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

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Joint work with Justin Grimmer, Harvard University

# Some context for related technology

- http://ow.ly/14hDU
- http://ow.ly/14h36

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- We focus on Cluster Analysis: simultaneously 1) invent categories and 2) assign documents to categories
- (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

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  - An organized list will make the search possible
  - E.g.,: consider two clusterings that differ only because one document (of many) moves from category 5 to 6

# Our Idea: Meaning Through Geography

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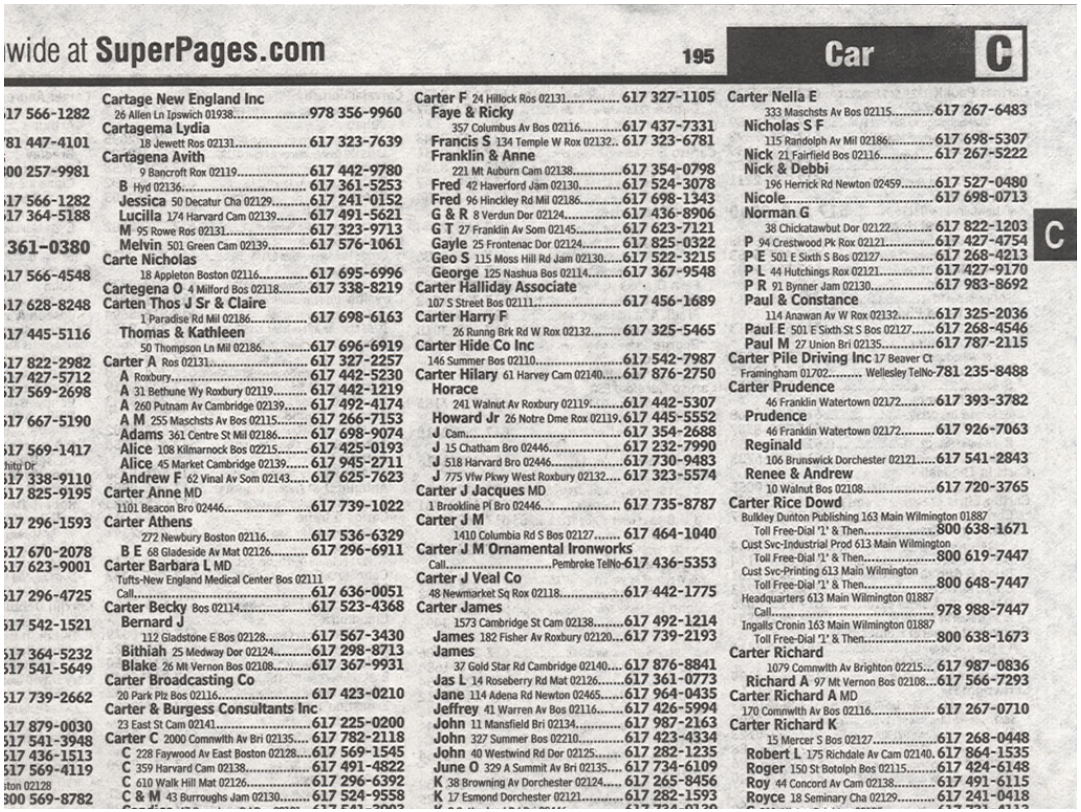

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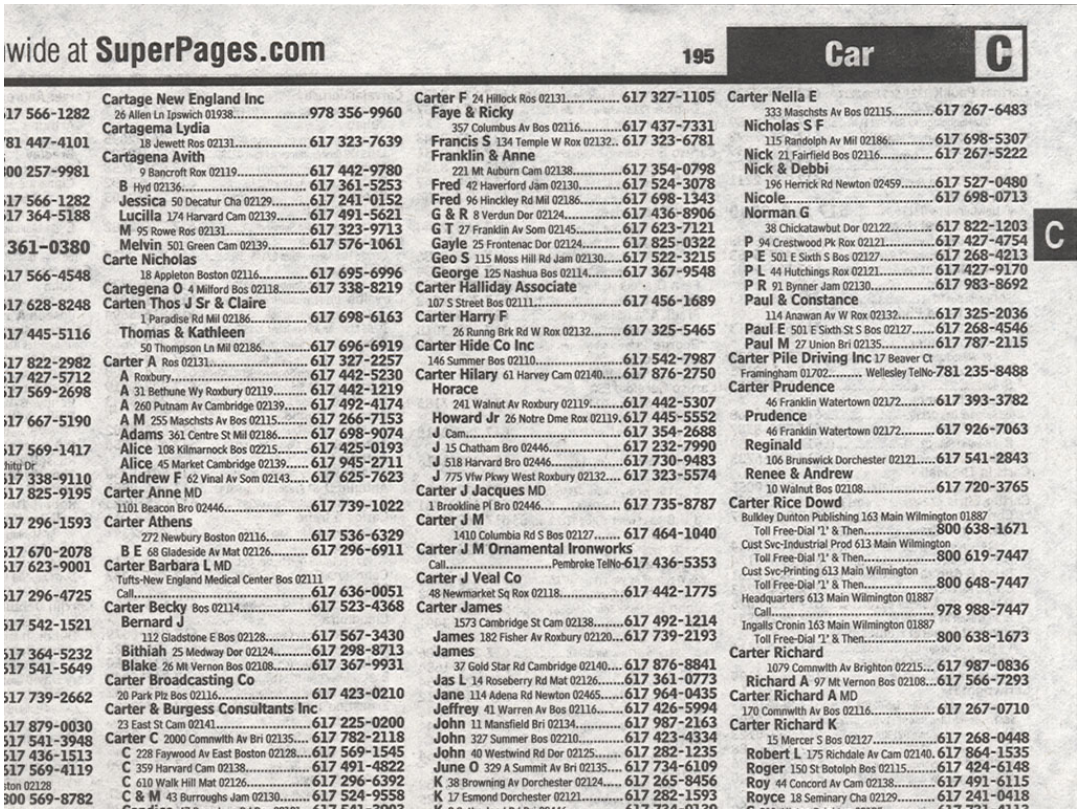

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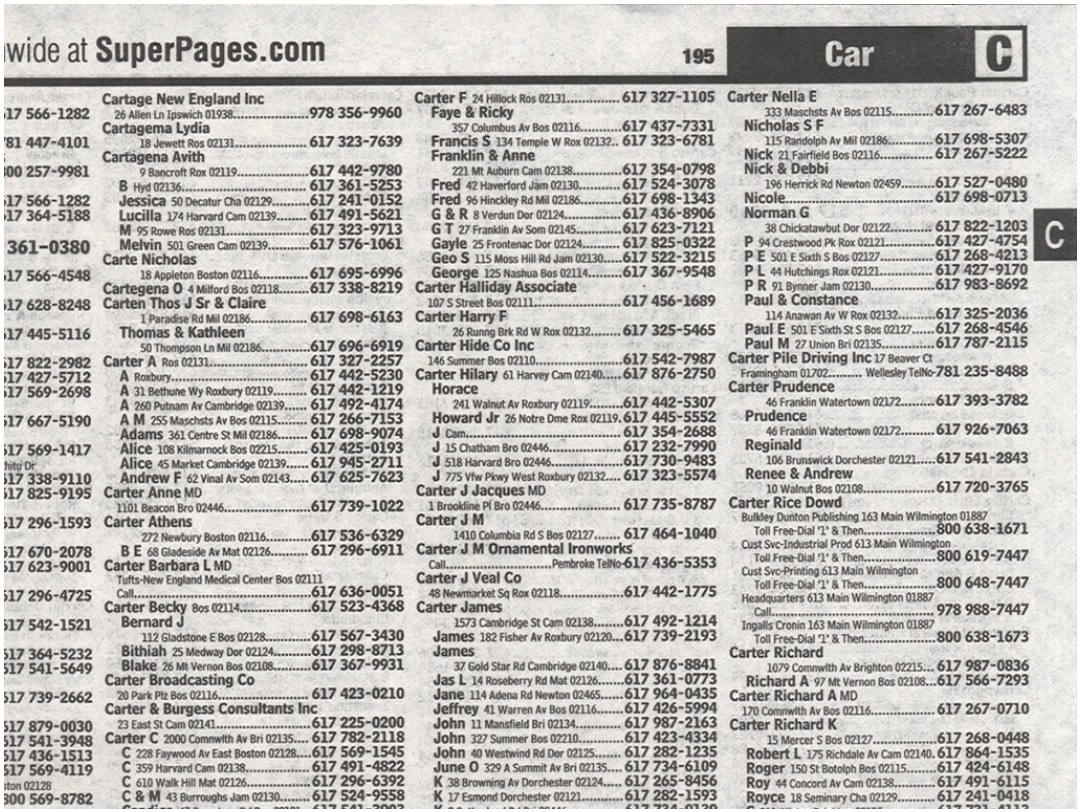
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Jessica 50 Decatur Cha 02129 617 241-0152
Lucilla 174 Harvard Cam 02139 617 491-5621
M 95 Rowe Ros 02131 617 323-9713
Melvin 501 Green Cam 02139 617 576-1061
Carte Nicholas 18 Appleton Boston 02116 617 695-6996
Cartegena O 4 Milford Bos 02118 617 338-8219
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 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 Tel No 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 Tel No 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 Bulldey 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
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Carter Richard K 15 Mercer S Bos 02127 617 268-0448
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⇝ We develop a (conceptual) geography of clusterings

