Statistical Inference, Learning and Models for Big Data

FIELDS

Nancy Reid
University of Toronto



Organizing committee: Ruslan Salakhutdinov (Chair), Dale Schuurmans, Yoshua Bengio, Hugh Chipman, Bin Yu August 12, 2015

FEBRUARY 9 - 13, 2015

Workshop on Optimization and Matrix Methods in Big Data

throughout the program will highlight cross-cutting themes, such as learning and visualization, as well as focus themes for





THEMATIC PROGRAM ON STATISTICAL INFERENCE, LEARNING, AND MODELS FOR

JANUARY JUNE, 2015

PROGRAM

IANUARY 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) Nicolai Meinshausen (ETH Zurich) Dale Schuurmans (Alberta) Bin Yu (UC Berkeley)

Snehelata Huzurbazar (Wyoming) Robert Tibshirani (Stanford)

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







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sizes spects of and models rence will e program,

Canadian Institute for Statistical Sciences

FIELDS

Fields Institute for Resesarch in the Mathematical Sciences



LDS GRAM
JANUARY 12 - 23, 201

Organizing Committee: Nancy Reid (Chair), Sallie Keller,







Pacific
Institute for
Mathematical
Sciences

both applied and theoretical aspects of statistical inference, learning and model in big data. The opening conference will serve as an introduction to the program

Warkshap on Big Data and Stati Centre de Recherches Mathématiques

Hugh Chipman, Bin Yu

Workshop on Optimization





g themes, such as learning and , as well as focus themes for , in the social, physical and life

Workshops

- Opening Conference and Bootcamp
- Statistical Machine Learning
- Optimization and Matrix Methods
- Visualization: Strategies and Principles
- Big Data in Health Policy
- Big Data for Social Policy
- Networks, Web mining, and Cyber-security
- Statistical Theory for Large-scale Data
- Challenges in Environmental Science
- Complex Spatio-temporal Data
- Commercial and Retail Banking

- Jan 9 23
- Jan 26 30
- Feb 9 11
- Feb 23 27
- Mar 23 27
- Apr 13 16
- May, CRM
- April, PIMS
- May, PIMS
- April, Fields
- May, Fields
- Closing Conference: Statistical and Computational Analytics chastering at June 12-13 vell as focus themes for
 - Deep Learning Summer School

August 3 - 12, CRM

And more LLDS INST

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









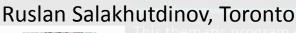


Statistical Machine Learning
Topics in Big Data

Industrial Problem Solving Workshop

Workshop May 25 rd 29 Statistical Machine Learning

Fields Summer Undergraduate Research Program
May to August, 2015





Mu Zhu, Waterloo



MDM 12 – Einat Gil et al.









Big Data – Big Topic

- Where to start?
- Look up some references

STATISTICAL INFERENCE,



big data

Web

News

Images

Videos

Books

More -

Search tools

About 770,000,000 results (0.32 seconds)

- Likelihood 78 m
- Statistical inference 7m

FEBRUARY 9 - 13, 2019

Workshop on Optimization and Matrix Methods in Big Data

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

The Blogosphere



Gil Press Contributor TECH 9/03/2014 @ 8:01AM | 12,133 views

12 Big Data Definitions: What's Yours?

+ Comment Now

+ Follow Comments

PROGRAM

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Opening Conference and Boot Camp
Organizing Committee: Nancy Reid (Chair), Sallie



JANUARY 26 -

Workshop on Big Data and Statistical Machine Learning
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FEBRUARY 9 - 13, 2015

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STEAMROLLED BY BIG DATA

BY GARY MARCUS

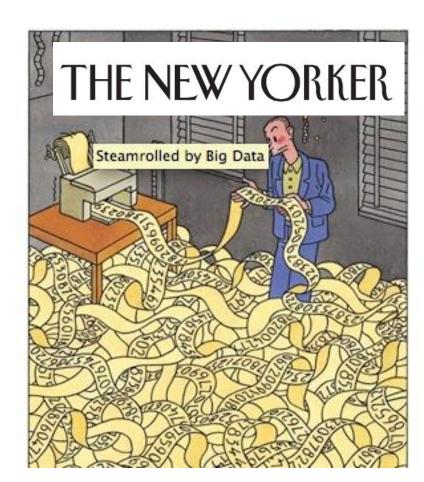








Five years ago, few people had heard the phrase "Big Data." Now, it's hard to go an hour without seeing it. In the past several months, the industry has been mentioned in dozens of New York Times stories, in every section from metro to business. (Wired has even already declared it passé: "STOP HYPING 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



