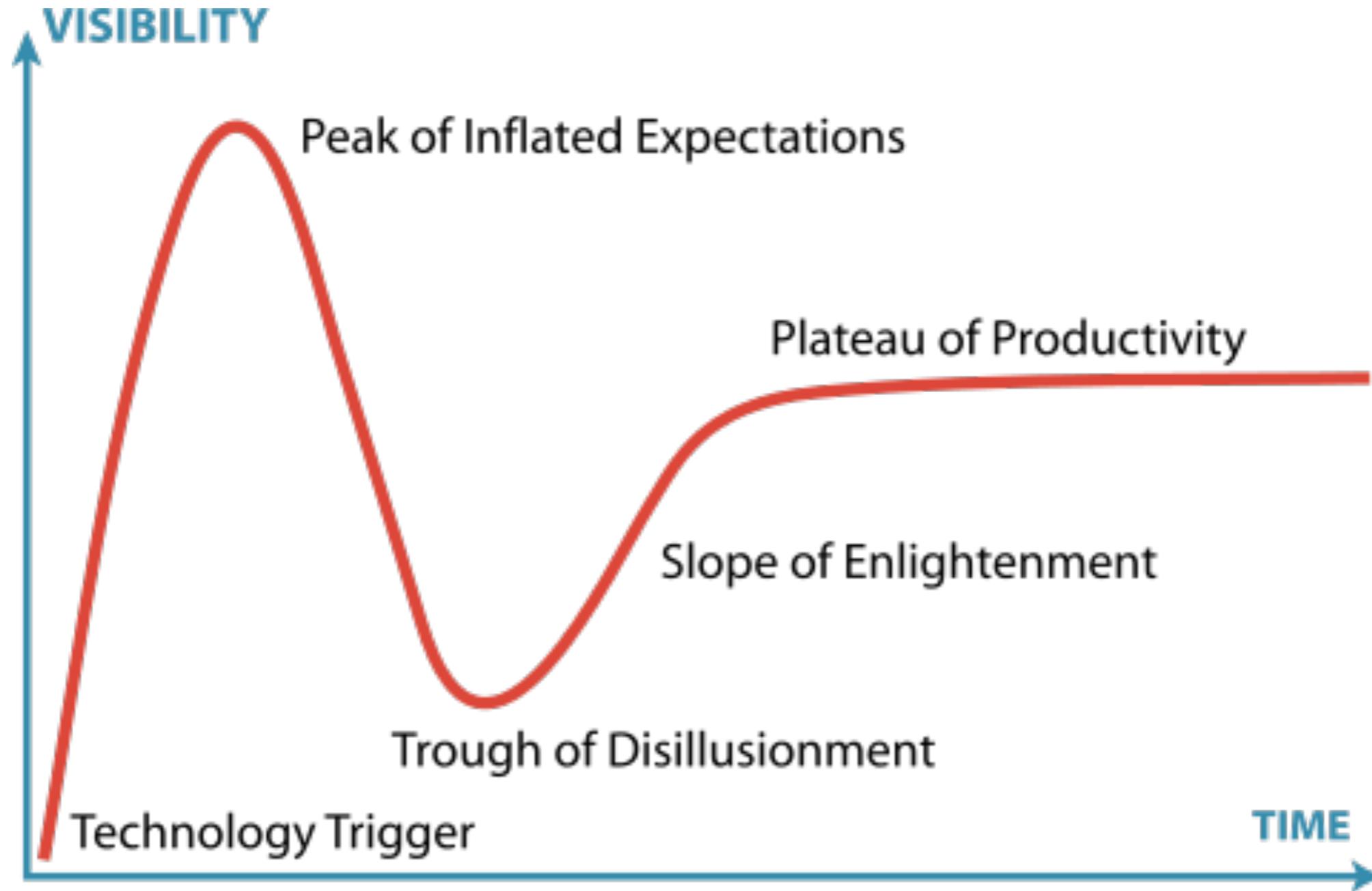


CS7280
TOPICS IN STATISTICS AND
DATA ANALYSIS

GARTNER HYPE CYCLE



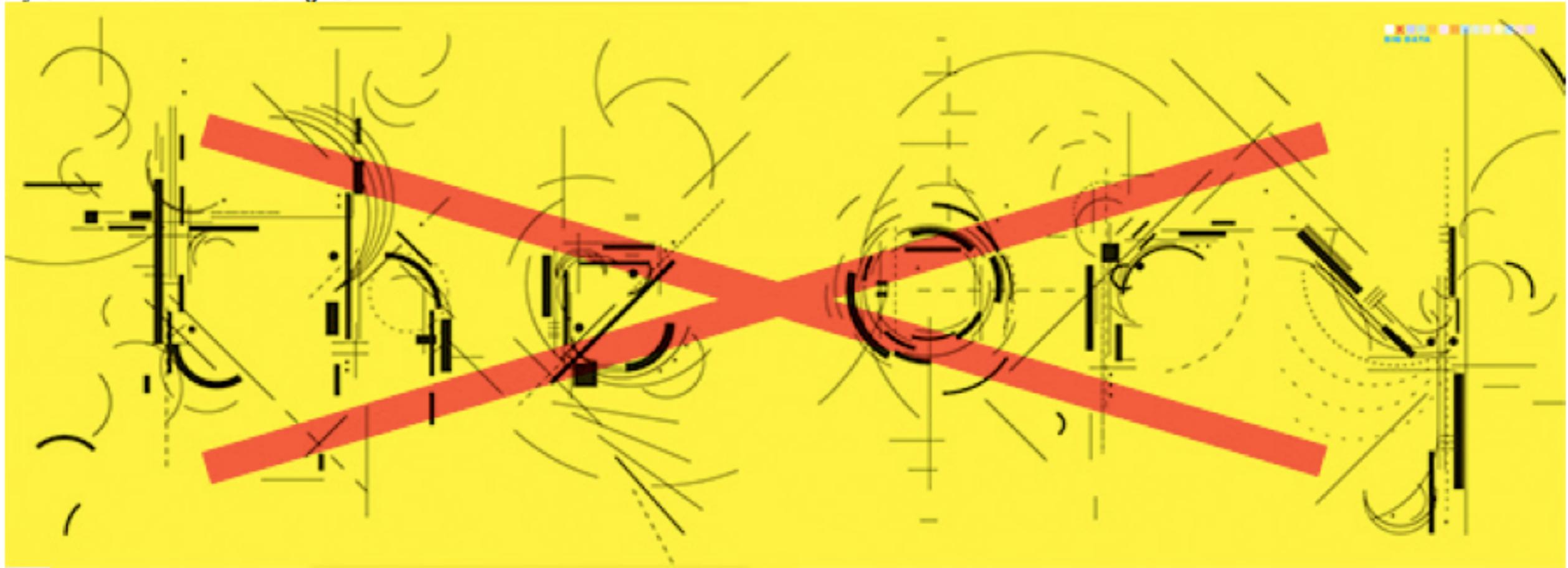
THE END OF THEORY?

WIRED MAGAZINE: 16.07

Science : Discoveries 

The End of Theory: The Data Deluge Makes the Scientific Method Obsolete

By Chris Anderson  06.23.08



THE END OF THEORY?

- Old science: models
 - ◆ All models are wrong, but some are useful (George Box)
- New science: just data
 - ◆ Do not need to know culture and conventions
 - ◆ Do not need to know the underlying mechanisms
 - ◆ All models are wrong, and increasingly you can succeed without them
- What is the new scientific method?
 - ◆ Statistical tools will crunch the numbers and offer a new way of understanding the world
 - ◆ ‘There's no reason to cling to our old ways. It's time to ask: What can science learn from Google?’

The Parable of Google Flu: Traps in Big Data Analysis

Large er
avoidabl
of big da

David Lazer,^{1,2*} Ryan Kennedy,^{1,3,4} Gary King,³ Alessandro Vespignani^{5,6,3}

In February 2013, Google Flu Trends (GFT) made headlines but not for a reason that Google executives or the creators of the flu tracking system would have hoped. *Nature* reported that GFT was predicting more than double the proportion of doctor visits for influenza-like illness (ILI) than the Centers for Disease Control and Prevention (CDC), which bases its estimates on surveillance reports from laboratories across the United States (1, 2). This happened despite the fact that GFT was built to predict CDC reports. Given that GFT is often held up as an exemplary use of big data (3, 4), what lessons can we draw from this error?

The problems we identify are not limited to GFT. Research on whether search or social media can



GOOGLE FLU TRENDS (GFT)

*Uses search keywords to predict reports by
Center for Disease Control*

- **Methodology**

- ◆ First version: find best matches among 50 million searchers to explain 1152 flu cases
- ◆ Later versions: improvements to eliminate other seasonal trend (e.g. basketball)

- **Underwhelming results**

- ◆ 2009: missed nonseasonal 2009 H1N1 influenza
- ◆ 2013: overestimated the proportion of doctor visits
- ◆ Not better than simpler predictions

- **Reasons for the challenges**

- ◆ Overfitting and confounding, lacks subject matter info
- ◆ Algorithm dynamics
 - changes to both queries and algorithms
- ◆ Cannot easily replicate the search results, poor documentation.

