

Actuarial Research Centre

Institute and Faculty of Actuaries

Big data: the unexpected, the unpredictable, and the unwanted

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The man that it was

Roots of actuarial and statistical work:

- Probability theory, from games of chance
- Data summarisation, from official statistics
- Observed regularities in data
 - Quetelet
 - Sir Edmund Halley and the first life table
 - John Graunt: Bills of Mortality
 - etc



Increasing number of data sources and types with different properties

- Surveys
- Panel data
- Administrative data
- Transaction data
- Web scraped data
- Social media data
-

Experimental/observational Big data Open data etc etc



Today companies like Google, which have grown up in an era of massively abundant data, don't have to settle for wrong models. **Indeed, they don't have to settle for models at all**

Chris Anderson

Google's founding philosophy is that we don't know why this page is better than that one: If the statistics of incoming links say it is, that's good enough Chris Anderson

That's right – *as far as it goes But it does not go far enough*



Statistical models



Making decisions in the modern world:

- Subjective
- Theory-driven models
- Data-driven models

Models vs algorithms

- Algorithms for prediction
- Models for understanding (and prediction)



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Theory-driven example

Model the relationship between the height from which a stone is dropped and the time it takes to hit the ground

→ Data
$$(H_i, t_i)$$
 $i = 1, ..., n$
→ Model $t = \sqrt{2H/a} + \varepsilon$ $H = a(t + \varepsilon)^2/2$



Weaknesses of theory-driven models

- Need a theory
- OK in theory rich domains
- Less so in other domains
- Bias, if you get theory wrong

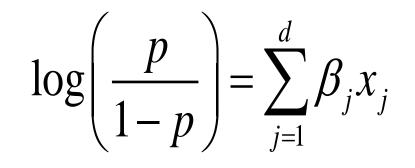


Data-driven example

Logistic regression model for the probability that someone will purchase a product

based on the values of their characteristics

 x_1, x_2, \dots, x_n





Weaknesses of data-driven models Assume:

- the future is like the past
- choose criterion to fit model to data
- good quality data
- no selection bias
- no gaming, feedback, etc
- Leading to

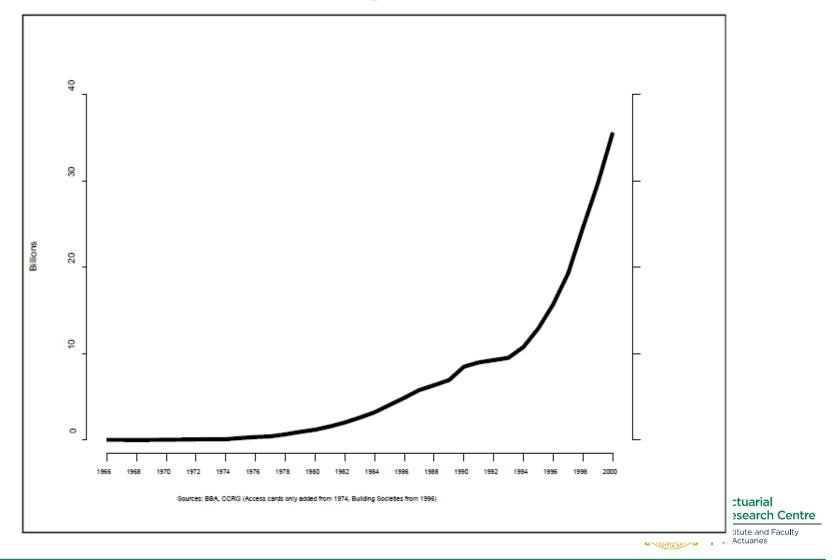
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- Brittleness: due to changes of circumstances
- Horses: algorithm choosing non-human features

