Computer-Assisted Clustering and Conceptualization from Unstructured Text

Gary King

Institute for Quantitative Social Science
Harvard University

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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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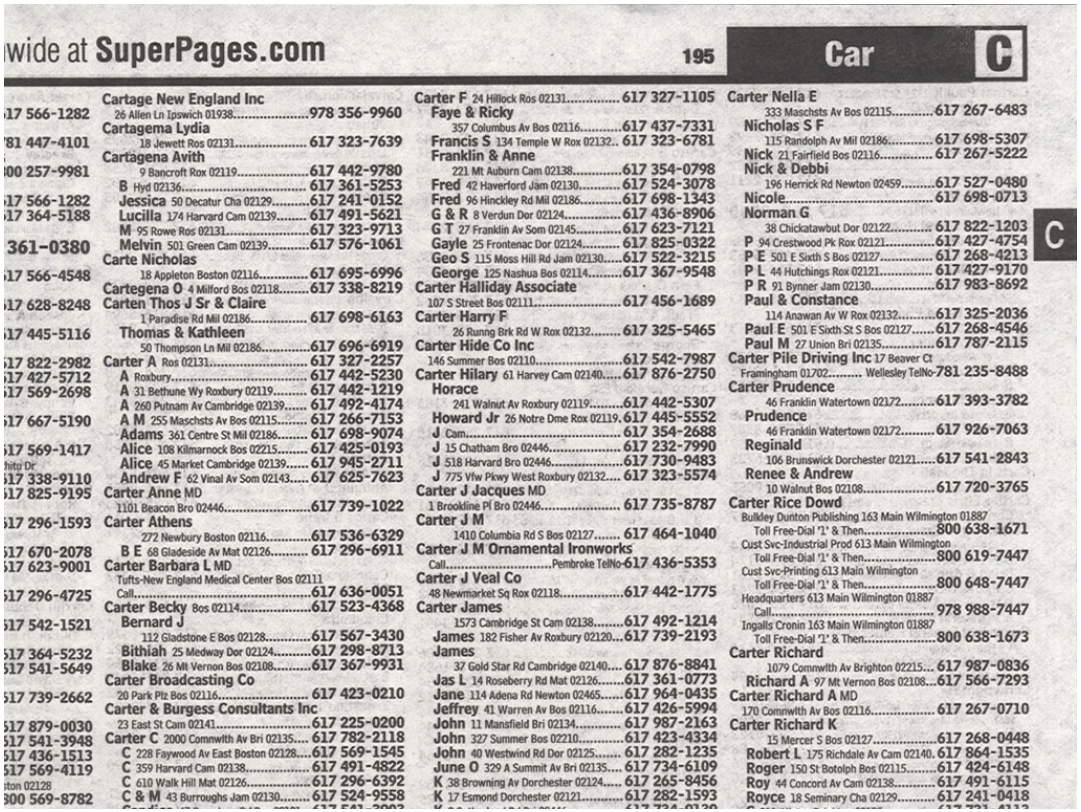
A list of unconnected addresses



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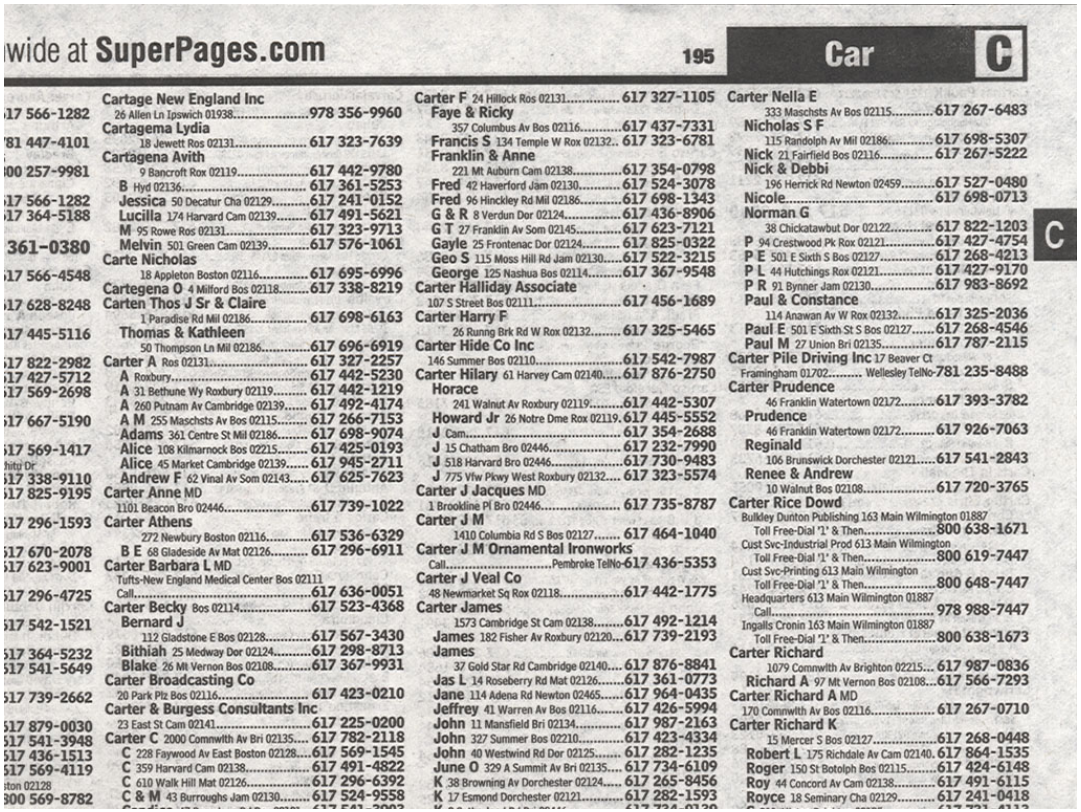

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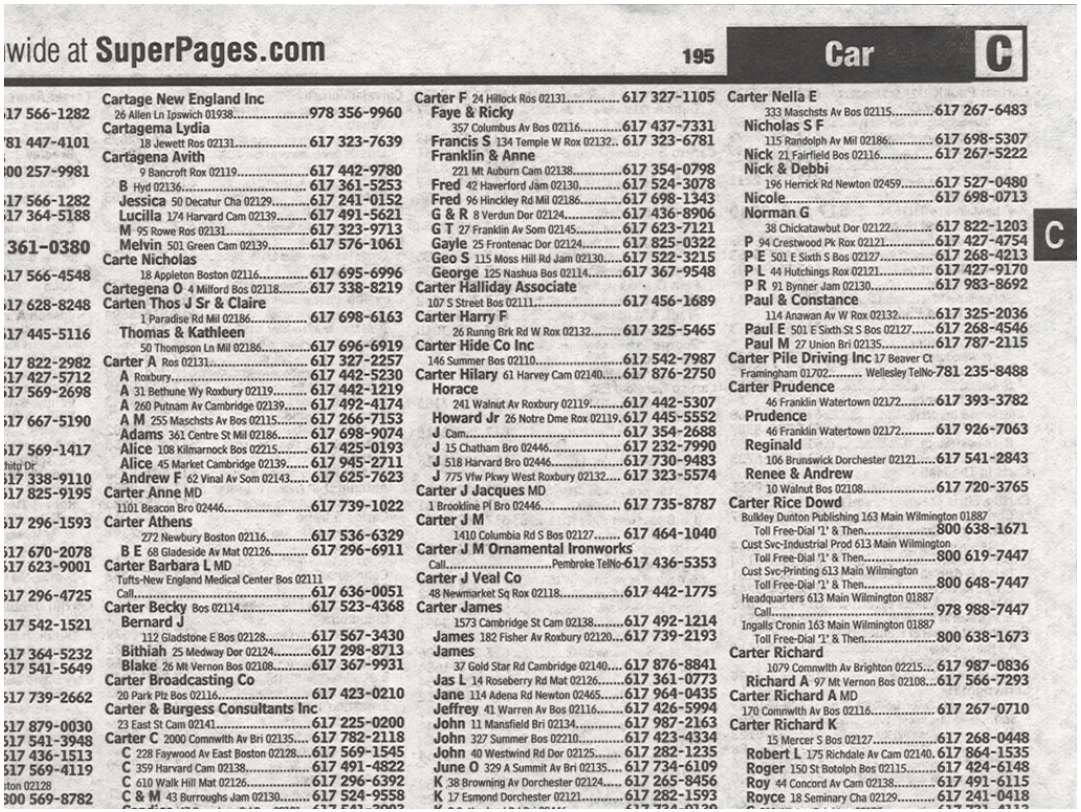
Set of clusterings ≈

A list of unconnected addresses



wide at **SuperPages.com** 195 **Car** C

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 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
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

