Quantitative Discovery of Qualitative Information: A General Purpose Document Clustering Methodology

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Harvard University

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Joint work with Justin Grimmer (Harvard $\rightsquigarrow$ Stanford)

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- (We focus on texts, our methods apply more broadly)

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- Its no surprise that automated algorithms can help, but which algorithms?

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- Deep problem in cluster analysis literature: no way to know which method will work ex ante
- No surprise: everyone's tried cluster analysis; very few are satisfied

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- The Question: How to organize all those clusterings?

Our Idea: Meaning Through Geography

Set of clusterings

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Set of clusterings ≈
A list of unconnected addresses

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Set of clusterings $\approx$

A list of unconnected addresses

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81 447-4101
00 257-9981
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17 364-5188
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17 566-4548
17 628-8248
17 445-5116
17 822-2982
17 427-5712
17 569-2698
17 667-5190
17 569-1417
hitu Dr
17 338-9110
17 825-9195
17 296-1593
17 670-2078
17 623-9001
17 296-4725
17 542-1521
17 364-5232
17 541-5649
17 739-2662
17 879-0030
17 541-3948
17 436-1513
17 569-4119
ton 02128
300 569-8782

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Alice 45 Market Cambridge 02139.........617 945-2711
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Carter Athens
272 Newbury Boston 02116.........617 536-6329
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Carter J Veal Co
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Carter James
1573 Cambridge St Cam 02138.........617 492-1214
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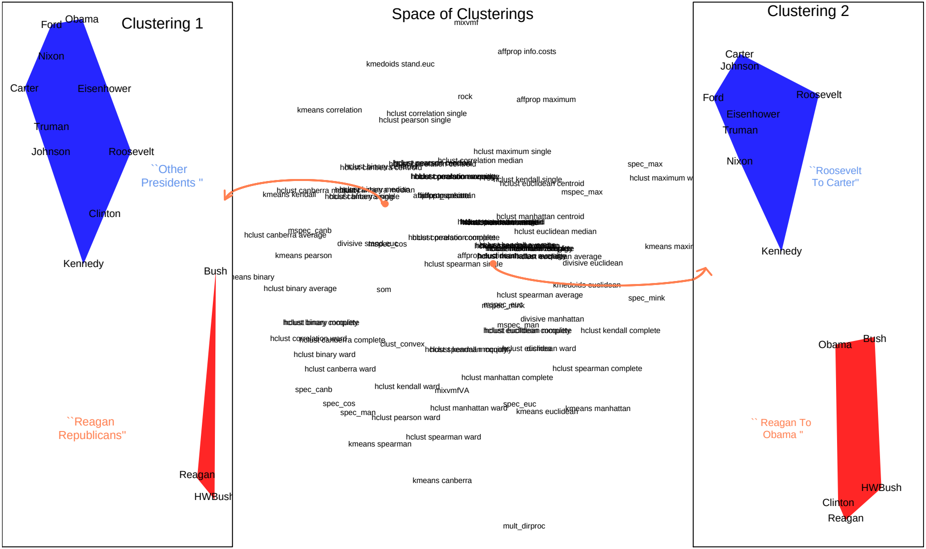
Many Thousands of Clusterings, Sorted & Organized

You choose one (or more), based on insight, discovery, useful information,. . .



Application-Independent Distance Metric: Axioms

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- ⇝ Only one measure satisfies all three (the "variation of information")
- Meila (2007): derives same metric using different axioms (lattice theory)

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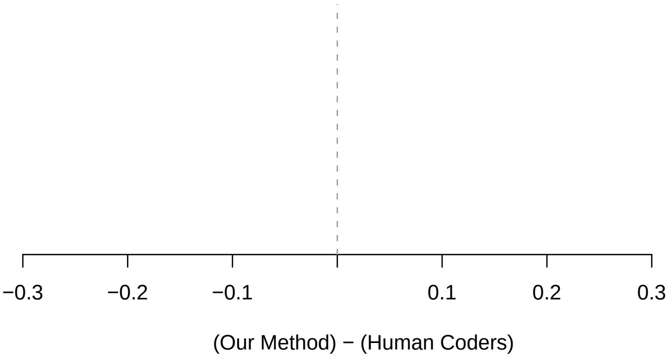

