Discovery

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Harvard University

covering joint work with

Justin Grimmer (Harvard) and Eleanor Powell (Harvard ⇝ Yale)

(talk @ Institute for Qualitative and Multimethod Research, Syracuse University, 5/26/09)

Reading

- Gary King and Eleanor Neff Powell. 2008. "How Not to Lie Without Statistics"
- Justin Grimmer and Gary King. 2009. "Quantitative Discovery of Qualitative Information: A General Purpose Document Clustering Methodology"

http://GKing.harvard.edu

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- The march of quantification across fields of academia, professions, commerce, sports, etc. (Moneyball, SuperCrunchers, Numerati)

Discovery

3 Steps

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- $\rightsquigarrow$ Integrated quant/qual: Computer-assisted qualitative analysis

The Problem: Discovery from Unstructured Text

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- (We analyze text; our methods apply more generally)

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- That we think of all this as astonishing ... is astonishing

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  - (Perhaps true by definition in unsupervised learning: If we knew the DGP, we wouldn't be at the discovery stage.)

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- But how to choose from an enormous list of clusterings?

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P 94 Crestwood Pk Rox 02121 .... 617 427-4754
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Richard A 97 Mt Vernon Bos 02108 .... 617 566-7293
Carter Richard A MD
170 Comnwlth 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

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

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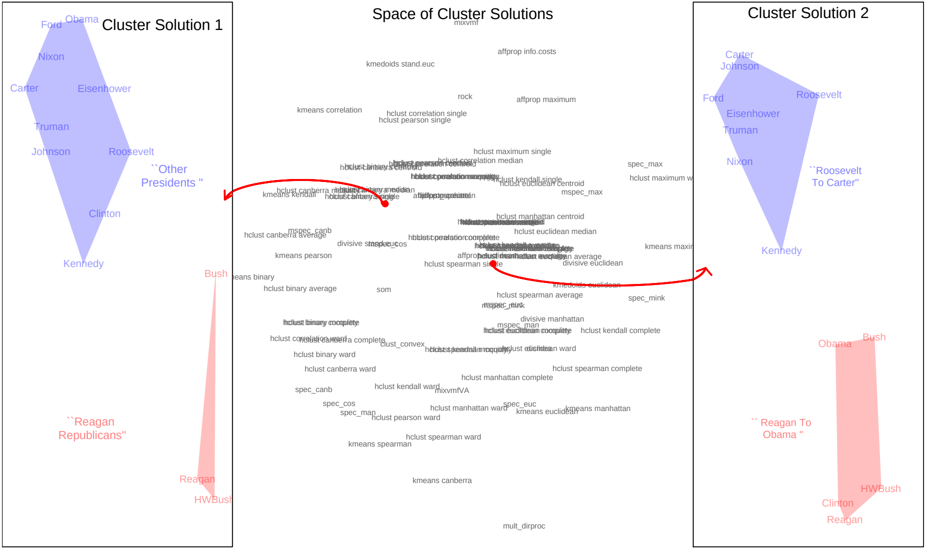
$\rightsquigarrow$ meaning revealed through a *geography* of clusterings

Many Thousands of Clusterings, Sorted & Organized

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



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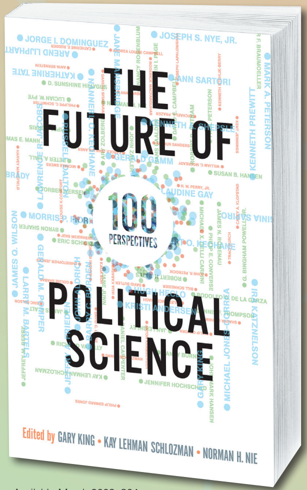
$\rightsquigarrow$ Only one measure satisfies all three (the "variation of information")



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p.s. The hand-coders did the evaluation!

Cluster Quality Experiments

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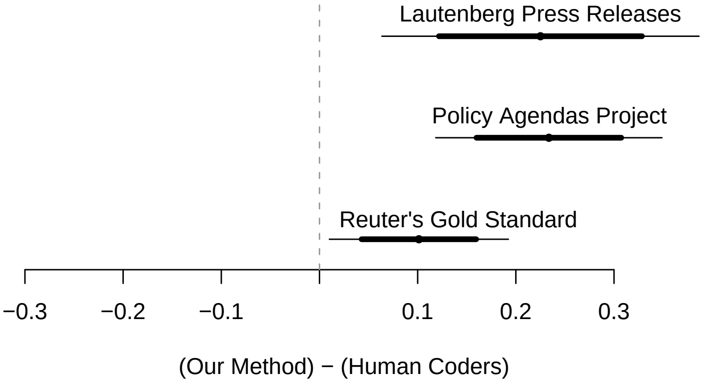

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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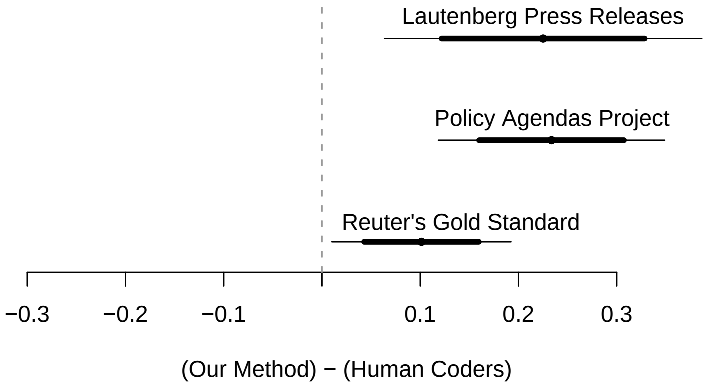

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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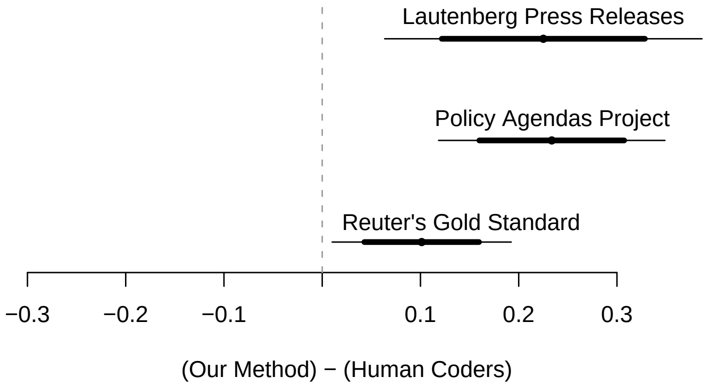

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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Substantive example of a finding, using our approach

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  - $\rightsquigarrow$ Is this what it means to be a member of a political party?

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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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- Multiple approaches: Integrated, not separate

For more information:

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