C

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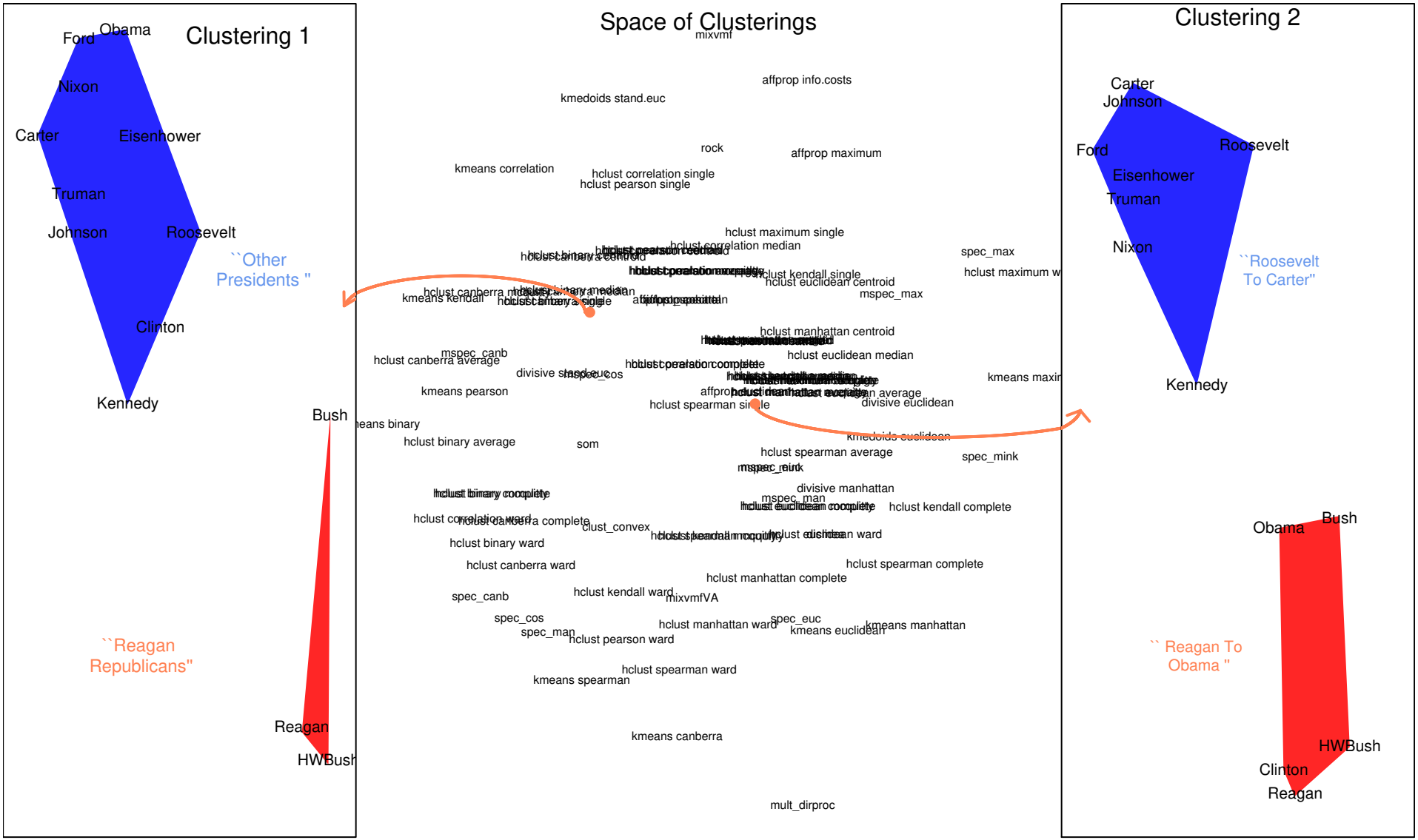
8. (Or, our new strategy: represent the entire bell space directly; no need to examine document contents)

Many Thousands of Clusterings, Sorted & Organized

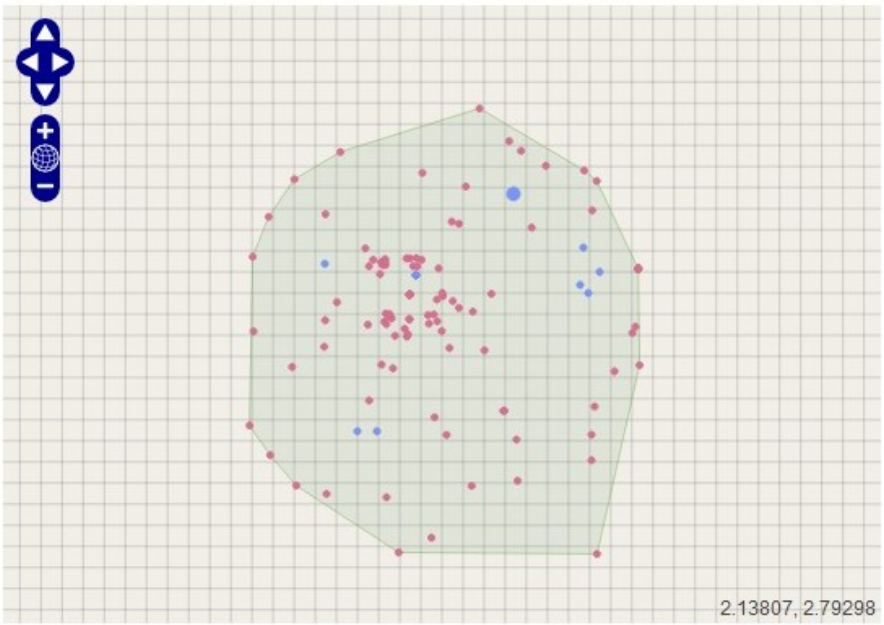
You choose one (or more), based on insight, discovery, useful information,. . .



Software Screenshot

Size: 244 Files
Description: NSF - Updated Set

< > Number of Clusters 5 5 Clusters (Low) 15 Clusters (Medium) 30 Clusters (High) Discoverable



Display History Clear History Display Method Points

Label	Coordinates	Clusters
an interesting clustering [Link]	-0.30819, 0.46229	5
methods-oriented clustering [Link]	0.84753, 1.42538	5

(*) Discoverable

Coordinates: 0.84753, 1.42538
Clusters: 5
Label [+] methods-oriented clustering
Export

29.51%
72
research community health science public practice global political national urban
Label [+]
View Detail

27.46%
67
data economic markets policy survey models financial use not risk
Label [+]
View Detail

21.72%
53
human social science systems behavioral networks brain spatial complex dynamics
Label [+]
View Detail

15.16%
37
education students school learning creative skills teaching cognitive college teachers
Label [+]
View Detail

6.15%
15
language linguistic speech data speakers computer semantic cultural variation documentation
Label [+]
View Detail

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

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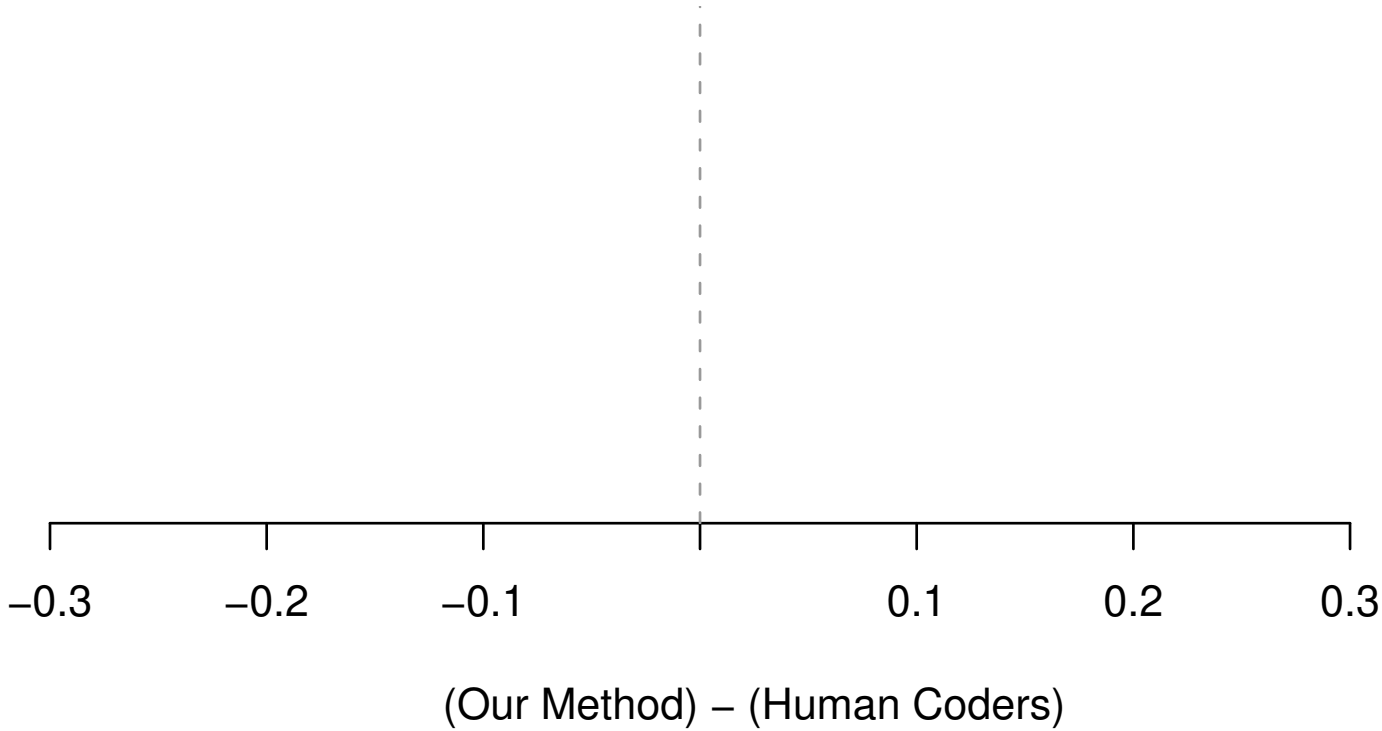