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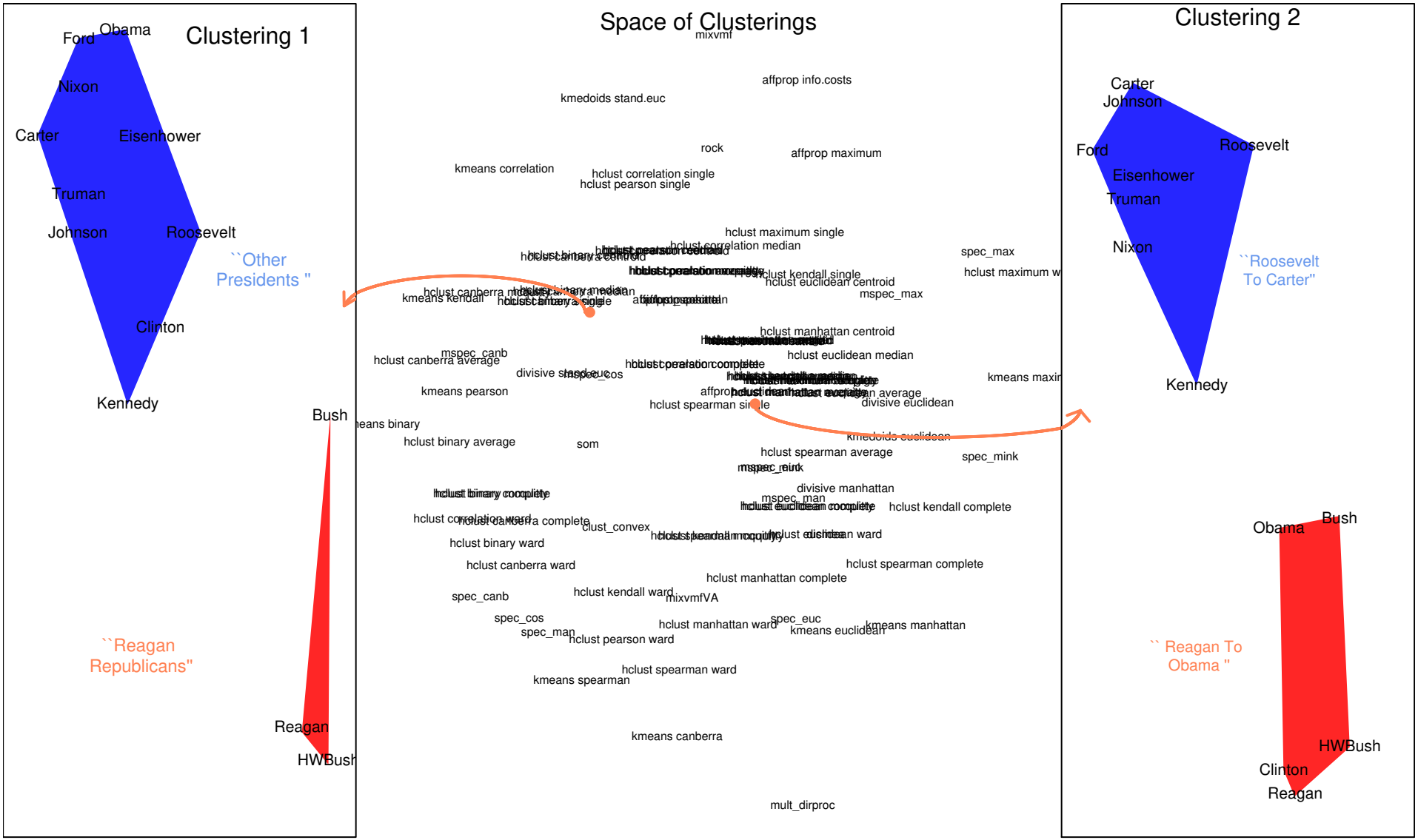
7. $\rightsquigarrow$ Millions of clusterings, easily comprehended (takes about 10-15 minutes to choose a clustering with insight)

# Many Thousands of Clusterings, Sorted & Organized

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



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

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  - Discovery $\Rightarrow$ You're the judge

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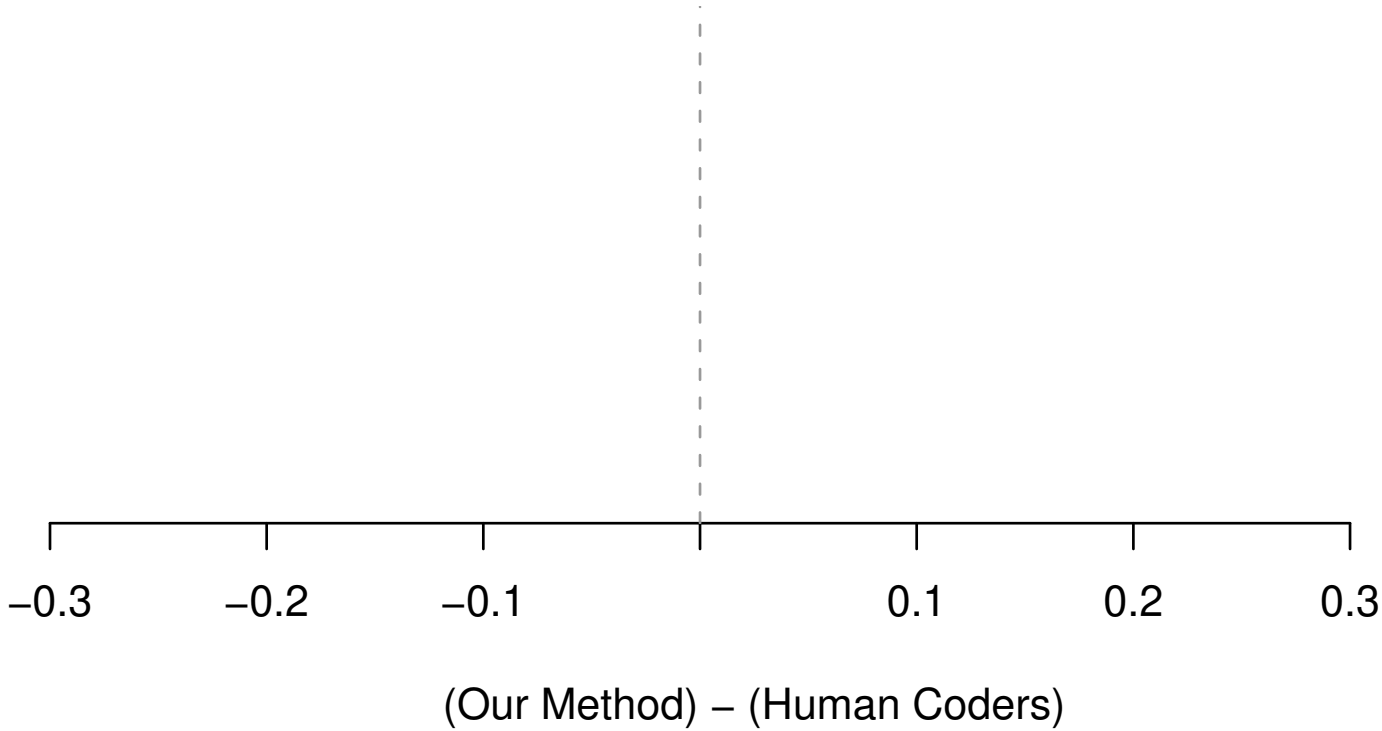

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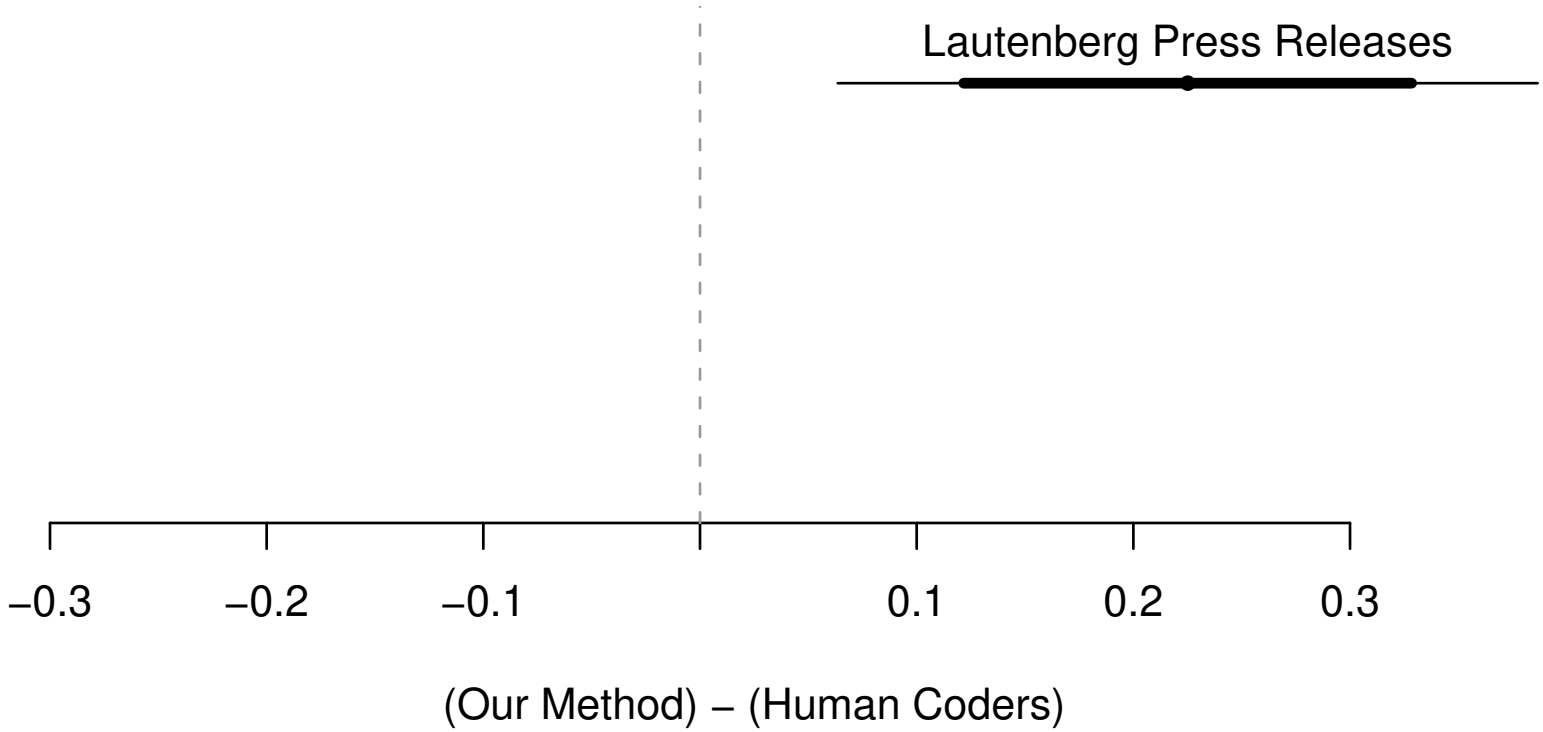


Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . . )

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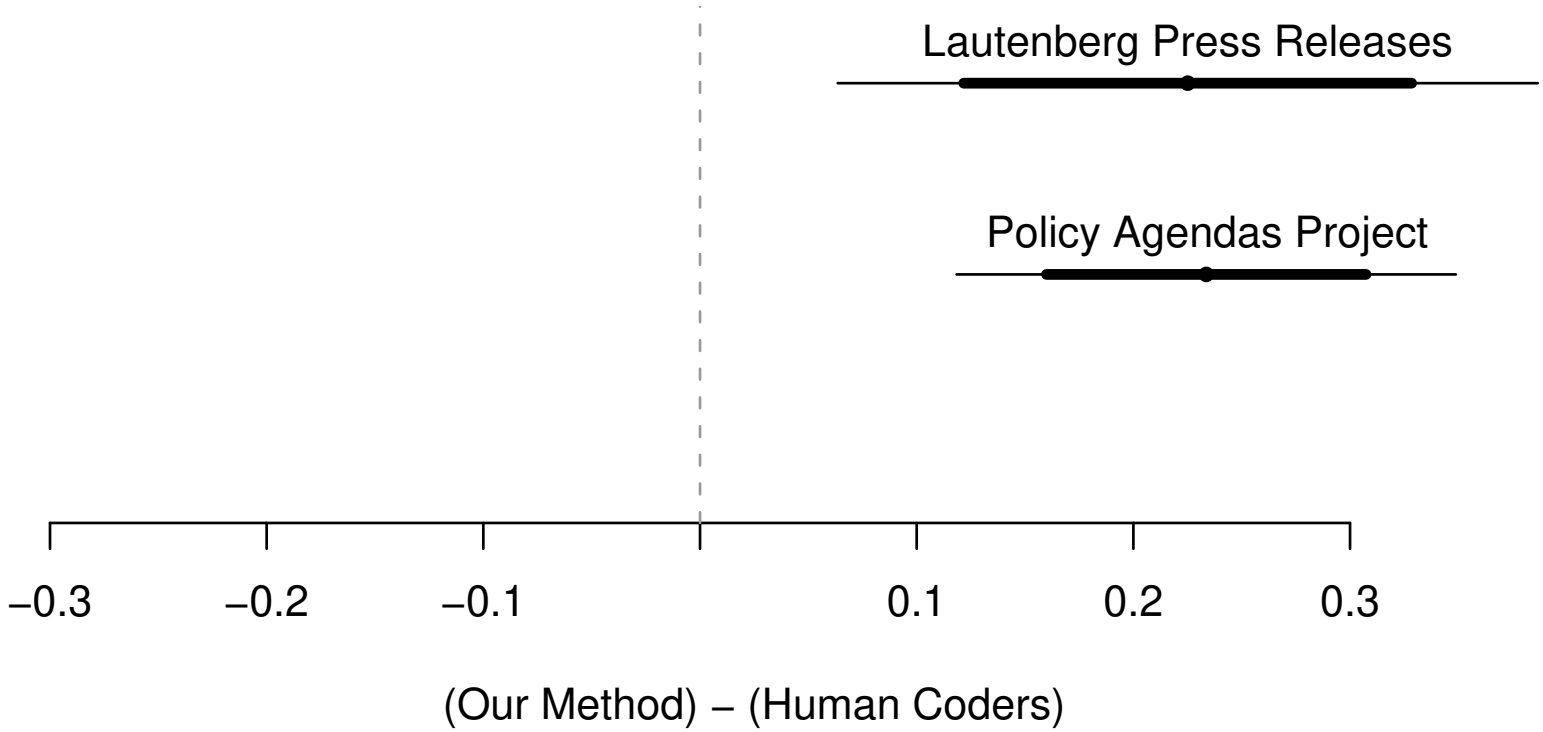


Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . . )

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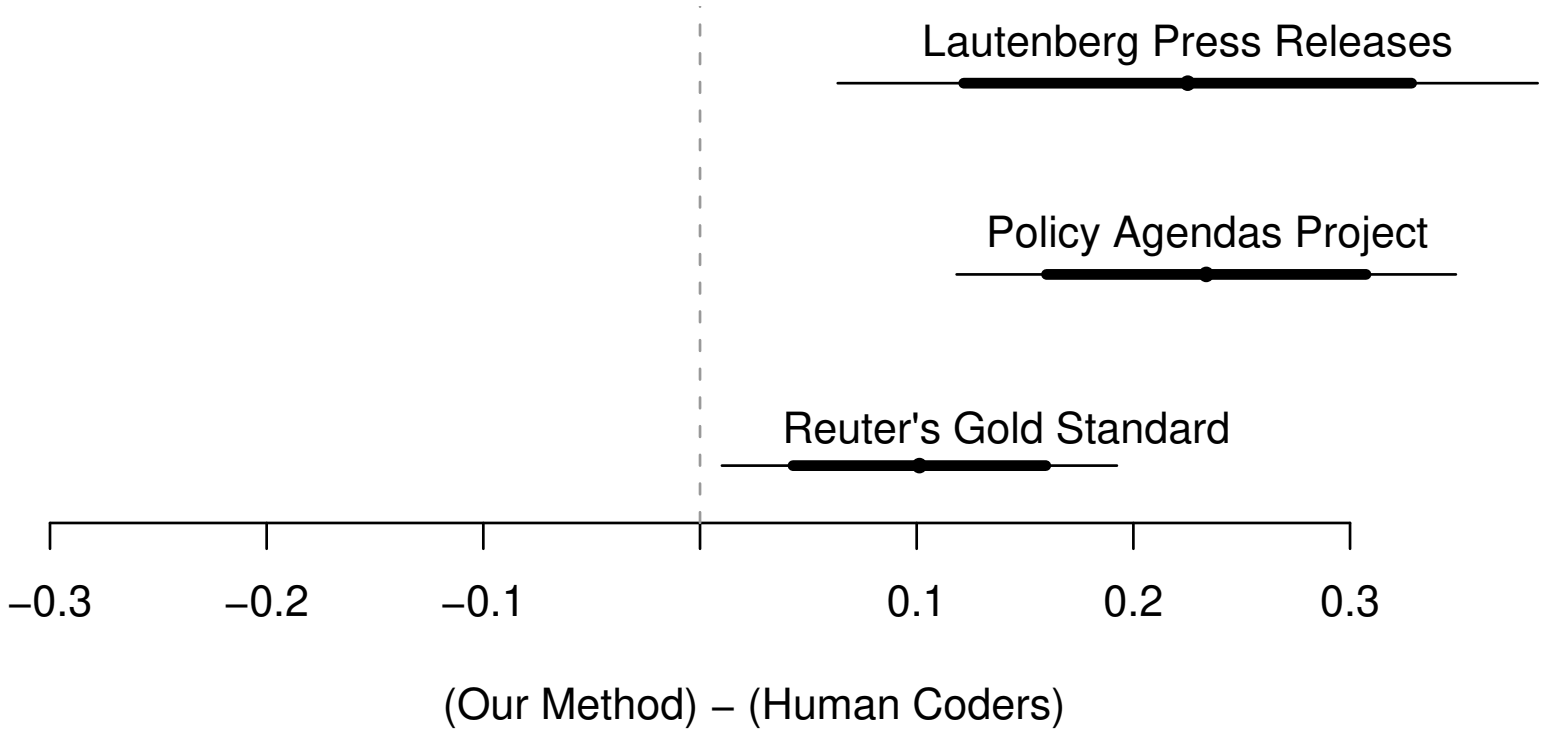


Reuter's: financial news (trade, earnings, copper, gold, coffee, . . . ); "gold standard" for supervised learning studies

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

# Example Discovery

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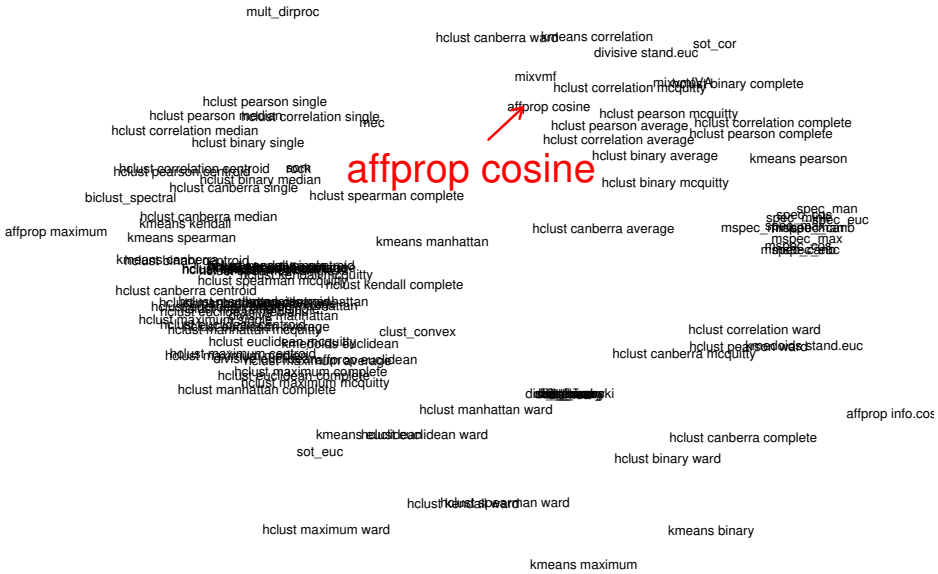


Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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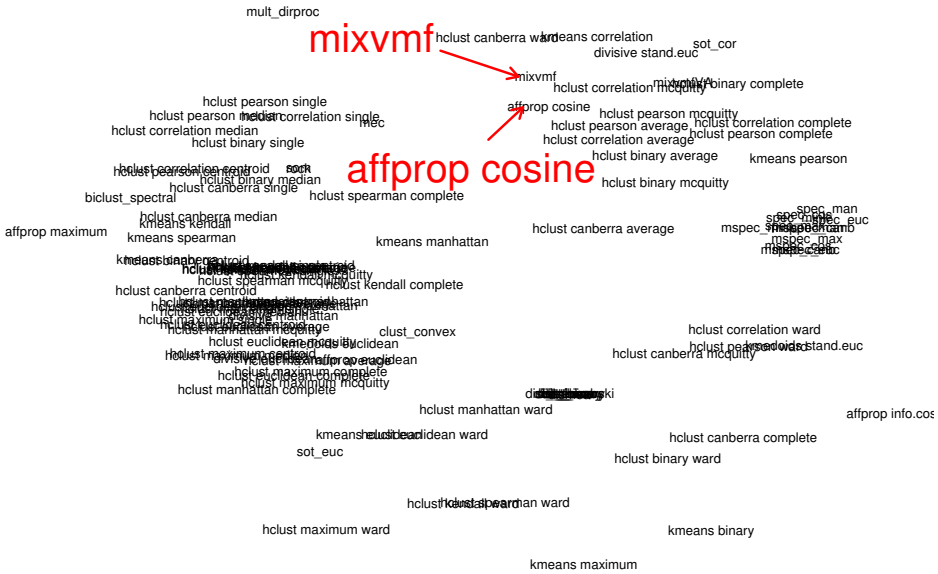


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Close to:

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

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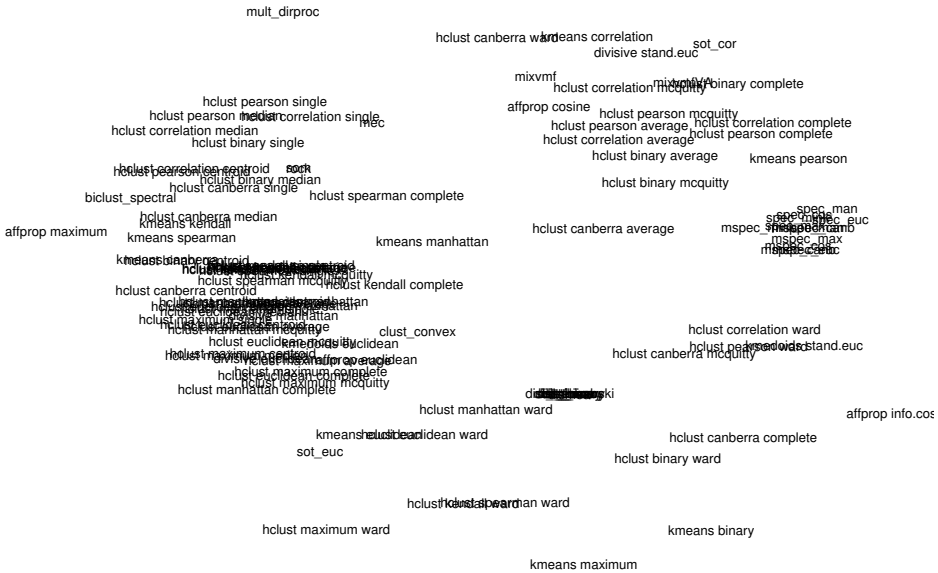
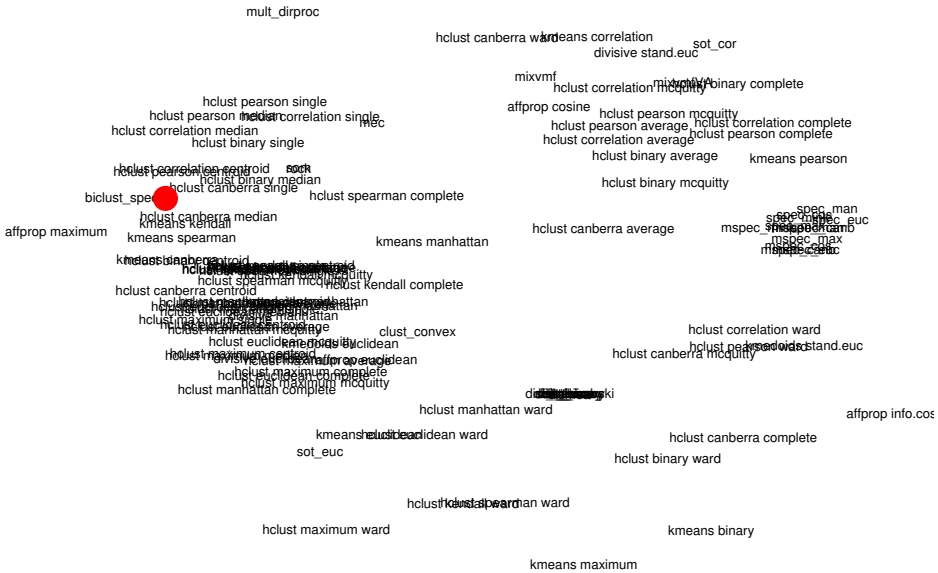



Space between methods:

# 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:

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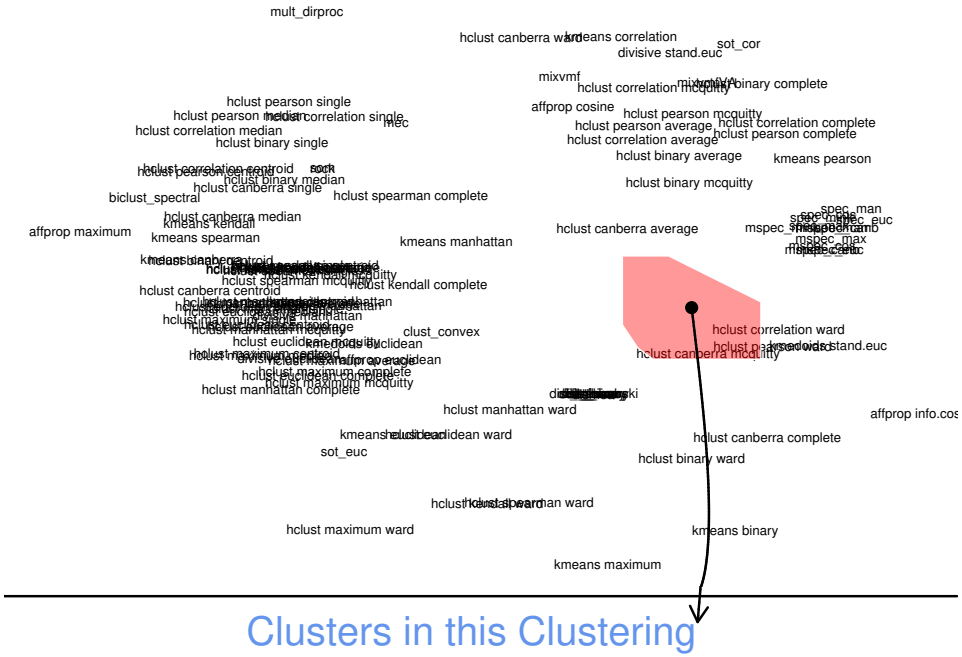
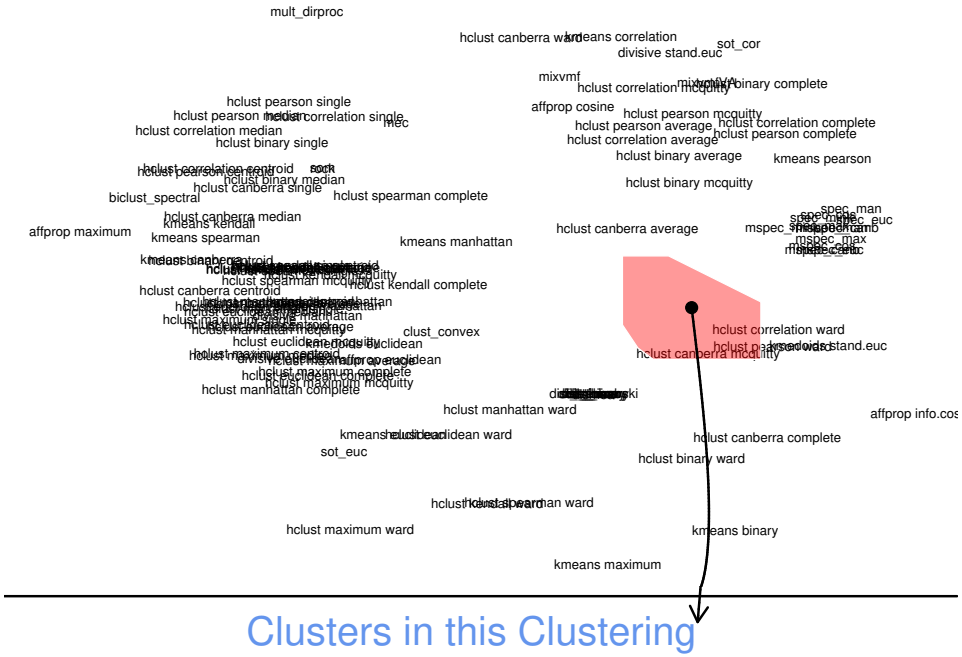
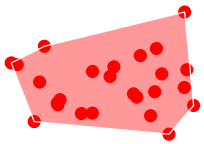



