

In Praise of Small Data

Statistical Science and Data Science

Nancy Reid
University of Toronto

Department of Statistics, OSU
April 11 2019



Statistics at a Crossroads

Examples: Statistics in the news

Statistical theory

Statistics and data science

Statistics at a Crossroads



- NSF workshop and report
- “... we are at a crossroads with an unprecedented opportunity to modernize ... to become the major player in data science, but also with a non-ignorable risk to make ourselves obsolete in the broad community of data science.”
- “... critical question, where do we go from here?”

The Annals of Mathematical Statistics



Vol. 33, No. 1, Mar., 1962

Published by: [Institute of Mathematical Statistics](https://www.jstor.org/stable/312810)

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“The future of data analysis can ... lead to the provision of a great service to all fields of science and technology. Will it? That remains to ... our willingness to take up the rocky road of real problems in preferences to the smooth road of unreal assumptions ... Who is for the challenge?”

THE FUTURE OF DATA ANALYSIS¹

BY JOHN W. TUKEY

Princeton University and Bell Telephone Laboratories

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THE FIELDS INSTITUTE

BIG DATA

THEMATIC PROGRAM ON STATISTICAL INFERENCE, LEARNING, AND MODELS FOR

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 Verran (Chair), Anura Anandkumar, Petros Drineas, Michael Friedlander, Nancy Reid, Martin Waaijenberg

FEBRUARY 23 - 27, 2015
Workshop on Visualization for Big Data: Strategies and Principles
 Organizing Committee: Nancy Reid (Chair), Susan Holmes, Snehalata Huzarbazar, 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 AARSMS 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), Ma Zhu (University of Waterloo)

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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.

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





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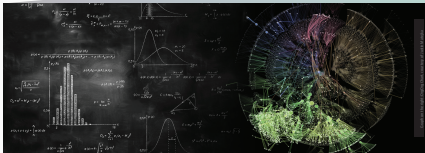
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www.fields.utoronto.ca/programs/scientific/14-15/bigdata







Statistical Inference, Learning and Models in Data Science



September 24 - 27, 2018 at THE FIELDS INSTITUTE
September 28, 2018 at MARS

This is a retrospective workshop for the 2015 thematic program *Statistical Models, Learning and Inference* for Big Data. We will reflect on recent progress and the shift in emphasis to data science in the intervening three years.

INVITED SPEAKERS

Edoardo Airoldi, *Harvard University*
Jimmy Ba, *University of Toronto*
Jelena Bradic, *University of California*
Fanny Chevalier, *University of Toronto*
Michael Correll, *Tableau*
Debbie Dupuis, *HEC Montreal*
Ruth Etzioni, *Fred Hutchinson Cancer Research Center*
Mark Fox, *University of Toronto*
Marzyeh Ghassemi, *MIT*
Laura Hatfield, *Harvard Medical School*
Heike Hofmann, *Iowa State University*
Eric Kolaczyk, *Boston University*
Todd Kuffner, *Washington University*

Simon Lacoste-Julien, *University of Montreal*
Rahul Mazumder, *MIT Sloan School*
Isabel Meirelles, *OCAD University*
Raymond Ng, *University of British Columbia*
Sofia Olhede, *University College London*
George Paliouras, *IFT Athens*
Greg Ridgeway, *University of Pennsylvania*
Veronika Rockova, *University of Chicago*
Mark Schmidt, *University of British Columbia*
Ravi Shroff, *New York University*
Nathan Srebro, *Toyota Technical Institute*
Yaoliang Yu, *University of Waterloo*
Francis Zwieters, *University of Victoria*

... more speakers on the Industry Day, on Friday September 28!

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David Davenaud, *University of Toronto*
Sallie Keller, *Virginia Tech*

Lisa Lix, *University of Manitoba*
Nancy Reid, *University of Toronto*
Nathan Taback, *University of Toronto*
Stephen Vavasis, *University of Waterloo*

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The role of Statistics in the era of big data

Edited by Laura Sangalli
Volume 136, Pages 1–170 (May 2018)

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On the role of statistics in the era of big data: A call for a debate
Piercesare Secchi
Pages 10–14

Examples: Statistics in the news

Example 1: human longevity

NEWS • 28 JUNE 2018

There's no limit to longevity, says study that revives human lifespan debate

Death rates in later life flatten out and suggest there may be no fixed limit on human longevity, countering some previous work.

Elie Dolgin

“the study included fewer than 100 people who lived to 110 or beyond”

“even small inaccuracies in the Italian longevity records could lead to a spurious conclusion”

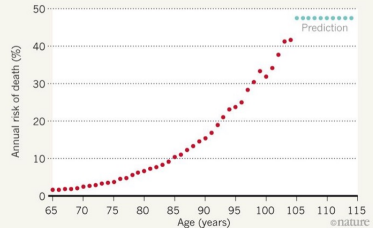
E. Dolgin, Nature

Rustagi Lecture 2019

Nature News
June 28 2018

LONGEVITY UNLIMITED

A person's chances of dying tend to increase throughout adulthood, but a model based on data from 3,836 people aged 105 or older predicts that this trend flattens out in the very elderly.



RESEARCH

HUMAN DEMOGRAPHY

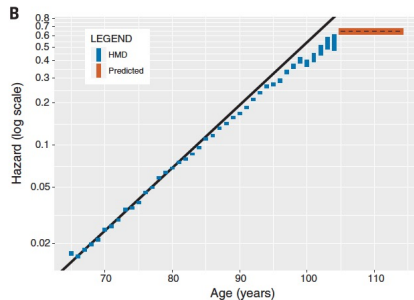
The plateau of human mortality: Demography of longevity pioneers

Elisabetta Barbi^{1*}, Francesco Lagona², Marco Marsili³,
James W. Vaupel^{4,5,6,7}, Kenneth W. Wachter⁸

Theories about biological limits to life span and evolutionary shaping of human longevity depend on facts about mortality at extreme ages, but these facts have remained a matter of debate. Do hazard curves typically level out into high plateaus eventually, as seen in other species, or do exponential increases persist? In this study, we estimated hazard rates from data on all inhabitants of Italy aged 105 and older between 2009 and 2015 (born 1896–1910), a total of 3836 documented cases. We observed level hazard curves, which were essentially constant beyond age 105. Our estimates are free from artifacts of aggregation that limited earlier studies and provide the best evidence to date for the existence of extreme-age mortality plateaus in humans.

