

# 2018 PSI Conference

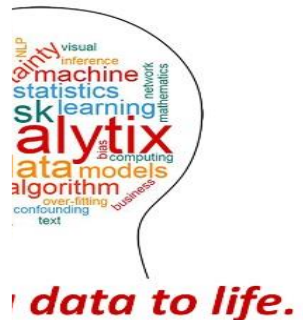
## Breaking Boundaries in Drug Development

Amsterdam  
3-6 June 2018

## Statistics and Data Science



Stephen J. Ruberg, PhD  
President  
Analytix Thinking, LLC



# Motivation

“... the time may not be very remote when it will be understood that for complete initiation as an efficient citizen of one of the new great complex world-wide States that are now developing, it is as necessary to be able to compute, to think in averages and maxima and minima, as it is now to be able to read and write.”

H. G. Wells  
Mankind in the Making,

“Statistical thinking will one day be as necessary for efficient citizenship as the ability to read and write.”

Samuel S. Wilks  
Presidential Address to the American Statistical Association  
December 28, 1950



Bringing data to life.



# Example #1

## Predicting Alzheimer's Disease

### Big Data - Biomarkers

# Predicting Alzheimer's Disease

## Problem Statement

There are no good treatments for Alzheimer's Disease

- By the time it is diagnosed, it may be too late.

Detecting it early may be a key to treatment or prevention

Current imaging approaches are expensive and invasive

Ideally, a blood test would be easy, cheap and very helpful



*Bringing data to life.*

# Predicting Alzheimer's Disease

## Researchers at ...

- University of Rochester School of Medicine
- University of California, Irvine School of Medicine
- Georgetown University Medical Center

## Study Outline

- Follow cognitively normal elderly patients over time
- Identify which patients “convert” to amnestic Mild Cognitive Impairment (aMCI) or Alzheimer's Disease (AD)
- Examine baseline blood proteins from “converters” and “non-converters” for differences



*Bringing data to life.*

# The (Statistical) Analytical Methods

“groups were defined primarily using a **composite measure of memory performance**”

“Metabolites defining the participant groups were selected using the **least absolute shrinkage and selection operator (LASSO) penalty**.”

“... metabolomic data from the untargeted **LASSO analysis** to build separate **linear classifier models** ...”

“... used receiver operating characteristic (**ROC analysis**) to assess the performance of the classifier models ...”

“... employed internal **cross-validation** ...”

“The optimal value of the **tuning parameter lambda**, which was obtained by the cross-validation procedure, was then used to **fit the model**.”

“... **matched ... participants** on the basis of age, sex and education level.”

“... used separate **multivariate ANOVA (MANOVA)** to examine discovery and validation group performance ...”

“... used **Tukey's honestly significant difference (HSD)** procedure for post hoc comparisons.”

“... quantitative profiling data was subjected to the **nonparametric Kruskal-Wallis test** ... followed by **Mann-Whitney U-tests** for post hoc pairwise comparisons .... Significance was adjusted for multiple comparisons using **Bonferroni's method ( $P < 0.025$ )**.”



Bringing data to life.

# The Results



Mar 09, 2014

## ABSTRACT

... Herein, we describe our lipidomic approach to detecting preclinical Alzheimer's disease in a group of cognitively normal older adults. **We discovered and validated a set of ten lipids from peripheral blood that predicted phenoconversion to either amnesic mild cognitive impairment or Alzheimer's disease within a 2–3 year timeframe with over 90% accuracy.** This biomarker panel, reflecting cell membrane integrity, may be sensitive to early neurodegeneration of preclinical Alzheimer's disease.



Bringing data to life.

# The Results

# EUREKA !!!!

A remarkable scientific  
breakthrough!!!!



***Bringing data to life.***



# The Publicity



In a first-of-its-kind study, researchers have developed a **blood test for Alzheimer's disease that predicts with astonishing accuracy** whether a healthy person will develop the disease.



*Bringing data to life.*



# Example #2

## Public Health

### Big Data – Social Media

# Social Media in Action

nature

LETTERS

## Detecting influenza epidemics from query data

Jeremy Ginsberg<sup>1</sup>, Matthew H. Mohebbi<sup>1</sup>, Rajan S. Patil<sup>1</sup>

Seasonal influenza epidemics are a major public health concern, causing tens of millions of respiratory illnesses and 250,000–500,000 deaths worldwide each year<sup>1</sup>. In addition to seasonal influenza, a new strain of influenza virus against which no previous immunity exists and that demonstrates human-to-human transmission could result in a pandemic with millions of fatalities<sup>2</sup>. Early detection of disease activity is often followed by a rapid response, can reduce the impact of both seasonal and pandemic influenza<sup>3,4</sup>. One way to improve early detection is to monitor health-seeking behaviour in the form of queries to online search engines, which are submitted by millions of users around the world each day. Here we present a method of analysing large numbers of Google search queries to track influenza-like illness in a population. Because the relative frequency of certain queries is highly correlated with the percentage of physician visits in which patients present with influenza-like symptoms, we can accurately estimate the current level of weekly influenza activity in each region of the United States, with a reporting lag of about one day. This approach may make it possible to use search queries to detect influenza epidemics in areas with a large population of web search users.

Traditional surveillance systems, including those used by the U.S. Centers for Disease Control and Prevention (CDC) and the European Influenza Surveillance Scheme (EISS), rely on both virological and clinical data, including influenza-like illness (ILI) physician visits. The CDC publishes national and regional data from these surveillance systems on a weekly basis, usually with a 1–2-week reporting lag. In an attempt to provide faster detection, innovative surveillance systems have been created to monitor indirect signals of influenza activity, such as call volume to telephone advice lines<sup>5</sup> and over-the-counter drug sales<sup>6</sup>. About 80 million American adults are believed to search online for information about specific diseases or medical problems each year<sup>7</sup>, making web search queries a unique and valuable source of information about health trends. Previous attempts at using online activity for influenza surveillance have counted search queries submitted to a Swedish medical website<sup>8</sup>, Hulth, G. Rydevik and A. Linde, manuscript in preparation), visits to certain pages on a US health website<sup>9</sup>, and user clicks on a search keyword advertisement in Canada<sup>10</sup>. A set of Yahoo search queries containing the words 'flu' or 'influenza' were found to correlate with virological and mortality surveillance data over multiple years<sup>11</sup>.

Our proposed system builds on this earlier work by using an automated method of discovering influenza-related search queries. By processing hundreds of billions of individual searches from 5 years of Google web search logs, our system generates more comprehensive models for use in influenza surveillance, with regional and state-level estimates of ILI activity in the United States. Widespread global use of online search engines may eventually enable models to be developed in international settings.

<sup>1</sup>Google Inc., 1600 Amphitheatre Parkway, Mountain View, California 94043, USA. <sup>2</sup>©2009 Macmillan Publishers Ltd.

February, 2009

www.nature.com/nature \$10

INTERNATIONAL WEEKLY JOURNAL OF SCIENCE

# nature

“Because the relative frequency of certain queries is highly correlated with the percentage of physician visits in which a patient presents with influenza-like symptoms, we can *accurately estimate the current level of weekly influenza activity in each region of the United States, with a reporting lag of about one day.*”

ILLI percentages estimated by our model (black) and provided by CDC (red) in the mid-Atlantic region, showing data available at four weeks in the 2007–2008 influenza season. During week 5 we detected a decreasing ILI percentage in the mid-Atlantic region; similarly, on 3 our model indicated that the peak ILI percentage had been reached week 8, with sharp declines in weeks 9 and 10. Both results were later confirmed by CDC ILI data.

# Social Media in Action



## Detecting influenza epidemics using search engine query data

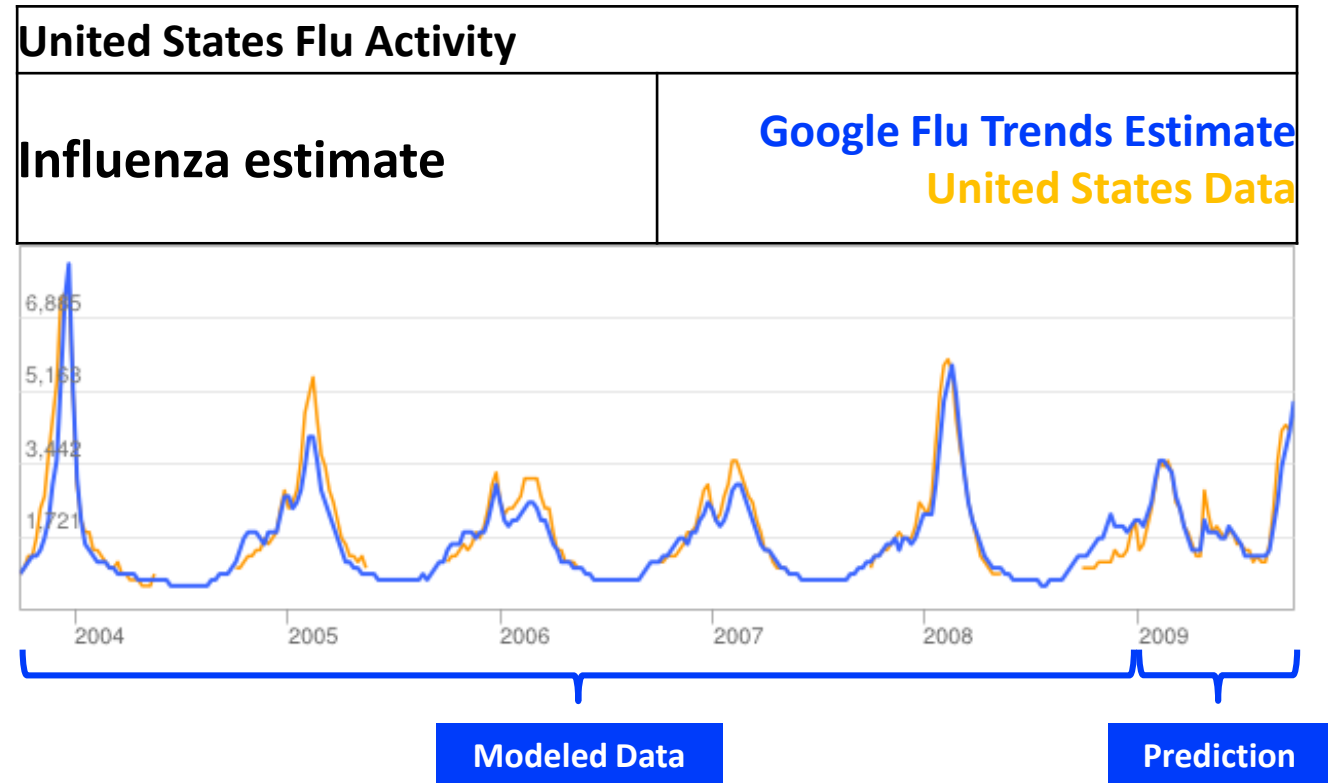
Seasonal influenza epidemics are a major public health concern, causing tens of millions of respiratory illnesses and 250,000 to 500,000 deaths worldwide each year<sup>1</sup>. In addition to seasonal influenza, a new strain of influenza virus against which no previous immunity exists and that demonstrates human-to-human transmission could result in a pandemic with millions of fatalities<sup>2</sup>. Early detection of disease activity, when followed by a rapid response, can reduce the impact of both seasonal and pandemic influenza<sup>3,4</sup>. One way to improve early detection is to monitor health-seeking behaviour in the form of queries to online search engines, which are submitted by millions of users around the world each day. Here we present a method of analysing large numbers of Google search queries to track influenza-like illness in a population. Because the relative frequency of certain queries is highly correlated with the percentage of physician visits in which a patient presents with influenza-like symptoms, we can accurately estimate the current level of weekly influenza activity in each region of the United States, with a reporting lag of about one day. This approach may make it possible to use search queries to detect influenza epidemics in areas with a large population of web search users.

“... analyzing large numbers of **Google queries** to track influenza-like illness in a population. Because the relative **frequency of certain queries is highly correlated with the percentage of physician visits** in which a patient presents with flu-like symptoms, we can accurately estimate the current level of weekly influenza activity ...”