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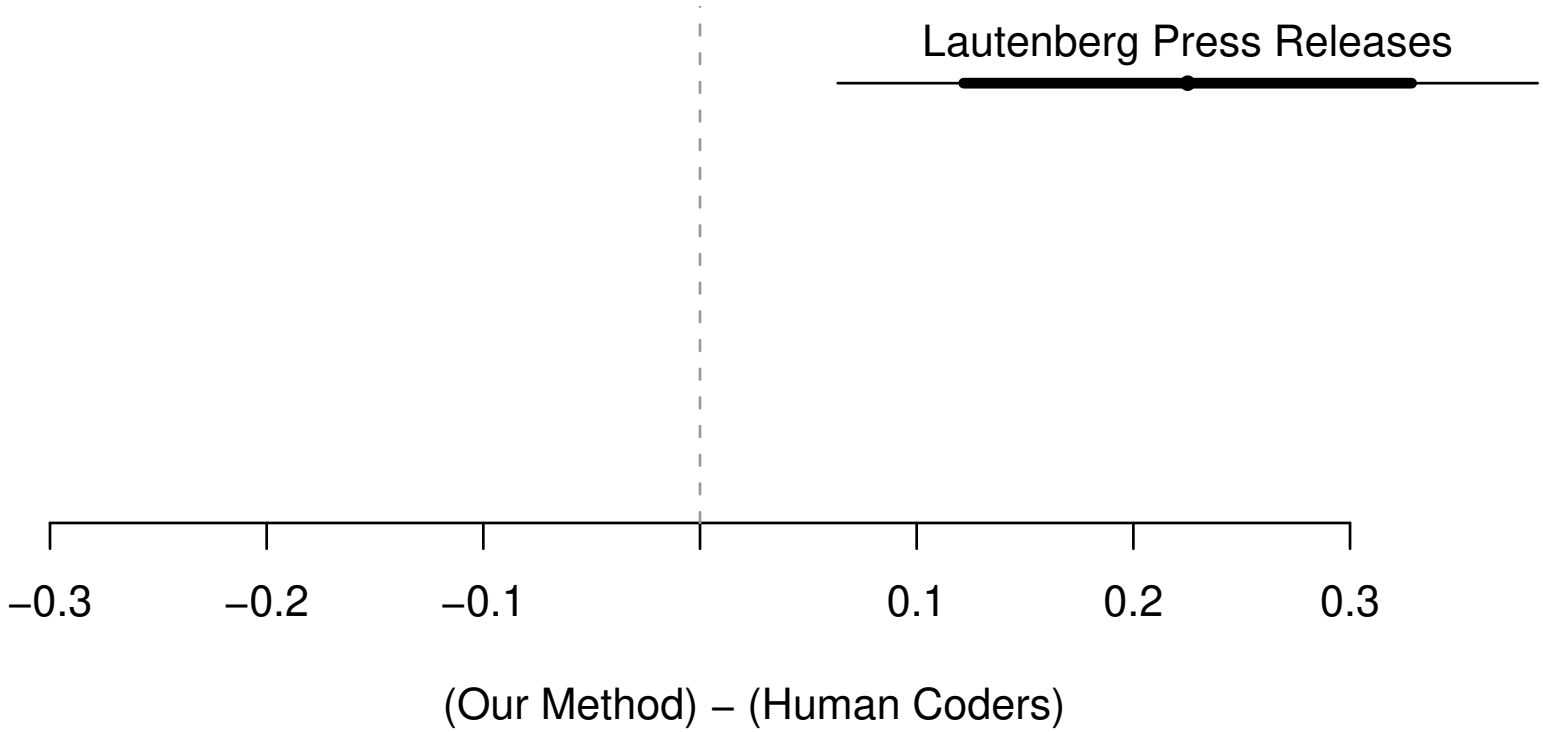

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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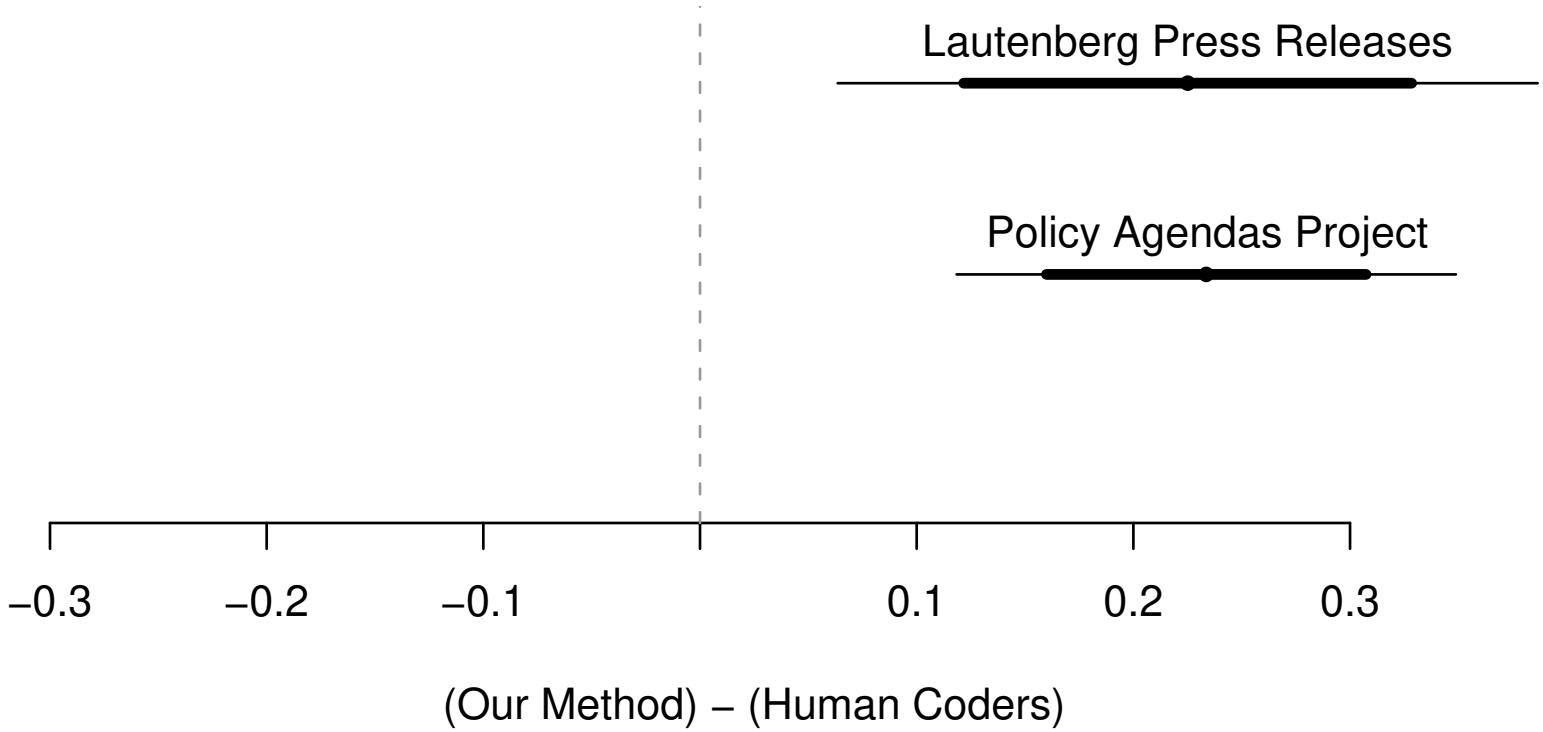

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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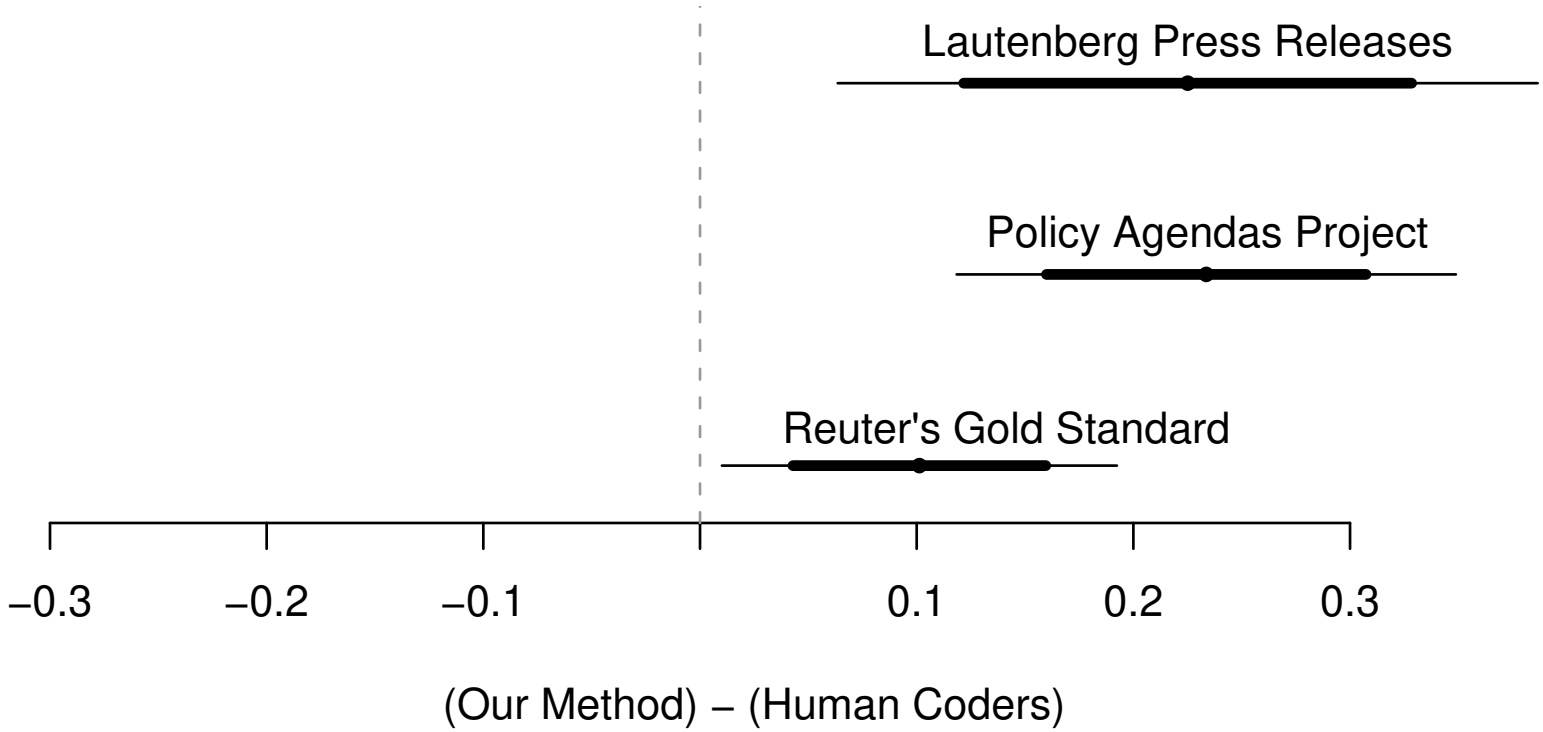

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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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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Example Discovery

