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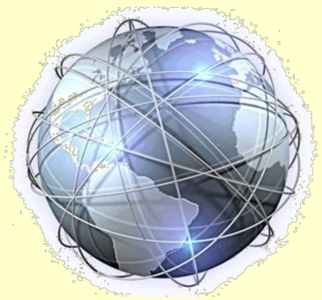


Big Data + Big Computers = Computational Psychology?

Joop Hox

Utrecht University

Big Data Symposium

Dubrovnik, 2019

How I started in Psychology

1969: Psychology is undergoing a paradigm shift

Exemplified in my course on experimental psychology

- Book 1

  (Author & Title successfully repressed)

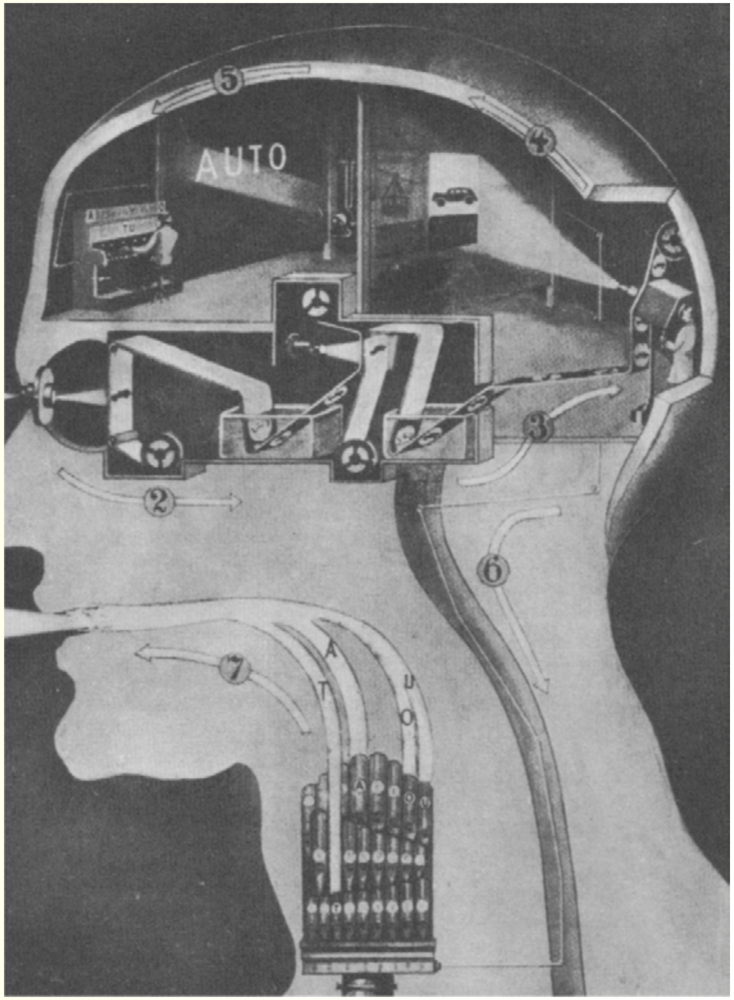
  - Behaviorist
  - All about rats (or pigeons)
- Virtually no research on human beings

- Book 2: Neisser (1967) *Cognitive Psychology*
  - Pattern Recognition
  - Visual & auditory cognition
  - Verbal memory
- All about human beings!
  - How we perceive, think

40 Years Later

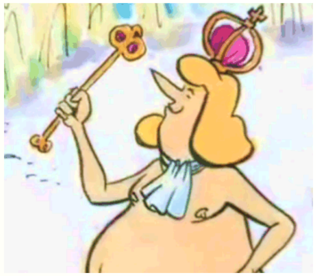
± 2010: Is Psychology undergoing another paradigm shift?

- Sternberg (2009) *Cognitive Psychology*
  – Much the same topics
  – Some attention to brain structures
- But much like Neisser
  – Cognitive structures viewed as 'demons' that carry out specific processes
  – MRI mentioned but hardly used
  – "Big Data" not mentioned



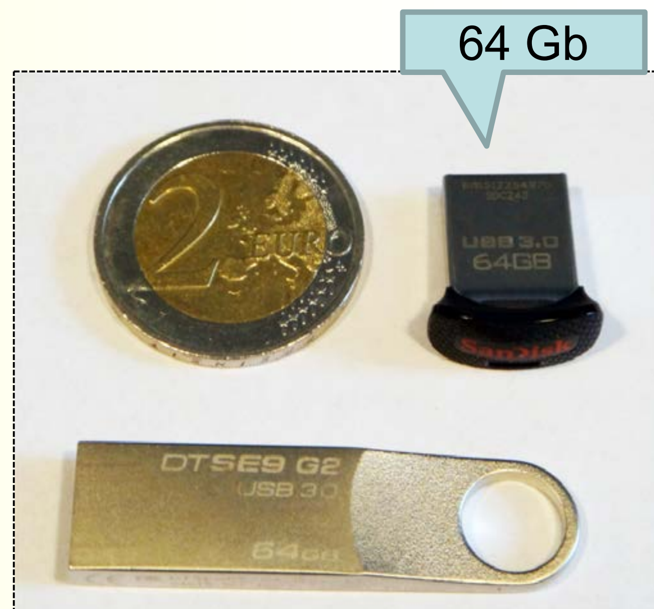
Structure of Presentation

- Big Data
- Data Analytics
- Simulation
- Computational Psychology
- What is in it for us?