GARTNER HYPE CYCLE

Emerging technologies 2014



Plateau will be reached in:

○ less than 2 years

● 2 to 5 years

● 5 to 10 years

▲ more than 10 years

⊗ obsolete before plateau

SPECIFIC ISSUES

- Large data hide true quantitative signal
- Large data generate spurious correlations
- Large data help mistake correlation for causation
- Large data amplify bias and confounding

‘A big computer, a complex algorithm and a long time does not equal science’

— Robert Gentleman

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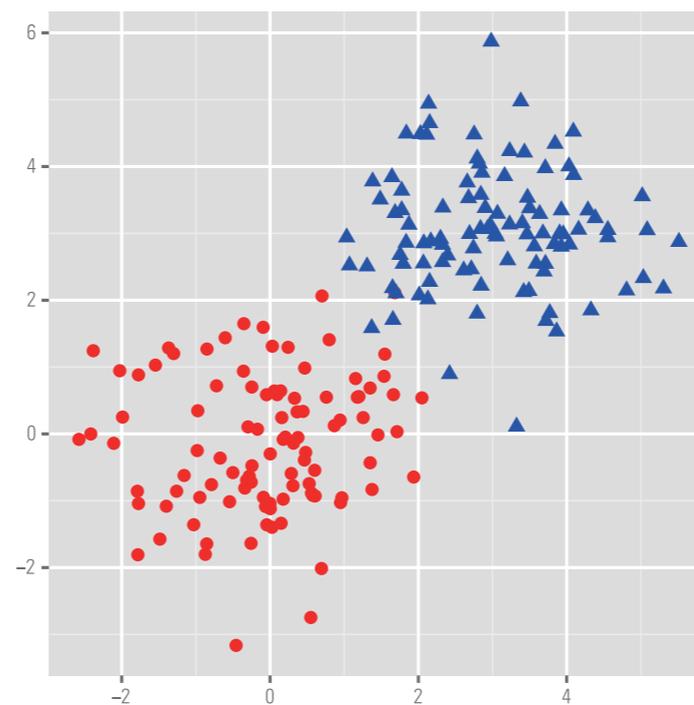
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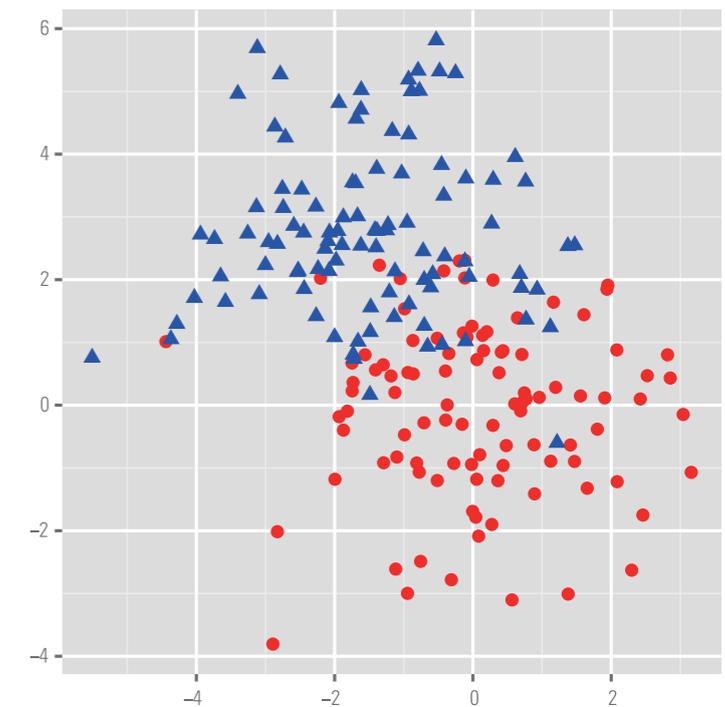
LARGE DATA HIDE SIGNAL

- A simulation study
 - 100 subjects
 - 2 groups
 - 10 differentially abundant proteins
- Plot the first two principle components
 - Expect good separation between the groups

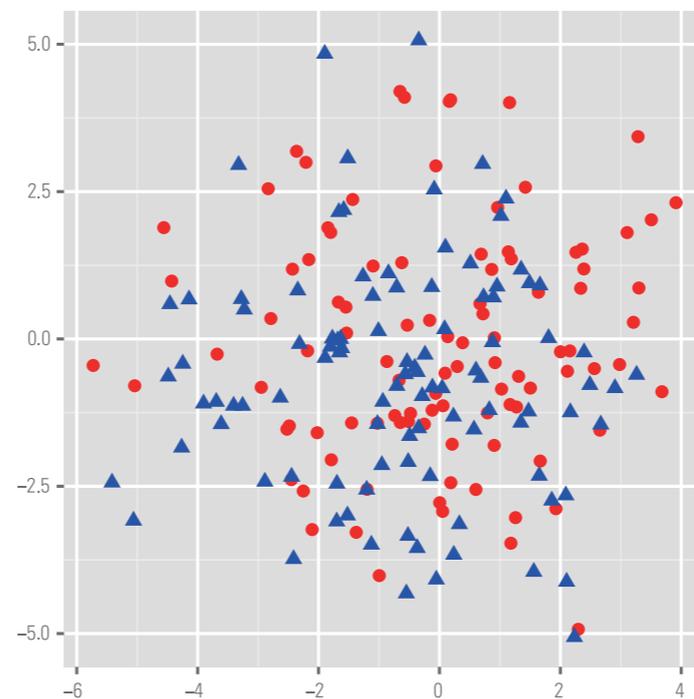
2 proteins



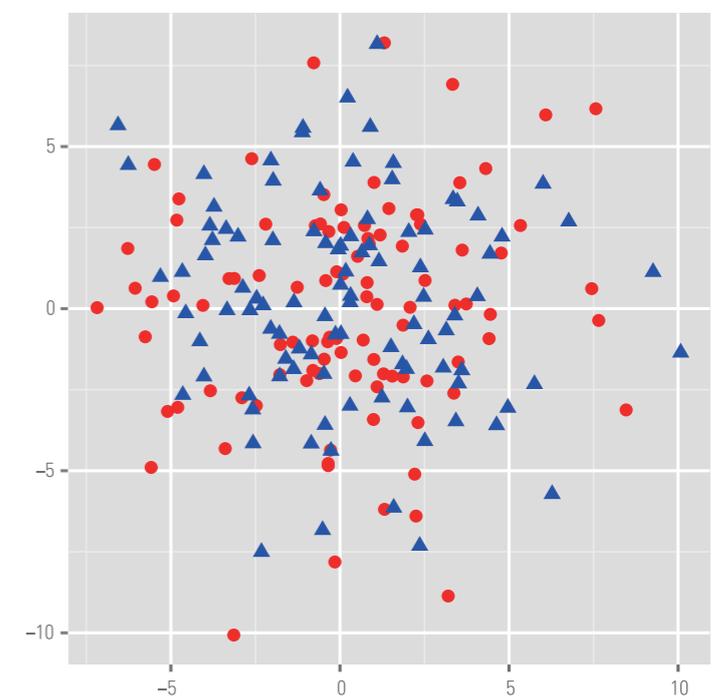
40 proteins



200 proteins



1,000 proteins



‘We are drowning in information but starved for knowledge’
— John Naisbitt

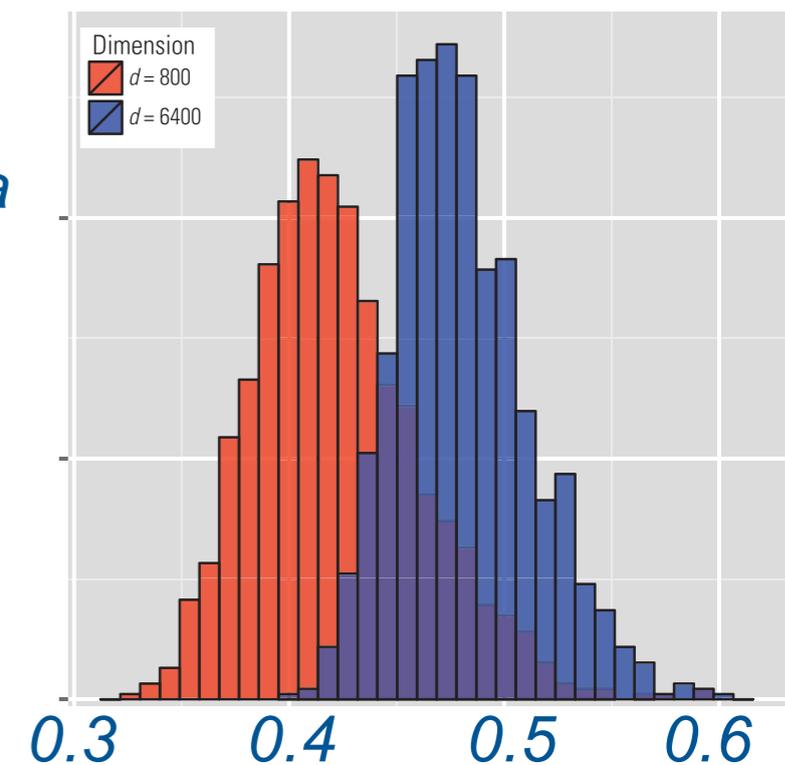
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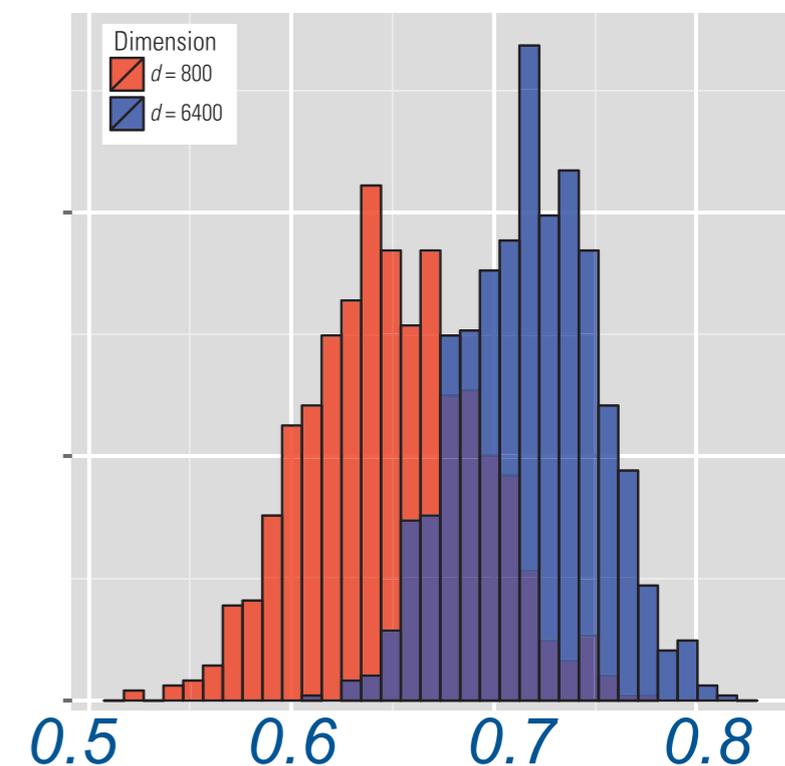
LARGE DATA HIDE SIGNAL