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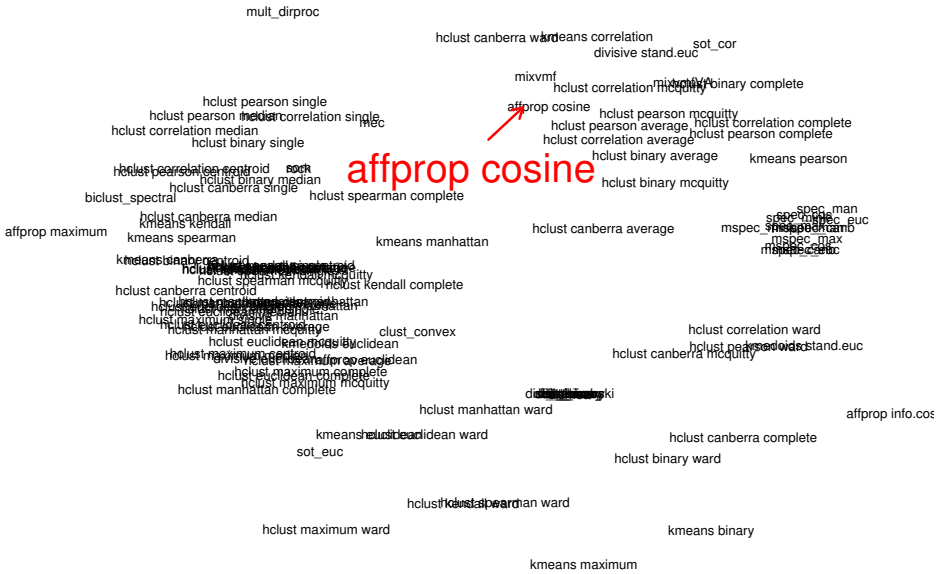

Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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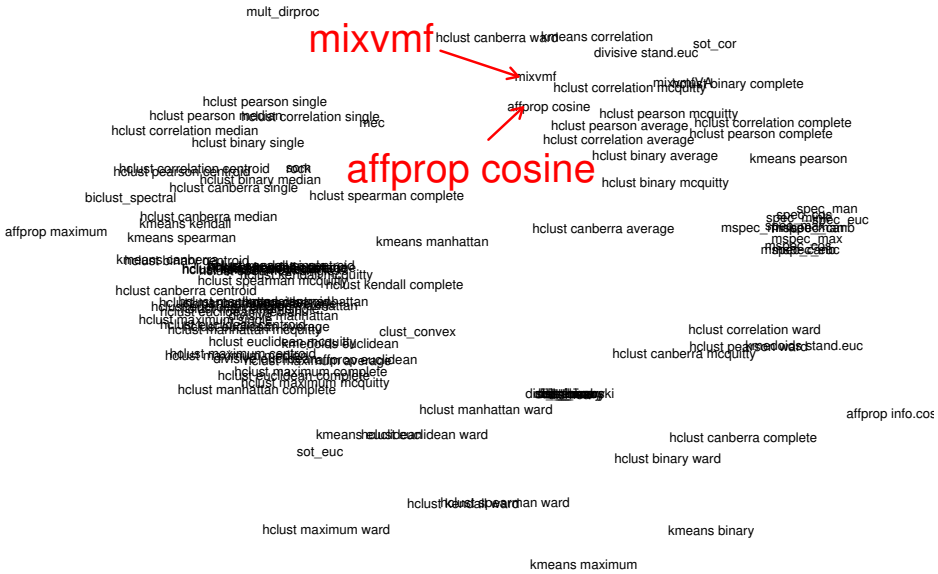
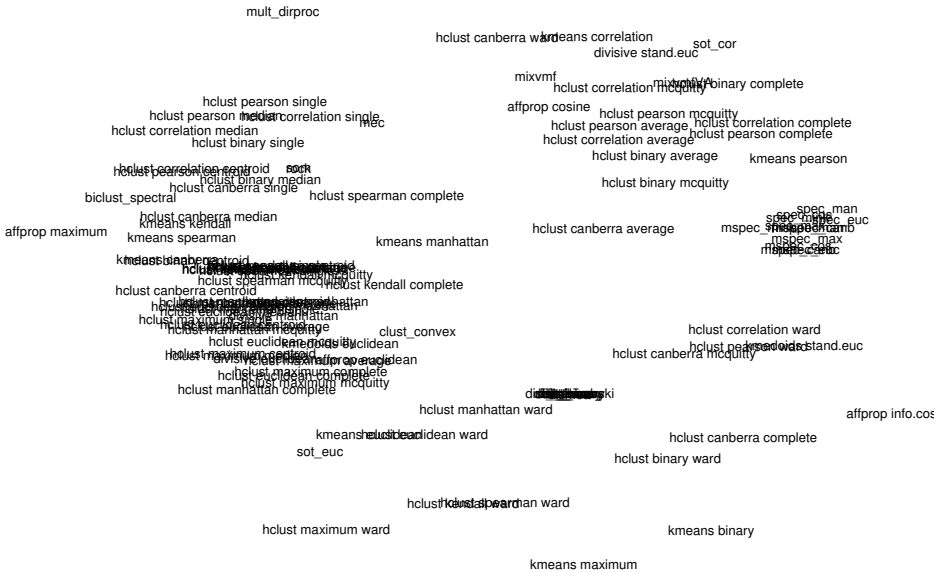


Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

Close to:

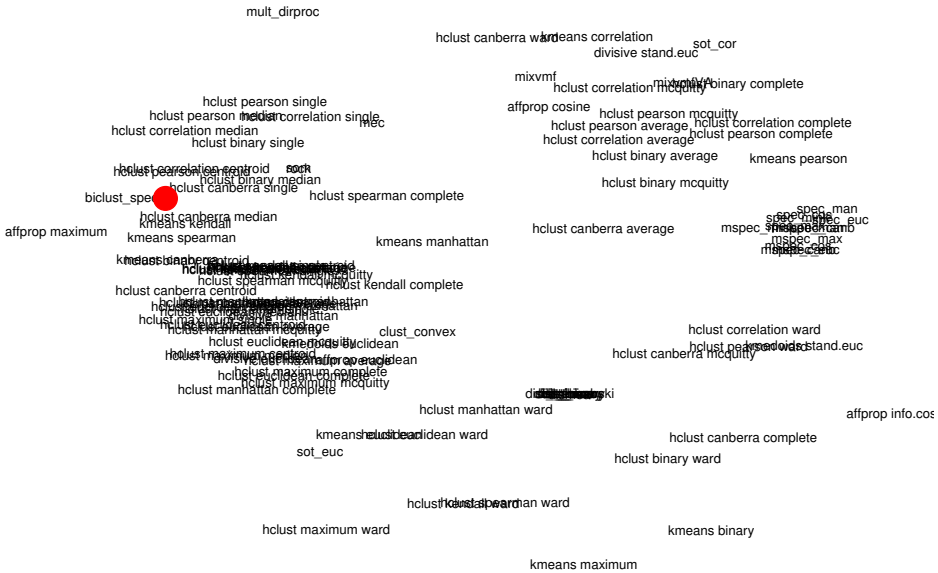
Mixture of von Mises-Fisher distributions (Banerjee et. al. 2005)

Example Discovery



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:

Example Discovery

Mixture:

0.39 Hclust-Canberra-McQuitty

Example Discovery

Mixture:

0.39 Hclust-Canberra-McQuitty

0.30 Spectral clustering
Random Walk
(Metrics 1-6)

Example Discovery

Mixture:

- 0.39 Hclust-Canberra-McQuitty
- 0.30 Spectral clustering Random Walk (Metrics 1-6)
- 0.13 Hclust-Correlation-Ward

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

Example Discovery

Mixture:

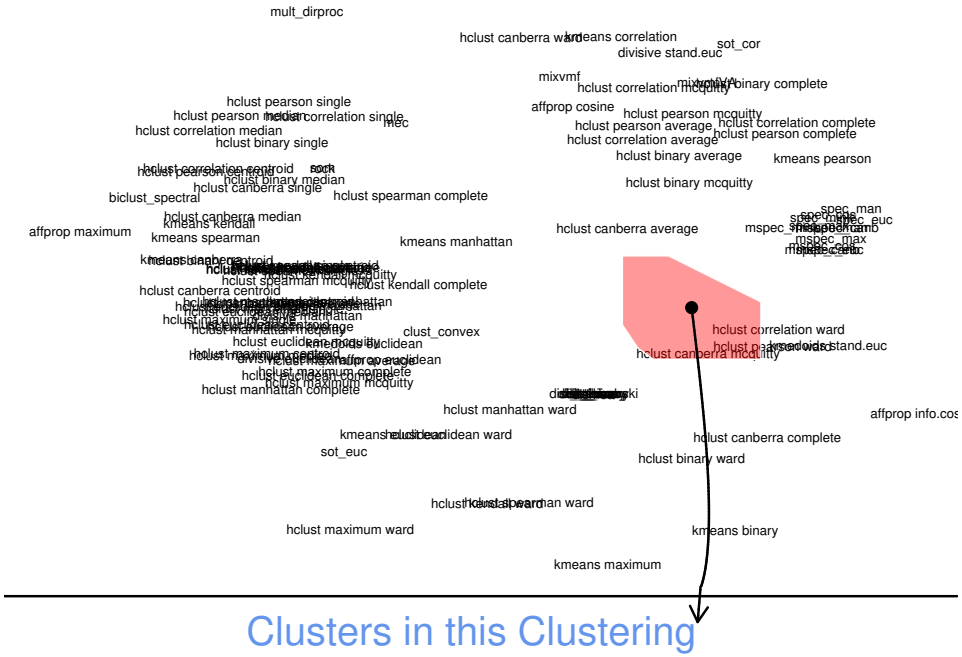
- 0.39 Hclust-Canberra-McQuitty
- 0.30 Spectral clustering Random Walk (Metrics 1-6)
- 0.13 Hclust-Correlation-Ward
- 0.09 Hclust-Pearson-Ward
- 0.05 Kmediods-Cosine

Example Discovery

Mixture:

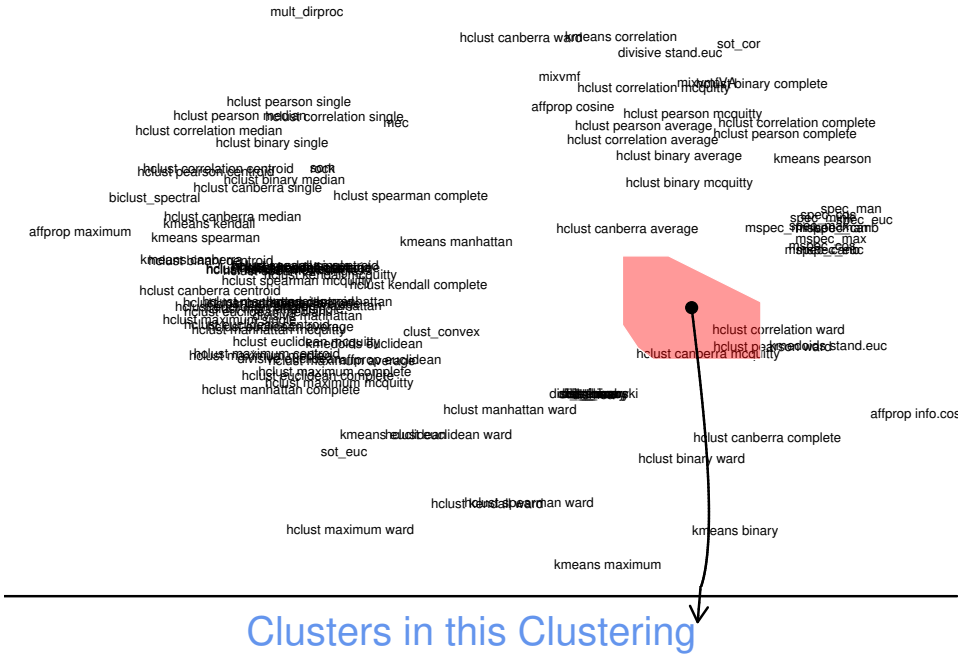
- 0.39 Hclust-Canberra-McQuitty
- 0.30 Spectral clustering Random Walk (Metrics 1-6)
- 0.13 Hclust-Correlation-Ward
- 0.09 Hclust-Pearson-Ward
- 0.05 Kmediods-Cosine
- 0.04 Spectral clustering Symmetric (Metrics 1-6)

Example Discovery

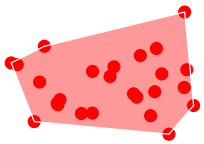


Mayhew

Example Discovery



Clusters in this Clustering

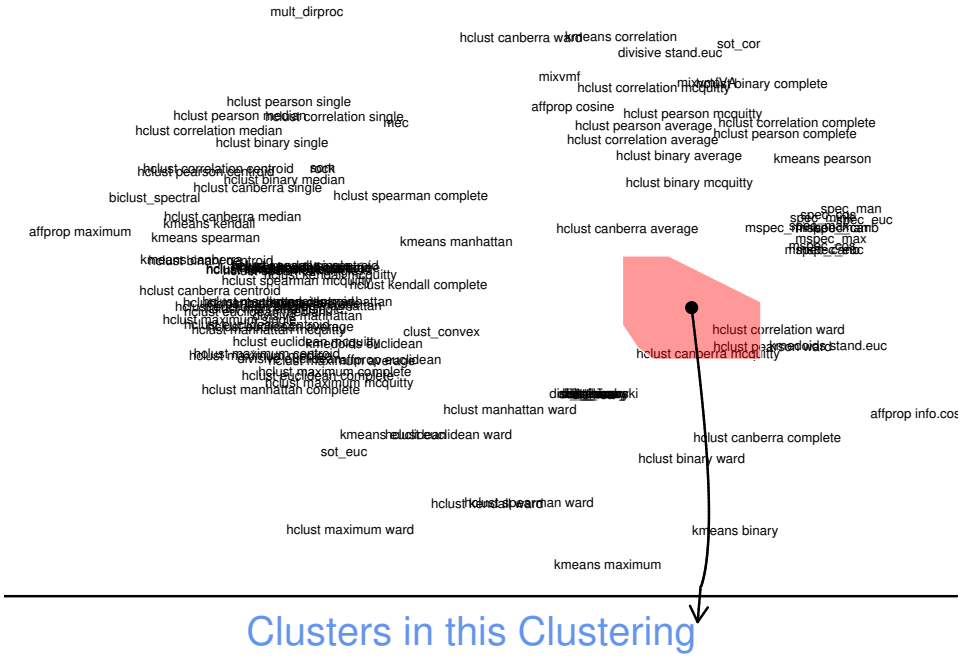


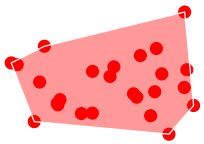
Credit Claiming
Pork

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





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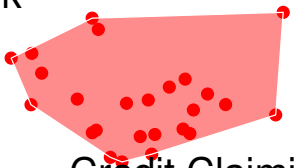
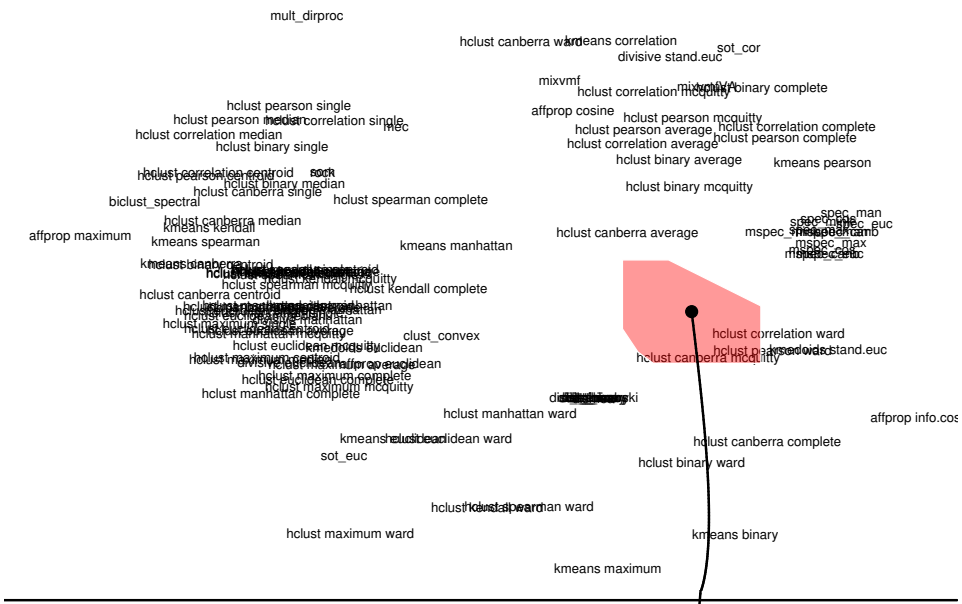


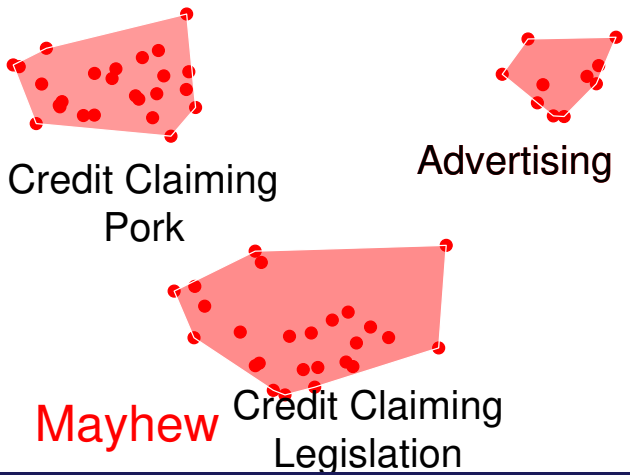
Mayhew

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

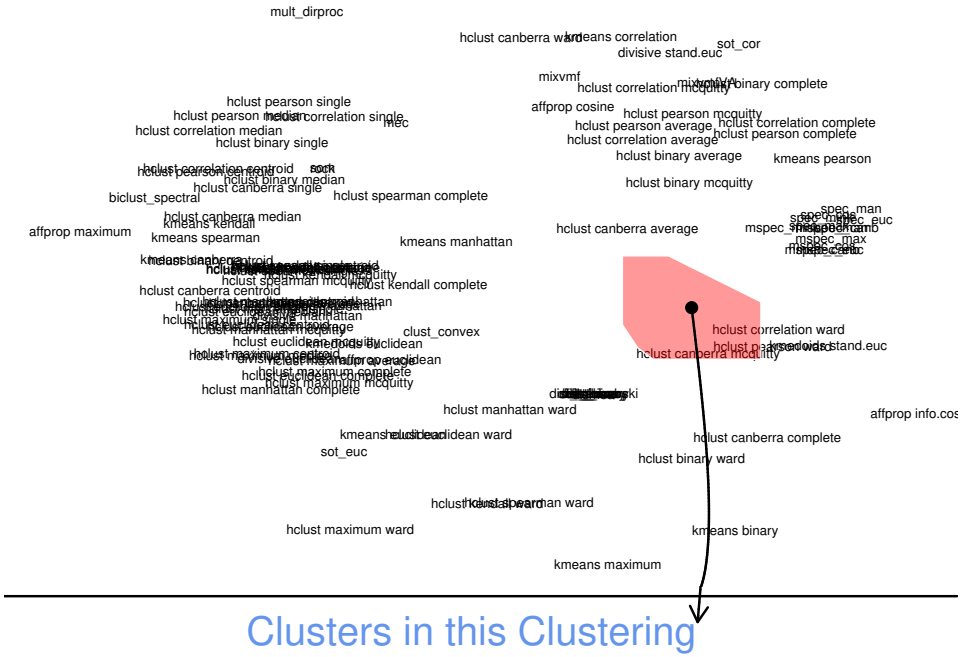




Advertising:

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

Example Discovery: Partisan Taunting



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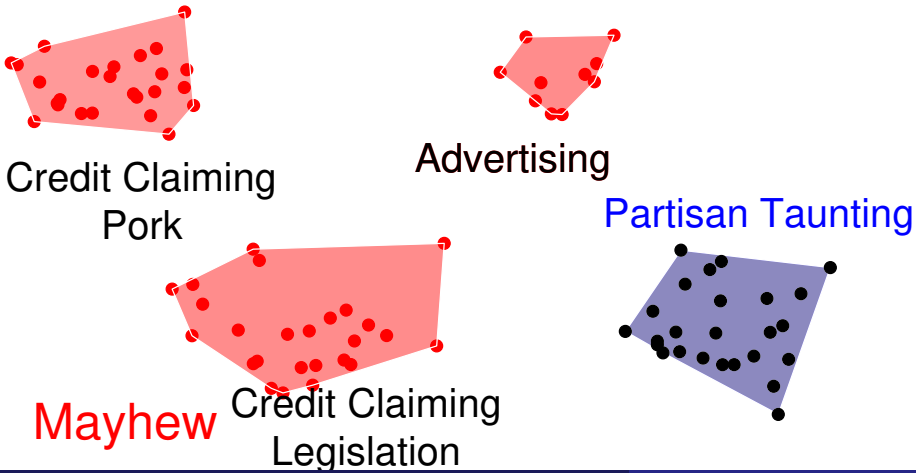
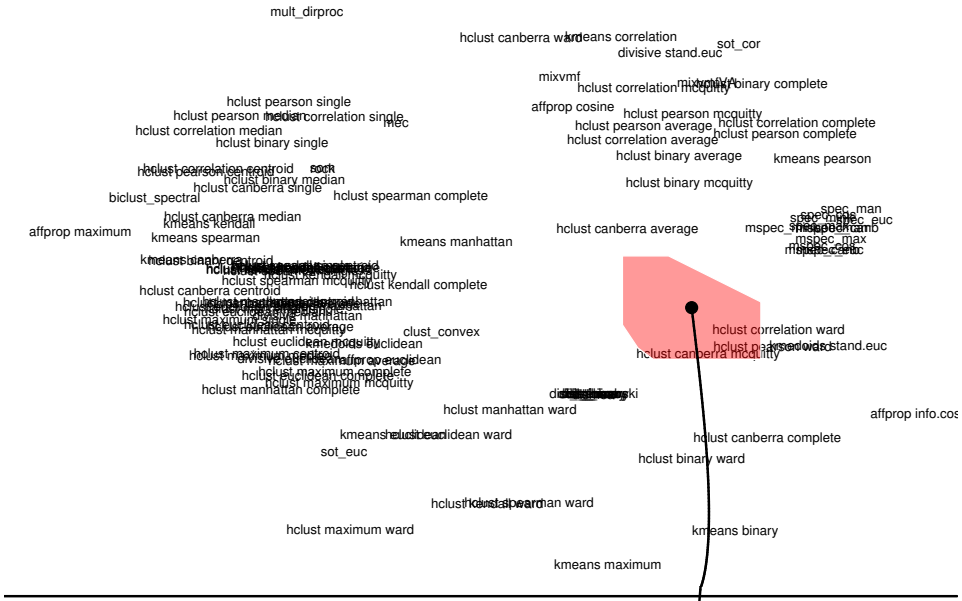


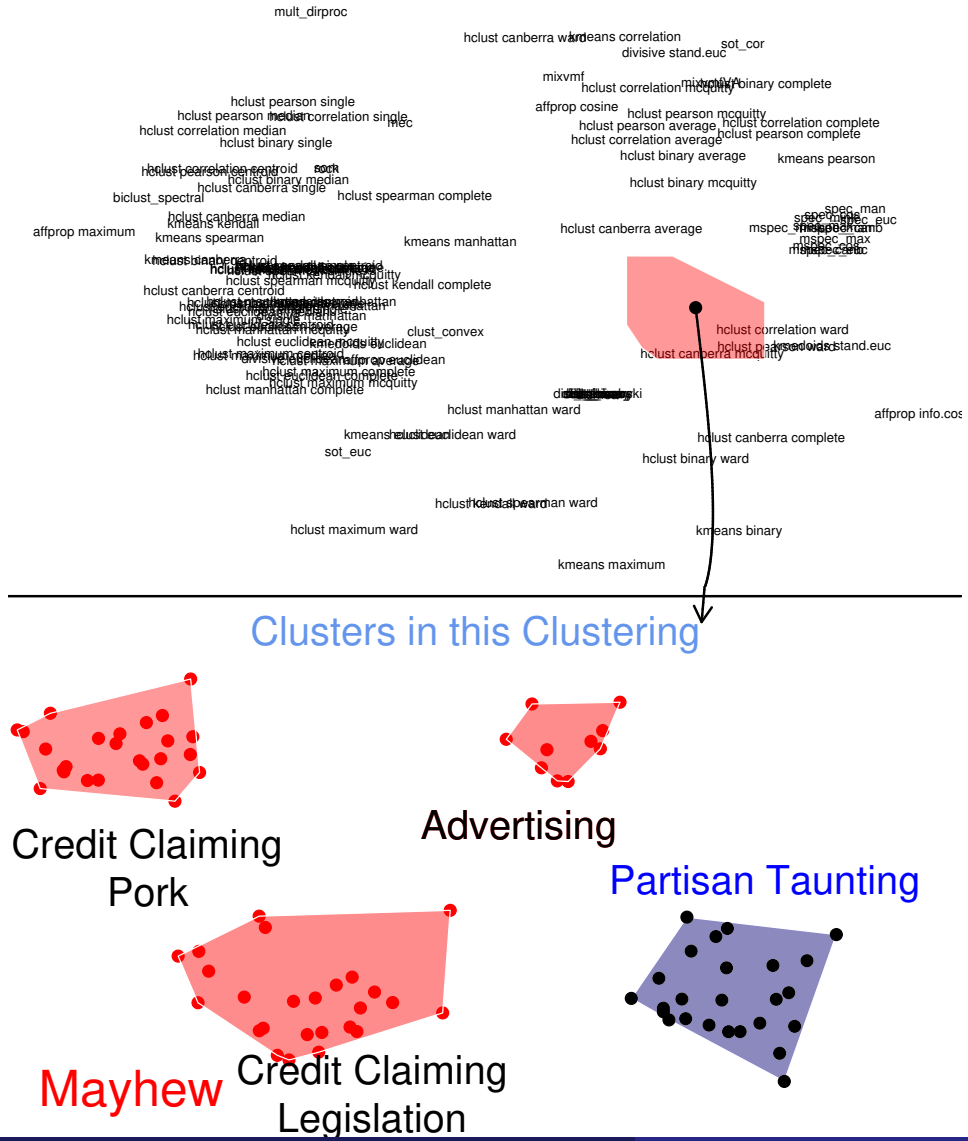
Partisan Taunting:
"Republicans Selling Out Nation on Chemical Plant Security"

Example Discovery: Partisan Taunting



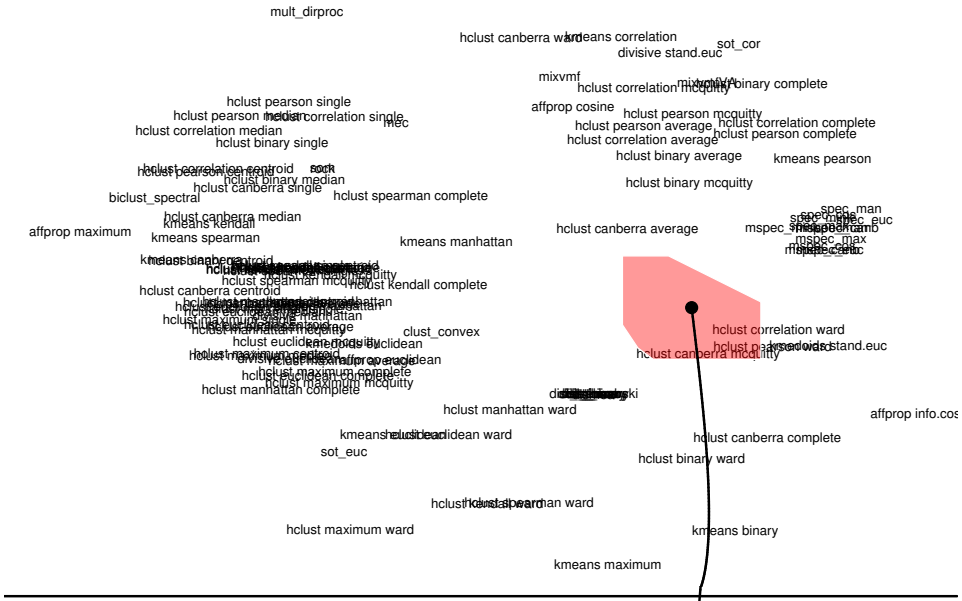
Partisan Taunting:
"Senator Lautenberg's amendment would change the name of. . . the Republican bill. . . to 'More Tax Breaks for the Rich and More Debt for Our Grandchildren Deficit Expansion Reconciliation Act of 2006"'

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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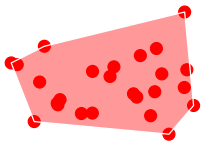
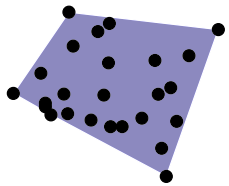
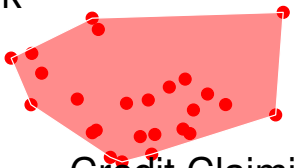


Credit Claiming
Pork

Advertising

Partisan Taunting





Mayhew

Credit Claiming
Legislation

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

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]

In Sample Illustration of Partisan Taunting

Taunting ruins deliberation

Sen. Lautenberg
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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]

In Sample Illustration of Partisan Taunting

Taunting ruins deliberation

Sen. Lautenberg
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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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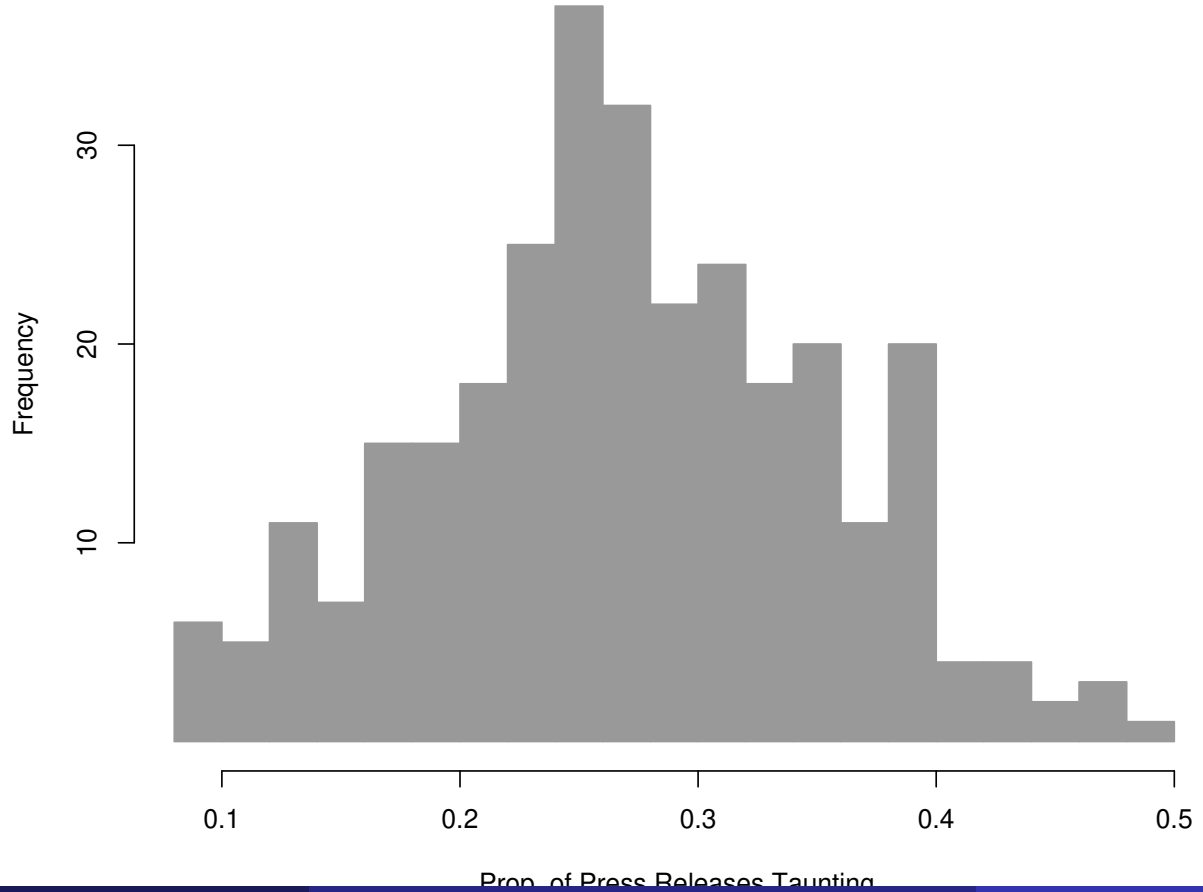