***Bringing data to life.***

# Social Media in Action



Bringing data to life.

# Social Media in Action

“Google web search queries can be used to **estimate ILI percentages accurately** in each of the nine public health regions of the United States. Because search queries can be processed quickly, the resulting **ILI estimates were consistently 1–2 weeks ahead of CDC** ILI surveillance reports. The early detection provided by this approach may become an **important line of defense against future influenza epidemics** in the United States, and perhaps **eventually in international settings**.”

ILI = Influenza-like illness



*Bringing data to life.*

# Triumph of Big Data

“... researchers have focused on the observation that search ‘predicts the present,’ meaning that search volume correlates with contemporaneous events.”

S. Goel et al.  
Proc. Natl. Acad. Sci. U.S.A., 107  
Oct 12, 2010, p. 17486

“... simple models and big data trump more-elaborate analytics approaches.”

A. McAfee, E. Brynjolfsson  
Harvard Business Review, 90  
Oct, 2012, p. 64



*Bringing data to life.*

# The Rest of the Story

## Part 1



*Bringing data to life.*



# Example #1

## Predicting Alzheimer's Disease

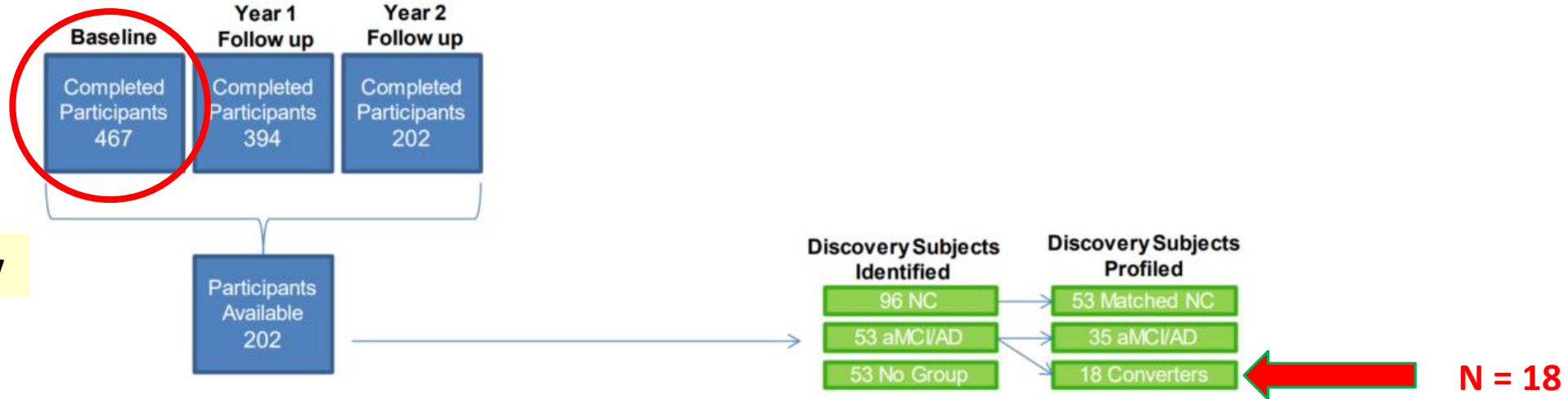
### Big Data - Biomarkers



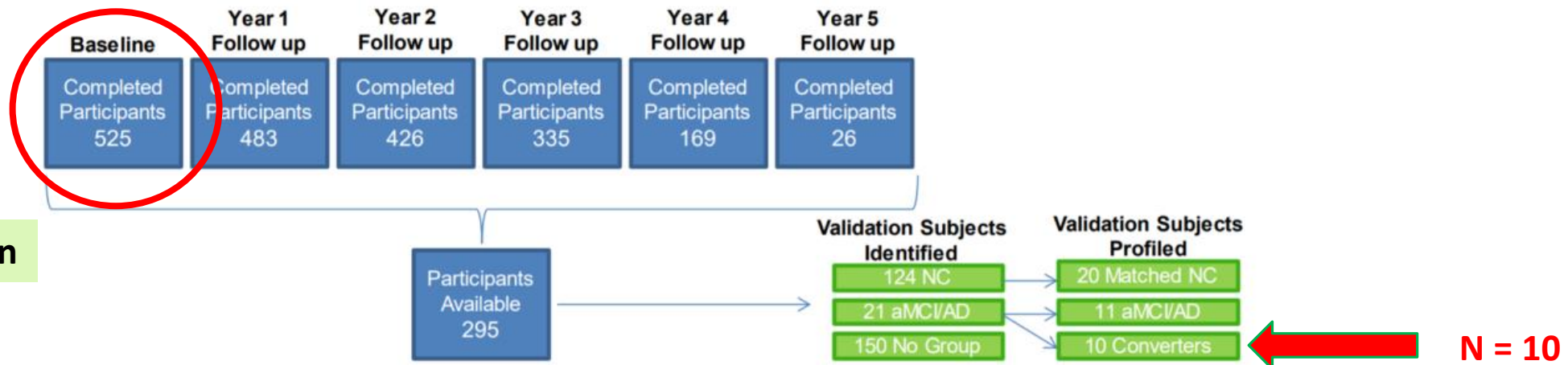
*Bringing data to life.*

# Patient Accounting

## Discovery



## Validation



Bringing data to life.

# Patient Accounting

## 467 volunteers

- Discovery Phase: 202 participants available
  - ◆ 149 met certain criteria for inclusion in the analysis
    - ◆ 53 with aMCI/AD
    - ◆ 96 normal
    - 18 converted from

Selection Bias ?!?

## 525 volunteers

- Validation Phase: 295 participants available
  - ◆ 144 met criteria for inclusion in the analysis
    - ◆ 21 with aMCI/AD
    - ◆ 124 normal
    - 10 converted from normal to aMCI/AD



Bringing data to life.

# The Statistical Analytical Methods



Bringing data to life.

# The Biological Analytical Methods

The actual data that was analyzed

- Sample storage and handling
- Sample storage time is confounded with groups

187 proteins analyzed

- Multiplicity !!!!



*Bringing data to life.*

# The Results – Part 2



## Blood metabolite markers of preclinical Alzheimer's disease in two longitudinally followed cohorts of older individuals

[Ramon Casanova](#), [Sudhir Varma](#), [Brittany Simpson](#), [Min Kim](#), [Yang An](#), [Santiago Saldana](#), [Carlos Riveros](#), [Pablo Moscato](#), [Michael Griswold](#), [Denise Sonntag](#), [Judith Wahrheit](#), [Kristaps Klavins](#), [Palmi V. Jonsson](#), [Gudny Eiriksdottir](#), [Thor Aspelund](#), [Lenore J. Launer](#), [Vilmundur Gudnason](#), [Cristina Legido Quigley](#), [Madhav Thambisetty](#)  

### RESULTS:

We failed to replicate these findings in a substantially larger study from two independent cohorts-the Baltimore Longitudinal Study of Aging ([BLSA],  $n = 93$ , AUC = 0.642, sensitivity/specificity of 51.6%/65.7%) and the Age, Gene/Environment Susceptibility-Reykjavik Study ([AGES-RS],  $n = 100$ , AUC = 0.395, sensitivity/specificity of 47.0%/36.0%). In analyses applying machine learning methods to all 187 metabolite concentrations assayed, we find a modest signal in the BLSA with distinct metabolites associated with the preclinical and symptomatic stages of AD, whereas the same methods gave poor classification accuracies in the AGES-RS samples.



Bringing data to life.

# Example #2

## Public Health

### Big Data – Social Media

# Social Media in Action

14 Mar 2014



BIG DATA

## The Parable of Google Flu: Traps in Big Data Analysis

David Lazer,<sup>1,2\*</sup> Ryan Kennedy,<sup>1,3,4</sup> Gary King,<sup>3</sup> Alessandro Vespignani<sup>5,6,3</sup>



Large errors in flu predictions were largely avoidable, which offers lessons for the use of big data.

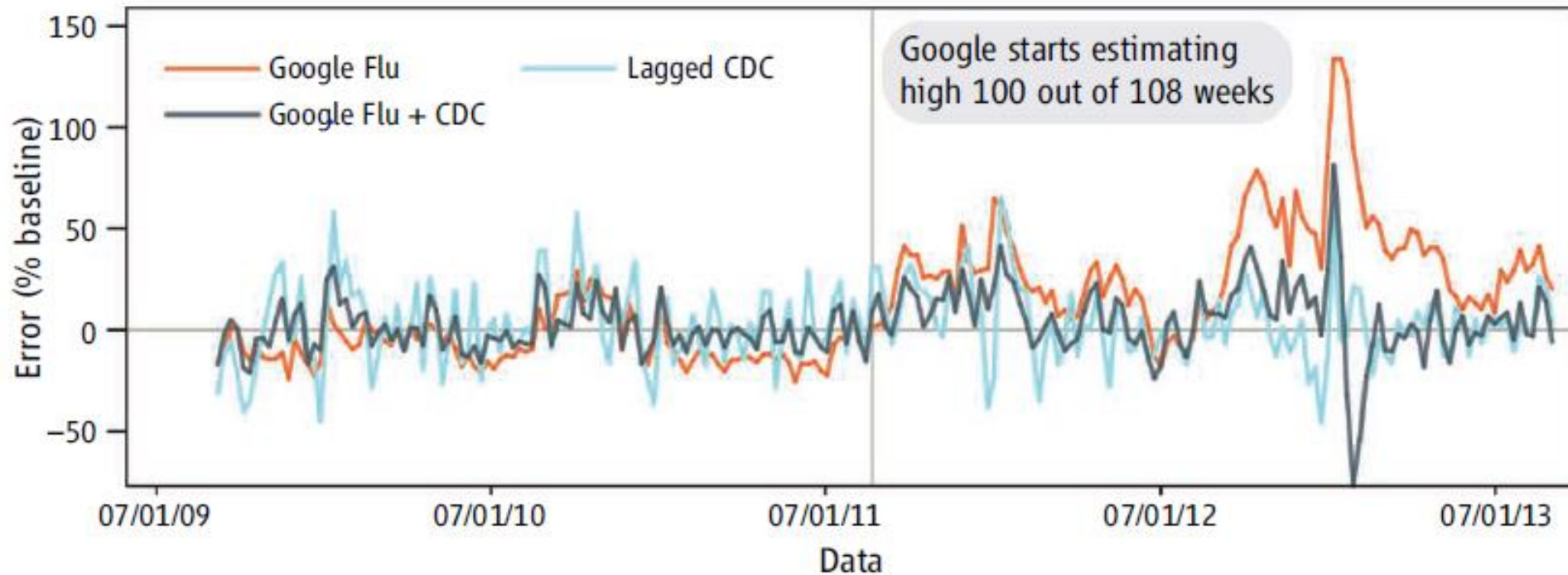


Bringing data to life.



# Social Media in Action

← Models built on data from 2003-2008.



Predictions become worse over time.



Bringing data to life.