- A simulation study
 - 60 subjects with quantitative phenotype
 - red: 800 proteins unrelated to phenotype
 - blue: 6400 proteins unrelated to phenotype
- Repeat 1,000 times

Max correlation between the phenotype and a protein



Max correlation between the phenotype and a linear combination of 4 proteins



‘With four parameters I can fit an elephant, and with five I can make him wiggle his trunk’

— John von Neumann

Drawing an elephant with four complex parameters

Jürgen Mayer

Max Planck Institute of Molecular Cell Biology and Genetics, Pfotenhauerstr. 108, 1 Germany

Khaled Khairy

European Molecular Biology Laboratory, Meyerhofstraße. 1, 69117 Heidelberg, Ger

Jonathon Howard

Max Planck Institute of Molecular Cell Biology and Genetics, Pfotenhauerstr. 108, 1 Germany

(Received 20 August 2008; accepted 5 October 2009)

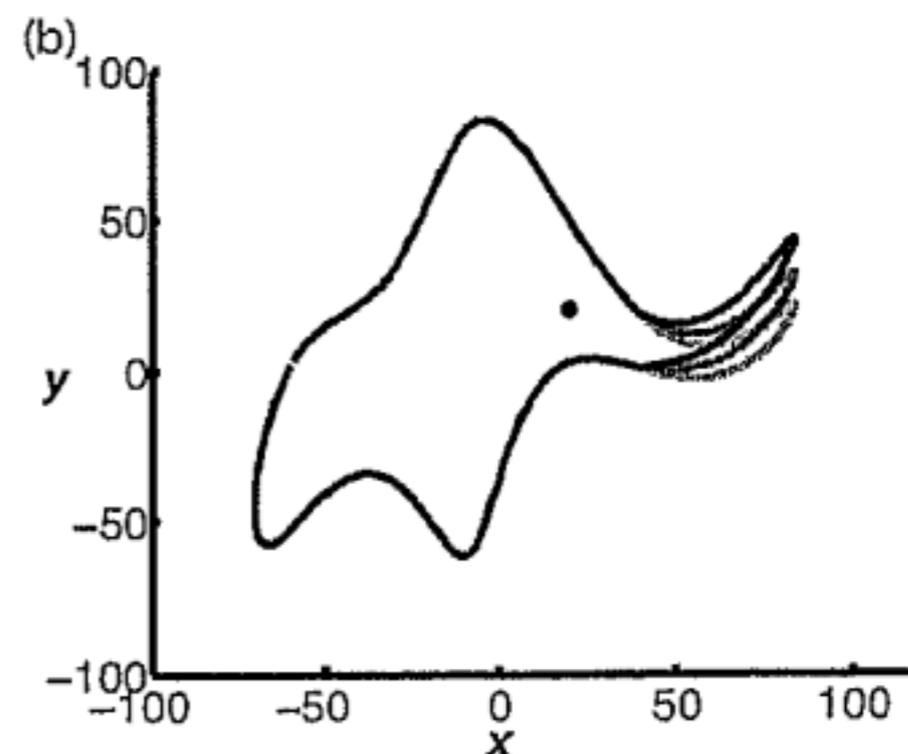
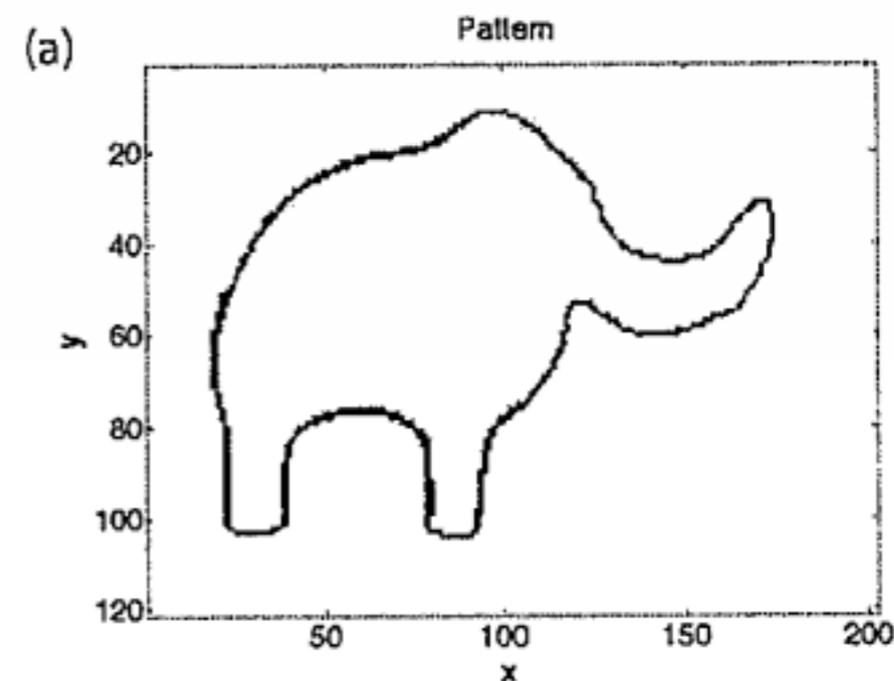
$$x(t) = \sum_{k=0}^{\infty} (A_k^x \cos(kt) + B_k^x \sin(kt)),$$

$$y(t) = \sum_{k=0}^{\infty} (A_k^y \cos(kt) + B_k^y \sin(kt)),$$

Table I. The five complex parameters p_1, \dots, p_5 that encode the elephant including its wiggling trunk.

Parameter	Real part	Imaginary part
$p_1 = 50 - 30i$	$B_1^x = 50$	$B_1^y = -30$
$p_2 = 18 + 8i$	$B_2^x = 18$	$B_2^y = 8$
$p_3 = 12 - 10i$	$A_3^x = 12$	$B_3^y = -10$
$p_4 = -14 - 60i$	$A_5^x = -14$	$A_1^y = -60$
$p_5 = 40 + 20i$	Wiggle coeff. = 40	$x_{\text{eye}} = y_{\text{eye}} = 20$

Fourier coordinate expansion with complex numbers as parameters



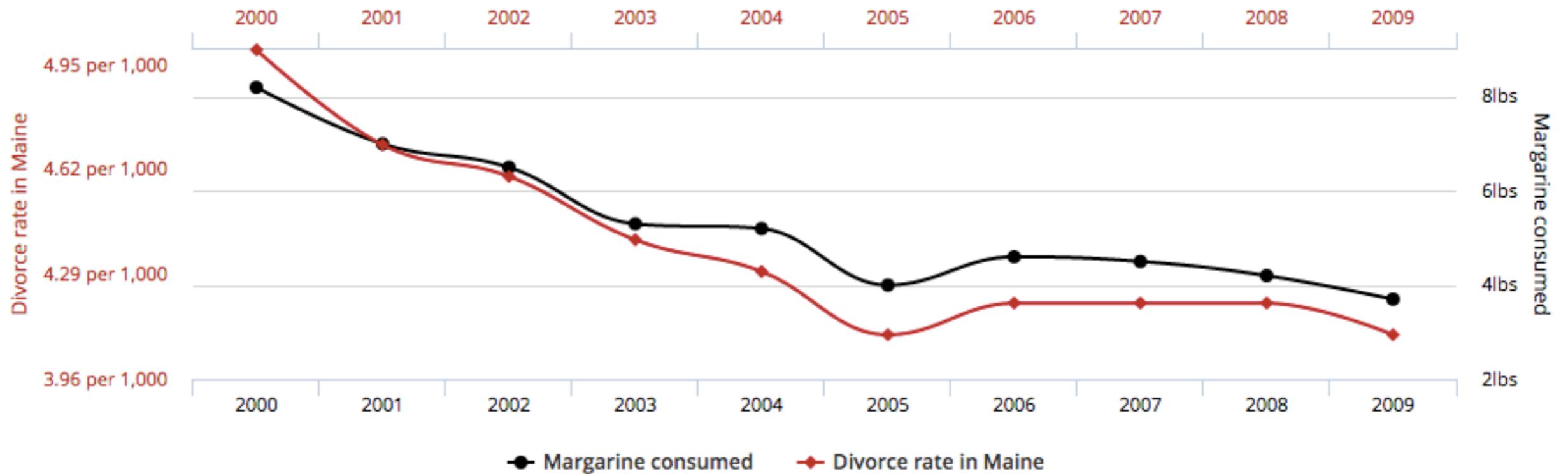
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SPURIOUS CORRELATIONS ABOUND