Buzzword #1: Big Data

- What is big data? How big must it be?
- John Tukey (19-fifties): big data is anything that won’t fit on one device



Big Data in General

- Origin in physical sciences: nuclear research, astrophysics all collect many *exabytes* of data
  - which must be stored and analyzed
- These massive amounts of data require new technology and analysis methods
- Recently, market research and later official statistics and social & behavioral science have picked up this trend

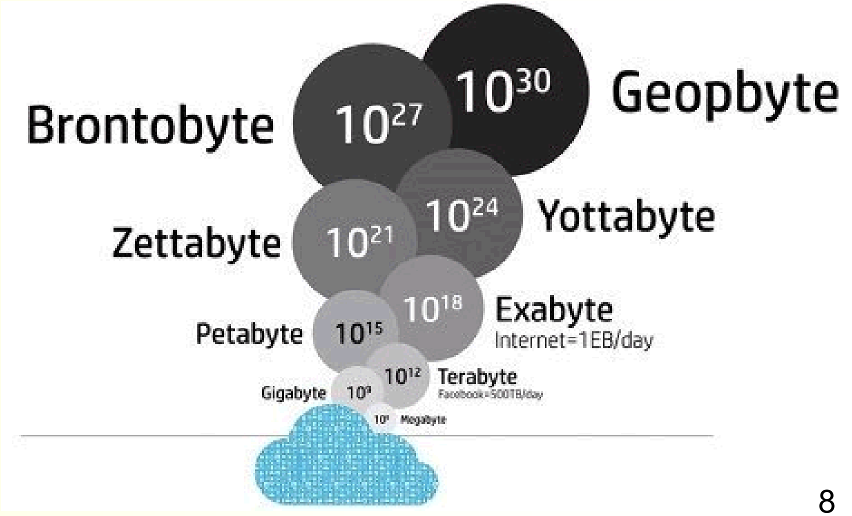
Exabytes?

- Byte - a single character
- Kilobyte - very short story
- Megabyte - small novel
- Gigabyte - TV movie
- Terabyte - daily data from NASA EOS
- Petabyte - daily data from EHT
- Exabyte - 5 Milliard CD-Roms
- Zettabyte - ± total internet traffic 2016
- Yottabyte - named after Yoda

Social Science Examples

- Mostly collecting data from social media
  - Twitter popular because of free data (1% sample) via twitter streaming API (also in R)
  - Discussion lists
- Examples
  - Collecting data on google searches
  - Combining survey and found data (BigSurv18)

- My own hard disk
  - 2 Tb
  - 6 SPSS files > 100 Mb
  - Largest SPSS file
    493 Mb



Do Social and Behavioral Sciences really have Big Data?

- Example from astronomy: the Event Horizon Telescope's photo of a black hole
- The Event Horizon Telescope (EHT) is not one single telescope, it is many
  - 8 locations
  - each >1 telescopes
  - 5 days observation
    - 1 petabyte / day
  - data sent on disks

So What do the EHT data look like?

- They definitely do not fit on one device!

Extended Example from Social Science

- Are human sexual cycles driven by culture or environment?
  - Pattern of birth dates not uniform over time
  - Cultural or environmental?
- IF Cultural

→ same pattern in similar cultures, everywhere

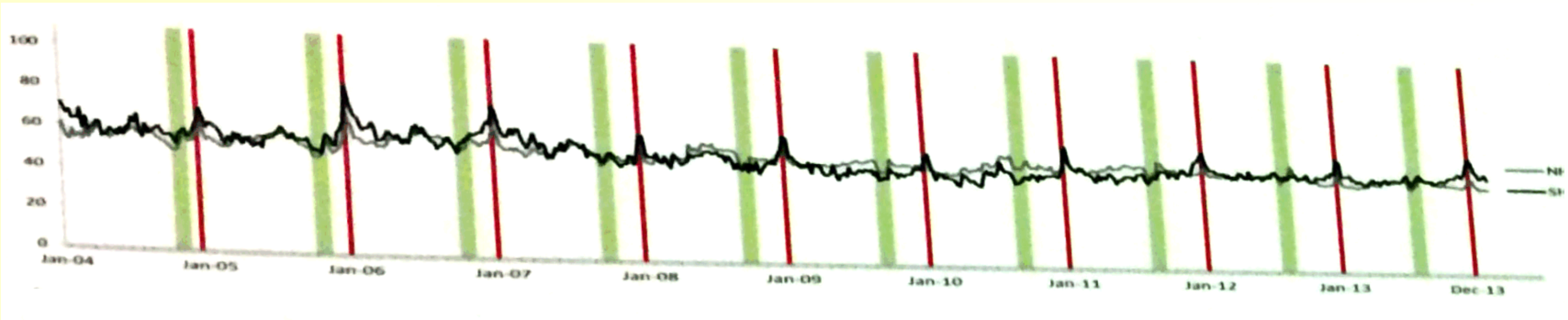
- IF Environmental

→ pattern reversed in Northern (NH) vs. Southern Hemisphere (SH)

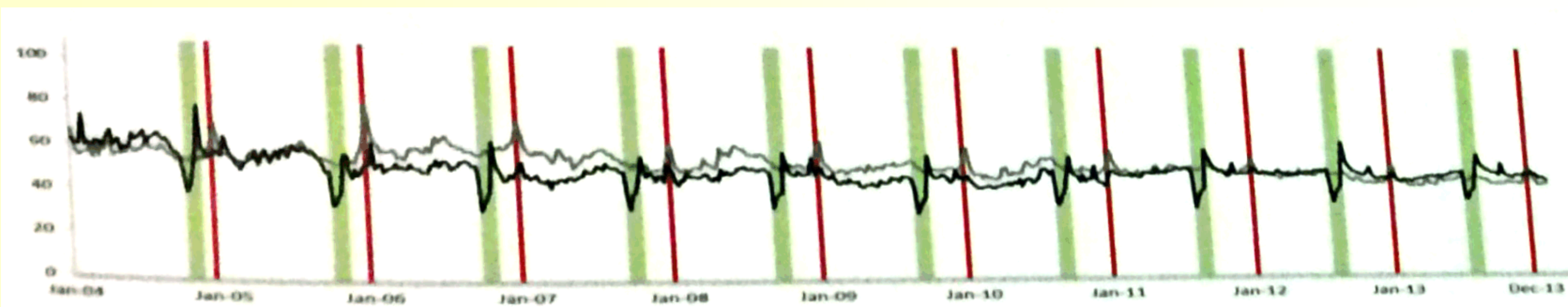
Human Sexual Cycles

- Data collection
  - Direct observation of sexual activity difficult
  - Survey suffers from image management
    - Both underreporting and boasting
  - Proxy: google “sex” searches, split across NH and SH, and Christian (C) and Muslim (M)
  - Observation period: 10 years
- Analysis: is pattern seasonal or cultural?
  - Cultural = related to important dates, such as Christmas (C) or Eid-al-Fitr (sugar feast) (M)

