Big Data is Not About the Data!

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Nina Zipser's Freshman Seminar: "Models of the World: Explaining the Past and Predicting the Future" 11/13/2018

[1] GaryKing.org

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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

CAMBRIDGE, Mass., Mar 16, 2011 (BUSINESS WIRE) -- Fast Company named

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- 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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  - Methods: little changed; mostly qualitative; a time when we've learned more about forecasting than at any time in history
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  - $\rightsquigarrow$ Trust fund needs $>$ \$800 billion more than SSA thought
  - Many other applications to different types of forecasts

Thresher.io: Finding Those Hiding in Plain Sight

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自由

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目由

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Example Substitution 1:

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Coding documents into categories

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  - (Lots of technology, but it's behind the scenes)

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Reverse Engineering China's 50c Party

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  - (Technically correct, & politically much easier)

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For more information

GaryKing.org

Institute for Quantitative Social Science
Harvard University