The Blogosphere s INSTITUTE



OPINION - big data - Business - memes

Stop Hyping Big Data and Start Paying Attention to 'Long Data'

BY SAMUEL ARBESMAN 01.29.13 | 9:30 AM | PERMALINK















The Blogosphere

Kim Crawley, researcher, InfoSec Institute

December 22, 2014

The problem with Big Data

Share this article:











Big Data is a big buzzword these days. It's completely understandable why so many people in tech talk about it, even though few people completely understand it.

So, what is Big Data?

With the massive growth of data centers worldwide in the past thirty years or so, we're creating, transmitting, and storing more data than ever before.

We're well beyond terabytes, petabytes and now even exabytes.

We're quickly zooming into zettabytes in global capacity and





The Blogosphere

datascience@berkeley Blog















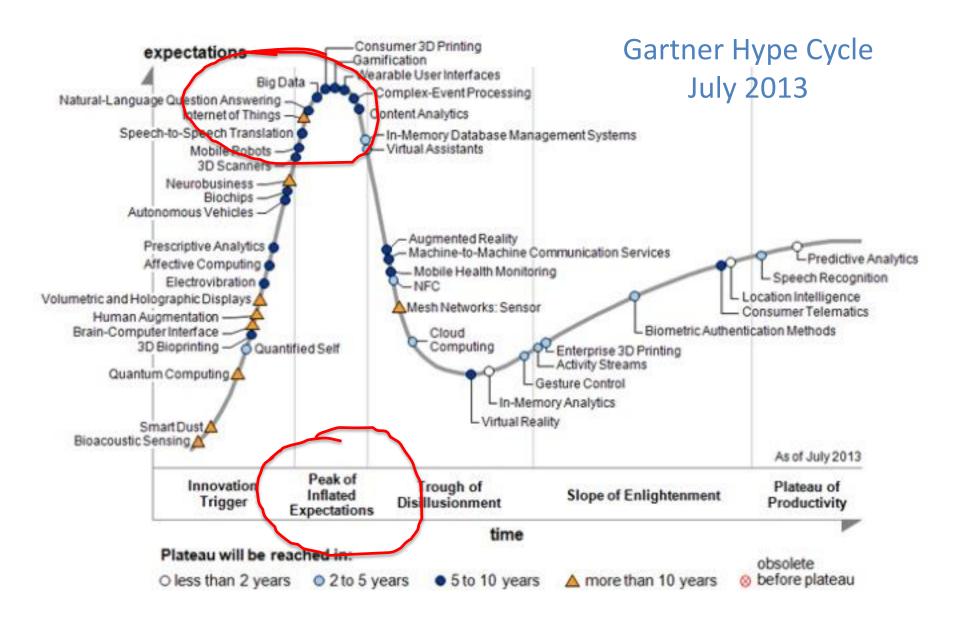
datascience@berkeley Blog

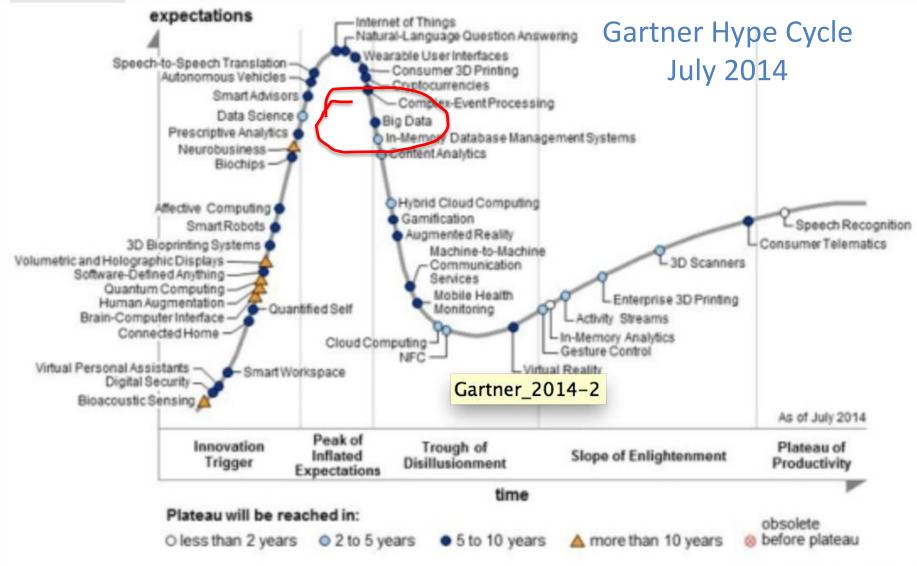
What Is Big Data?

