Statistical Inference, Learning and Models for Big Data

Nancy Reid
University of Toronto
October 16, 2015

FIELDS

THE FIELDS INSTITUTE

THEMATIC PROGRAM ON STATISTICAL INFERENCE, LEARNING, AND MODELS FOR BIG DATA

JANUARY - JUNE, 2015

PROGRAM

JANUARY 12 – 23, 2015
Opening Conference and Boot Camp
Organizing Committee: Nancy Reid (Chair), Sallie Keller, Lisa Lix, Bin Yu

JANUARY 26 – 30, 2015
Workshop on Big Data and Statistical Machine Learning
Organizing committee: Ruslan Salakhutdinov (Chair), Dale Schuurmans, Yoshua Bengio, Hugh Chipman, Bin Yu

FEBRUARY 9 – 13 , 2015
Workshop on Optimization and Matrix Methods in Big Data
Organizing Committee: Stephen Vavasis (Chair), Anima Anandkumar, Petros Drineas, Michael Friedlander , Nancy Reid, Martin Wainwright

FEBRUARY 23 – 27, 2015
Workshop on Visualization for Big Data: Strategies and Principles
Organizing Committee: Nancy Reid (Chair), Susan Holmes, Snehelata Huzurbazar, Hadley Wickham, Leland Wilkinson

MARCH 23 – 27, 2015
Workshop on Big Data in Health Policy
Organizing Committee: Lisa Lix (Chair), Constantine Gatsonis , Sharon-Lise Normand

APRIL 13 – 17, 2015
Workshop on Big Data for Social Policy
Organizing Committee: Sallie Keller (Chair), Robert Groves, Mary Thompson

JUNE 13 – 14, 2015
Closing Conference
Organizing Committee: Nancy Reid (Chair), Sallie Keller, Lisa Lix, Hugh Chipman, Ruslan Salakhutdinov, Yoshua Bengio, Richard Lockhart
to be held at AARMS of Dalhousie University

GRADUATE COURSES

JANUARY TO APRIL 2015
Large Scale Machine Learning
Instructor: Ruslan Salakhutdinov (University of Toronto)

JANUARY TO APRIL 2015
Topics in Inference for Big Data
Instructors: Nancy Reid (University of Toronto), Mu Zhu (University of Waterloo)

This thematic program emphasizes both applied and theoretical aspects of statistical inference, learning and models in big data. The opening conference will serve as an introduction to the program, concentrating on overview lectures and background preparation. Workshops throughout the program will highlight cross-cutting themes, such as learning and visualization, as well as focus themes for applications in the social, physical and life sciences. It is expected that all activities will be webcast using the FieldsLive system to permit wide participation. Allied activities planned include workshops at PIMS in April and May and CRM in May and August.

ORGANIZING COMMITTEE

Yoshua Bengio (Montréal)
Hugh Chipman (Acadia)
Sallie Keller (Virginia Tech)
Lisa Lix (Manitoba)
Richard Lockhart (Simon Fraser)
Nancy Reid (Toronto)
Ruslan Salakhutdinov (Toronto)

INTERNATIONAL ADVISORY COMMITTEE

Constantine Gatsonis (Brown)
Susan Holmes (Stanford)
Snehelata Huzurbazar (Wyoming)
Nicolai Meinshausen (ETH Zurich)
Dale Schuurmans (Alberta)
Robert Tibshirani (Stanford)
Bin Yu (UC Berkeley)

For more information, allied activities off-site, and registration, please visit:
www.fields.utoronto.ca/programs/scientific/14-15/bigdata

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Canadian Institute for Statistical Sciences

CANSSI INCASS

Fields Institute for Resesarch in the Mathematical Sciences

FIELDS

Pacific Institute for Mathematical Sciences

CRM

Centre de Recherches Mathématiques

NSERC CRSNG

Ontario

Workshops

- Opening Conference and Bootcamp Jan 9 – 23
- Statistical Machine Learning Jan 26 – 30
- Optimization and Matrix Methods Feb 9 – 11
- Visualization: Strategies and Principles Feb 23 – 27
- Big Data in Health Policy Mar 23 – 27
- Big Data for Social Policy Apr 13 – 16

- Networks, Web mining, and Cyber-security May, CRM
- Statistical Theory for Large-scale Data April, PIMS
- Challenges in Environmental Science May, PIMS
- Complex Spatio-temporal Data April, Fields
- Commercial and Retail Banking May, Fields

- Closing Conference: Statistical and Computational Analytics June 12 – 13, Halifax
- Deep Learning Summer School August 3 – 12

And more

Distinguished Lecture Series in Statistics

Terry Speed, ANU, April 9 and 10

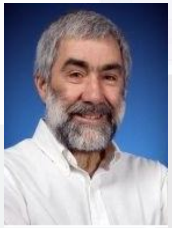
Bin Yu, UC Berkeley, April 22 and 23

Coxeter Lecture Series

Michael Jordan, UC Berkeley, April 7 – 9

Distinguished Public Lecture,

Andrew Lo, MIT, March 25



Graduate Courses

Statistical Machine Learning

Topics in Big Data

Ruslan Salakhutdinov, Toronto

Mu Zhu, Waterloo

Industrial Problem Solving Workshop

May 25 – 29

Fields Summer Undergraduate Research Program

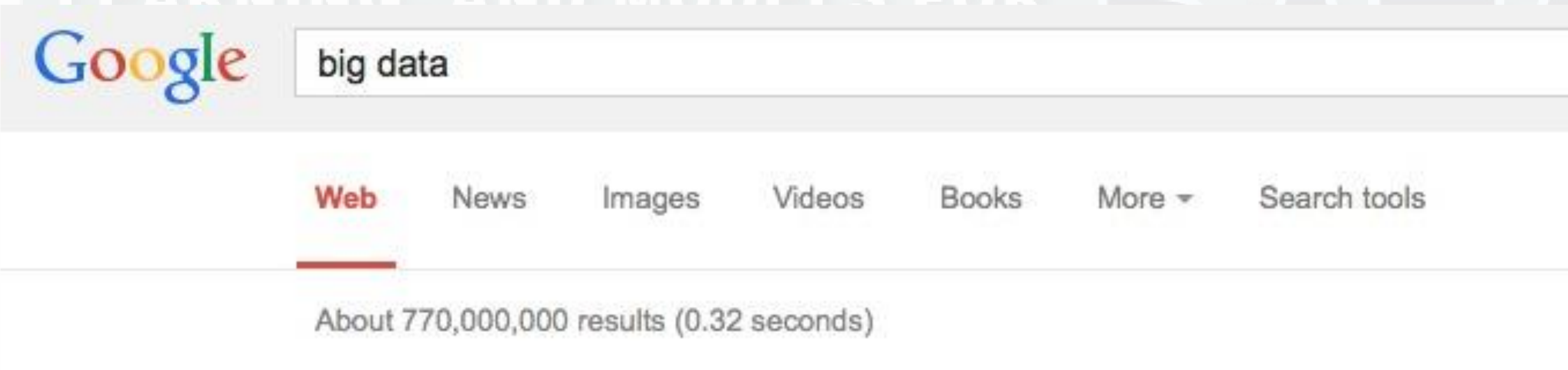
May to August, 2015

Watch events on Fields*Live*

MDM 12 – Einat Gil et al.

Big Data – Big Topic

- Where to start?
- Look up some references



- Likelihood 78 m
- Statistical inference 7m

MARCH 29, 2013

STEAMROLLED BY BIG DATA

BY GARY MARCUS

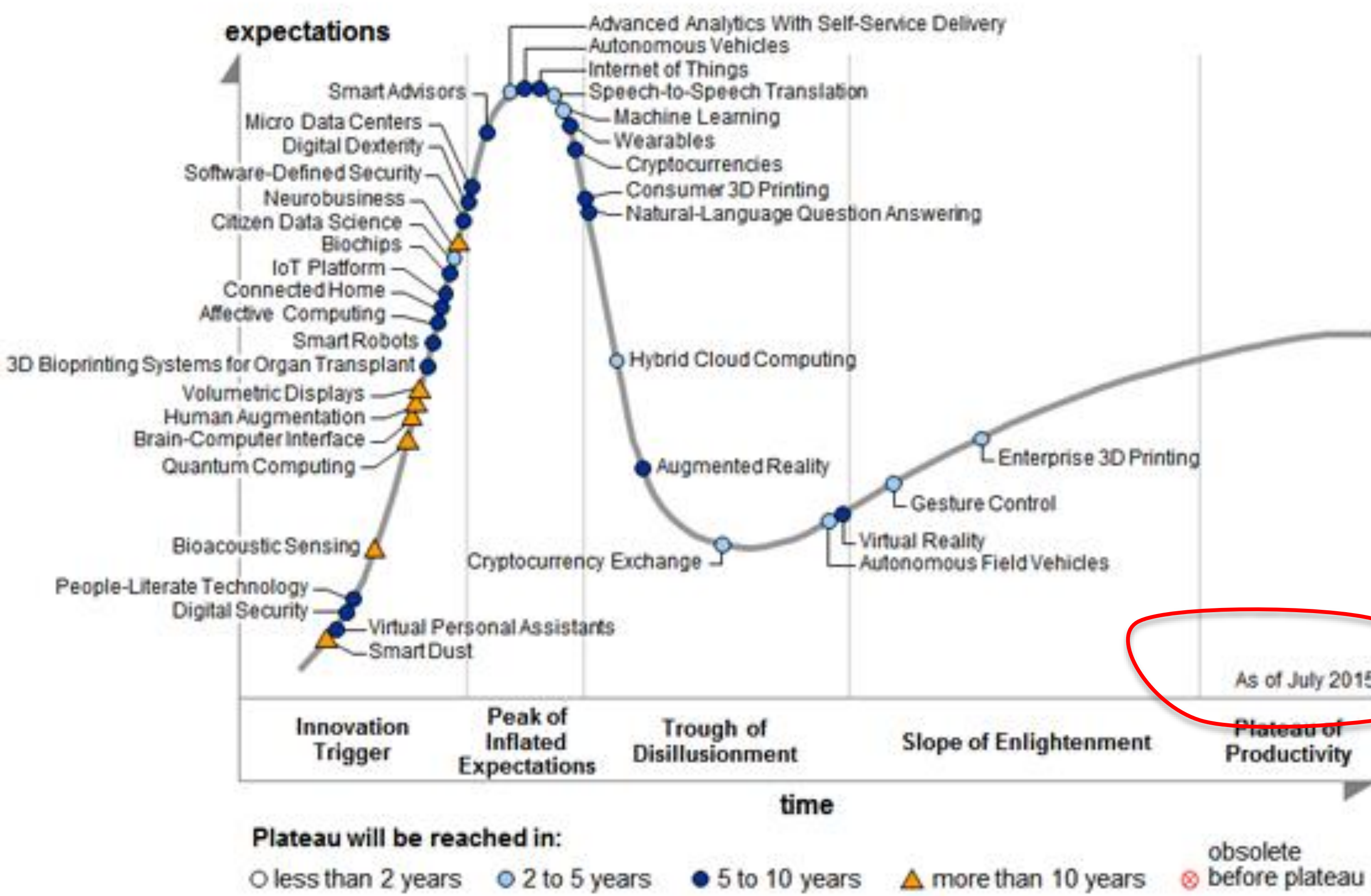
Five years ago, few people had heard the phrase "Big Data." Now, it's hard to go an hour without seeing it. In the past several months, the industry has been mentioned in dozens of New York *Times* stories, in every section from metro to business. (*Wired* has even already declared it passé: "STOP HYPING BIG DATA AND START PAYING ATTENTION TO 'LONG DATA'.") At least one corporation, the business-analytics firm SAS, has a Vice-President of Big Data. Meanwhile, nobody seems quite sure exactly what the phrase

