Computer-Assisted Clustering and Conceptualization from Unstructured Text

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[1] Based on joint work with Justin Grimmer (Harvard $\rightsquigarrow$ 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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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 Commwlth 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 Commwlth Av Brighton 02215 617 987-0836
Richard A 97 Mt Vernon Bos 02108 617 566-7293
Carter Richard A MD 170 Commwlth Av Bos 02116 617 267-0710
Carter Richard K 15 Mercer S Bos 02127 617 268-0448
Robert L 175 Richdale Av Cam 02140 617 864-1535
Roger 150 St Botolph Bos 02115 617 424-6148
Roy 44 Concord Av Cam 02138 617 491-6115
Royce 18 Seminary Cha 02129 617 241-0418

⇝

⇝ We develop a (conceptual) geography of clusterings

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Make it easy to choose best clustering from millions of choices

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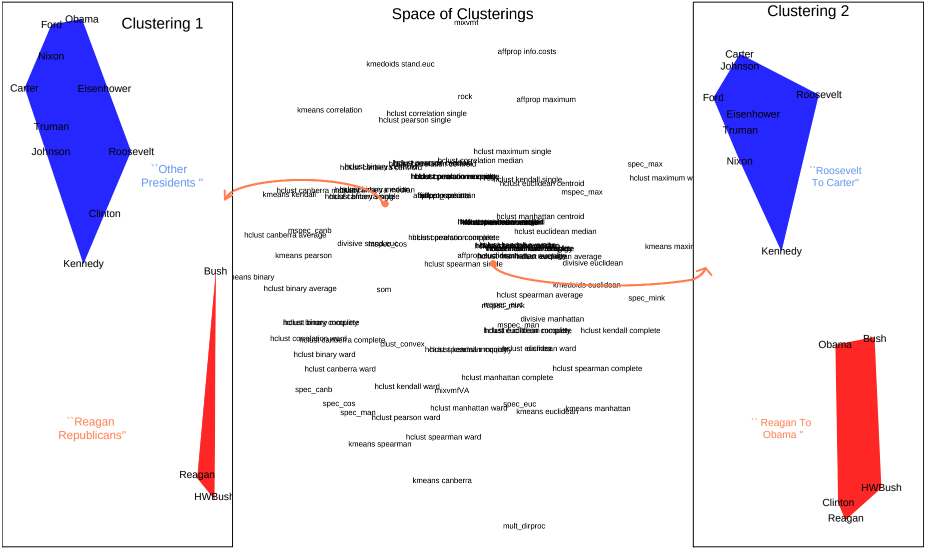
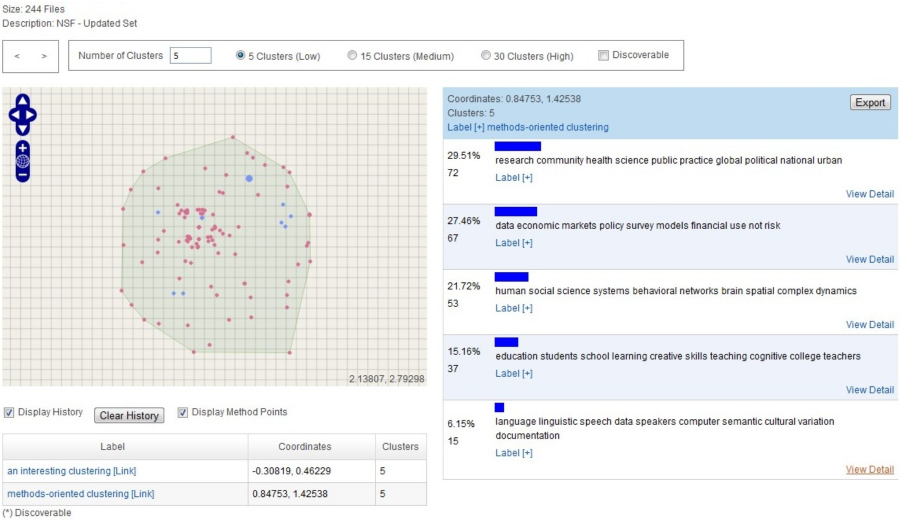
8. (Or, our new strategy: represent the entire bell space directly; no need to examine document contents)