Divorce rate in Maine correlates with Per capita consumption of margarine

Correlation: 99.26% (r=0.992558)



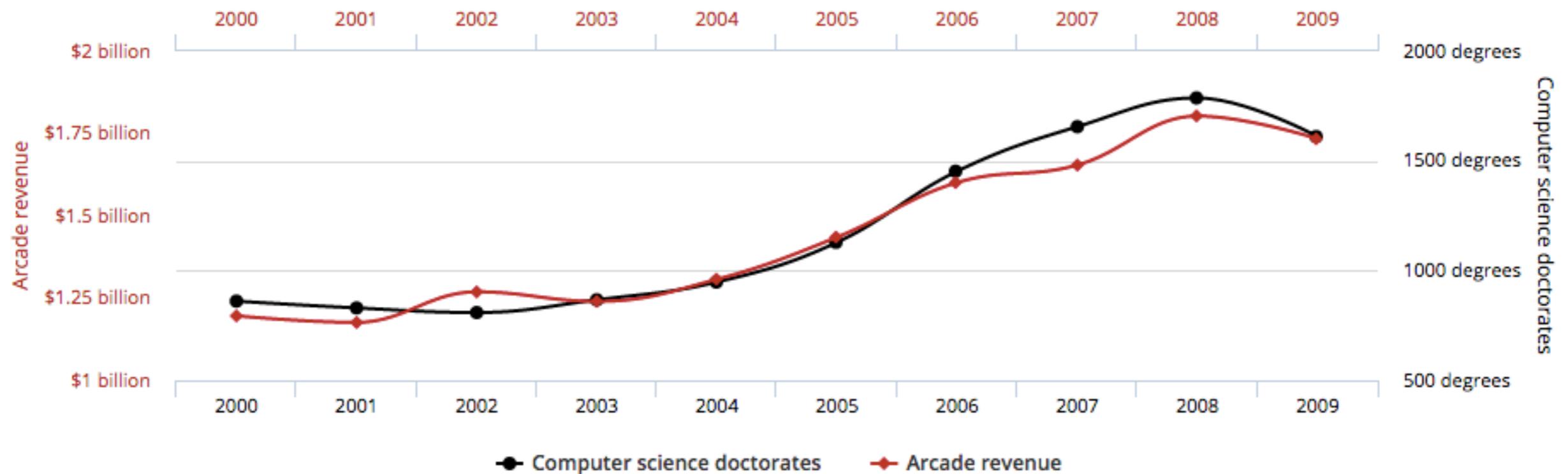
tylervigen.com

Data sources: National Vital Statistics Reports and U.S. Department of Agriculture

SPURIOUS CORRELATIONS ABOUND

Total revenue generated by arcades
correlates with
Computer science doctorates awarded in the US

Correlation: 98.51% ($r=0.985065$)



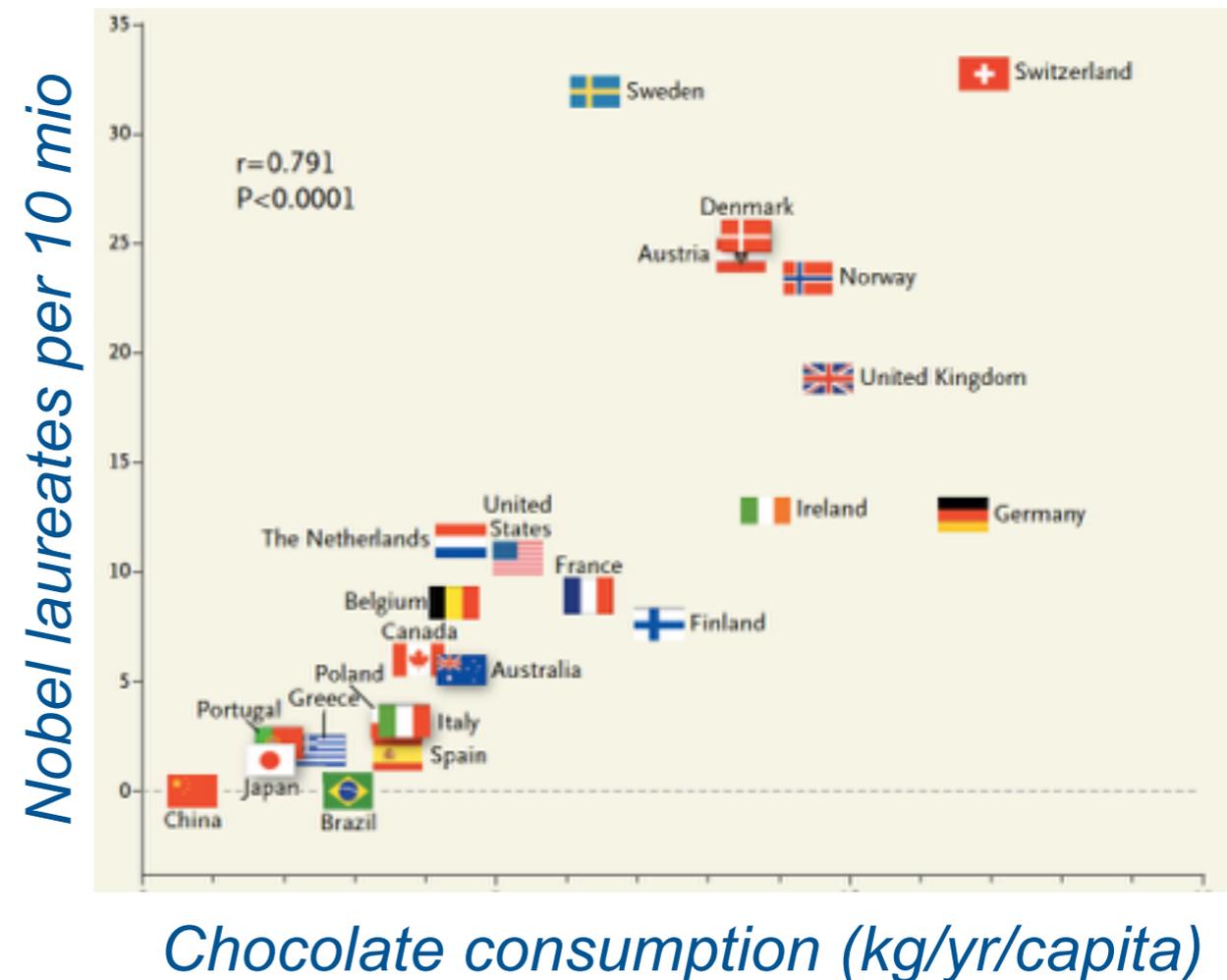
tylervigen.com

Data sources: U.S. Census Bureau and National Science Foundation

SPURIOUS CORRELATIONS ABOUND

Easy to dismiss when we understand the context

- Premier medical journal
 - *Nobel prize is related to cognitive ability*
 - *flavanols (organic molecules present in chocolate) are linked to cognitive ability*
- Technical flows
 - *Nobel prize winners between 1900-2011*
 - *Chocolate consumption after 2002*
 - *Countries with many Nobel prizes have a high Human Development Index and high per capita income*