Gartner Hype Cycle
July 2013

Gartner Hype Cycle
July 2014

falling-99183_640 →

https://etechlib.wordpress.com/tag/hype-cycle/



The Blogosphere

I view "Big Data" as just the latest manifestation of a cycle that has been rolling along for quite a long time

Steve Marron, June 2013

- Statistical Pattern Recognition
- Artificial Intelligence
- Neural Nets
- Data Mining
- Machine Learning

As each new field matured, there came a recognition that in fact much was to be gained by studying connections to statistics

Big Data Types

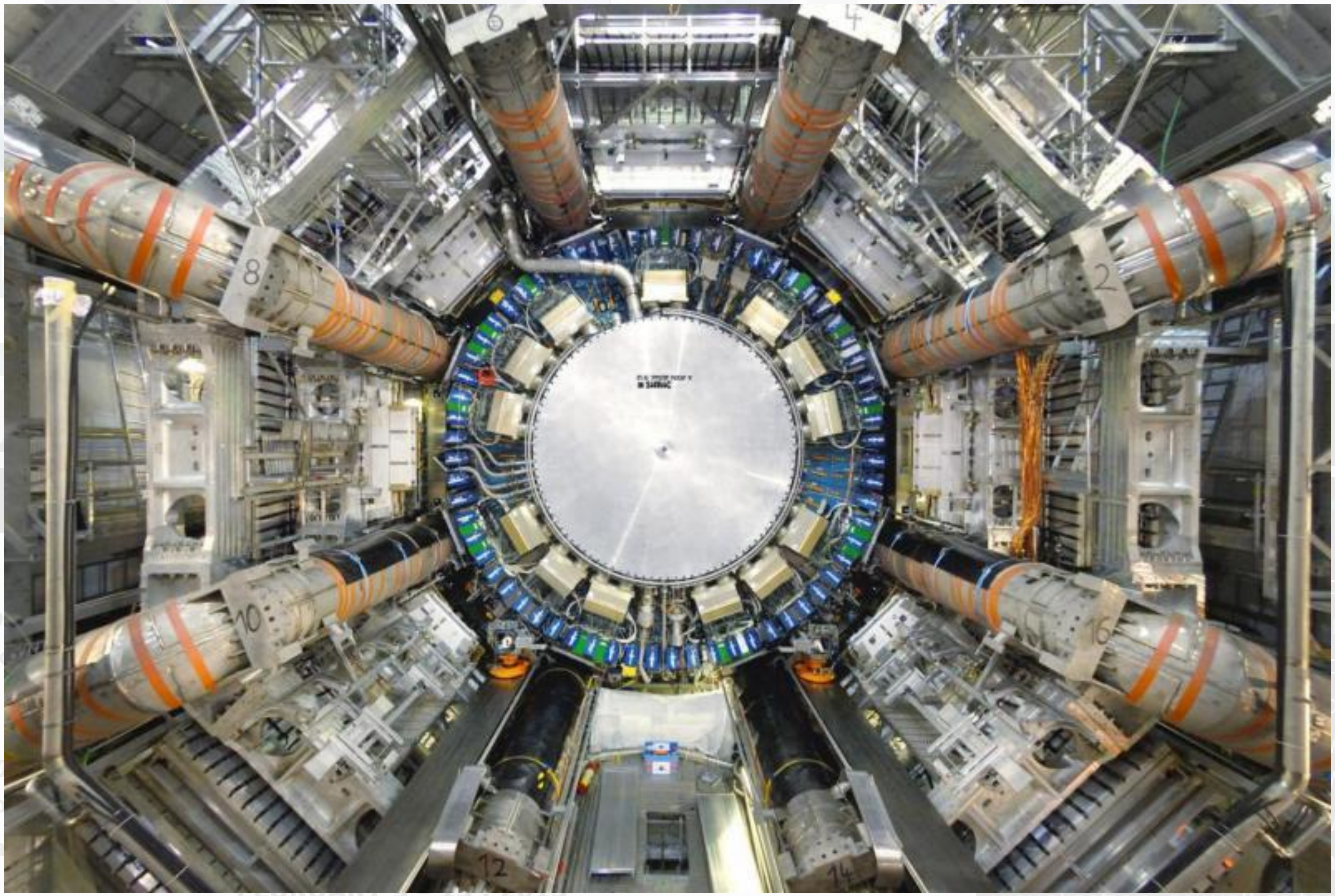
- Data to confirm scientific hypotheses
- Data to explore new science
- Data generated by social activity – shopping, driving, phoning, watching TV, browsing, banking, …

- Data generated by sensor networks – smart cities
- Financial transaction data
- Government data – surveys, tax records, welfare rolls, …
- Public health data – health records, clinical trials, public health surveys

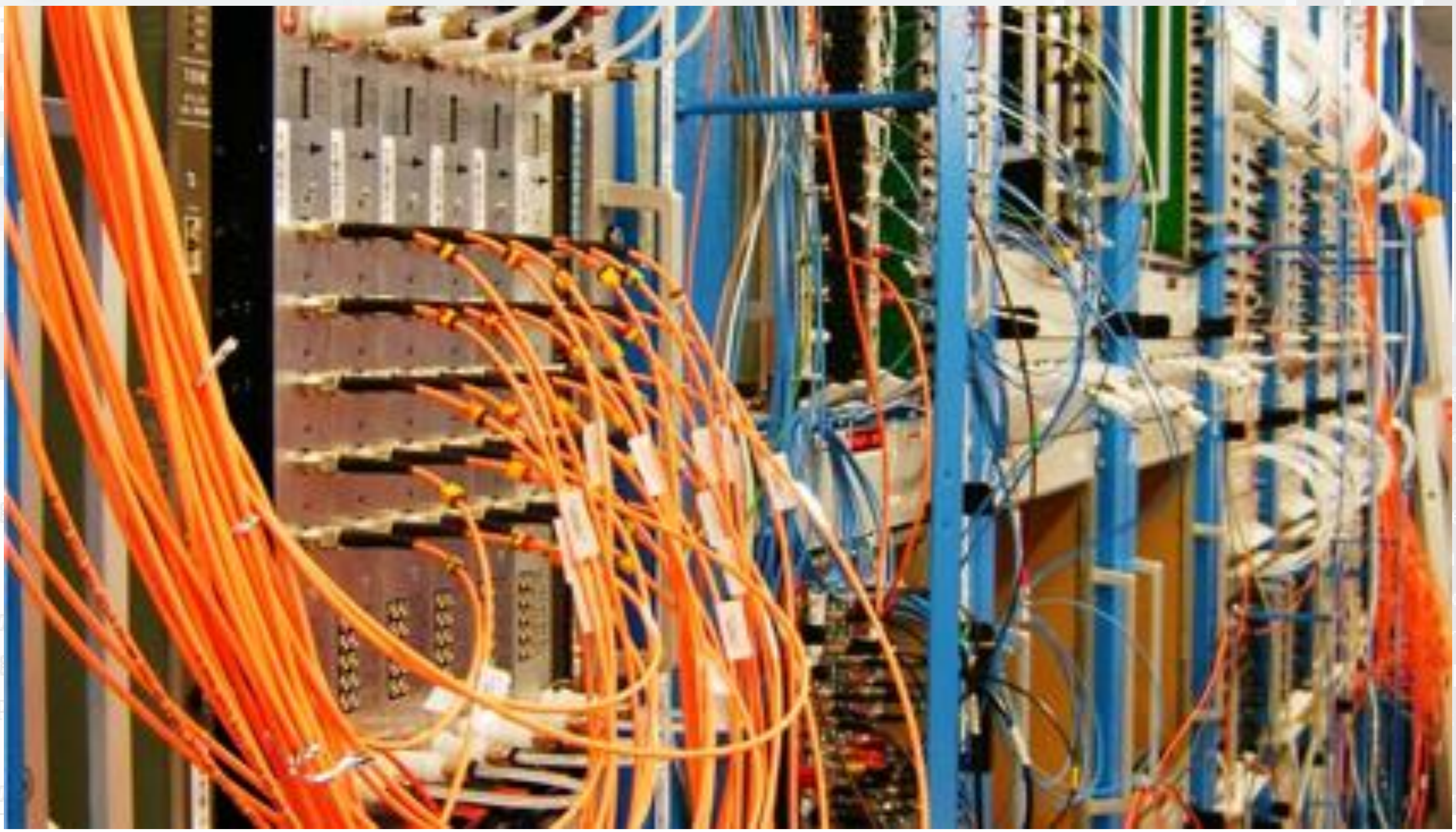
Jordan 06/2014

The Atlas experiment – CERN

http://atlas.ch/what_is_atlas.html#5



If all the data from ATLAS were recorded, this would fill 100,000 CDs per second. This would create a stack of CDs 450 feet high every second, which would reach to the moon and back twice each year. The data rate is also equivalent to 50 billion telephone calls at the same time. ATLAS actually only records a fraction of the data (those that may show signs of new physics) and that rate is equivalent to 27 CDs per minute. http://atlas.ch/what_is_atlas.html - 5