# What Is a Data Scientist?



*uncertainty*

probability

variability

*prediction*

design

confidence

*error*

*inference*



*uncertainty*  
accountant

*probability*  
auditor

*variability*  
actuary

tabulator

*prediction*  
finance officer

*statistician*

analyst  
*design*

comptroller

number cruncher  
*confidence*

bookkeeper  
*error*

treasurer  
*inference*

# What Is a Data Scientist?

## Thinking Like A Data Scientist - Part I<sup>1</sup>

*The goal of the “thinking like a data scientist” process is to identify, brainstorm and/or uncover new variables that are better predictors of business performance.*

## Refined Thinking like

*Data science is about identifying variables that might be better predictors of performance.*



Bill Schmarzo (1/5/2015)

s<sup>2</sup> **!?!?**  
at might be better predictors

Bill Schmarzo 12/25/2017

<sup>1</sup> <http://www.grgroups.com/blog/thinking-like-a-data-scientist-part-i>

<sup>2</sup> [https://infocus.dellemc.com/william\\_schmarzo/refined-thinking-like-a-data-scientist-series/](https://infocus.dellemc.com/william_schmarzo/refined-thinking-like-a-data-scientist-series/)

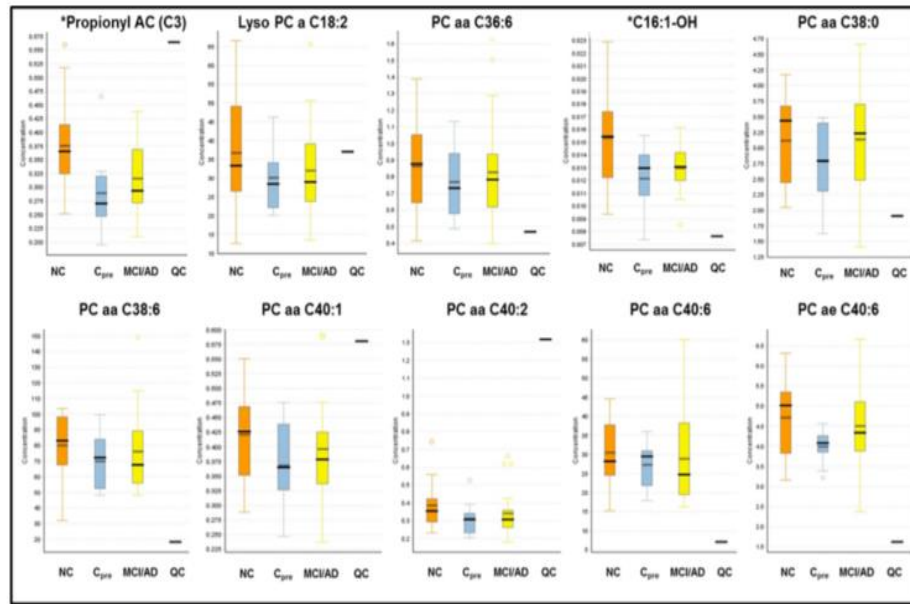




# Data Scientists and Statisticians



## FOCUS ON THE ANSWER



## FOCUS ON THE PROCESS / METHOD



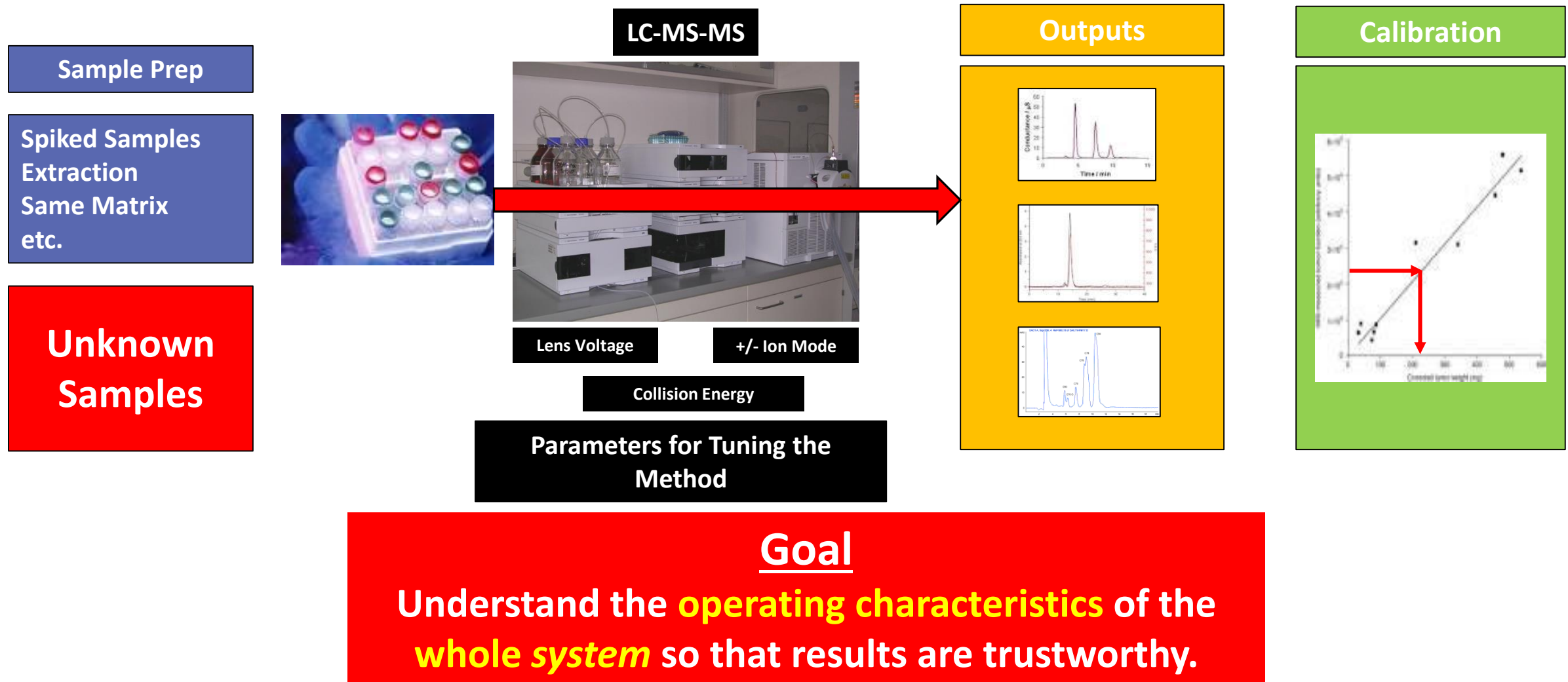
Bringing data to life.

# The Basics of Statistical Thinking

## The Statistical Analysis Process

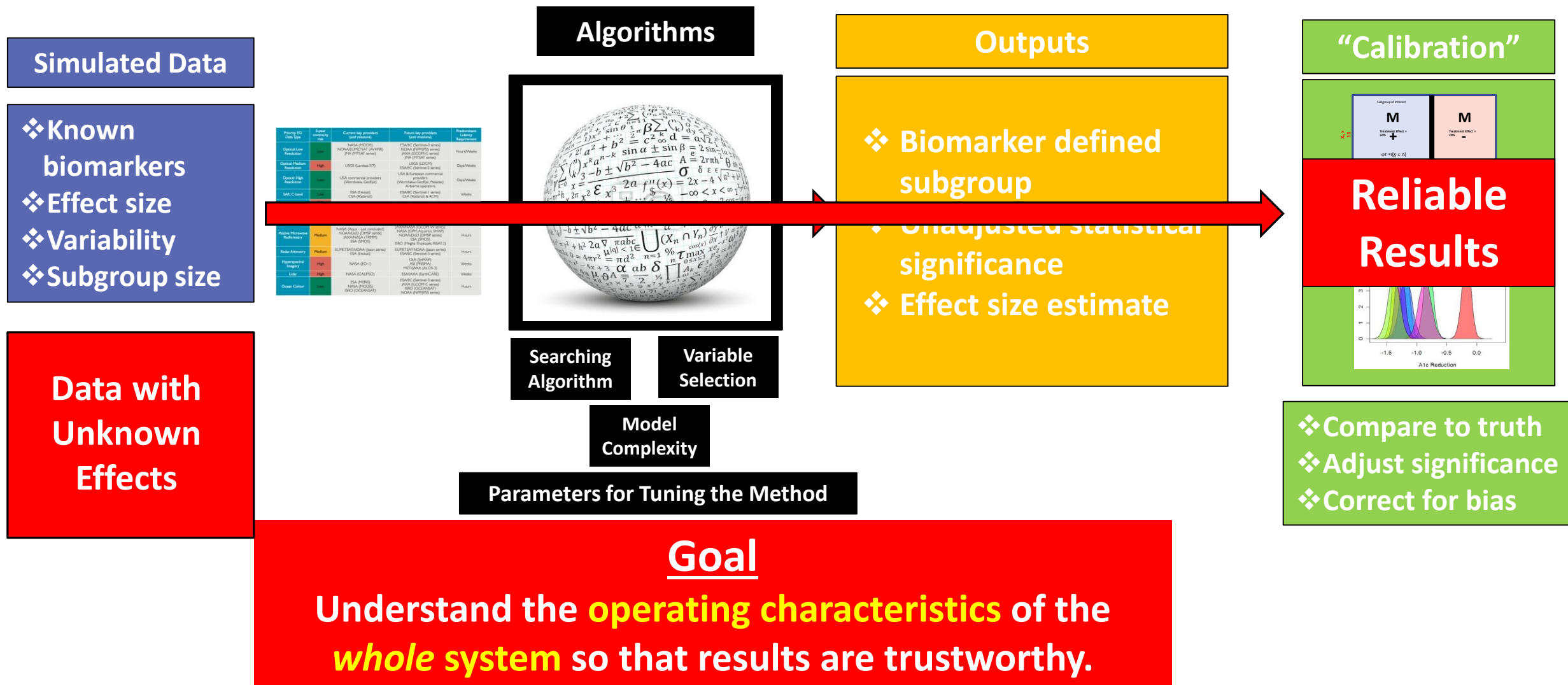
(that scientists can understand)

# Bioanalytical Method Development





# Statistical Method Development





# Data Scientists and Statisticians



## MULTIVARIATE

## P-VALUES

## MULTIPLICITY

## BAYES

### Circulation: Cardiovascular Genetics

#### Original Article

15 Jan 2015

Pharmacogenomic Determinants of the Cardiovascular Effects of Dalcetrapib

Jean-Claude Tardif<sup>1\*</sup>, Éric Rhéaume<sup>1</sup>, Louis-Philippe Lemieux Perreault<sup>2</sup>, Jean C. Grégoire<sup>1</sup>, Yassamin Feroz Zada<sup>2</sup>, Géraldine Asselin<sup>2</sup>, Sylvie Provost<sup>2</sup>, Amina Barhdadi<sup>2</sup>, David Rhainds<sup>3</sup>, Philippe L. L'Allier<sup>1</sup>, Reda Ibrahim<sup>1</sup>, Ruchi Upmanyu<sup>4</sup>, Eric J. Niesor<sup>4</sup>, Renée Benghozi<sup>4</sup>, Gabriela Suchankova<sup>4</sup>, Fouzia Laghrissi-Thode<sup>5</sup>, Marie-Claude Guertin<sup>6</sup>, Anders G. Olsson<sup>7</sup>, Ian Mongrain<sup>2</sup>, Gregory G. Schwartz<sup>8</sup> and Marie-Pierre Dubé<sup>9</sup>



**Conclusions**—The effects of dalcetrapib on atherosclerotic outcomes are determined by correlated polymorphisms in the ADCY9 gene.

100 potential biomarkers

- Prior probability of success ( $H_0$  is false) = **0.20**
- Prior on  $H_0$  is true (none are predictive) = 0.80
- Uniform prior per biomarker = **0.20/100 = 0.002**

Observed p-value = **0.0001** for one biomarker

- Bonferroni adjusted p-value  $\leq 100 * 0.0001 = 0.01$

Bayesian posterior  $\text{pr}(H_0 \text{ is false}) \leq \mathbf{0.44}$ .

Berger, JO, Wang X, Shen L (2014) A Bayesian Approach to Subgroup Identification, Journal of Biopharmaceutical Statistics, 24:1, 110-129.



Bringing data to life.

# Data Scientists and Statisticians

## MULTIVARIATE

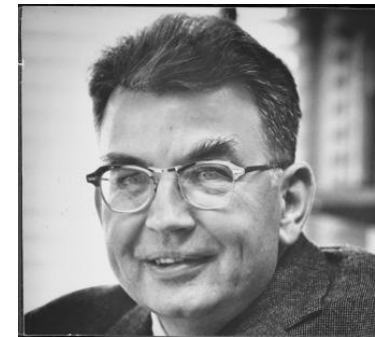
“Give me a big enough data set, and I guarantee that I can find the patterns in it.”

Prominent Data Science Researcher  
Distinguished Professor  
Major US University

## MULTIPLICITY

“Torture the data long enough, and they will confess to anything.”

