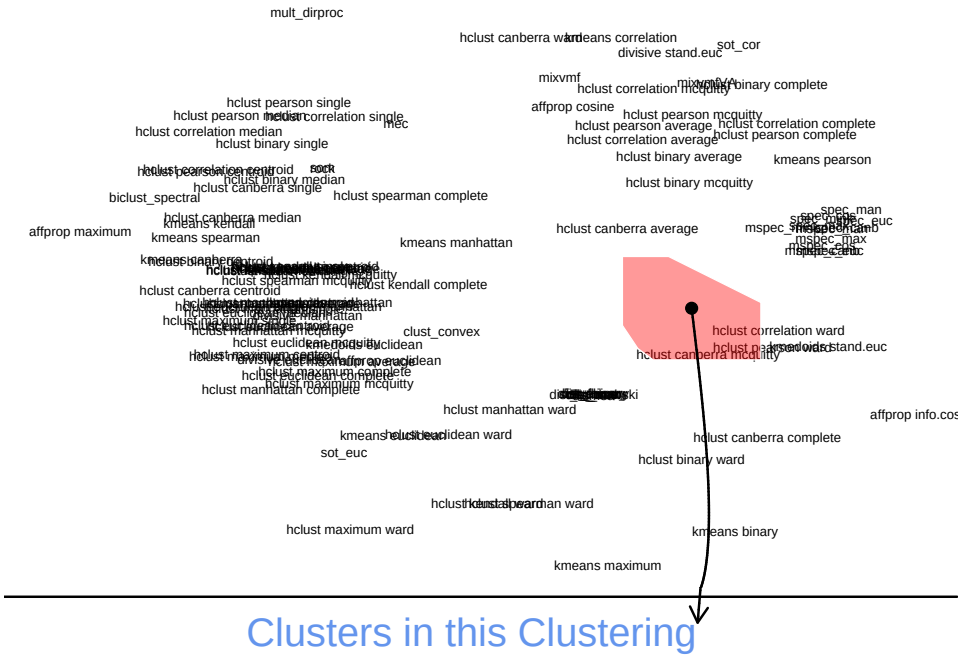
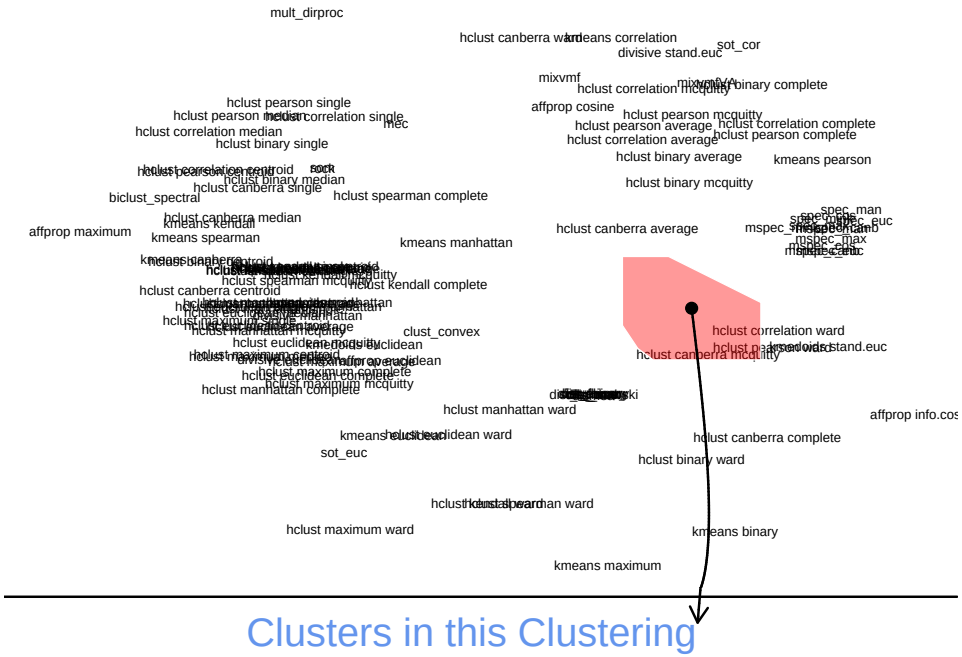
Example Discovery

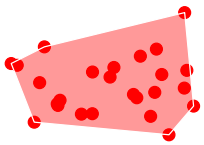


Mayhew

Example Discovery



Clusters in this Clustering

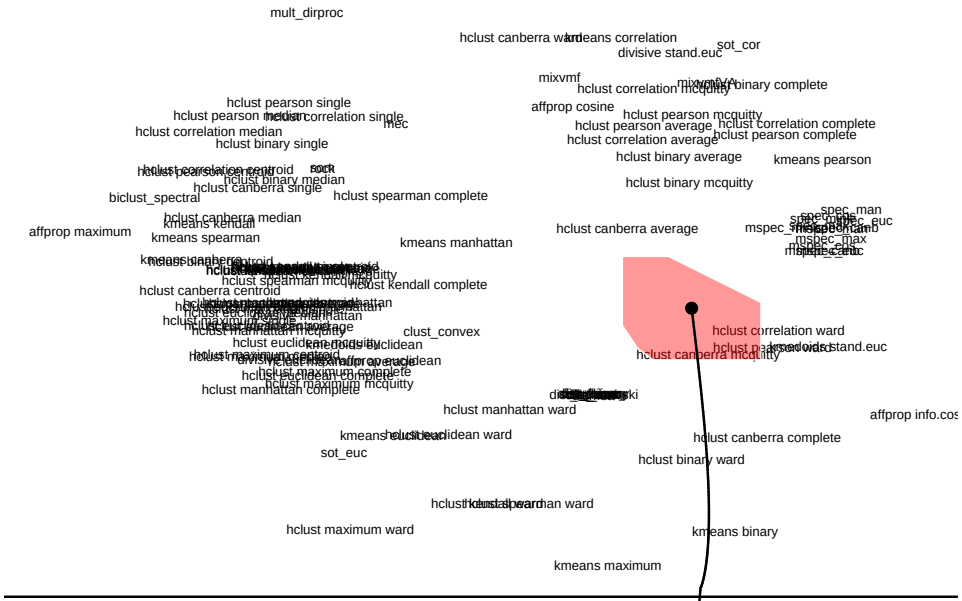


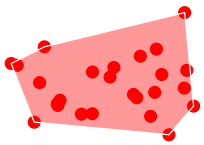
Credit Claiming
Pork

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





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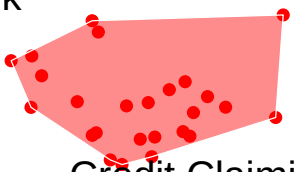
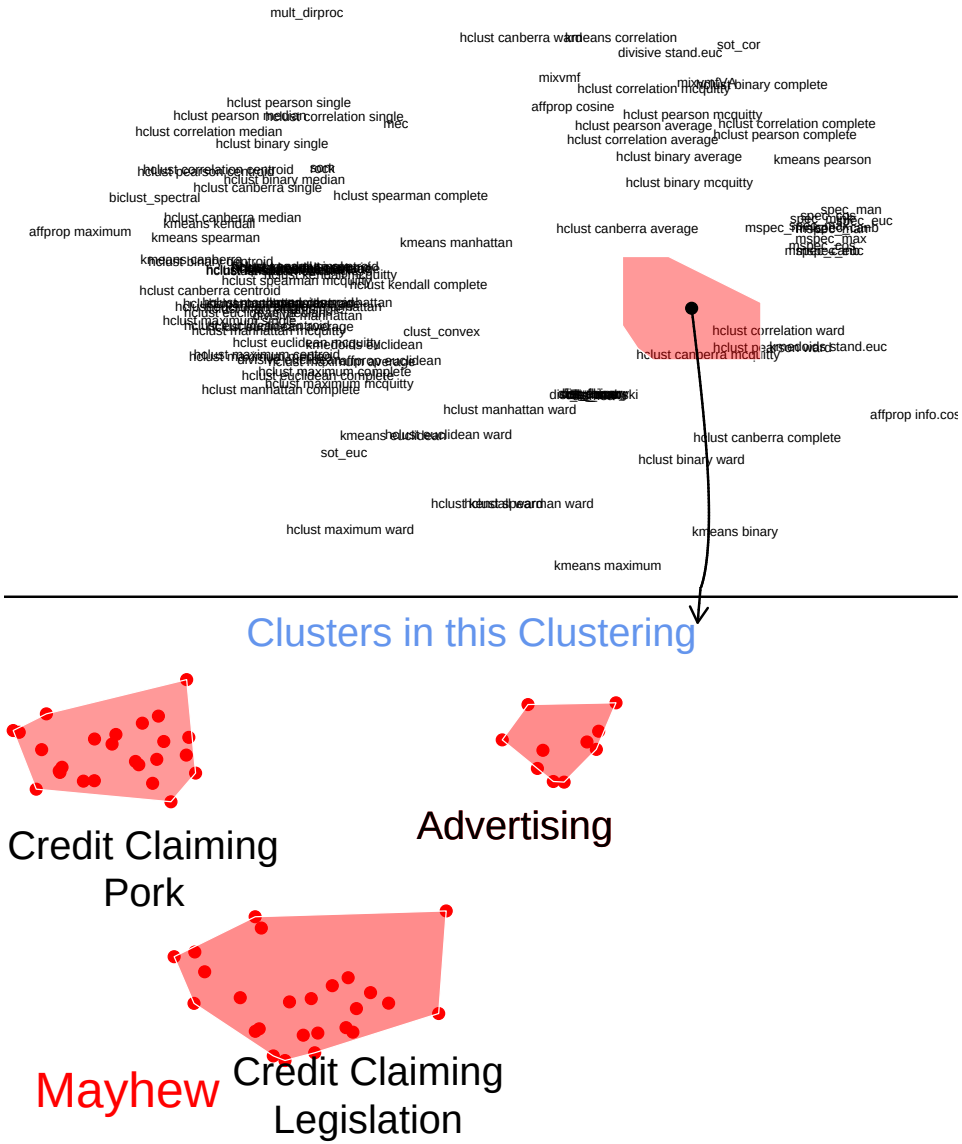