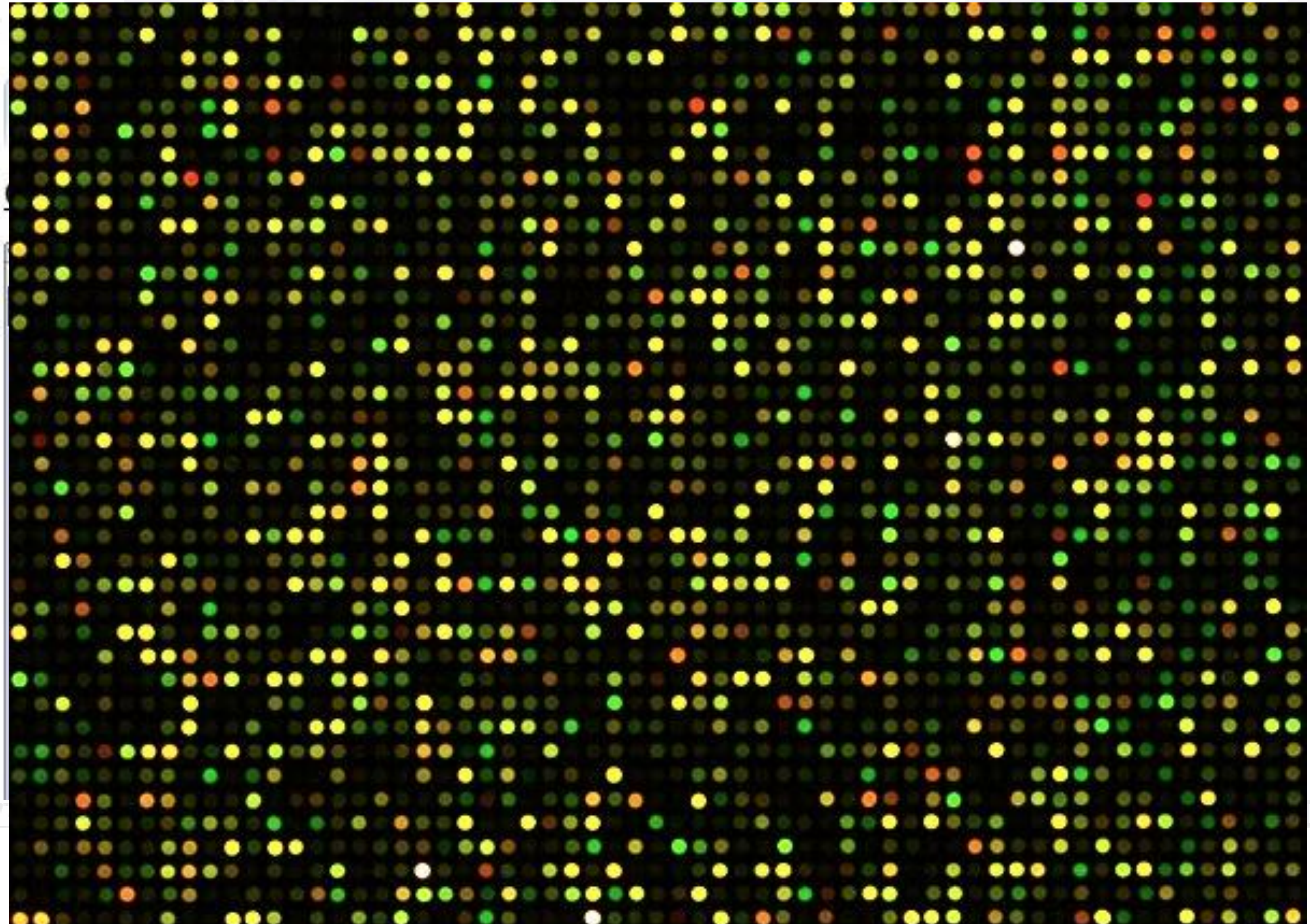


Exploration: the Square Km Array

https://www.skatelescope.org/location/

- The Square Kilometre Array (SKA) project is an international effort to build the world's largest radio telescope, with a square kilometre (one million square metres) of collecting area.
- World leading scientists and engineers designing and developing a system which will require supercomputers faster than any in existence in 2013, and network technology that will generate more data traffic than the entire Internet.