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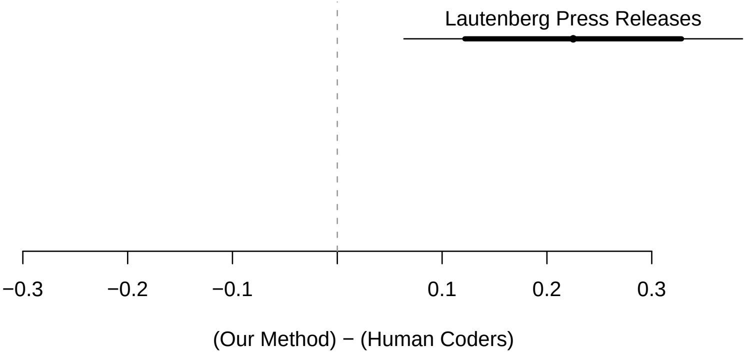

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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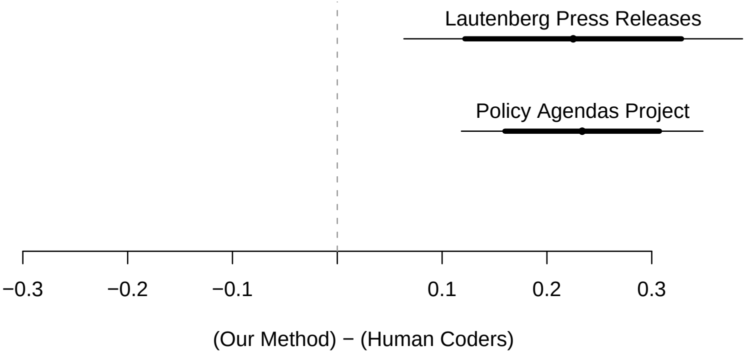

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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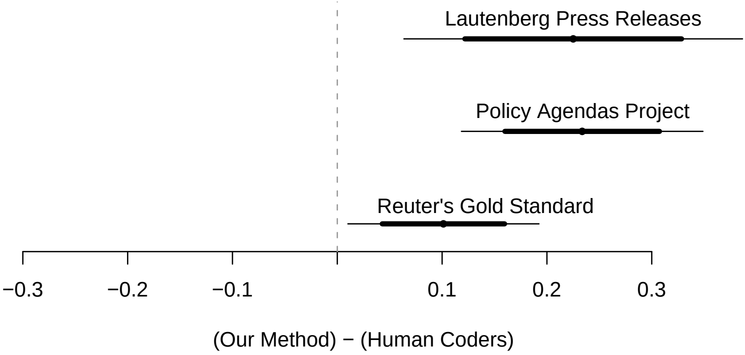

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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Our Method 1 → vMF 1 → vMF 2 → Our Method 2 → K-Means 1 → K-Means 2

"Genetic testing":

Our Method 1 → {Our Method 2, K-Means 1, K-means 2} → Dir Proc. 1 → Dir Proc. 2

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- Apply our method

Example Discovery

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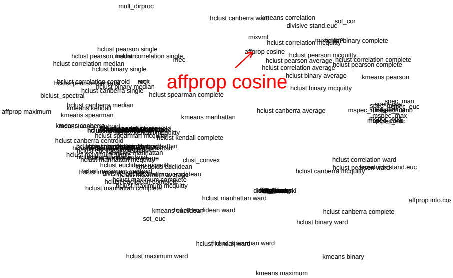

Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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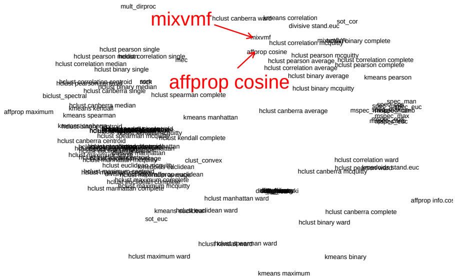

