Computer-Assisted Clustering and Conceptualization from Unstructured Text

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(talk at University of Kentucky, 4/20/2012)

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

A Method for Computer Assisted Conceptualization

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- 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 ≈
A list of unconnected addresses

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Set of clusterings $\approx$

A list of unconnected addresses

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Cartage New England Inc
26 Allen Ln Ipswich 01938....................978 356-9960
Cartagema Lydia
18 Jewett Ros 02131.................. 617 323-7639
Cartagena Avith
9 Bancroft Rox 02119..................617 442-9780
B Hyd 02136..................617 361-5253
Jessica 50 Decatur Cha 02129..........617 241-0152
Lucilla 174 Harvard Cam 02139........617 491-5621
M 95 Rowe Ros 02131..................617 323-9713
Melvin 501 Green Cam 02139...........617 576-1061
Carte Nicholas
18 Appleton Boston 02116.............617 695-6996
Cartegena O 4 Milford Bos 02118.........617 338-8219
Carten Thos J Sr & Claire
1 Paradise Rd Mil 02186.............. 617 698-6163
Thomas & Kathleen
50 Thompson Ln Mil 02186............617 696-6919
Carter A Ros 02131.........................617 327-2257
A Roxbury.................................617 442-5230
A 31 Bethune Wy Roxbury 02119.........617 442-1219
A 260 Putnam Av Cambridge 02139...... 617 492-4174
A M 255 Maschsts Av Bos 02115.......617 266-7153
Adams 361 Centre St Mil 02186........617 698-9074
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 Commwth 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
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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
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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
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15 Mercer S Bos 02127.................617 268-0448
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⇝ We develop a (conceptual) geography of clusterings

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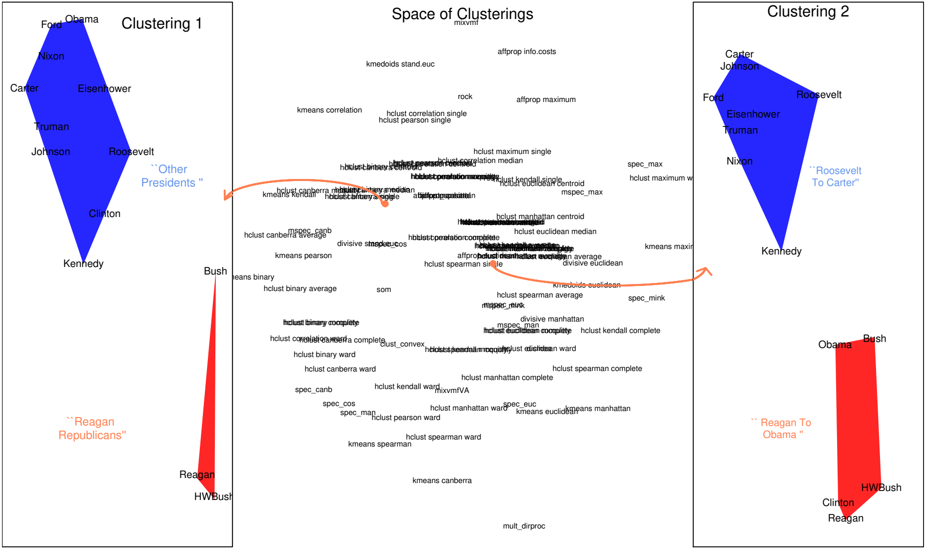
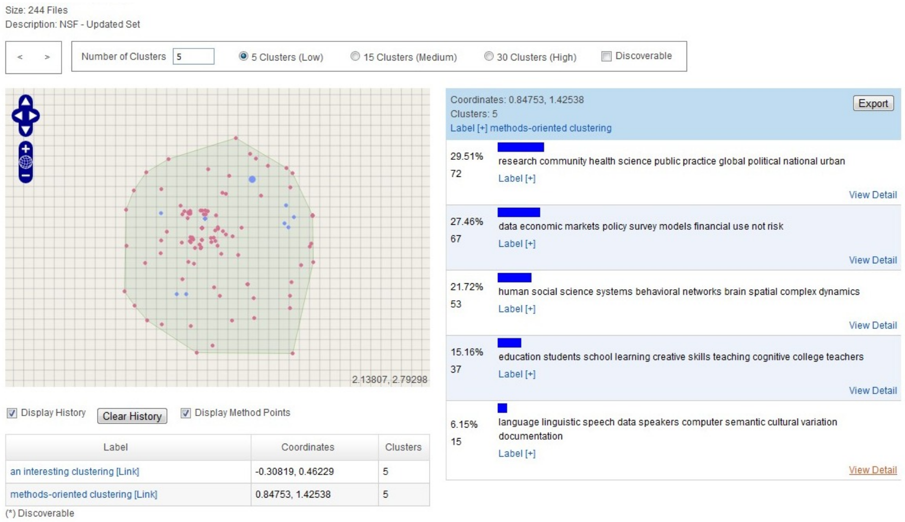
8. (Or, our new strategy: represent the entire bell space directly; no need to examine document contents)