Mayhew

# Example Discovery



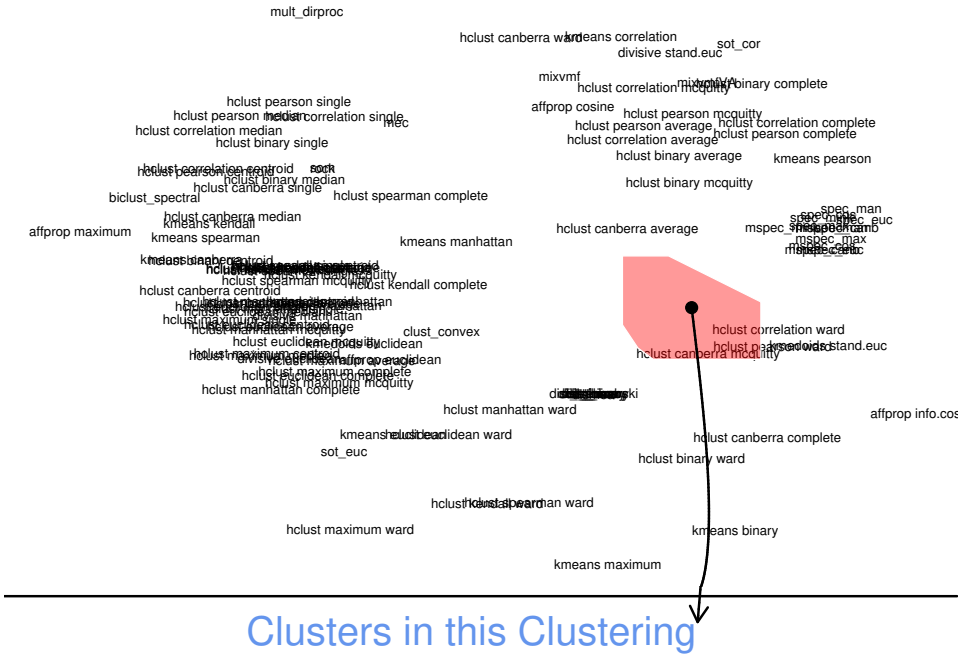



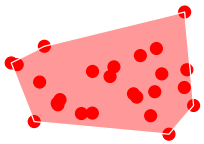
Credit Claiming
Pork

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



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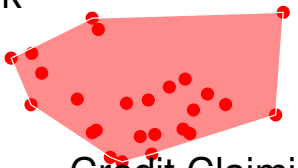
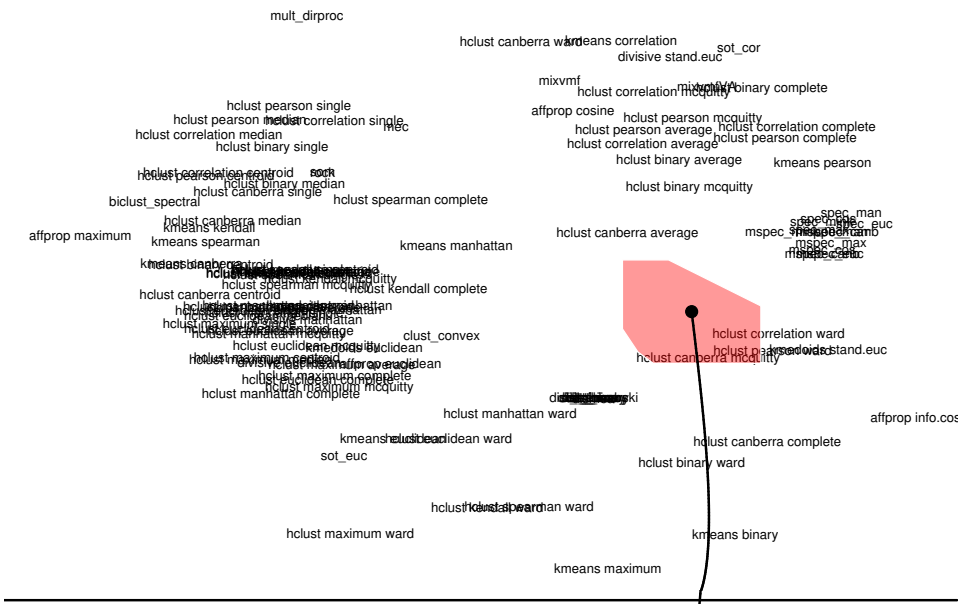


Mayhew

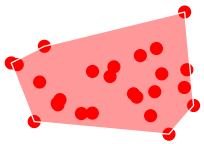
Credit Claiming
Legislation

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




Clusters in this Clustering



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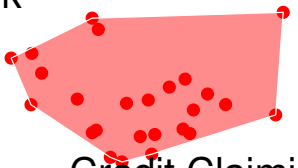
Pork

Advertising

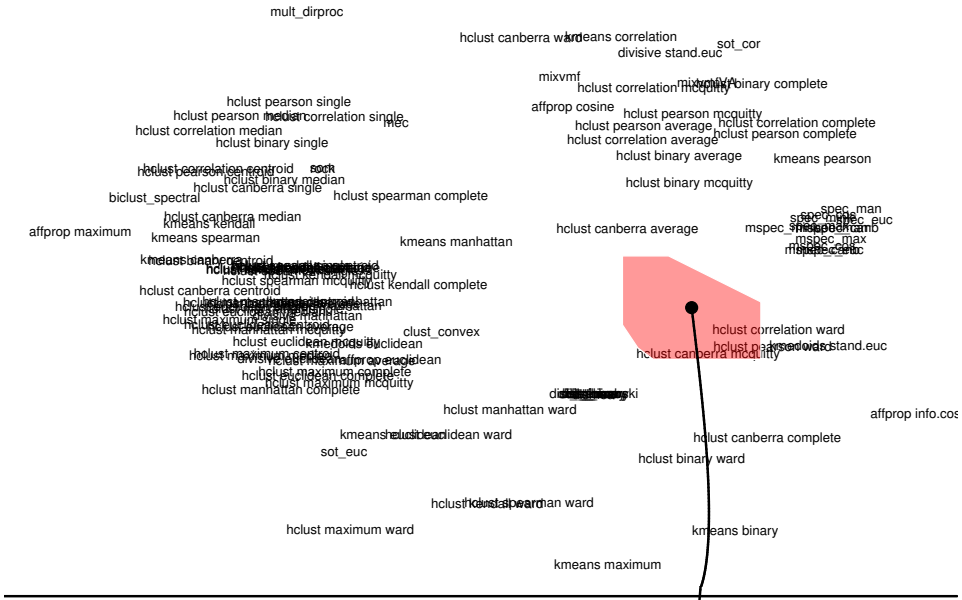


Mayhew

Credit Claiming
Legislation

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

# Example Discovery: Partisan Taunting

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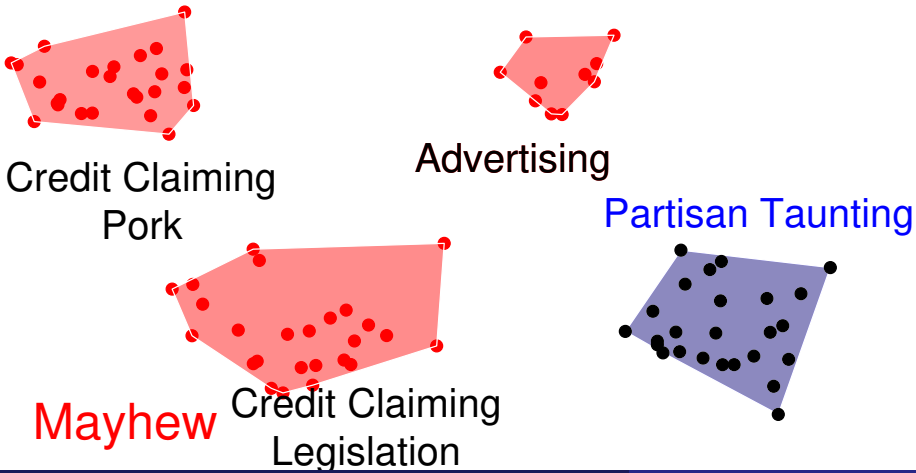
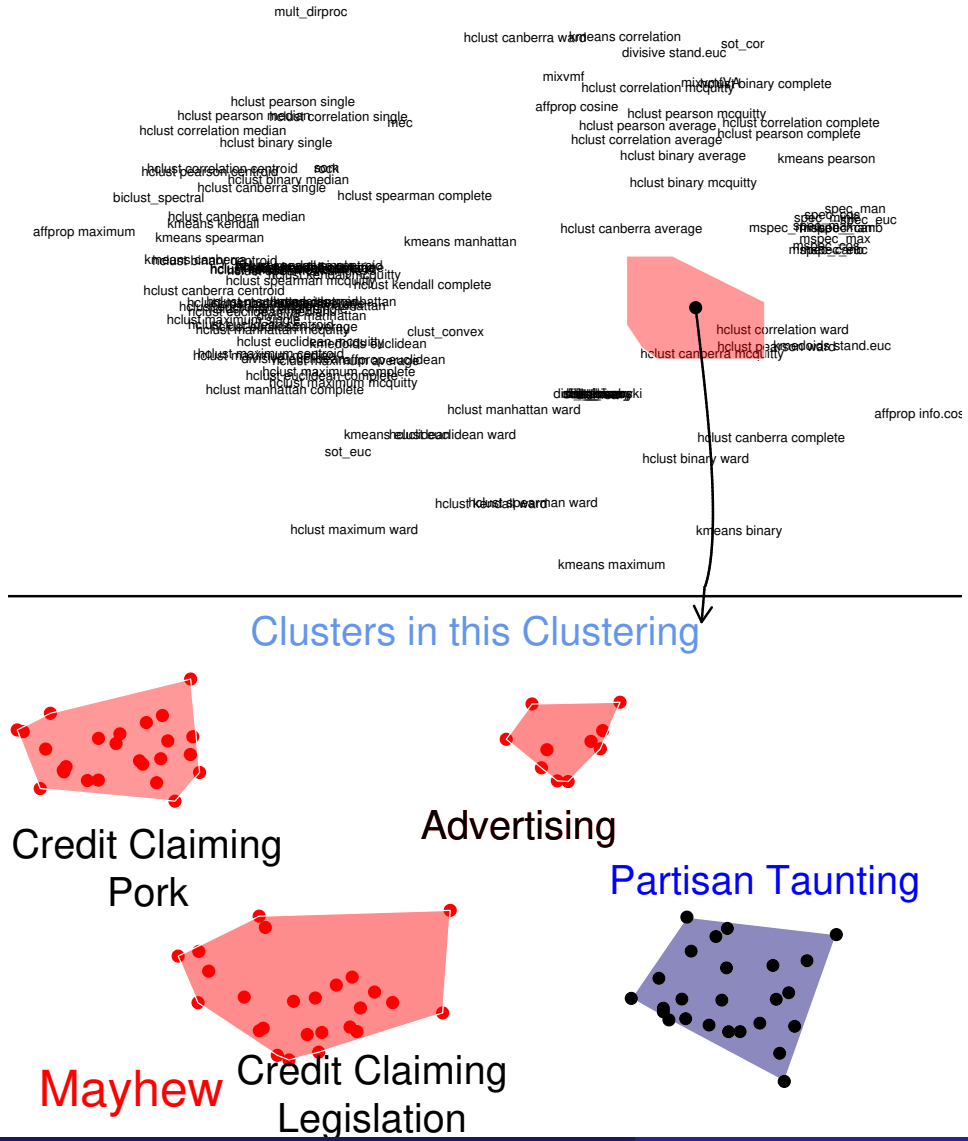


