The Changing Evidence Base of Social Science Research

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(Miller Converse Lecture Series talk, 4/9/09)

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   - No investigator control
   - Little impartiality: Governments, newspapers, NGOs, etc.

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- Huge opportunities with web surveys: marginal cost ≈ 0, but what about selection?

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- Advances in statistical methods, informatics, & software

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- Many more coming. . .

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$\rightsquigarrow$ Bigger changes than social science has ever seen

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- Copies at `http://gking.harvard.edu`

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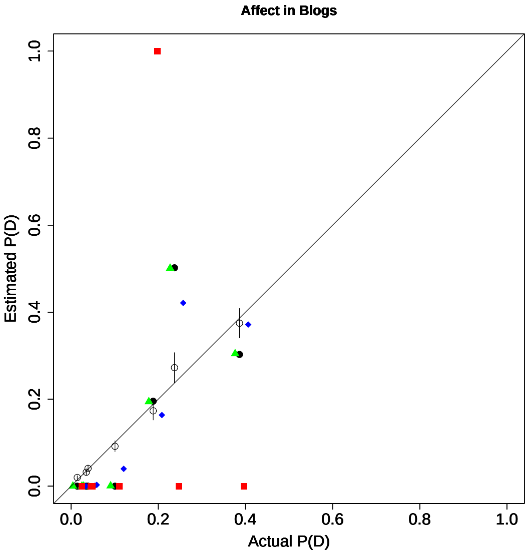
  - New methodology: unbiased category proportions, even when the best classification accuracy is low

Out-of-sample Comparison: 60 Seconds vs. 8.7 Days



Reactions to John Kerry's Botched Joke

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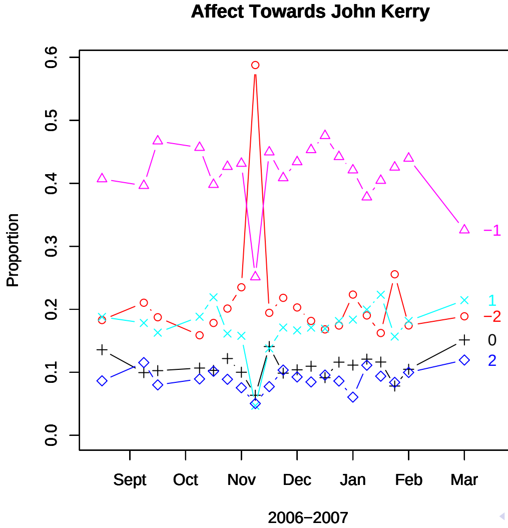

Our Software can Read Better than You!

- Reference: Justin Grimmer and Gary King. "Quantitative Discovery from Qualitative Information: A General-Purpose Document Clustering Methodology"

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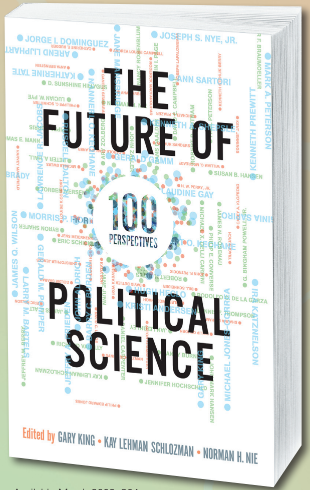
  - Social scientists: discovery of useful information
    $\rightsquigarrow$ We show how to connect substance and method



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Evaluators' Rate Machine Choices Better Than Their Own

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

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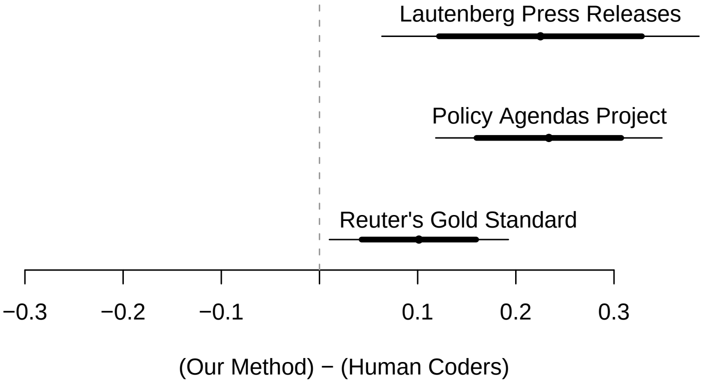

Lautenberg: 200 Senate Press Releases (appropriations, economy, education, tax, veterans, . . .)

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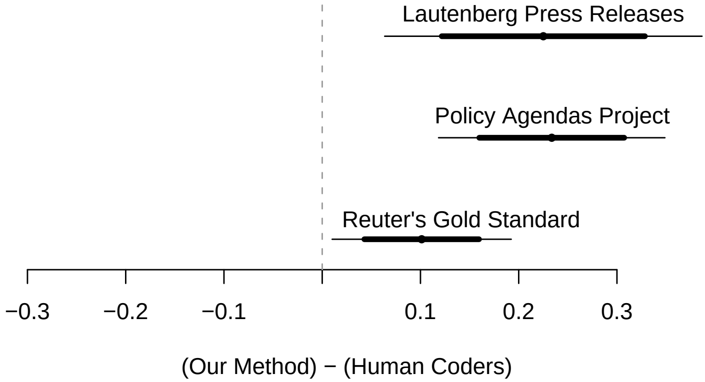

Policy Agendas: 213 quasi-sentences from Bush's State of the Union (agriculture, banking & commerce, civil rights/liberties, defense, . . .)

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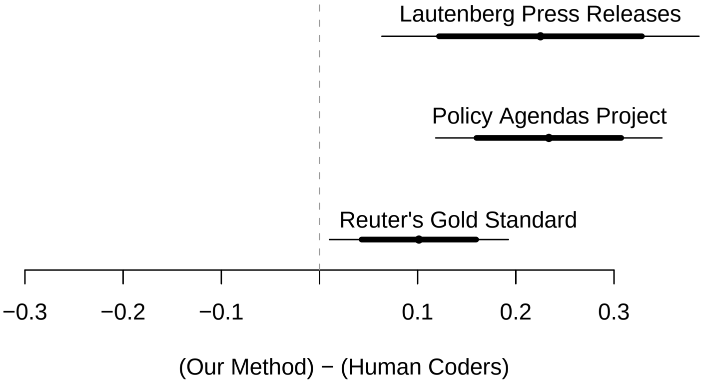

Reuter's: financial news (trade, earnings, copper, gold, coffee, . . .); "gold standard" for supervised learning studies

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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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7. Electoral activity: ballot images, precinct-level results, individual-level registration, primary participation, and campaign contributions

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12. Scholarly Data: the replication movement in academia, led in part by political science, is massively increasing data sharing

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  - Will you wait to be replaced? or put in the effort to convert and learn how to use the new information to learn about the social and political worlds?

For more information:

http://GKing.Harvard.edu