Mayhew

Credit Claiming
Legislation

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"

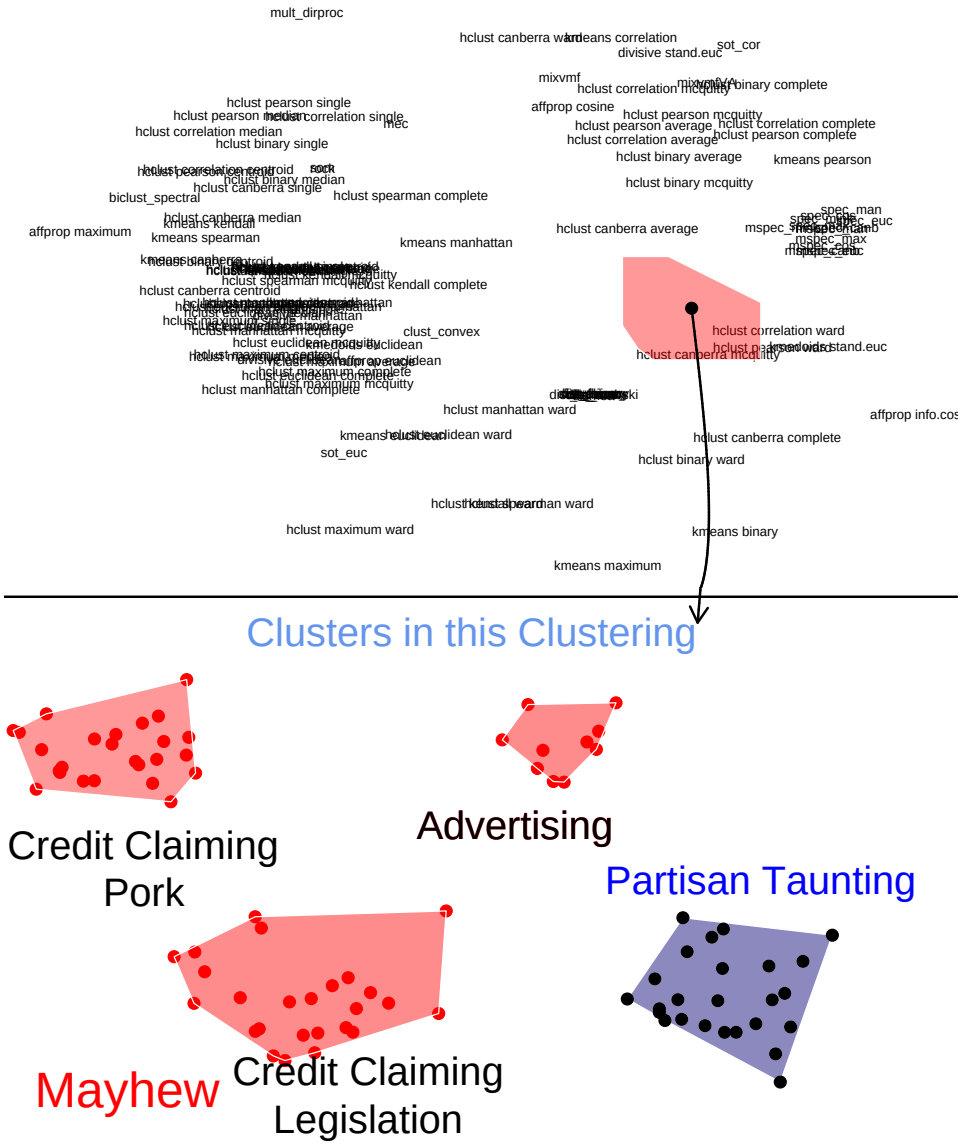
Example Discovery



Advertising:

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

Example Discovery: Partisan Taunting



Clusters in this Clustering

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]

In Sample Illustration of Partisan Taunting

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Consequences for representation: Deliberative, Polarization, Policy

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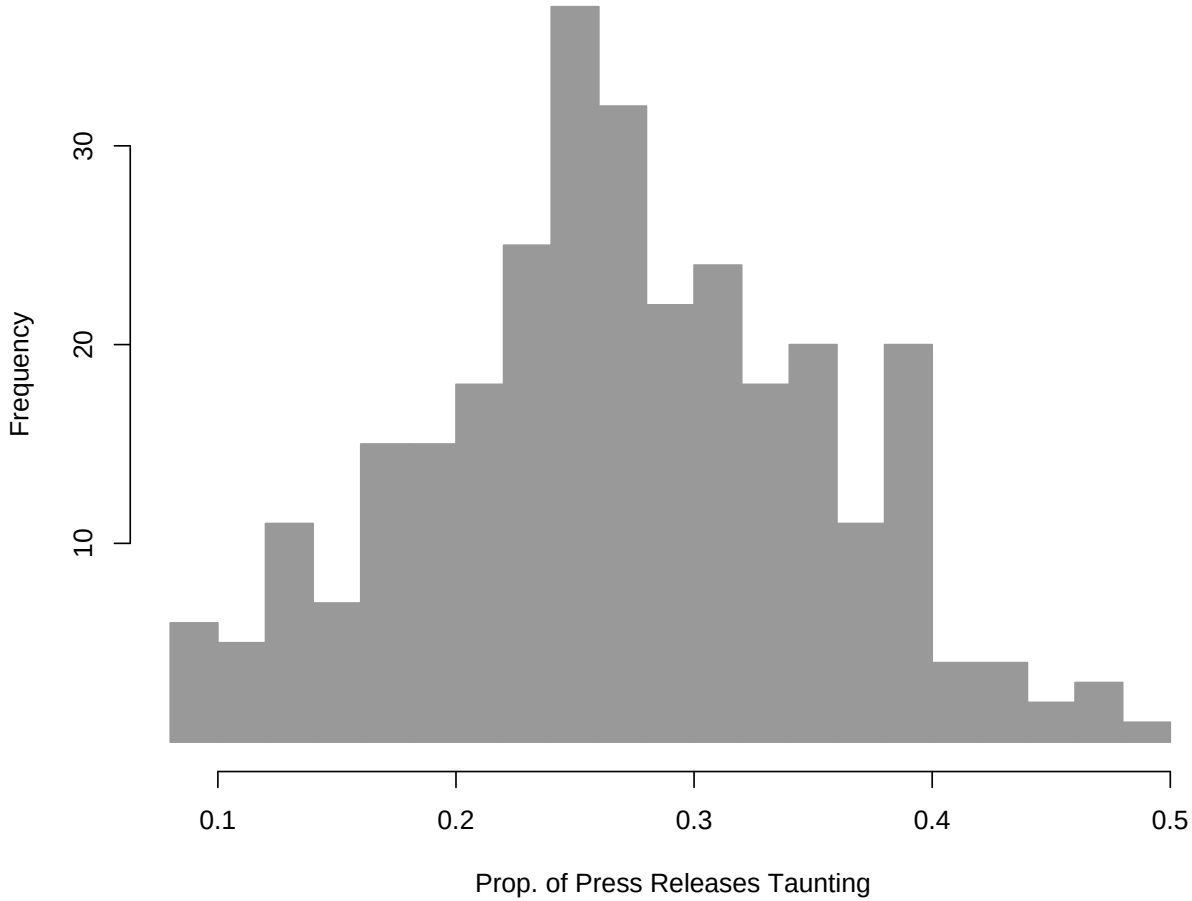