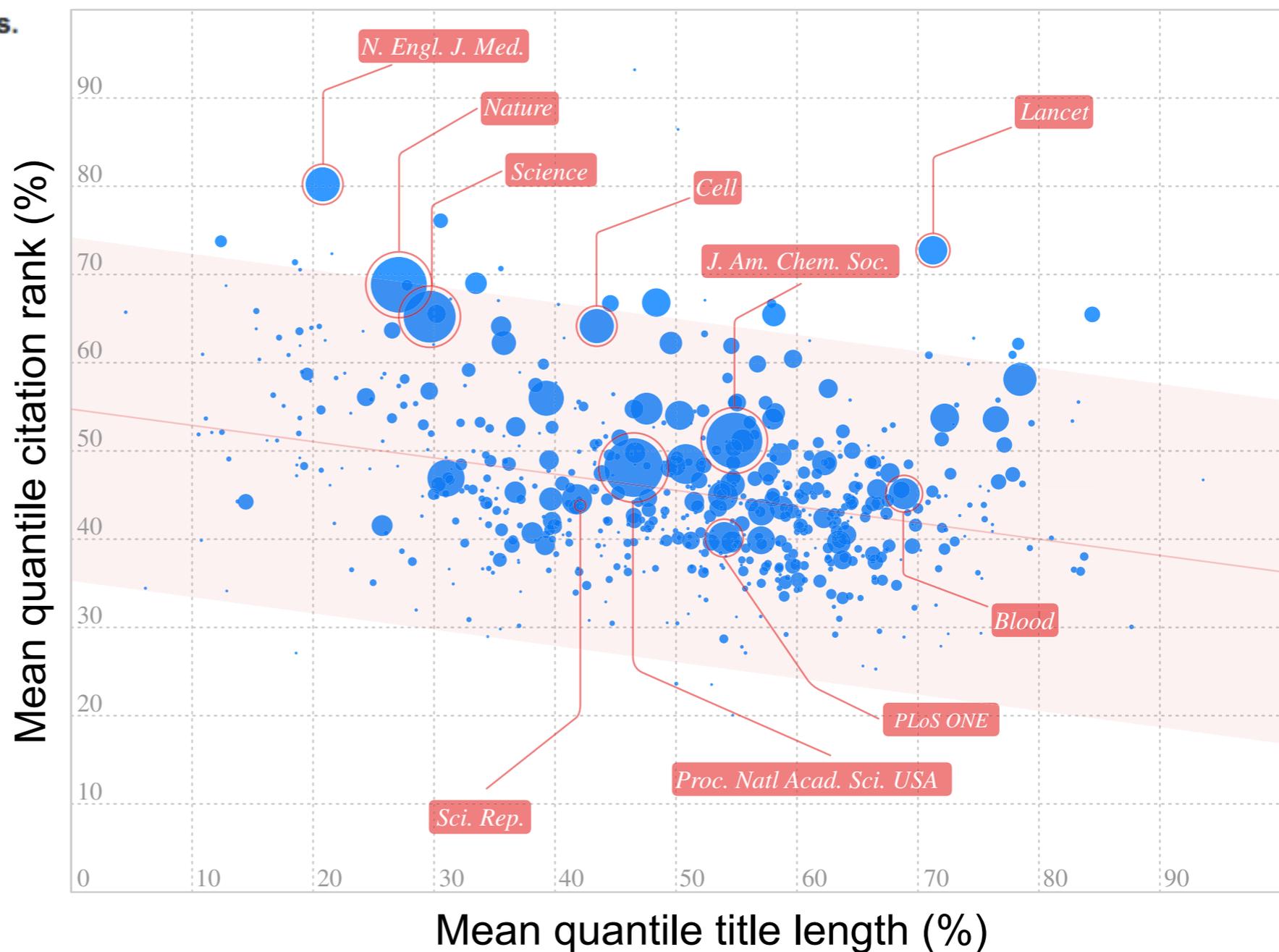




Papers with shorter titles get more citations

Intriguing correlation mined from 140,000 papers.

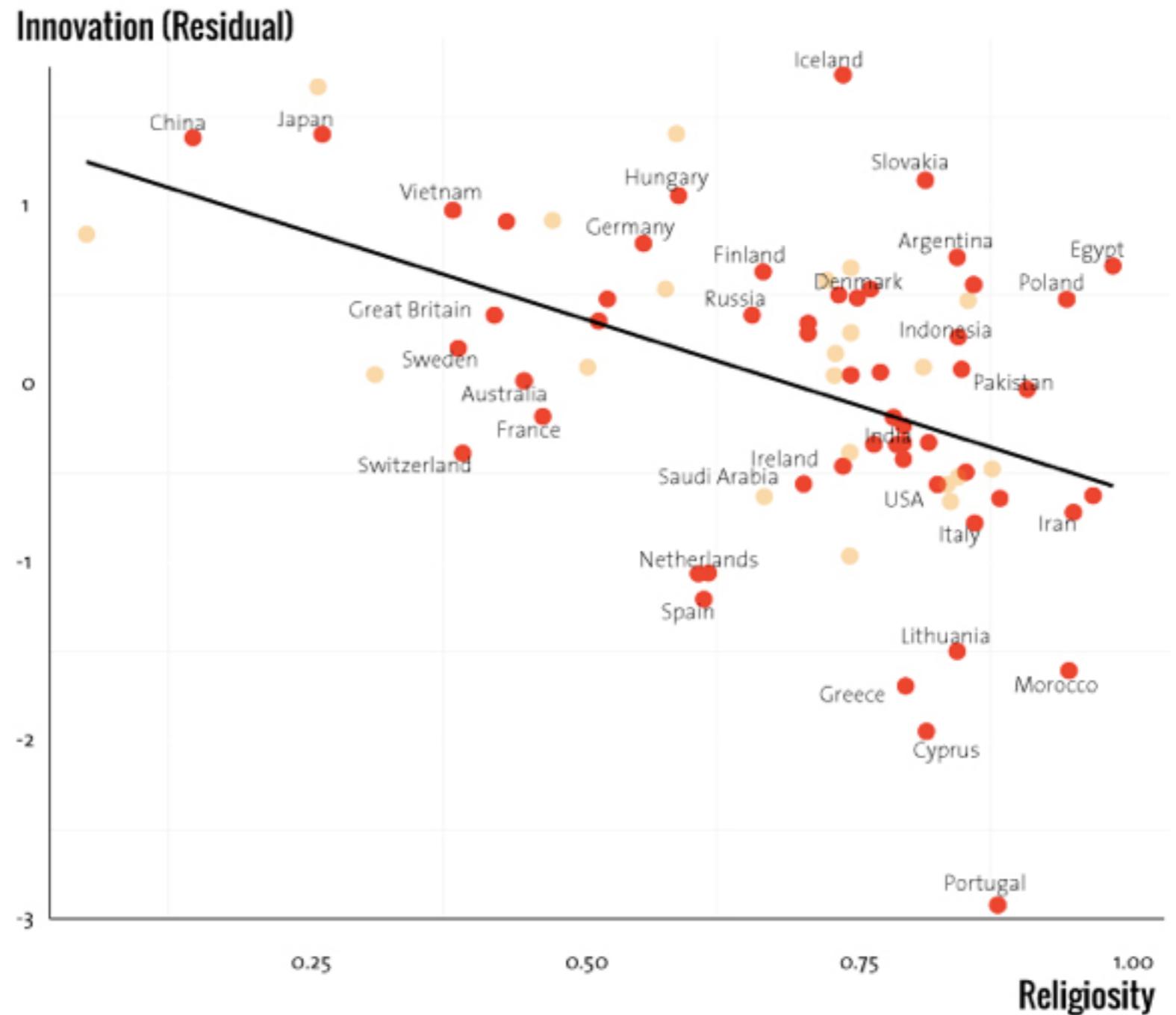
Boer Deng



A. Letchford et al., Royal Society Publishing, 2015

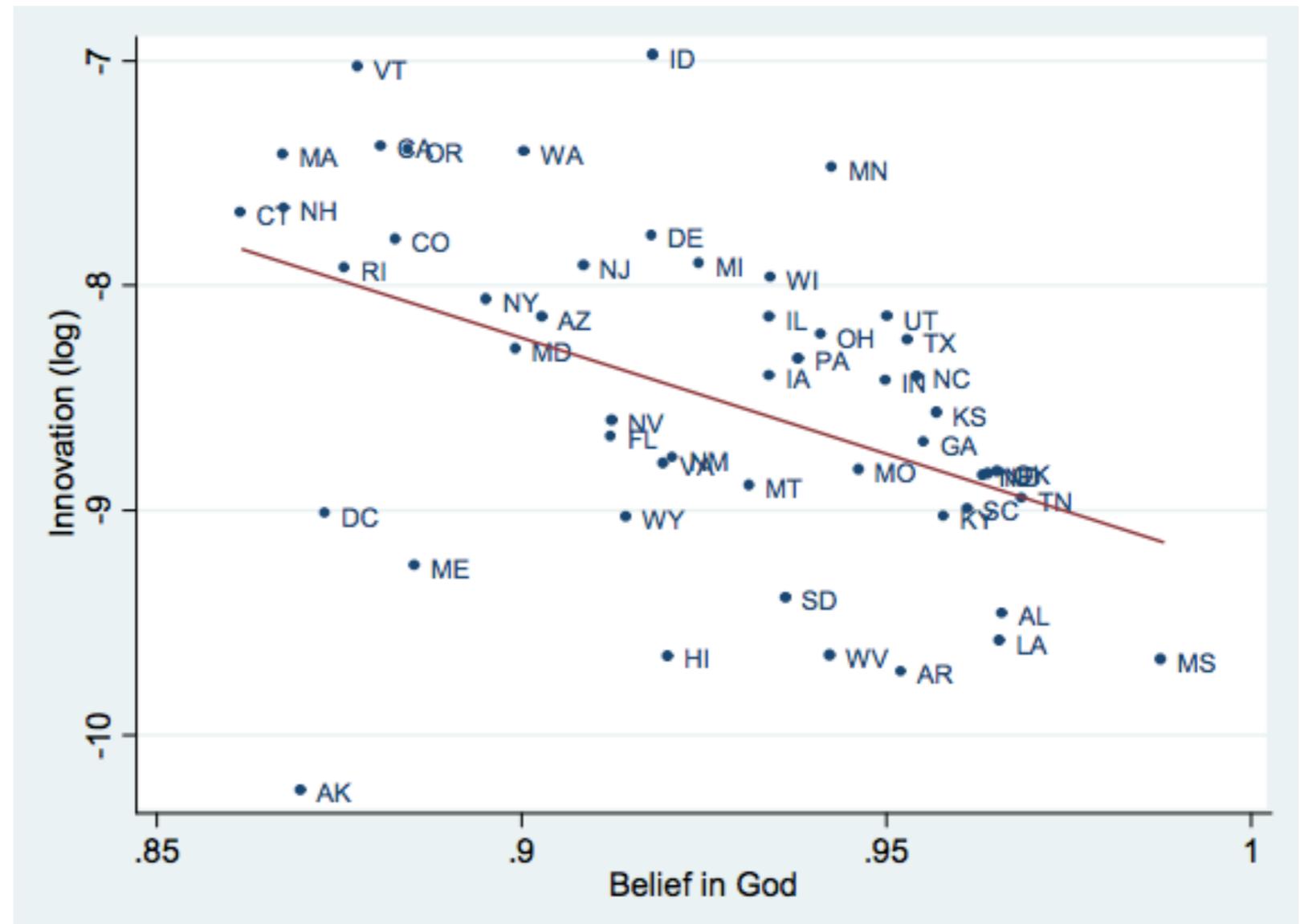
SPURIOUS CORRELATIONS ABOUND

Not easy to dismiss when the context is unknown



SPURIOUS CORRELATIONS ABOUND

Not easy to dismiss when the context is unknown



‘Correlation doesn’t imply causation, but it does waggle its eyebrows suggestively and gesture furtively while mouthing ‘look over there’

