Computer-Assisted Clustering and Conceptualization from Unstructured Text

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[1] Based on joint work with Justin Grimmer (Harvard ⇝ Stanford)

A Method for Computer Assisted Conceptualization

- Conceptualization through Classification: "one of the most central and generic of all our conceptual exercises. . . . the foundation not only for conceptualization, language, and speech, but also for mathematics, statistics, and data analysis. . . . Without classification, there could be no advanced conceptualization, reasoning, language, data analysis or,for that matter, social science research." (Bailey, 1994).

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- Main goal: Switch from Fully Automated to Computer Assisted

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- Fully automated algorithms can help, but which ones?

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- No surprise: everyone's tried cluster analysis; very few are satisfied

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- Question: How to organize clusterings so humans can understand?

Our Idea: Meaning Through Geography

Set of clusterings

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Set of clusterings $\approx$
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Alice 108 Kilmarnock Bos 02215.... 617 425-0193
Alice 45 Market Cambridge 02139.... 617 945-2711
Andrew F 62 Vinal Av Som 02143.... 617 625-7623
Carter Anne MD
1101 Beacon Bro 02446....617 739-1022
Carter Athens
272 Newbury Boston 02116....617 536-6329
B E 68 Gladeside Av Mat 02126.... 617 296-6911
Carter Barbara L MD
Tufts-New England Medical Center Bos 02111
Call....617 636-0051
Carter Becky Bos 02114....617 523-4368
Bernard J
112 Gladstone E Bos 02128....617 567-3430
Bithiah 25 Medway Dor 02124....617 298-8713
Blake 26 Mt Vernon Bos 02108....617 367-9931
Carter Broadcasting Co
20 Park Plz Bos 02116.... 617 423-0210
Carter & Burgess Consultants Inc
23 East St Cam 02141....617 225-0200
Carter C 2000 Comnwlth Av Bri 02135.... 617 782-2118
C 228 Faywood Av East Boston 02128....617 569-1545
C 359 Harvard Cam 02138.... 617 491-4822
C 610 Walk Hill Mat 02126....617 296-6392
C & M 43 Burroughs Jam 02130....617 524-9558

Carter F 24 Hillock Ros 02131....617 327-1105
Faye & Ricky
357 Columbus Av Bos 02116....617 437-7331
Francis S 134 Temple W Rox 02132.. 617 323-6781
Franklin & Anne
221 Mt Auburn Cam 02138....617 354-0798
Fred 42 Haverford Jam 02130....617 524-3078
Fred 96 Hinckley Rd Mil 02186....617 698-1343
G & R 8 Verdun Dor 02124....617 436-8906
G T 27 Franklin Av Som 02145....617 623-7121
Gayle 25 Frontenac Dor 02124.... 617 825-0322
Geo S 115 Moss Hill Rd Jam 02130....617 522-3215
George 125 Nashua Bos 02114....617 367-9548
Carter Halliday Associate
107 S Street Bos 02111....617 456-1689
Carter Harry F
26 Runng Brk Rd W Rox 02132.... 617 325-5465
Carter Hide Co Inc
146 Summer Bos 02110....617 542-7987
Carter Hilary 61 Harvey Cam 02140....617 876-2750
Horace
241 Walnut Av Roxbury 02119....617 442-5307
Howard Jr 26 Notre Dme Rox 02119. 617 445-5552
J Cam.... 617 354-2688
J 15 Chatham Bro 02446.... 617 232-7990
J 518 Harvard Bro 02446....617 730-9483
J 775 Vfw Pkwy West Roxbury 02132.... 617 323-5574
Carter J Jacques MD
1 Brookline Pl Bro 02446.... 617 735-8787
Carter J M
1410 Columbia Rd S Bos 02127.... 617 464-1040
Carter J M Ornamental Ironworks
Call....Pembroke TelNo-617 436-5353
Carter J Veal Co
48 Newmarket Sq Rox 02118....617 442-1775
Carter James
1573 Cambridge St Cam 02138....617 492-1214
James 182 Fisher Av Roxbury 02120...617 739-2193
James
37 Gold Star Rd Cambridge 02140.... 617 876-8841
Jas L 14 Roseberry Rd Mat 02126....617 361-0773
Jane 114 Adena Rd Newton 02465....617 964-0435
Jeffrey 41 Warren Av Bos 02116....617 426-5994
John 11 Mansfield Bri 02134.... 617 987-2163
John 327 Summer Bos 02210....617 423-4334
John 40 Westwind Rd Dor 02125.... 617 282-1235
June O 329 A Summit Av Bri 02135.... 617 734-6109
K 38 Browning Av Dorchester 02124.... 617 265-8456
K 17 Esmond Dorchester 02121....617 282-1593