Exploration: microarray



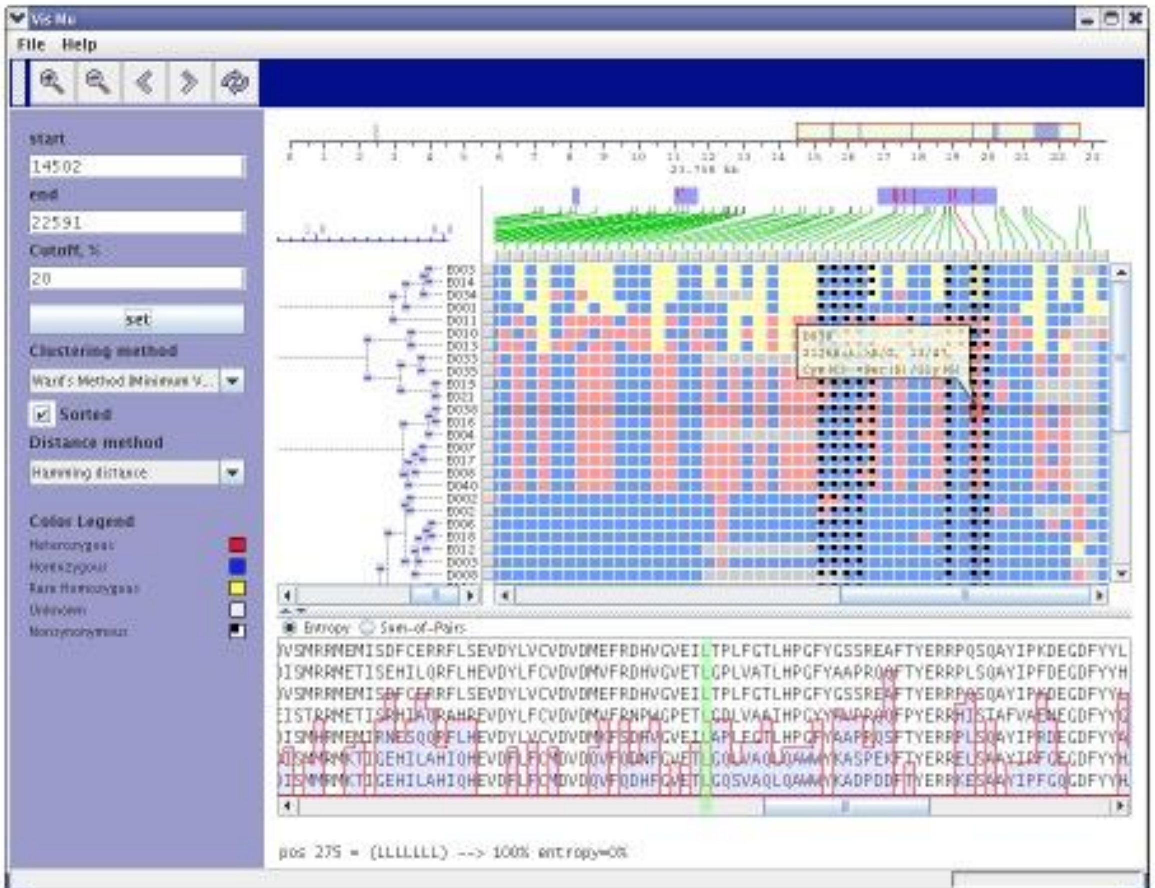
VISTA

Tools for Comparative Genomics

VISTA Home | Custom Alignment | Browser | Enhancer DB | Downloads | Publications

SNP-VISTA

GeneSNP-VISTA: Visualization of mutations in genes



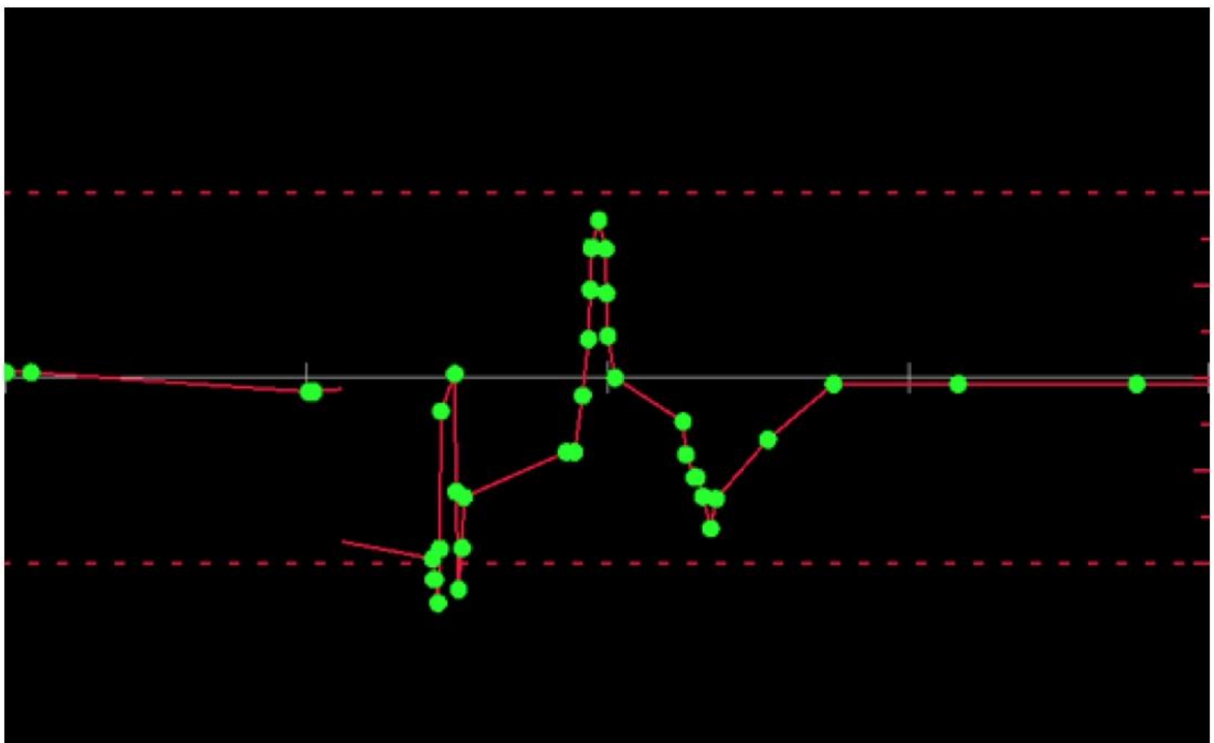
Social Activity

TECHNOLOGY

BOSTON'S 'STREET BUMP' APP TRIES TO AUTOMATICALLY MAP POTHOLES WITH ACCELEROMETERS AND GPS

By Clay Dillow   Posted February 10, 2011

247 Shares



Big Data Structures

- Too much data: Large N
  - Bottleneck at processing
  - Computation
  - Estimates of precision
- Very complex data: small n, large p
- New types of data: networks, images, …
- “Found” data: credit scoring, government records, …

Big data: are we making a big mistake?

Economist, journalist and broadcaster **Tim Harford** delivered the 2014 *Significance* lecture at the Royal Statistical Society International Conference. In this article, republished from the *Financial Times*, Harford warns us not to forget the statistical

“Big data” has arrived, but big insights have not

Highlights from the workshops

- Jan 9 – 23: Bootcamp
- Jan 26 – 30: Statistical Machine Learning
- Feb 9 – 11: Optimization and Matrix Methods
- Feb 23 – 27: Visualization: Strategies and Principle
- Mar 23 – 27: Health Policy
- April 13 – 16: Social Policy

Opening Conference and Bootcamp

- Overview
  - Robert Bell, ATT: “Big Data: it’s not the data”
  - Candes, Stanford: Reproducibility
  - Altman, Penn State: Generalizing PCA

- One day each: inference, environment, optimization, visualization, social policy, health policy, deep learning, networks

- Franke, Plante, et al. (2015): “A data analytic perspective on Big Data”, http://arxiv.org/abs/1509.02900

Big Data and Statistical Machine Learning

- Roger Grosse – Scaling up natural gradient by factorizing Fisher information
- Samy Bengio – The battle against the long tail
- Brendan Frey – The infinite genome project

Statistical Machine Learning

- Grosse, R. and Salakhutdinov, R. (2015). Scaling up natural gradient by factorizing Fisher information.

  Proceedings of the 37th *International Conference on Machine Learning.*

- Markov Random Field is essentially an exponential family model:

$$p(x) = \frac{1}{Z(\eta)} h(x) \exp\{\eta^T t(x)\}$$

- Restricted Boltzmann machine is a special case:

$$p(v, h; \eta) = \frac{1}{Z(\eta)} \exp\{a^T v + b^T h + v^T W h\},$$

$$\eta = (a, b, W)$$

Statistical Machine Learning

$$p(v, h; \eta) = \frac{1}{Z(\eta)} \exp\{a^T v + b^T h + v^T W h\}$$

- natural gradient ascent

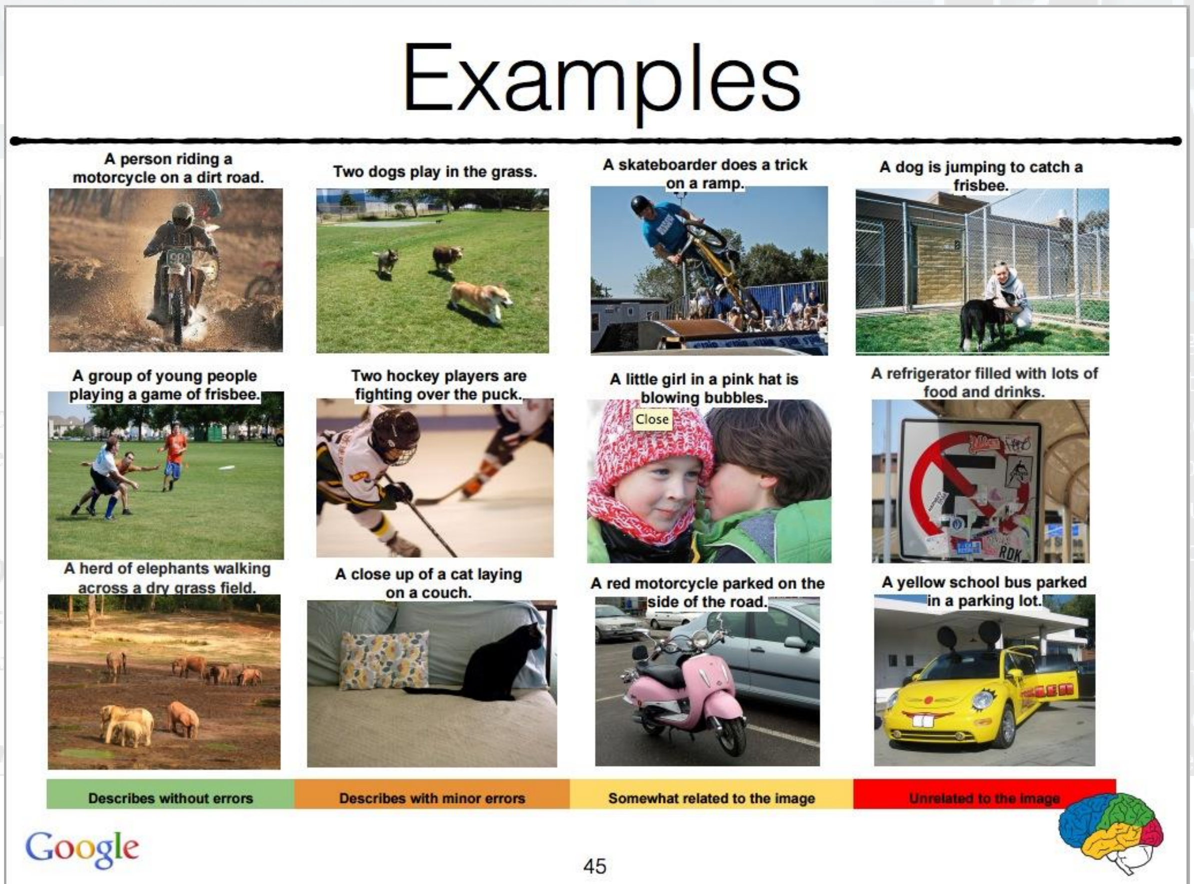
$$\eta \longleftarrow \eta + \epsilon\, i(\eta)^{-1} \nabla_\eta \ell(\eta; v, h)$$

- uses Fisher information as metric tensor
- Gaussian graphical model approximation to force sparse inverse

Girolami and Calderhead (2011); Amari (1987); Rao (1945)

Statistical Machine Learning

- Bengio, S. (2015). The battle against the long tail. [slides]