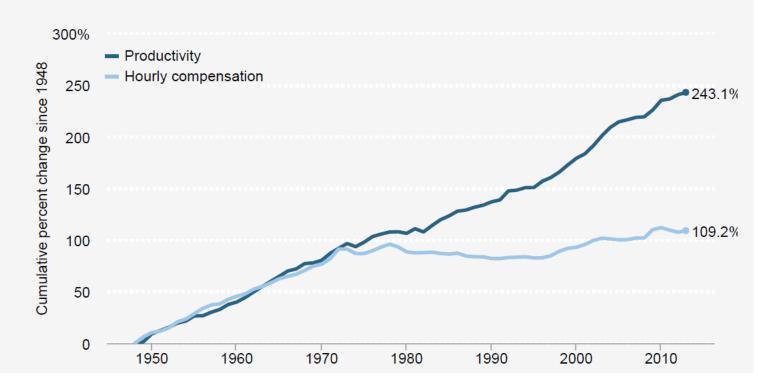


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The future is like the past



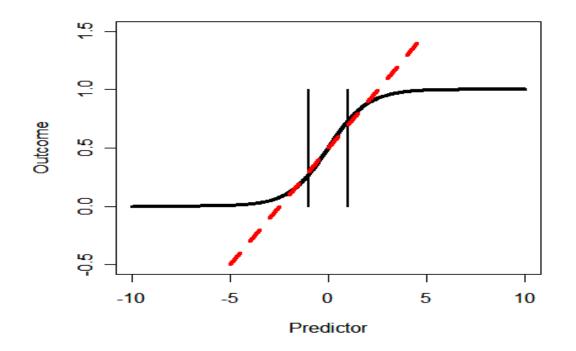
Disconnect between productivity and typical worker compensation,* 1948–2013



Bivens et al (2014) Raising America's pay. Economic Policy Institute, Briefing Paper 378, June 4, 2014.



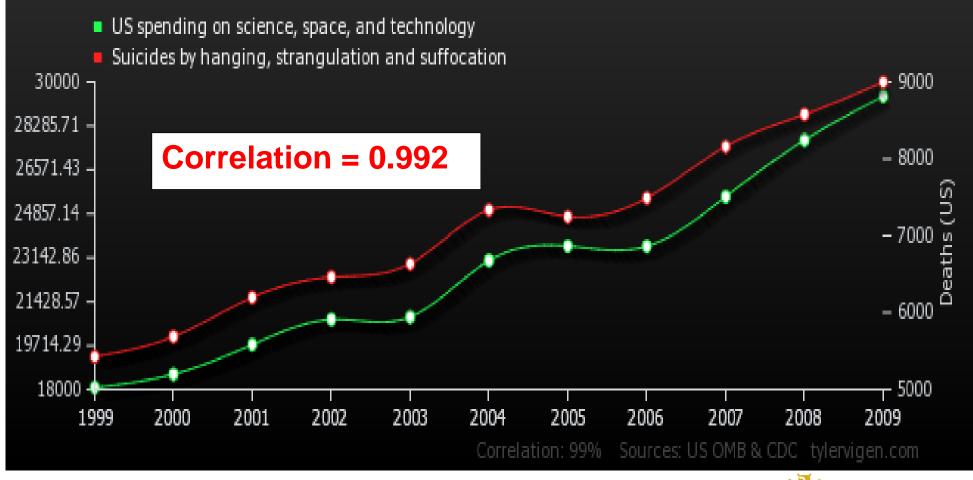
Failure to model range of variation:



- → Predictive models may break down
- → Regression to the mean because underestimating variation

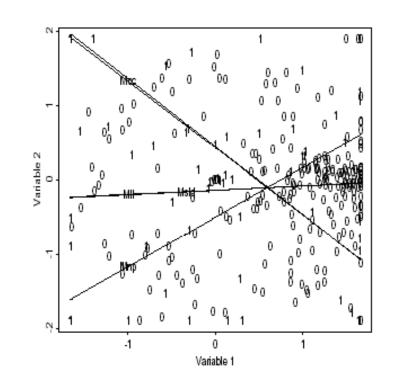


Example: Spurious correlations





Need to choose criterion to fit model to data

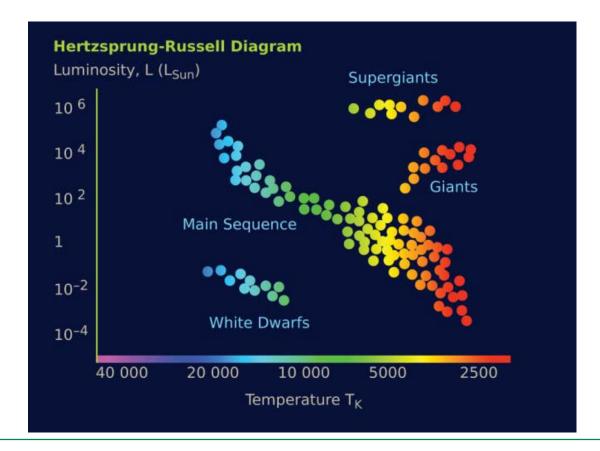


Ionosphere data, Benton (2001)