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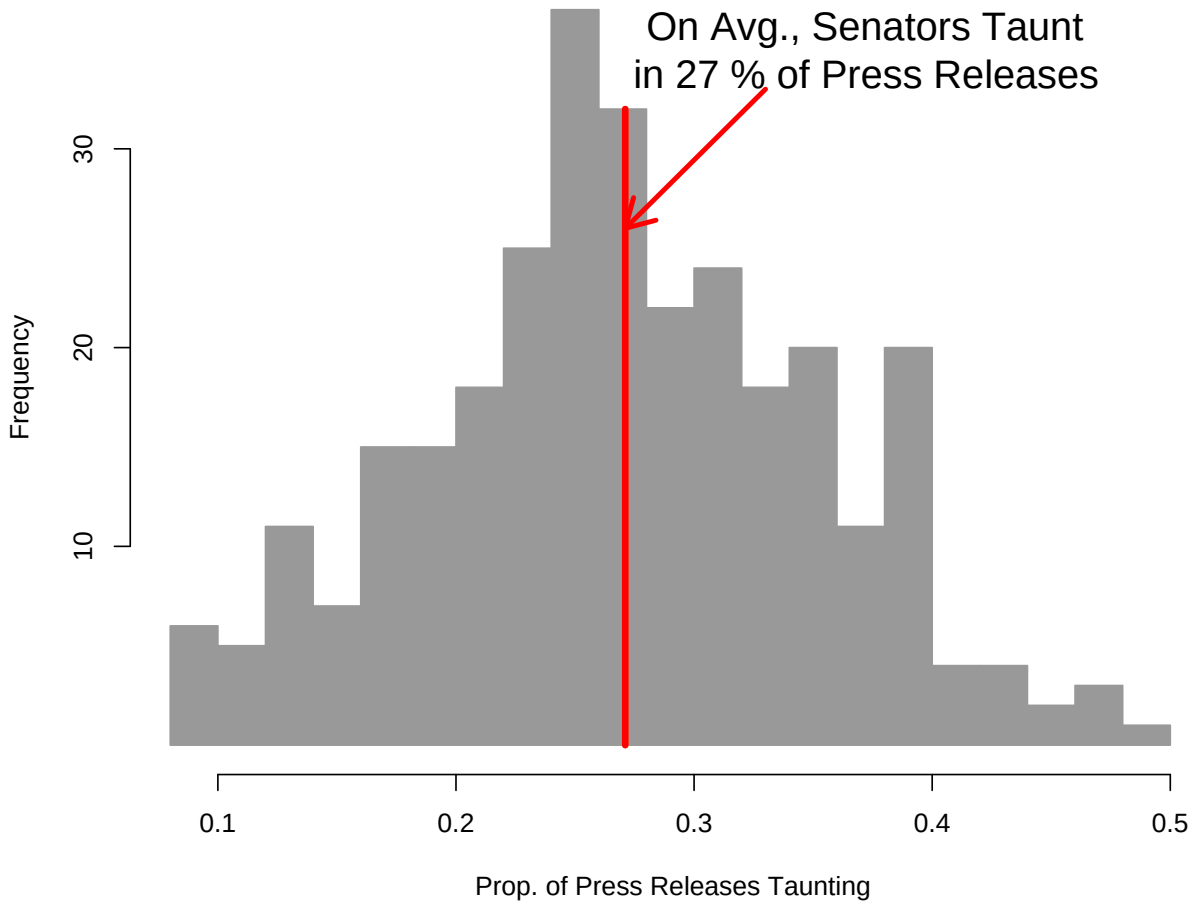
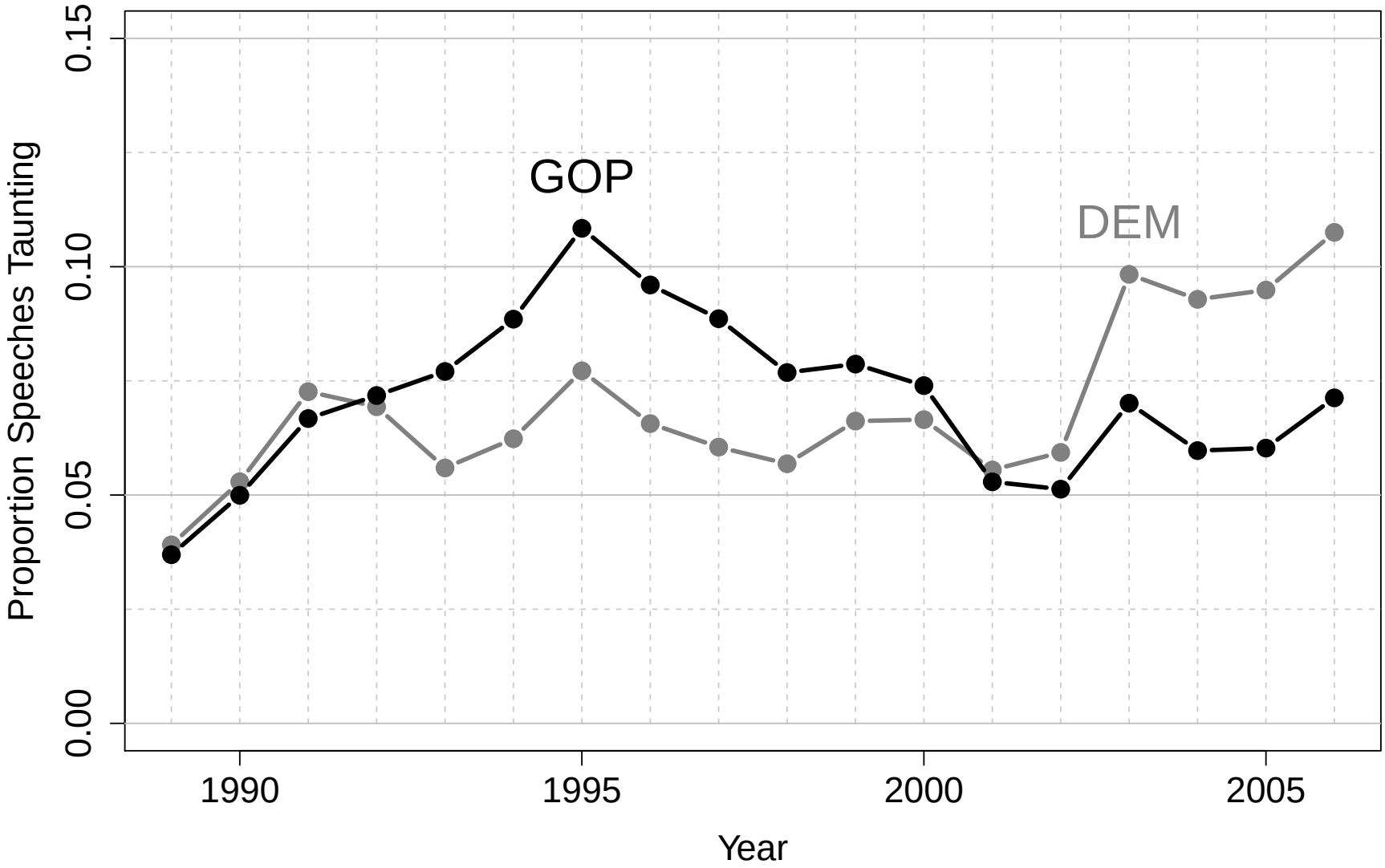