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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  - Discovery ⇒ You're the judge

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  - automated visualization to choose one clustering

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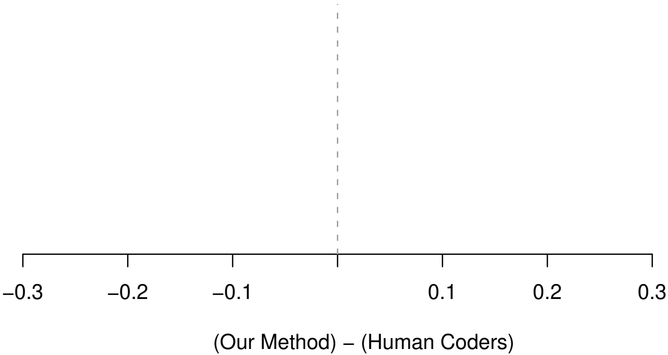

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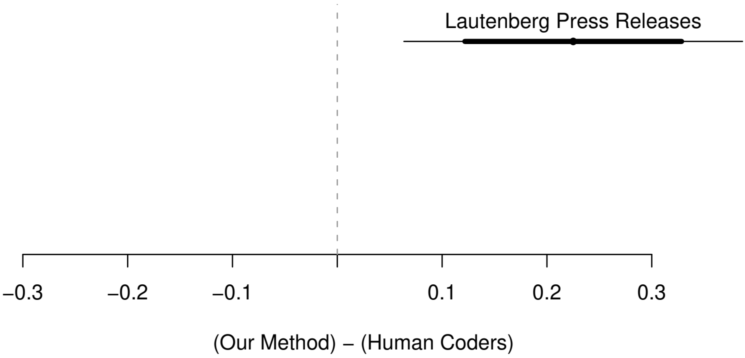
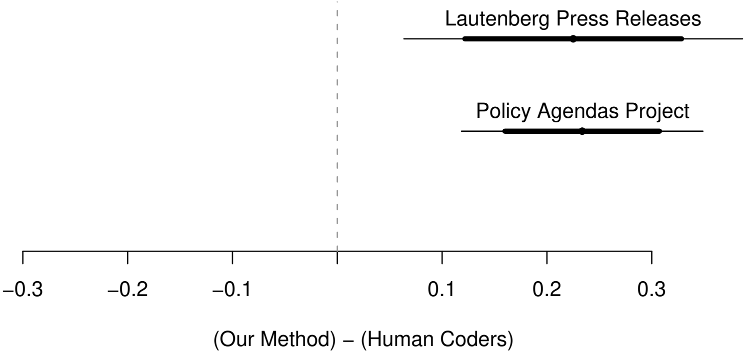


Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

Evaluation 1: Cluster Quality



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

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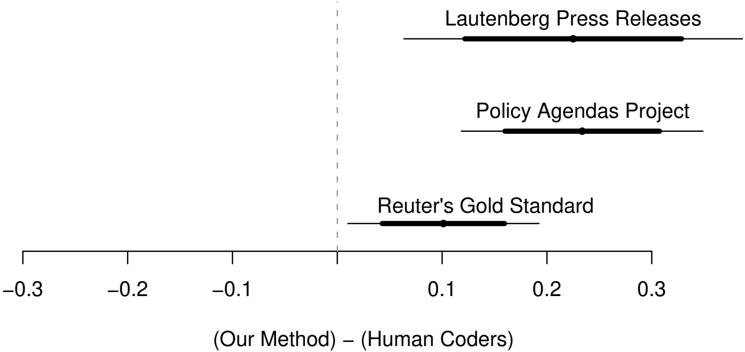

Reuter's: financial news (trade, earnings, copper, gold, coffee, ...); "gold standard" for supervised learning studies

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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

Evaluation 3: What Do Members of Congress Do?