Science

June 29 2018



“We observed level hazard curves, which were essentially constant beyond age 105”

“... provide the best evidence to date for the existence of extreme-age mortality plateaus”

“ ‘This study is unlikely to be the last word on the age-limit dispute’, says Haim Cohen, a molecular biologist at Bar-Ilan University in Ramat-Gan Israel. ‘I’m sure that the debate is going to continue’”

Dolgin, Nature, June 2018



“The capacity for data entry and age inflation errors provides a sufficient model to explain late-life mortality patterns observed by Barbi and colleagues ”

Rustagi Lecture 2019

FORMAL COMMENT

Plane inclinations: A critique of hypothesis and model choice in Barbi et al

Saul Justin Newman  *

Research School of Biology, The Australian National University, Acton, ACT, Australia

* saul.newman@anu.edu.au

Abstract


This study highlights how the mortality plateau in Barbi and colleagues can be generated by low-frequency, randomly distributed age-misreporting errors. Furthermore, sensitivity of the



“... claims of Barbi and colleagues rest on nearly 4,000 carefully validated cases from an established registration system. A critique like Newman’s, ... can hardly carry force.”

FORMAL COMMENT

Hypothetical errors and plateaus: A response to Newman

Kenneth W. Wachter  *

Department of Demography, University of California, Berkeley, California, United States of America

* wachter@demog.berkeley.edu

Abstract

Newman questions recent claims about a plateau in mortality rates for Italians beyond age 105 on the basis of a hypothetical model. His model implies implausibly high error rates for

- claims that age-misreporting can generate spurious late life plateaus
- Barbi et al (2018) fit a parametric model and used likelihood ratio test to compare to a constant hazard for age > 105
- Newman argued that a modelling choice they made influenced their results
- “of the 861 ... combinations tested, the model selected by Barbi et al generated the single largest late-life mortality plateau”
- **statistics:** Gompertz model, LRT, power analysis $h(x) = ae^{bx}e^{\beta_1 C + \beta_2 M}$
- **data science:** 861 such fits, plus simulated errors with probabilities ranging from 10^{-3} to 10^{-6}
- **domain science:** all inhabitants of Italy aged ≥ 105 years 2009–2015 (3836 cases) + Human Mortality Database

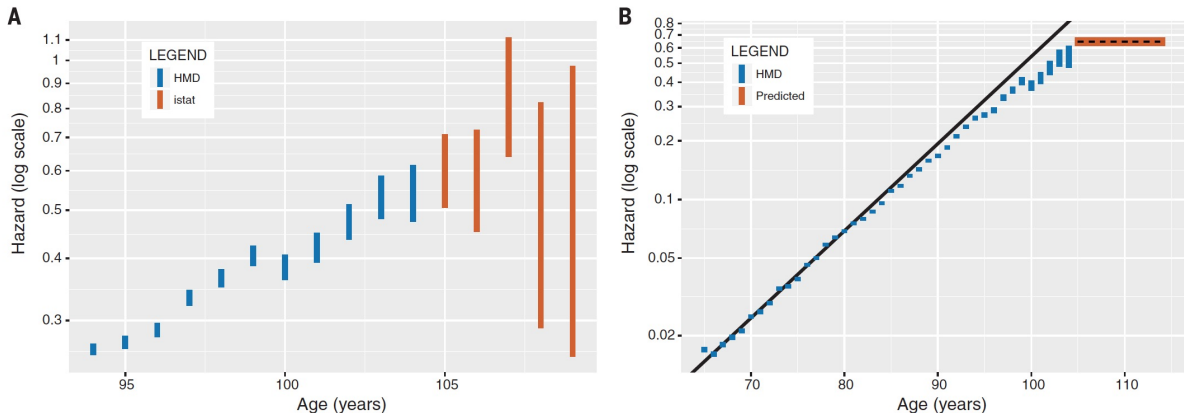


Fig. 1. Yearly hazards on a logarithmic scale for the cohort of Italian women born in 1904. Confidence intervals were derived from Human Mortality Database (HMD) data for ages up to 105 and from ISTAT data beyond age 105. **(A)** Closeup with 95% confidence intervals based solely on single-cohort data. **(B)** Broad view with estimated plateau beyond age 105 (black dashed line) and 95% confidence bands (orange) predicted from the model parameters based on the full ISTAT database, along with a straight-line prediction (black) from fitting a Gompertz model to ages 65 to 80.

Example 2: wildfire

B.C. wildfires stoked by climate change, likely to become worse: study

Jeff Lewis

Jan 8 2019

Globe & Mail

JEFF LEWIS > ENVIRONMENT REPORTER
PUBLISHED JANUARY 8, 2019
UPDATED 18 HOURS AGO

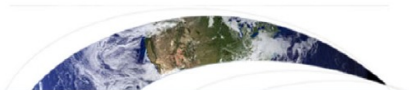


A helicopter flies over a wildfire southwest of the town of Cache Creek, B.C., on July 18, 2017.

BEN NELMS/REUTERS

TRENDING

- 1** **OPINION**
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- 3** Jagmeet Singh gets his chance as Trudeau calls three by-elections, including in Burnaby South
- 4** BMO slices 1,000 points from its Toronto stock market forecast
- 5** Toronto's Vena secures \$115-million in financing from U.S. private-equity firms



Earth's Future



RESEARCH ARTICLE

10.1029/2018EF001050





Key Points:

- An event attribution analysis is performed for the record-breaking wildfire season of 2017 in BC
- Anthropogenic climate change greatly increased the likelihood of extreme warm temperatures and high fire risk
- A strong anthropogenic climate change contribution is also found for the large area burned

Supporting Information:

- Supporting Information S1

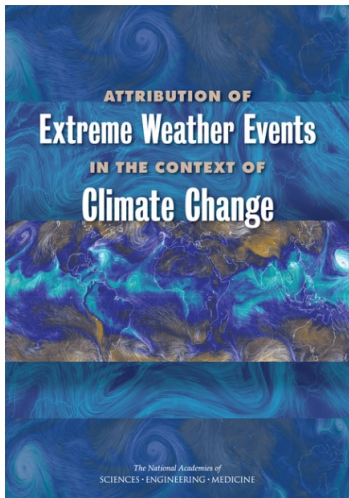
Attribution of the Influence of Human-Induced Climate Change on an Extreme Fire Season