Human Sexual Cycles: Results

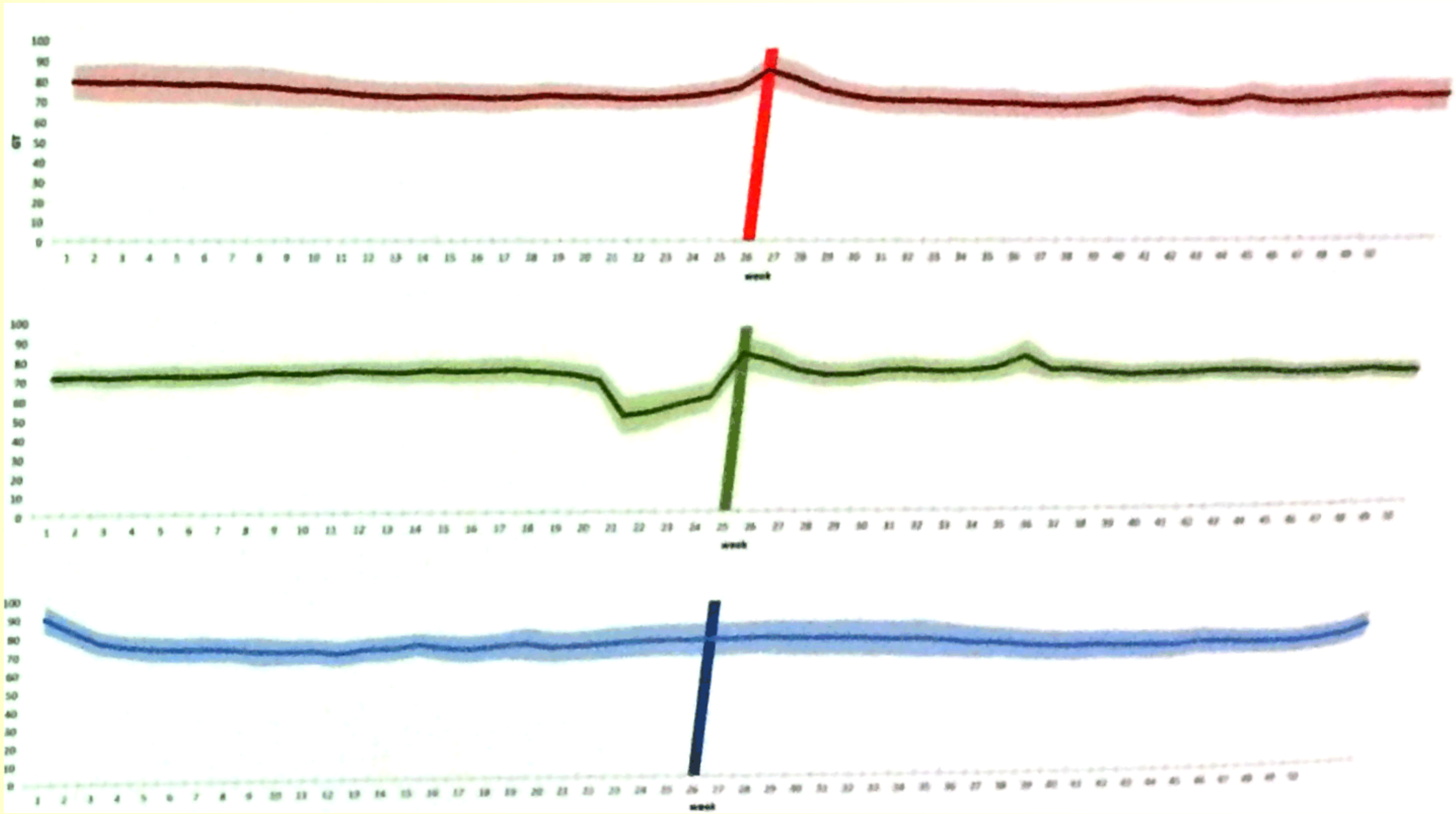


Averaged ‘sex’ searches for all countries. Weeks containing Ramadan and Christmas are in green and red. NH and SH.



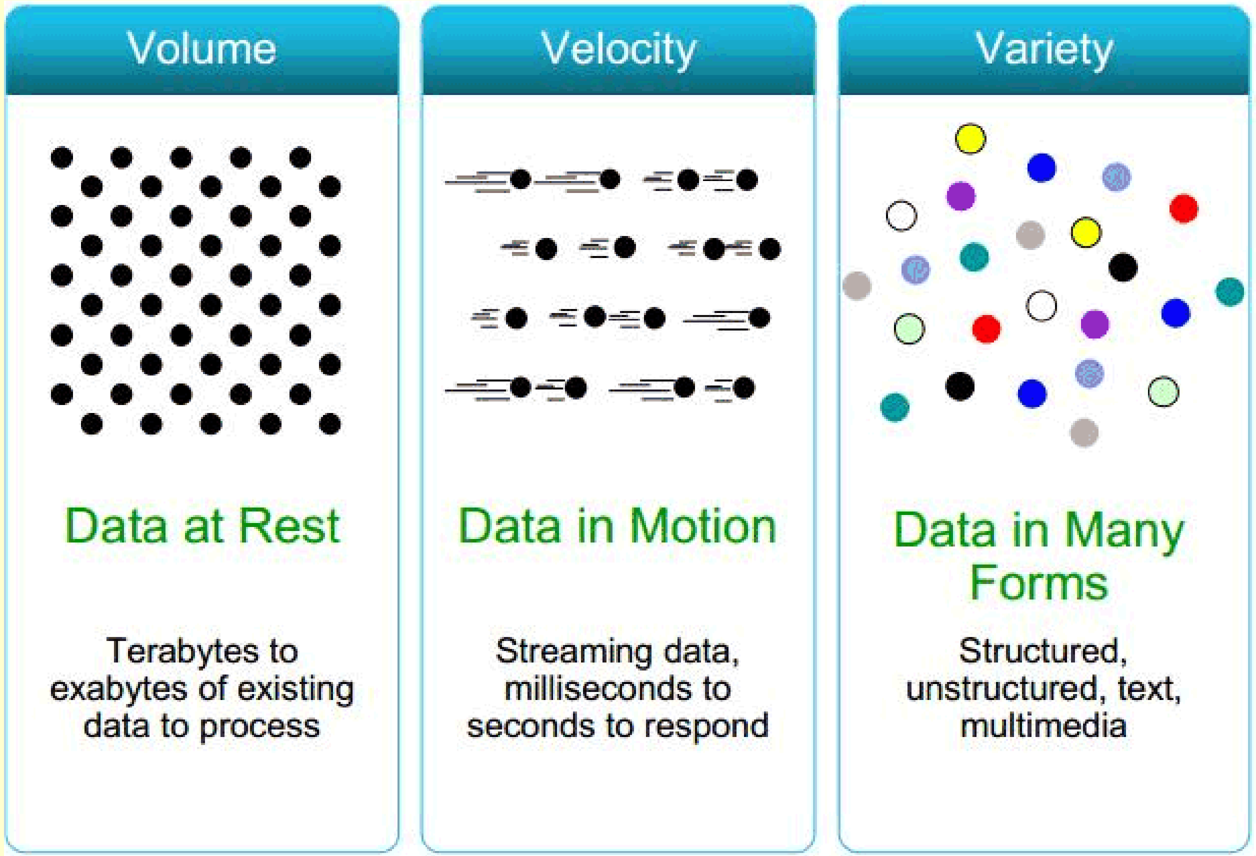
Averaged ‘sex’ searches for all countries. Weeks containing Ramadan and Christmas are in green and red. C and M.

