



Things every actuary should know about data science

A guide for the perplexed

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What is data science?

At the Center of It All: Data Science

Or: “The Collision between Statistics and Computation”

- The skill set underlying business analytics is increasingly called **data science**.
- Data science goes beyond:
 - Traditional statistics
 - Business intelligence [BI]
 - Information technology

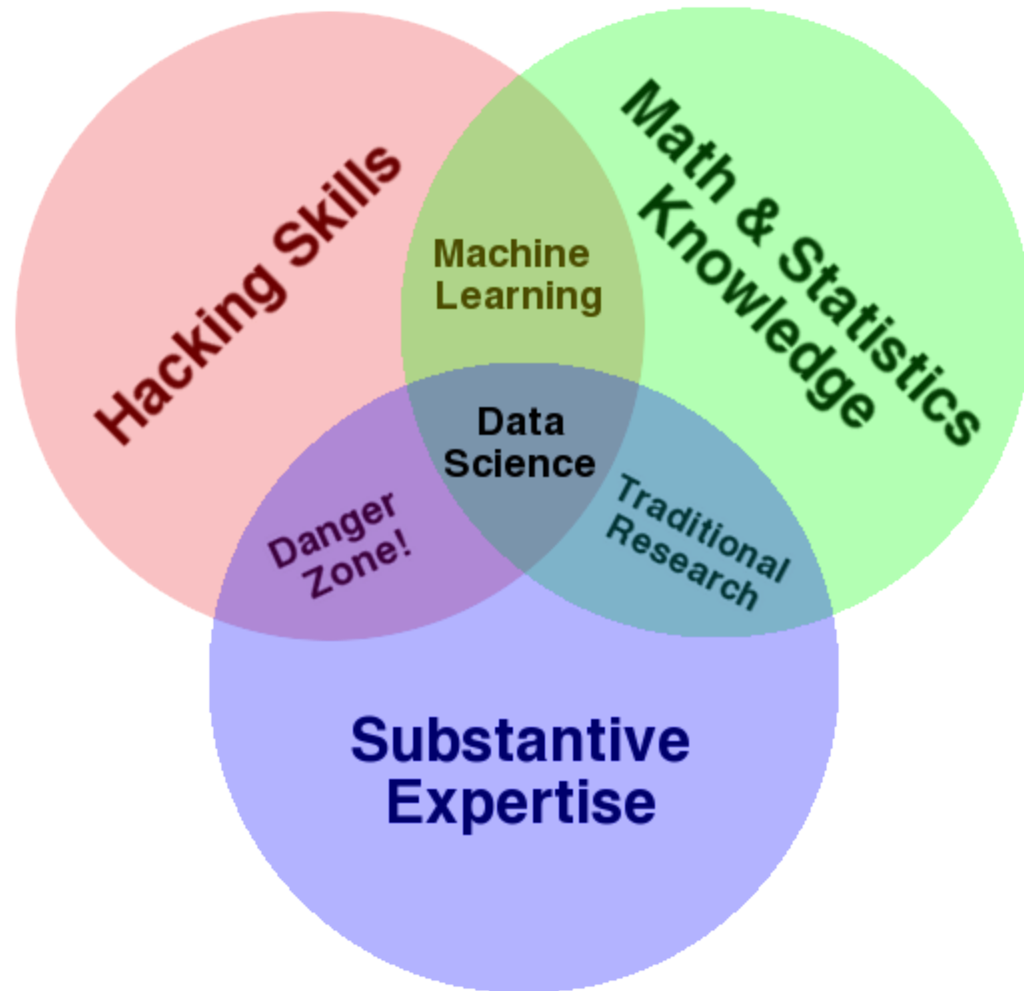


Image borrowed from Drew Conway's blog

<http://www.dataists.com/2010/09/the-data-science-venn-diagram>

At the Center of It All: Data Science

Or: “The Collision between Statistics and Computation”