Optimum error rate: top-left to bottom-right Optimum Gini: bottom-left to top right



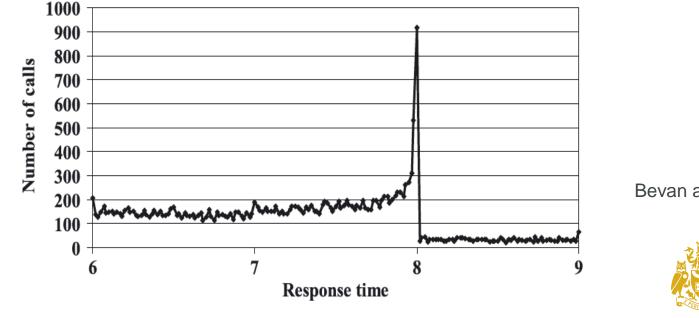
Risk of mismatch between aims and algorithms Different cluster methods revealing different shapes Long sausage shapes vs compact clusters





Campbell's law: The more any quantitative social indicator is used for social decision-making, the more subject it will be to corruption pressures and the more apt it will be to distort and corrupt the social processes it is intended to monitor

- e.g. schools enter for public exams only those expected to excel
- e.g. ambulance response times



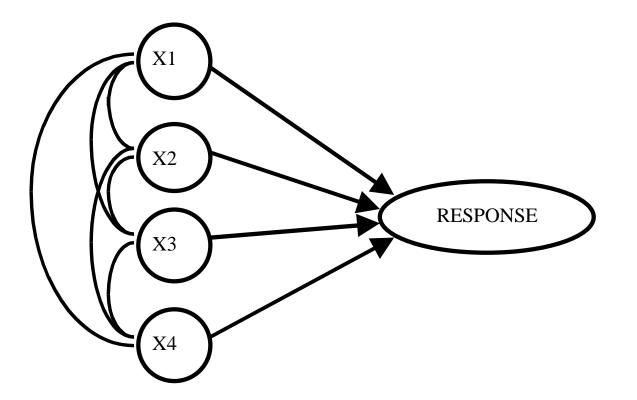
Bevan and Hamblin, 2009



Adding substance



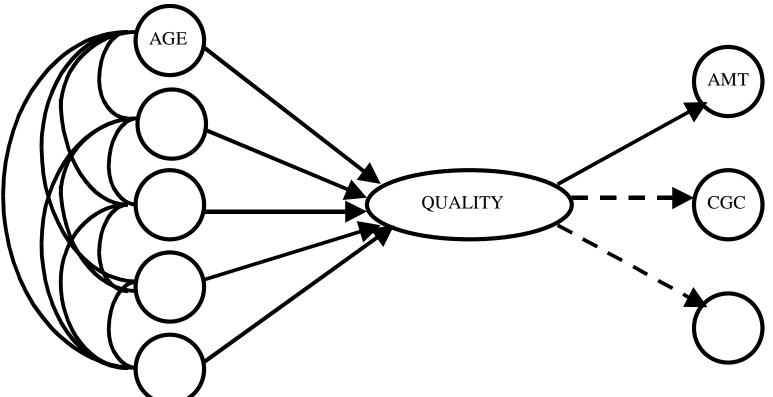
Data driven model



Age, income, other loans,....



Theory-driven model



Age, income, other loans,....

CCJs, defaults, months in arrears, parking tickets, speeding fines,....



Data quality



'The majority of insurers around the world

"The majority of insurers around the world are failing to ensure the data that feeds their artificial intelligence (AI) systems is accurate, potentially undermining their business decisions."

The Actuary, 25th April 2018



Not the data you want, but a distorted version

"Two students suffered 'life threatening reactions' when they were given enough caffeine for 300 cups of coffee. ... spent several days in ICU...dialysis... Should have been given 0.3g of caffeine. Instead they were given 30g."