Over Time Taunting Rates in Speeches



Topic and Mixed Membership Models

Clustering

Document $\rightsquigarrow$ One Cluster

Doc 1

Doc 2

Doc 3

$\vdots$

Doc N

Cluster 1

Cluster 2

$\vdots$

Cluster K

Topic and Mixed Membership Models

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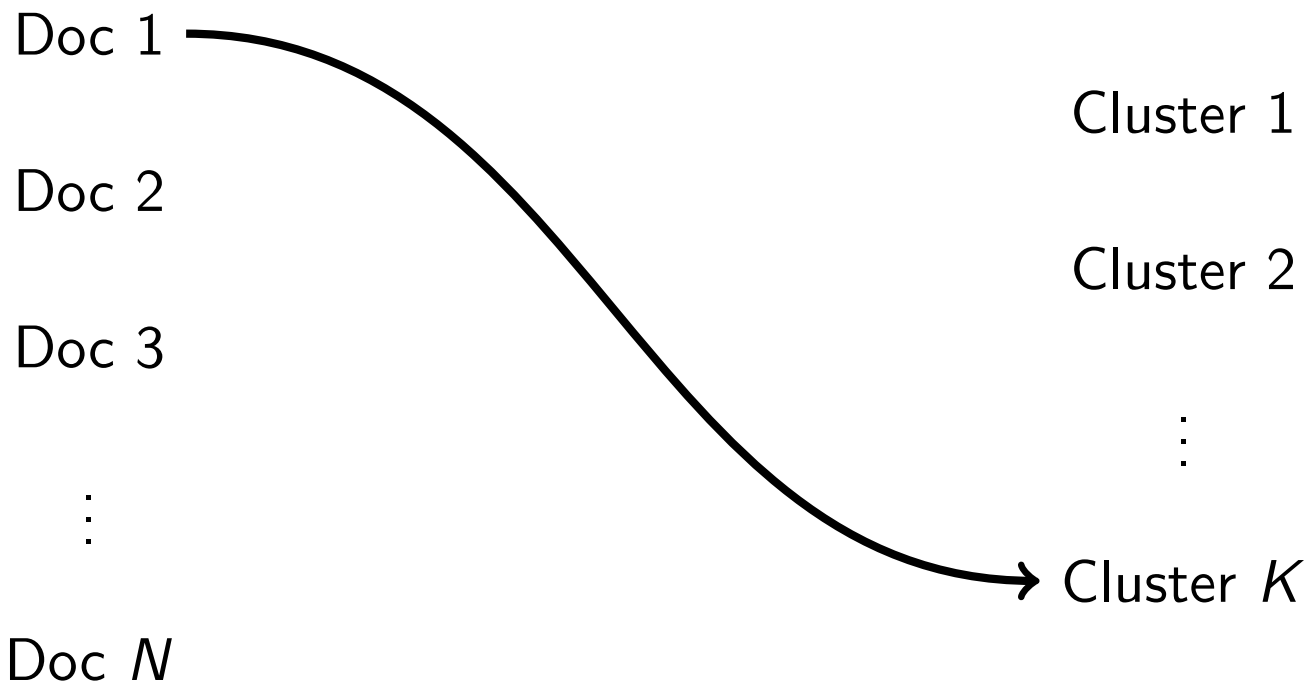

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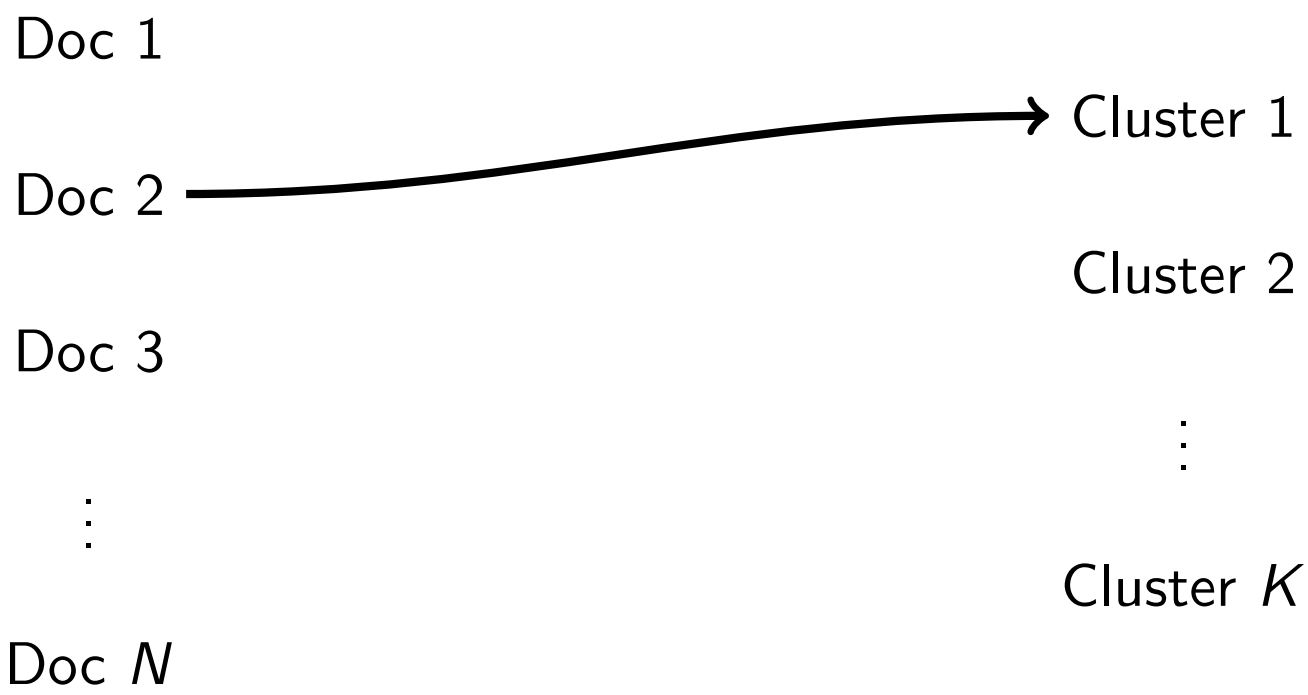

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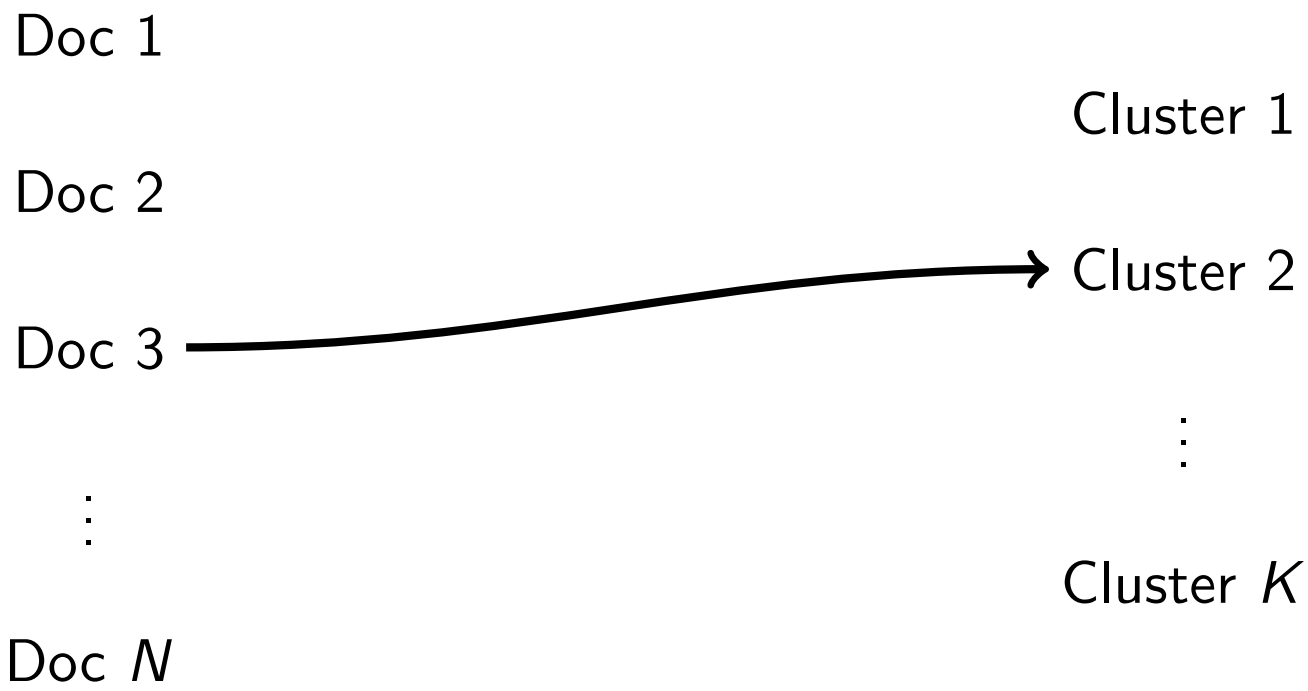