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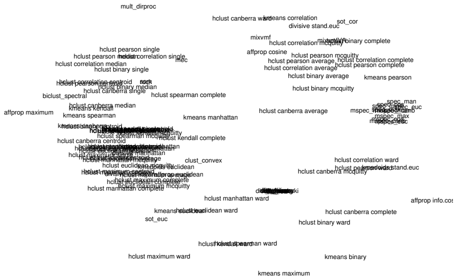
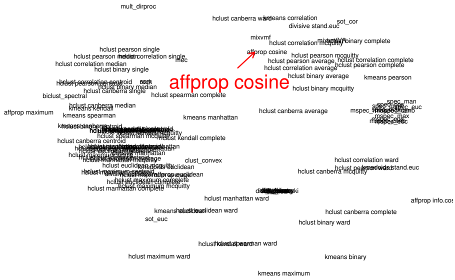
- Data: 200 press releases from Frank Lautenberg's office (D-NJ)
- Apply our method

Example Discovery

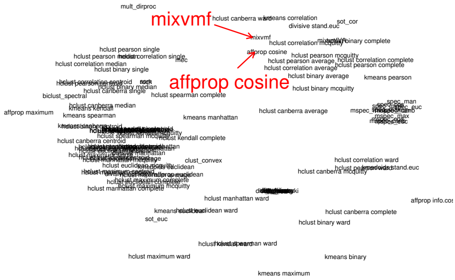


Example Discovery



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

Example Discovery



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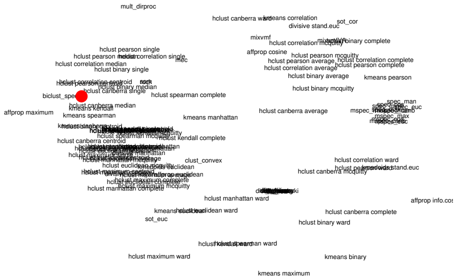
Close to:

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

Example Discovery

Space between methods:

Example Discovery



Space between methods:

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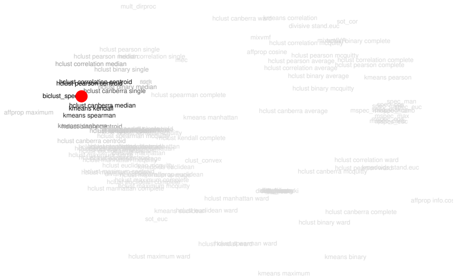
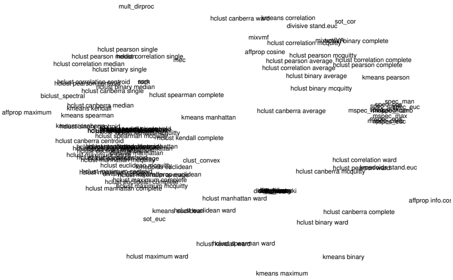


Space between methods:

local cluster ensemble

Example Discovery



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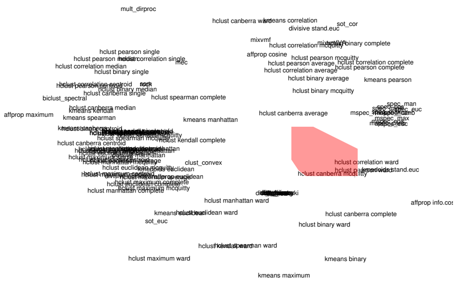

Found a region with particularly insightful clusterings

Example Discovery

Mixture:

Mixture:

0.39 Hclust-Canberra-McQuitty

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- 0.04 Spectral clustering Symmetric (Metrics 1-6)

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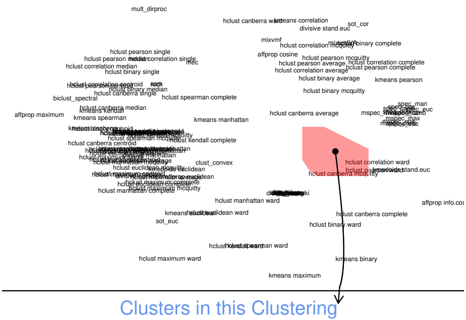
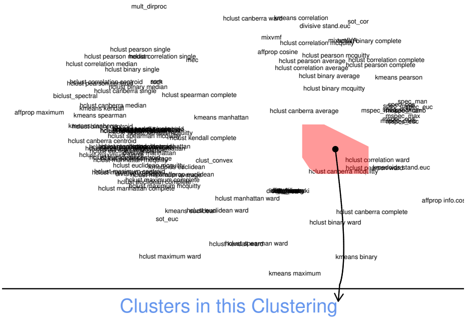
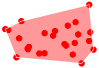