Sir Ronald Coase  
Nobel Prize in Economics  
1991



*Bringing data to life.*



# Data Scientists and Statisticians



## BIG DATA

### Google Flu Trends

Observation	Influenza Like Illness	Doctor Visit	Search Term 1	Search Term 2	Search Term 3	...	Search Term 50,000,000
1	Y	Y	Y	N	N		Y
2	N	N	Y	N	N		N
3	Y	N	N	N	Y		Y
...							
1152	N	N	Y	N	N		Y

### Large p, small N problem

- As p gets large, more (useless?) correlations emerge
- An N gets large, everything becomes significant

## RIGHT DATA

“If you are trying to find a needle in a haystack, the worst thing you can do is add more hay.”

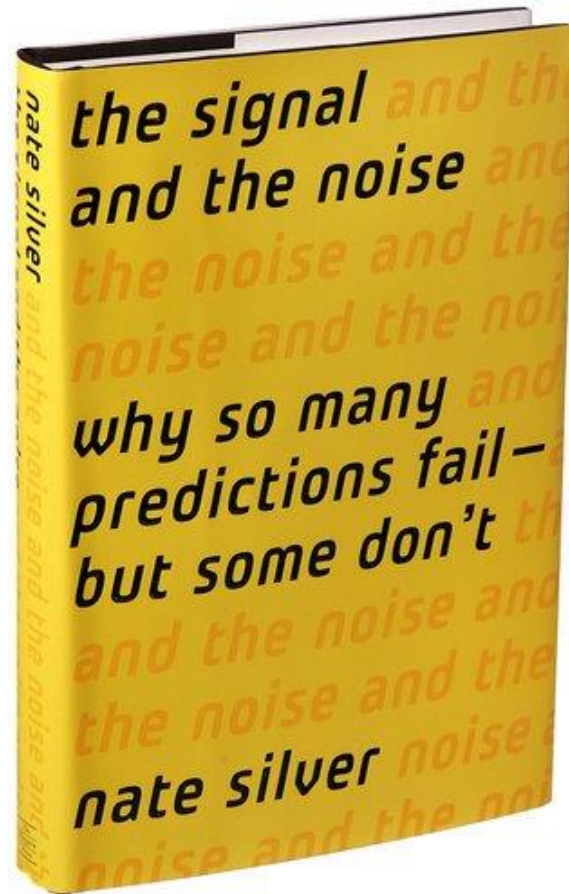
Steve Ruberg  
Your Run-of-the-Mill Statistician  
July, 2015



Bringing data to life.

# Data Scientists and Statisticians

## More Information, More Problems



**“We face danger whenever information growth outpaces our understanding of how to process it. ... it can still take a long time to translate information into useful knowledge, and that **if we are not careful, we may take a step back** in the meantime.”**



Bringing data to life.



# Data Scientists and Statisticians



# Big Data is Dead

# Alexander Thamm

November 23, 2017

“Big Data, Small Data, Little Data, Fast Data, and Smart Data are all ‘Just Data.’”

“ ... forecast quality does not depend on the volume of the data. Just Data means that, above all, the **right data** needs to be incorporated into analysis.”



***Bringing data to life.***

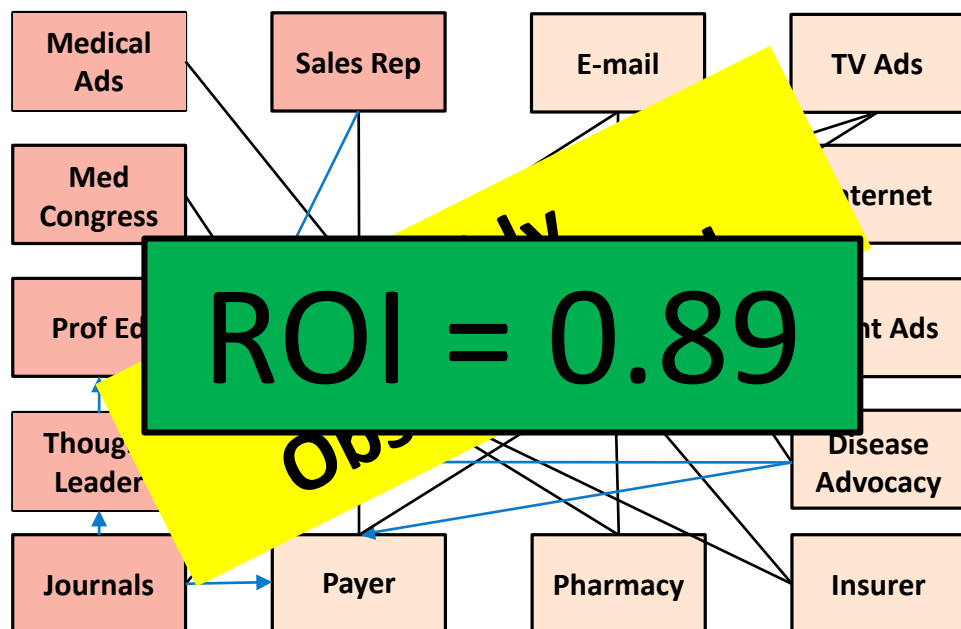
<https://www.linkedin.com/pulse/big-data-dead-just-regardless-quantity-structure-speed-thamm>



# Data Scientists and Statisticians

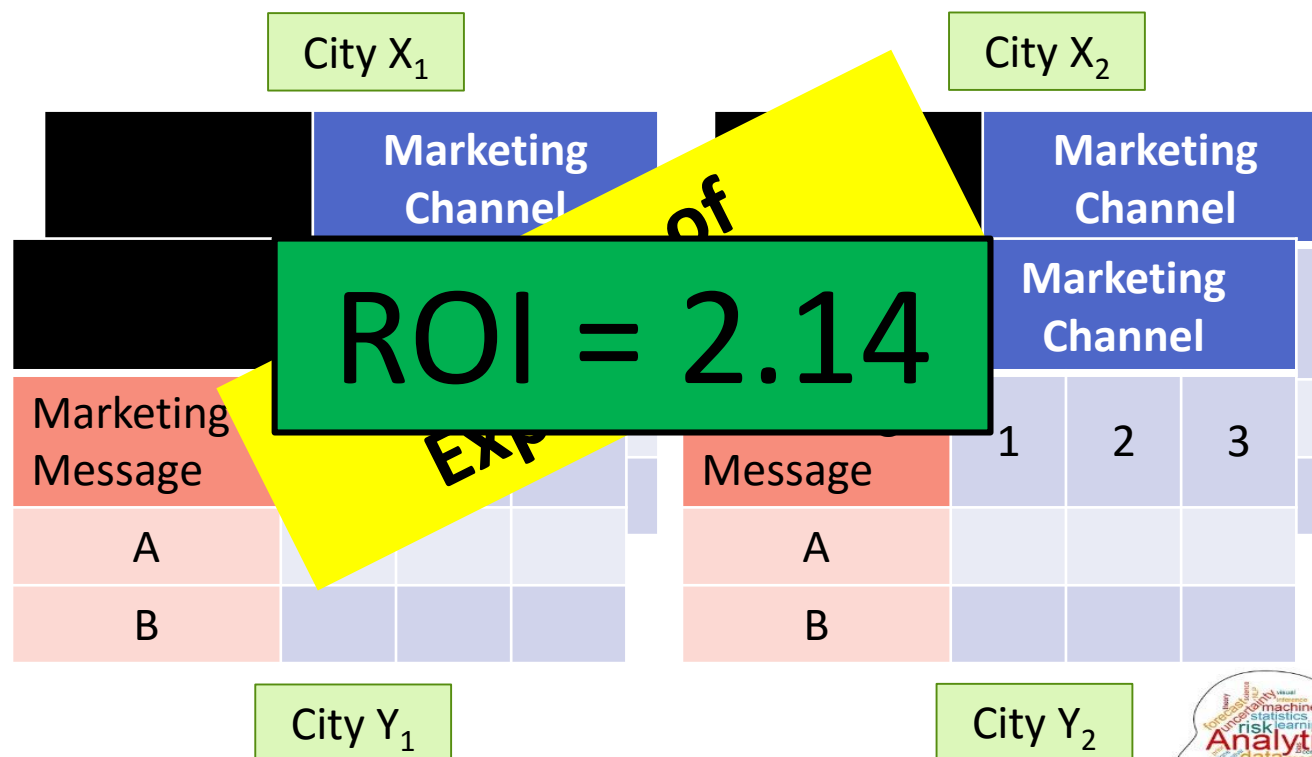


## BIG DATA



Prescription Ecosystem (US)

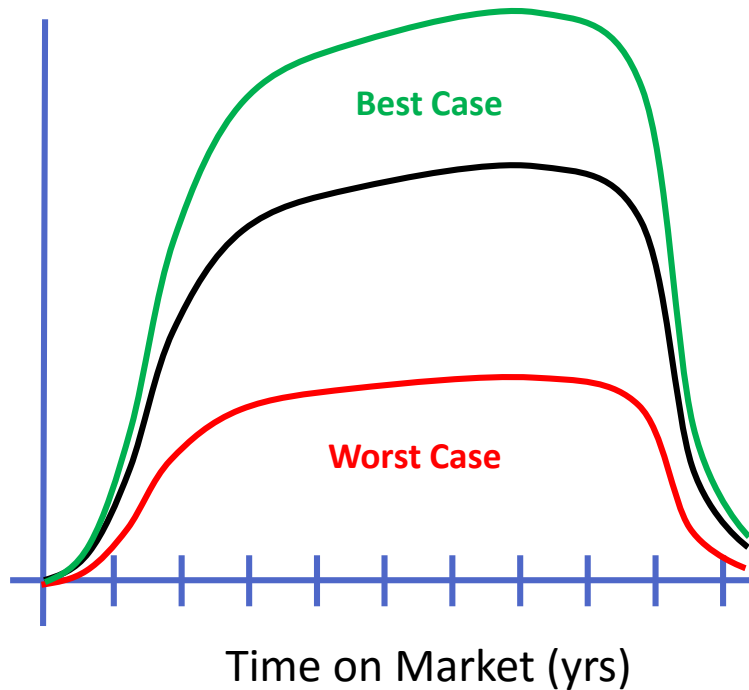
## RIGHT DATA



Bringing data to life.



Forecasted Revenues (\$MM)

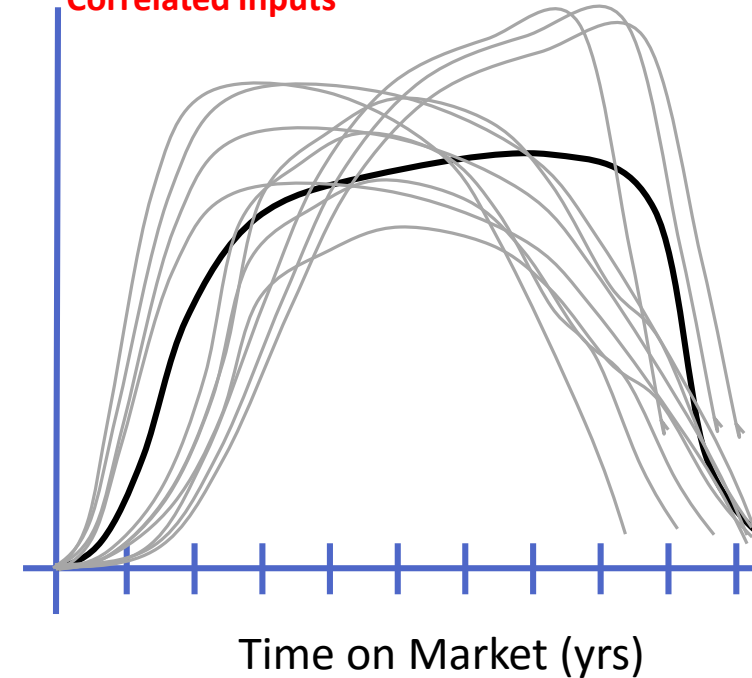


$$\underline{Y = F(X) + \varepsilon}$$

## Uncertainty

### Correlated Inputs

## SIMULATE







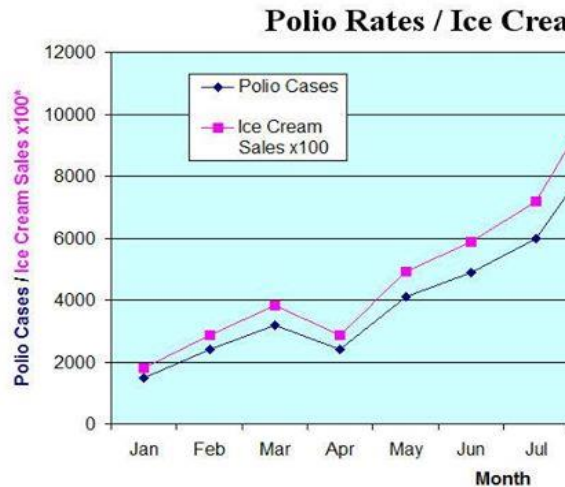
# Data Scientists and Statisticians



## CORRELATION

## CAUSATION

### The Real Cause of Polio!



**“We do not need causation anymore. Correlation is enough with big data.”**

**Partner and Data Scientist  
Large Business Consulting Company**

Eliminating ice cream was  
as part of an anti-polio diet!

