

Big Data is Not About the Data! The Power of Modern Analytics

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

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2. Worldwide cause-of-death estimates for



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- **Thresher:** New technology to discover the right keywords



Thresher: Finding Those Hiding in Plain Sight

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Example Substitution 1:

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自由

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Example Substitution 1:

自由 “Freedom”

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Example Substitution 1:

自由

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CENSORED

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Example Substitution 1:

自由
目田

“Freedom”

“Eye field”

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Example Substitution 1:

自由
目田

“Freedom”

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“Eye field” (nonsensical)

Thresher: Finding Those Hiding in Plain Sight

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和谐

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

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Modern Analytics to Improve Student Learning

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 - Want to try it here? see Perusall.com

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- *Distracts*; redirects public attention from criticism and central issues to *cheerleading* and positive discussions of valence issues

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For more information

GaryKing.org

Institute for Quantitative Social Science
Harvard University