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

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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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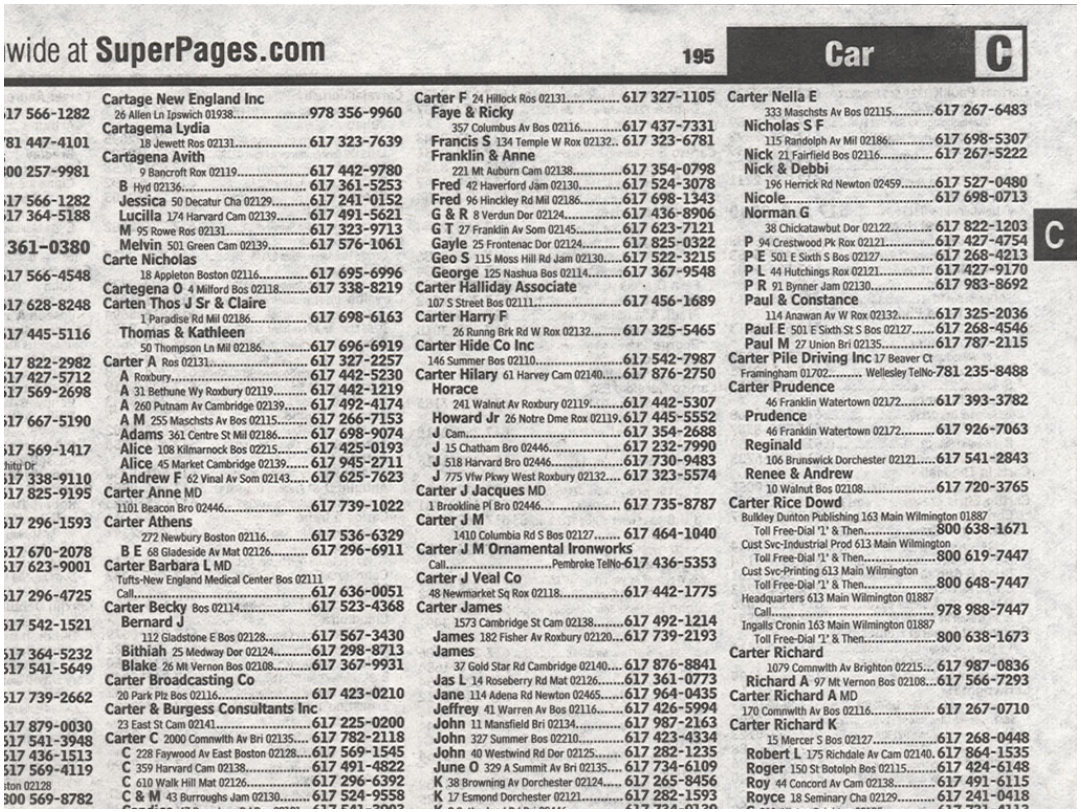

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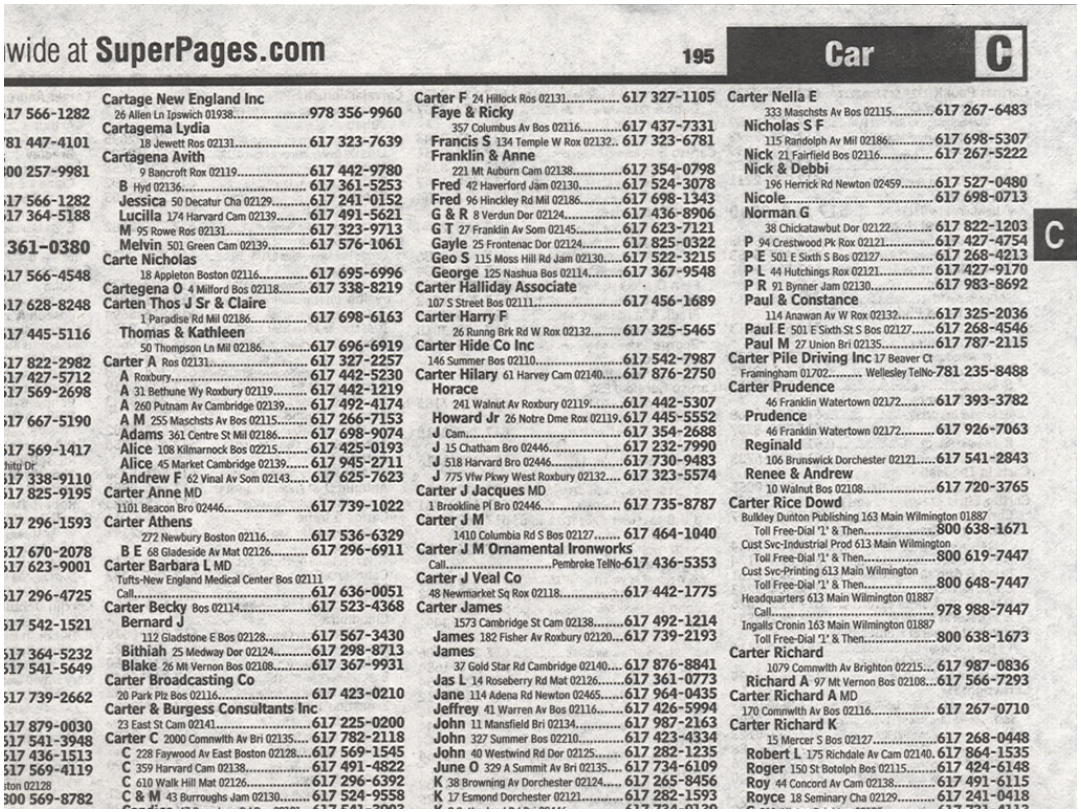

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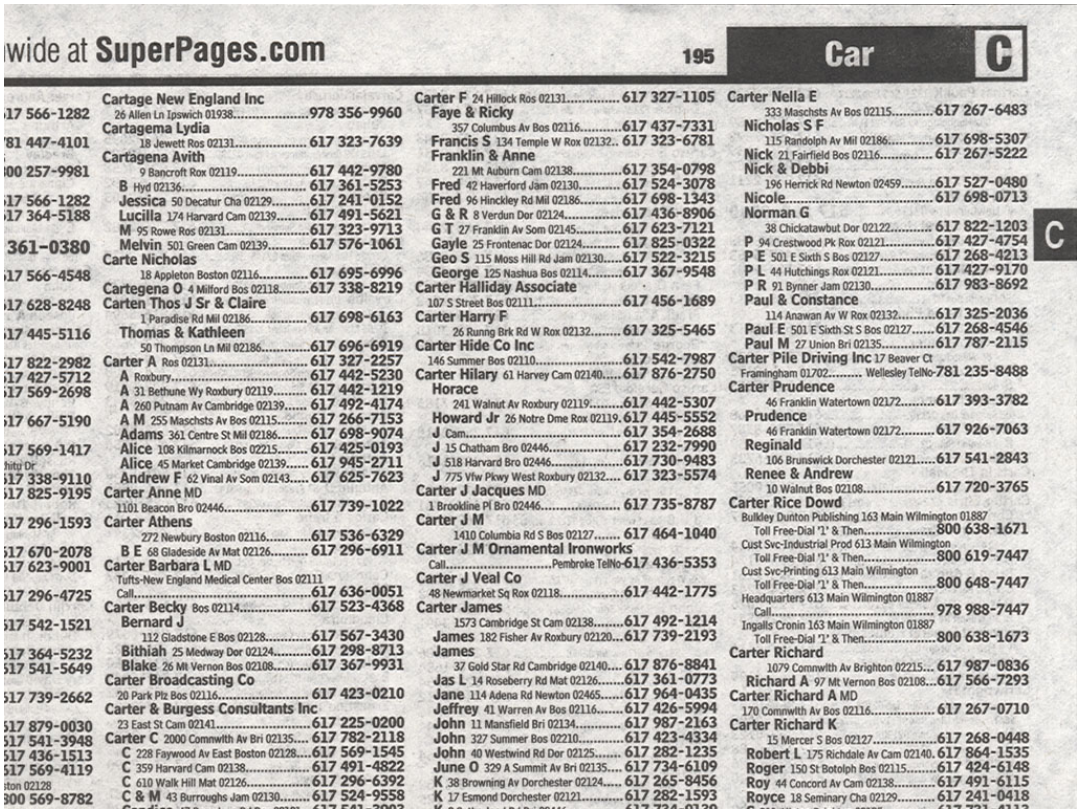

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50 Thompson Ln Mil 02186 ..... 617 696-6919
Carter A Ros 02131 ..... 617 327-2257
A Roxbury 617 442-5230
A 31 Bethune Wy Roxbury 02119 ..... 617 442-1219
A 260 Putnam Av Cambridge 02139 ..... 617 492-4174
A M 255 Maschsts Av Bos 02115 ..... 617 266-7153
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 Commwith 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
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
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Carter Richard
1079 Commwith Av Brighton 02215 ..... 617 987-0836
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Roy 44 Concord Av Cam 02138 ..... 617 491-6115
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C