M. C. Kirchmeier-Young^{1,2} , N. P. Gillett² , F. W. Zwiers¹ , A. J. Cannon³ , and F. S. Anslow¹

¹Pacific Climate Impacts Consortium, University of Victoria, Victoria, British Columbia, Canada, ²Canadian Centre for Climate Modelling and Analysis, Environment and Climate Change Canada, Victoria, British Columbia, Canada,

³Climate Research Division, Environment and Climate Change Canada, Victoria, British Columbia, Canada

Abstract A record 1.2 million ha burned in British Columbia, Canada's extreme wildfire season of 2017. Key factors in this unprecedented event were the extreme warm and dry conditions that prevailed at the time, which are also reflected in extreme fire weather and behavior metrics. Using an event attribution method and a large ensemble of regional climate model simulations, we show that the risk factors affecting the event, and the area burned itself, were made substantially greater by anthropogenic climate change. We show over 95% of the probability for the observed maximum temperature anomalies is due to



The relatively young science of extreme event attribution seeks to tease out the influence of human-caused climate change from other factors, such as natural sources of variability like El Niño, as contributors to individual extreme events.

Consensus Report

National Academy of Sciences
Engineering and Medicine

- “anthropogenic climate change increased the area burned by a factor of 7 - 11”
- “We use a large ensemble of CanRCM4 ... consisting of 50 realizations on a 50-km grid. Each realization is driven by a member of the CanESM2 ... large ensemble ... We utilize data from 1961 to 2020.”
- “A data set of gridded maximum (and minimum) temperature and precipitation anomalies was created by interpolating monthly values calculated from surface station observations relative to a 30-year climatology. Observational data was acquired from numerous sources and interpolated using a thin plate spline methodology.”
- “... values for each year and large ensemble realization were pooled together for two time periods: 1961-1970 and 2011-2020, resulting in 500 values for each decade (10 years x 50 realizations). ”

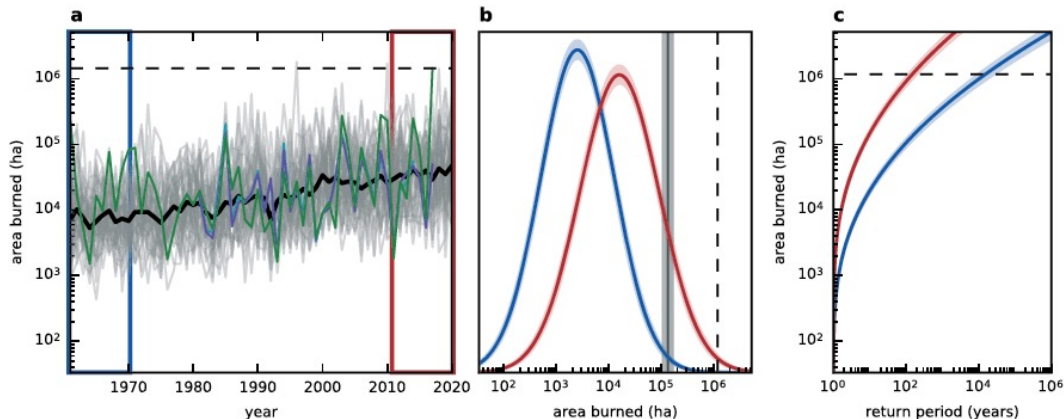


Figure 5. Time series (a, log scale) of regression-predicted annual burned area in the BC Southern Cordillera for bias-corrected CanRCM4 realizations (gray) and ensemble mean (bold), reanalysis (turquoise/purple), and observations (green). The dashed line marks the observed 2017 value. Probability distributions (b) for area burned amounts (log scale) from decades outlined in corresponding colors in (a). The gray bar indicates the area burned amount in the distribution¹⁸ with reduced anthropogenic influence (blue) of a corresponding percentile to the 2017 amount (dashed line) in the

- complex computer simulation of global climate
- creation of regional climate scenarios
- combined with available observational data
- modelled with regression and kernel density estimation

mathematics
numerical analysis
mathematics, statistics

statistics, data science

statistics
mathematics

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The Canadian Regional Climate Model Large Ensemble

The CanRCM4 large ensemble is a 50-member ensemble from 1950-2100 with all historical forcings for the North American Domain. Each ensemble member is driven by a member of the CanESM2 large ensemble (<https://open.canada.ca/data/en/dataset/aa7b8823-1d1e-49ff-a8fb-68076a4a477c>). The model, forcings, variable names, and file formats all follow those used in the Coordinated Regional Downscaling Experiment (CORDEX). Simulations were run to 2005 using CMIP5 historical forcings and then to 2100 using RCP 8.5 forcings following the Coupled Model Intercomparison Project Phase 5 (CMIP5) protocols, which were employed for the CanESM2 large ensemble. The CanRCM4 large ensemble is an extension of the CanESM2 large ensemble proposed by the Canadian Sea Ice and Snow Evolution Network (CanSISE) Climate Change and Atmospheric Research (CCAR) Network project.

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TRANSCRIPT

Bad Diets Are Responsible For More Deaths Than Smoking, Global Study Finds

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Health effects of dietary risks in 195 countries, 1990–2017: a systematic analysis for the Global Burden of Disease Study 2017

[GBD 2017 Diet Collaborators](#)

Open Access • Published: April 03, 2019 • DOI: [https://doi.org/10.1016/S0140-6736\(19\)30041-8](https://doi.org/10.1016/S0140-6736(19)30041-8)

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PlumX Metrics

[Summary](#)[Introduction](#)[Methods](#)[Results](#)[Discussion](#)

Summary

Background

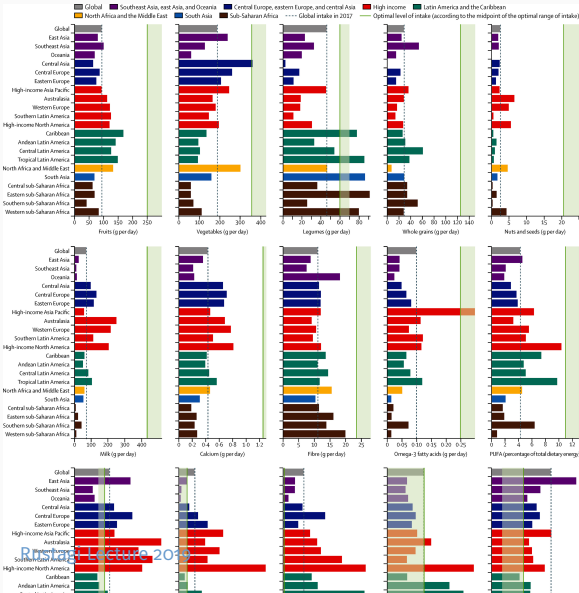
Suboptimal diet is an important preventable risk factor for non-communicable diseases (NCDs); however, its impact on the burden of NCDs has not been systematically evaluated. This study aimed to evaluate the consumption of major foods and nutrients across 195 countries and to quantify the impact of their suboptimal intake on NCD mortality and morbidity.