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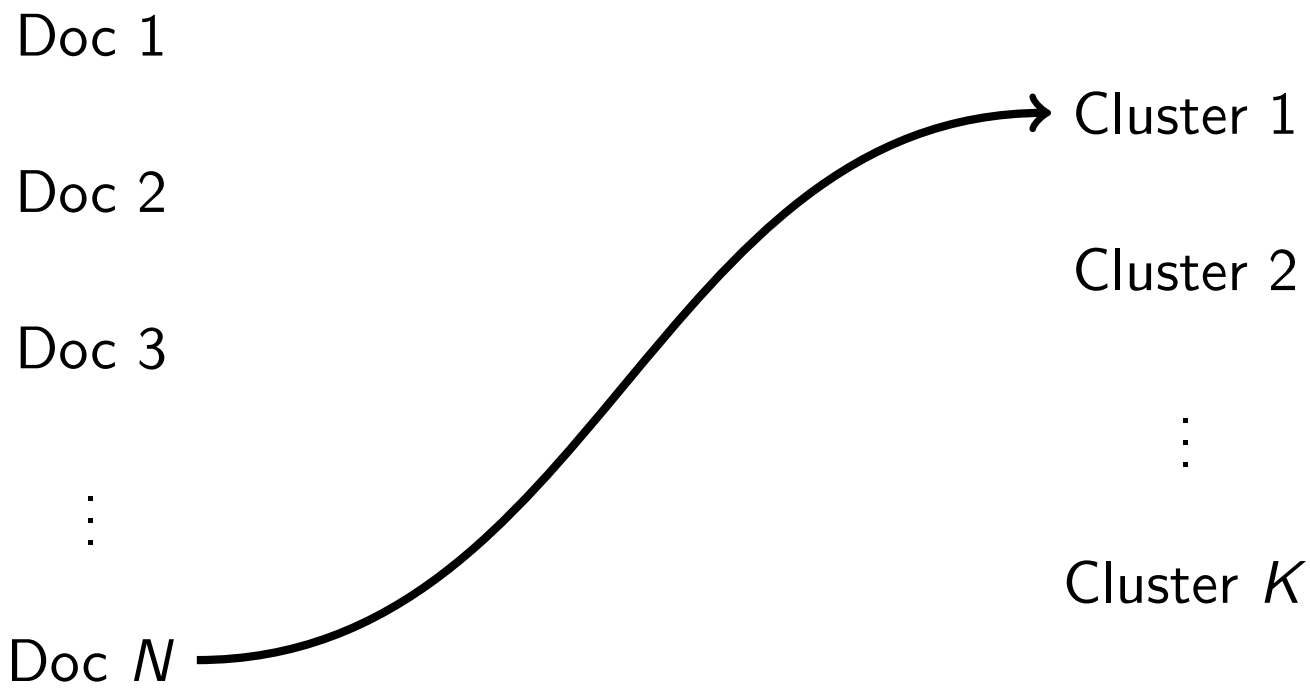

Topic and Mixed Membership Models

Topic Models (Mixed Membership)

Document $\rightsquigarrow$ Many clusters

Doc 1

Doc 2

Doc 3

$\vdots$

Doc N

Cluster 1

Cluster 2

$\vdots$

Cluster K

Topic and Mixed Membership Models

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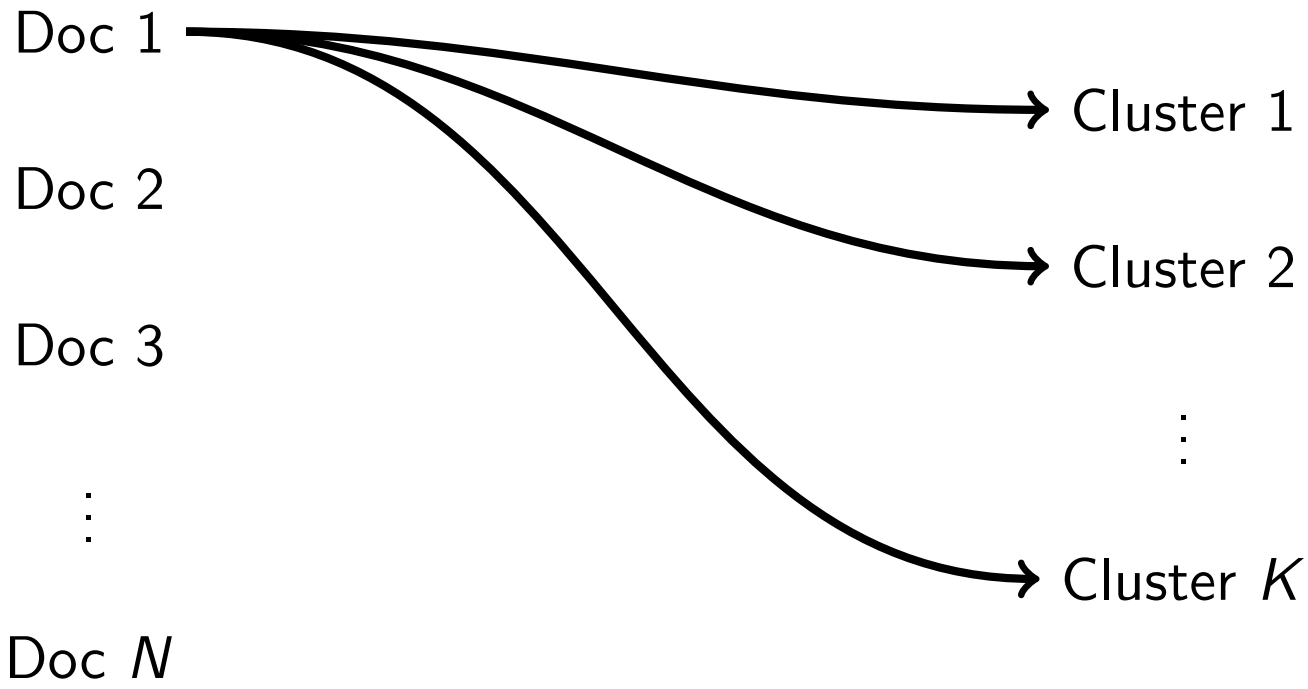

Topic Models

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1) Topical Prevalence Matrix (DxK)

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$$\boldsymbol{\pi} = \left[\begin{array}{c|cccc} & Topic1 & Topic2 & \dots & TopicK \\ \hline Doc1 & .2 & .1 & \dots & 0.05 \\ Doc2 & .2 & .1 & \dots & .3 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ DocD & 0 & 0 & \dots & .5 \end{array}\right]$$

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Topic Models

Two matrices estimated: $W \approx \pi\mu$

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Latent Dirichlet Allocation

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Maintained assumptions: Bag of words/fix number of topics ex ante.

What this means in pictures

Say you have
a lot of people.

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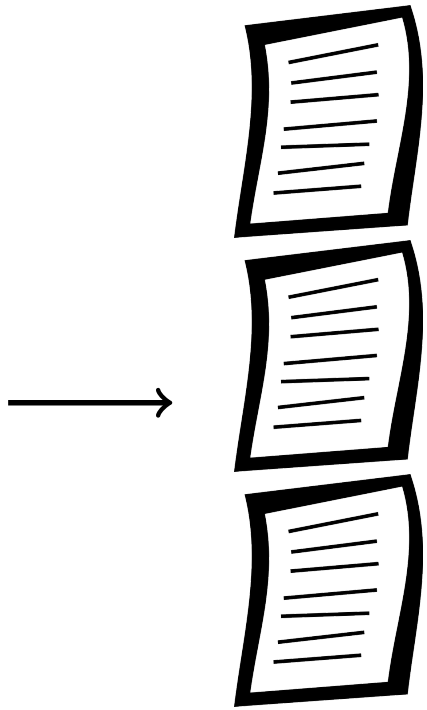

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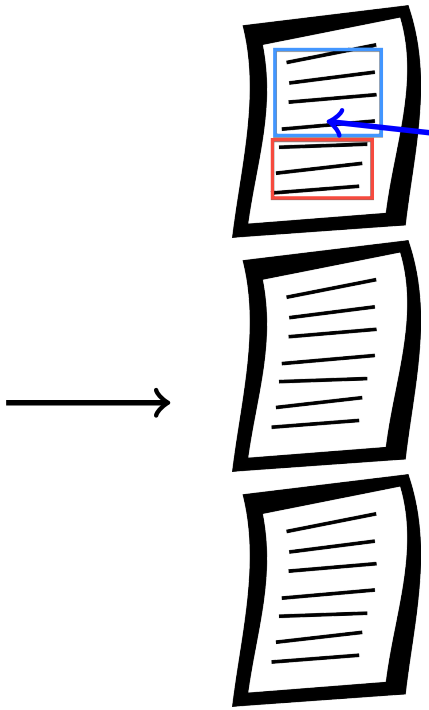

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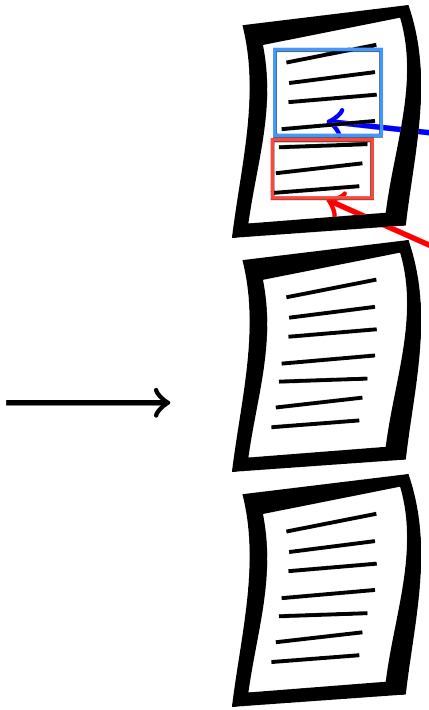

