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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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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  - >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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  - Many other applications to different types of forecasts

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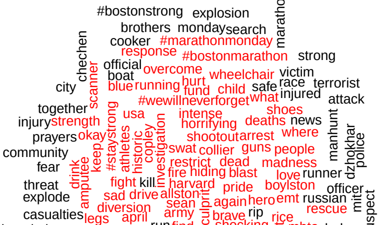

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  - (Technically correct, & politically much easier)

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- Build a new discipline of data science

For more information

GaryKing.org

Perusall.com

Institute for Quantitative Social Science
Harvard University