Big Data is Not About the Data!

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- In each: without new analytics, the data are useless

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Fast Company Names Crimson Hexagon Number Seven on "The 10 Most Innovative Companies in Web" List Leading Social Intelligence Firm Recognized For Revolutionary Measurement of Consumer Opinions in Social Media

Published: Wednesday, 16 Mar 2011 | 9:20 AM ET Text Size

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2. Worldwide cause-of-death estimates for World Health Organization

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Bias in U.S. Social Security Administration Forecasts

- Social Security: single largest government program; lifted a whole generation out of poverty; extremely popular
- Forecasts: used for programs comprising $> 50\%$ of the US expenditures; e.g., if retirees draw benefits longer than expected, the Trust Fund runs out
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  - $\rightsquigarrow$ Trust fund needs $>$ \$800 billion more than SSA thought
  - Many other applications to different types of forecasts

Thresher: Finding Those Hiding in Plain Sight

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Modern Analytics to Improve Student Learning

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Reverse Engineering China's 50c Party

The Government Surreptitiously Fabricating Social Media Posts

- Prevailing view of scholars, activists, journalists, social media participants:

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  - (Technically correct, & politically much easier)

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For more information

GaryKing.org

Institute for Quantitative Social Science
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