Carter Nella E
333 Maschsts Av Bos 02115....617 267-6483
Nicholas S F
115 Randolph Av Mil 02186....617 698-5307
Nick 21 Fairfield Bos 02116.... 617 267-5222
Nick & Debbi
196 Herrick Rd Newton 02459....617 527-0480
Nicole....617 698-0713
Norman G
38 Chickatawbut Dor 02122.... 617 822-1203
P 94 Crestwood Pk Rox 02121....617 427-4754
P E 501 E Sixth S Bos 02127.... 617 268-4213
P L 44 Hutchings Rox 02121.... 617 427-9170
P R 91 Bynner Jam 02130....617 983-8692
Paul & Constance
114 Anawan Av W Rox 02132....617 325-2036
Paul E 501 E Sixth St S Bos 02127....617 268-4546
Paul M 27 Union Bri 02135....617 787-2115
Carter Pile Driving Inc 17 Beaver Ct
Framingham 01702.... Wellesley TelNo-781 235-8488
Carter Prudence
46 Franklin Watertown 02172....617 393-3782
Prudence
46 Franklin Watertown 02172....617 926-7063
Reginald
106 Brunswick Dorchester 02121....617 541-2843
Renee & Andrew
10 Walnut Bos 02108....617 720-3765
Carter Rice Dowd
Bulkley Dunton Publishing 163 Main Wilmington 01887
Toll Free-Dial '1' & Then....800 638-1671
Cust Svc-Industrial Prod 613 Main Wilmington
Toll Free-Dial '1' & Then....800 619-7447
Cust Svc-Printing 613 Main Wilmington
Toll Free-Dial '1' & Then....800 648-7447
Headquarters 613 Main Wilmington 01887
Call.... 978 988-7447
Ingalls Cronin 163 Main Wilmington 01887
Toll Free-Dial '1' & Then....800 638-1673
Carter Richard
1079 Comnwlth Av Brighton 02215... 617 987-0836
Richard A 97 Mt Vernon Bos 02108...617 566-7293
Carter Richard A MD
170 Comnwlth Av Bos 02116.... 617 267-0710
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15 Mercer S Bos 02127....617 268-0448
Robert L 175 Richdale Av Cam 02140. 617 864-1535
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Roy 44 Concord Av Cam 02138....617 491-6115
Royce 18 Seminary Cha 02129....617 241-0418