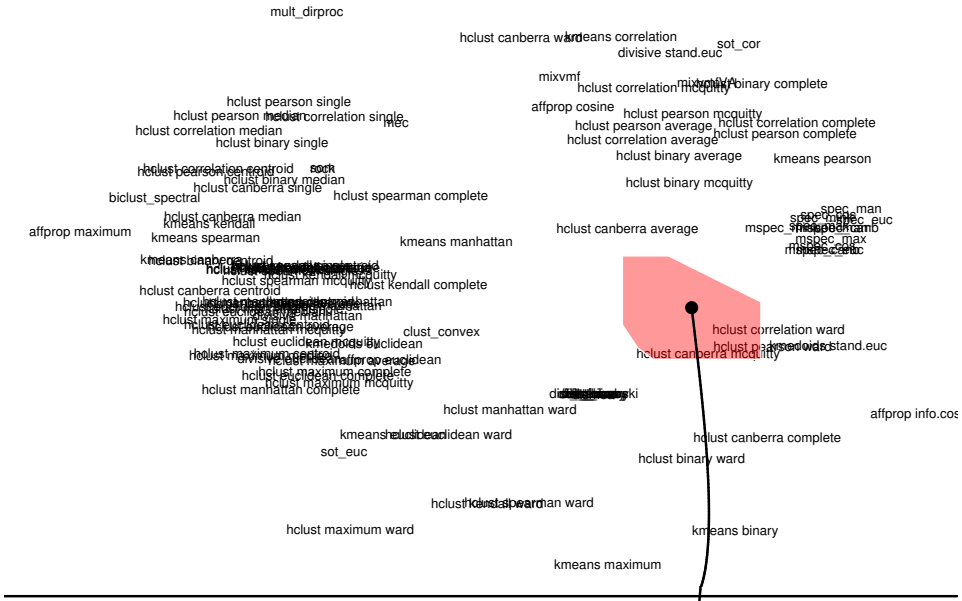

Partisan Taunting:
"Republicans Selling Out Nation on Chemical Plant Security"

# 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

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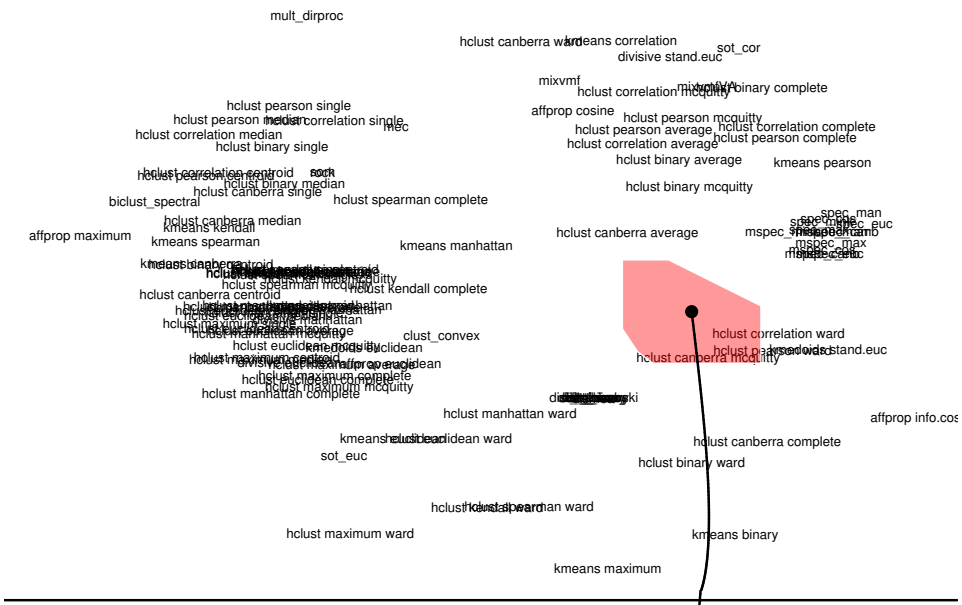
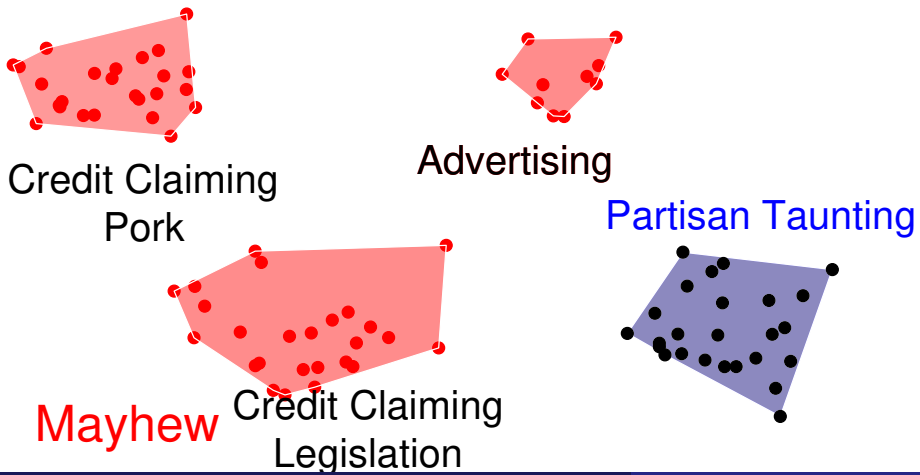



Clusters in this Clustering

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Taunting ruins deliberation

# 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]

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- "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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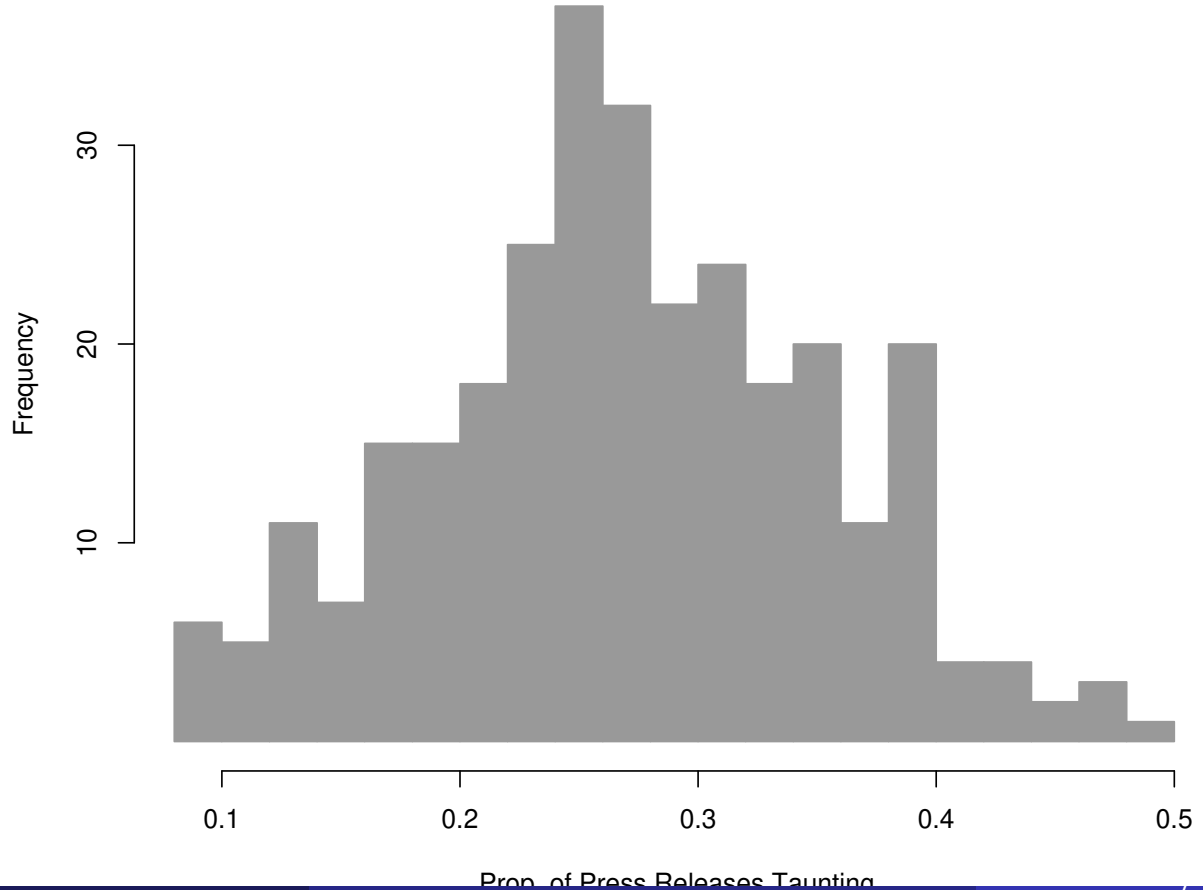