September 3rd, 2014 by Jenna Dutcher 5 Comments

Filed Under: Big Data datascience@berkeley

To settle the question once and for all, we asked more than 40 thought leaders in publishing, fashion, food, automobiles, medicine, marketing, and every industry in between how exactly they would define the phrase "big data." Their answers might surprise you! Take a look below to find out what big data is:





falling-99183_640 →

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

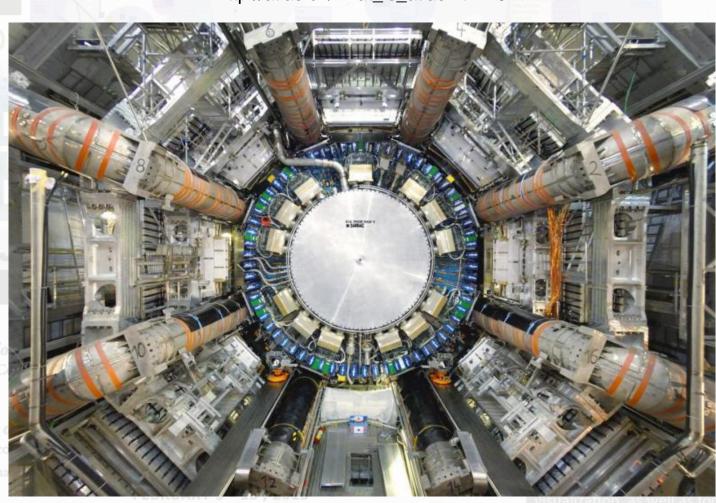
As each new field matured, there came a recognition that in fact much was to be gained by studying connections to statistics

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



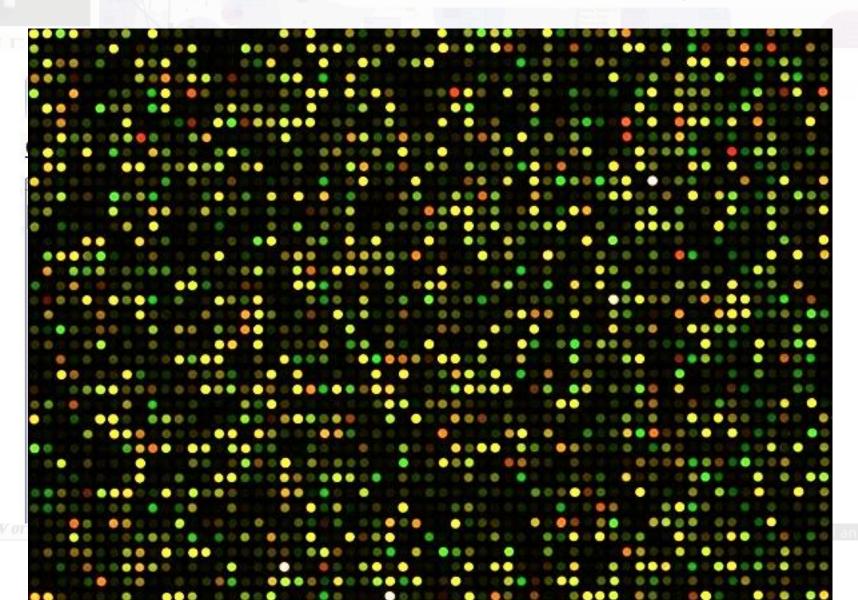
If all the data from ATLAS were recorded, this would fill 100,000 CDs per second. This would create a stack of CDs 450 feet high every second, which would reach to the moon and back twice each year. The data rate is also equivalent to 50 billion telephone calls at the same time. ATLAS actually only records 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