Mayhew

Example Discovery



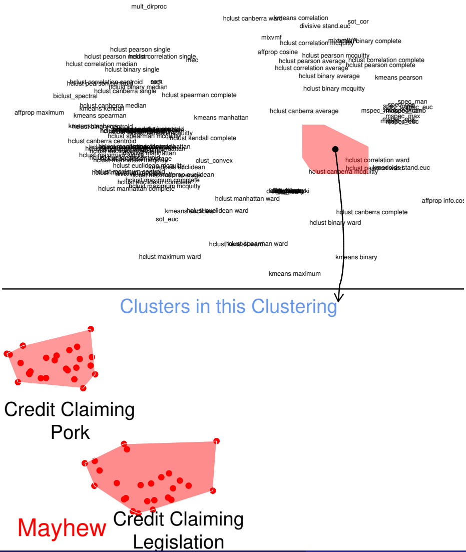


Credit Claiming
Pork

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

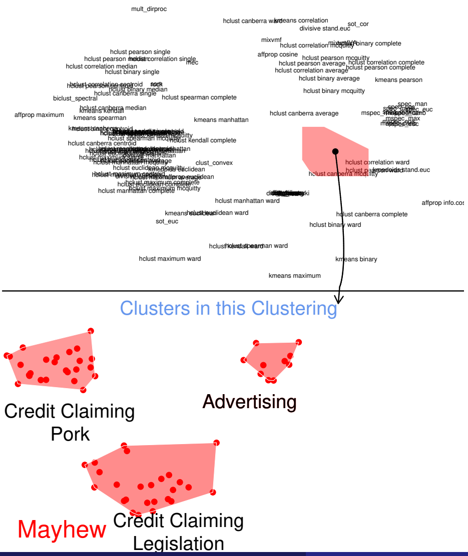
Example Discovery



Credit Claiming, Legislation:

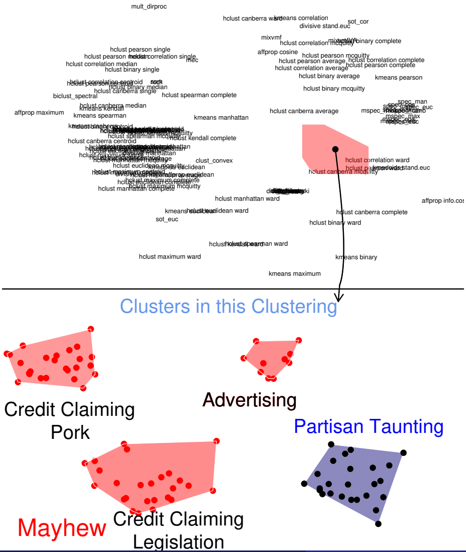
"As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period"

Example Discovery



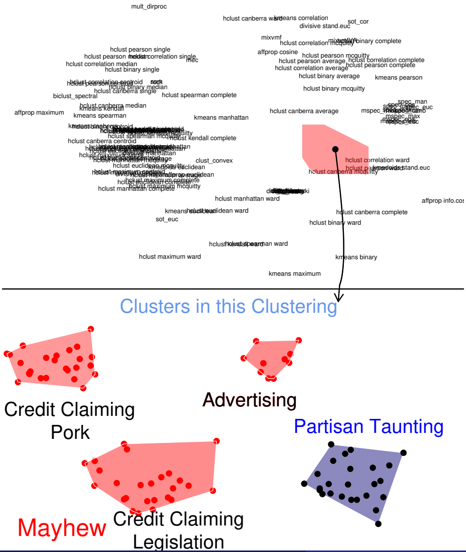
Advertising:
“Senate Adopts Lautenberg/Menendez Resolution Honoring Spelling Bee Champion from New Jersey”

Example Discovery: Partisan Taunting



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

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"'

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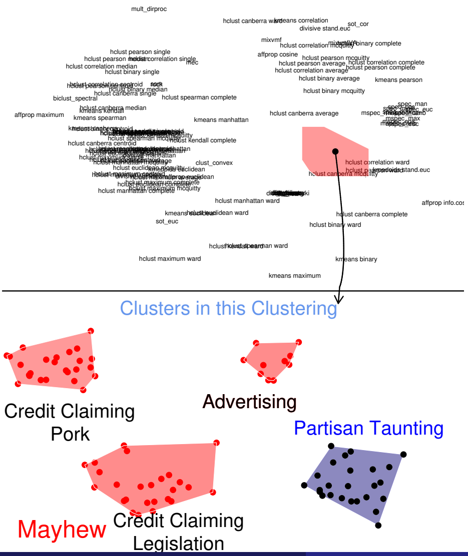