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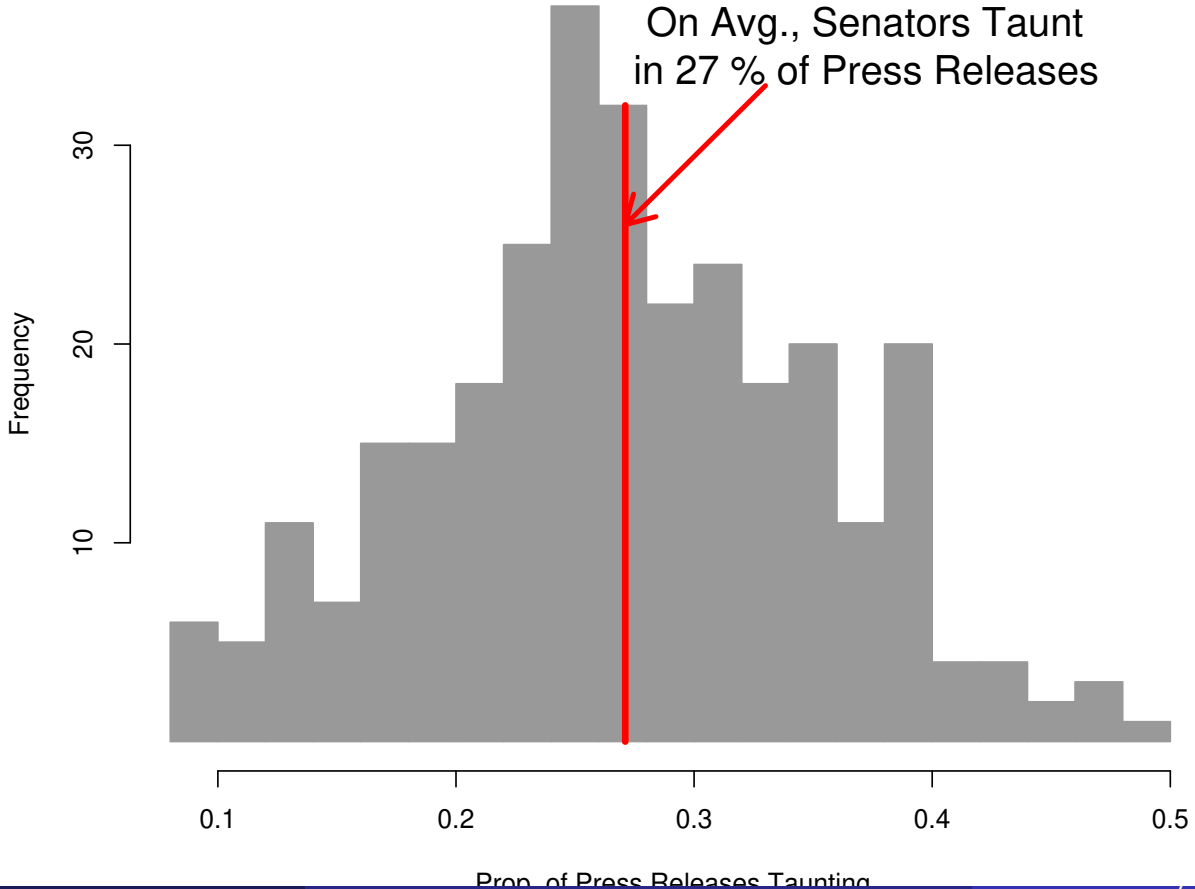
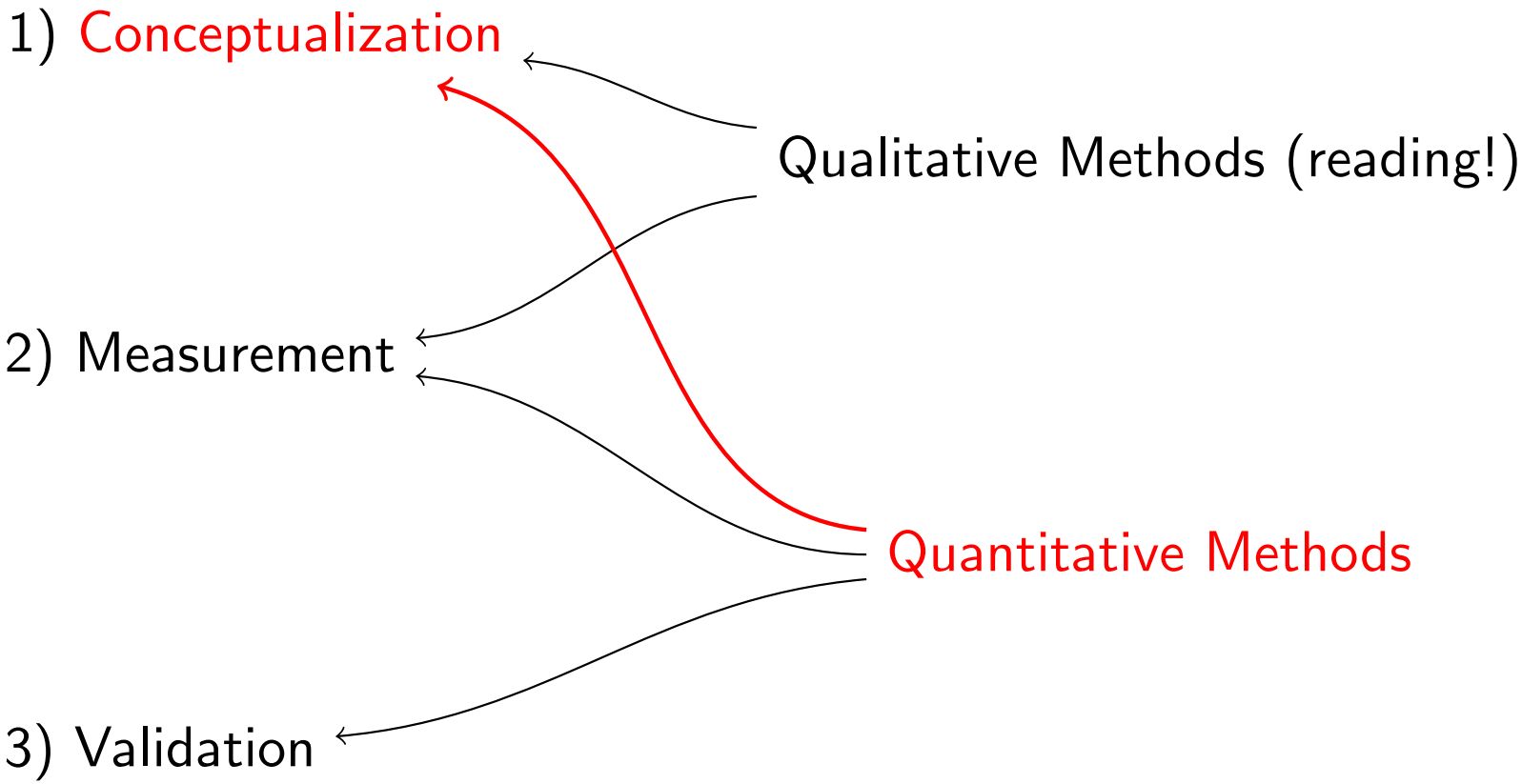
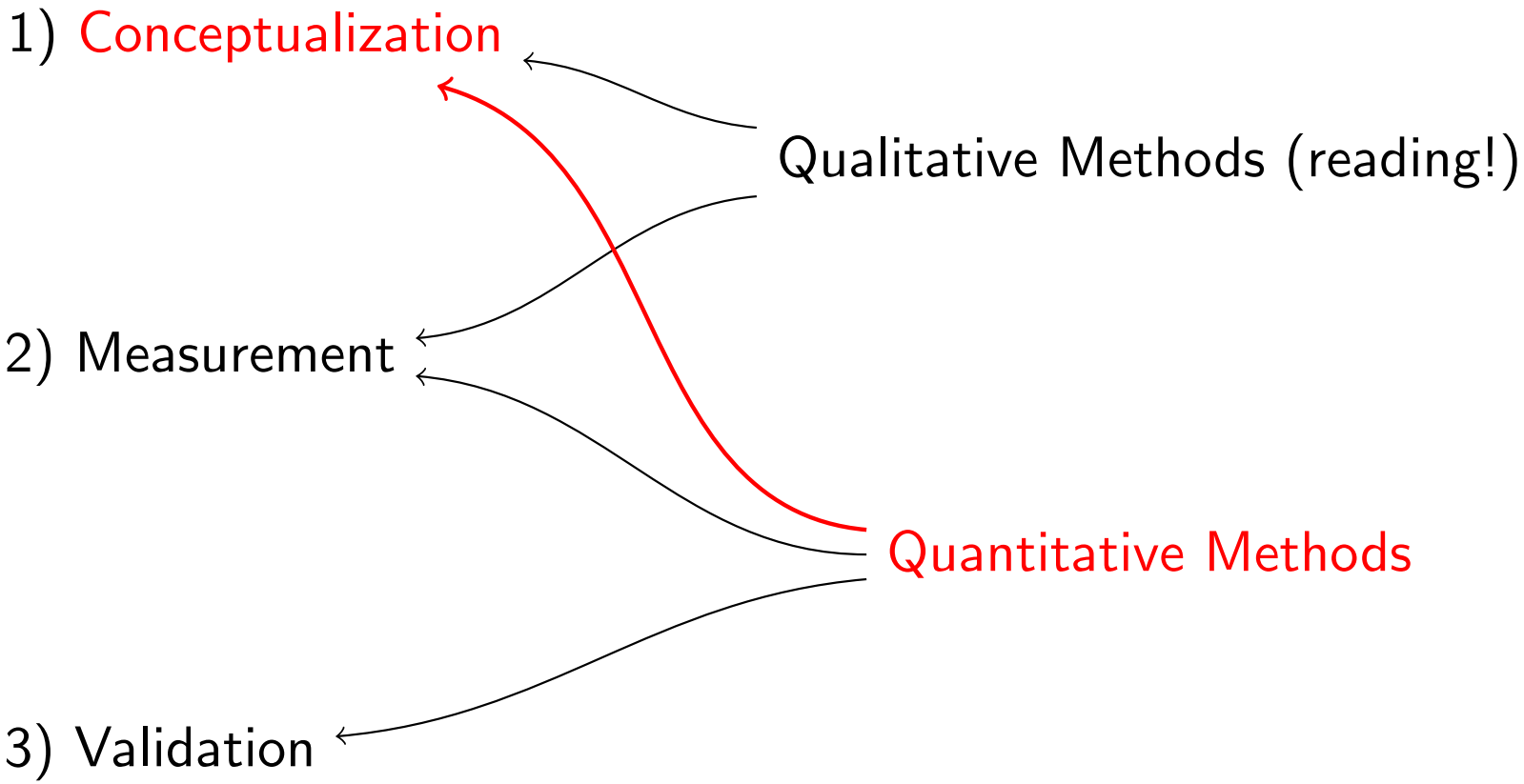


