Big Data is Not About the Data!

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Shanghai Jiao Tong University, 1/4/2017

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The Spectacular Success of Quantitative Social Science

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- Our solution: **Perusall**
  - A new type of collaborative e-reader, with novel data analytics, and cutting-edge behavioral research
  - $>90\%$ of students do the reading
  - Solitary reading assignments $\rightsquigarrow$ engaging collective activities
  - Intrinsic motivation: collaborative annotation in threads
  - Extrinsic motivation: automated grading of annotations & engagement (better than instructors can do on their own)
  - Novel data analytics: keep students on track, with automated personal guidance, nudges, non-adversarial grading
  - Instructors save time, stay engaged: automated student confusion reports
  - Want to try it at SJTU? see Perusall.com

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- Does not argue; does not engage on controversial issues

Reverse Engineering China's "50c Party"

- ~~Prevailing view of scholars, activists, journalists, social media participants: 50c party argues against those who criticize the government, its leaders, and their policies~~ *Wrong*
- Fabricates 450M social media posts a year!
- Does not argue; does not engage on controversial issues
- Distracts; redirects public attention from criticism and central issues to cheerleading and positive discussions of valence issues

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  - (Technically correct, & politically much easier)

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- Build a new discipline of data science

For more information

GaryKing.org

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Institute for Quantitative Social Science
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