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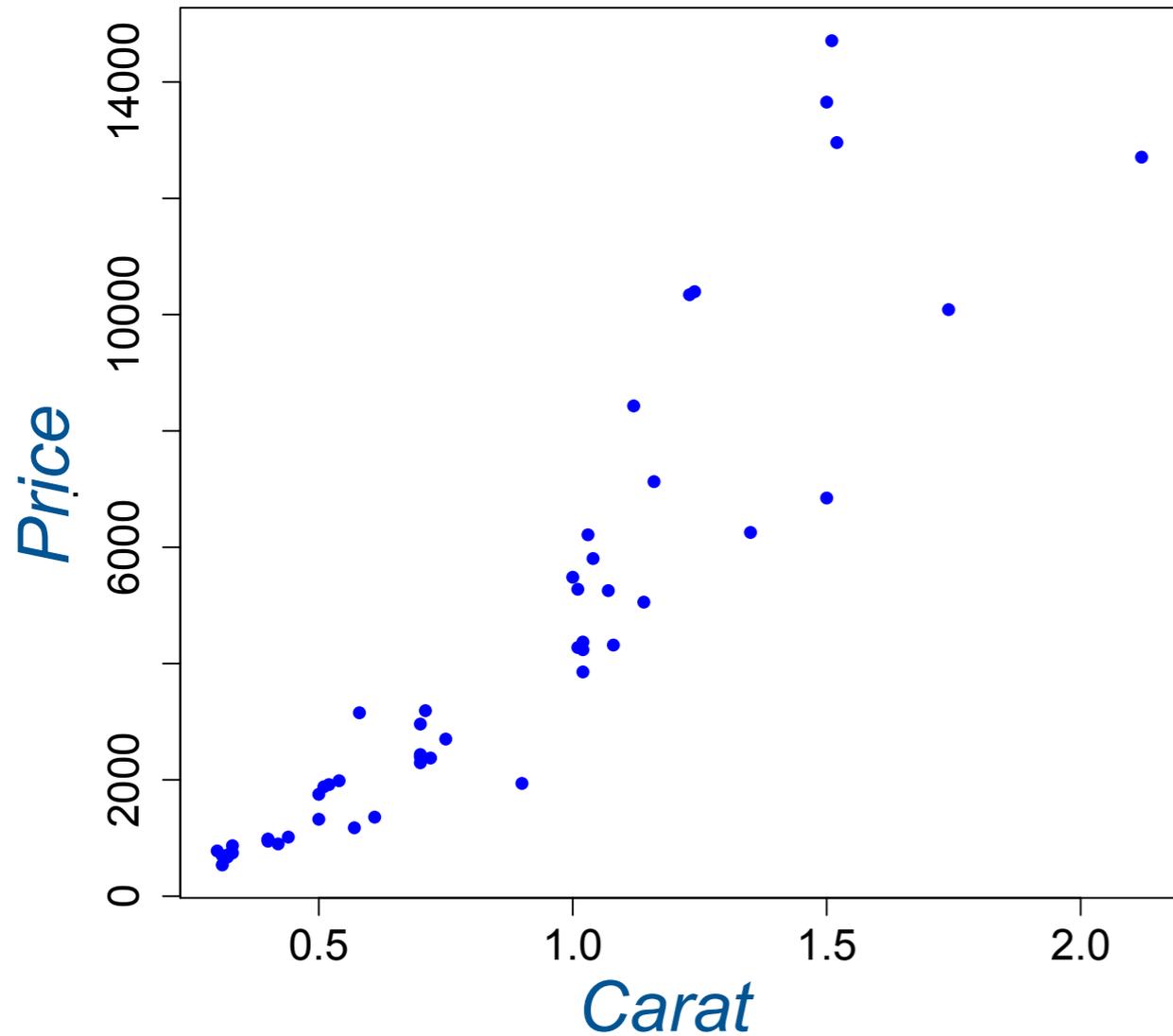


EXAMPLE

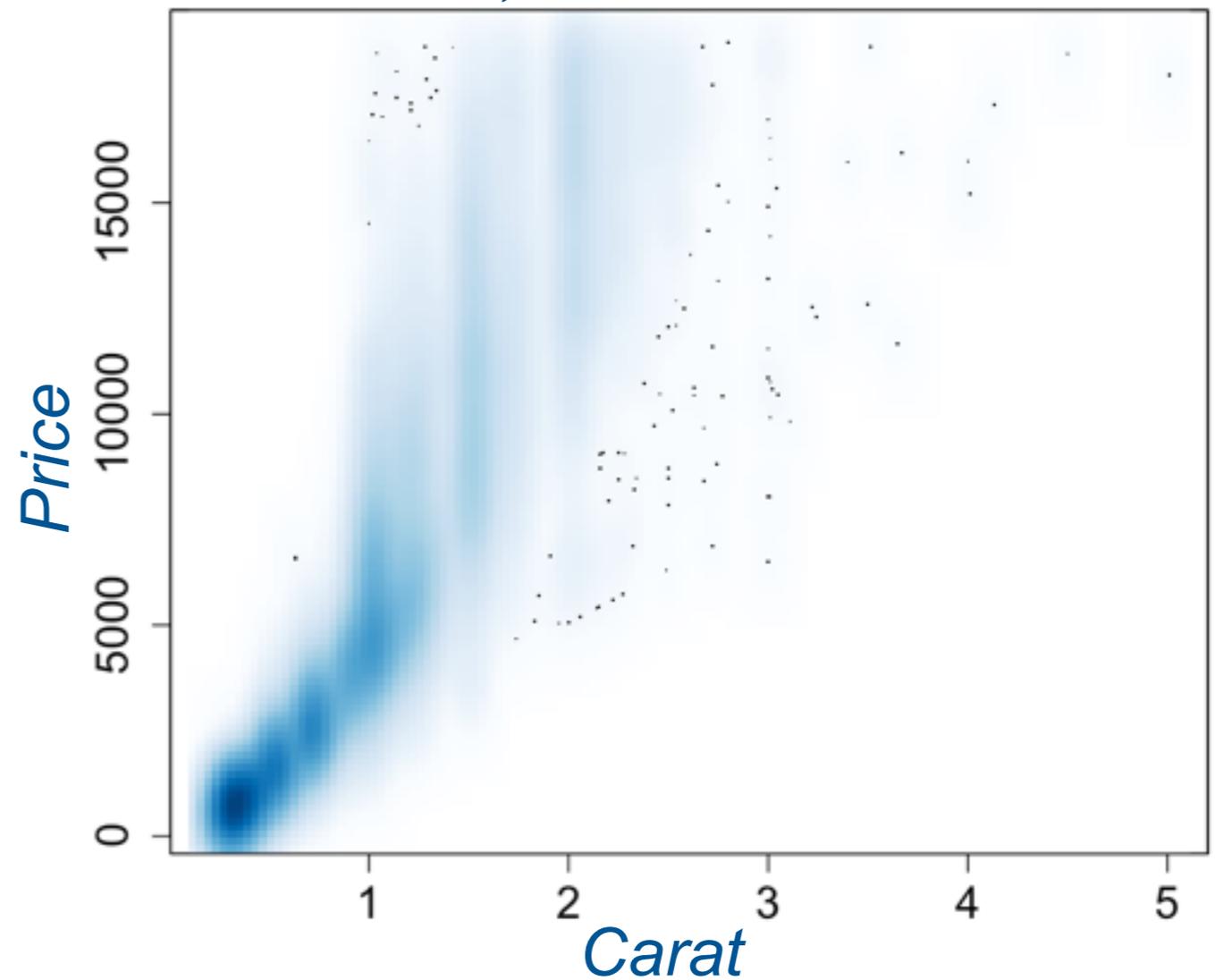
53,940 diamonds

carat	color	price
0.23	E	326
0.21	E	326
0.23	E	327
0.29	I	334
0.31	J	335
.....		