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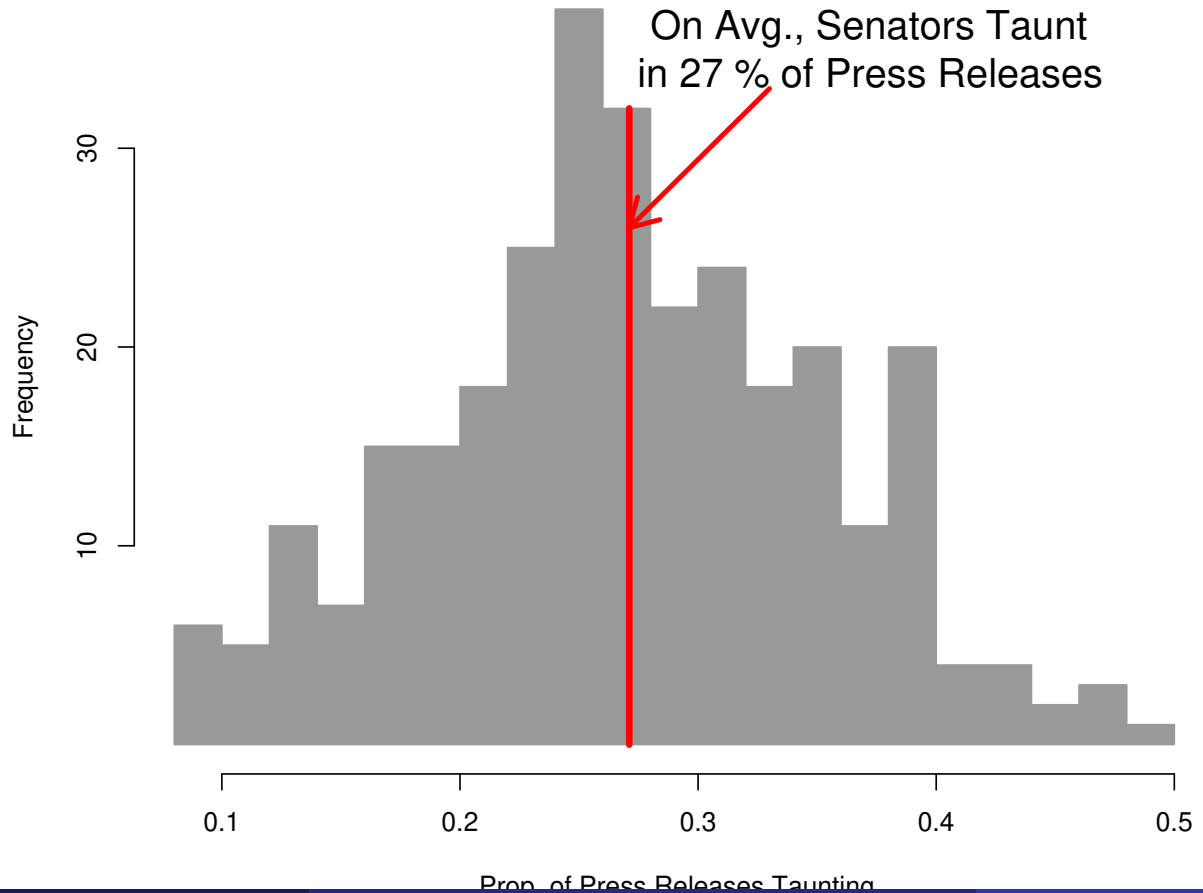
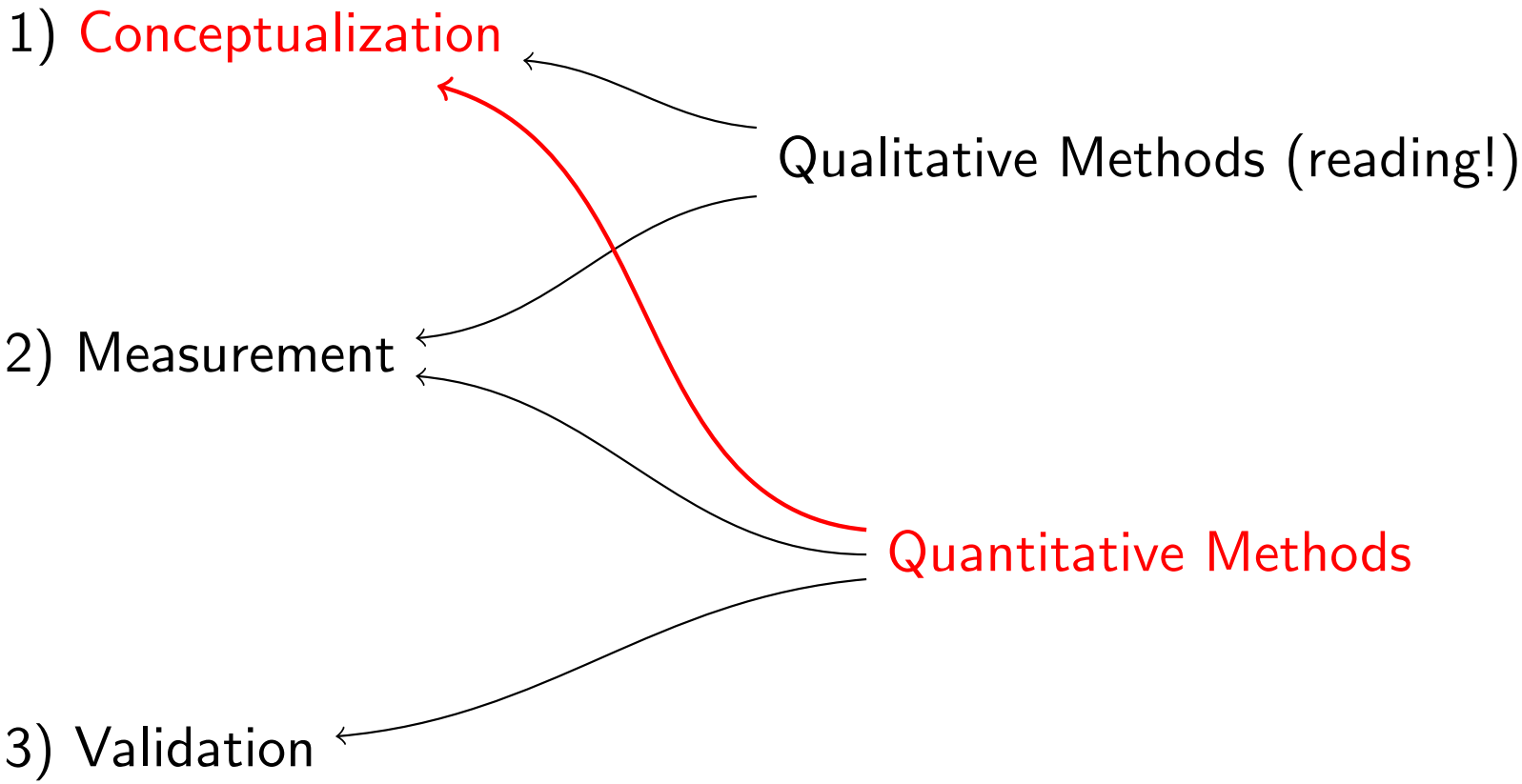
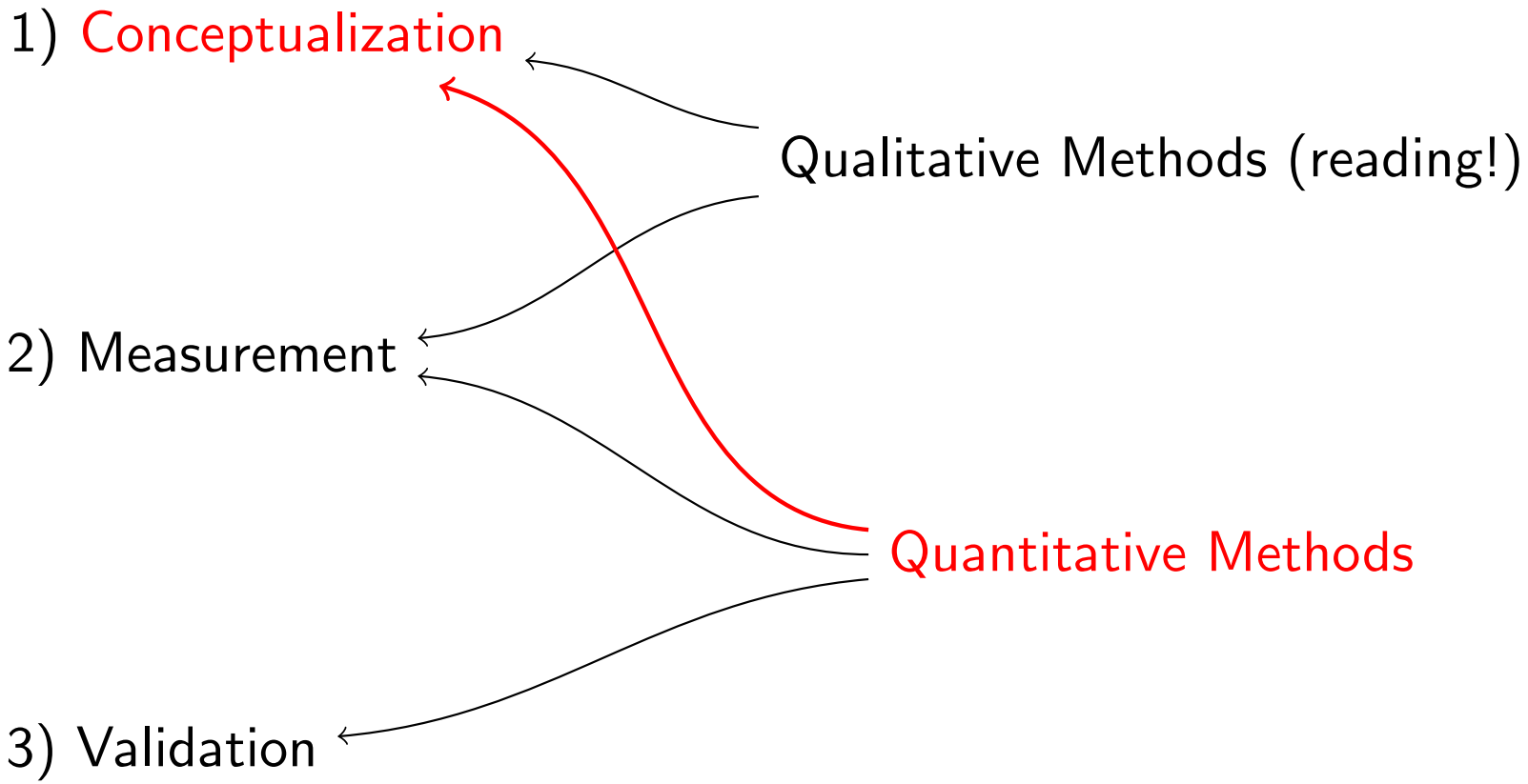