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

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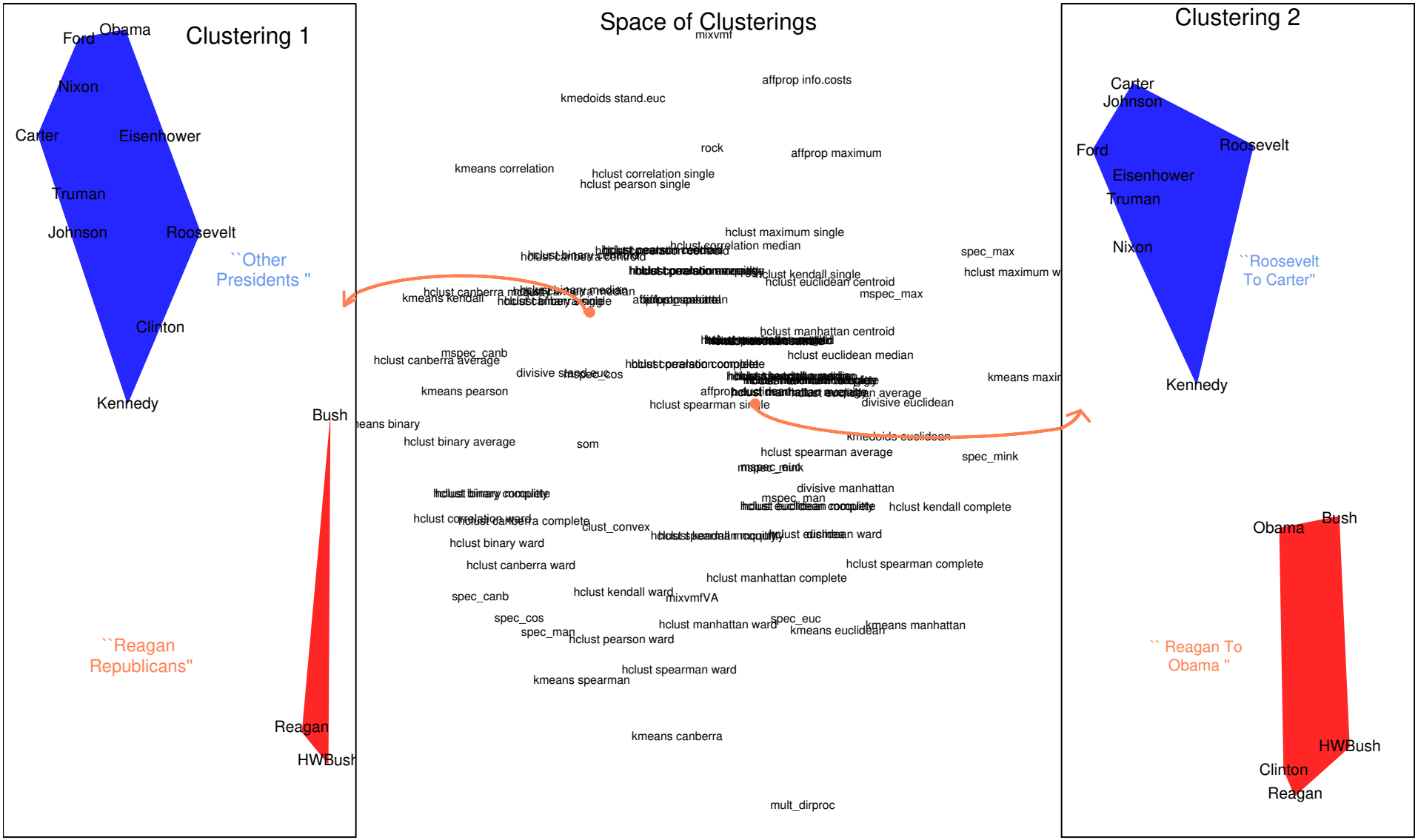
7. $\rightsquigarrow$ Millions of clusterings, easily comprehended (takes about 10-15 minutes to choose a clustering with insight)

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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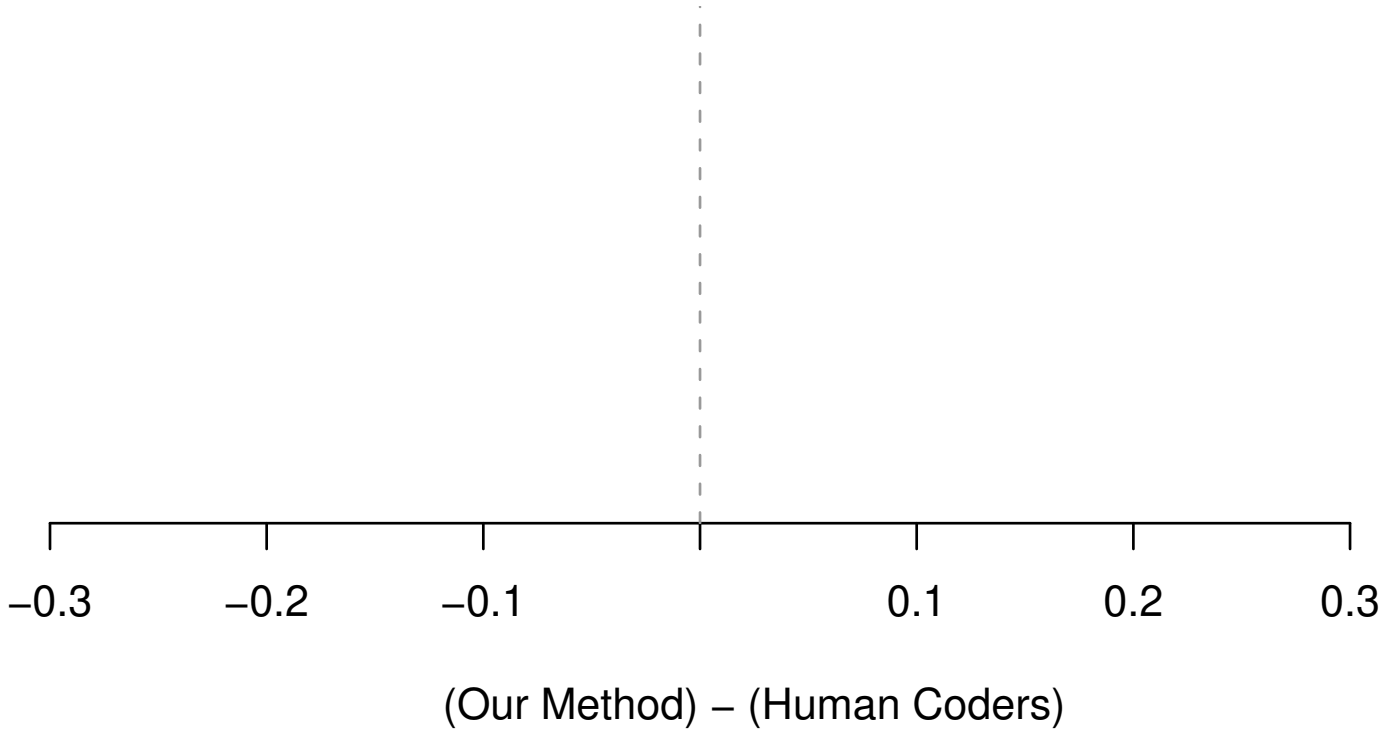

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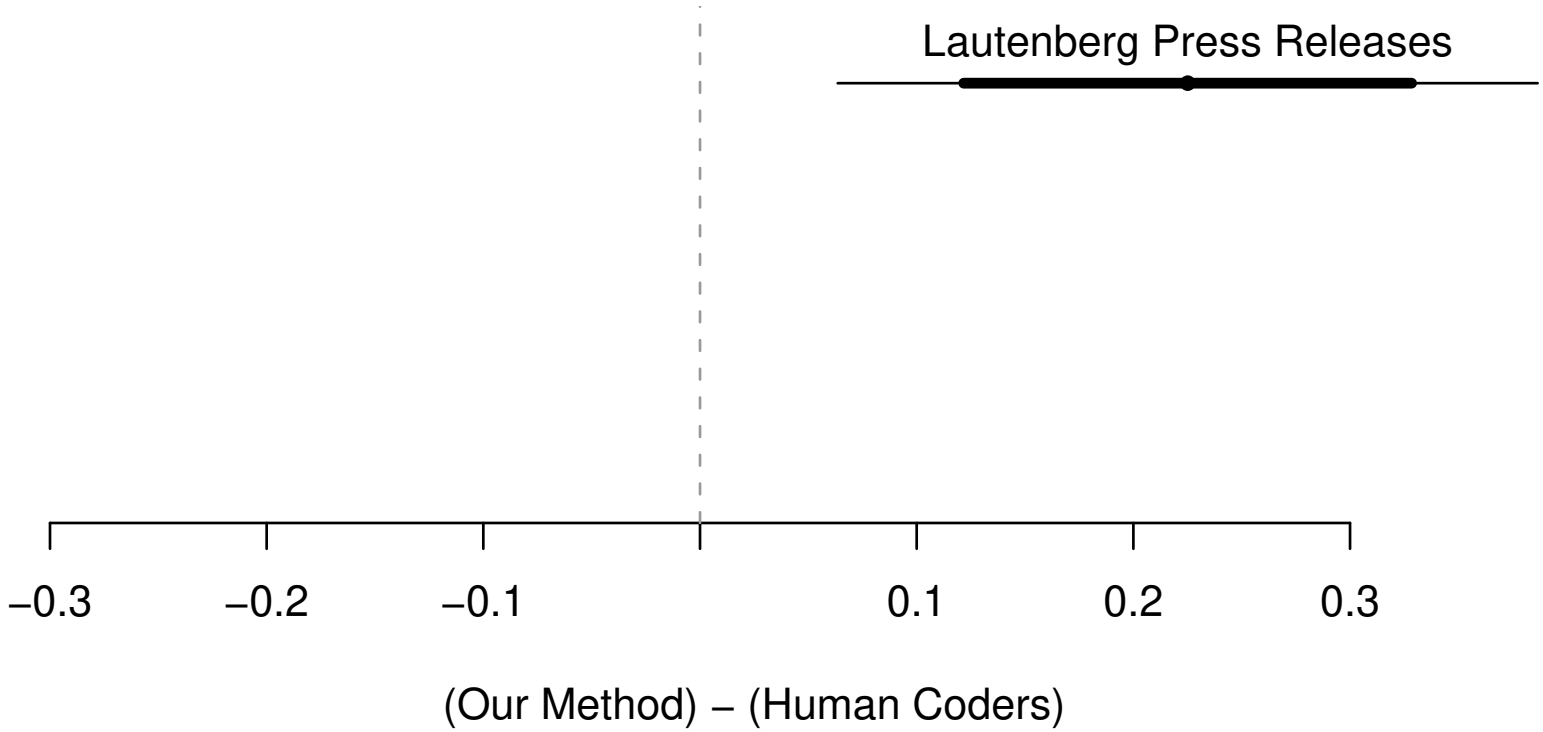

