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

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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

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

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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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Example Substitution 1:

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Example Substitution 1:

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

Example Substitution 1: Homograph

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

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For more information

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