C

$\rightsquigarrow$

$\rightsquigarrow$ We develop a (conceptual) geography of clusterings

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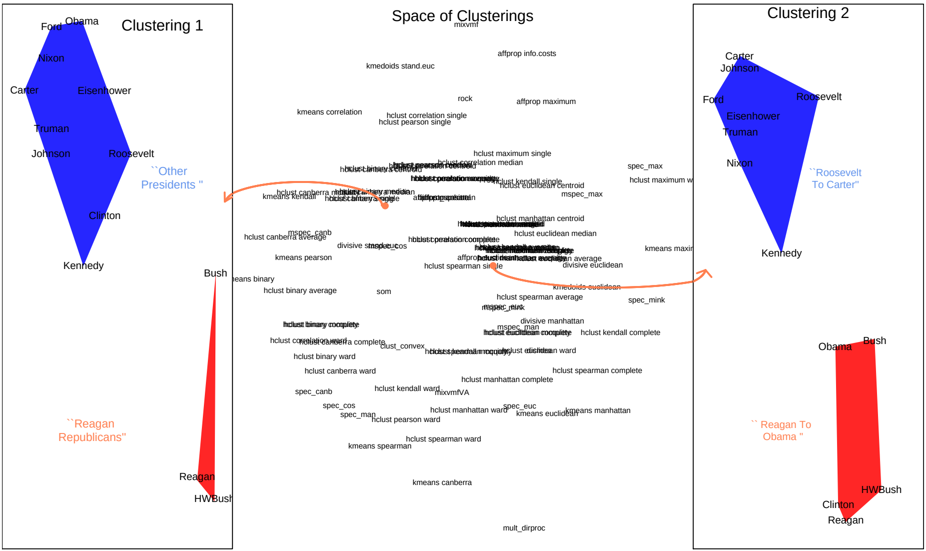
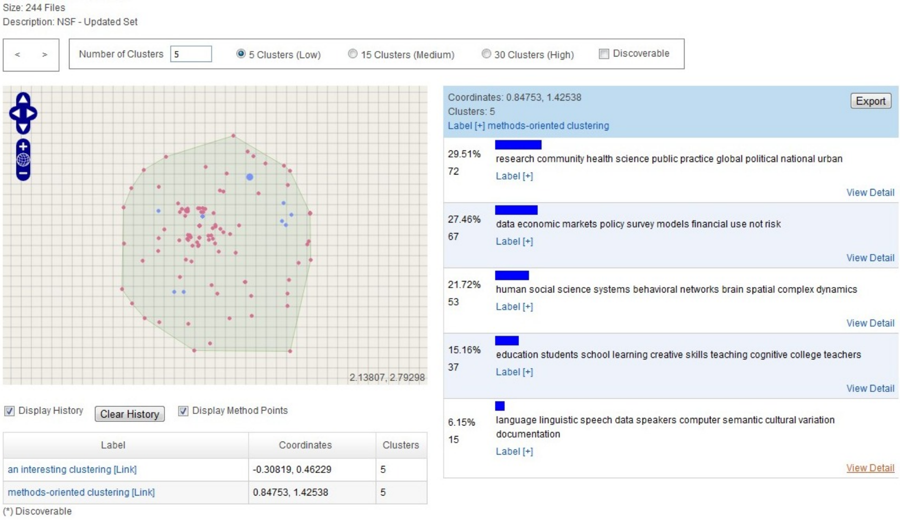
8. (Or, our new strategy: represent the entire bell space directly; no need to examine document contents)

Many Thousands of Clusterings, Sorted & Organized

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



Software Screenshot



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- (Meila, 2007, derives same metric using different axioms & lattice theory)

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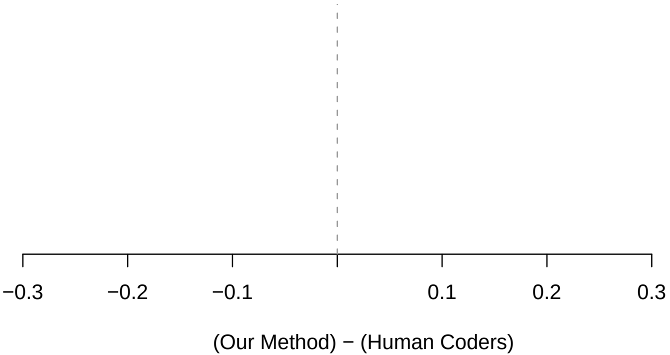

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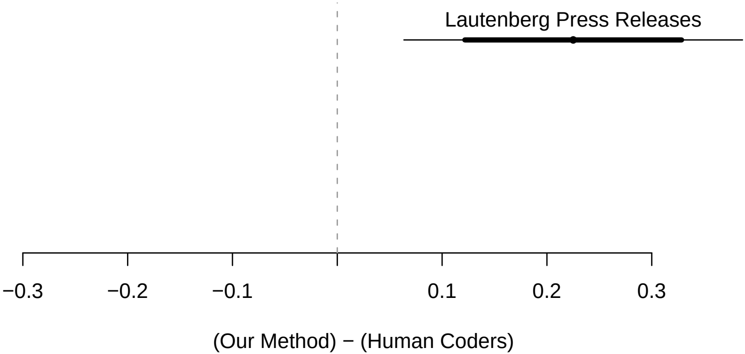

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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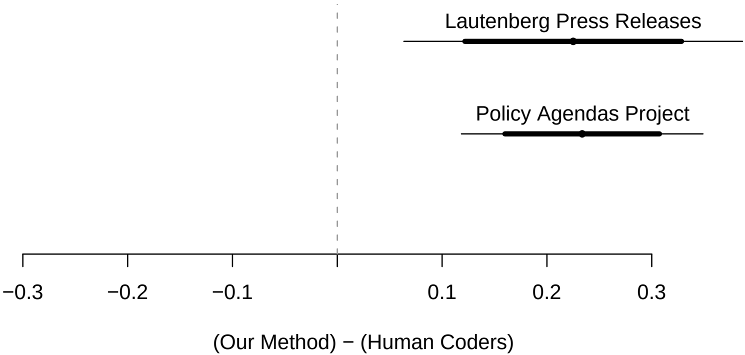