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Close to:

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

Example Discovery

Space between methods:

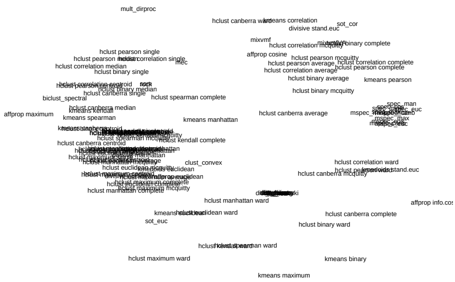
Example Discovery

Space between methods:

Example Discovery

Space between methods:
local cluster ensemble

Example Discovery



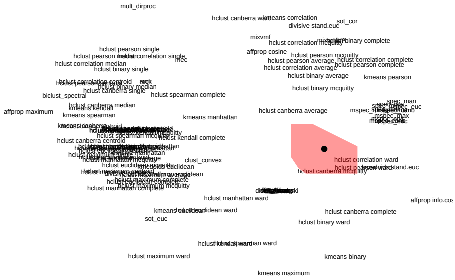
Example Discovery

Found a region with particularly insightful clusterings

Example Discovery

Mixture:

Example Discovery



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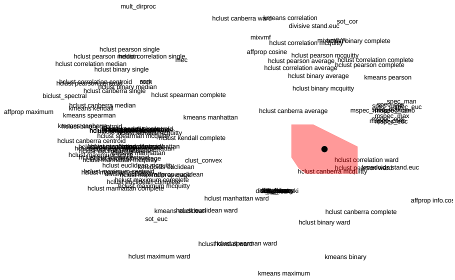

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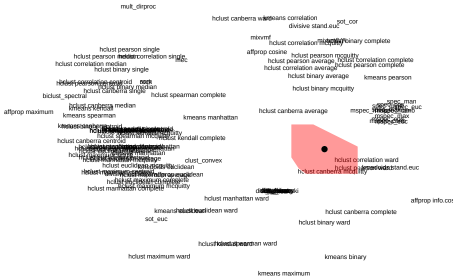

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- 0.04 Spectral clustering Symmetric (Metrics 1-6)

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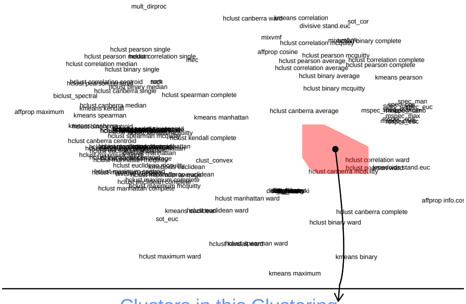
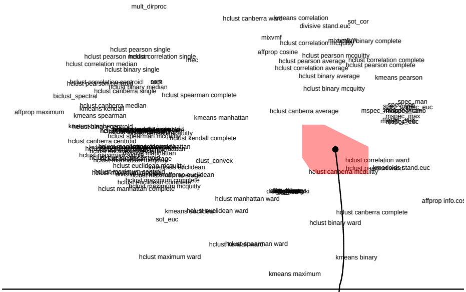


Clusters in this Clustering

Mayhew

Example Discovery



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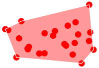
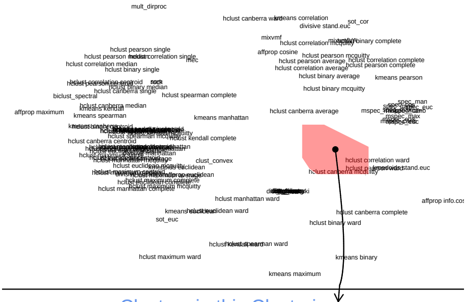