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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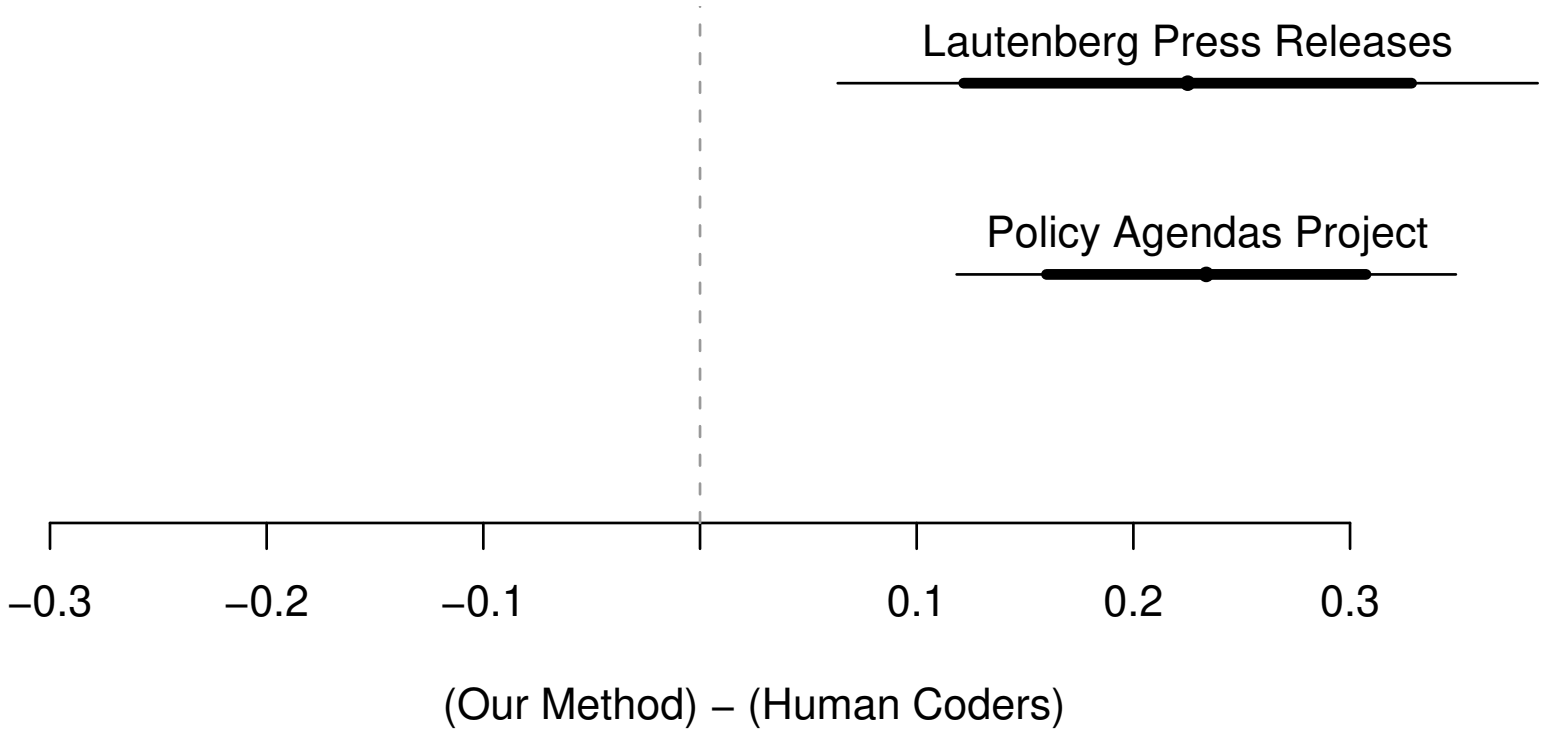

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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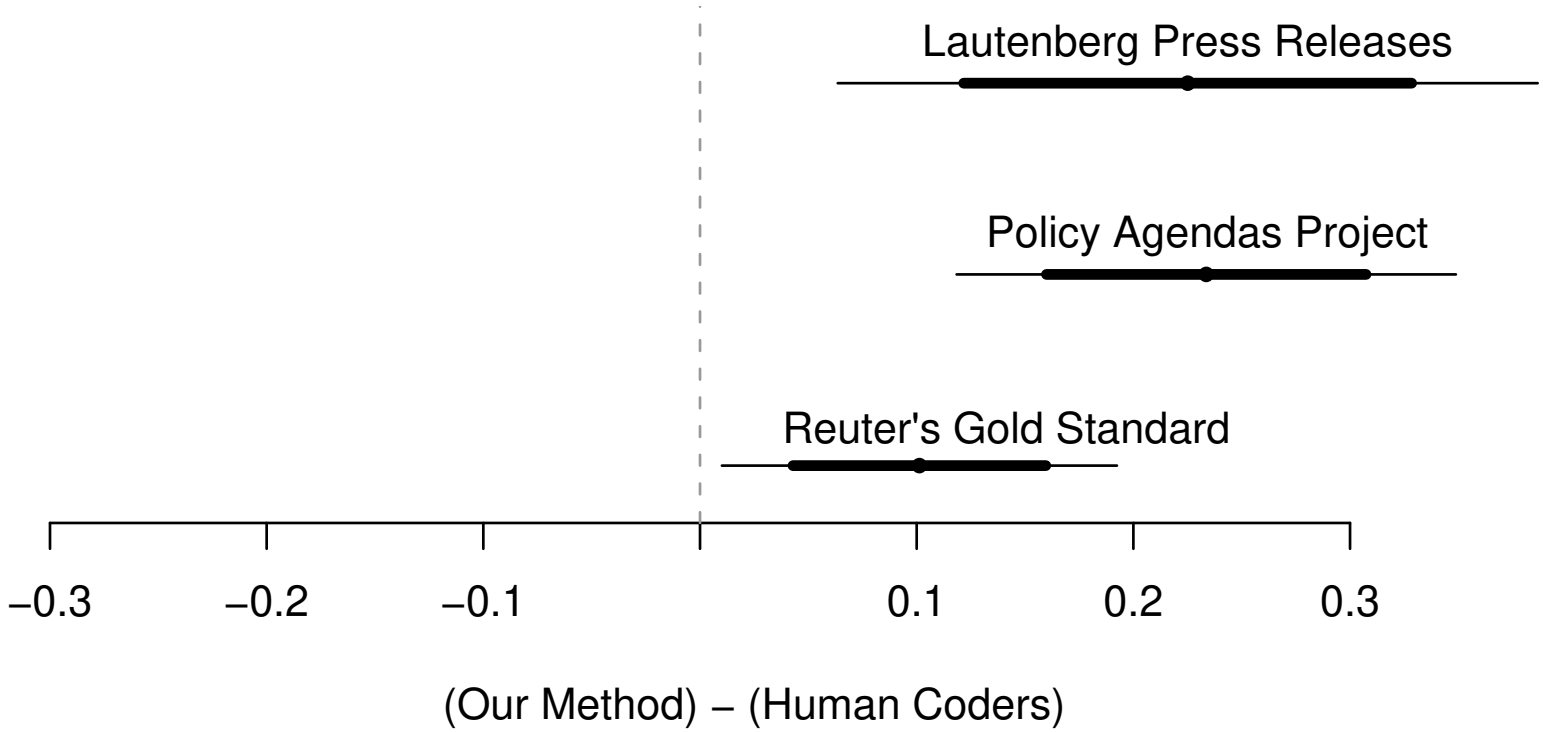

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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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

Example Discovery

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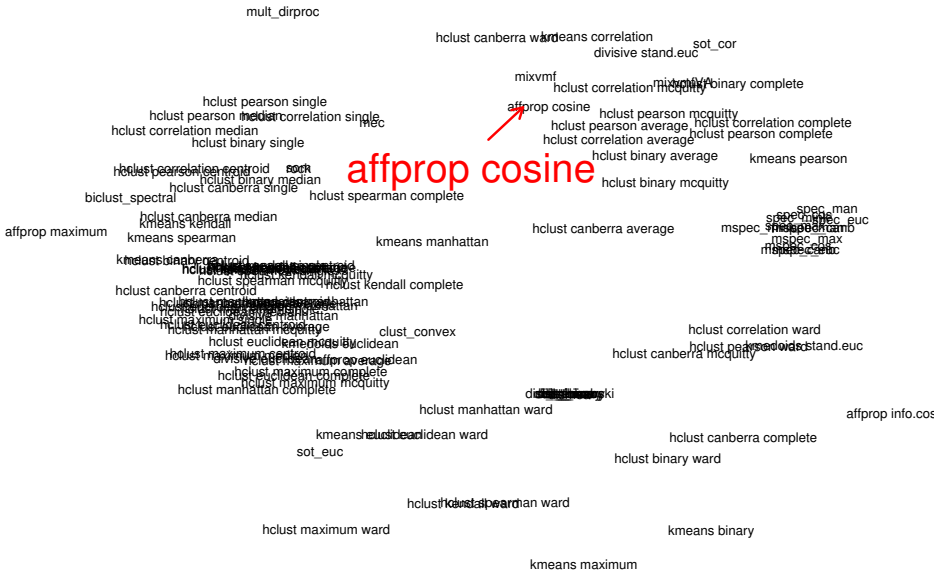

Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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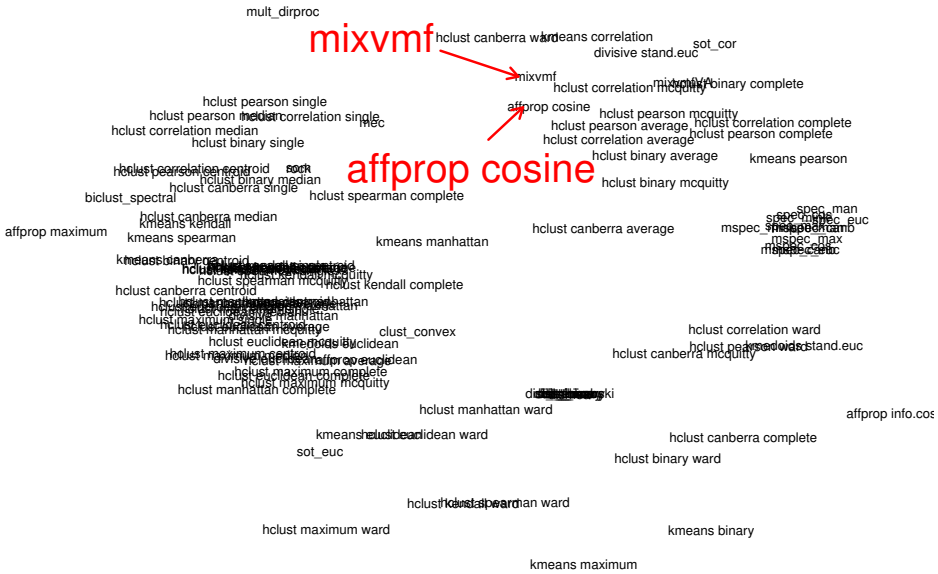