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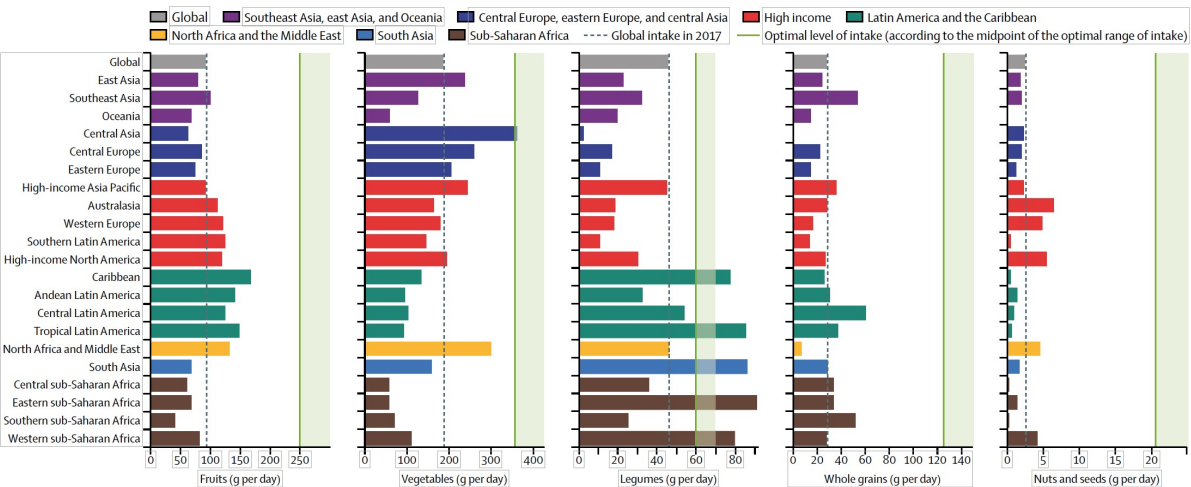
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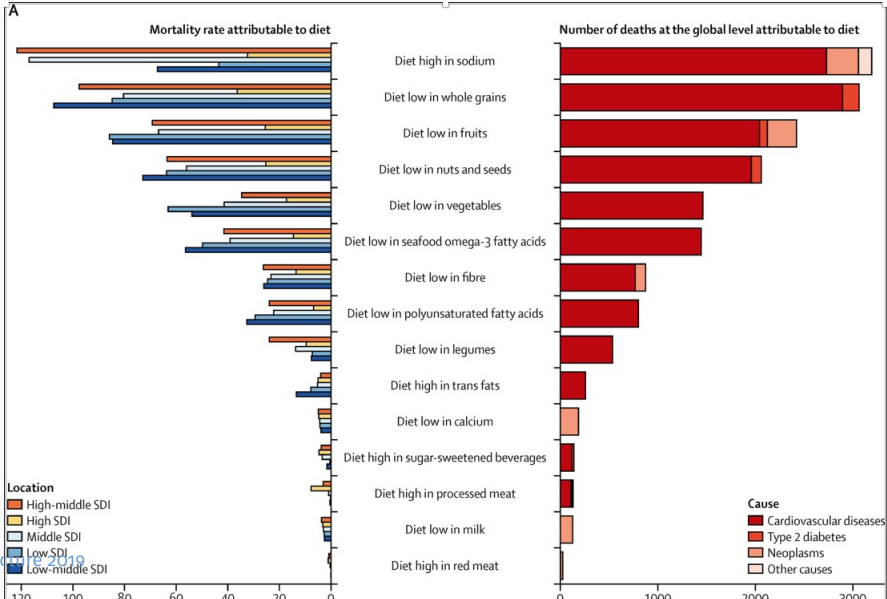
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Updates

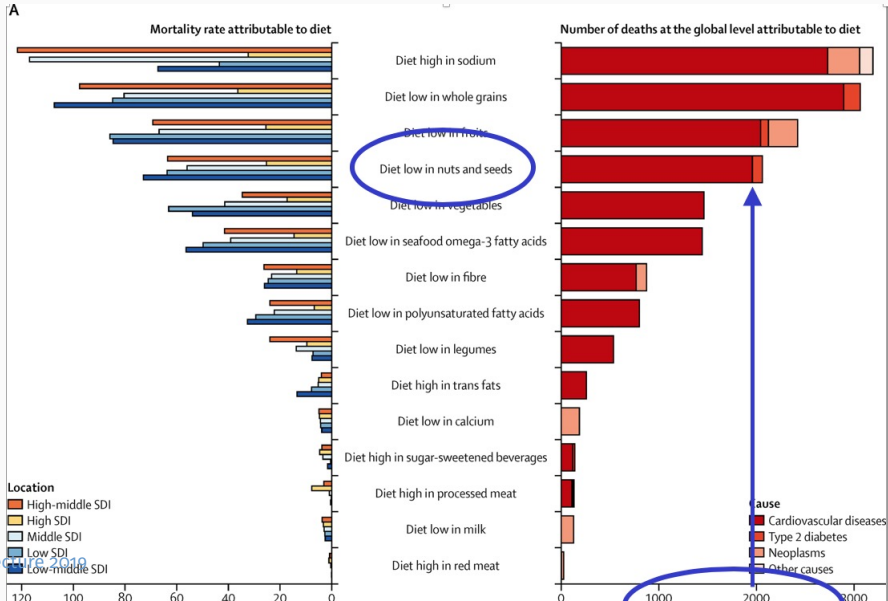
- “this study aimed to evaluate the consumption of major foods and nutrients across 195 countries and to quantify the impact of their suboptimal intake”
- “we estimated the proportion of disease-specific burden attributable to each dietary risk factor”
- “analysis included the intake of each dietary factor, the effect size of the dietary factor on disease endpoint, and the level of intake associated with the lowest risk of mortality”
- “... we calculated the number of deaths and DALYs attributable to diet for each disease outcome”
- “In 2017, **11 million** (95% uncertainty interval [UI] 10–12) **deaths** and 255 million (234–274) DALYs were attributable to dietary risk factors.”
- “High intake of **sodium (3 million [1–5] deaths and 70 million [34–118] DALYs)**, **low intake of whole grains (3 million [2–4] deaths and 82 million [59–109] DALYs)**, and **low intake of fruits (2 million [1–4] deaths and 65 million [41–92] DALYs)** were the leading dietary risk factors”