Human Sexual Cycles: Results



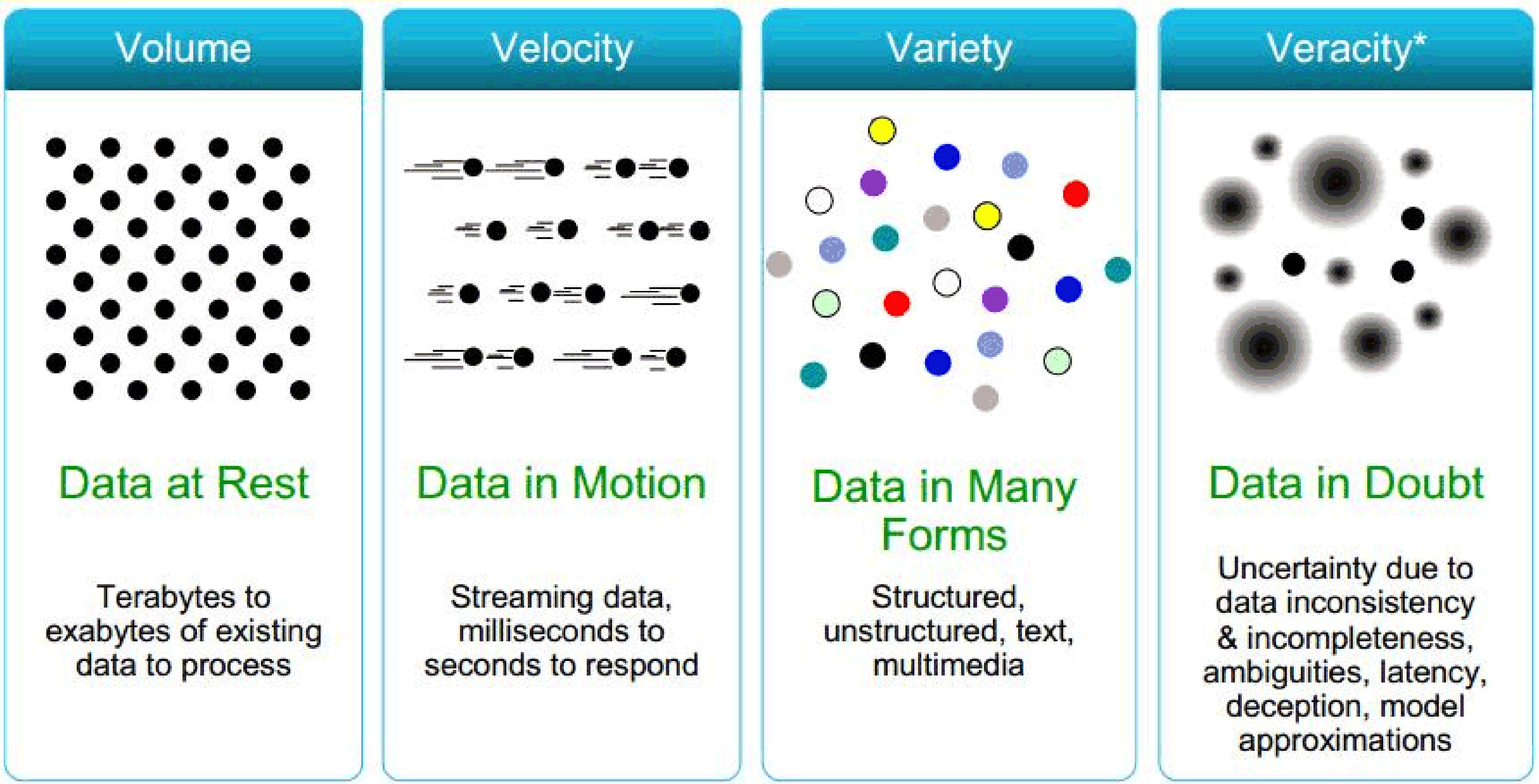
Averaged Z-scores of 1) Christian countries centered on Christmas, 2) Muslim countries centered on Eid-al-Fitr and SH countries centered on Summer Solstice

Characteristics of Big Data: the Classical Three V's



http://www.rosebt.com/blog/data-veracity

Characteristics of Big Data: the 4th V



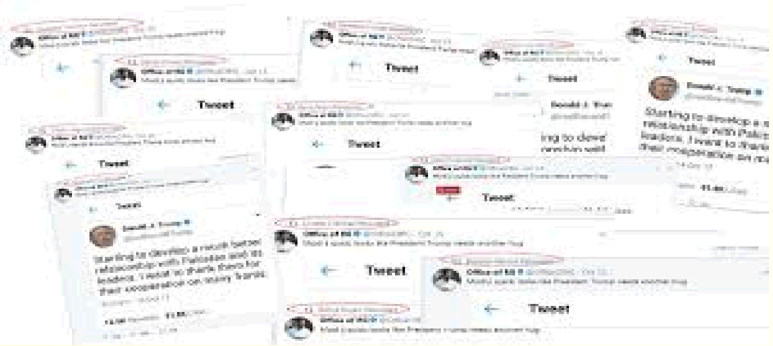
http://www.rosebt.com/blog/data-veracity