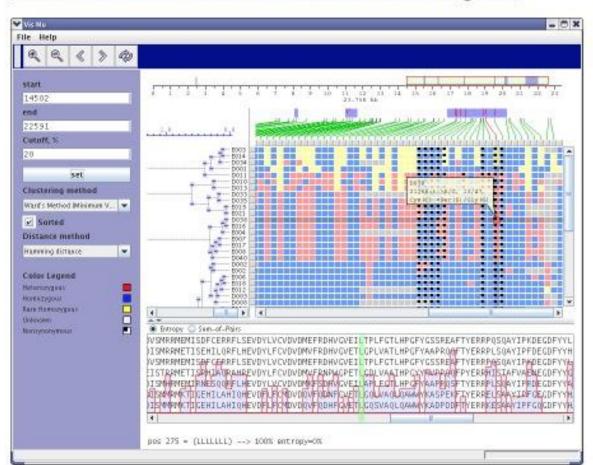


Tools for Comparative Genomics

VISTA Home Custom Alignment Browser Enhancer DB Downloads Publications

SNP-VISTA

GeneSNP-VISTA: Visualization of mutations in genes



Social Activity Do



POPULAR SCIENCE

TECHNOLOGY

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

By Clay Dillow Posted February 10, 2011

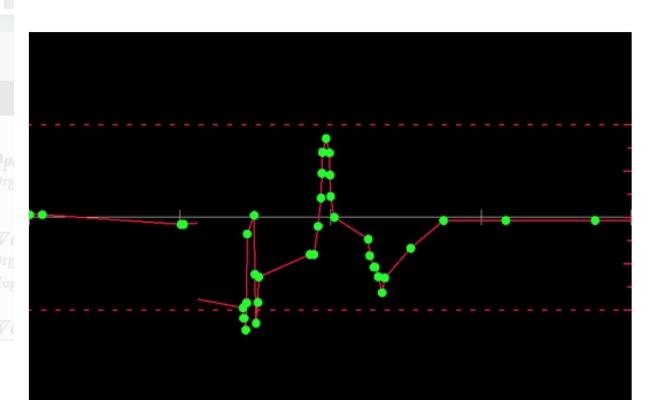








247 Shares





Big Data Structures

- Too much data: Large N
 - Bottleneck at processing
 - A * Computation Models For
 - Estimates of precision

PROGRAM

- 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

JANUARY 26 - 30, 2015

Workshop on Big Data and Statistical Machine Learning

"Big data" has arrived, but big insights have not

FEBRUARY 9 - 13, 2015

Workshop on Optimization and Matrix Methods in Big Data

Highlights from the workshops

- Jan 9 23: Bootcamp
- Jan 26 30: Deep Learning
- Feb 9 11: Optimization
- Feb 23 27: Visualization
- Mar 23 27: Health Policy
- April 13 16: Social Policy

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Opening Conference and Bootcamp

- Overview
 - Bell: "Big Data: it's not the data"
 - Candes: Reproducibility
 - Altman: Generalizing PCA

PROGRAM

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

Big Data and Statistical Machine Learning

 Roger Grosse – Scaling up natural gradient by factorizing Fisher information

LEARNING, AND MODELS FOR

Samy Bengio – The battle against the long tail

PROGRAM

JANUARY 12 - 23, 2015

Brendan Frey – The infinite genome project

JANUARY 26 – 30, 2015

W orkshop on Big Data and Statistical Machine Learning
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FEBRUARY 9 - 13, 2015

Workshop on Optimization and Matrix Methods in Big Data

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

to appear in 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:

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

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

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

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)

• Bengio, S. (2015). The battle against the long

tail. slides

Examples

























Describes without errors

Describes with minor errors

Somewhat related to the image

Google

45

Some you win, some you lose

Image-recognition software's analysis of what a picture represents



"A person riding a motorcycle on a dirt road"



"A yellow school bus parked in a car park"

Source: "Show and Tell: A Neural Image Caption Generator", Oriol Vinyals, Alexander Toshev, Samy Bengio, Dumitru Erhan

p on Optimization and Matrix Methods in Big Data

Optimization

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

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

- 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 $heta_t \hat{ heta}$ (iterates)

LEARNI

JANU

Opening Conference
Organizing Committee:

Workshop on Big Dat Organizing committee: R Hugh Chipman, Bin Yu

Workshop on Optimi

Logistic regression with non-convex regularizer



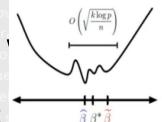
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well as focus themes for
an esocial, physical and life

Wainwright and **Loh**

- a family of non-convex problems
- with constraints on the loss function (loglikelihood) 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.