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Close to:

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

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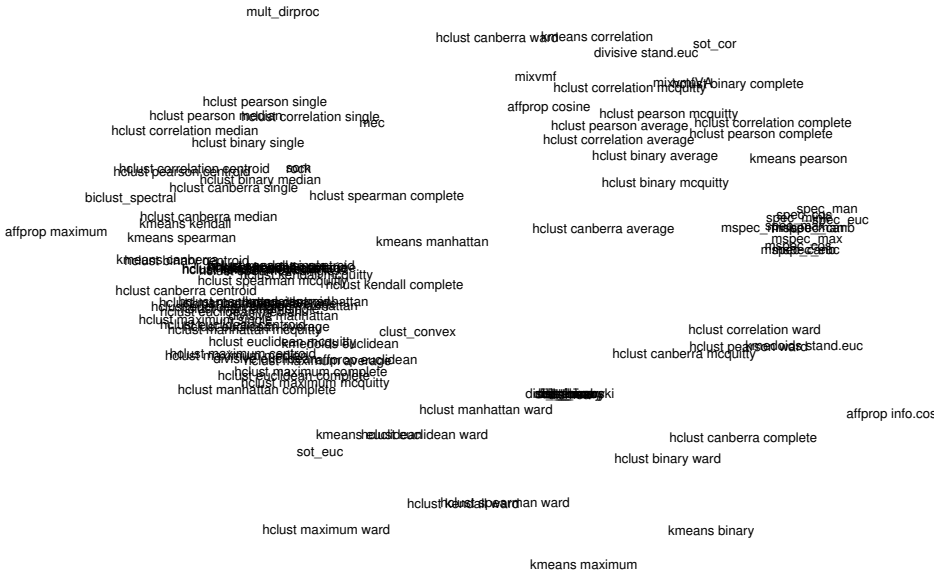
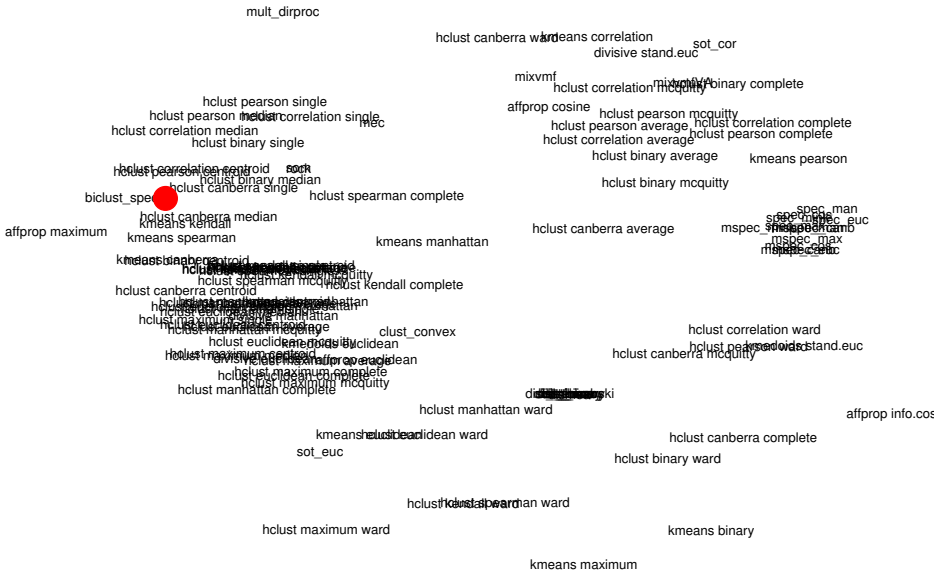


Space between methods:

Example Discovery



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local cluster ensemble

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Found a region with particularly insightful clusterings

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Mixture:

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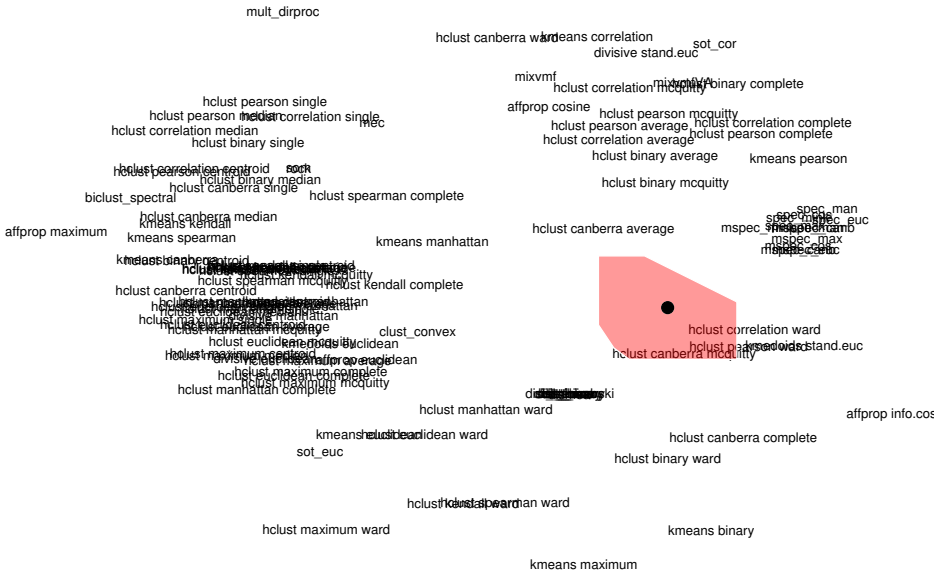

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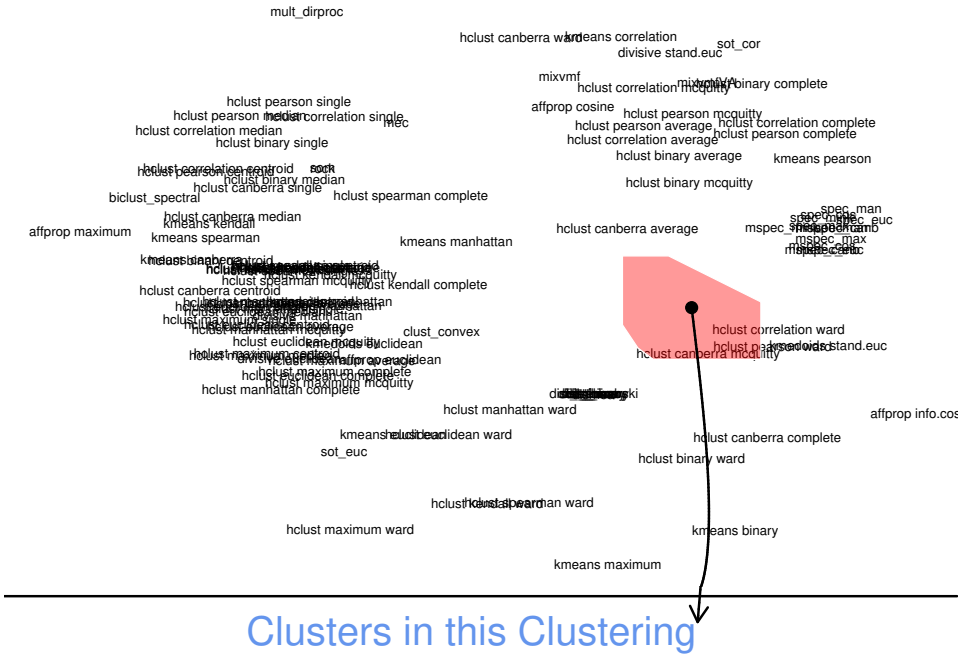
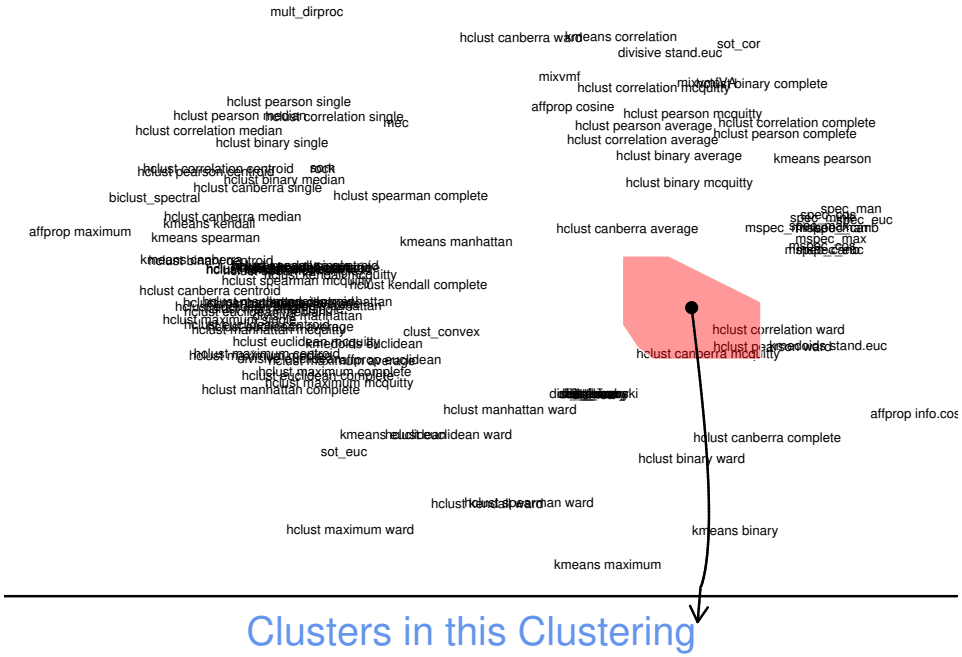
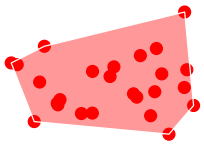