Statistical Machine Learning

"The rise of the machines", *Economist*, May 9 2015

Optimization

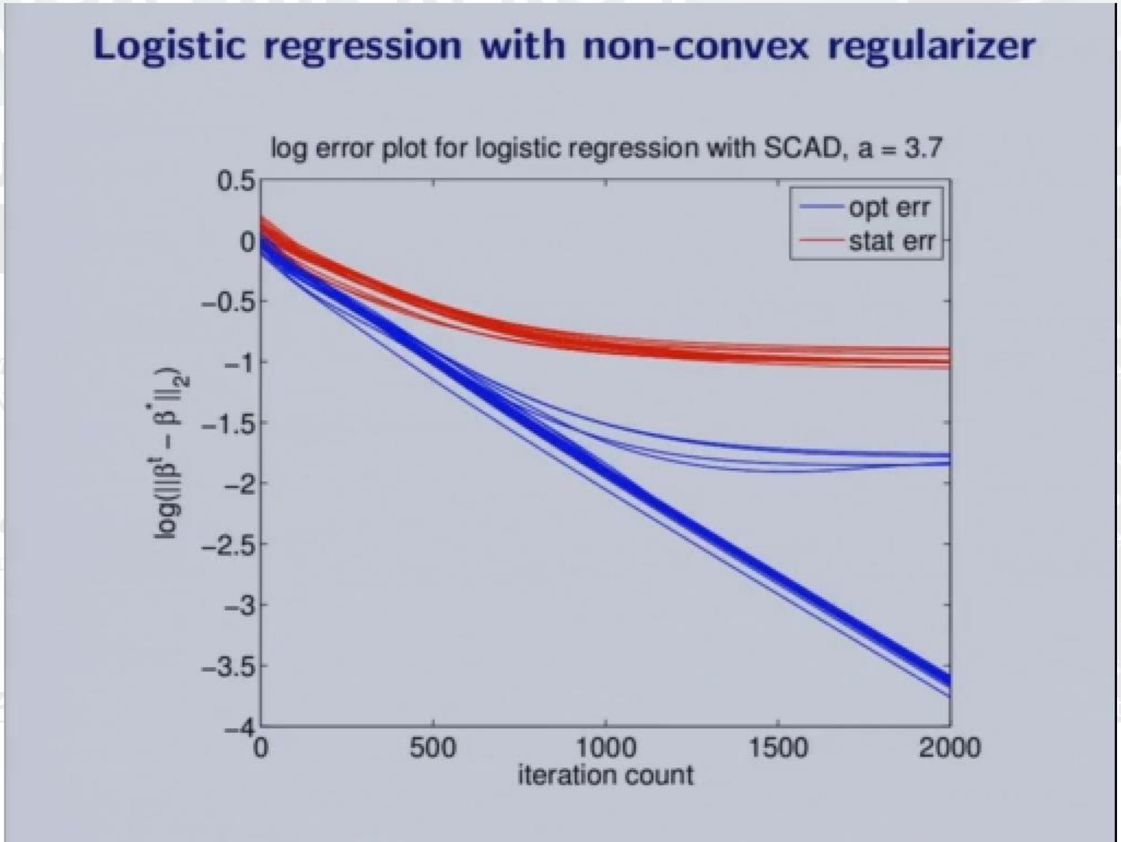
- Wainwright – non-convex optimization
- example: regularized maximum likelihood

$$\max_{\theta}\{\frac{1}{n}\sum_{i=1}^{n}\log f(y_i \mid x_i;\theta) + \mathcal{P}_{\lambda}(\theta)\}$$

- lasso penalty $||\theta||_1$ is convex relaxation of $||\theta||_0$
- many interesting penalties are non-convex
- optimization routines may not find global optimum

Wainwright and Loh

- distinction between statistical error $\hat{\theta} - \theta^*$
- and optimization error $\theta_t - \hat{\theta}$ (iterates)

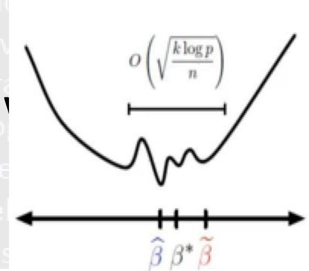


Wainwright and Loh

- a family of non-convex problems
- with constraints on the loss function (log-likelihood) and the regularizing function (penalty)
- conclusion: any local optimum will be close enough to the true value
- conclusion: can recover the true sparse vector under further conditions

Loh, P. and Wainwright, M. (2015). Regularized *M*-estimators nonconvexity. *J Machine Learning Res.* 16, 559-616.

Loh, P. and Wainwright, M. (2014). Support recovery without incoherence. http://arxiv.org/abs/1412.5632



Visualization for Big Data
Strategies and Principles

- data representation
- data exploration via filtering, sampling and aggregation
- visualization and cognition
- information visualization
- statistical modeling and software
- cognitive science and design

Visualization for Big Data:
Strategies and Principles

National Science Foundation
WHERE DISCOVERIES BEGIN

QUICK LINKS

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Funding

- Find Funding
- A-Z Index of Funding Opportunities
- Recent Funding Opportunities
- Upcoming Due Dates
- Advanced Funding Search
- Interdisciplinary Research
- How to Prepare Your Proposal

Email Print Share

Crosscutting

Critical Techniques and Technologies for Advancing Foundations and Applications of Big Data Science & Engineering (BIGDATA)

CONTACTS

Name	Dir/Div	Name	Dir/Div
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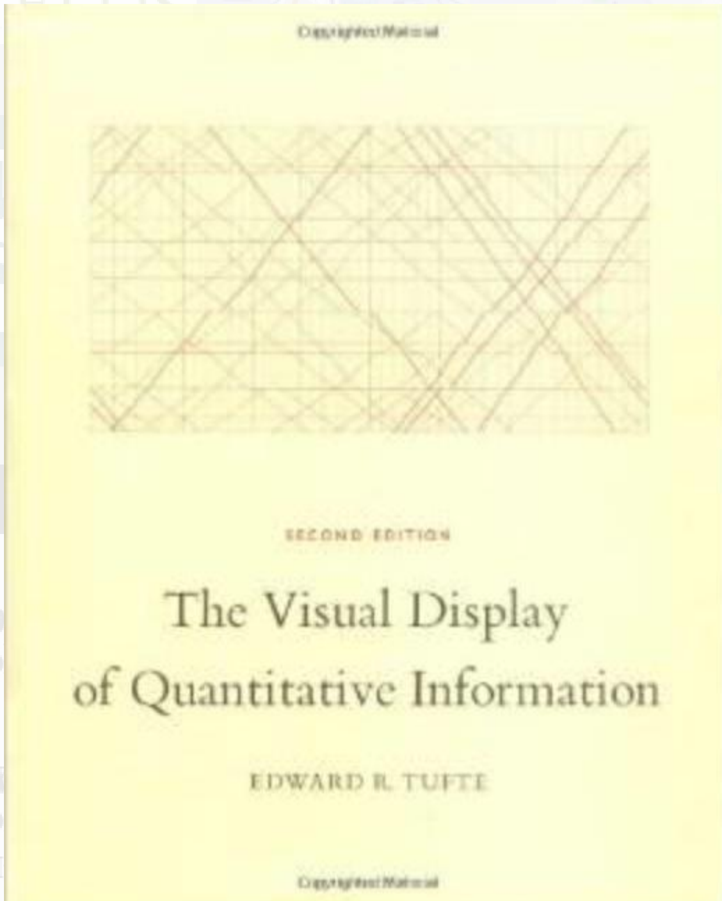
Balasubramanian Kalyanasundaram	CISE/CCF	Amy Apon	
Elizabeth R. Blood	BIO/EF	Helen T. Martin	EHR/DRL
George Haddad	ENG/ECCS	Mona Zaghloul	ENG/ECCS

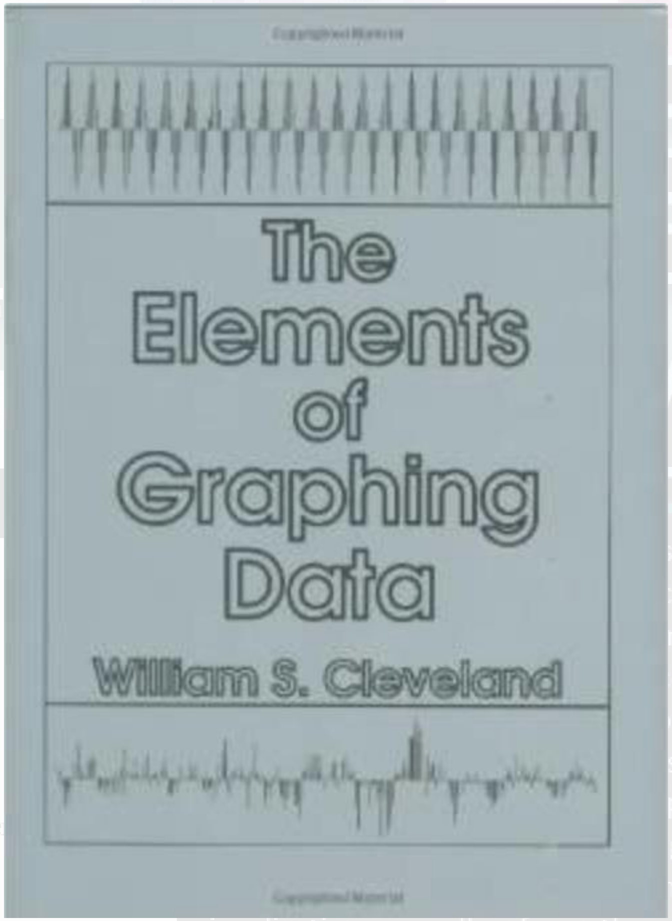
Visualization for Big Data:
Strategies and Principles

In addition to approaches such as search, query processing, and analysis, visualization techniques will also become critical across many stages of big data use--to obtain an initial assessment of data as well as through subsequent stages of scientific discovery.