dietary intake (age-standardized)
colours = regions
one panel per food







Health Effects of Dietary Risks in 195 Countries: Findings from the Global Burden of Diseases Study 2017

Supplementary appendix

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$$PAF_{asct} = \frac{\int_l^u RR_{as}(x)P_{asct}(x)dx - RR_{as}(TMREL)}{\int_l^u RR_{as}(x)P_{asct}(x)dx}$$

$$Total\ attributable\ deaths_{asct} = \sum_{o=1}^w Death_{oasct} PAF_{oasct}$$

Assuming no correlation between dietary factors, we estimated the PAFs and number of deaths for the overall effect of all dietary factors relevant to each outcome based on the following equations:

$$PAF_{oasct} = 1 - \prod_i^n (1 - PAF_{ioasct})$$

$$Total\ attributable\ deaths_{asct} = \sum_{o=1}^w Death_{oasct} PAF_{oasct}$$

Supplemental Table 2. Citation of the epidemiological studies used to evaluate the causal relationship between dietary risk-outcome pairs in Supplemental Table 1.

Risk	Outcome	Citation/Note
Diet high in processed meat	Colon and rectum cancer	World Cancer Research Fund, American Institute for Cancer Research, Imperial College London. WCRF/AICR Systematic Literature Review Continuous Update Project Report: The Associations between Food, Nutrition and Physical Activity and the Risk of Colorectal Cancer. Oct 2010.
Diet high in processed meat	Ischaemic heart disease	Micha R, Wallace SK, Mozaffarian D. Red and processed meat consumption and risk of incident coronary heart disease, stroke, and diabetes mellitus: a systematic review and meta-analysis. <i>Circulation</i> 2010; 121: 2271–83.
Diet high in processed meat	Diabetes mellitus	Pan A, Sun Q, Bernstein AM, et al. Red meat consumption and risk of type 2 diabetes: 3 cohorts of US adults and an updated meta-analysis. <i>Am J Clin Nutr</i> 2011; 94: 1088–96.
Diet high in sugar-sweetened beverages	Diabetes mellitus	Imamura F, O'Connor L, Ye Z, et al. Consumption of sugar sweetened beverages, artificially sweetened beverages, and fruit juice and incidence of type 2 diabetes: systematic review, meta-analysis, and estimation of population attributable fraction. <i>BMJ</i> 2015; 351: h3576.
Diet high in sugar-sweetened beverages	Ischaemic heart disease	Xi B, Huang Y, Reilly KH, et al. Sugar-sweetened beverages and risk of hypertension and CVD: a dose-response meta-analysis. <i>Br J Nutr</i> 2015; 113: 709–17.
Diet low fibre	Colon and rectum cancer	World Cancer Research Fund, American Institute for Cancer Research, Imperial College London. WCRF/AICR Systematic Literature Review Continuous Update Project Report: The Associations between Food, Nutrition and Physical Activity and the Risk of Colorectal Cancer. Oct 2010.
Diet low fibre	Ischaemic heart disease	Threapleton DE, Greenwood DC, Evans CE, et al. Dietary fibre intake and risk of cardiovascular disease: systematic review and meta-analysis. <i>BMJ (Clinical research ed)</i> 2013; 347: f6879.
Diet low in calcium	Colon and rectum cancer	World Cancer Research Fund, American Institute for Cancer Research, Imperial College London. WCRF/AICR Systematic Literature Review Continuous Update Project Report: The Associations between Food, Nutrition and Physical Activity and the Risk of Colorectal Cancer. Oct 2010.
Diet low in seafood omega-3 fats	Ischaemic heart disease	Chowdhury R, Stevens S, Gorman D, et al. Association between fish consumption, long chain omega 3 fatty acids, and risk of cerebrovascular disease: systematic review and meta-analysis. <i>BMJ (Clinical research ed)</i> 2012; 345: e6698.
Diet low in polyunsaturated fats	Ischaemic heart disease	Farvid MS, Ding M, Pan A, et al. Dietary linoleic acid and risk of coronary heart disease: a systematic review and meta-analysis of prospective cohort studies. <i>Circulation</i> 2014; 130: 1568–78.
Diet low in polyunsaturated fats	Ischaemic heart disease	Mozaffarian D, Micha R, Wallace S. Effects on coronary heart disease of increasing polyunsaturated fat in place of saturated fat: a systematic review and meta-analysis of randomized controlled trials. <i>PLoS Med</i> 2010; 7: e1000252.
Diet high in trans fats	Ischaemic heart disease	Mozaffarian D, Clarke R. Quantitative effects on cardiovascular risk factors and coronary heart disease risk of replacing partially hydrogenated vegetable oils with other fats and oils. <i>Eur J Clin Nutr</i> . 2009; 63(Suppl 2): S22–33.
Diet high in trans fats	Ischaemic heart disease	