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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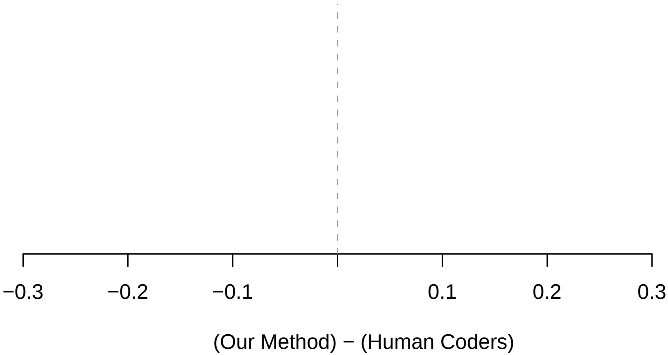

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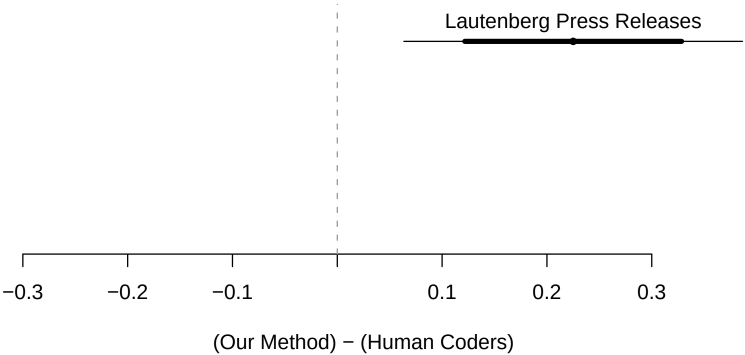

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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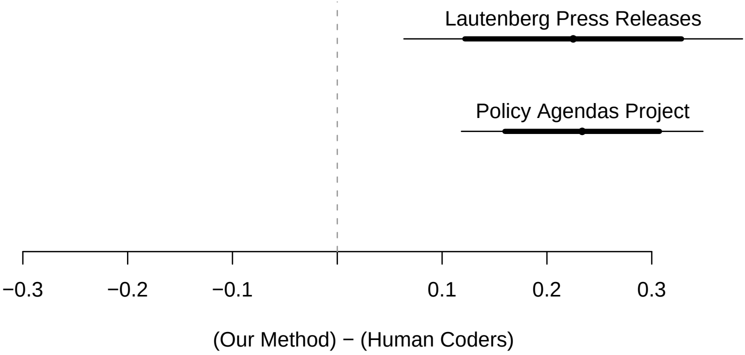

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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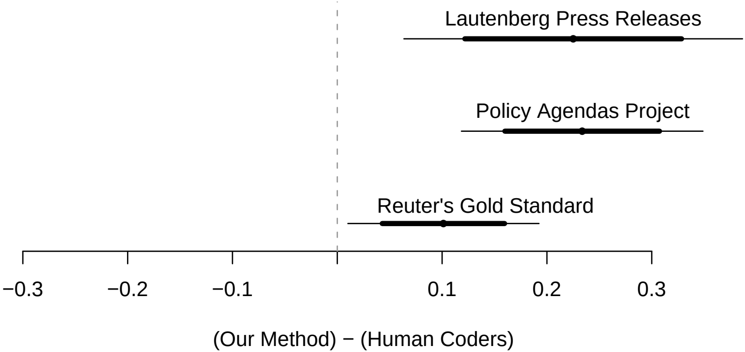

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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"Genetic testing":

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

Evaluation 3: What Do Members of Congress Do?

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- Apply our method

Example Discovery

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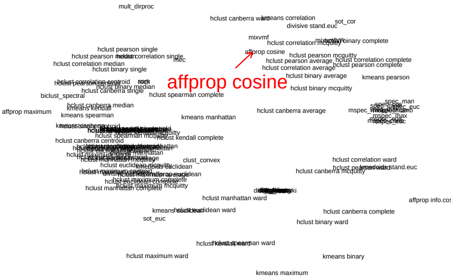

Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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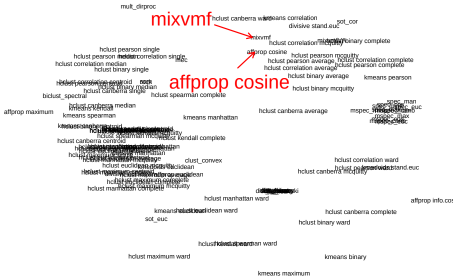