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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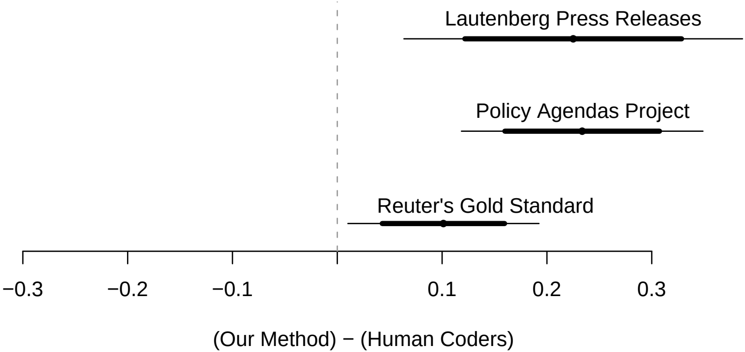

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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"Genetic testing":

Our Method 1 $\rightarrow$ {Our Method 2, K-Means 1, K-means 2} $\rightarrow$ Dir Proc. 1 $\rightarrow$ Dir Proc. 2

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- Apply our method

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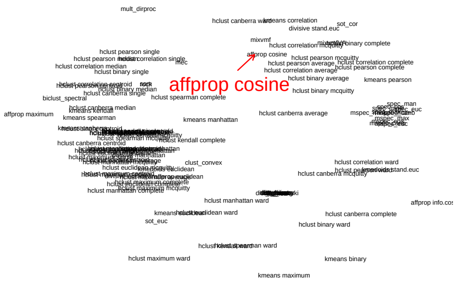

Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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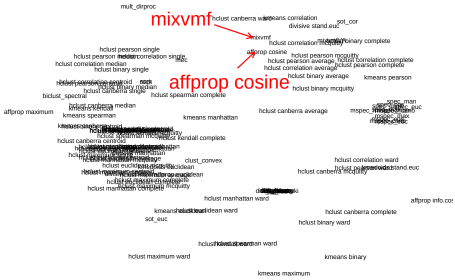

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Close to:

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

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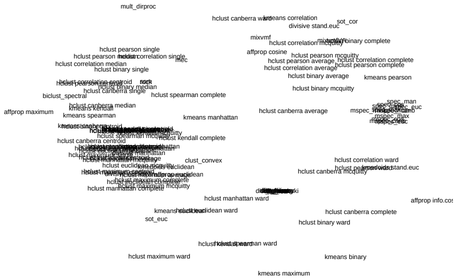

Space between methods:

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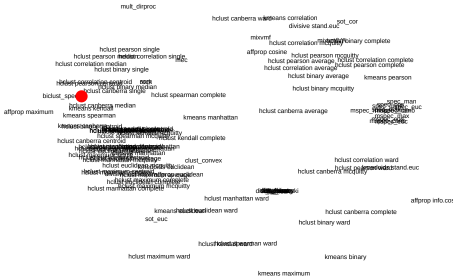

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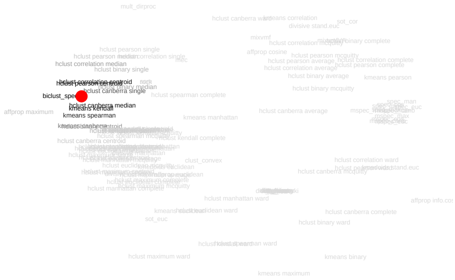


Space between methods:

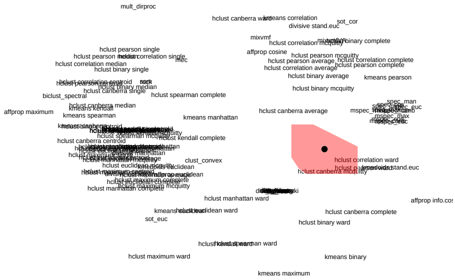
local cluster ensemble

Example Discovery

Example Discovery

Found a region with particularly insightful clusterings

Example Discovery



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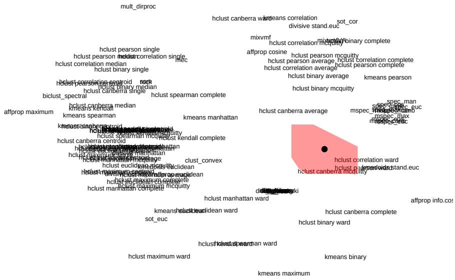

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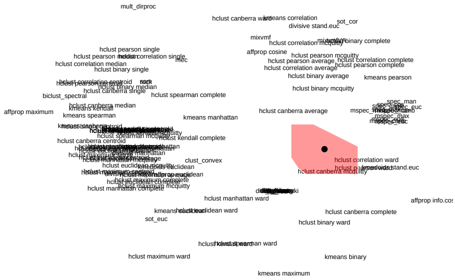

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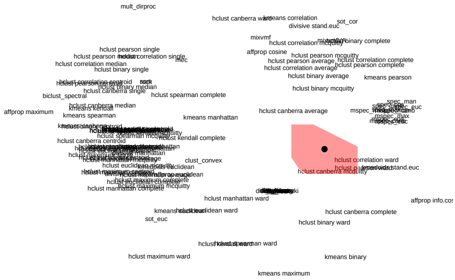

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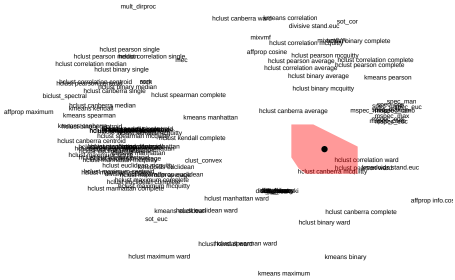
0.05 Kmediods-Cosine

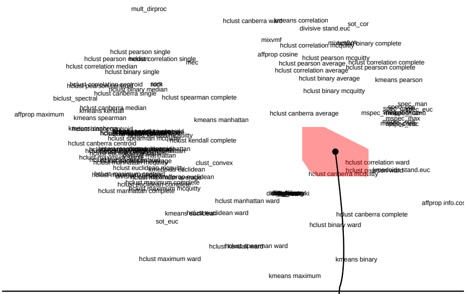
Example Discovery



Mixture:

- 0.39 Hclust-Canberra-McQuitty
- 0.30 Spectral clustering Random Walk (Metrics 1-6)
- 0.13 Hclust-Correlation-Ward
- 0.09 Hclust-Pearson-Ward
- 0.05 Kmediods-Cosine
- 0.04 Spectral clustering Symmetric (Metrics 1-6)

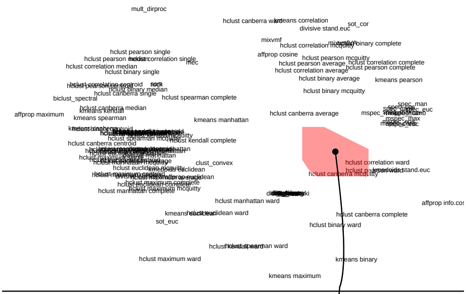
Example Discovery



Clusters in this Clustering

Mayhew

Example Discovery



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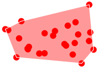


Credit Claiming
Pork

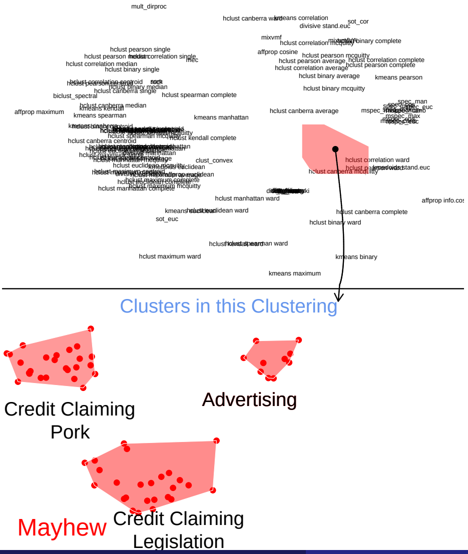
Credit Claiming, Pork:
"Sens. Frank R. Lautenberg (D-NJ) and Robert Menendez (D-NJ) announced that the U.S. Department of Commerce has awarded a $100,000 grant to the South Jersey Economic Development District"