Warm  
Weather

More Ice  
Cream



MORE POLIO



Bringing data to life.



# Data Scientists and Statisticians



## ASSOCIATION

ASSOCIATION OF DISRUPTED  
CIRCADIAN RHYTHMICITY WITH MOOD  
DISORDERS, SUBJECTIVE  
WELLBEING, AND COGNITIVE  
FUNCTION: A CROSS-SECTIONAL  
STUDY OF 91 105 PARTICIPANTS FROM  
THE UK BIOBANK

LAURA M LYALL<sup>1</sup>, PHD, CATHY A WYSE<sup>2</sup>,  
PHD, ... DANIEL J SMITH<sup>1</sup>, MD

INSTITUTE OF HEALTH AND WELLBEING, UNIVERSITY OF GLASGOW, GLASGOW, UK  
INSTITUTE OF BIODIVERSITY, ANIMAL HEALTH AND COMPARATIVE MEDICINE,  
UNIVERSITY OF GLASGOW, GLASGOW, UK

The Lancet, Psychiatry  
May 15, 2018

## CAUSATION?

### FINDINGS INTERPRETATION

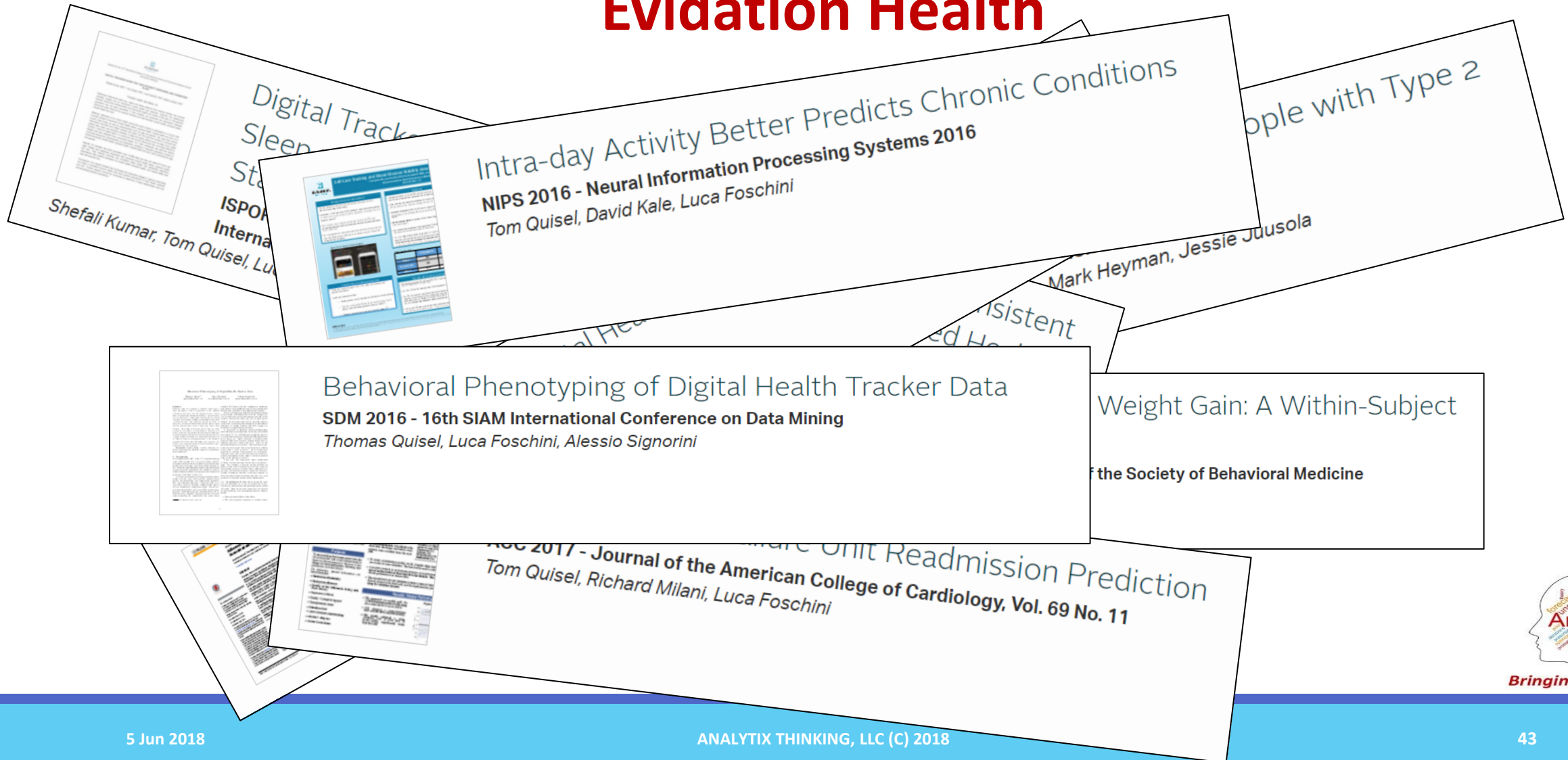
“... 91 105 participants with accelerometry data ... reduction ...  
“Circadian disruption is reliably associated with various  
was associated with increased risk of adverse mental health and wellbeing outcomes.  
including major depressive disorder (odds ratio 1.05, 95% CI  
1.04–1.08). Lower relative amplitude might be linked to increased  
susceptibility to mood disorders.”  
lifetime bipolar disorder (1.11, 1.03–1.20),  
greater mood instability (1.02, 1.01–1.04),  
higher neuroticism scores (incident rate ratio 1.01, 1.01–1.02),  
...”



Bringing data to life.

# Data Scientists and Statisticians

## Evidation Health



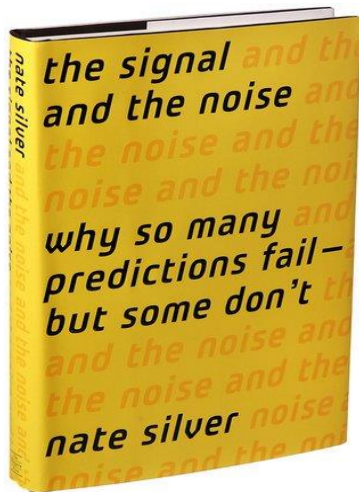
Bringing data to life.



# Data Scientists and Statisticians

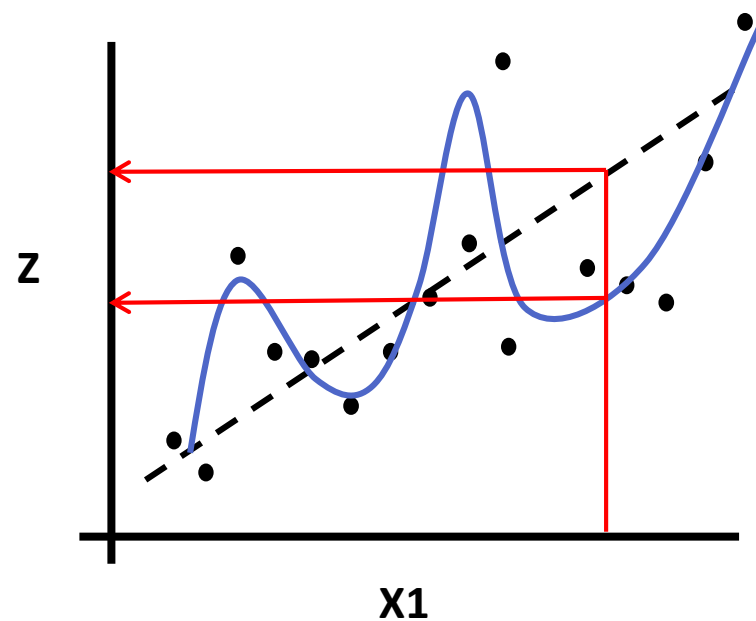


## OVER-FITTING



“The biggest problem you never heard of.”

## FITTING



“GFT overlooks considerable information that could be extracted by traditional statistical methods.”

Science



Bringing data to life.



# Data Scientists and Statisticians



## DATA SCIENTISTS

Applied – Good enough  
Cool problems  
Pictures – Holistic – Broad  
Bold – Confident  
Communicators  
Plentiful  
Patterns – Associations (“might”)  
Information  
Big Data

## STATISTICIANS

Pure – Perfect  
Cool math  
Equations – Details – Caveats  
Cautious – Skeptical  
Analyzers  
Rare  
**Causal effects**  
**Inference – Pr (Correct Decision)**  
**Right Data – Design of Experiments**



*Bringing data to life.*



# Data Scientists and Statisticians



## DATA SCIENTISTS

Computer Scientists

Epidemiologists

Pharmacokineticists

Outcomes Scientists

Bioinformaticists

Business Analysts

Econometrics

## APPROACH

“might be”

Associations

$Y = f(X)$

Associations

Focus on WHAT not HOW

Correlation

$Y = f(X)$



*Bringing data to life.*

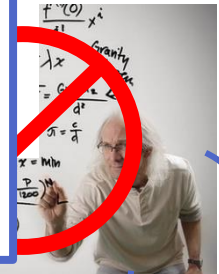


# Are Statisticians THE ANSWER?



“The future of statistics is bright.  
It is not as clear for statisticians.”

Steve Ruberg and Bill Louv  
JSM, 1991



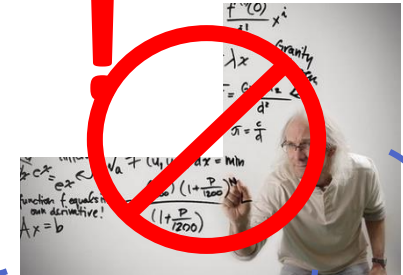
S. J. Ruberg and W. C. Louv (1991) "The Statistician as Strategist." 1991 Proceedings of the Section on Statistical Education, American Statistical Association, 8-15.



