Computer-Assisted Clustering and Conceptualization

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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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Set of clusterings $\approx$

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17 445-5116
17 822-2982
17 427-5712
17 569-2698
17 667-5190
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17 338-9110
17 825-9195
17 296-1593
17 670-2078
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17 542-1521
17 364-5232
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A list of unconnected addresses

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⇝ We develop a (conceptual) geography of clusterings

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4. Develop an application-independent distance metric between clusterings, a metric space of clusterings, and a 2-D projection

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Make it easy to choose best clustering from millions of choices

1. Code text as numbers (in one *or more* of several ways)
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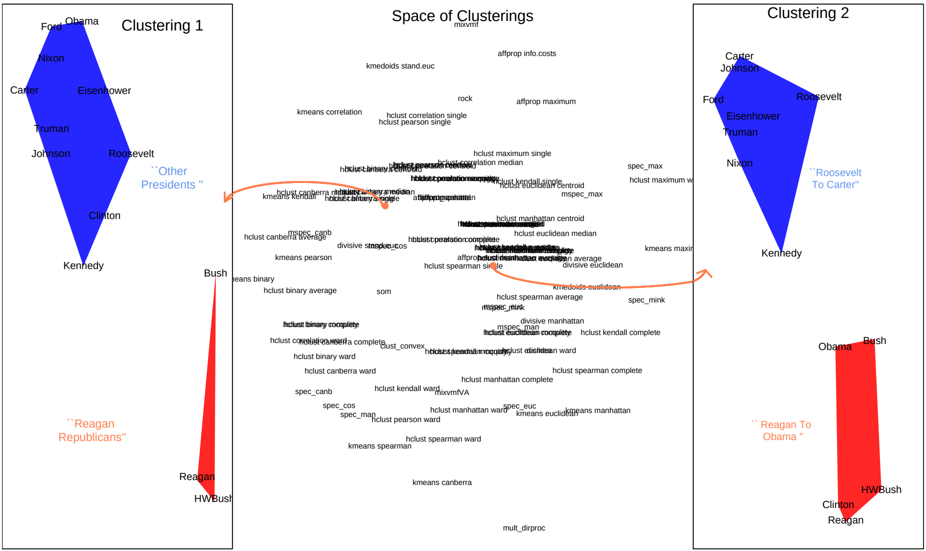
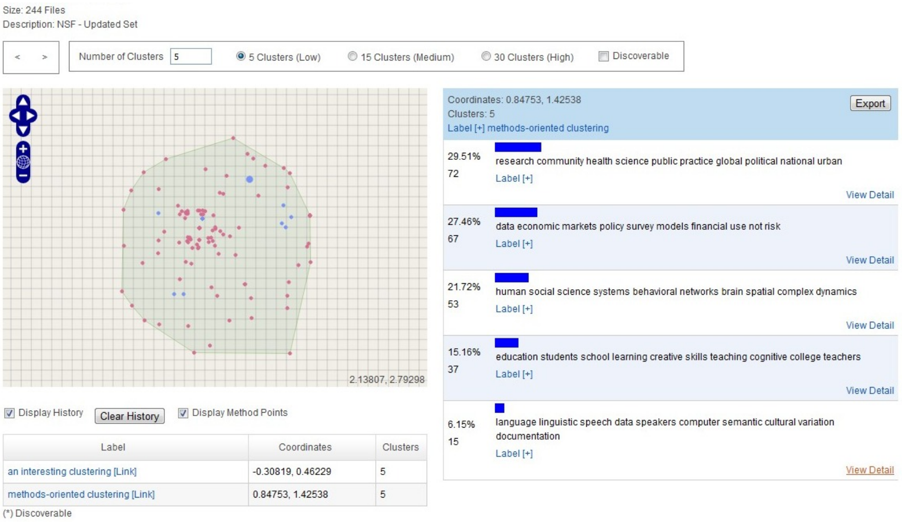
7. $\rightsquigarrow$ Millions of clusterings, easily comprehended