Mayhew

Example Discovery

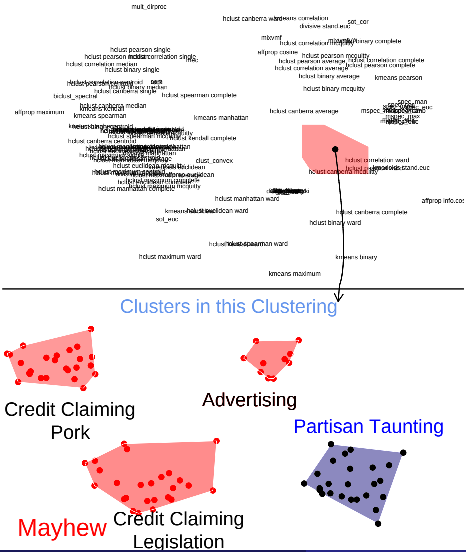
Credit Claiming, Legislation:
"As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period"

Example Discovery



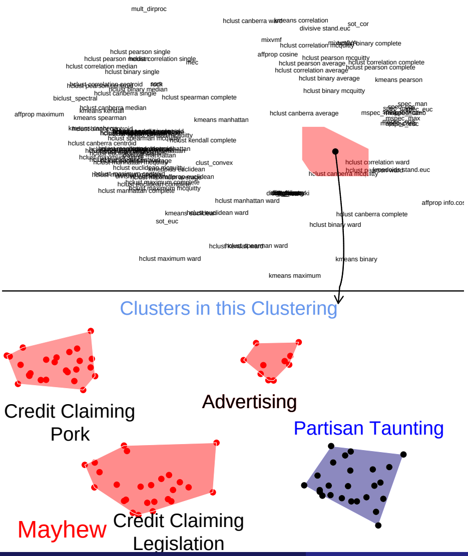
Advertising:
"Senate Adopts Lautenberg/Menendez Resolution Honoring Spelling Bee Champion from New Jersey"

Example Discovery: Partisan Taunting



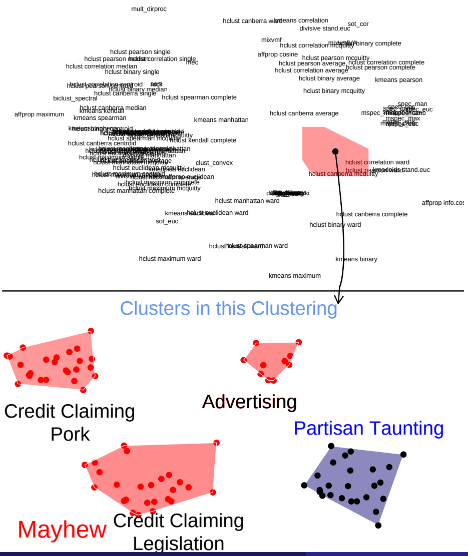
Partisan Taunting:
"Republicans Selling Out Nation on Chemical Plant Security"

Example Discovery: Partisan Taunting



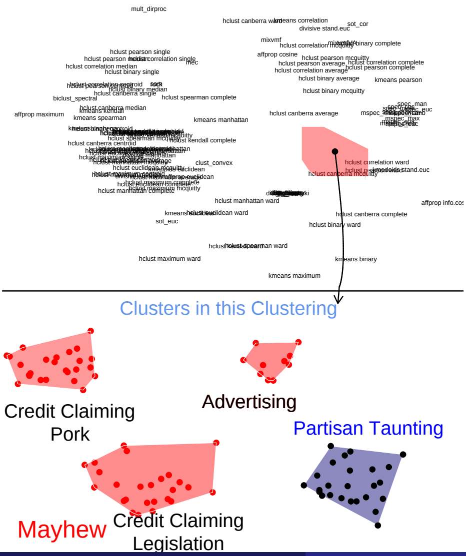
Partisan Taunting:
"Senator Lautenberg's amendment would change the name of. . . the Republican bill. . . to 'More Tax Breaks for the Rich and More Debt for Our Grandchildren Deficit Expansion Reconciliation Act of 2006"'