diet high in trans fats	Ischaemic heart disease	Mozaffarian D, Clarke R. Quantitative effects on cardiovascular risk factors and coronary heart disease risk of replacing partially hydrogenated vegetable oils with other fats and oils. <i>Eur J Clin Nutr.</i> 2009; 63(Suppl 2): S22-3.
diet high in trans fats	Ischaemic heart disease	http://www.bmj.com/content/bmj/suppl/2015/08/11/bmj.h3978.DC1/sour025275.ww2_default.pdf ; pg. 44
diet high in sodium and high systolic blood pressure	n/a	Aburto NJ, Ziolkovska A, Hooper L, Elliott P, Cappuccio FP, Meerpohl JJ. Effect of lower sodium intake on health: a systematic review and meta-analyses. <i>BMJ</i> 2013; 346: f1326.
diet high in sodium	Stomach cancer	World Cancer Research Fund, American Institute for Cancer Research. Food, Nutrition, Physical Activity, and the Prevention of Cancer: a Global Perspective. Washington DC: AICR, 2007.
diet high in sodium	Stomach cancer	D'Elia, Lanfranco, Giovanni Rossi, Renato Ippolito, Francesco P. Cappuccio, and Pasquale Strazzullo. 2012. "Habitual Salt Intake and Risk of Gastric Cancer: A Meta-Analysis of Prospective Studies." <i>Clinical Nutrition</i> 31: 489–98. doi:10.1016/j.clnu.2012.01.003.
diet low in nuts and seeds	Ischaemic heart disease and diabetes mellitus	Experimental evidence on the relationship of nuts with ischaemic heart disease and diabetes mellitus come from the PREDIMED trial; a randomized trial consisting of three arms: a Mediterranean diet with extra-virgin olive oil, a Mediterranean diet with nuts, and a control diet. Given that the intake of dietary factors other than nuts changed in the intervention arms of this trial, the observed effect might be fully attributable to nuts.
diet high in sodium	Cardiovascular diseases	Evidence on the direct effect of sodium on cardiovascular disease mainly comes from prospective cohort studies. Considering that, in GBD, we have only evaluated the effect of sodium mediated through systolic blood pressure, we did not present epidemiologic evidence on the direct effect of sodium on cardiovascular disease in this table. Evidence on the effect of sodium on systolic blood pressure mostly comes from randomized controlled trials. While some of these studies evaluated the relationship between sodium and systolic blood pressure, we did not identify a systematic evaluation of these studies.

The PREDIMED trial



PREDIMED trial



predimed trial - Google Search



predimed trial **retraction**



predimed trial **nejm**



predimed trial **mediterranean diet**



predimed plus trial

The NEW ENGLAND JOURNAL *of* MEDICINE

CORRESPONDENCE



**Retraction and Republication: Primary Prevention
of Cardiovascular Disease with a Mediterranean Diet.
N Engl J Med 2013;368:1279-90.**



BMJ 2019;364:l341 doi: 10.1136/bmj.l341 (Published 7 February 2019)

Page 1 of 5



ANALYSIS

PREDIMED trial of Mediterranean diet: retracted, republished, still trusted?

Arnav Agarwal and **John P A Ioannidis** consider what we can learn from the retraction and republication of an influential trial of Mediterranean diet

- 15 dietary risk factors
- consumption: nutrition surveys supplemented with sales data
- measurement of consumption: 24h dietary recall if available
- “spatiotemporal Gaussian process regression to estimate mean intake by age, sex, country and year”
- “for each diet-disease pair ... published meta-analyses of prospective observational studies .. to estimate the relative risk of mortality ...”
- relative risk converted to population attributable fraction
- then converted to mortality estimates

re nuts and seeds: PREDIMED – risk reduction of approximately 3 major cardiovascular events per 1000 person-years among adults 55 – 80 years old at high cv risk, in Spain



→ observational studies →

THE LANCET



All coverage

 Radio Canada International - ENGLISH

Poor diet responsible for 1 in 5 deaths: study

5 days ago



 Yahoo News

The diet mistakes that could be killing us

5 days ago



 Ahran Online

One in five deaths worldwide linked to unhealthy diet - Health - Life & Style

5 days ago



 The National

Death by diet more likely than by smoking, drugs or blood pressure, finds global study

5 days ago • International



 EurekAlert

The Lancet: Globally, 1 in 5 deaths are associated with poor diet

6 days ago

 The Week UK

The countries with the healthiest and unhealthiest diets revealed

5 days ago



 DW News

Poor eating habits killing millions globally, study says

5 days ago • International



 Daily Mail

Poor diet kills more than smoking and hypertension, Bill Gates study reveals

6 days ago



 The Times of Israel

Israel has lowest rate of diet-related deaths in the world, major study finds

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 Bloomberg

It Isn't Just Meat That's Killing You

5 days ago



 Mirror Online

Bangers and burgers 'cause 4,000 DEATHS a year' study claims

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 National Post

Poor diets heavy in salt and sugar kill one in five people, global study finds

5 days ago



 American Council on Science and Health

Can We Eat Our Way to Health (Or at Least Avoid Dying)?

5 days ago



 Lab Manager Magazine

One in five Deaths Associated with Poor Diet Globally

5 days ago



 Daijworld.com

Poor diet causes hundreds of deaths in India



 The Straits Times

1 in 5 deaths globally due to poor diet; study warns eating too much sugar, salt and meat killing millions



TIME



What we aren't eating is killing us, global study finds

By Sandra Lubchenco, CNN
Updated 7:40 PM ET, Wed April 3, 2019



One in five people are eating themselves to an early death: Global study

Ashley May, USA TODAY Published 9:04 p.m. ET April 3, 2019 | Updated 9:57 p.m. ET April 3, 2019


THE TIMES OF ISRAEL

Israel has lowest rate of diet-related deaths in the world, major study finds

Analysis published in The Lancet finds fruit, vegetables, nuts and seeds are instrumental in avoiding deadly diseases


Statistical theory

- causality
- data on networks
- multivariate extremes
- quantile regression
- high-dimensional inference
- model selection
- sparsity
- inference after model selection
- multivariate responses
- nonparametric, robust methods
- foundations
- ...



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Journal of the Royal Statistical Society
Statistical Methodology
Series B



Banff International Research Station
for Mathematical Innovation and Discovery

Biometrika Advance Access published June 29, 2015

WHOA-PSI 2018

doi: 10.1093/biomet/asv033

Workshop on Higher-Order Asymptotics and Post-Selection Inference

September 8-10

Big data and precision

BY D. R. COX

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Why is this model important? SUMMARY

So-called big data are likely to have complex structure, in particular implying that estimates of precision obtained by applying standard statistical procedures are likely to be misleading, even if the point estimates of parameters themselves may be reasonably satisfactory. While this possibility is best explored in the context of each special case, here we outline a fairly general representation of the accretion of error in large systems and explore the possible implications for the estimation of regression coefficients. The discussion raises issues broadly parallel to the distinction between short-range and long-range dependence in time series theory.