Mayhew

Example Discovery



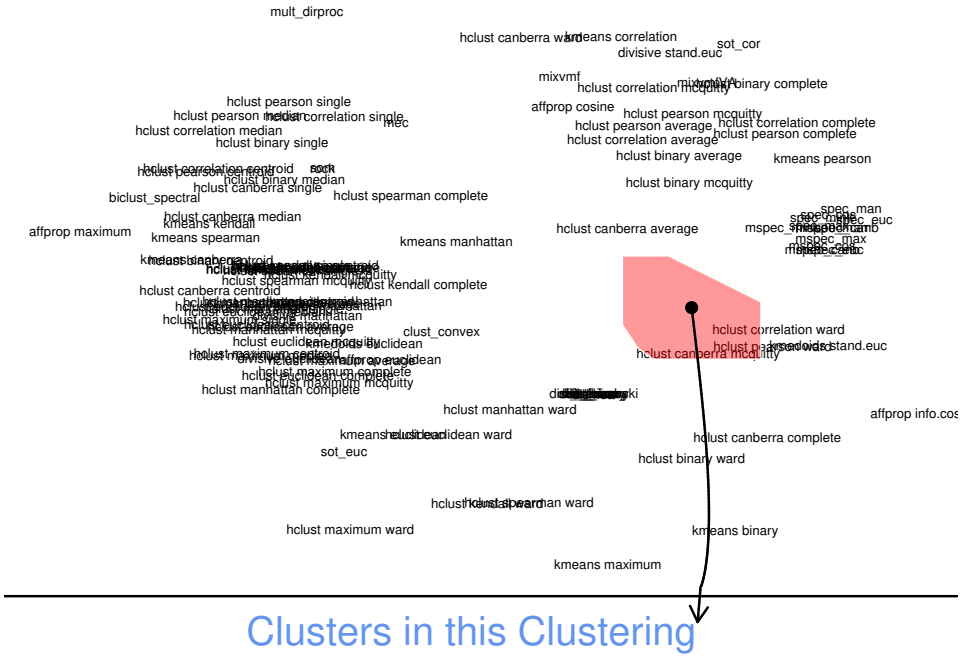


Credit Claiming
Pork

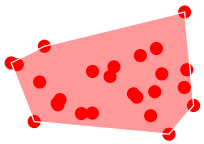
Credit Claiming, Pork:
"Sens. Frank R. Lautenberg (D-NJ) and Robert Menendez (D-NJ) announced that the U.S. Department of Commerce has awarded a $100,000 grant to the South Jersey Economic Development District"

Mayhew

Example Discovery



Clusters in this Clustering



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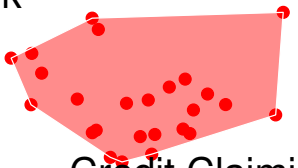
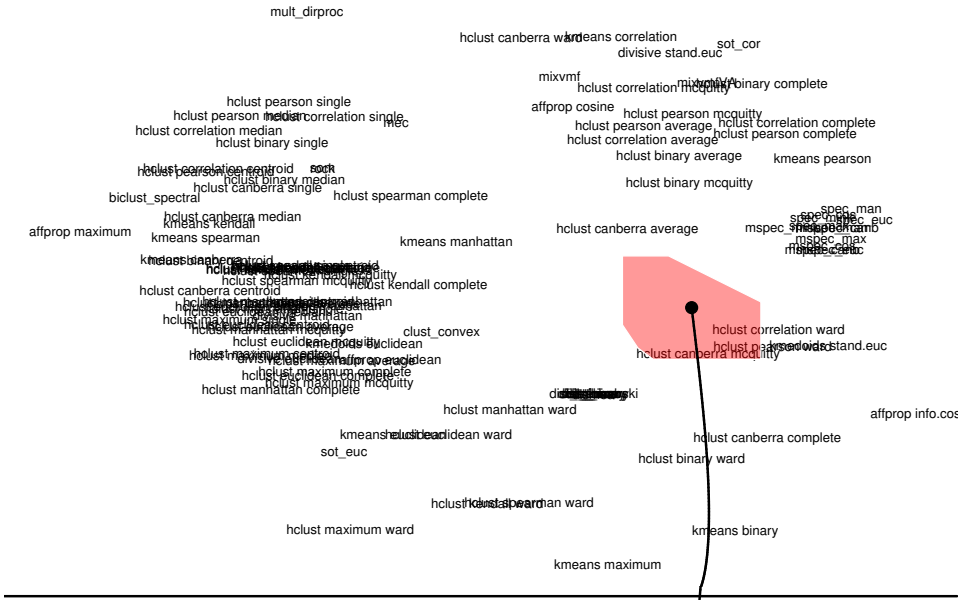


Mayhew

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



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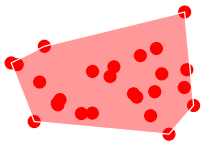
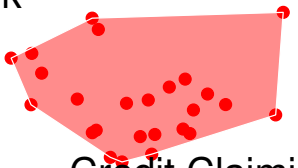


Credit Claiming
Pork

Advertising

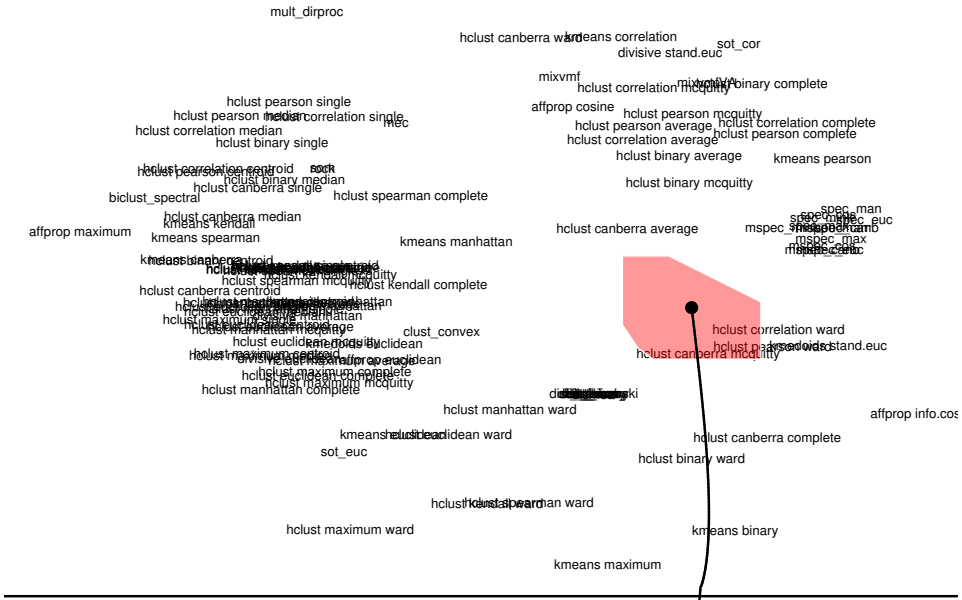


Mayhew

Credit Claiming
Legislation

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

Example Discovery: Partisan Taunting



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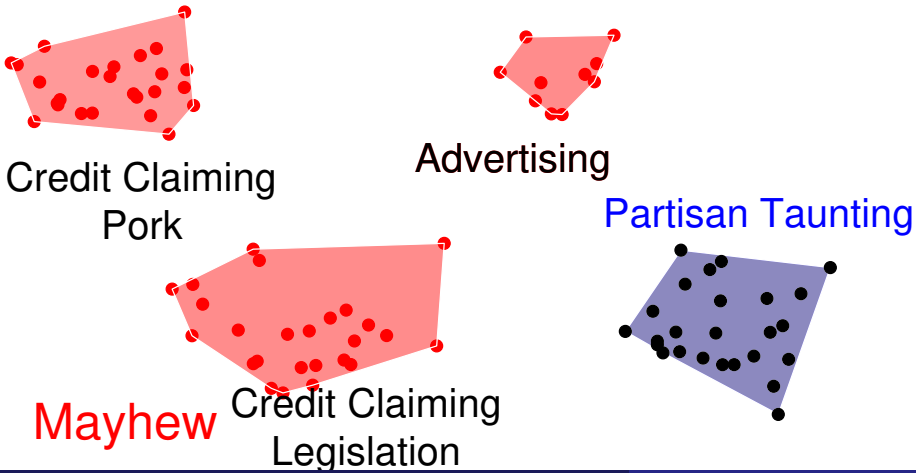
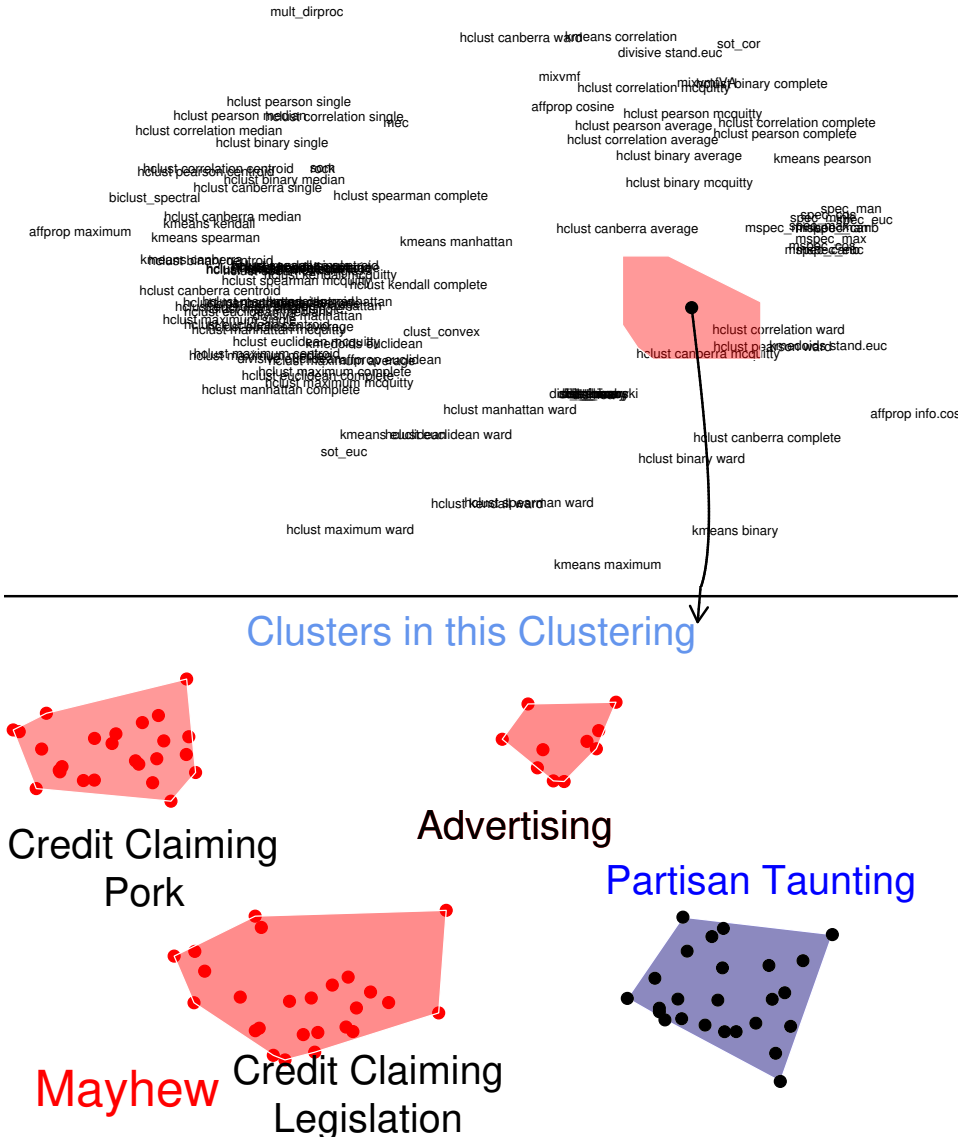