The Promise of Big Data

- Individual behavior increasingly leaves digital traces, which can be collected
- Expensive data collections replaced by inexpensive ‘found’ data
- Sampling replaced by *N* = *All*
- Large data sets permit complex analyses
  - The end of theory (Wired, 2008)
  - Automatic modeling, Data based modeling

The Problems of Big Data the 4th V: Veracity

- Is N really all?
  - Who are we missing? Who are included several times? Can we generalize?
    - Representativity, *external validity*
  - Example: in the 2016 American elections about 30% of the tweets about Clinton or Trump were generated by bots



The Problems of Big Data the 4^{th} V: Veracity

- Data is never just ‘found’ & is never ‘organic’
  - Who created the data for what purpose?
  - What do we measure? What do we fail to measure?
    - *Operationalization* problem = *Construct validity*
- Classical scale development
  - start with construct, chose indicators (top down)
- Big data
  - start with data, munge, transform, aggregate
  - transform data to making it ready for analysis

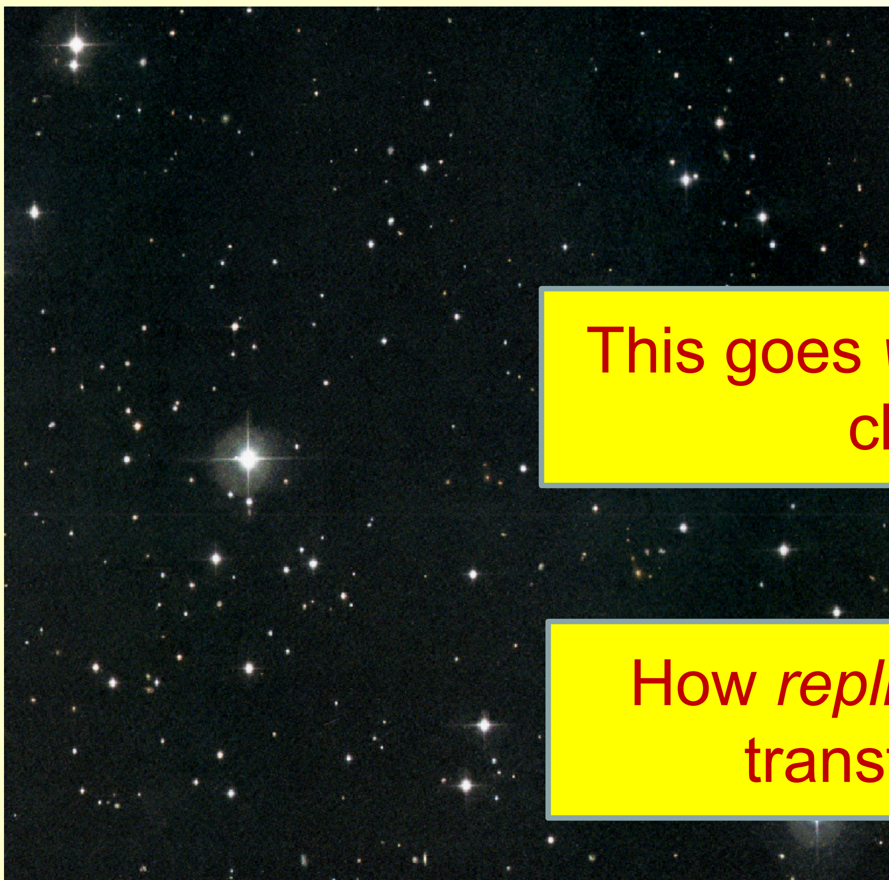
The Problems of Big Data the 4th V: Veracity

- Data: munge, transform, aggregate
  - Extract raw data, use algorithms (sorting, parsing, projecting on existing data structure) to prepare for analysis

How *replicable* are these transformations?

The Problems of Big Data
the 4th V: Veracity

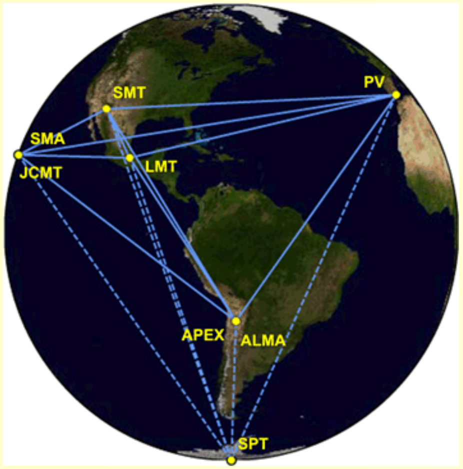
- Data: munge, transform, aggregate

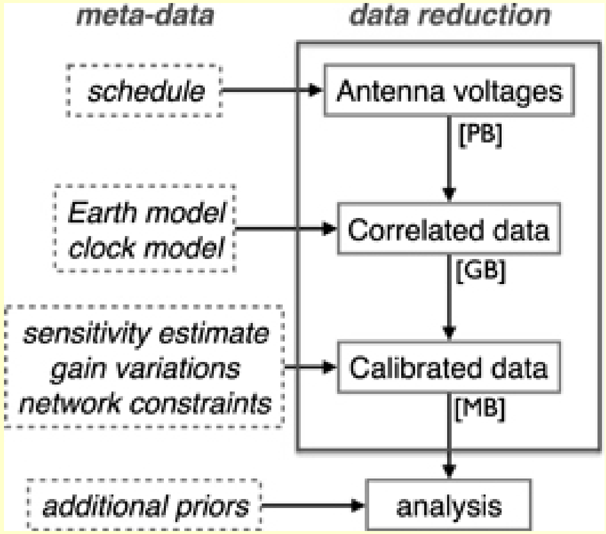


This goes *way beyond* data cleaning!

How *replicable* are these transformations?