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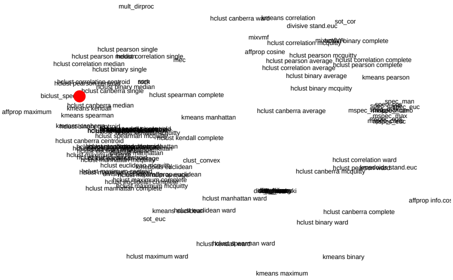
Close to:

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

Example Discovery

Space between methods:

Example Discovery



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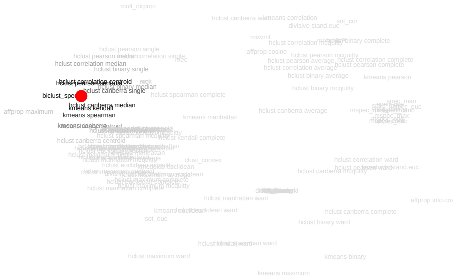


Space between methods:

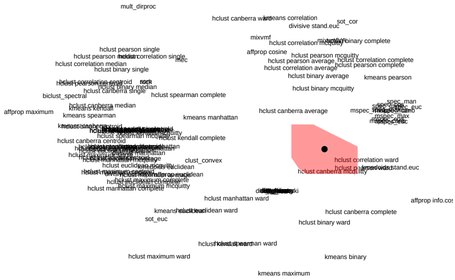
local cluster ensemble

Example Discovery

Example Discovery

Found a region with particularly insightful clusterings

Example Discovery



Mixture:

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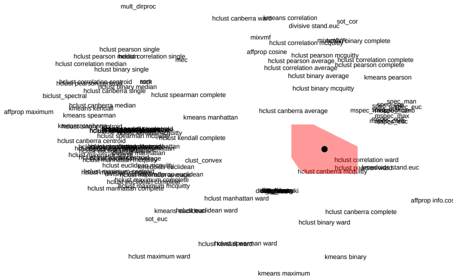

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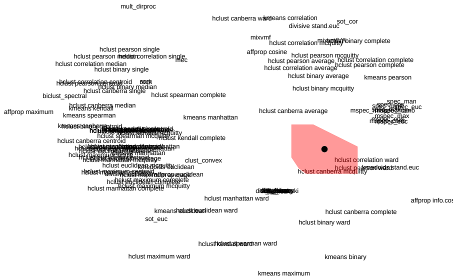

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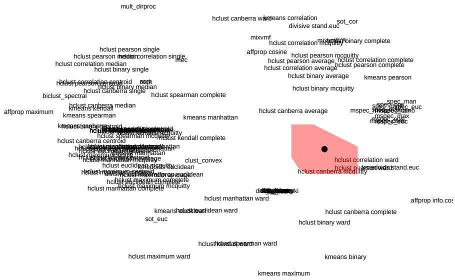

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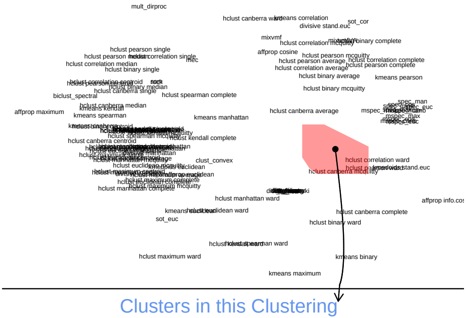
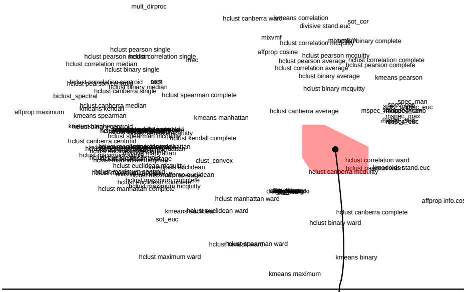
- 0.04 Spectral clustering Symmetric (Metrics 1-6)