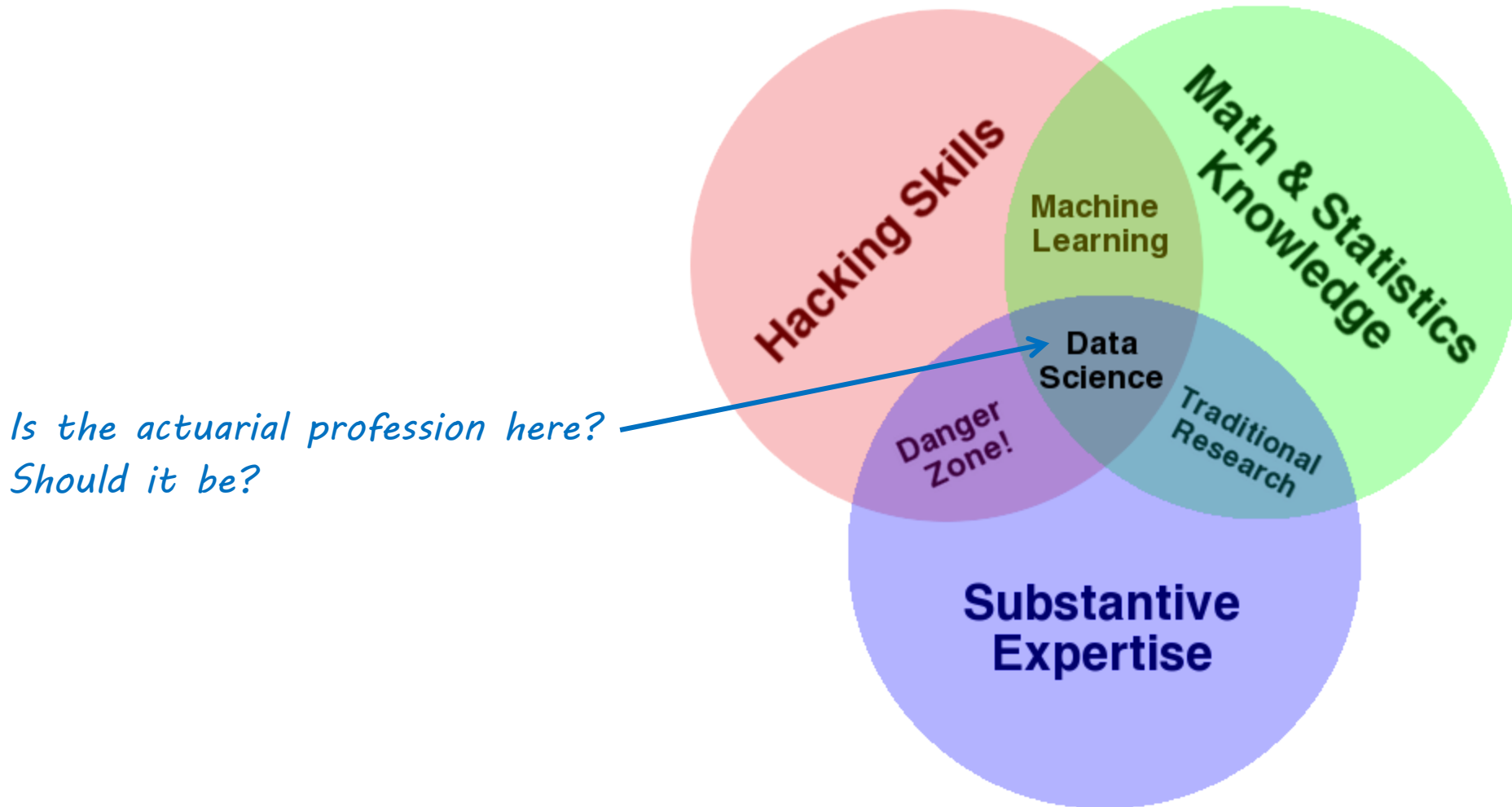


Image borrowed from Drew Conway's blog
<http://www.dataists.com/2010/09/the-data-science-venn-diagram>

At the Center of It All: Data Science

Or: “The Collision between Statistics and Computation”