Example of the black hole photo





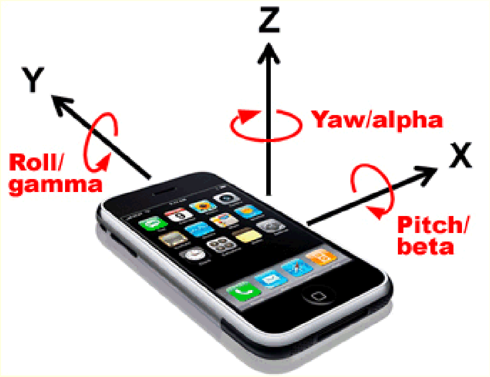
- Data from 8 sites
- Observations in wide frequency bands over time, about 350 terabytes per telescope per day
- Combined and calibrated, different kinds of noise removed, et cetera.
- *Publicly reported in painstaking detail online*

Sensor Data are not Objective

- Sensor measurement ≠ behaviour
  - Device turned off or not worn
  - Sensors do not always measure target behavior
  - Sensors are not completely reliable
- Example: pedometer (fitbit, smartphone)
  - Research shows high quality devices on average within 10%, smartphones within 20%
  - Data depends on device, app, operating systems, ways of walking

The Accuracy of Pedometer

- The step counter in your smartphone is not counting steps
  - It records movement over time in 3 dimensions
  - Then an algorithm estimates the # of steps



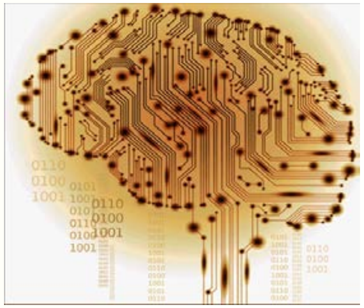
  - Accuracy depends on the sensor + algorithm
    - Different devices, different sensor + algorithm
    - Different app or upgrade OS may induce differences

Summary So Far

- External validity
  - Population > Device owners / Twitter users > Participation > Actual data collection
- Operationalisation
  - Transform observations into data: what construct are we measuring
- Reliability
  - If we repeat the measurement, will we get the same results?

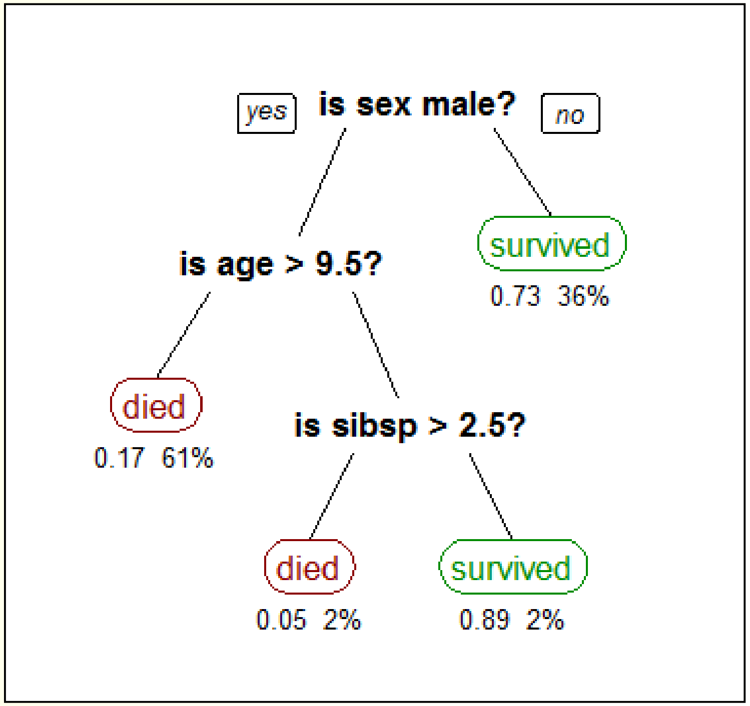
Buzzword #2: Analytics

- Aka Predictive analytics, data mining, machine learning…
- White box: regression, clustering, tree methods
  - White box: models and parameters can be interpreted
- Black box: neural networks, deep learning
  - Model in box is unknown



Popular Techniques

- Prediction
  - Regression
  - Tree methods
- Classification
  - k-means clustering
  - k nearest neighbors
- Innovations
  - Adaptation to large data sets, cluster computing
  - Ensemble methods



Let The Data Speak

- Modeling typically data driven, resampling and hold-out methods to avoid overfitting
- *k*-fold: divide data randomly in *k*=10 parts, do 10 times: search for model on 9/10 of data, test (validate) on 1/10 hold-out
  - Repeat several times (repeated *k*-fold)
  - Other methods exist, but k-fold very effective
- Random forest
  - Many trees with random selection of variables

Big Data Analytics

- Origin is applied mathematics in real world
  - Often developed by computer scientists
  - Terminology is different
    - e.g. “examples”=“cases”, “features”=“IV”
  - Emphasis strongly on prediction and classification
- Emphasis *not* on theory or understanding
  - e.g. deep learning by training a neural network yields results, but not interpretations

Soccer Example

- Do soccer referees give more red cards to dark skin toned players?
  - Data: player (N=2053) demographics (GB, DE, FR, ES), referees (N=3147), # of player-referee encounters, # of red cards, skin tone coded from photos, 146028 dyads
  - Not BIG data, but data from *hell*: cross-classified multilevel, very skewed outcome (mean prop. reds 0.004), sparse data

https://osf.io/gvm2z/

Soccer Example: What Techniques?

- Significance no criterion: r=0.006, p=0.02
- Techniques
  - Regression 14
  - Multilevel 11
  - Other 3
  - All techniques depend on modeling and interpreting coefficients
- Results mixed, depending on choices for model and covariates

Soccer Example Analytics Approach

- Take (almost) all covariates
  - Some were redundant
- Do 10-fold: run model (all covariates) with and without skin color predictor
  - Count proportion of correct predictions for receiving red card, both models, in test subsamples
  - Calculate mean proportion across 10 test samples
- Do this 100 times

Results Analytics on Soccer Data

	Proportion of correctly predicted red cards		
	Model *with* skin color	Model *without* skin color	Difference
Fold 1	0.0353	0.0382	-0.0029
Fold 2	0.0324	0.0353	-0.0029
Fold 3	0.0324	0.0353	-0.0029
Fold 4	0.0294	0.0324	-0.0029
Fold 5	0.0382	0.0441	-0.0059
Fold 6	0.0206	0.0265	-0.0059
Fold 7	0.0382	0.0412	-0.0029
Fold 8	0.0265	0.0353	-0.0088
Fold 9	0.0353	0.0412	-0.0059
Fold 10	0.0440	0.0499	-0.0059
Mean	0.0332	0.0379	-0.0047
Mean 100 repetitions			-0.0060

- First 10-fold + mean proportions
- Model with skin color is doing *worse* ($p=0.002$)