Many Thousands of Clusterings, Sorted & Organized

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



Software Screenshot



Evaluating Performance

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    - Discovery $\Rightarrow$ You're the judge

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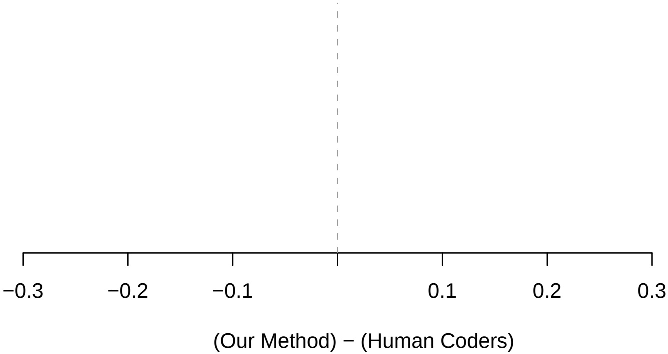

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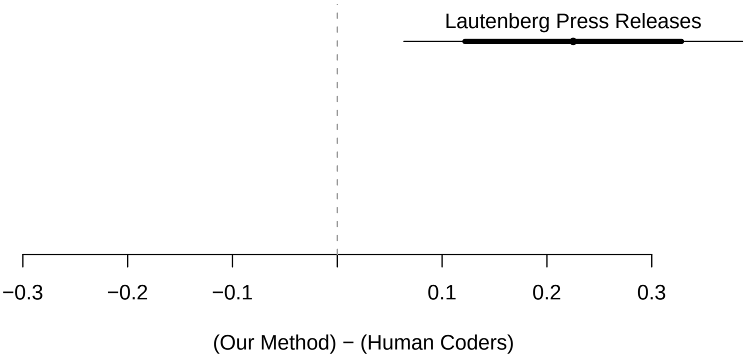

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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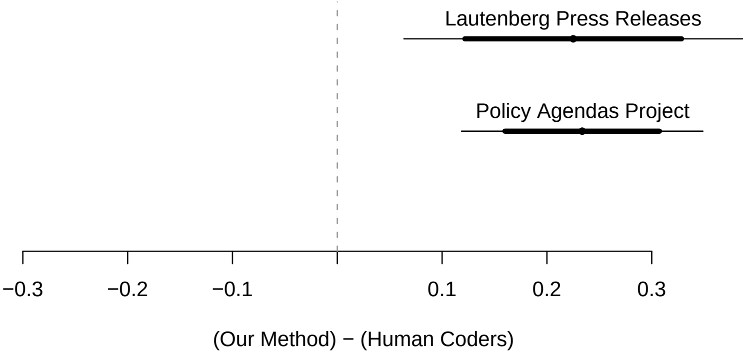

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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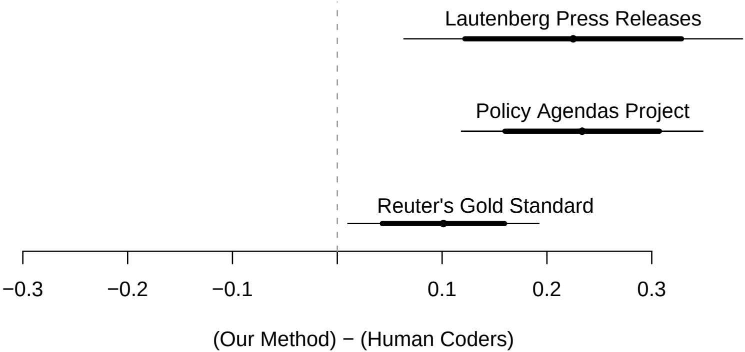

Reuter's: financial news (trade, earnings, copper, gold, coffee, ...); "gold standard" for supervised learning studies

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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

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

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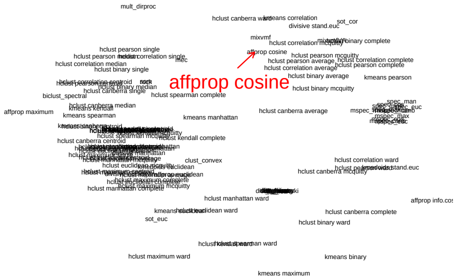