Visualization for Big Data:
Strategies and Principles

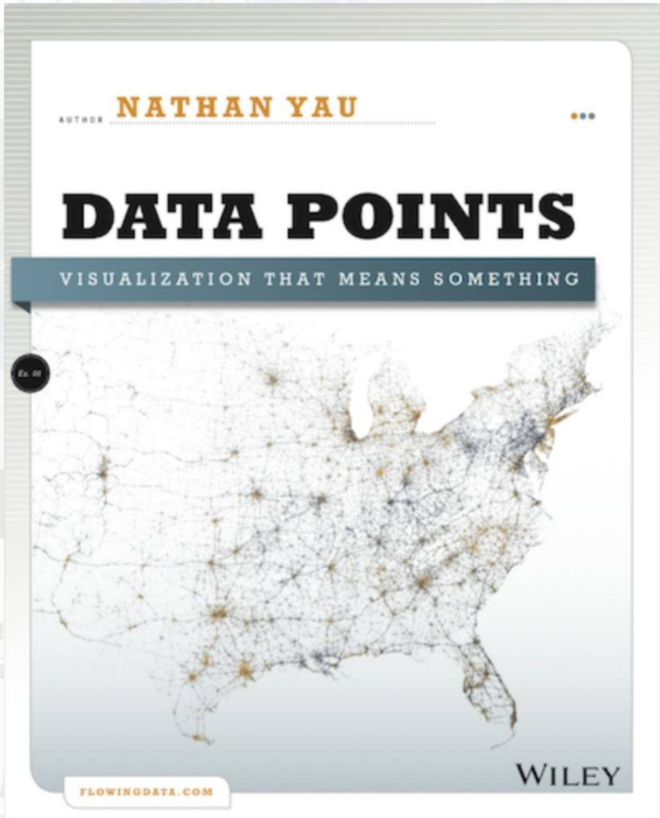


1983

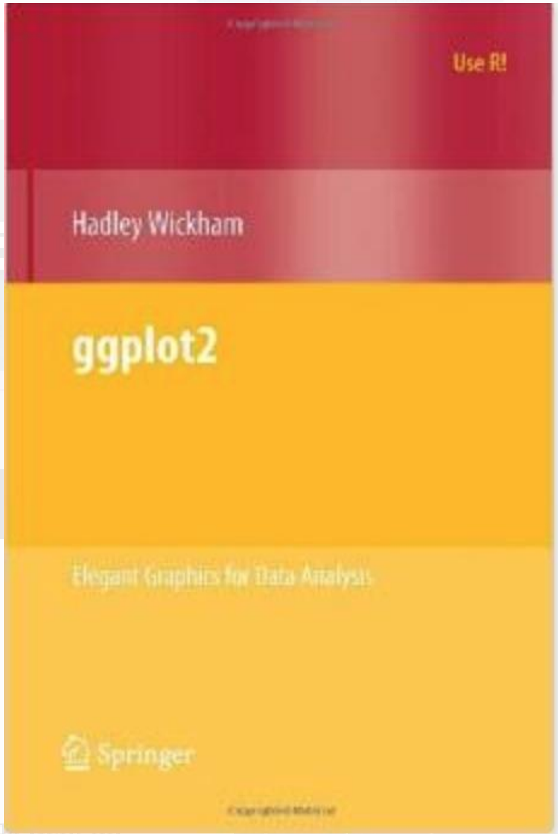


1985

Visualization for Big Data:
Strategies and Principles



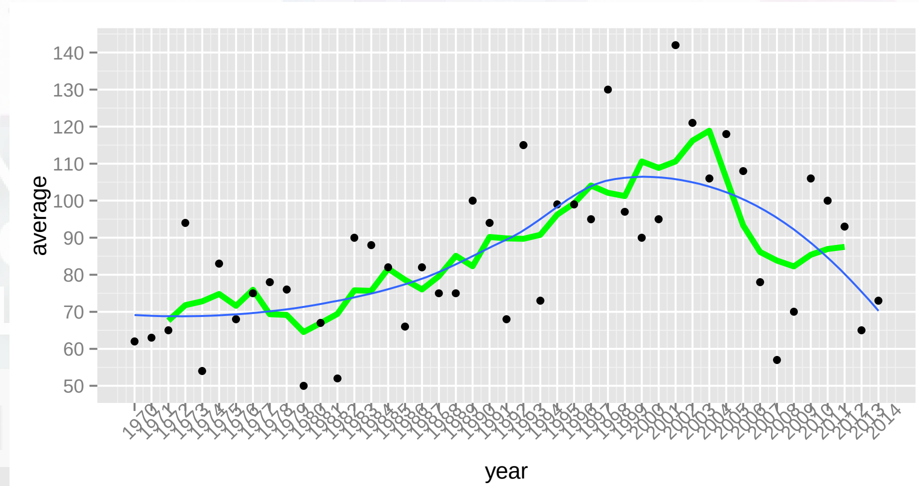
2013



2009

Statistical Graphics

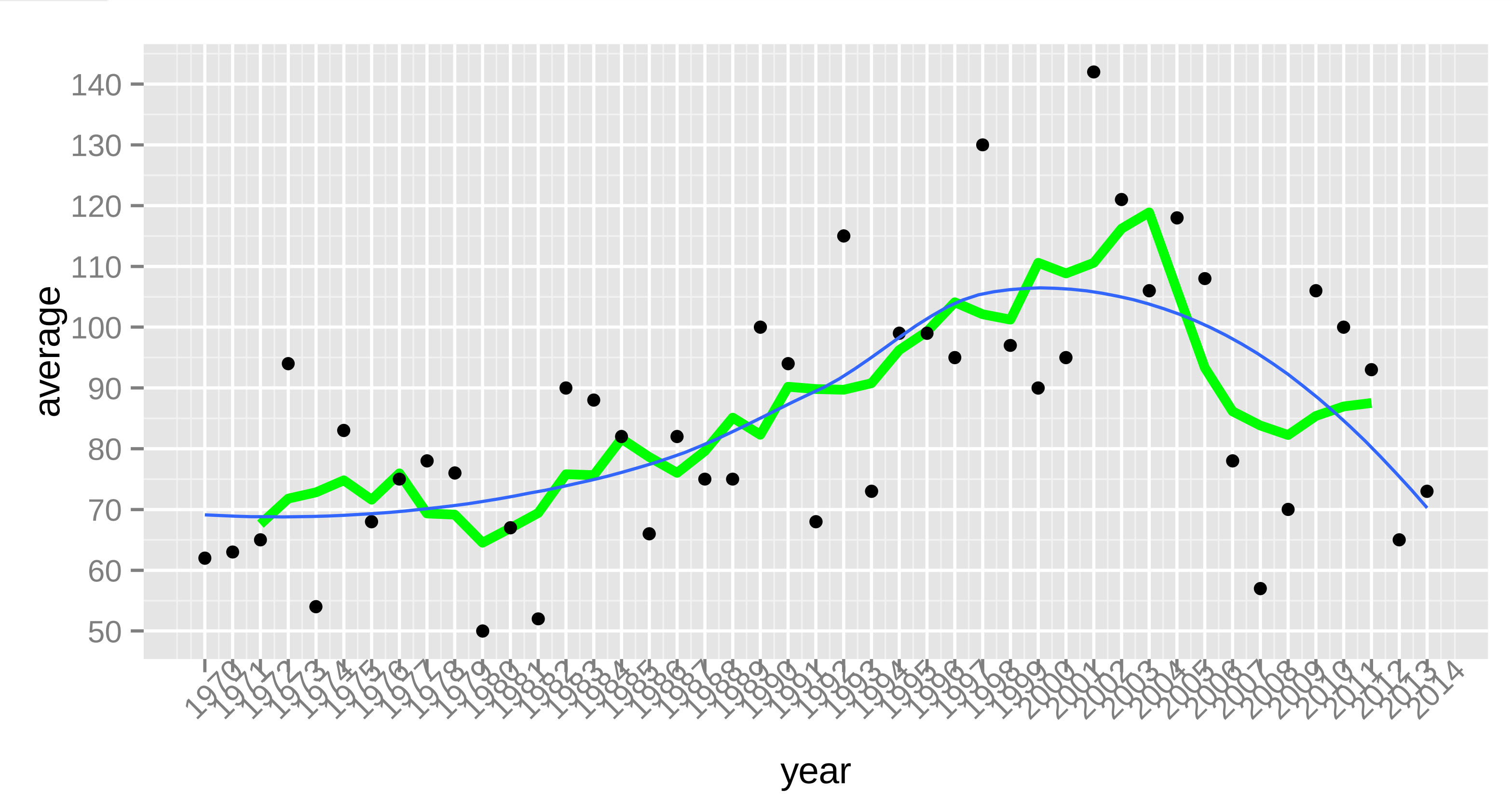
- convey the data clearly
- focus on key features
- easy to understand



- research in perception
- aspects of cognitive science

- must turn ‘big data’ into small data

- Rstudio, R Markdown
- `ggplot2, ggvis, dplyr, tidyr,`
- [cheatsheets]()




```
honeyplot +
    geom_line(aes(honey$year,honey$runmean),col = "green",size=1.5) +
    geom_point(aes(honey$year,honey$average),)  +
    scale_x_continuous(breaks=1970:2014) +
    geom_smooth(method="loess",span=.75,se=F)  +
    scale_y_continuous(breaks=seq(0,140,by=10))  +
    theme(axis.text.x = element_text(angle=45))
```

Information Visualization

- http://www.infovis.org
- a process of transforming information into visual form
- relies on the visual system to perceive and process the information
- http://ieeevis.org/
- involves the design of visual data representations and interaction techniques

Highlights

- Sheelagh Carpendale: info-viz

  http://innovis.cpsc.ucalgary.ca/

- representation
- presentation
- interaction

- Example: Edge Maps web page

Highlights

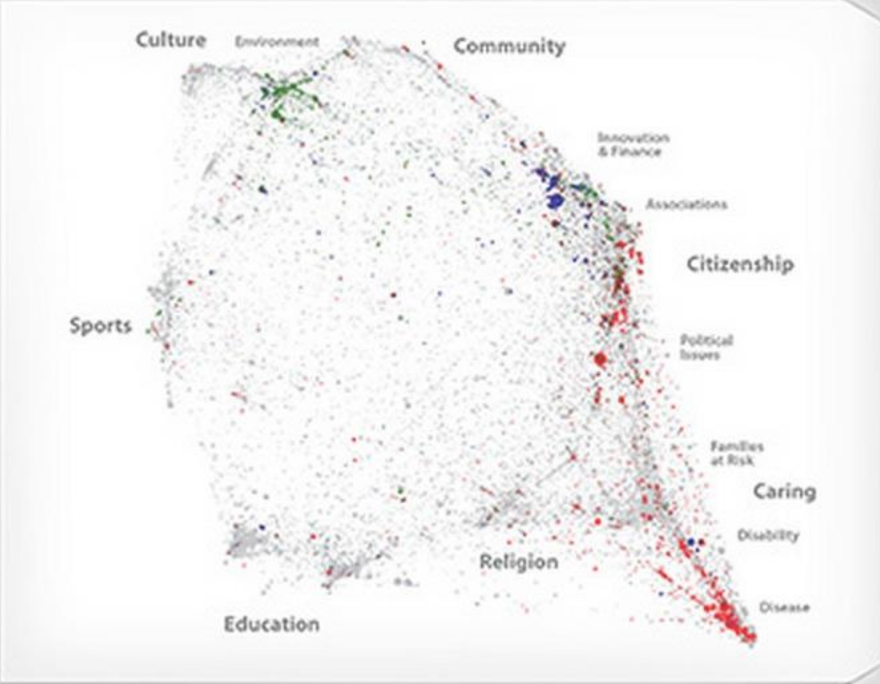
- [Katy Borner](): scientific visualization
- advances understanding or provides solutions for real-world problems
- impacts a particular application