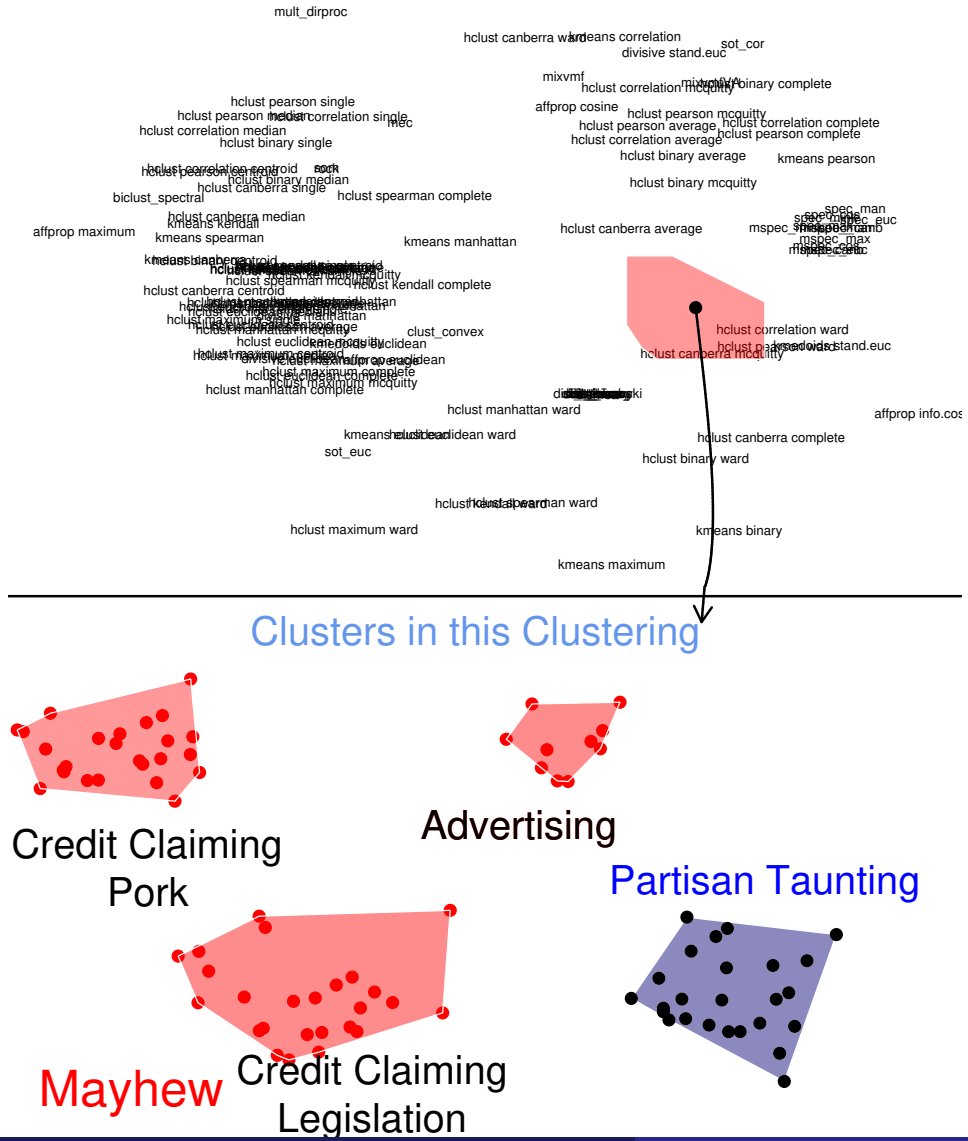
Partisan Taunting:
"Republicans Selling Out Nation on Chemical Plant Security"

Example Discovery: Partisan Taunting



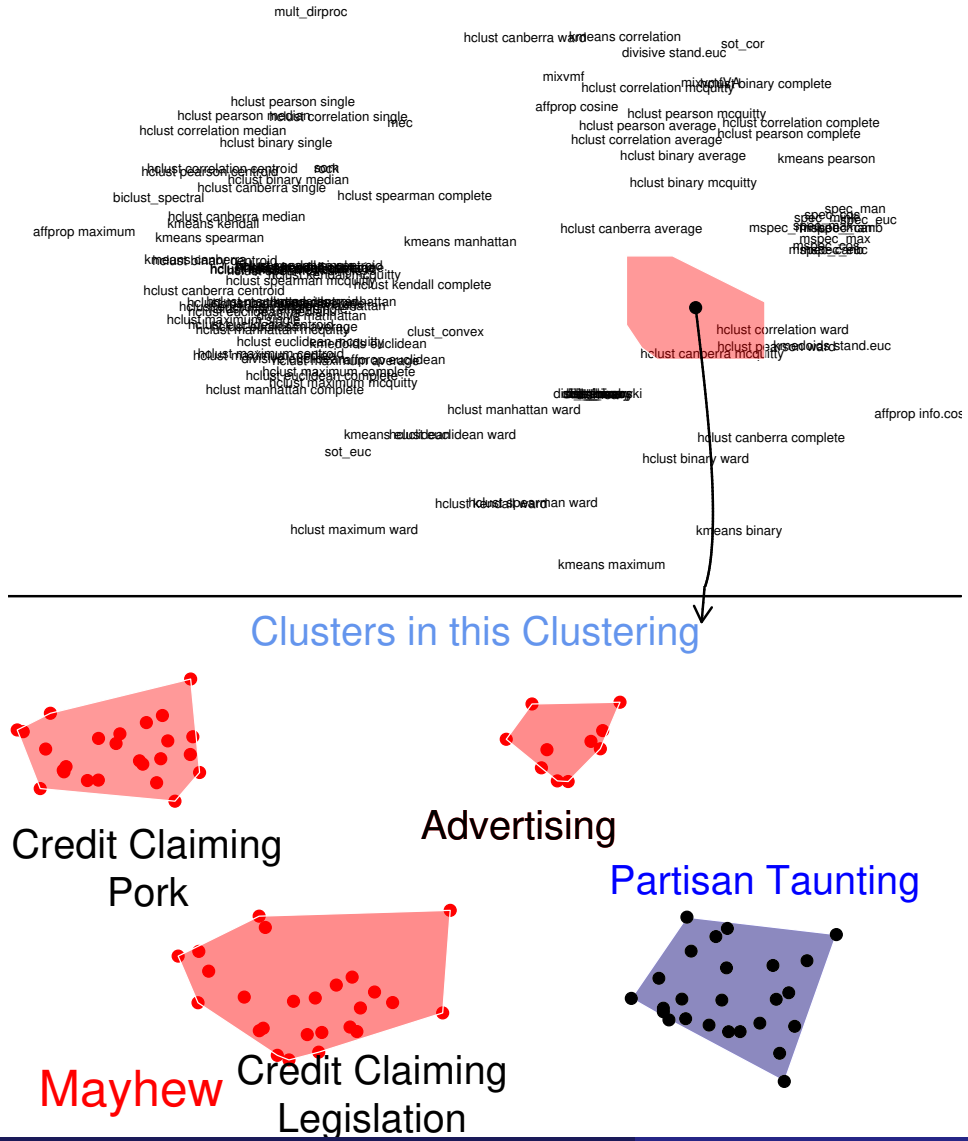
Partisan Taunting:
"Senator Lautenberg's amendment would change the name of ...the Republican bill...to 'More Tax Breaks for the Rich and More Debt for Our Grandchildren Deficit Expansion Reconciliation Act of 2006' "

Example Discovery: Partisan Taunting



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

Example Discovery: Partisan Taunting



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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]