Summary So Far

- Big data analytics have produced analysis methods that are *really useful*
- Ensemble methods use a large amount of model fitting, including choice of variables and cases, and tuning of model parameters
  - Overfitting is certainly an issue

Buzzword #3: Simulation

- Statistical simulation
  - Generate flawed data to study analysis method
- Model based simulation
  - Specify a computer model of a complex system and study the model
- Agent based simulation
  - Place virtual agents in a computer generated environment, and study their interactions

Model Based Simulation

- Based on substantive knowledge
  - Each system studies requires their own model
- Example: deep dyslexia
  - Dyslexia = “unite” read as “untie”
  - Deep dyslexia = “rose” read as “tulip”
- Suggests two different loci of damage
  - However, a neural network model assuming that words are stored not in one location but distributed, can generate both kinds of dyslexia
- fMRI has shown distributed lexicon

O’Reilly & Munakata, 2000

Agent Based Simulation

- Virtual agents interact in a computer generated environment
  - Agent behavior is governed by rules
  - Rules are varied, results observed
- Very old example: ALDOUS
  - ALDOUS simulates interactions between 2 agents that each have values on 3 attributes
  - Which leads to surprisingly complex behavior chains

Loehlin 1965

Agent Based Modeling

- Current technology allows a multiple agents and multiple attributes
- Example: Axelrod's evolution of cooperation
  - How can cooperation evolve with competition for resources and no central authority?
  - Simulated agent interactions with agents that are friendly or greedy in a prisoners' dilemma
  - In the long run, friendly interactions bring greater gains for both agents

Axelrod's Challenge

- A simulated tournament where agents play an repeated prisoners dilemma game
  - Axelrod's champion: Tit-For-Tat TFT)
    - Start friendly, then do what the other did last time
- Challenge: design strategy to defeat TFT
- Each agent faced all others 200 times, plus a copy of itself and a random agent
  - This repeated 5×
  - 14 agents, 120000 moves, 240000 choices
- Original tournament: TFT wins BIG

Axelrod's Legacy

- In a second tournament, TFT wins again
- Later winner are even more friendly than TFT
- Lates simulations are more larger and more complex
  - e.g. assuming groups or societies
  - Winning agents greater chance of replication
  - Studying social networks by interacting agents
    - Phelps (2012) simulates 3.6×10^5 interactions which replicate real world research results

Buzzword #4: Computational Psychology

- “In short, a computational social science is emerging that leverages the capacity to collect and analyze data with an unprecedented breadth and depth and scale.” (Lazer et al., 2009)
- “The increasing integration of technology into our lives has created unprecedented volumes of data on society’s everyday behaviour” (Conte et al., 2012)

Computational Social & Behavioral Science

- Combination of social/behavioral science, computer science and statistics
  - Big data and information extraction
  - Analytics
  - Simulation
- Interdisciplinary
- Old rules still apply: issues with external validity, construct validity, reliability

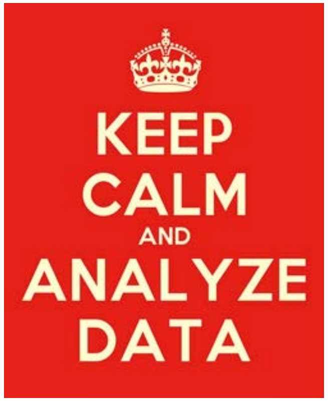
What is in it for US?

Adoption of new techniques, especially when developed in applied (e.g., marketing) research has often been slow, for example:

- Telephone survey methodology
- Computer assisted psychological testing
- Web (probability) panels

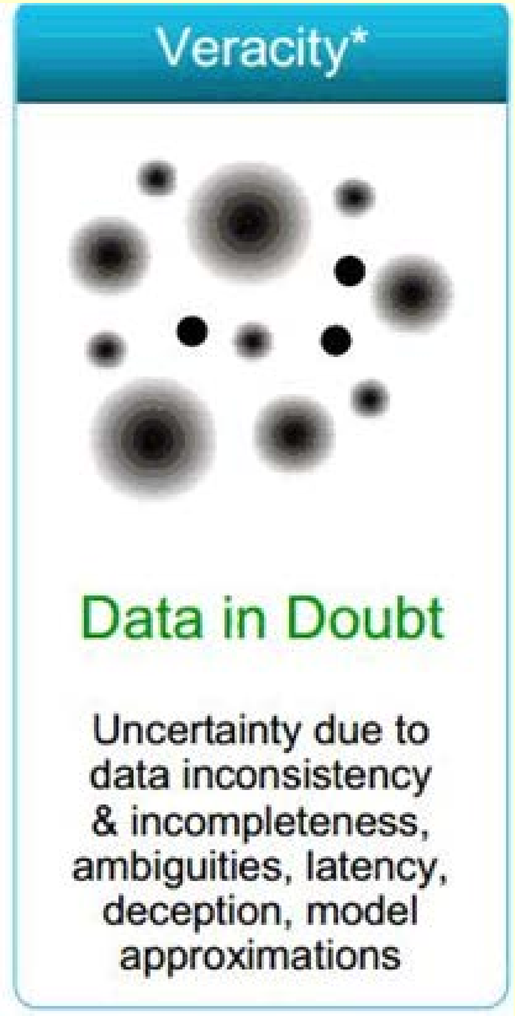
- Big data / analytics?

What is in it for US?



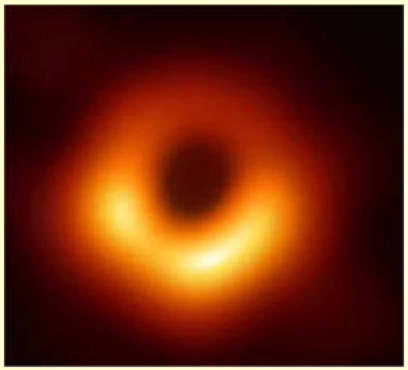
- Let the data speak
  - Different attitude: more data driven analysis, less model driven estimation
    - By training we are all multivariate modelers
  - Many techniques in ‘data analytics’ are familiar
    - Regression, classification, correspondence analysis, lots of resampling methods
    - Learning curve less steep than often feared
  - “NO BODY OF DATA TELLS US ALL we need to know ABOUT ITS OWN ANALYSIS” (Tukey, EDA, p115)
    - Translation: *Data Don’t Speak*