Some key words: Components of variance; Large data; Long-range dependence; Multilevel model; Time series

Download this video (133M)

1. INTRODUCTION

Big data raise several essentially statistical issues. There may be concern over data quality and the standardization of definitions and with the rationale for inclusion in the data base. Importantly also, there is a distinction between investigations in which the research questions are at least broadly defined from

- causality
- data on networks
- multivariate extremes
- quantile regression
- **high-dimensional inference**
- model selection
- sparsity
- inference after model selection
- multivariate responses
- nonparametric, robust methods
- **foundations**
- ...

- how to get from data to conclusions
- with generalizable strategies
- what principles do we use to develop these strategies
- how are these strategies to be evaluated
efficiency, precision
- probability to describe physical haphazard variability
subject to empirical validation
frequentist
- probability to describe the uncertainty of knowledge
degree of belief
Bayesian

Bayesian, Fiducial, and Frequentist (BFF) Conferences

APPLY

***** Deadline for applications for this workshop is March 20, 2019 *****

Applications received after March 20th are subject to availability.

Location

This workshop will be held at Penn Pavilion on the campus of Duke University.
Rustagi Lecture 2019

- probability to describe physical haphazard variability

frequentist

- probabilities represent features of the “real” world in somewhat idealized form
- subject to empirical test and improvement

- probability to describe the uncertainty of knowledge

Bayesian

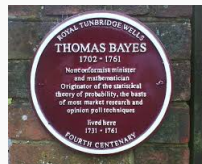
- measures rational or “impersonal” degree of belief,
or
- measures a particular person’s degree of belief
- linked to personal decision making

Jeffreys, 1939,1961

F.P. Ramsey, 1926

- confidence intervals or p -values refer to empirical probabilities
- inference is assessed by behaviour of the procedure under hypothetical repetition
- the Bayesian approach to inference describes uncertainty of knowledge
- this can be interpreted empirically by appeal to a notion of calibration

“[7 – 11]”



- causality
- data on networks
- multivariate extremes
- quantile regression
- **high-dimensional inference**
- model selection
- sparsity
- inference after model selection
- multivariate responses
- nonparametric, robust methods
- **foundations**
- ...

High-dimensional asymptotic theory

- $f(y; \theta)$, $y \in \mathbb{R}^n$, $\theta \in \mathbb{R}^p$

y_1, \dots, y_n independent

- classical: p fixed, $n \rightarrow \infty$

$$\sqrt{n}(\hat{\theta} - \theta)V^{-1/2} \xrightarrow{d} N_p(0, I)$$

- semi-classical: $p_n/n \rightarrow 0$, or $p_n^{3/2}/n \rightarrow 0$

Huber 70, Portnoy 80s; Sartori 90s, Lunardon '18, ...

- **moderate dimension** $p_n/n \rightarrow \kappa \in (0, 1)$

Candes '17, Lei/Bickel/El Karoui '18, Coolen et al. '19

- high dimension $p_n \sim n^\alpha$

$$p > n$$

- ultra-high dimension $p_n \sim e^n$

- $\hat{\beta} = \arg \min \frac{1}{n} \sum_{i=1}^n \rho(y_i - x_i^T \beta)$

M-estimator

- coordinate-wise asymptotic normality

$$\max_j d_{TV} \left\{ \mathcal{L} \left(\frac{\hat{\beta}_j - E(\hat{\beta}_j)}{\sqrt{\text{var}(\hat{\beta}_j)}} \right), N(0, 1) \right\} = o(1)$$

- “For instance for least-squares, standard degrees of freedom adjustments effectively take care of many dimensionality-related problems”
- in least squares, ‘standard degrees of freedom adjustments’ can be derived using higher order asymptotics for p fixed
- e.g. $n = 50, p = 30$ or $n = 500, p = 300$

moderate or classical?

- normal theory linear regression
- exact test available based on t -statistic $t = (\hat{\beta}_j - \beta_j)/v_{jj}$
- all likelihood quantities are functions of t, n and p
- modified log-likelihood root, derived from higher order asymptotics depends only on $t, n - p$

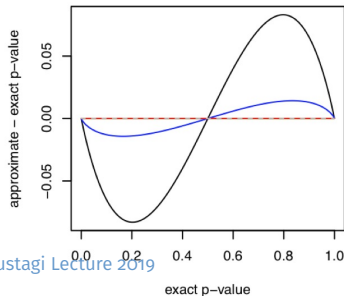
$$y = X\beta + \sigma\epsilon, \epsilon \sim N(0, 1)$$

least squares = mle

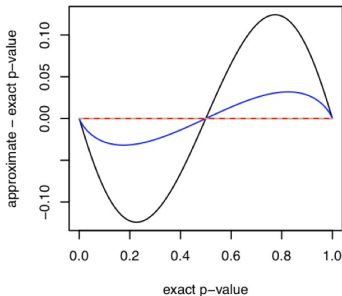
r^* depends on $t, n, n - p$

Plot of differences between approximate and exact p -values for one-sided alternative against the true p -value:

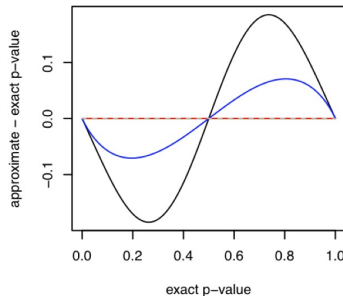
n=4000, p=2000



n=4000, p=2600



n=4000, p=3200



logistic regression

$$\log \frac{p_i}{1-p_i} = \mathbf{x}_i^T \beta, \quad y_i \sim \text{Bernoulli}(p_i)$$

- if the MLE exists, then

$$p/n \rightarrow \kappa \in (0, 1)$$

$$\frac{1}{p} \sum_{j=1}^p (\hat{\beta}_j - a_* \beta_j) \rightarrow 0; \quad \frac{1}{p} \sum_{j=1}^p (\hat{\beta}_j - a_* \beta_j)^2 \rightarrow \sigma_*^2$$

- Likelihood Ratio Test for $H : \beta_j = 0$ has scaled χ^2

$$w(\beta_j) = 2\{\ell(\hat{\beta}) - \ell(\tilde{\beta}_{(j)})\} \xrightarrow{d} \frac{\kappa \sigma_*^2}{\lambda_*} \chi_1^2$$