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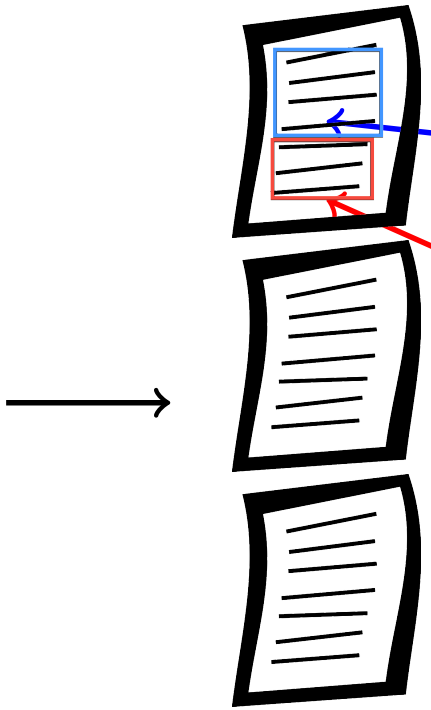

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Politics

congress, nations, power, votes, agreement, bargaining

Statistics

estimator, data, analysis, variance, model, inference

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2. The proportion of each document in each topic

STM = LDA + Contextual Information

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- STM provides two ways to include contextual information

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Group A

Group B

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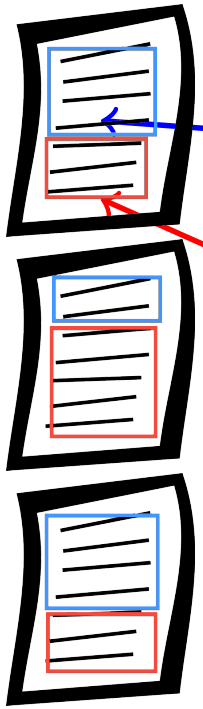

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- IR question: why is Japan now willing to engage militaristic foreign action?

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Japanese Campaign Manifestos (Catalinac 2011)

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Japanese Elections:

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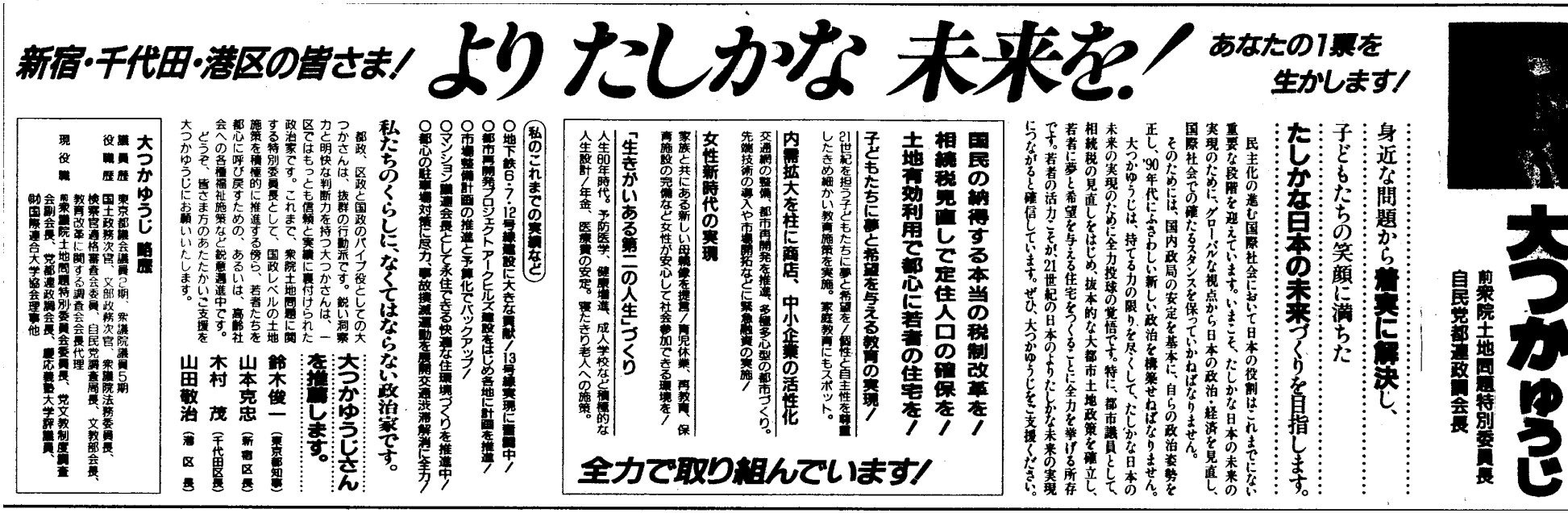
- Required to submit manifestos for all candidates to National Diet

Japanese Campaign Manifestos (Catalinac 2011)

Typical Manifesto:



新宿・千代田・港区の皆さま！

よりたしかな未来を！

あなたの1票を生かします！

大つかゆうじ

前衆院土地問題特別委員長
自民党都連政調会長

身近な問題から着実に解決し、
子どもたちの笑顔に満ちた
たしかな日本の未来づくりを目指します。

民主化の進む国際社会において日本の役割はこれまでにない重要な段階を迎えています。いまこそ、たしかな日本の未来の実現のために、グローバルな視点から日本の政治・経済を見直し、国際社会での確たるスタンスを保っていかねばなりません。

そのためには、国内政局の安定を基本に、自らの政治姿勢を正し、'90年代にふさわしい新しい政治を構築せねばなりません。

大つかゆうじは、持てる力の限りを尽くして、たしかな日本の未来の実現のために全力投球の覚悟です。特に、都市議員として相続税の見直しをはじめ、抜本的な大都市土地政策を確立し、若者に夢と希望を与える住宅をつくることに全力を挙げる所存です。若者の活力こそが、21世紀の日本のよりたしかな未来の実現につながると確信しています。ぜひ、大つかゆうじをご支援ください。

国民の納得する本当の税制改革を！
相続税見直しで定住人口の確保を！
土地有効利用で都心に若者の住宅を！

子どもたちに夢と希望を与える教育の実現！
21世紀を担う子どもたちに夢と希望を／個性と自主性を尊重したきめ細かい教育施策を実施。家庭教育にもスポット。

内需拡大を柱に商店、中小企業の活性化
交通網の整備、都市再開発を推進、多極多心型の都市づくり。先端技術の導入や市場開拓などに緊急融資の実施。

女性新時代の実現
家族と共にある新しい母親像を提言／育児休業、再教育、保育施設の完備など女性が安心して社会参加できる環境を！

「生きがいある第二の人生」づくり
人生80年時代。予防医学、健康増進、成人学校など積極的な人生設計／年金、医療費の安定。寝たきり老人への施策。

全力で取り組んでいます！

（私のこれまでの実績など）

○地下鉄6・7・12号線建設に大きな貢献／13号線実現に奮闘中！
○都市再開発プロジェクトアークヒルズ建設をはじめ各地に計画を推進！
○市場整備計画の推進と予算化でバックアップ！
○マンション建設促進委員長として永住できる快適な住環境づくりを推進中！
○都心の駐車場対策に応力、事故撲滅運動を展開交通洪滞解消に全力！

私たちのくらしに、なくてはならない政治家です。

都政、区政と国政のパイプ役としての大つかさんは、抜群の行動派です。鋭い洞察力と明快な判断力を持つ大つかさんは、一区ではもっとも信頼と実績に裏付けられた政治家です。これまで、衆院土地問題に関する特別委員長として、国政レベルの土地施策を積極的に推進する傍ら、若者たちを都心に呼び戻すための、あるいは、高齢社会への各種福祉施策など鋭意邁進中です。

どうぞ、皆さま方のあたたかいご支援を大つかゆうじにお願いいたします。

大つかゆうじさんを推薦します。

鈴木俊一（東京都知事）
山本克忠（新宿区長）
木村　茂（千代田区長）
山田敬治（港区長）

大つかゆうじ 略歴

議員歴　東京都議会議員3期、衆議院議員5期
役職歴　国土政務次官、文部政務次官、衆議院法務委員長、検察官適格審査会委員、自民党調査会長、文教部会長、教育改革に関する調査会会長代理
現役職　前衆議院土地問題特別委員会委員長、党文教制度調査会副会長、党都連政調会長、慶応義塾大学評議員、㈱国際連合大学協会理事他