Example Discovery

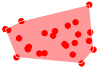


Mayhew

Example Discovery



Clusters in this Clustering

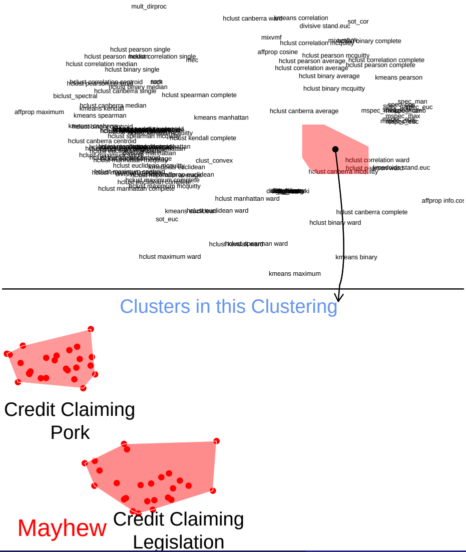


Credit Claiming
Pork

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"

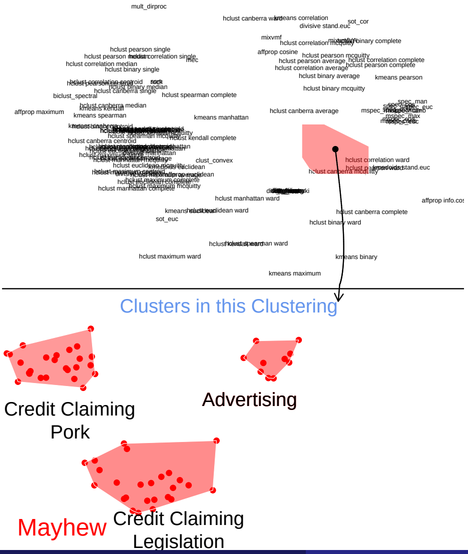
Mayhew

Example Discovery



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"

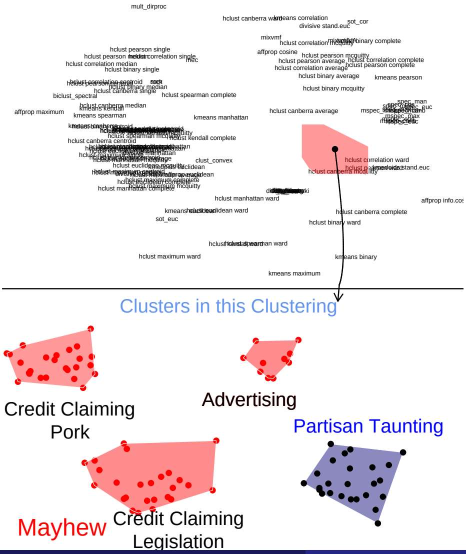
Example Discovery



Advertising:

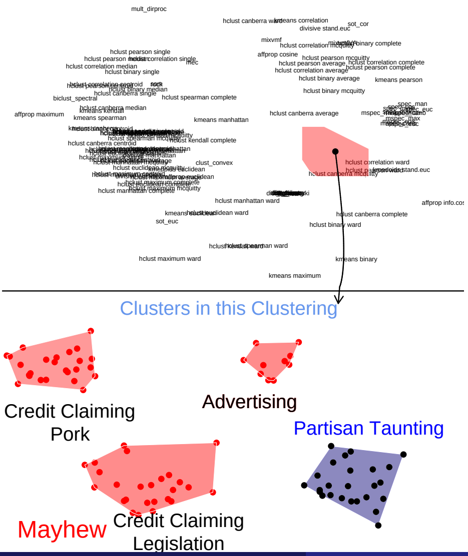
"Senate Adopts Lautenberg/Menendez Resolution Honoring Spelling Bee Champion from New Jersey"

Example Discovery: Partisan Taunting



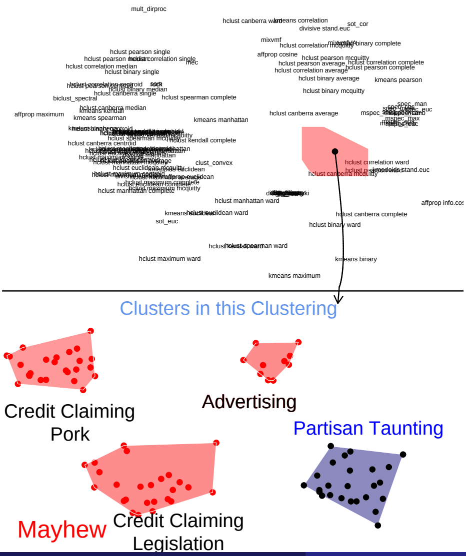
Partisan Taunting:
"Republicans Selling Out Nation on Chemical Plant Security"