50 diamonds



53,940 diamonds





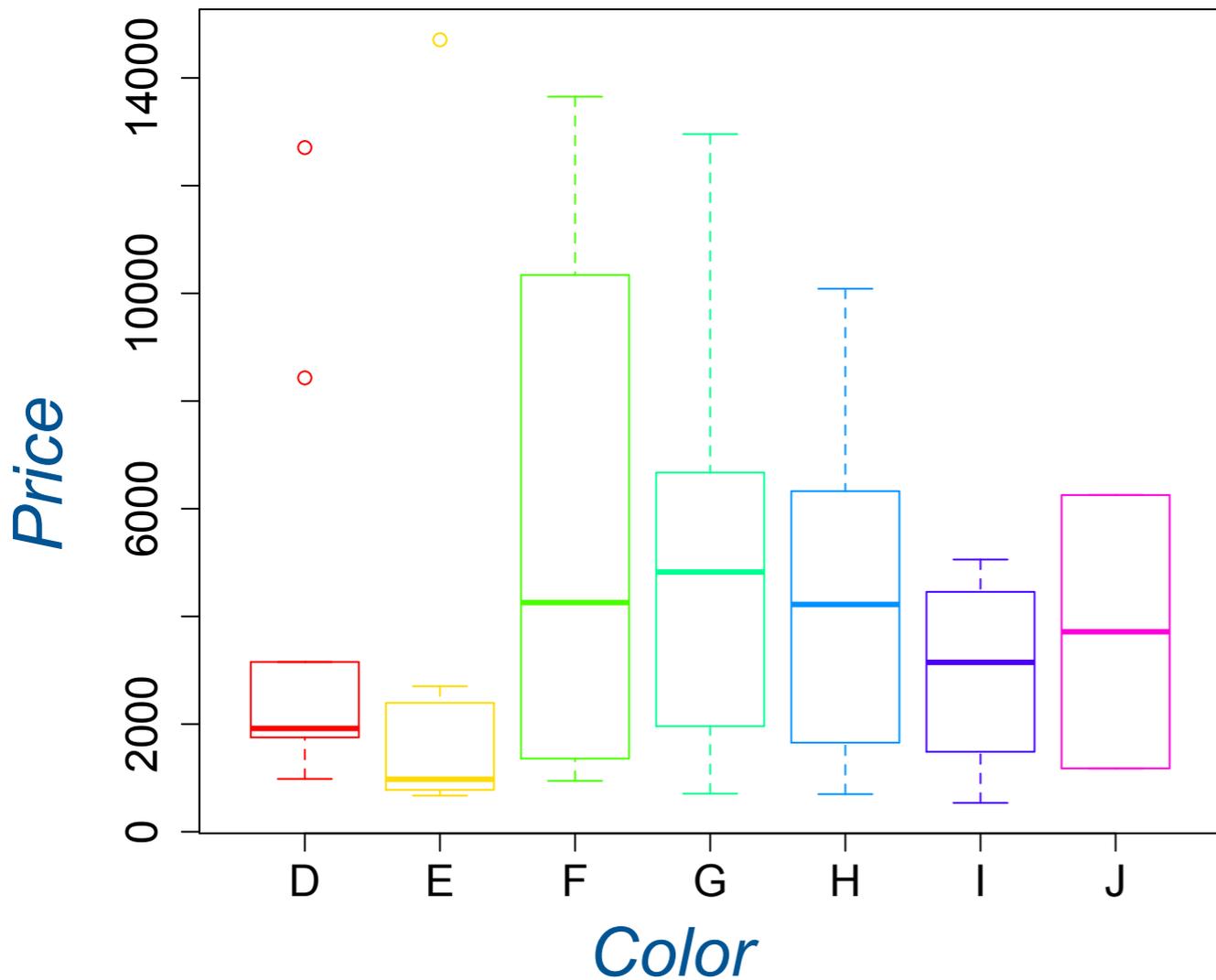
EXAMPLE

53,940 diamonds

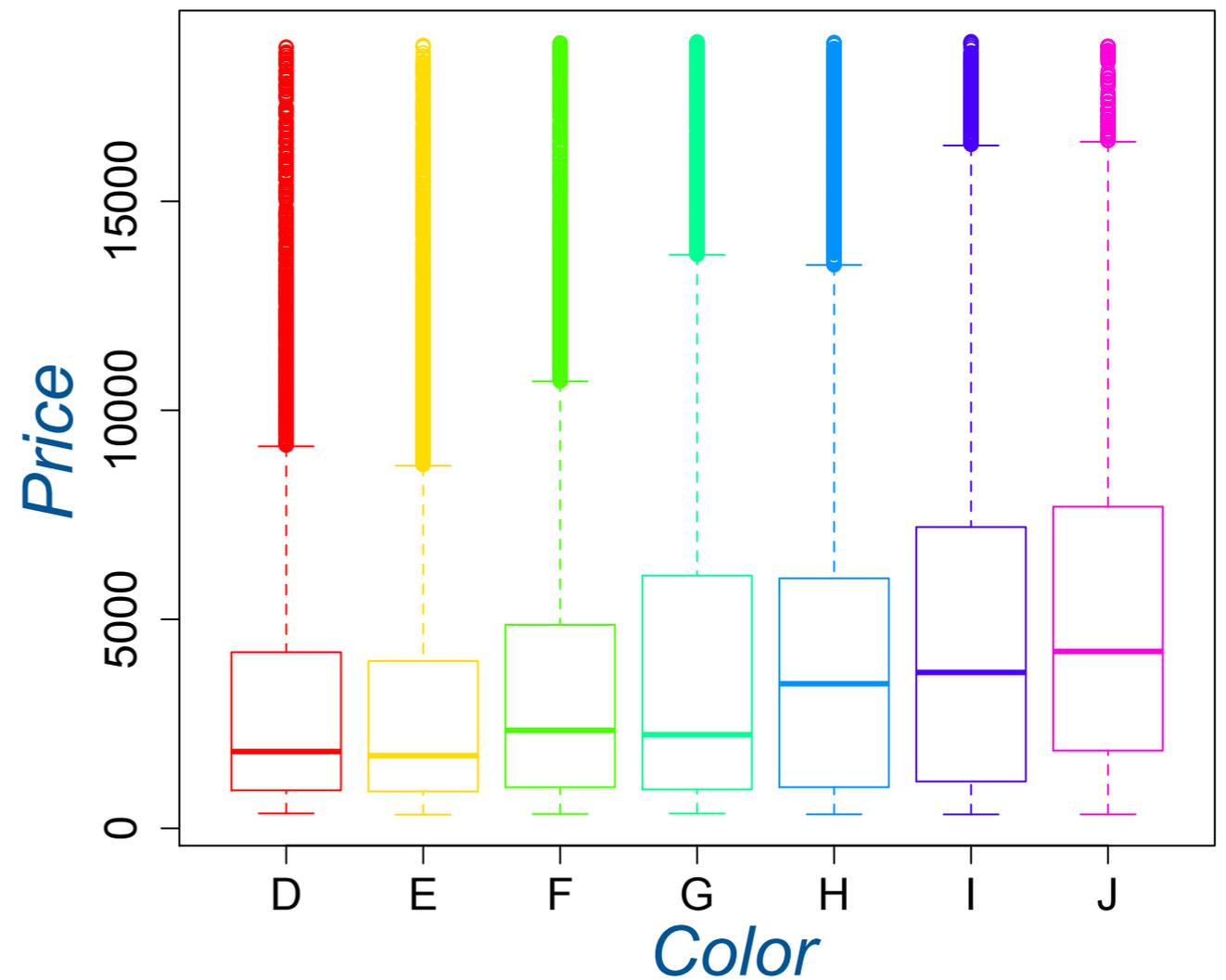
- New discovery!
- ◆ later colors cost more!

carat	color	price
0.23	E	326
0.21	E	326
0.23	E	327
0.29	I	334
0.31	J	335
.....		