Example Discovery: Partisan Taunting



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

Example Discovery: Partisan Taunting



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Taunting ruins deliberation

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Sen. Lautenberg on Senate Floor 4/29/04

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

In Sample Illustration of Partisan Taunting

Taunting ruins deliberation

Sen. Lautenberg
on Senate Floor
4/29/04

- "Senator Lautenberg Blasts Republicans as 'Chicken Hawks' " [Government Oversight]
- "The scopes trial took place in 1925. Sadly, President Bush's veto today shows that we haven't progressed much since then" [Healthcare]

Taunting ruins deliberation

Sen. Lautenberg on Senate Floor 4/29/04

- "Senator Lautenberg Blasts Republicans as 'Chicken Hawks' " [Government Oversight]
- "The scopes trial took place in 1925. Sadly, President Bush's veto today shows that we haven't progressed much since then" [Healthcare]
- "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

- Discovered using 200 press releases; 1 senator.

Out of Sample Confirmation of Partisan Taunting

- Discovered using 200 press releases; 1 senator.
- Confirmed using 64,033 press releases; 301 senator-years.

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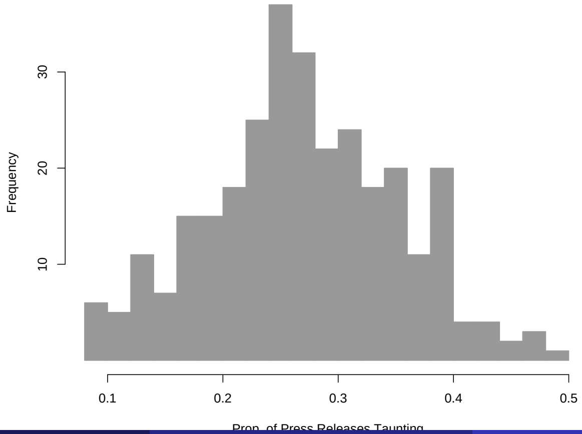

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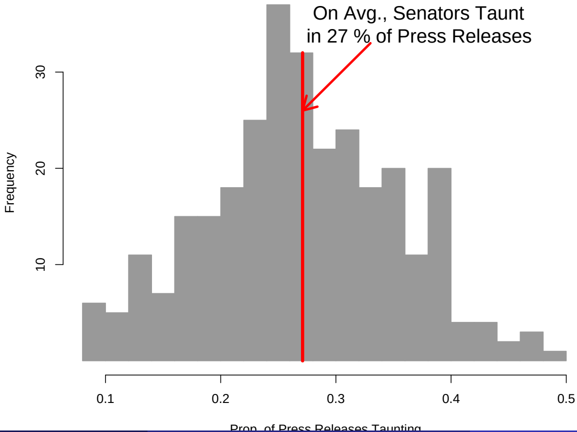

Quantitative Methods for Qualitative Conceptualization

1) Conceptualization

Qualitative Methods (reading!)

2) Measurement

Quantitative Methods

3) Validation

Quantitative methods for conceptualization and discovery

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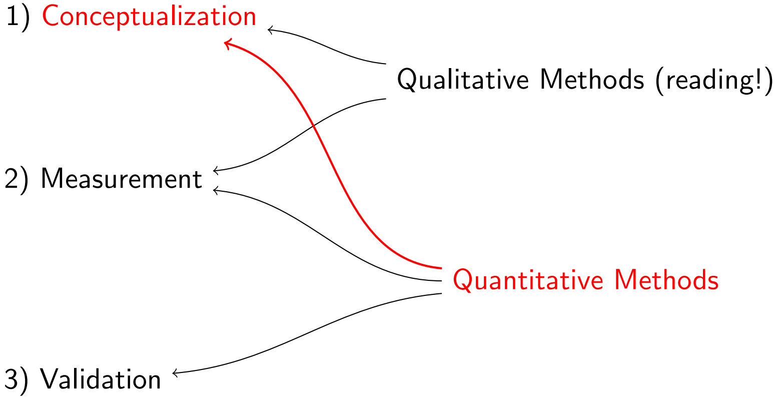

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Quantitative methods for conceptualization and discovery

- Few formal methods designed explicitly for conceptualization
- Belittled: "Tom Swift and His Electric Factor Analysis Machine" (Armstrong 1967)
- Evaluation methods measure progress in discovery

For more information

http://GKing.Harvard.edu