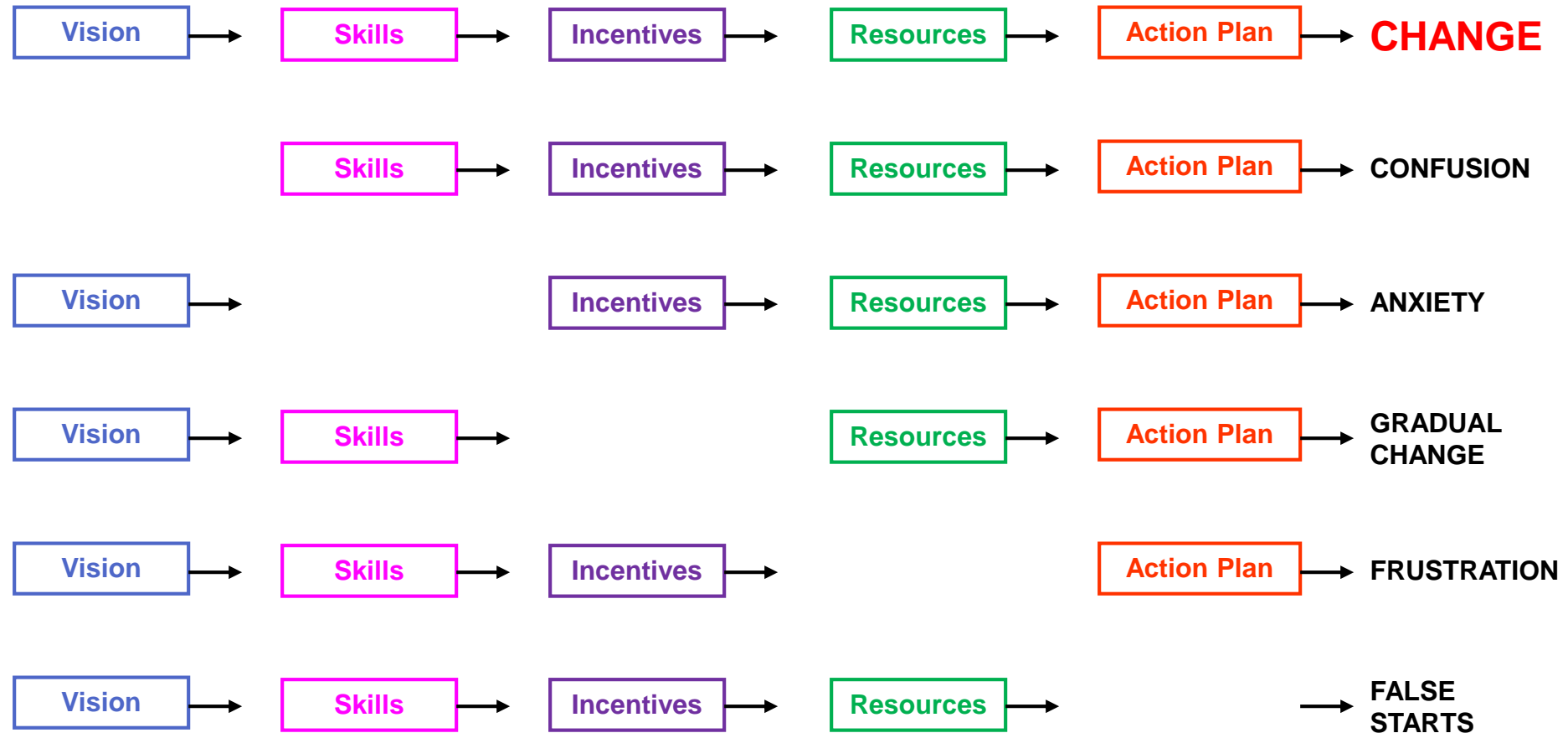
# Are Statisticians THE ANSWER?



**CLEARLY NOT**



# Leading Disruptive/Complex Change



Without adequate **Communication** of each of these elements, it is the same as not having the element present.

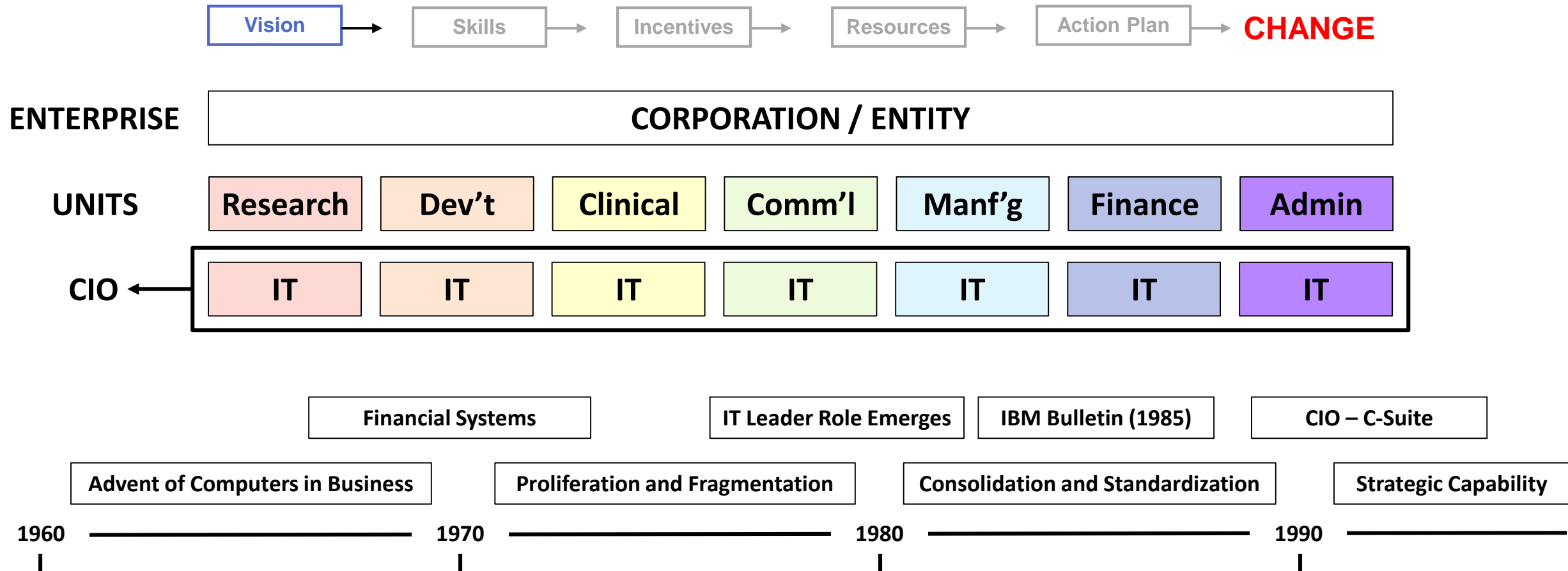
# Leading Disruptive/Complex Change



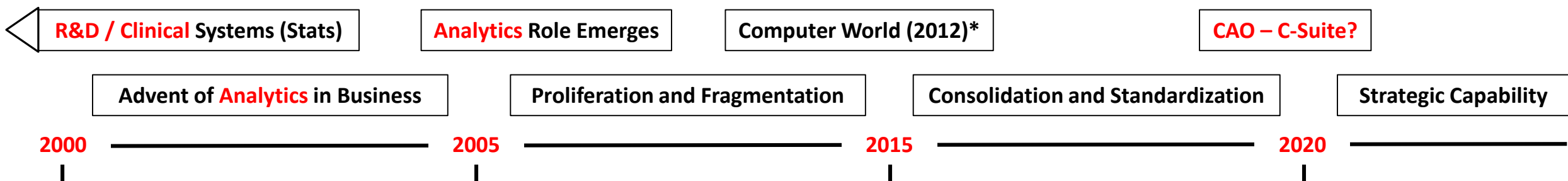
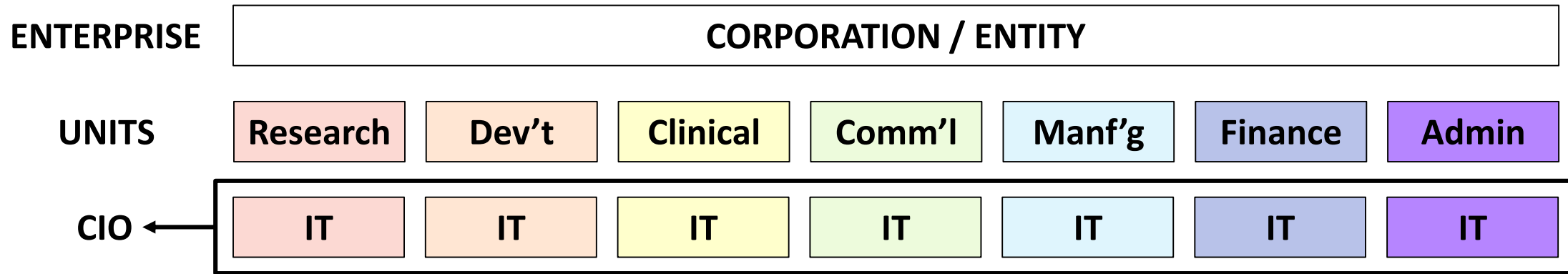
“A **vision** is a compelling image of an achievable future.”

Laura Berman Fortgang

# Leading Disruptive/Complex Change

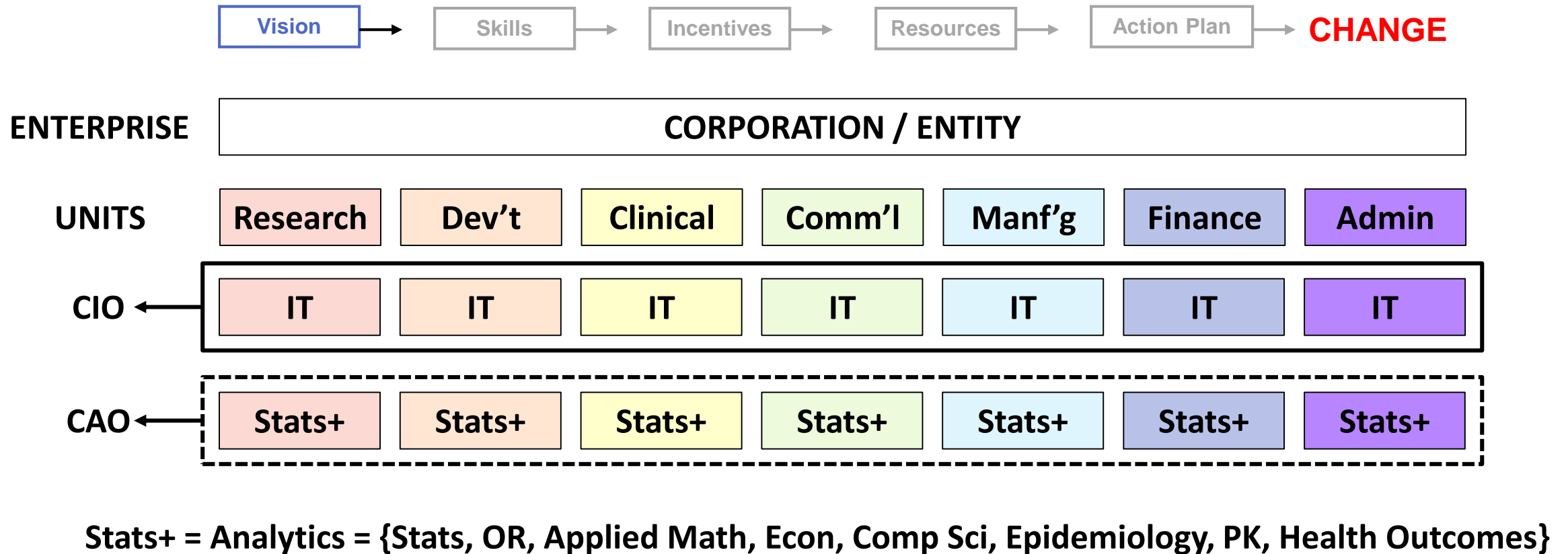


# Leading Disruptive/Complex Change



\*<https://www.computerworld.com/article/2492218/big-data/time-has-come-for-chief-analytics-officers.html>

# Leading Disruptive/Complex Change



**Communication:** Focus and Alignment ... + ... Relentless pursuit and messaging

# Leading Disruptive/Complex Change



## ✓ Technical Skills

# Soft Skills

- **Leadership**
- Communication, negotiation, influence
- Practical, applied
- Subject matter acumen

# How to get soft skills in school?

- Undergraduate training



**Communication:** Internal programs offered consistently



# Leading Disruptive/Complex Change



Show me the money!

- Reduce cost
- Speed cycle time
- Increase probability of success
- Change strategy, influence a decision



“I will give you 2 statisticians for 6 months ...”