Credit Claiming
Pork

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

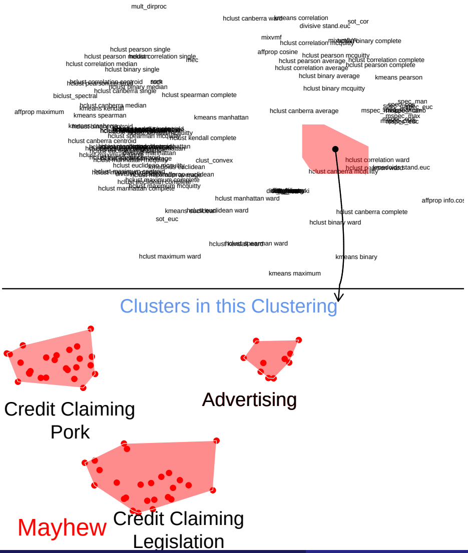
Example Discovery



Clusters in this Clustering

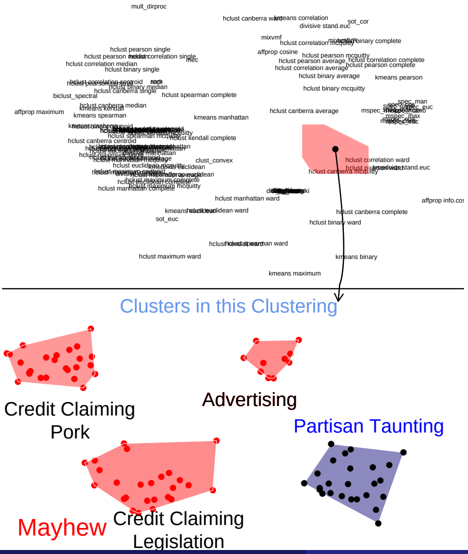
Credit Claiming, Legislation:
"As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period"

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"

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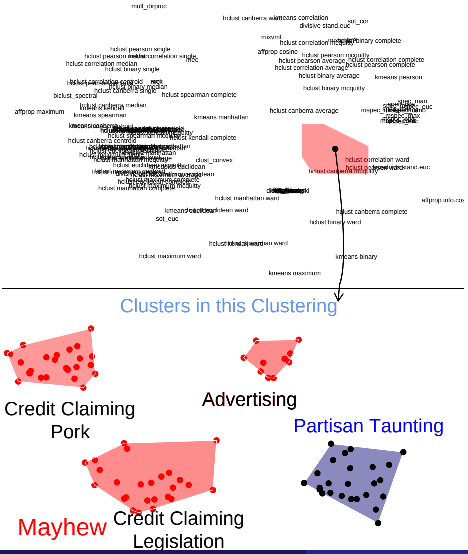

Partisan Taunting:

"Senator Lautenberg's amendment would change the name of ...the Republican bill...to 'More Tax Breaks for the Rich and More Debt for Our Grandchildren Deficit Expansion Reconciliation Act of 2006' "

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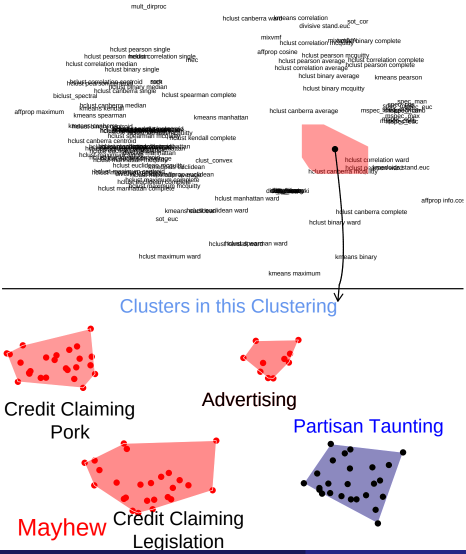

Definition: Explicit, public, and negative attacks on another political party or its members

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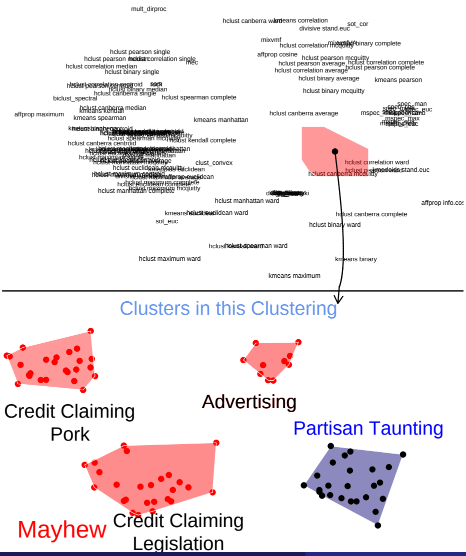