Red point: a clustering by Affinity Propagation-Cosine (Dueck and Frey 2007)

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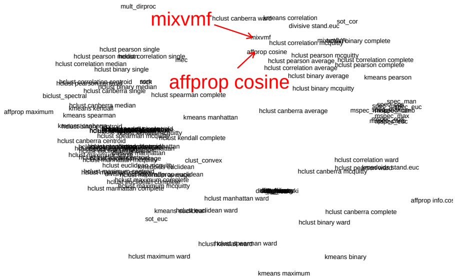

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Close to:

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

Example Discovery

Space between methods:

Example Discovery

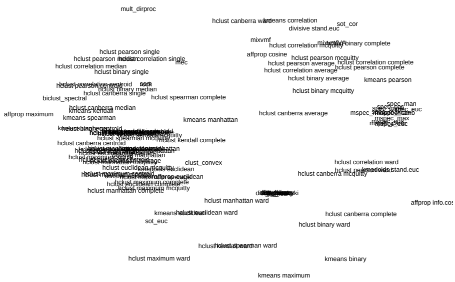
Space between methods:

Example Discovery

Space between methods:

local cluster ensemble

Example Discovery



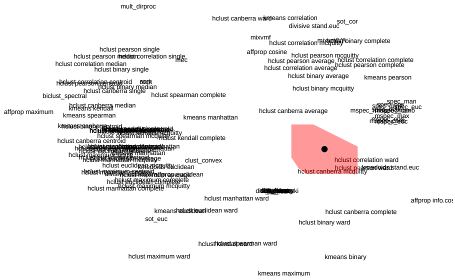
Example Discovery

Found a region with particularly insightful clusterings

Example Discovery

Mixture:

Example Discovery



Mixture:

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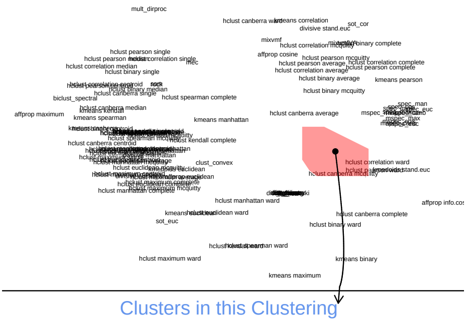
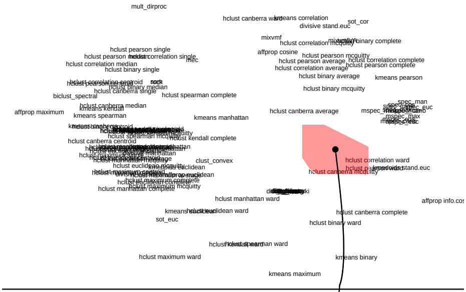
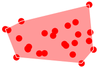


Mayhew

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"

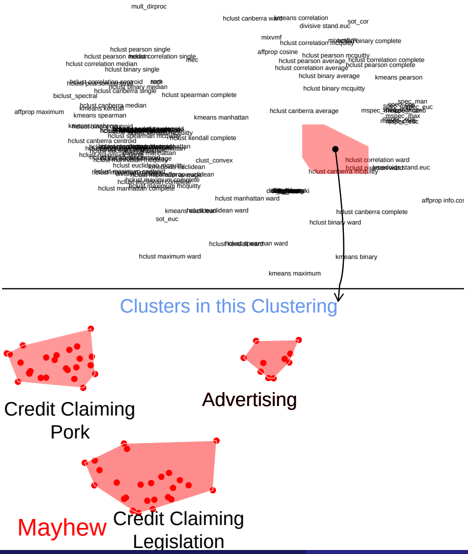
Mayhew

Example Discovery

Credit Claiming, Legislation:

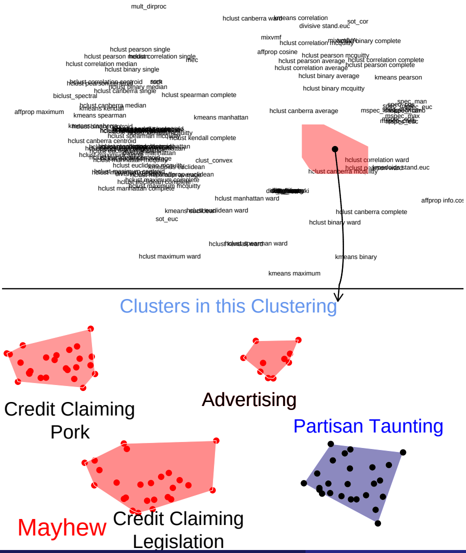
"As the Senate begins its recess, Senator Frank Lautenberg today pointed to a string of victories in Congress on his legislative agenda during this work period"

Example Discovery



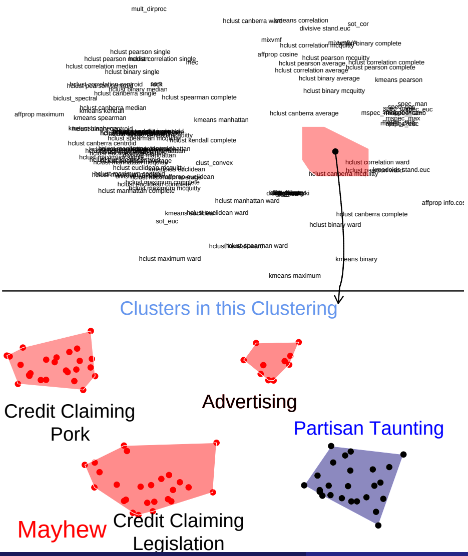
Advertising:
"Senate Adopts Lautenberg/Menendez Resolution Honoring Spelling Bee Champion from New Jersey"

Example Discovery: Partisan Taunting



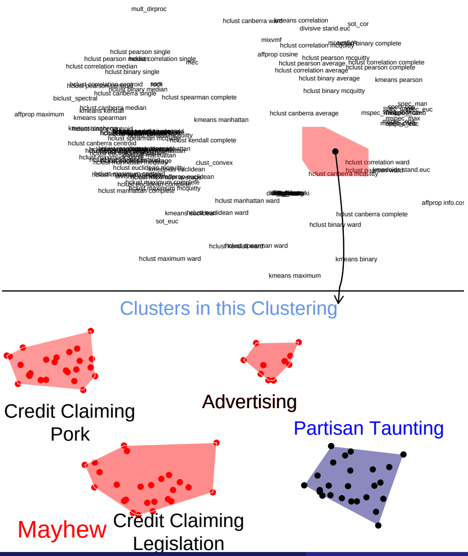
Partisan Taunting:
"Republicans Selling Out Nation on Chemical Plant Security"

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

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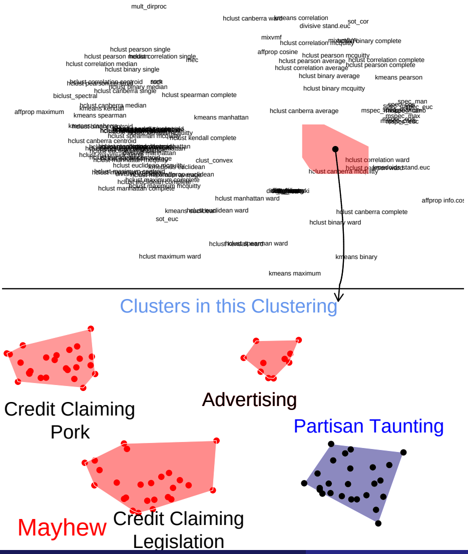

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Taunting ruins deliberation

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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- "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.