# Advancing the Objective of Discovery




Quantitative methods for conceptualization: aiding discovery

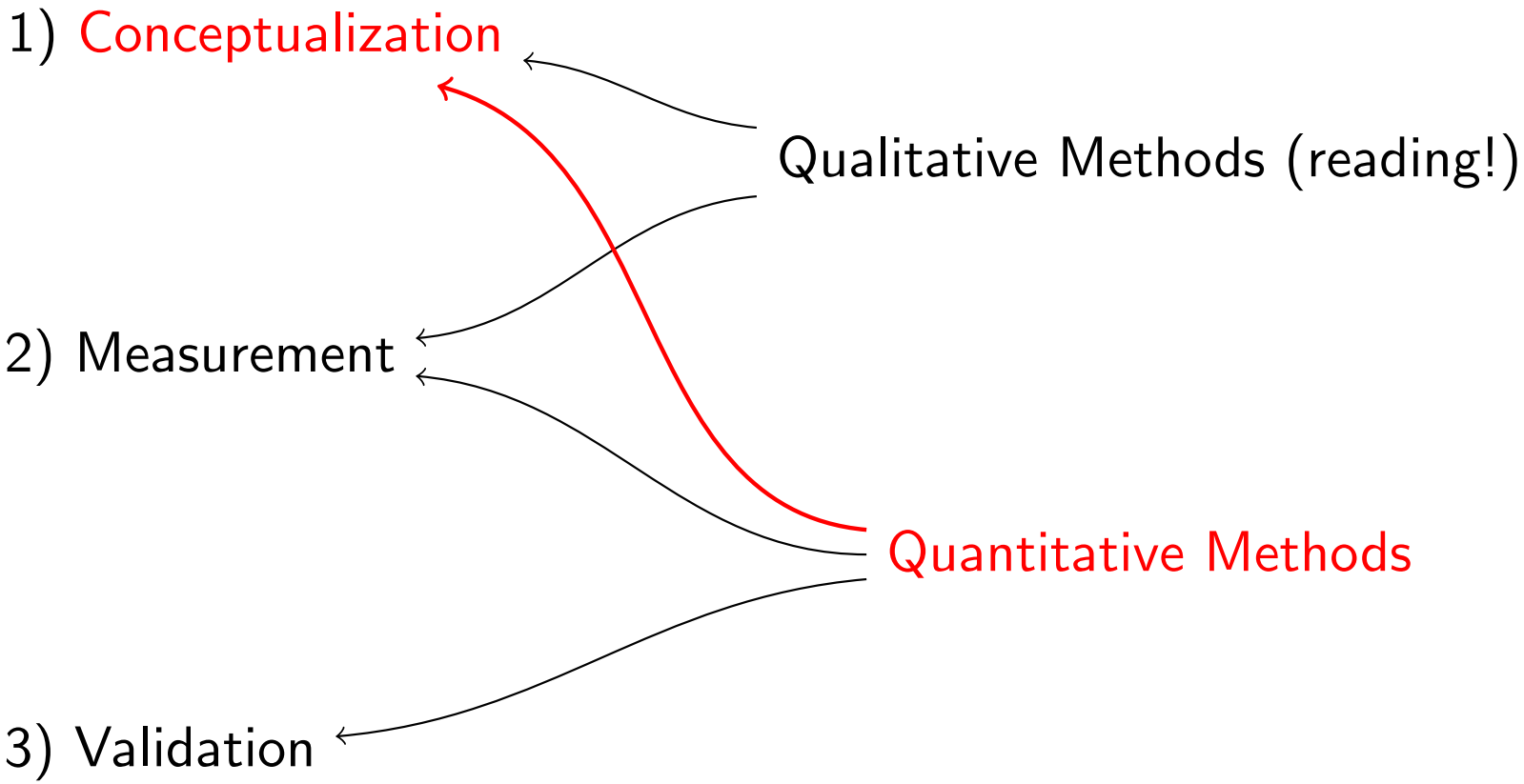
# Advancing the Objective of Discovery




Quantitative methods for conceptualization: aiding discovery

- Few formal methods designed explicitly for conceptualization

# Advancing the Objective of Discovery

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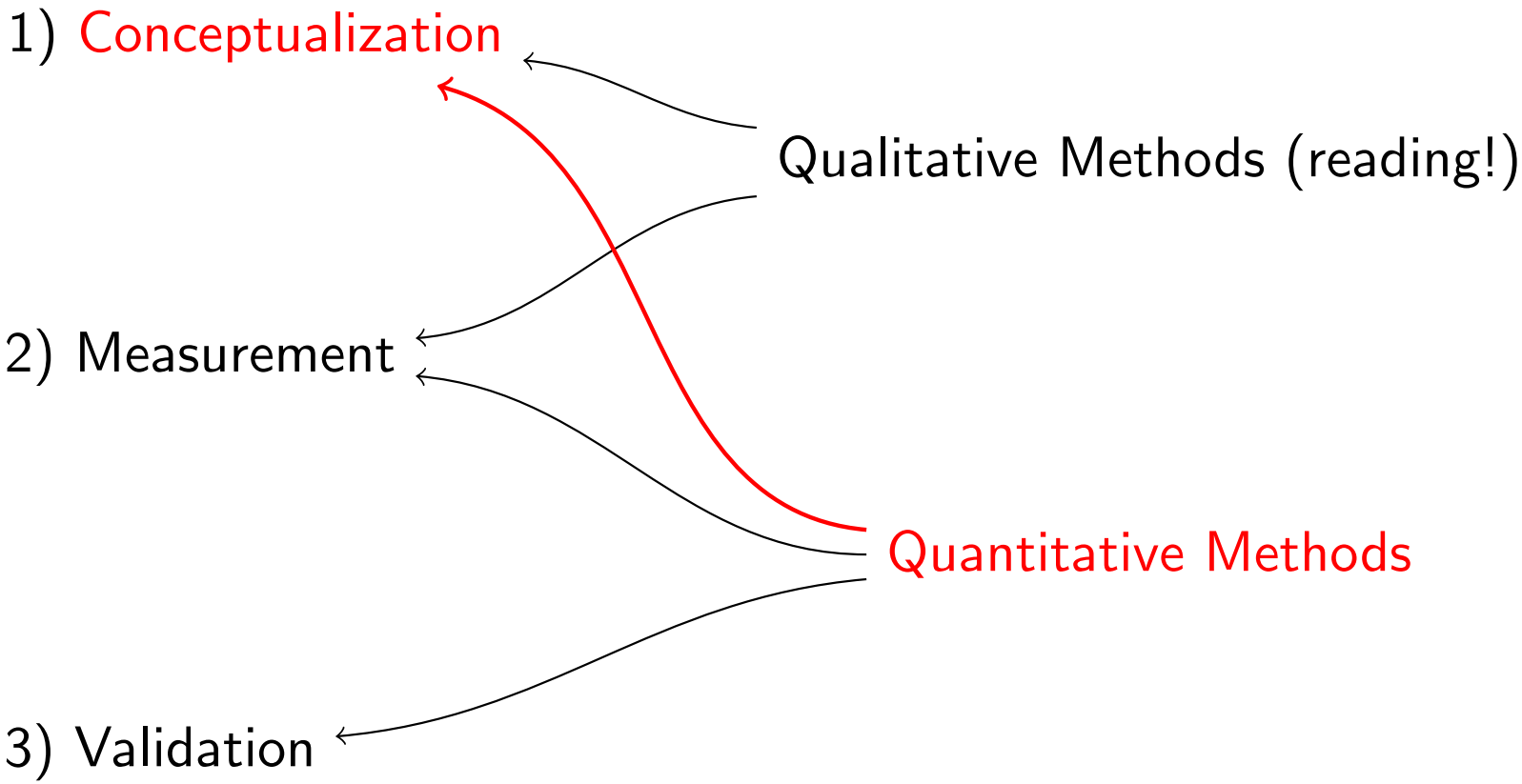


Quantitative methods for conceptualization: aiding discovery

- 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 (on adding zooming out to the human ability to zoom in)

http://GKing.Harvard.edu