The Times, 26 January 2017

The Mars Climate Orbiter

Launched 1998, but communication lost on September 1999 when the spacecraft trajectory brought it too close to Mars ... because one of the software teams forgot to convert Imperial units to SI units



"Poor data quality costs the US economy around \$3.1 trillion per year"

Source: IBM



Causes of poor quality data

Human error:

Shares in J-Com losing \$ shares for 1 yen each, in:

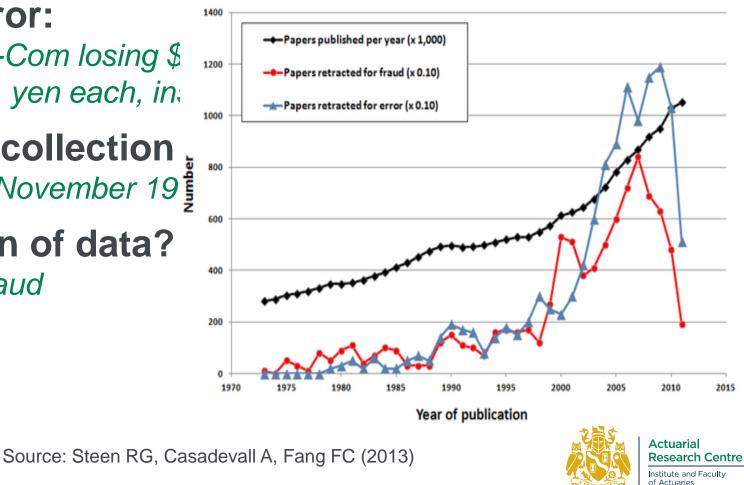
Poor data collection

Peak at 11 November 19

Fabrication of data?

Scientific fraud

Retractions as a function of total publications

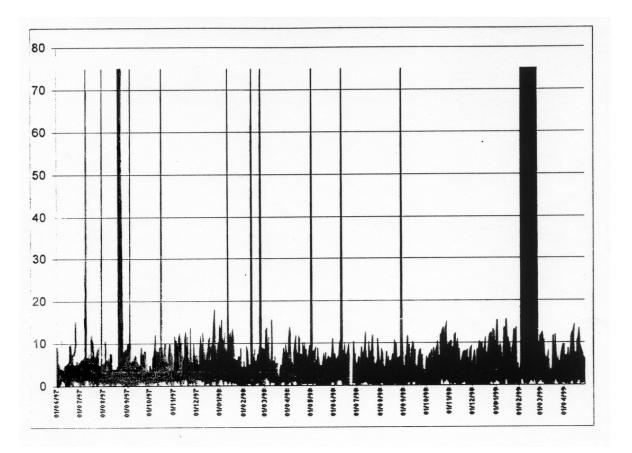


Berry and Linoff (2000) example: *"The data is clean because it is automatically generated – no human ever touches it"*

But it turned out that 20% of transactions had "arrived before they were sent not only did people never touch the data, but they didn't set the clocks on the computers either"



Not merely human error





Bad data can occur in an unlimited number of ways

Cannot check a billion values by hand

The computer is a necessary intermediary



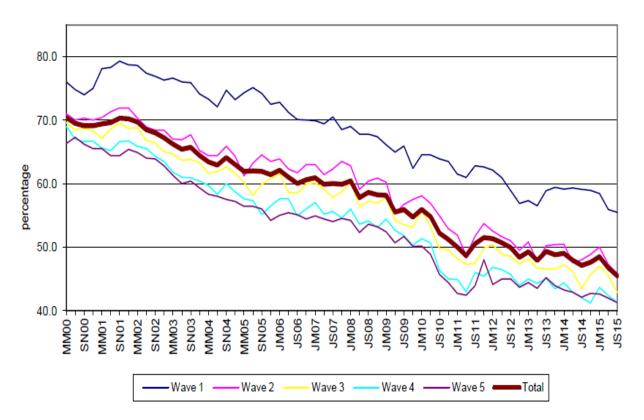
Maintain a healthy scepticism

Twyman's Law:

Any figure that looks interesting or different is usually wrong



Non-response and refusals



LFS quarterly survey wave-specific response rates: March-May 2000 to July-Sept 2015 Source: http://www.ons.gov.uk/ons/guide-method/method-quality/ specific/labour-market/labour-force-survey/index.html

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The magazine survey which asks readers one question:

"Do you reply to magazine surveys?"