Example Discovery: Partisan Taunting



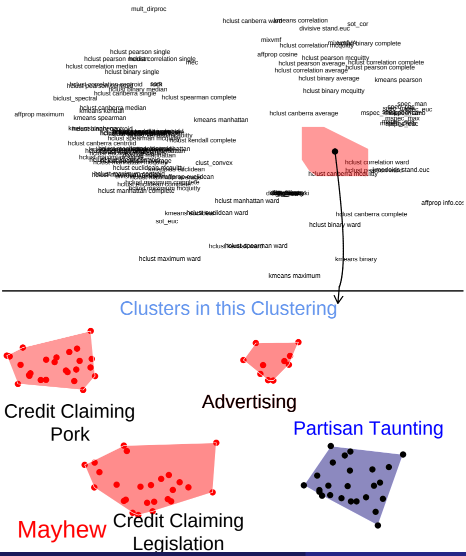
Partisan Taunting: "Senator Lautenberg's amendment would change the name of. . . the Republican bill. . . to 'More Tax Breaks for the Rich and More Debt for Our Grandchildren Deficit Expansion Reconciliation Act of 2006'"

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

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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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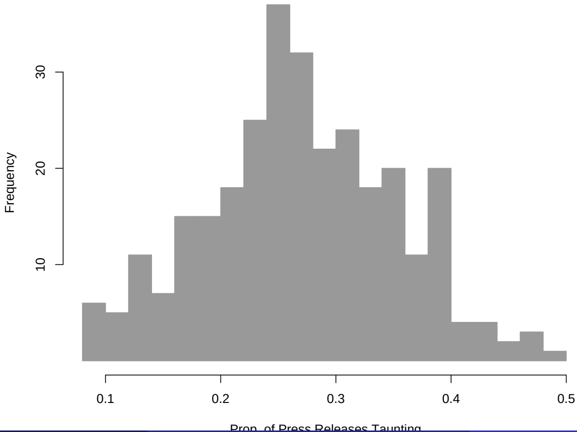

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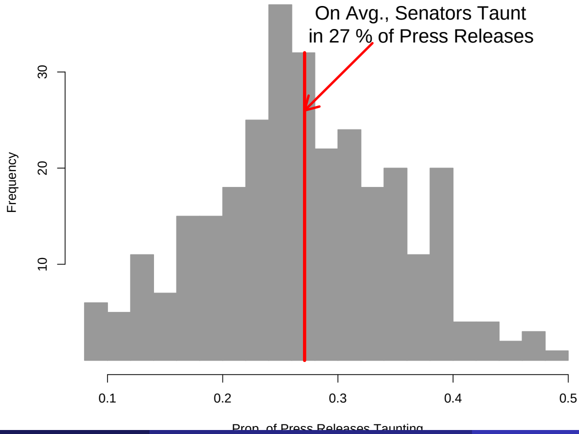


Quantitative Methods for Qualitative Conceptualization

1) Conceptualization

Qualitative Methods (reading!)

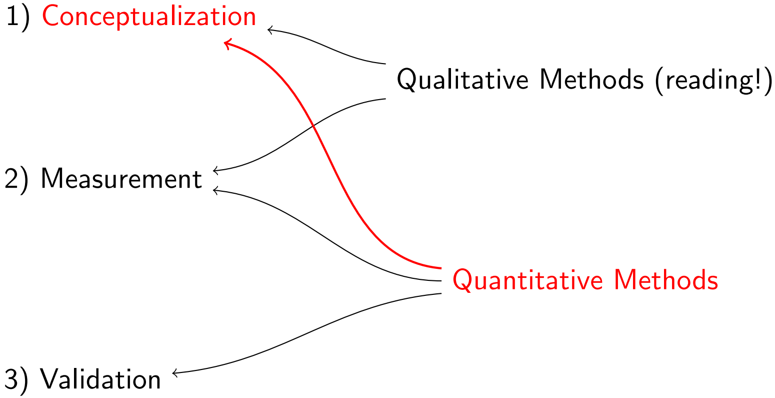
2) Measurement

Quantitative Methods

3) Validation

Quantitative methods for conceptualization and discovery

Quantitative Methods for Qualitative Conceptualization



Quantitative methods for conceptualization and discovery

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- Evaluation methods measure progress in discovery

For more information

http://GKing.Harvard.edu