Japanese Campaign Manifestos (Catalinac 2011)

Japanese Elections:

- Election Administration Commission runs elections $\rightarrow$ district level
- Required to submit manifestos for all candidates to National Diet
- Collected from 1950- 2009

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- Harder for Japanese

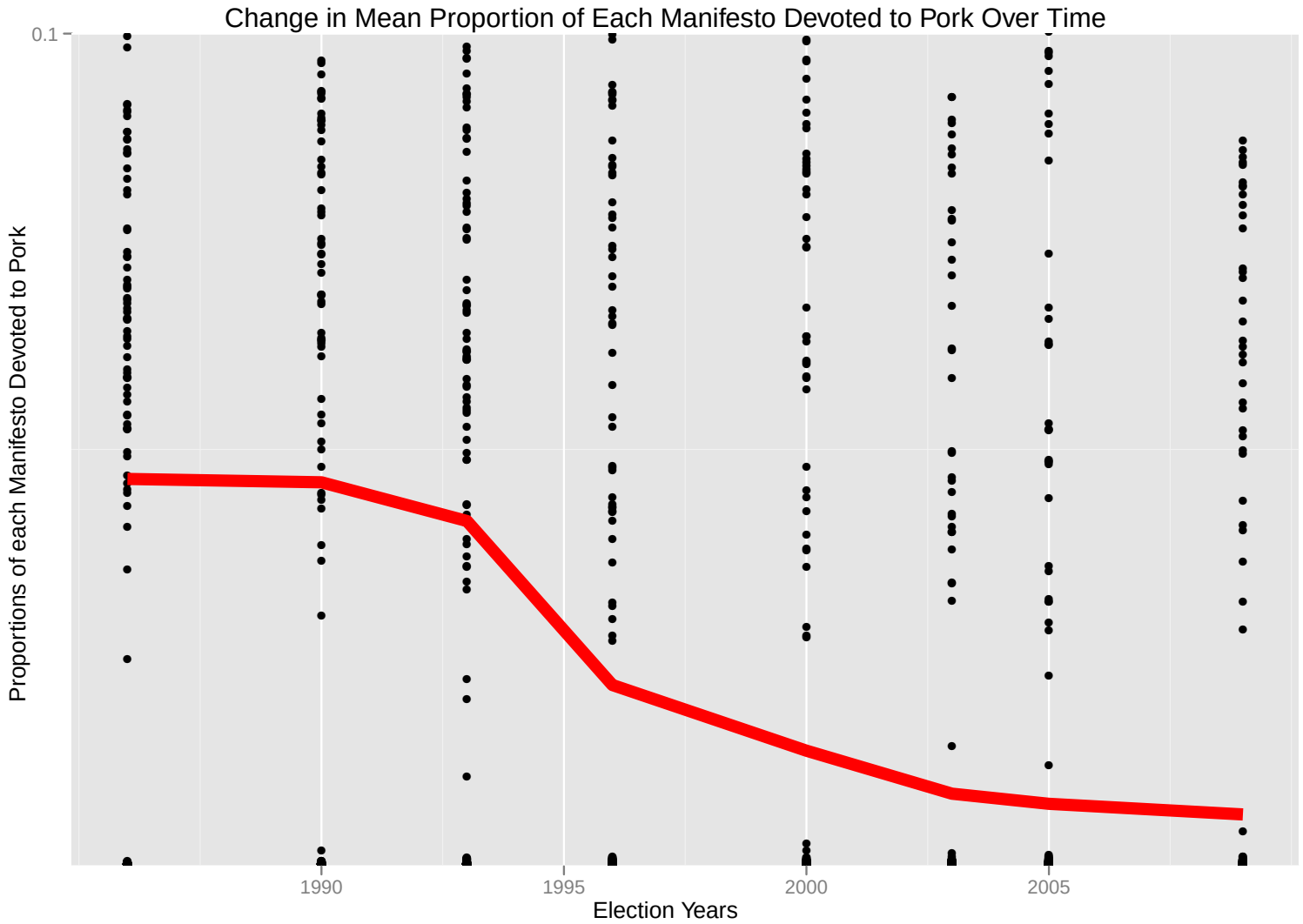
Japanese Campaign Manifestos (Catalinac 2014)

- Applies Vanilla LDA
- Output: topics (with Japanese characters)

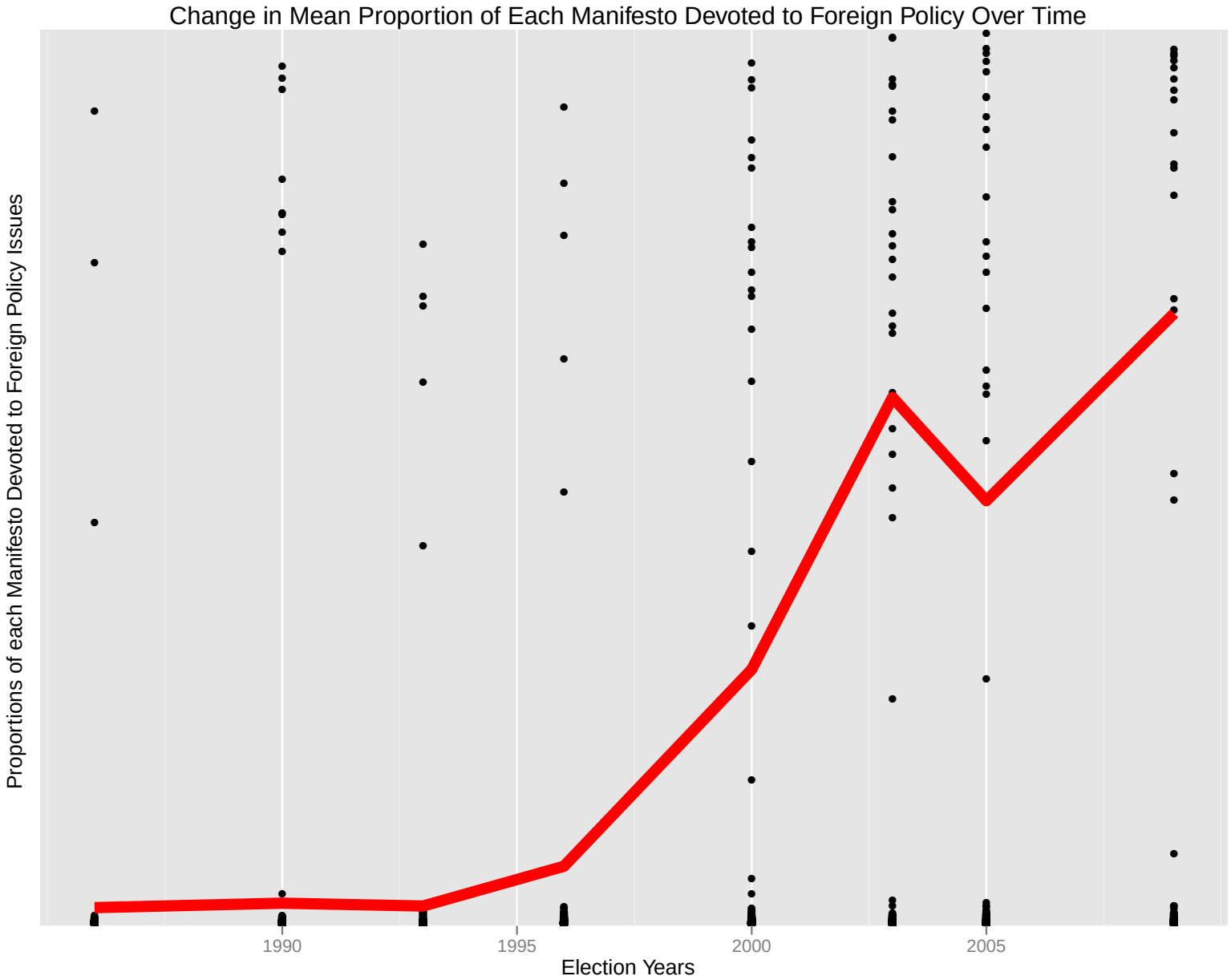
Japanese Campaign Manifestos (Catalinac 2011)

Topic 1	Topic 2	Topic 3	Topic 4	Topic 5	Topic
改革	年金	推進	区	政治	日本
郵政	円	整備	政策	改革	国
民営	廃止	図る	地域	国民	外交
小泉	改革	つとめる	まち	企業	国家
構造	兆	社会	鹿児島	自民党	社会
政府	実現	対策	全力	日本	国民
官	無駄	振興	選挙	共産党	保障
推進	日本	充実	国政	献金	安全
民	増税	促進	作り	金権	地域
自民党	削減	安定	横浜	党	拉致
日本	一元化	確立	対策	選挙	経済
制度	政権	企業	中小	禁止	守る
民間	子供	実現	発電	憲法	問題
年金	地域	中小	推進	腐敗	北朝鮮
実現	ひと	育成	エネルギー	団体	教育
進める	サラリーマン	制度	企業	区	責任
断行	制度	政治	声	ソ連	力
地方	議員	地域	実現	守る	創る
止める	金	福祉	活性	平和	安心
保障	民主党	事業	自民党	円	目指す
財政	年間	改革	地方	反対	誇り
作る	一掃	確保	尽くす	真	憲法
賛成	郵政	強化	商店	是正	可能
社会	道路	教育	いかす	一掃	道
国民	交代	施設	全国	悪政	未来
公務員	社会保険庁	生活	政党	抜本	ひと
力	月額	支援	ひと	定数	再生
経済	手当	環境	支援	政党	将来
国	談合	発展	経済	金丸	解決
安心	支援	施策	福祉	改悪	基本
Postal privatization	Reducing Wasteful Public Spending	Pork for the District	Policies for the district	Political Reform	Nation

Japanese Campaign Manifestos (Catalinac 2011)



Japanese Campaign Manifestos (Catalinac 2011)



Albertson and Gadarian: Anxiety and Immigration

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Treatment/Control:

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- "... When you think about immigration, what makes you worried?..."