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- "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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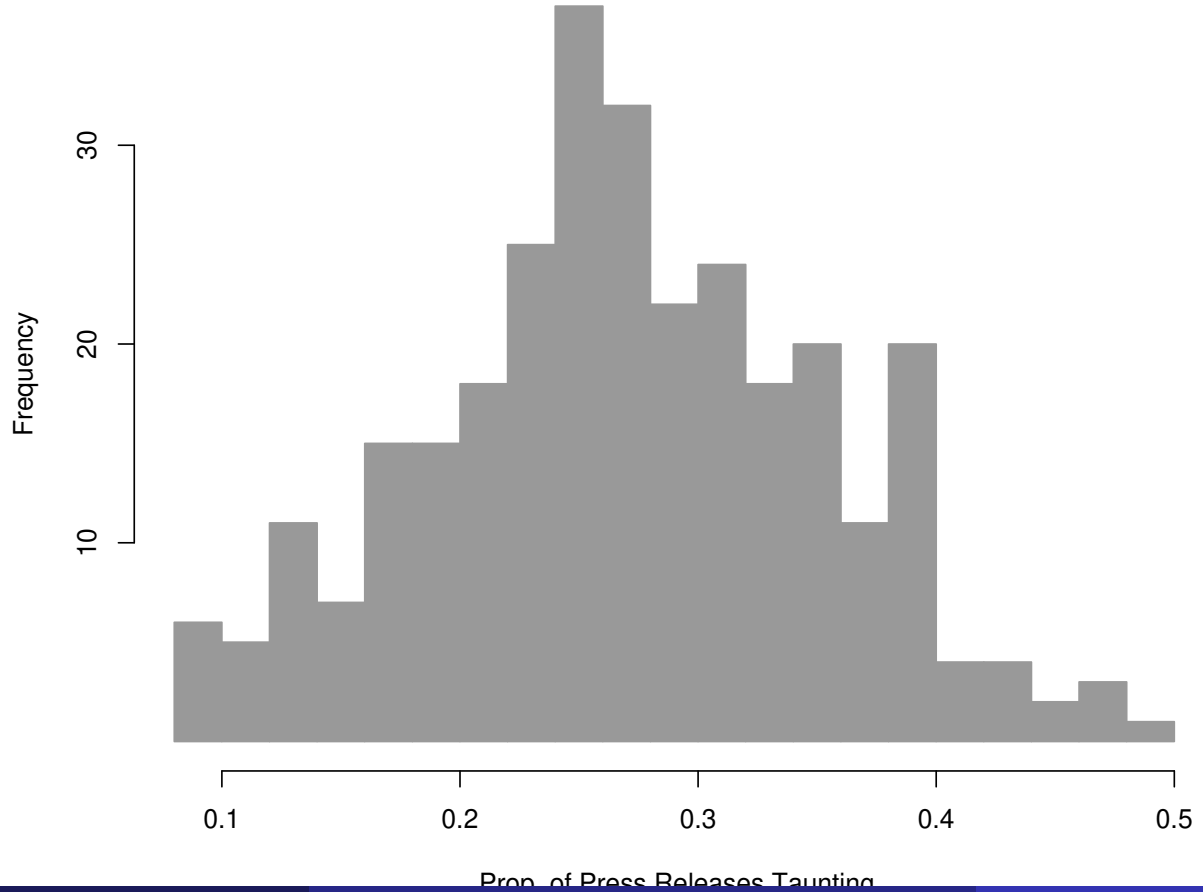

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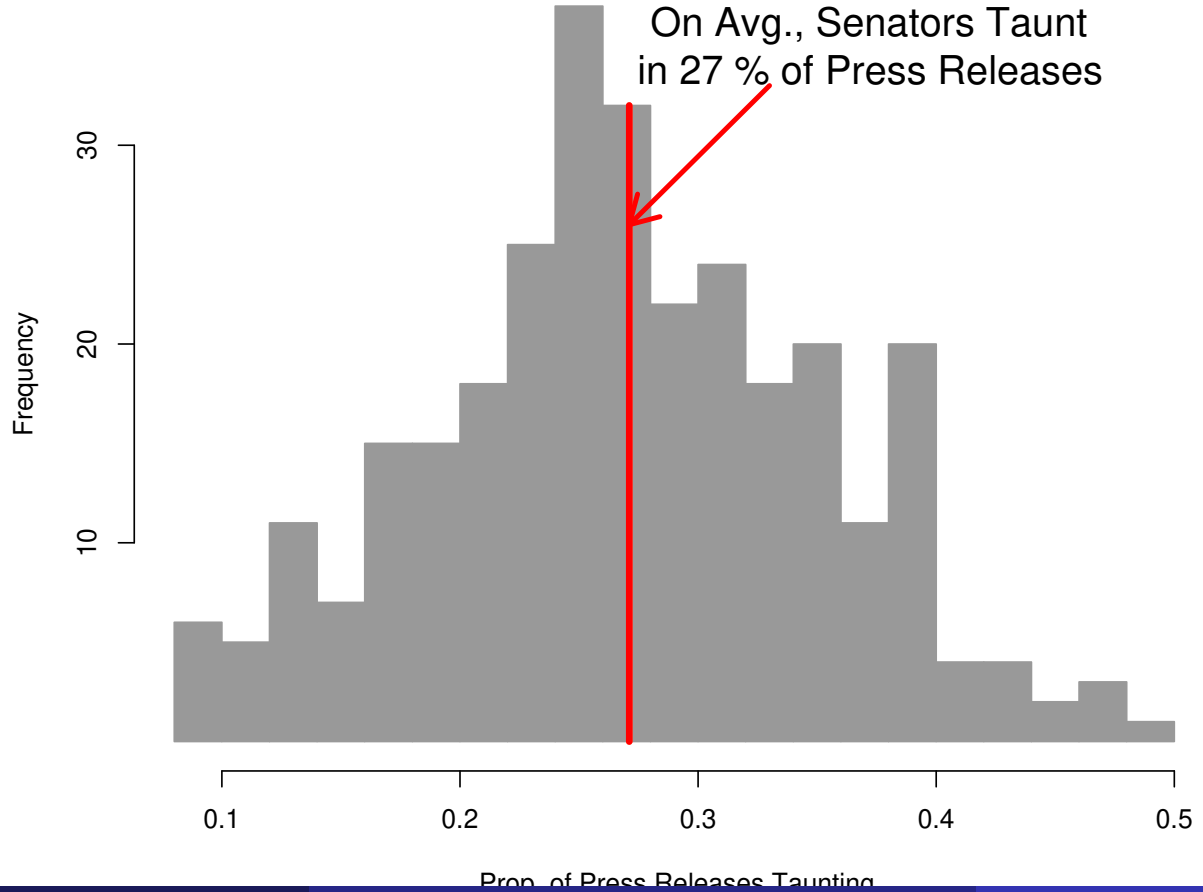
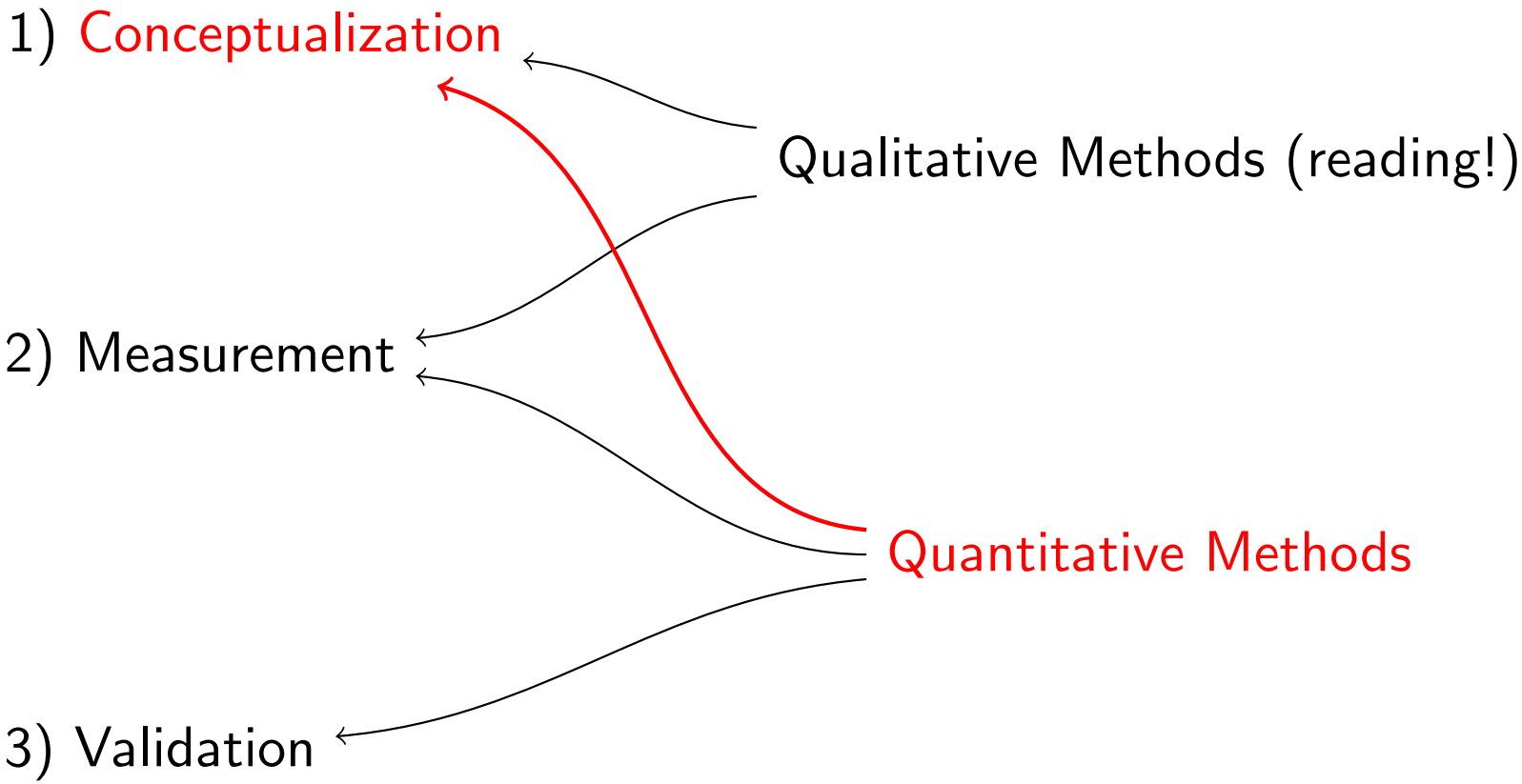
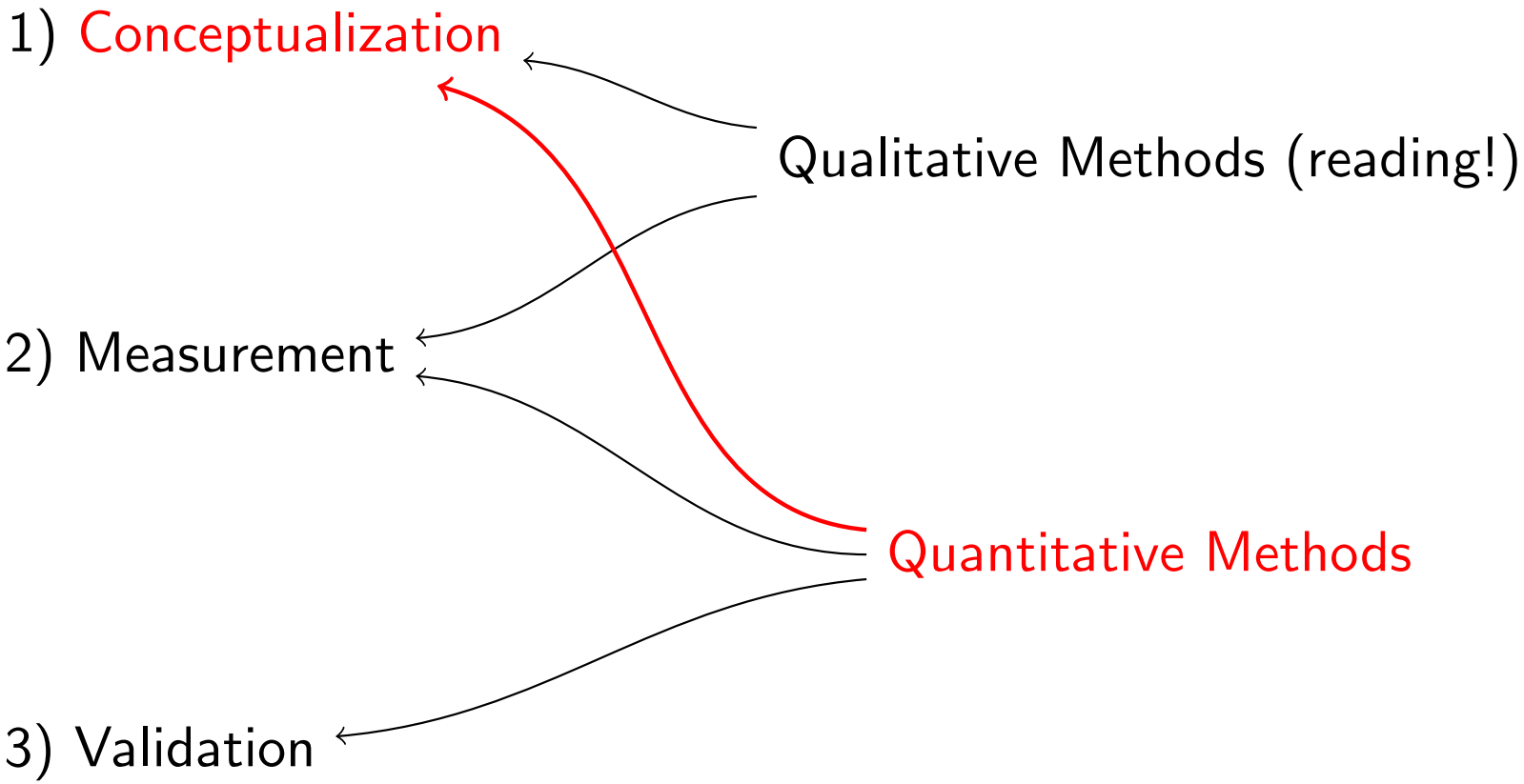