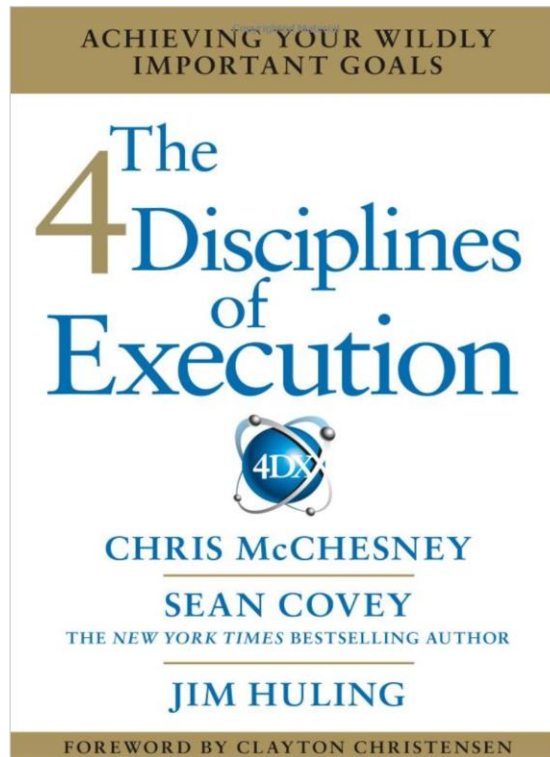
“Can you do that?”

**Communication:** Create metrics and tell the success stories → Management; internal publications; seminars ...



*Bringing data to life.*

# Leading Disruptive/Complex Change



## 1. Focus on the Wildly Important

Initially ... squeeze

- Prioritize, Synergize, Stop dabbling

Then re-assign people

- Experienced + newer

Link cross-functional resources

**Communication:** Workshops, Summits, Partnerships across functions ... Explain what will NOT get done



Bringing data to life.

# Leading Disruptive/Complex Change



## Need a Playbook

1. Define **capabilities** that align with business goals
2. **DEDICATE** resources (remember the squeeze)
3. Portfolio of projects / use cases / initiatives
4. Initially ... quick wins
5. Metrics, story-telling
6. See #3 – rinse and repeat

Communication: Town Halls, Functional and Corporate forums

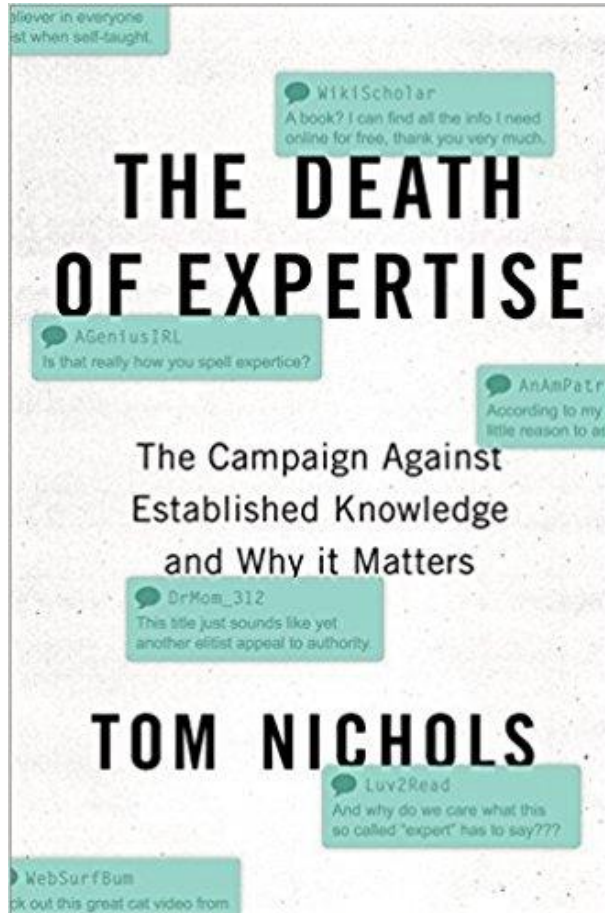


Bringing data to life.

# DISCUSSION



# DISCUSSION



## Data Science Revolution

Fast answers

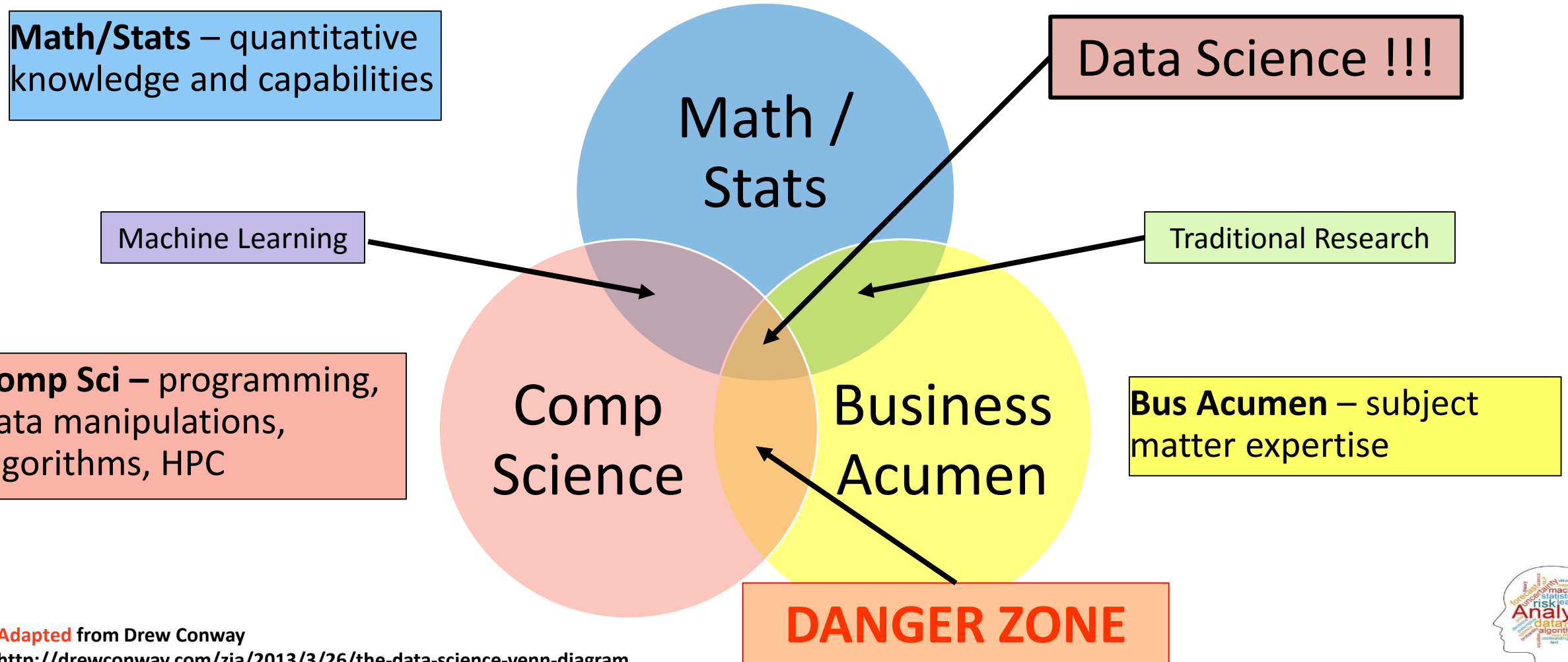
Superficial answers

Sans Uncertainty / Probability

Incorrect answers

Bias, Over-fitting, Multiplicity ...

# DISUCSSION



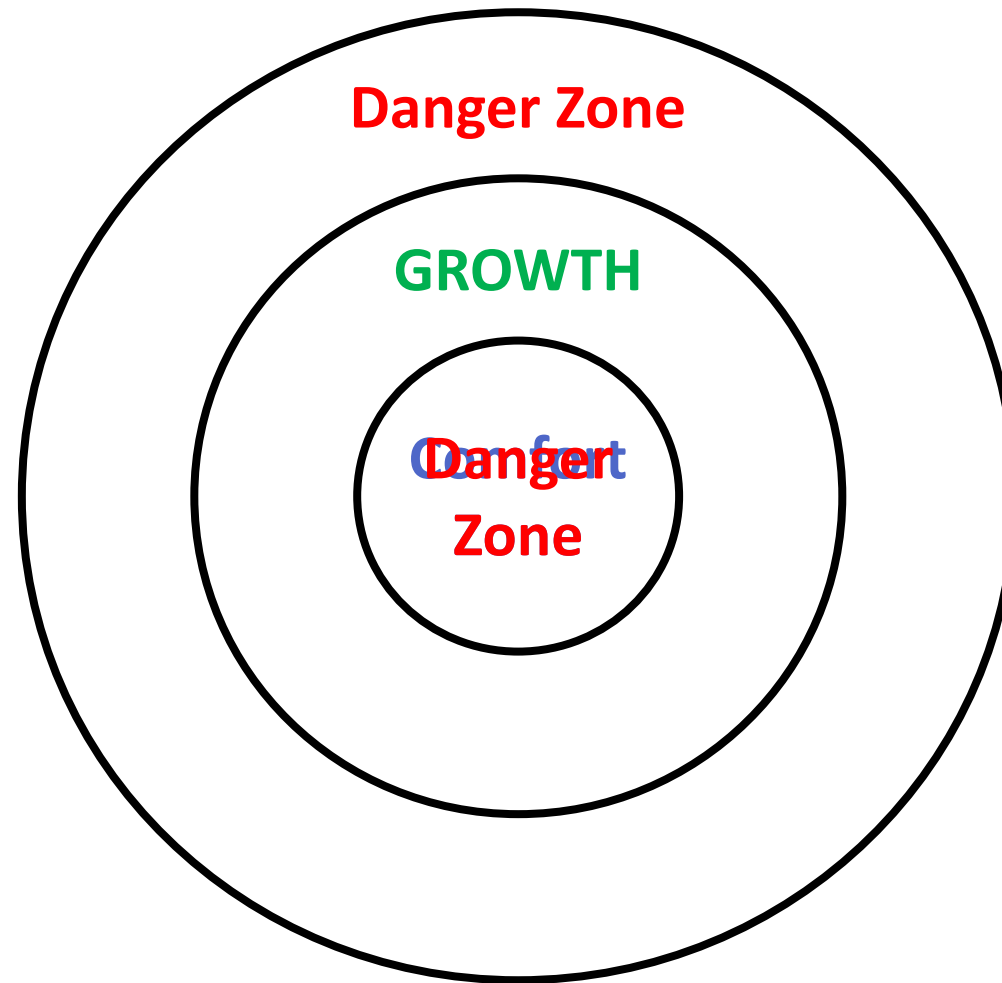
**Adapted** from Drew Conway

<http://drewconway.com/zia/2013/3/26/the-data-science-venn-diagram>



***Bringing data to life.***

# DISCUSSION



from Jessica Hagy, *Indexed*



Bringing data to life.