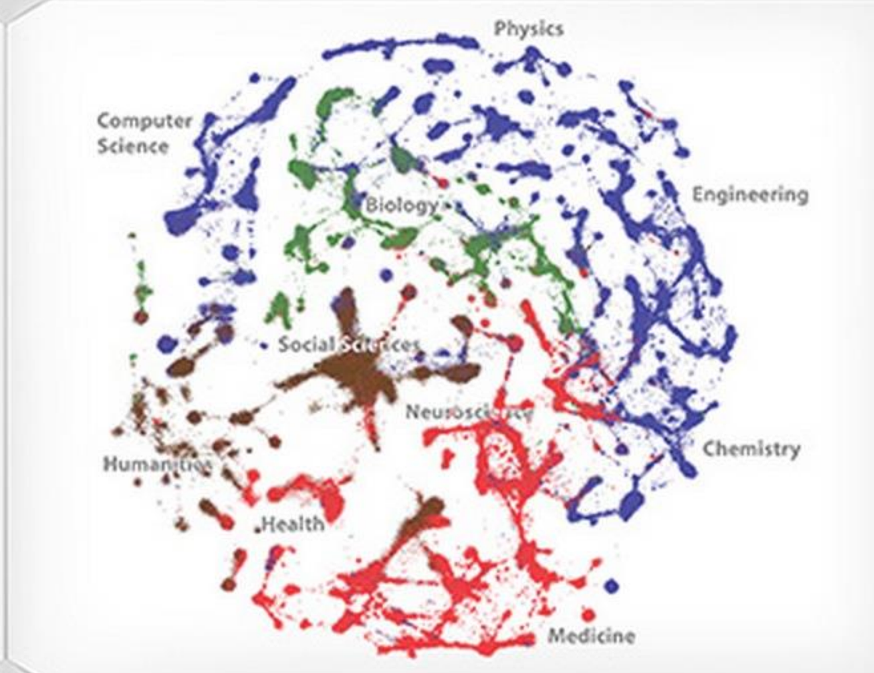
- http://scimaps.org/

Exploring the Relationships Between
a Map of Altruism and a Map of Science

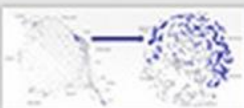
How is altruism related to science? Altruism is about individual selfless intentions. Science is about discovery and problem solving. On the surface these two facets of society may seem unrelated. In reality they may be strongly linked. Altruistic missions explain historical (and may predict future) patterns of scientific investments. The map of altruism (left) represents altruistic missions, and displays the relative positions of nearly 100,000 non-profit organizations (NPOs) in the United States based on mission-related text from their websites. This map of altruism reveals the issues that we care most about as a society: *Culture*, *Sports*, *Education*, *Religion*, *Community*, *Citizenship*, and *Caring*. The map of science (right) represents decades of funded research in the natural and medical sciences, engineering, technology, social sciences and humanities. It displays over 43,000,000 documents that are grouped together using a combination of citation and textual similarity.

These two maps are shown side-by-side to illustrate how the altruistic intentions of a society correlate with where we focus our discovery and problem solving efforts. The map of science has been divided into four major areas, shown in four different colors. NPOs whose National Taxonomy of Exempt Entities (NTEE) codes indicate that they explicitly fund scientific activities in these four areas are correspondingly colored in the map of altruism. Altruistic missions associated with these four areas are considered in more detail below, along with projections of how altruistic missions not currently associated with funding of scientific research might benefit from such funding in the future.





Historical



Citizenship is linked to *Physics*, *Chemistry*, *Engineering* and *Computer Science*. The specific aspect of *Citizenship* active here is the belief that funding should be provided for entrepreneurship and innovation so that the economy can flourish. The funding of science-based innovation from governments and NPOs is reasonably mature and is expected to remain high.

Citizenship is a major factor in the funding of the *Social Sciences*. The specific aspect of *Citizenship* active here is aligned with the belief that rational analysis and the scientific method can contribute to the resolution of political issues. 'Think tanks' are examples of non-profit organizations that are funded from this altruistic motive.

Caring is the basis for funding medical research. The aspects of *Caring* vary, and include curing of disease, providing opportunities for the disabled, and the treatment of mental health issues. A scientific understanding of these issues has been well funded by individuals, e.g., through donations to NPOs; and through government funding, e.g., the National Institutes of Health.

Culture and Citizenship contribute to the funding of environmental research. *Culture* supports that aspect of environmental research that is more concerned with the preservation of our planet for the future enjoyment of our children. *Citizenship* supports the research focusing on innovative solutions and political tradeoffs which arise from the toxic consequences of current practices.

Future

All Seven Aspects of Altruism are potentially important for childhood development. Scientific research related to this topic is currently focused on social issues, e.g., risk factors, and *Education*. The altruism map raises an interesting question: Is this the right balance, or should more scientific attention be paid to childhood development in other areas, such as *Culture*, *Community*, *Sports*, and *Citizenship*? Time will tell.

Community is an important altruistic mission that represents a potential funding opportunity. We know very little about how different communities (geographical, professional, social, etc.) have evolved in terms of providing altruistic services to their members. There are lessons to be learned from how communities variously emphasize *Culture*, *Sports*, *Education*, *Religion*, *Care*, or *Civic* responsibility.

Highlights

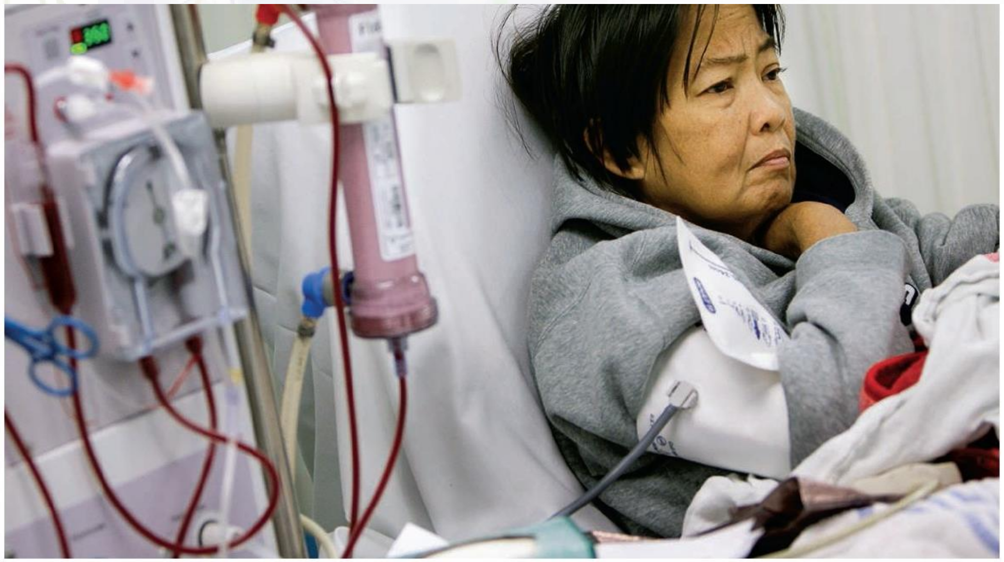
- Alex Gonçalves: Visualization for the masses

- to build communion
- for social change
- powerful stories
- “duty of beauty”http://www.nytimes.com/newsgraphics/2014/02/14/fashion-week-editors-picks/

Big Data for Health Policy

- Pragmatic clinical trials
  - Patrick Heagerty, Fred Hutchison
- Linking health and other social data-bases
  - Thérèse Stukel, ICES
- Privacy

Heagerty – Pragmatic Clinical Trials



One pragmatic clinical trial compares different approaches to dialysis. Studies like this will enroll a broader cohort, including more women and minorities.

MEDICAL RESEARCH

Clinical trials get practical

Many clinical trials don't help doctors make decisions. A new breed of studies aims to change that

By **Jennifer Couzin-Frankel**, *in Philadelphia, Pennsylvania*

trials will involve more women, more minorities, a range of incomes," says Monique Anderson, a cardiologist at Duke University

tend to focus on health behaviors or compare available treatments, not test experimental drugs, although that could change.

Nine Collaboratory trials are under way. One tests whether patients on dialysis are more likely to survive and stay healthier if the dialysis treatment itself lasts longer. The study is randomizing about 400 dialysis centers around the country to either continue with their usual routine—dialysis typically ranges from about 3 to 5 hours in the United States—or administer it for at least 4.25 hours. Patients receive information about the trial at their clinic and a toll-free number to call if they have questions for the research team or wish to opt out.

An opt-out model is an option only for some of the lowest risk clinical trials: U.S. regulations require active informed consent for studies of experimental drugs. Because current pragmatic trials are comparing approaches doctors already use routinely, even ethicists agree that enrolling everyone, unless someone objects, is often reasonable.

Other challenges come in figuring out the best way to design pragmatic studies.

