Big Data is Not About the Data!

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Institute for Quantitative Social Science
Harvard University

Talk at the *MIT Analytics Lab*, 9/29/2015

[1] GaryKing.org

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

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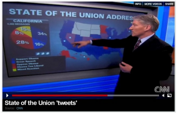

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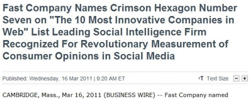

Fast Company Names Crimson Hexagon Number Seven on "The 10 Most Innovative Companies in Web" List Leading Social Intelligence Firm Recognized For Revolutionary Measurement of Consumer Opinions in Social Media

Published: Wednesday, 16 Mar 2011 | 9:20 AM ET

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

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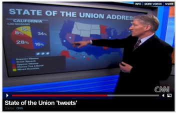

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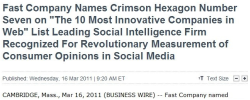

Fast Company Names Crimson Hexagon Number Seven on "The 10 Most Innovative Companies in Web" List Leading Social Intelligence Firm Recognized For Revolutionary Measurement of Consumer Opinions in Social Media

Published: Wednesday, 16 Mar 2011 | 9:20 AM ET

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

2. Worldwide cause-of-death estimates for World Health Organization

The Solvency of Social Security

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  - $\rightsquigarrow$ Trust fund needs $\approx$ \$800 billion more than SSA thought
  - Other applications to insurance industry, public health, etc.

Following Conversations that Hide in Plain Sight

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Example Substitution 1:

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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 “Freedom” CENSORED

目田

Following Conversations that Hide in Plain Sight

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自由	“Freedom”	CENSORED
目田	“Eye field”	

Following Conversations that Hide in Plain Sight

Example Substitution 1:

自由	“Freedom”	CENSORED
目田	“Eye field”	(nonsensical)

Following Conversations that Hide in Plain Sight

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Example Substitution 2:

和谐

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自由	“Freedom”	CENSORED
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和谐	“Harmonious [Society]”	(official slogan)

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

Example Insights from Computer-Assisted Reading

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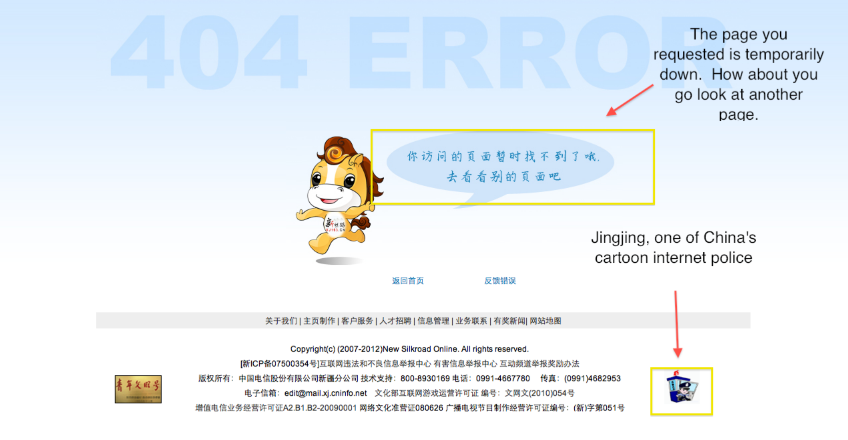
- We had the content of millions of censored Chinese posts!

Censorship is not Ambiguous: Example Error Page



404 ERROR

你访问的页面暂时找不到了哦,
去看看别的页面吧

The page you requested is temporarily down. How about you go look at another page.

Jingjing, one of China's cartoon internet police

返回首页 反馈错误

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电子信箱：edit@mail.xj.cninfo.net 文化部互联网游戏运营许可证 编号：文网文(2010)054号
增值电信业务经营许可证A2.B1.B2-20090001 网络文化准营证080626 广播电视节目制作经营许可证编号：(新)字第051号

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  - (paradoxically) very revealing about the goals, intentions, and actions of the Chinese leadership

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  - Thus, we can use criticism & censorship to predict:

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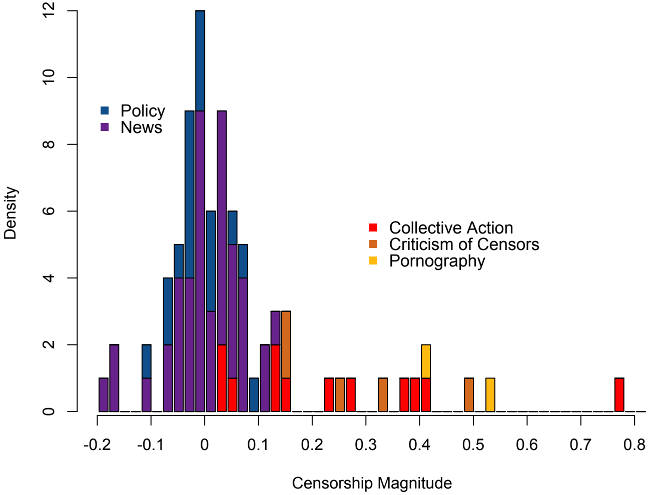
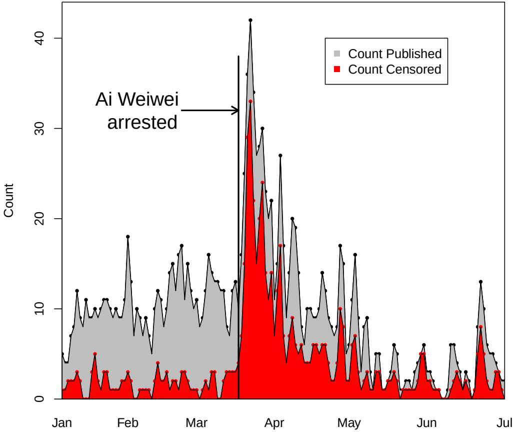
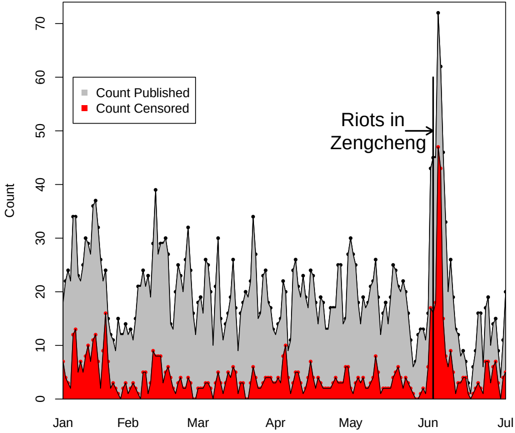
What Types of Events Are Censored?



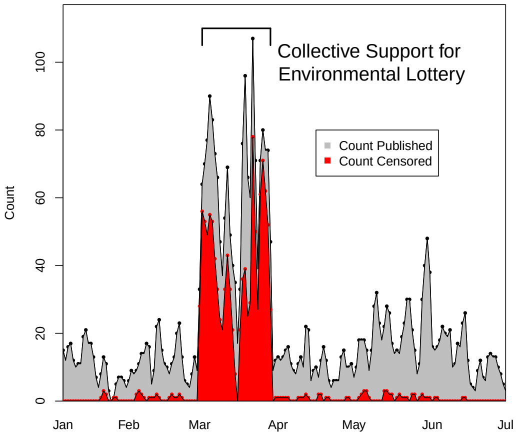
Censoring Collective Action: Ai Weiwei's Arrest



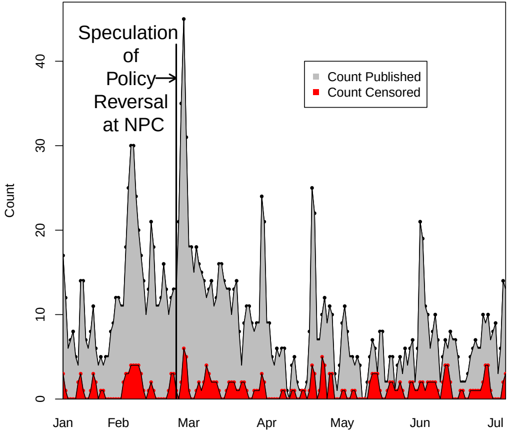
Censoring Collective Action: Riots in Zencheng



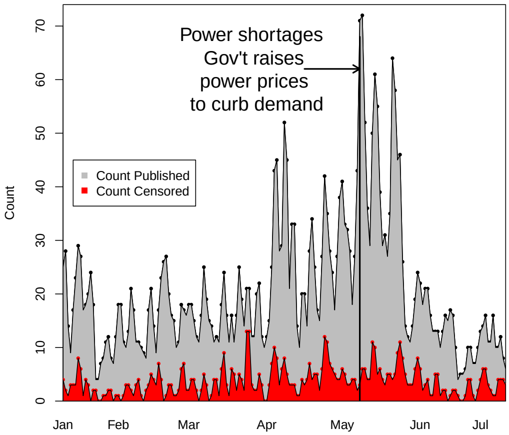
Censoring Collective Action: Environmental Lottery Rally



Low Censorship on Policy: One Child



Low Censorship on News: Power Prices



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For more information

GaryKing.org