# DISCUSSION

The

Washington's lawyer surplus  
How to do a nuclear deal with Iran

**“Models which can be ‘tuned’ in many**

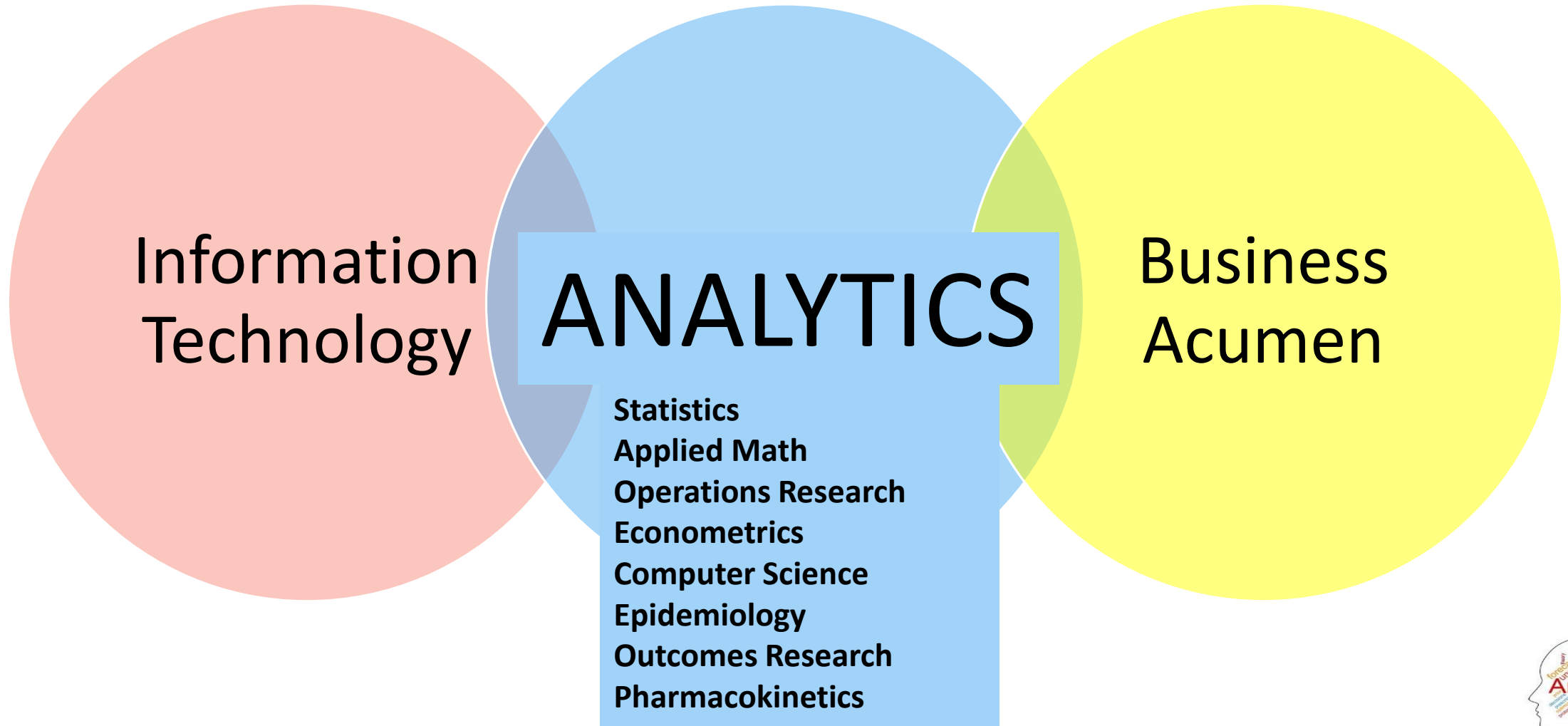
Lack of reproducibility  
in research  
... and in business?

October 21, 2013



*Bringing data to life.*

# DISCUSSION



*Bringing data to life.*

# CONCLUSION

We (Stats) have we

ore ...

Data  
Mining

(you nar  
Informa

... but not capitalize



Machine  
Learning

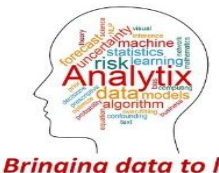
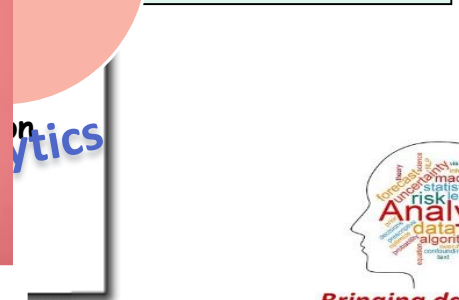
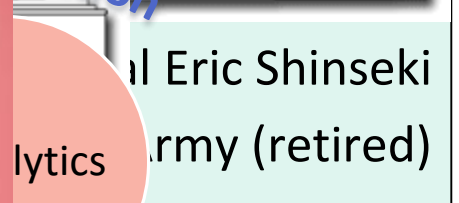
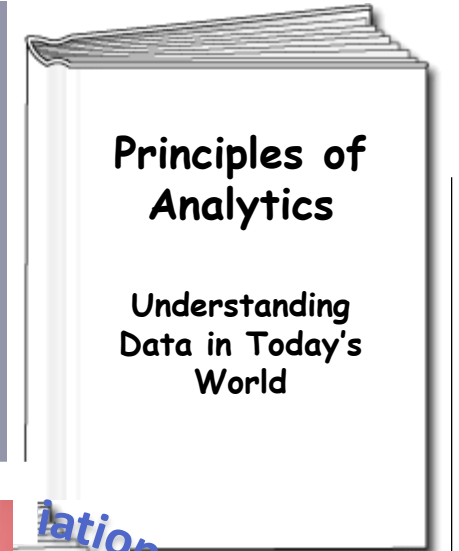
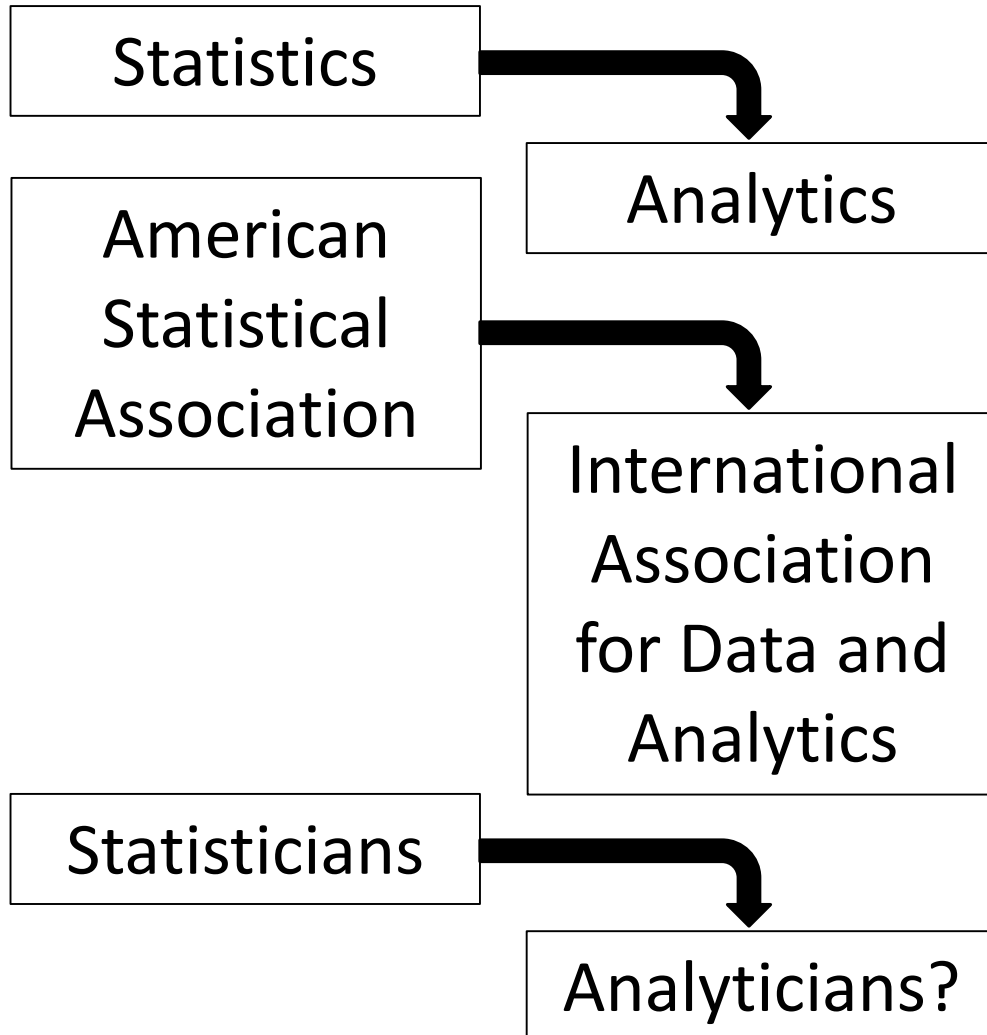
entum.

...



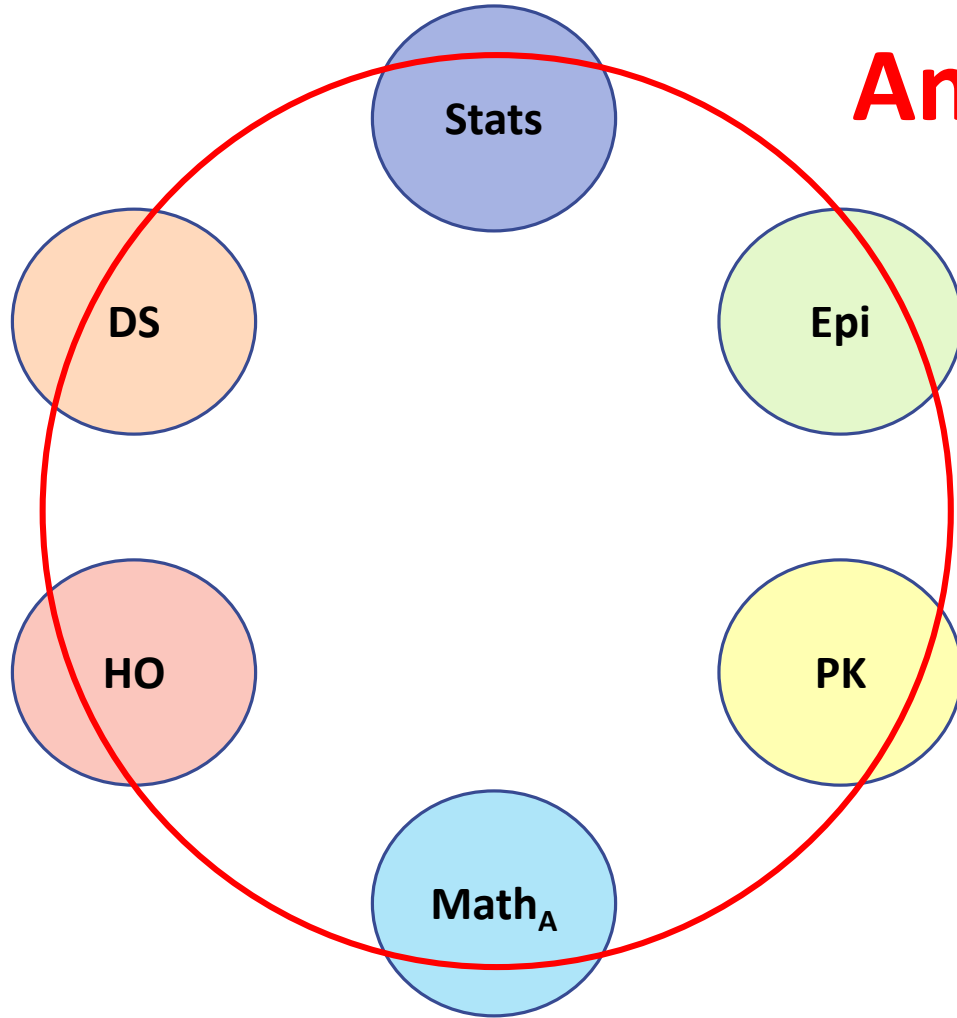
Bringing data to life.

# CONCLUSION



# CONCLUSION

## **Analytics Community**



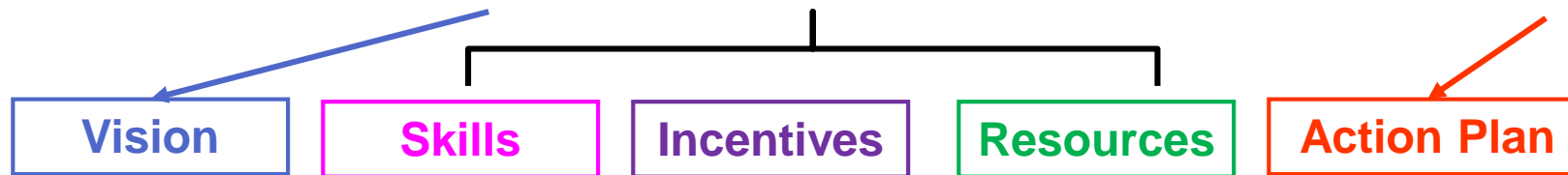
**“There is no progress  
without conflict.”**

George Bernard Shaw



*Bringing data to life.*

# CONCLUSION



John Schaar



*Bringing data to life.*

Grazie!

ありがとうございました!

Gracias!

धन्यवाद!

Спасибо!

Thank you!

Dank je!

Danke!

Tack!

Je vous remercie!

Obrigado!

謝謝!