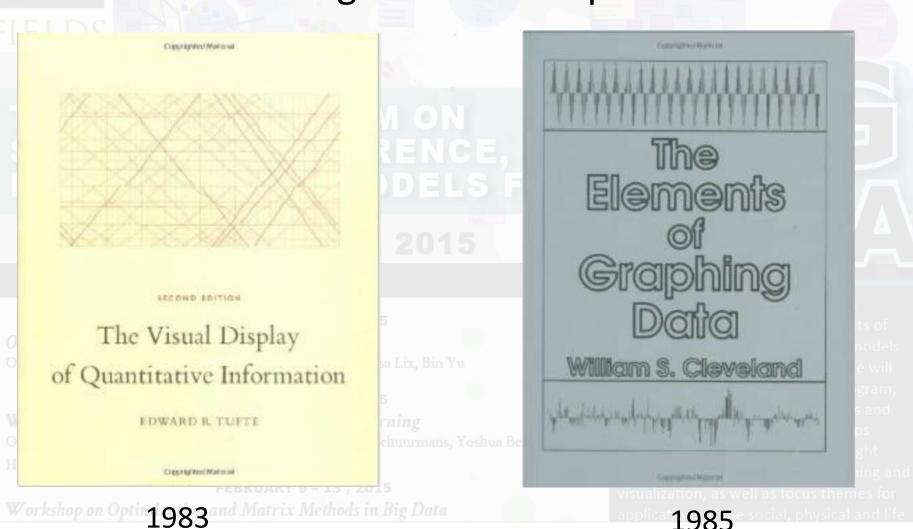
Loh, P. and Wainwright, M. (2014). Support recovery without incoherence. Arxiv preprint



Visualization for Big Data Strategies and Principles

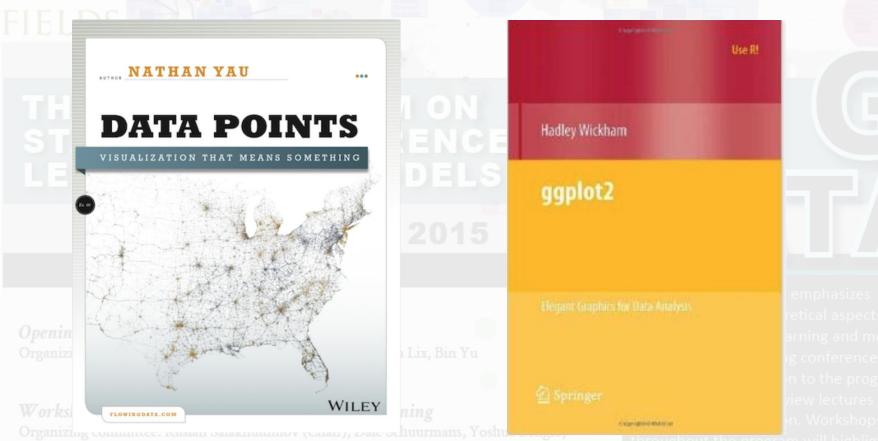
- data representation
- data exploration via filtering, sampling and aggregation
- visualization and cognition
- information visualization
- statistical modeling and software
 - cognitive science and design

Visualization for Big Data: Strategies and Principles



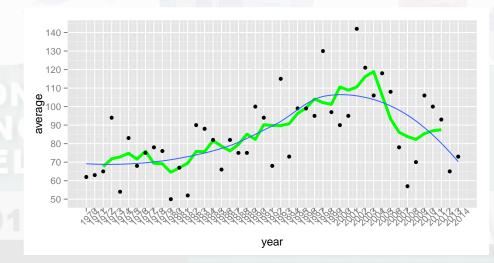
Visualization for Big Data:

Strategies and Principles

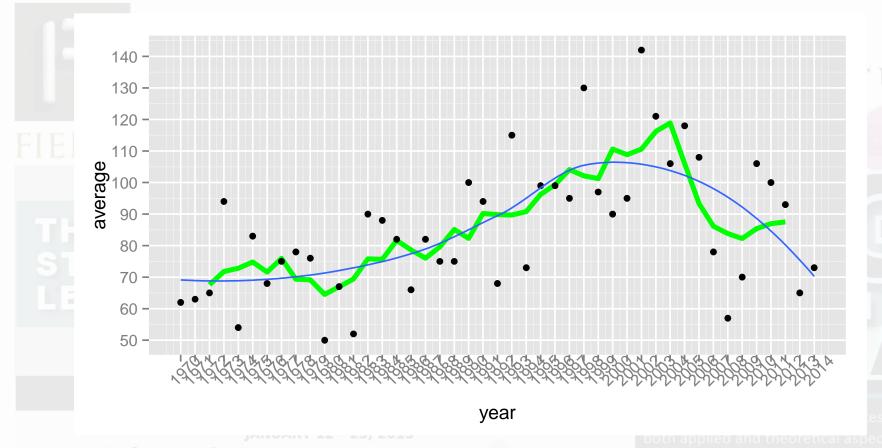


Statistical Graphics

- 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*RUARY 9 13, 2015



```
honeyplot + me ked (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 5

- 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 ELDS INSTIT

Sheelagh Carpendale: info-viz

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

STATISTICAL INFERENCE, LEARNING, AND MODELS FOR

- representation
- presentation RAM
- interaction

Organizing Committee: Nancy Reid (Chair), Sallie Keller, Lisa Lix, Bin Yu

JANUARY 26 - 30, 2015

Workshop on Big Data and Statistical Machine Learning

Example: Edge Maps

FEBRUARY 9 - 13, 2015

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visualization, as well as focus themes for

Highlights ELDS INSTITUTI

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

PROGRAM

IANUARY 12 - 23, 2015

http://scimaps.org/

JANUARY 26 - 30, 2015

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FEBRUARY 9 - 13, 2015

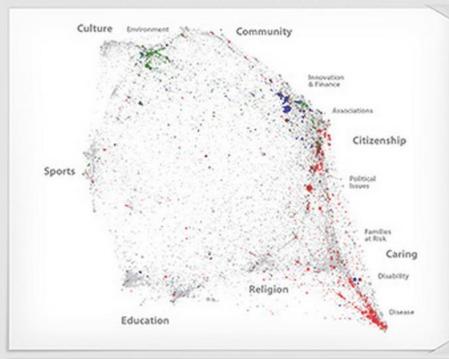
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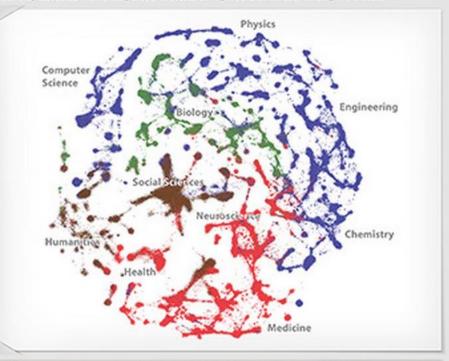
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Exploring the Relationships Between a Map of Altruism and a Map of Science

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 Coring. The map of science in the internal seconds 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.







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.



Caring is the basis for funding medical research. The aspects of Cering 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.



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.



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.

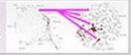




All Seven Aspects of Altruism are potentially important for childhood development, Scientific research related to this topic is currently focused on social issues, e.g., risk factors, and Education. The altruism map raises an interesting question; is this the right belance, or should more scientific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



Highlights ELDS INSTIT

Alex Gonçalves: Visualization for the masses

THEMATIC PROGRAM ON

- to build communion LS FOR
- for social change
- powerful stories
- "duty of
 - beauty"http://www.nytimes.com/newsgraphi
 - cs/2014/02/14/fashion-week-editors-picks/

Big Data for Health Policy

- Pragmatic clinical trials
- Patrick Heagerty, Fred Hutchison

LEARNING, AND MODELS FOR

- Linking health and other social data-bases
 - Thérèse Stukel, ICES

Opening Conference and Boot Camp
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Privacy January 26 – 30, 2015

Workshop on Big Data and Statistical Machine Learning

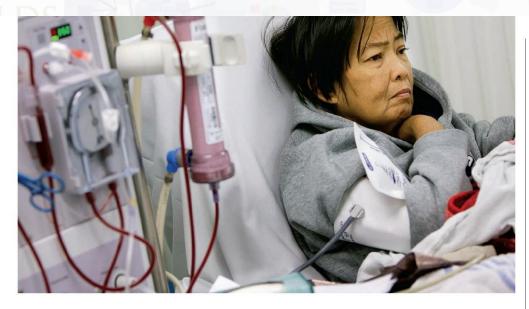
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Heagerty – Pragmatic Clinical Trials