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Albertson and Gadarian: Anxiety and Immigration

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- Human coders using pre-established coding categories (Fear, Anger, Enthusiasm)

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Treatment/Control:

- "... When you think about immigration, what makes you worried?..."
- "... When you think about immigration, what do you think of?..."

Original analysis:

- Human coders using pre-established coding categories (Fear, Anger, Enthusiasm)
- Treatment had impact on Fear and Anger.

Topics

- Topic 1

Topics

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Topics

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  - illeg, job, immigr, tax, pai, american, care, welfar, crime, system, secur, social, cost, health, servic, school, languag

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  - "problems caused by the influx of illegal immigrants who are crowding our schools and hospitals, lowering the level of education and the quality of care in hospitals."

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- Topic 2

Topics

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  - illeg, job, immigr, tax, pai, american, care, welfar, crime, system, secur, social, cost, health, servic, school, languag
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  - immigr, illeg, legal, border, need, worri, mexico, think, countri, law, mexican, make, america, worker

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  - "i worry about the republican party doing something very stupid. this country was built on immigration, to deny anyone access to citizenship is unconstitutional. what happened to give me your poor, sick, and tired?"

Effects on Topic 1

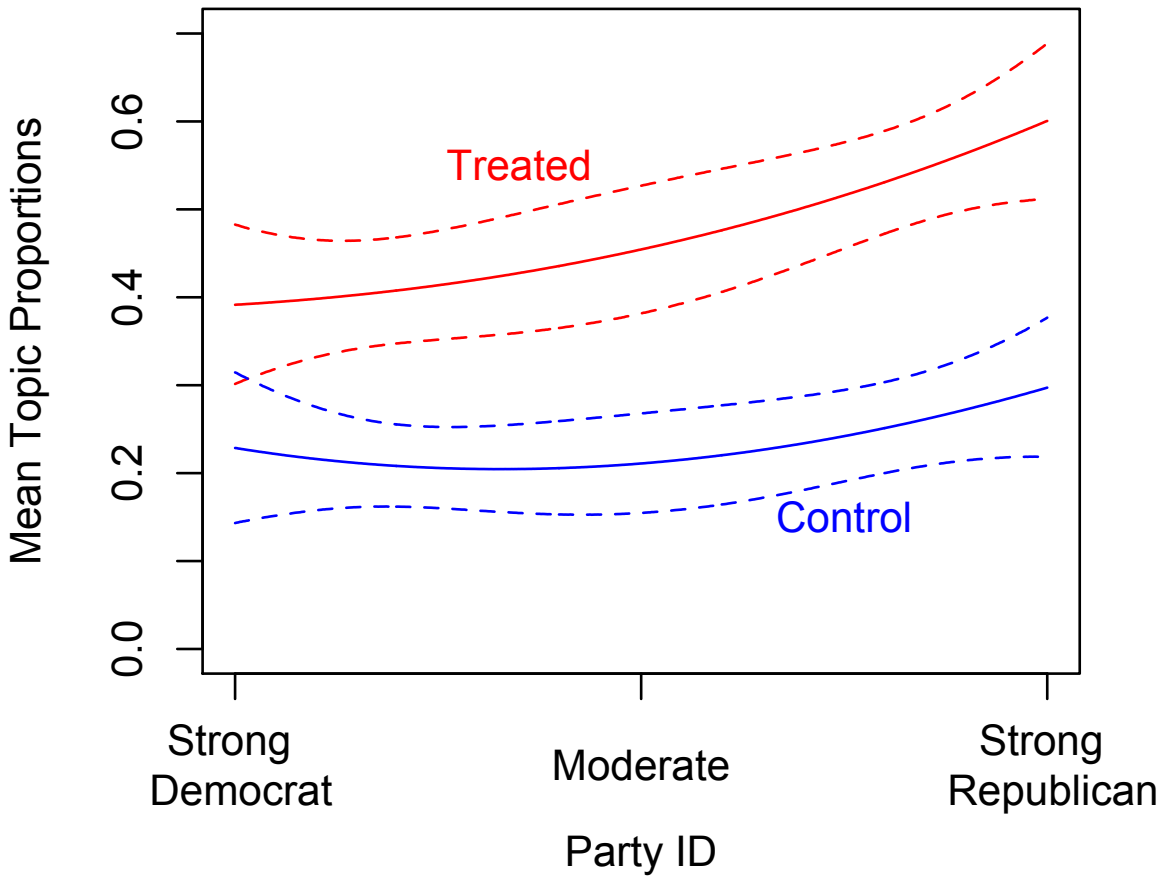
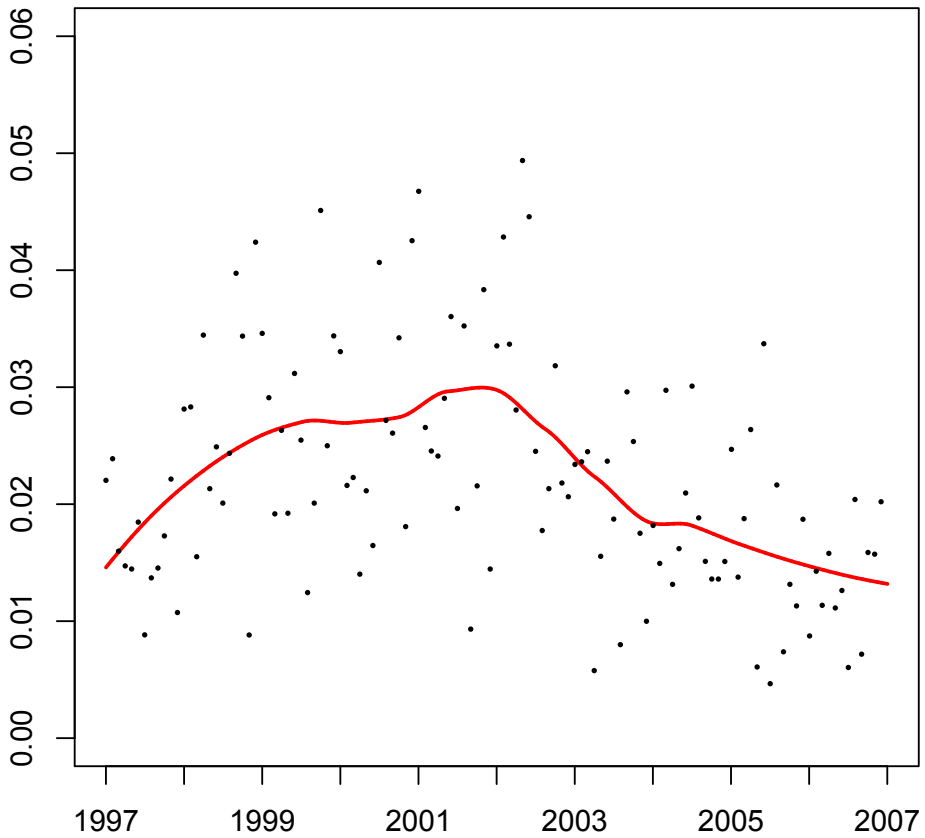


Figure: Topic 1.

Different Newspapers, Different Perspectives



Associated Press

polic protest gong arrest
falun detain author releas
follow prison inform offic
wang crackdown activist
movement sentenc center squar
china demonstr zhang
tiananmen dissid investig

Xinhua

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suspect case custom organ
author depart order china
properti told accord sentenc
terrorist

Different Newspapers, Different Perspectives