Quantitative Methods for Qualitative Conceptualization



Quantitative methods for conceptualization and discovery

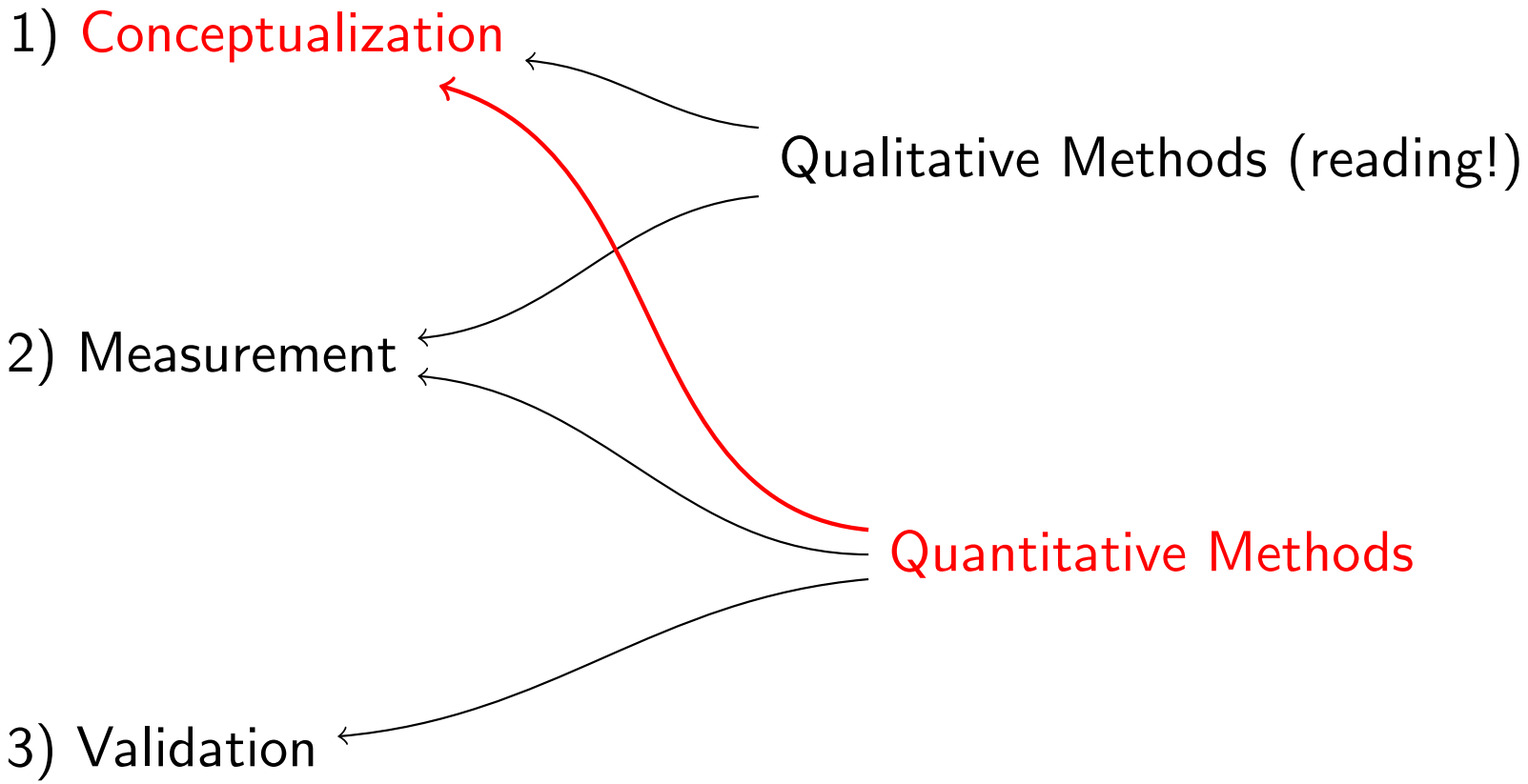
Quantitative Methods for Qualitative Conceptualization



Quantitative methods for conceptualization and discovery

- Few formal methods designed explicitly for conceptualization

Quantitative Methods for Qualitative Conceptualization



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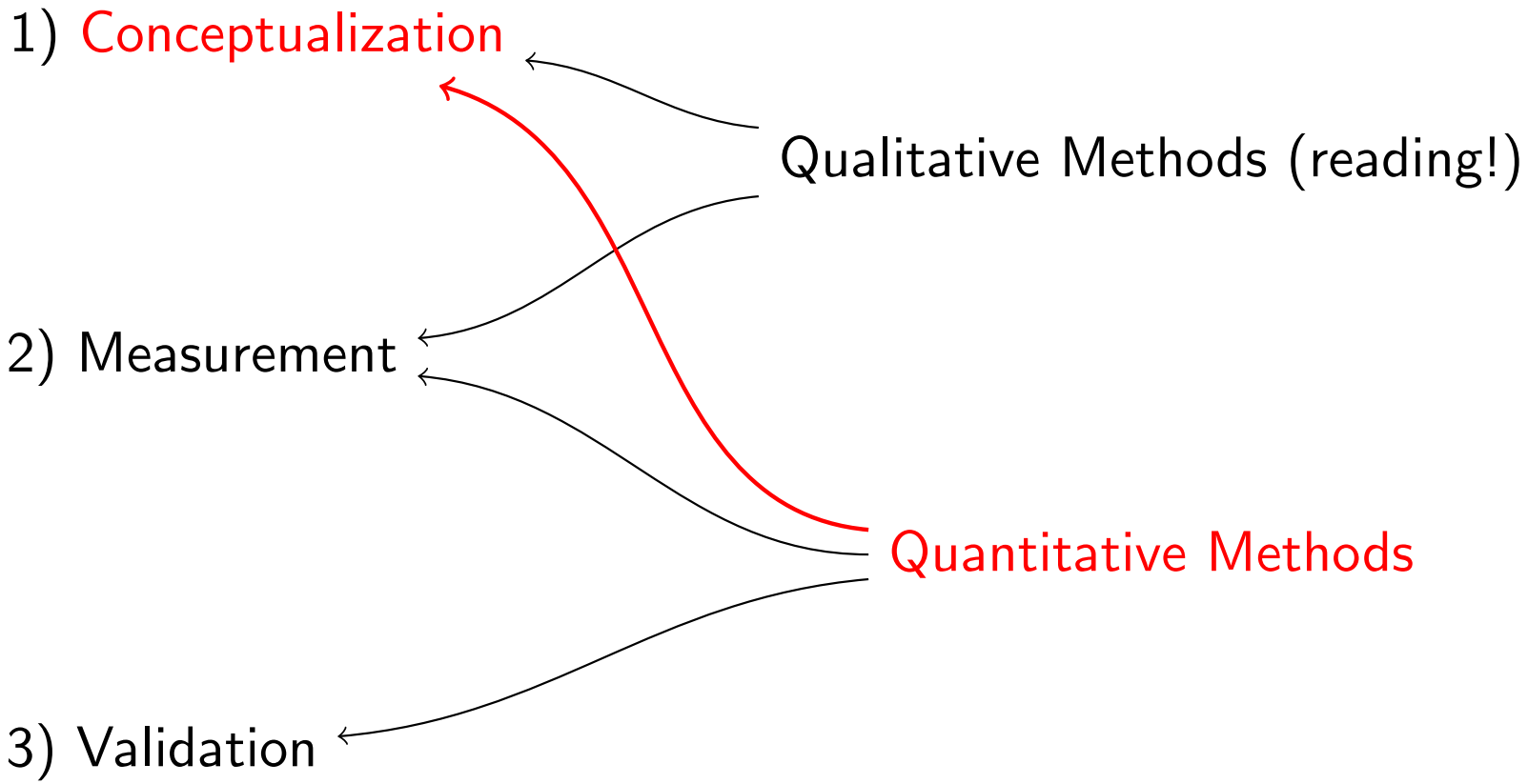
Quantitative Methods for Qualitative Conceptualization



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