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

Gary King
Institute for Quantitative Social Science
Harvard University

joint work with
Justin Grimmer (Harvard University)

(talk at the Northeast Methodology Program, New York University, 4/17/09)

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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⇝

⇝ We develop a geography of clusterings

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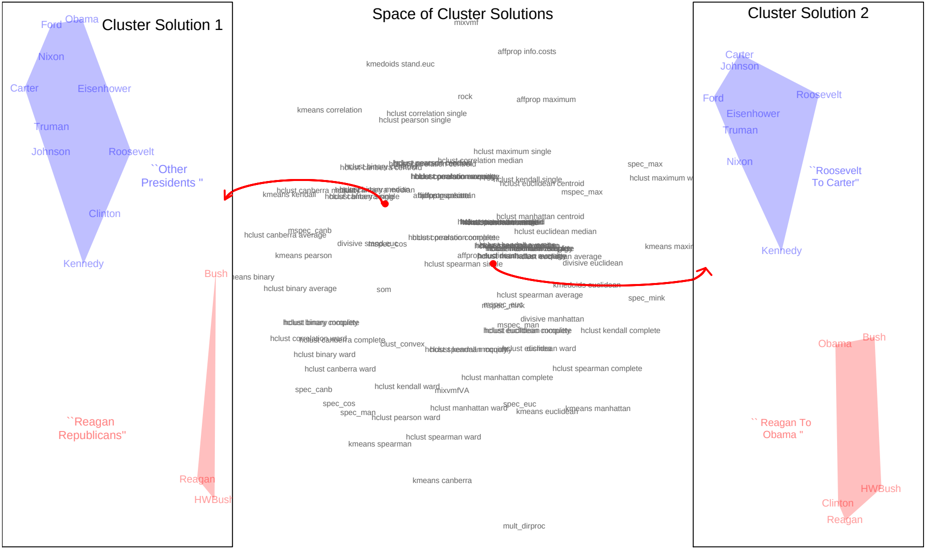
$\rightsquigarrow$ meaning revealed through a *geography* of clusterings

Many Thousands of Clusterings, Sorted & Organized

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



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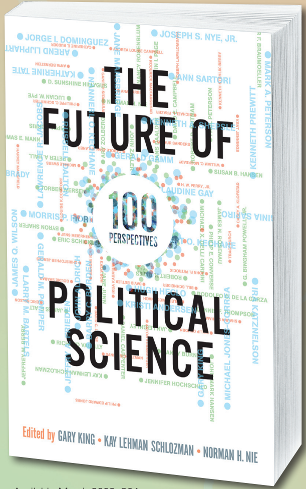
$\rightsquigarrow$ Only one measure satisfies all three (the "variation of information")



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

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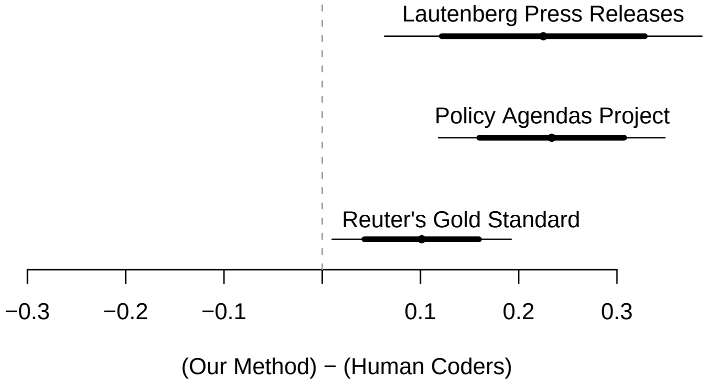

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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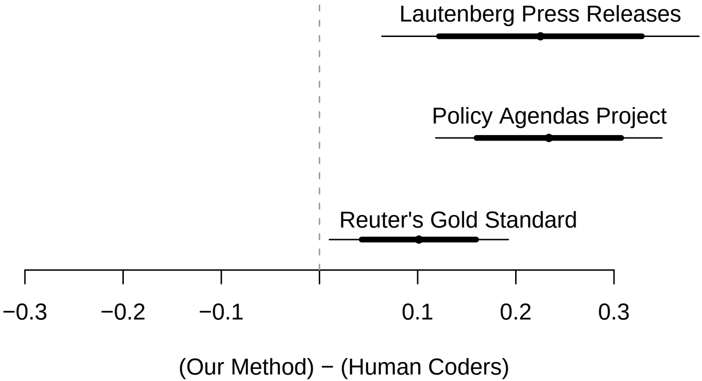

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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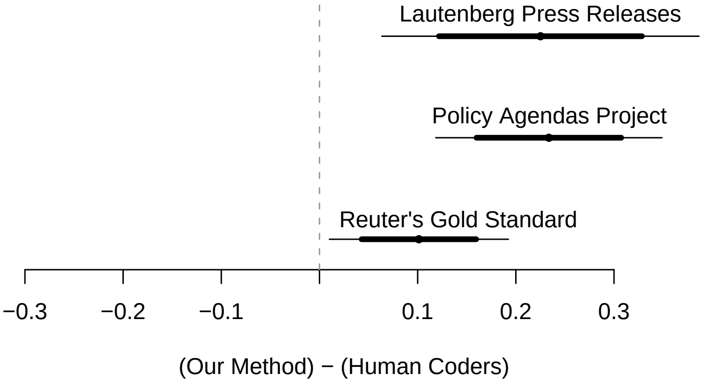

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

What do Members of Congress Do?

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Substantive example of a finding, using our approach

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  - $\rightsquigarrow$ Perhaps this is what it means to be a member of a political party in the U.S.?

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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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  - Evaluating new individual methods: (1) distance from existing methods and their averages, (2) usefulness of discoveries in given data sets.

For more information:

http://GKing.Harvard.edu