Definition: Explicit, public, and negative attacks on another political party or its members

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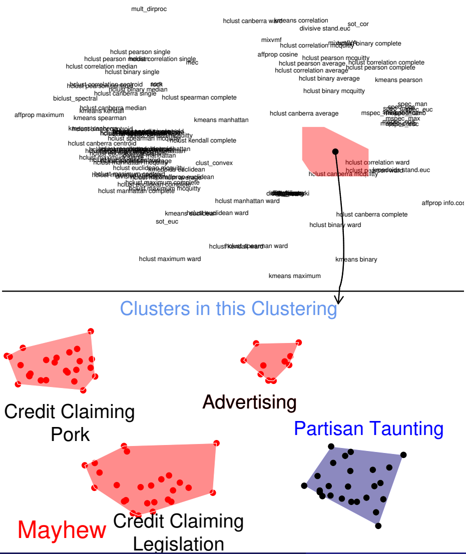

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Taunting ruins deliberation

In Sample Illustration of Partisan Taunting

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Sen. Lautenberg on Senate Floor 4/29/04

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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

- Discovered using 200 press releases; 1 senator.

Out of Sample Confirmation of Partisan Taunting

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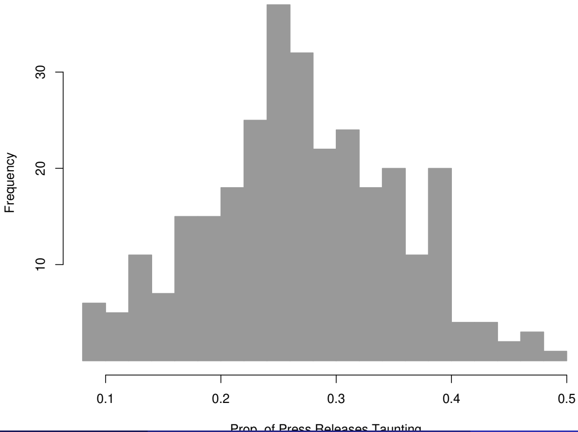

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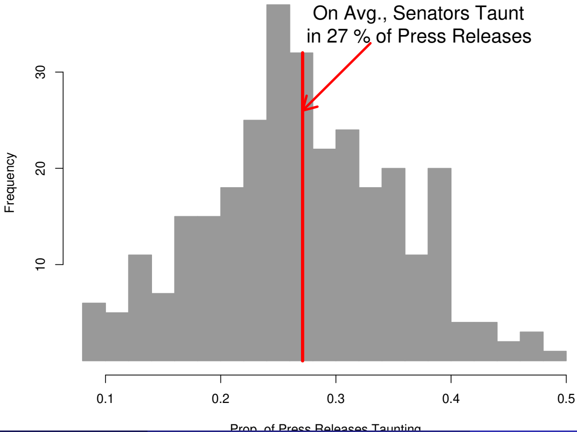

Quantitative Methods for Qualitative Conceptualization

1) Conceptualization

Qualitative Methods (reading!)

2) Measurement

Quantitative Methods

3) Validation

Quantitative methods for conceptualization and discovery

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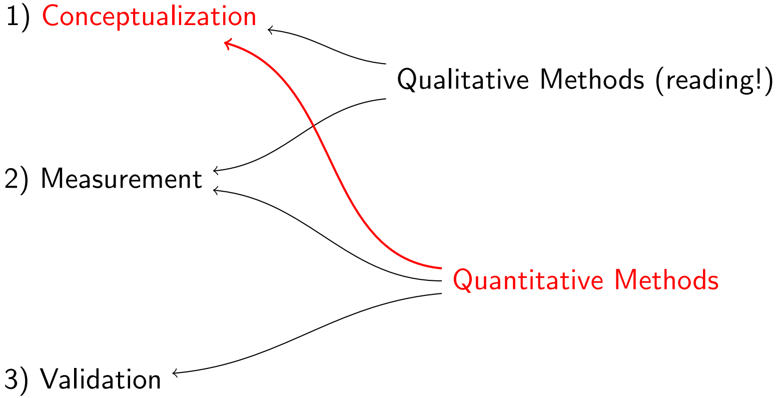

Quantitative methods for conceptualization and discovery

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- Evaluation methods measure progress in discovery

For more information

http://GKing.Harvard.edu