- $(a_*, \sigma_*, \lambda_*)$ characterized as the solution of three equations
- e.g. $n = 50, p = 30$ or $n = 500, p = 300$

moderate or classical?

logistic regression

$$\log \frac{p_i}{1 - p_i} = \mathbf{x}_i^T \beta, \quad y_i \sim \text{Bernoulli}(p_i)$$

- if the MLE exists, then

$$p/n \rightarrow \kappa \in (0, 1)$$

$$\frac{1}{p} \sum_{j=1}^p (\hat{\beta}_j - a_* \beta) \rightarrow 0; \quad \frac{1}{p} \sum_{j=1}^p (\hat{\beta}_j - a_* \beta)^2 \rightarrow \sigma_*^2$$

- in logistic regression, change the score equation a little
maximum likelihood estimate always exists

Firth 93; Kosmidis/Firth 09

- usual limit theory seems to be fine with large p

Sartori; Lunardon 18

Statistics and data science



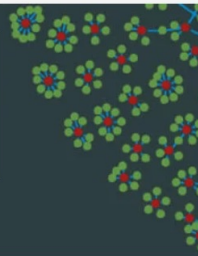
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Volume 1, 2014



Volume 1, 2014

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☐ What Is Statistics?

Stephen E. Fienberg

Full Text HTML

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About This Journal

The *Annual Review of Statistics and Its Application* informs statisticians, and users of statistics about major methodological advances and the computational tools that allow for their implementation.

- an art and a science
- a set of tools and methods, ... [and] computation
- a way of thinking about data
- what statisticians do and how they think about what they do
- interacts vigorously with astronomy, biology, engineering, geology, medicine and public health, and many social sciences, including political science, law, sociology, psychology, anthropology, archeology, history, ... ”
- ‘A distinguishing feature of the statistics profession, and the methodology it develops, is the focus on a set of cautious principles for drawing scientific conclusions from data.’
Lindsay 2004

- start with a scientific question
- assess how data could shed light on this
- plan data collection
- consider of sources of variation and how careful planning can minimize their impact
- develop strategies for data analysis: modelling, computation, methods of analysis
- assess the properties of the methods and their impact on the question at hand
- communicate the results: accurately but not pessimistically
- visualization strategies, conveyance of uncertainties

What is Data Science?

- a course?
- a set of courses?
- a job?
- **a new field of research?**
- **a collaboration?**

Berkeley Division of Data Sciences

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Data 8: Foundations of Data Science

University of Toronto New Undergraduate Program Proposal

(This template has been developed in line with the University of Toronto's Quality Assurance Process.)

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... what is data science?

- short-hand for “lots of data”, “complicated data”, “data of uncertain provenance”
- an undergraduate or post-graduate program of training
- a job description
- a new multi-disciplinary field of study
- combining mathematics, statistics, computer science, domain science
- increased emphasis on privacy, fairness, communication, visualization, impact on policy, workflow and reproducible research



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??

Blake & Olhede, 2016

data acquisition

data preservation

Making data trustable and usable
Management of data
Modelling and Analysis
Reproducibility
Dissemination and Visualization

Security and privacy

Ethics, policy and social impact

... data science workflow

Making data trustable and usable
Management of data

provenance, sampling, cleaning, digitizing
size, speed, accessibility

Modelling and Analysis
Reproducibility
Dissemination and Visualization

interpretable vs predictive methods
accessibility and impact
data, code, output

mathematics statistics computer science domain expertise

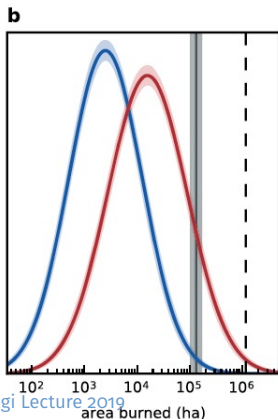
Security and privacy

disclosure limitation, anonymization,
encryption

Ethics, policy and social impact

fairness and transparency

- data \rightarrow conclusions
- data \rightarrow uncertainty about conclusions



“the annual burned areas of this same percentile are smaller by a factor of 7 - 11”

“the best-fit regression model was used, with shading indicating 90% confidence intervals”

Theory of Statistical Inference

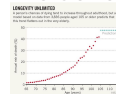
- how to get from data to conclusions
- with generalizable strategies
- what principles do we use to develop these strategies
- how are these strategies to be evaluated efficiency, precision
- a long history of the subject; using probability to both develop statistical methods and to evaluate their performance
Bayes, Laplace, Gauss; Student, Fisher, Neyman, Pearson, Jeffreys, ...
- leading to confidence intervals, p -values, estimates and standard errors, etc.

- correlation/dependence/heterogeneity/multiple scales
- rare events
- subgroup analyses/'data slices'
- complex models/many parameters/high-dimensional inference
- ...

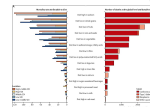
wildfires



extremes

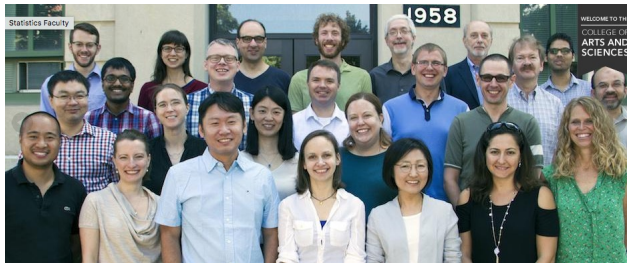


diet and mortality



sparsity, new asymptotics

Thank you!



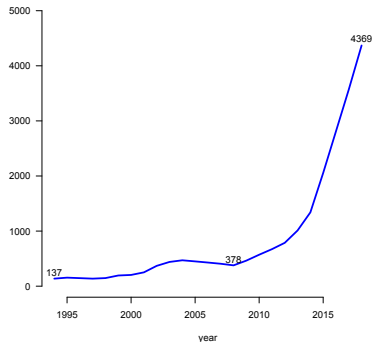
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- launched in 2012
- funded 2014–2021 by Natural Sciences and Engineering Research Council
- national scope, virtual institute
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multidisciplinary, multi-institution, statistical leadership, scientific engagement

... collaborations



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- statistical genetics
- spatial modelling
- machine learning (with CS)
- visualization (with CS)
- demography (with Sociology)
- astrostatistics (with A and A)
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