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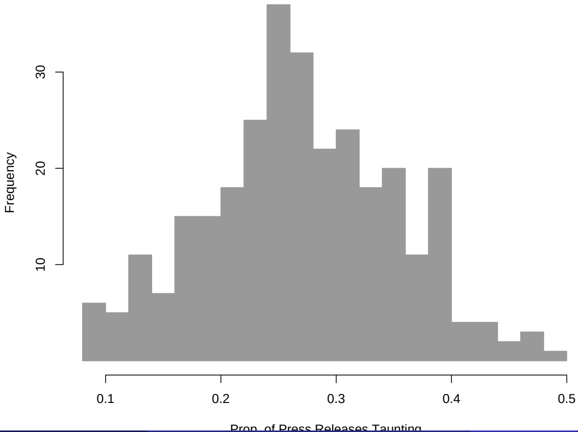

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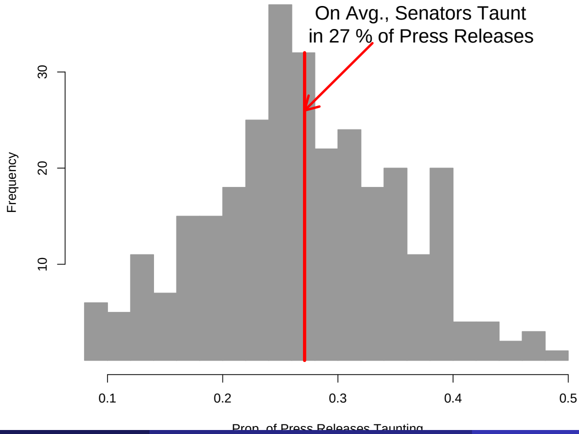

Quantitative Methods for Qualitative Conceptualization

1) Conceptualization

Qualitative Methods (reading!)

2) Measurement

Quantitative Methods

3) Validation

Quantitative methods for conceptualization and discovery

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- Few formal methods designed explicitly for conceptualization

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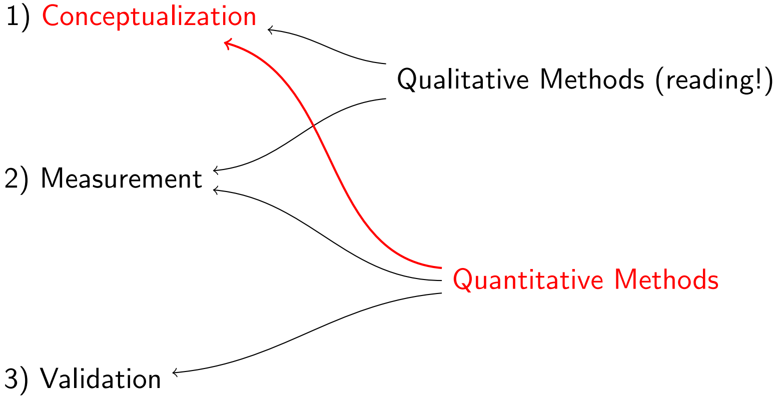

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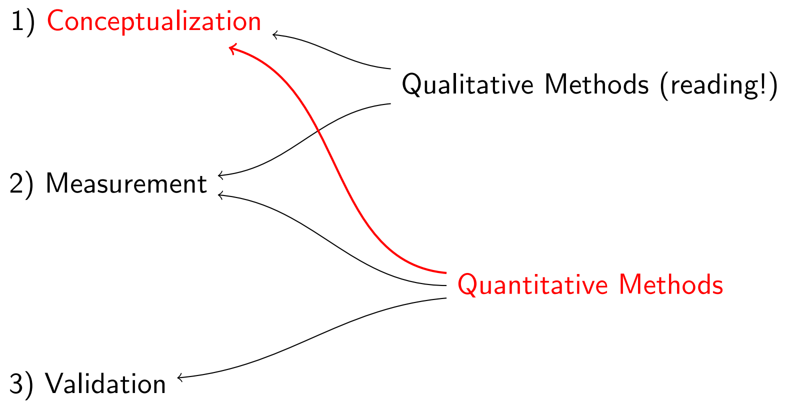

Quantitative methods for conceptualization and discovery

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- Belittled: "Tom Swift and His Electric Factor Analysis Machine" (Armstrong 1967)
- Evaluation methods measure progress in discovery

For more information

http://GKing.Harvard.edu