Heagerty – Pragmatic Clinical Trials

Common Trial Designs

Parallel

Time
1
X
X
X
X
O
O
O
O

Crossover

Time

1	2
X	O
X	O
X	O
X	O
O	X
O	X
O	X
O	X

Lisa Lix, U Manitoba

Heagerty – Pragmatic Clinical Trials

Stepped Wedge Design

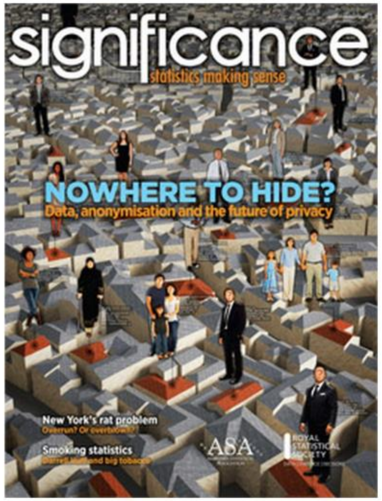
Time

1	2	3	4	5
O	X	X	X	X
O	O	X	X	X
O	O	O	X	X
O	O	O	O	X

Lisa Lix, U Manitoba

Big Data for Social Policy

Significance - October 2014 (Volume 11 Issue 4)



News, Interview and Editorial

Using Xbox polls to predict elections. The ISIS terror in numbers. Why South Koreans are heading for extinction. Tackling the reproducibility problem. How statistical models helped in the aftermath of the Boston Marathon bombings. And finally ... Fantasy author Jasper Fforde explains his theory of expectation-influenced probability.

Visualisation

Cultural movements

Mauro Martino on cognitive computing and mapping the migration of Western culture.

Special report: Data and privacy

Now you see me, now you don't

Does data anonymisation work? The answer depends on who you talk to. But finding a way to preserve privacy while sharing valuable data is crucial to the future of our information society.

Privacy

- anonymization/de-identification “HIPAA rules”
  - privacy commissioner of Ontario:
  - “Big Data and Innovation, Setting the record straight: De-identification does work”
  - Narayanan & Felten (July 2014) “No silver bullet: De-identification still doesn’t work”
- multi-party communication (Andrew Lo, MIT)
- statistical disclosure limitation and differential privacy

  Slavkovic, A. -- Differentially Private Exponential Random Graph Models and Synthetic Networks

- Statistical Disclosure Limitation
  - released data is typically counts, or magnitudes, cross-classified by various characteristics – gender, age, region, …
  - an item is sensitive if its publication allows estimation of another value of the entity too precisely
  - rules designed to prohibit release of data in cells at ‘too much’ risk, and prohibit release of data in other cells to prevent reconstruction of sensitive items – Cell Suppression

- computer science -- privacy-preserving data-mining; multi-party computation, differential privacy

- theoretical work on differential privacy has yielded solutions for function approximation, statistical analysis, data-mining, and sanitized databases
- it remains to see how these theoretical results might influence the practices of government agencies and private enterprise

What did we learn?

1. Statistical models are complex, high-dimensional
   - regularization to induce sparsity
   - sparsity assumed or imposed
   - layered architecture complex graphical models
   - dimension reduction PCA, ICA, etc.
   - ensemble methods aggregation of predictions

2. Computational challenges include size and speed
   - ideas of statistical inference get lost in the machine

3. Data owners understand 2., but not 1.

4. Data science may be the best way to combine these

Gartner Hype Cyc
July 2014

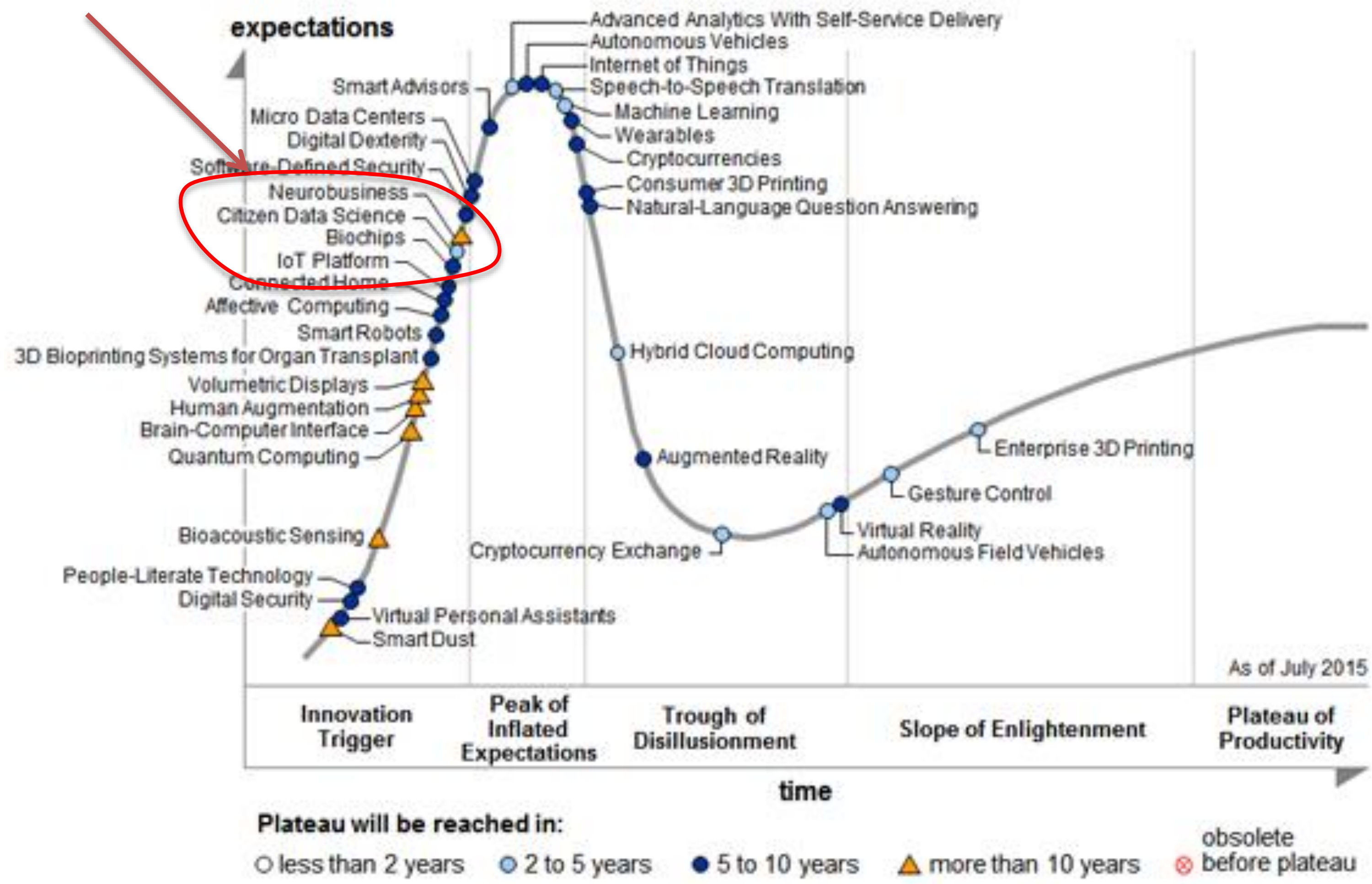
falling-99183_640 →

http://www.gartner.com/technology/research/hype-cycles/

https://etechlib.wordpress.com/tag/hype-cycle/

July 2015

"Citizen Data Science"



What did I learn?

- Big Data is real, and here to stay

- Big Data often quickly becomes small
  - by making models more and more complex
  - by looking for the very rare/extreme points
  - through visualization

- Big Insights build on old ideas
  - planning of studies, bias, variance, inference

- Big Data is a Big Opportunity

A few resources

- Franke, Plante et al. (2015). Statistical inference, learning and models in big data.
  - http://arxiv.org/abs/1509.02900

- Talks from the closing workshop

  for the Big Data program

- data science programs: U Michigan, Beijing, Johns Hopkins, UC Berkeley, Columbia, NYU, Dalhousie, UBC, U Toronto, ...

A haphazard web walk

Science, 28.11.2014

Khoury & Ioannidis
"Big Data Meets Public Health"

Ruths & Pfeffer
"Social media for large studies of behaviour"

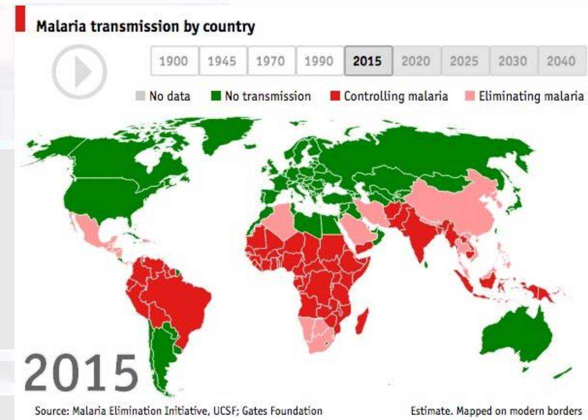
McGill Newsroom re Ruths & Pfeffer
"Social media data pose pitfalls for studying behaviour"

A haphazard web walk

Graphic Detail (*The Economist*)

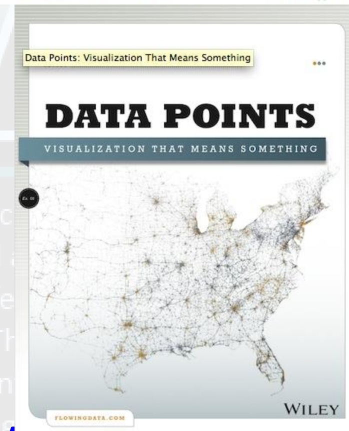
“A new chart or map every working day”

October 14: The shrinking malaria map



Data Points (Nathan Yau)

“Visualization that means something”



“The Best Data Visualization Projects of 2014”

http://flowingdata.com/2014/12/19/the-best-data-visualization-projects-of-2014-2/?utm_source=dlvr.it&utm_medium=twitter

A haphazard web walk

Big data Music Industry http://venturebeat.com/2014/12/18/how-big-data-can-change-the-music-industry/

The problem with big data http://www.scmagazine.com/the-problem-with-big-data/article/388691/

Open models http://radar.oreilly.com/2014/11/we-need-open-models-not-just-open-data.html

Katy Borner's exhibit http://scimaps.org

David Donoho on Data Science