And discovers that apparently *all* the readers reply to surveys

The Actuary, July 2006, editorial: "A couple of months ago I invited all 16,245 of you to participate in our online survey concerning the sex of actuarial offspring."

"... Well, I'm pleased to say that a number of you (13, in fact) replied to our poll."



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Other aspects of bad data:

relevance, timeliness, consistency, coherence, availability, and accessibility



It is also a good rule not to put overmuch confidence in the observational results that are put forward until they have been confirmed by theory

Sir Arthur Eddington, New Pathways in Science (The University of Michigan Press, 1959), p.211.



If the data can speak for themselves

They can also lie for themselves David Hand

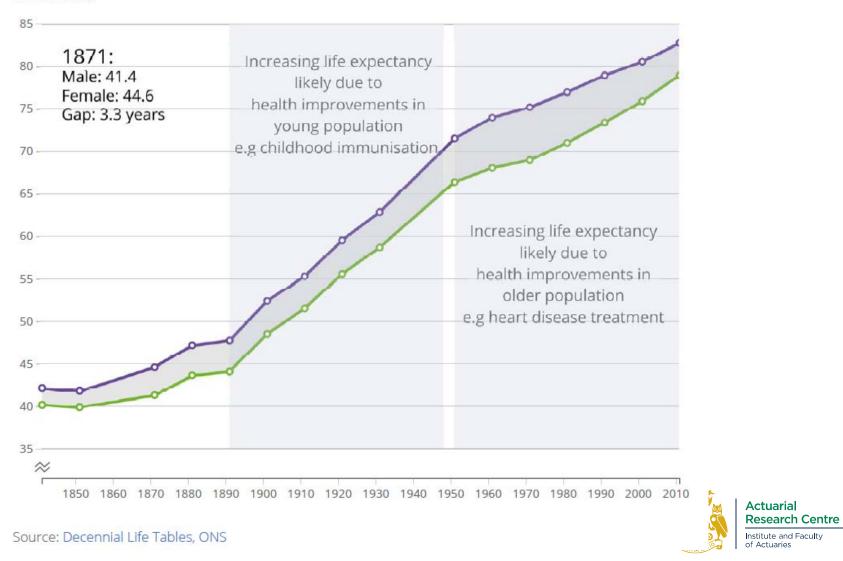


Longevity



male female

life expectancy



New York Times, 18 December, 2013

"A stunning increase in the life expectancy of New Yorkers over the past 20 years, compared with the rest of the country, has been driven by sharp declines in deaths from AIDS, homicide, smokingrelated illnesses and, in a surprising twist, an increase in the numbers of immigrants, a new study has found.

The magnitude of the gains recalls those that followed major public health improvements, like the advent of sewage systems at the end of the 19th century."

https://www.nytimes.com/2013/12/19/nyregion/life-expectancy-of-new-yorkers-rises-with-immigration-increase-study-finds.htm

"Immigrants have much lower rates of smoking, AIDS and alcohol-related illnesses than native-born Americans, he said. The significant fall in homicides, down by 77 percent in the city since 1990, and death rates from AIDS, down by 85 percent over the same period, have helped drive improving life expectancies, according to the study.

foreign-born people live longer and life expectancy is pulled up by that..."



The economic parallel

- The productivity paradox
- Changing work patterns
- The gig economy

Competition from new types of source Changing shopping habits

- Declining footfall
- Consumers spending less in stores but more on the internet
- £1 in 5 is now spent with online retailers



- Kodak and Polaroid's film-based model destroyed by digital photography
- Blockbuster Video rental vs Netflix streaming
- Amazon vs Toys R Us, Maplin, etc

Established companies miss disruptive innovations **because they give their customers what they want** - instead of coming up with new things they don't yet know they want

The next big thing is not the current big thing



"With enough data, the numbers speak for themselves"

Chris Anderson in Wired magazine, 2008

"the most reckless and treacherous of all theorists is he who professes to let facts and figures speak for themselves, ..." Alfred Marshall, Inaugural Lecture to Chair in Political

Economy, Cambridge, 1885





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thank you !

marine market to be have