Advancing the Objective of Discovery



Quantitative methods for conceptualization: aiding discovery

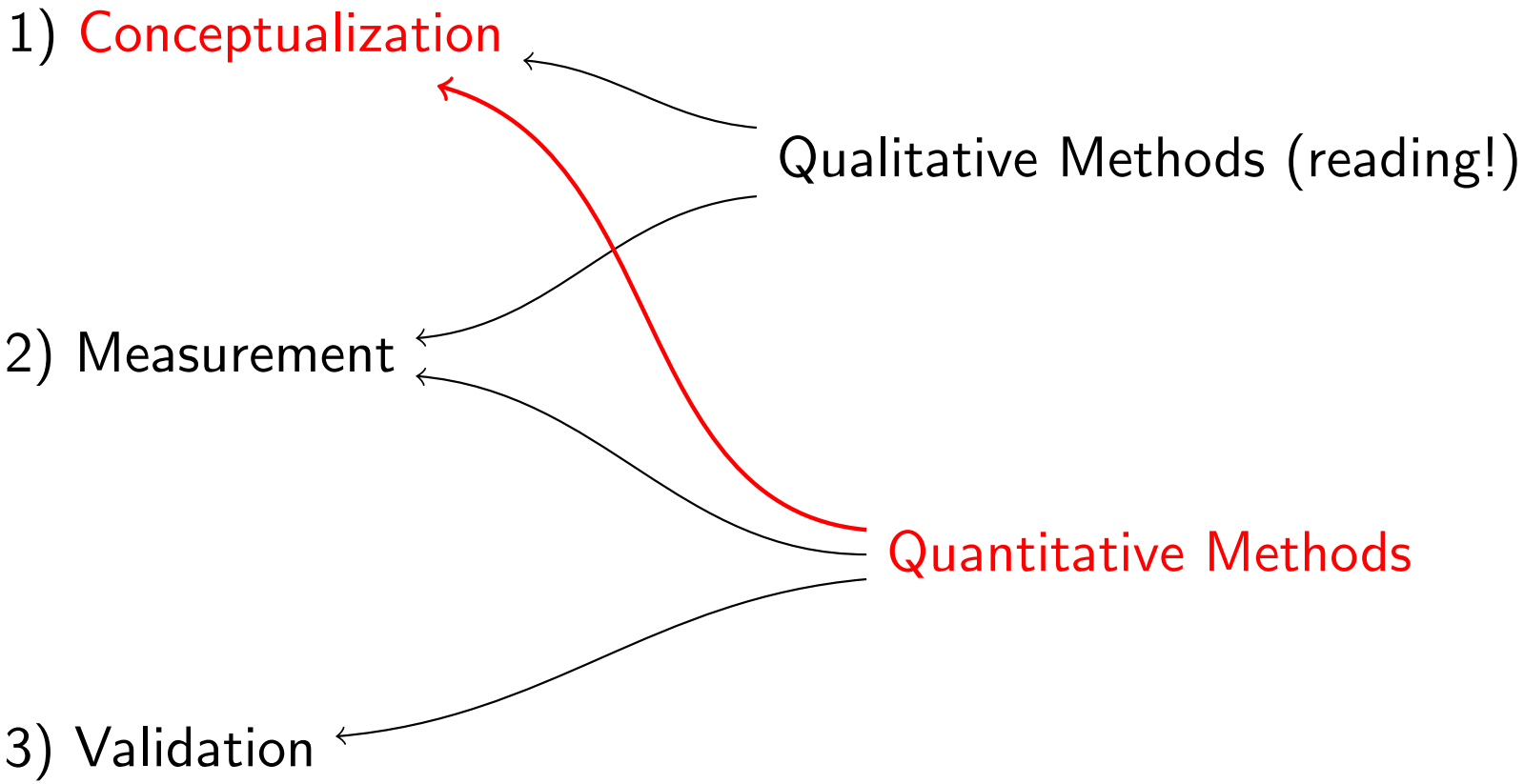
Advancing the Objective of Discovery



Quantitative methods for conceptualization: aiding discovery

- Few formal methods designed explicitly for conceptualization

Advancing the Objective of Discovery



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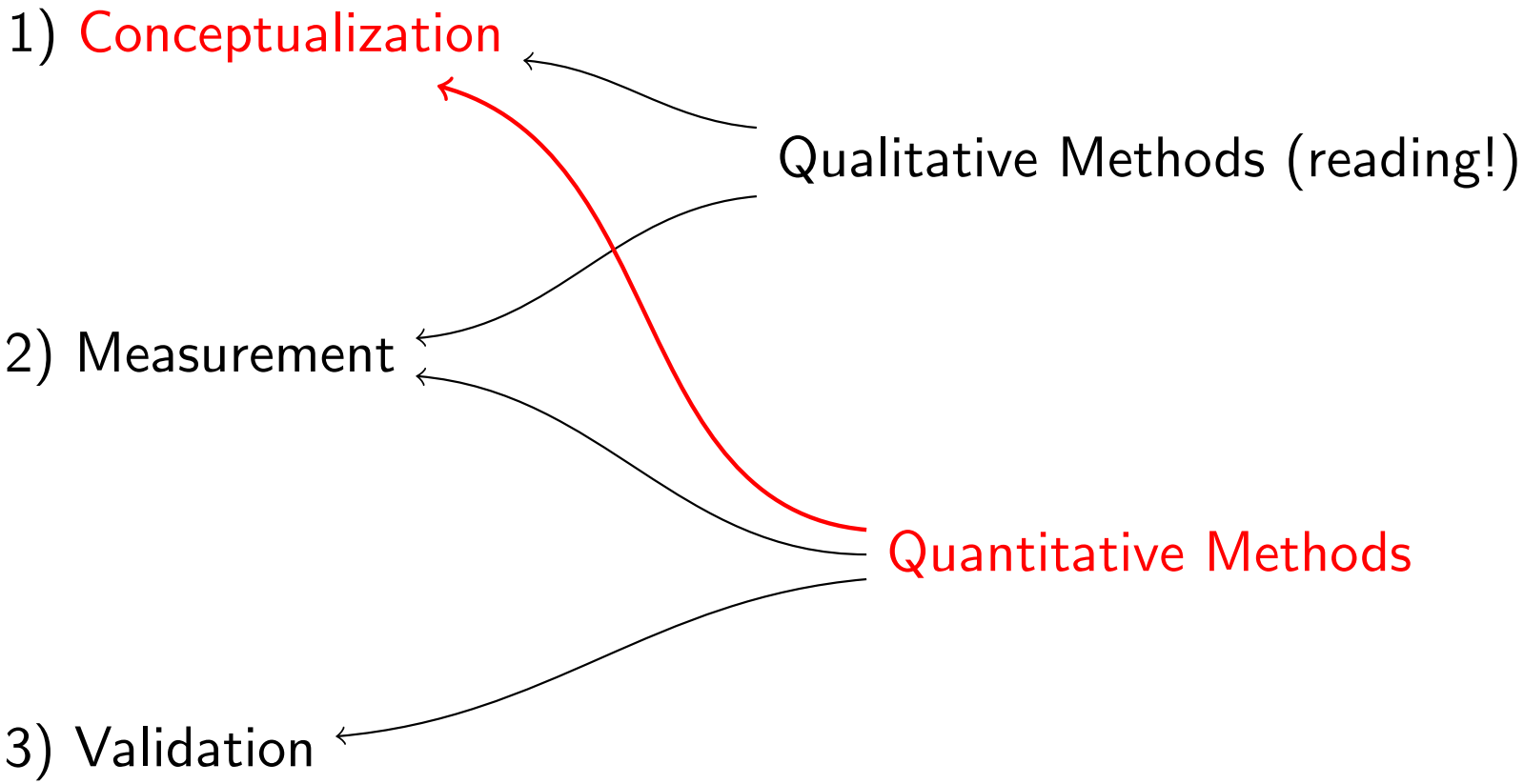
Advancing the Objective of Discovery



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