50 diamonds



53,940 diamonds



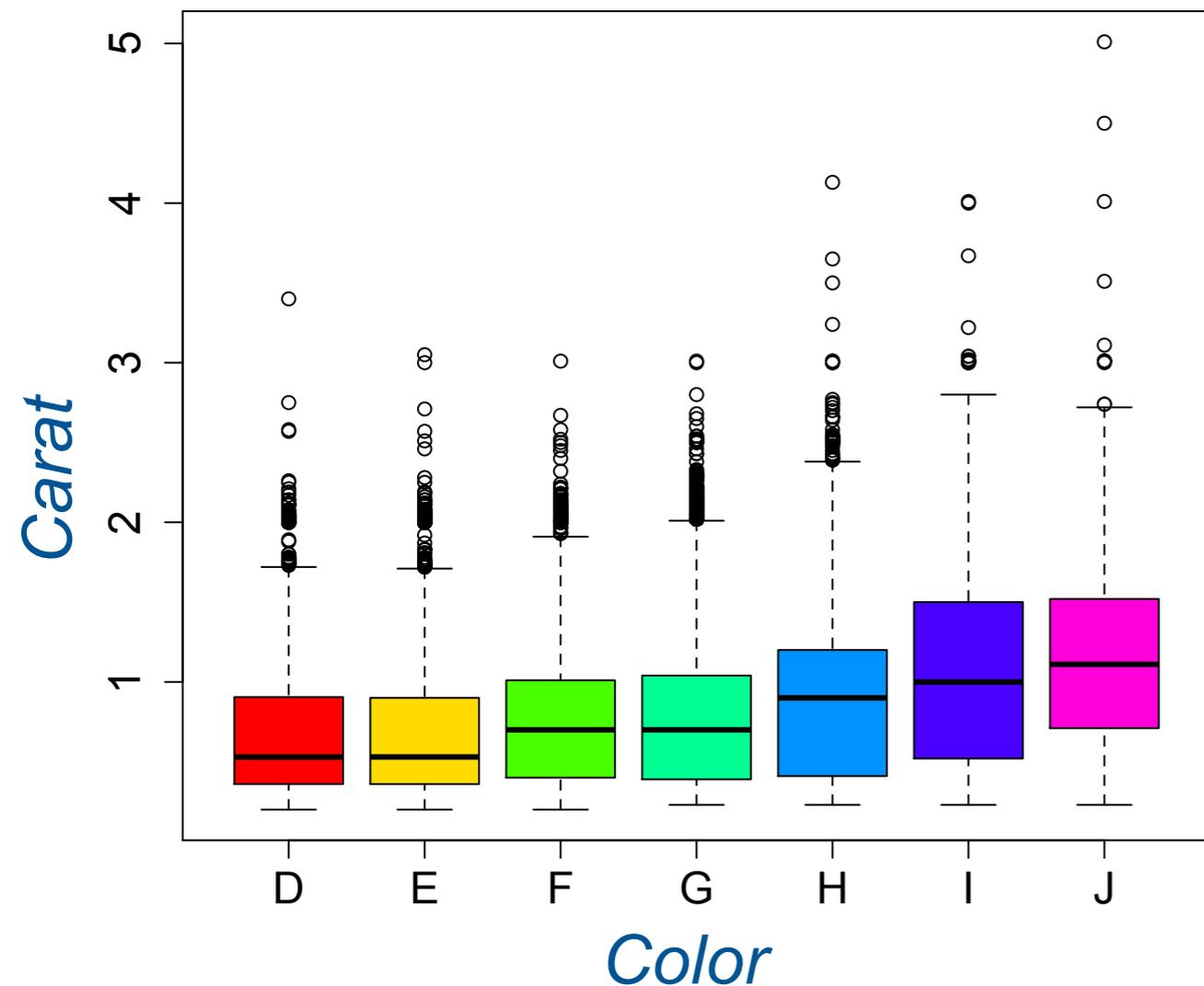


EXAMPLE

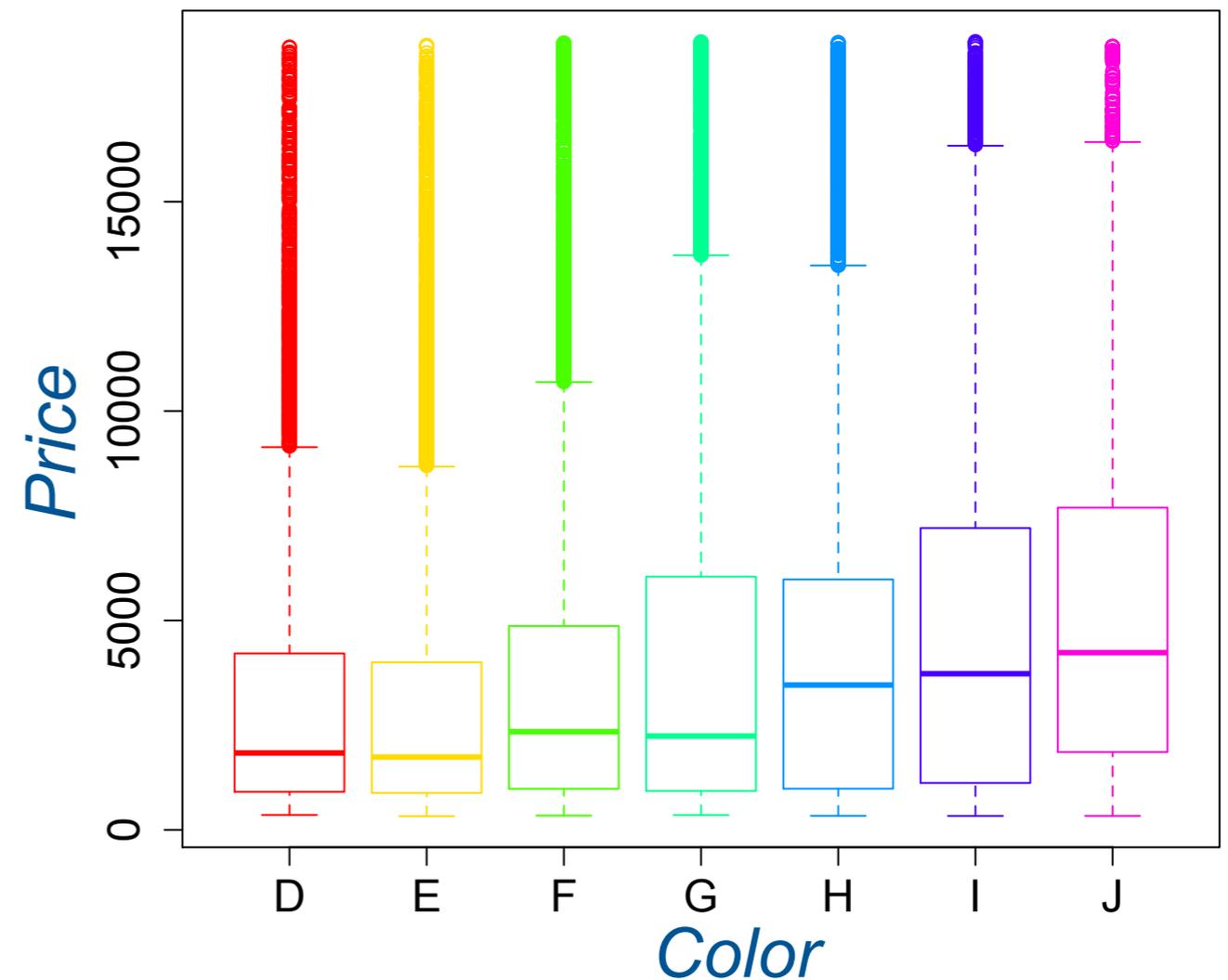
- Subject matter knowledge
 - ◆ later colors are cheaper
 - ◆ they also weigh more
 - ◆ Both color and weight affect price

carat	color	price
0.23	E	326
0.21	E	326
0.23	E	327
0.29	I	334
0.31	J	335
.....		

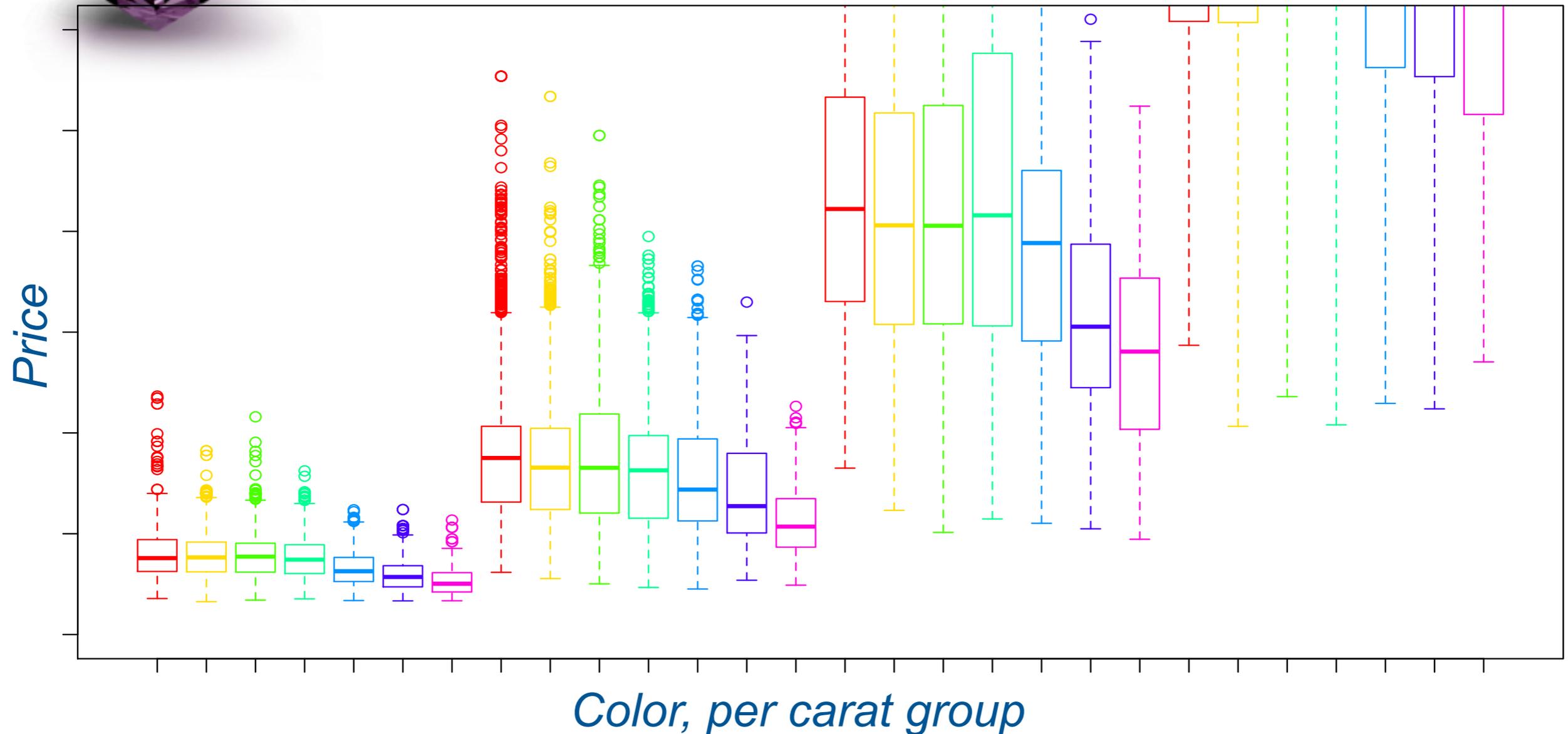
53,940 diamonds



53,940 diamonds



EXAMPLE



‘To call in the statistician after the experiment is done may be no more than asking him to perform a post-mortem examination: he may be able to say what the experiment died of’

— Ronald Fisher

SUMMARY

- More data \neq more information
- We should:
 - ◆ state clearly the scientific question
 - ◆ follow the fundamental principles of experimental design
 - ◆ select methods that are appropriate for the question
 - more complexity does not mean more insight!
 - ◆ use problem-specific information
- Data and algorithms do not substitute thinking through the problem

‘There are no routine statistical questions, only questionable statistical routines’

— D. R. Cox