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

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

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Time

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Crossover

Time

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X O

X O

X O

O X

O X

O X

O X

Heagerty – Pragmatic Clinical Trials

Stepped Wedge Design

		1 ime		
1	2	3	4	5
O	X	X	X	X
O	O	\mathbf{X}	\mathbf{X}	\mathbf{X}
O	O	O	\mathbf{X}	\mathbf{X}
O	O	O	O	\mathbf{X}

Big Data for Social Policy STITUTE



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.

Significance

Nowhere To Hipe?

Total problem

Smoking statistics

ASA

Lighter

ASA

serve as an introduction to the program, concentrating on overview lectures and

Carnegie Mellon University

Journal of Privacy and Confidentiality

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Privacy FIELDS INSTIT

- anonymization/de-identification "HIPAA rules"
 - privacy commissioner of Ontario:
 - "Big Data and Innovation, Setting the record straight: Deidentification does work"
 - Narayanan & Felten (July 2014) "No silver bullet: Deidentification still doesn't work"

PROGRAM

- 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

PROGRAM

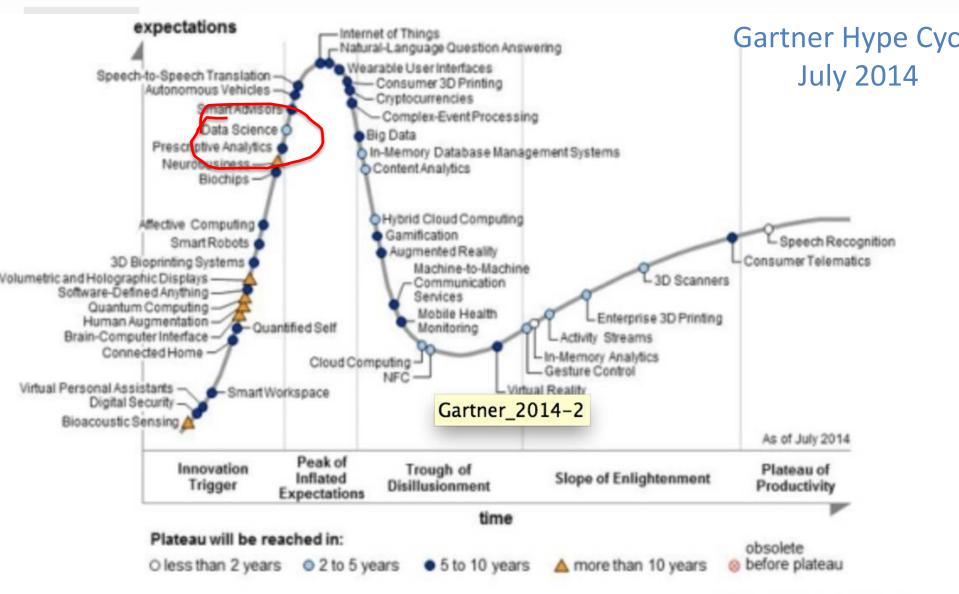
- computer science -- privacy-preserving data-mining; multi-party computation, differential privacy
- theoretical work on differential privacy has yielded solutions for function approximation, statistical analysis, data-mining, and sanitized databases
- it remains to see how these theoretical results 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

PROGRAM

- 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



falling-99183_640 →

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. preprint: account of the opening workshop

 Talks from the closing workshop for the Big Data program

 data science programs: Beijing, Johns Hopkins, Berkeley, Columbia, NYU, Dalhousie

A haphazard web walk

Science article (Khoury & Ioannidis) Big Data Meets Public Health

http://www.sciencemag.org.myaccess.library.utoronto.ca/content/346/6213/1054.full

Science Article (Ruths & Pfeffer) Social media for large studies of behaviour

http://www.sciencemag.org.myaccess.library.utoronto.ca/content/346/6213/1063.full

McGill Newsroom re above Science article: http://www.mcgill.ca/newsroom/channels/news/social-media-data-pose-pitfalls-studying-behaviour-240450

A haphazard web walk

Economist Data Viz

http://www.economist.com/blogs/graphicdetail/2014/12/new-data-

<u>visualisations?fsrc=scn%2Ftw%2Fdc%2F&%3Ffsrc%3Dscn%2F=tw%2Fdc Interactive visualizations (dec 2)</u>

JANUARY JUNE, 2015

Flowing Data — books http://flowingdata.com/data-points/

Best Viz 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

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