What Can We Contribute



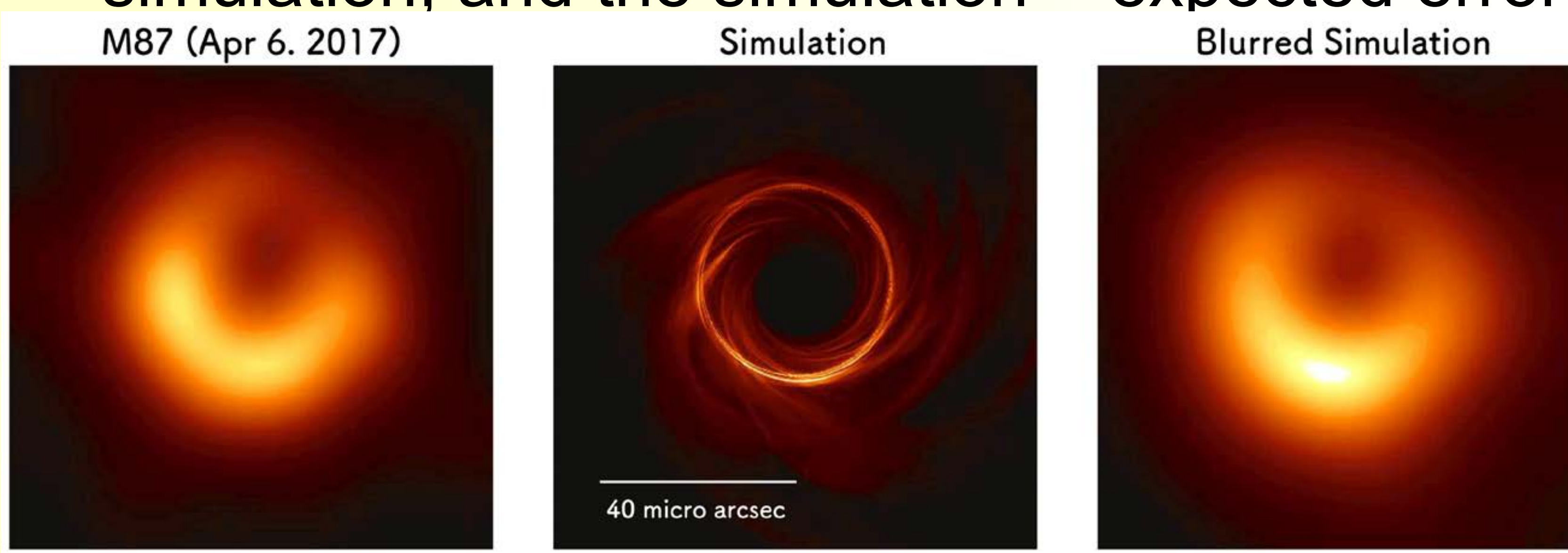
- Remember the ‘veracity’ thing?
  - There is too much in there!
  - It is useful to distinguish internal, external & construct validity,
  - and reliability of measurement,
  - statistical conclusion validity,
  - model approximations,
  - and many other issues well-known to social and behavioral scientists (= US)

Let’s Go Back to the Black Hole



- After 2 years of data munging, synthesis and aggregation, this is the picture!

- Compare the ‘observed’ picture with the simulation, and the simulation + expected error



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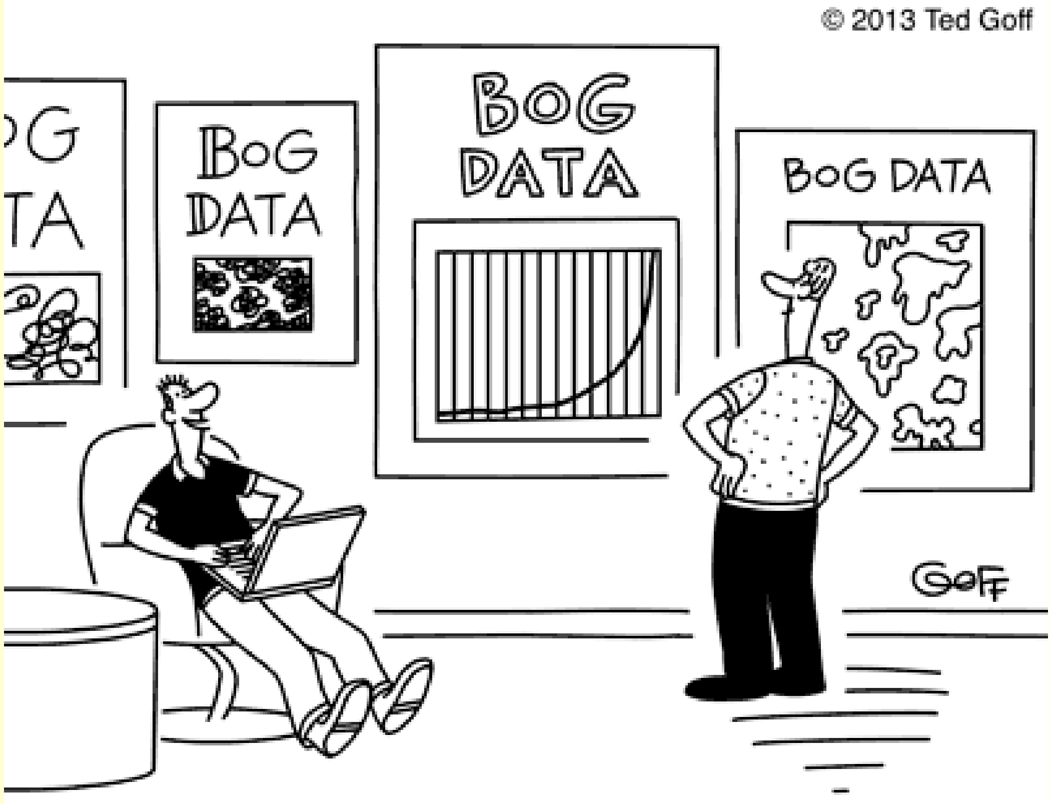

"It's amazing how we've transformed the industry as a result of my typo."

Why is Big Data Transforming Social Science?

1. Greater reliability than surveys

2. Ability to measure new variables (e.g., emotions)

3. Universal coverage → can “zoom in” to subgroups

4. Large samples → can approximate scientific experiments

From a course by a Harvard economist