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Taunting ruins deliberation

In Sample Illustration of Partisan Taunting

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Sen. Lautenberg on Senate Floor 4/29/04

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

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- "Every day the House Republicans dragged this out was a day that made our communities less safe." [Homeland Security]

Out of Sample Confirmation of Partisan Taunting

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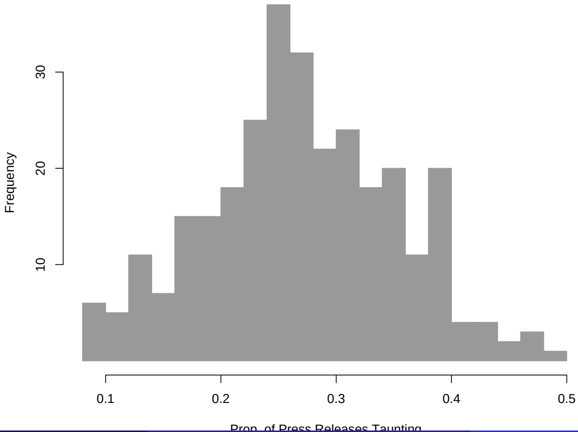

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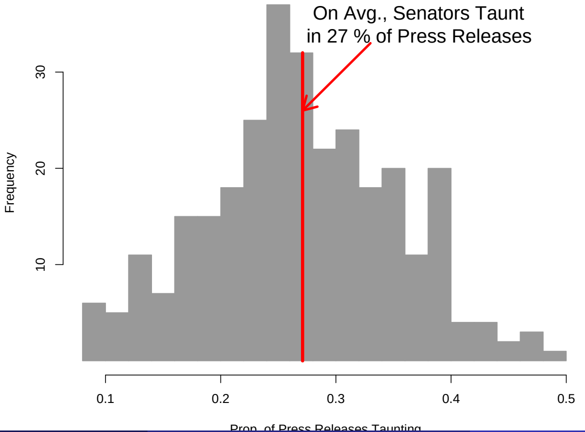

Advancing the Objective of Discovery

1) Conceptualization

Qualitative Methods (reading!)

2) Measurement

Quantitative Methods

3) Validation

Quantitative methods for conceptualization: aiding discovery

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Quantitative methods for conceptualization: aiding discovery

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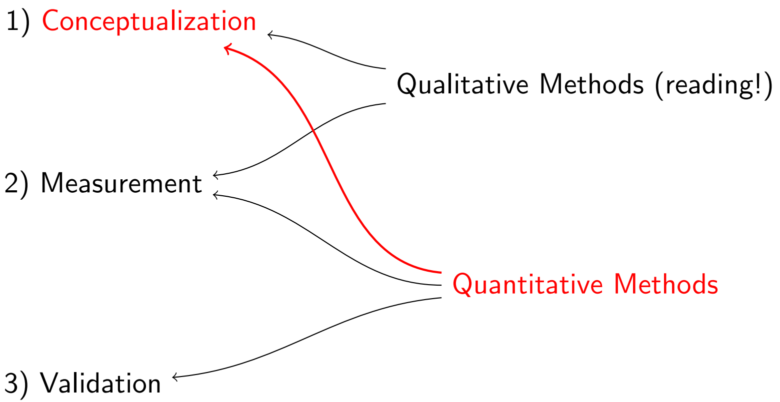

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Quantitative methods for conceptualization: aiding discovery

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- Belittled: "Tom Swift and His Electric Factor Analysis Machine" (Armstrong 1967)
- Evaluation methods measure progress in discovery

For more information (on adding zooming out to the human ability to zoom in)

http://GKing.Harvard.edu