

Big Data is Not About the Data!

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Talk at Microsoft, 2/5/2015

¹GaryKing.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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Published: Wednesday, 16 Mar 2011 | 9:29 AM ET Text Size
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2. Worldwide cause-of-death estimates for



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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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Social Psychological Conditions that make Bias *Possible*

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自由

Following Conversations that Hide in Plain Sight

Example Substitution 1:

自由 “Freedom”

Following Conversations that Hide in Plain Sight

Example Substitution 1:

自由

“Freedom”

CENSORED

Following Conversations that Hide in Plain Sight

Example Substitution 1:

自由
自由

“Freedom”

CENSORED

Following Conversations that Hide in Plain Sight

Example Substitution 1:

自由
目田

“Freedom”

“Eye field”

CENSORED

Following Conversations that Hide in Plain Sight

Example Substitution 1:

自由
目田

“Freedom”

CENSORED

“Eye field” (nonsensical)

Following Conversations that Hide in Plain Sight

Example Substitution 1: Homograph

自由
目田

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自由
目田

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Example Substitution 2:

Following Conversations that Hide in Plain Sight

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自由
目田

“Freedom”

CENSORED

“Eye field” (nonsensical)

Example Substitution 2:

和谐

Following Conversations that Hide in Plain Sight

Example Substitution 1: Homograph

自由
目田

“Freedom”

CENSORED

“Eye field” (nonsensical)

Example Substitution 2:

和谐

“Harmonious [Society]” (official slogan)

Following Conversations that Hide in Plain Sight

Example Substitution 1: Homograph

自由
目田

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The same task: (1) Long tail search, (2) Government and industry analyst's job,

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The same task: (1) Long tail search, (2) Government and industry analyst's job, (3) language drift (#BostonBombings ~> #BostonStrong),

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CENSORED

“River crab” (irrelevant)

They can't follow the conversation; Thresher can.

The same task: (1) Long tail search, (2) Government and industry analyst's job, (3) language drift (#BostonBombings ~> #BostonStrong), (4) Child pornographers, (5) Look-alike modeling, (6) Starting point for other automated text methods, (7) Infinitely improvable classification, eDiscovery

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

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- How common is it? **27% of all Senatorial press releases!**

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For more information

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