*Or is it here?
Is that ok?*

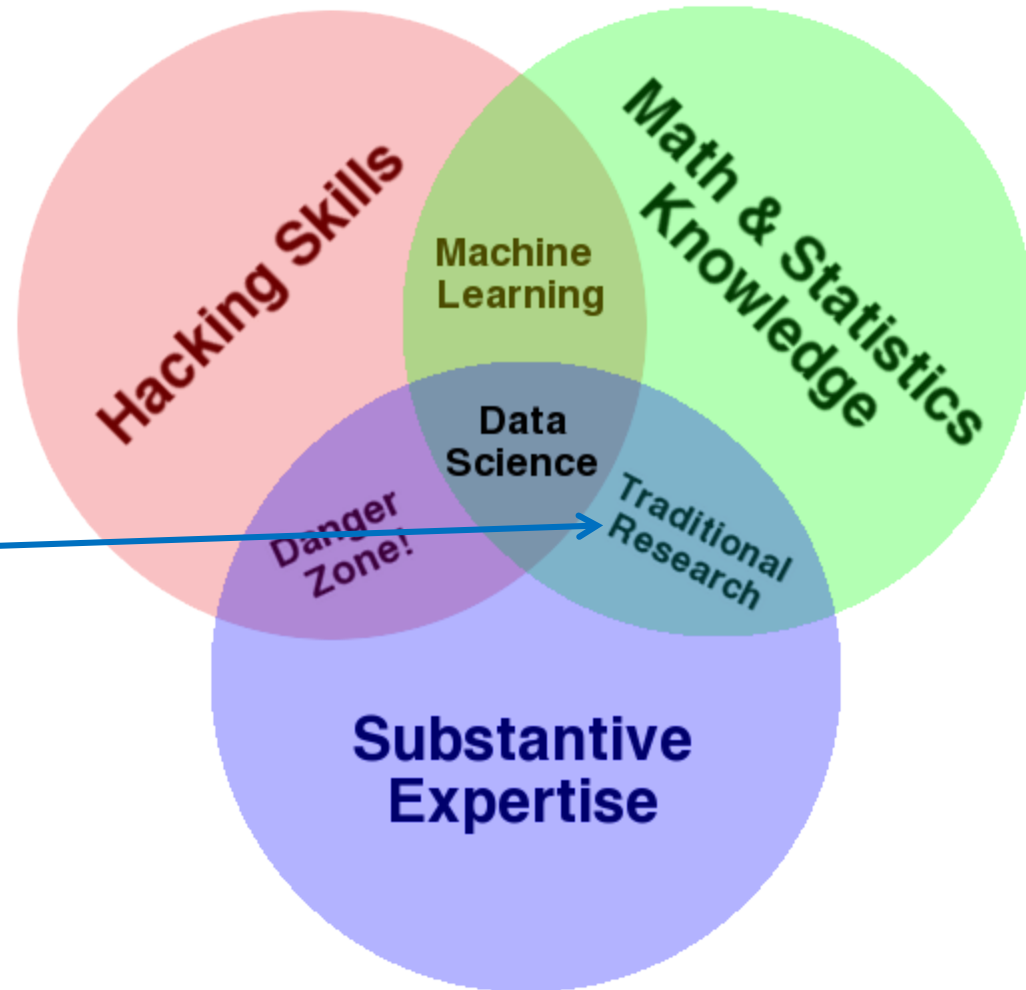
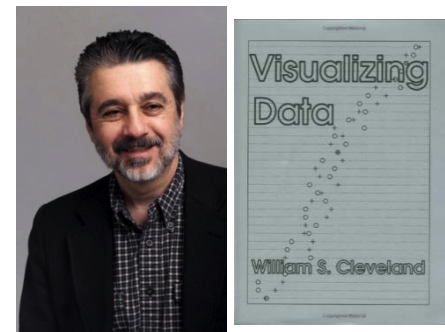


Image borrowed from Drew Conway's blog
<http://www.dataists.com/2010/09/the-data-science-venn-diagram>

The origin of “Data Science”



Data Science: An Action Plan for Expanding the Technical Areas of the Field of Statistics

William S. Cleveland
Statistics Research, Bell Labs
wsc@bell-labs.com

Abstract

An action plan to enlarge the technical areas of statistics focuses on the data analyst. The plan sets out six technical areas of work for a university department and advocates a specific allocation of resources devoted to research in each area and to courses in each area. The value of technical work is judged by the extent to which it benefits the data analyst, either directly or indirectly. The plan is also applicable to government research labs and corporate research organizations.



The screenshot shows the Harvard Business Review website interface. At the top left is the Harvard Business Review logo, which includes a shield with a cross and three open books, followed by the text "Harvard Business Review". To the right of the logo is a search bar. Below the logo is a dark navigation bar with white text for "THE MAGAZINE", "BLOGS", "AUDIO & VIDEO", "BOOKS", and "WEBINAR". Underneath the navigation bar is a light gray banner with the text "Guest | limited access" on the left and "Register today and save 20%* off your first order" on the right. The main content area features the text "THE MAGAZINE" in orange, followed by "October 2012" in a large, dark blue font. Below this is a horizontal line, and then the article title "Data Scientist: The Sexiest Job of the 21st Century" in a large, bold, black font. At the bottom of the article preview, it says "by Thomas H. Davenport and D.J. Patil".

The culture of data science

“The best thing about being a statistician is that you get to play in everyone’s back yard.”

*-- John Tukey
Princeton/Bell Labs*



“The dominant trait among data scientists is an intense curiosity... This often entails the associative thinking that characterizes the most creative scientists in any field.”

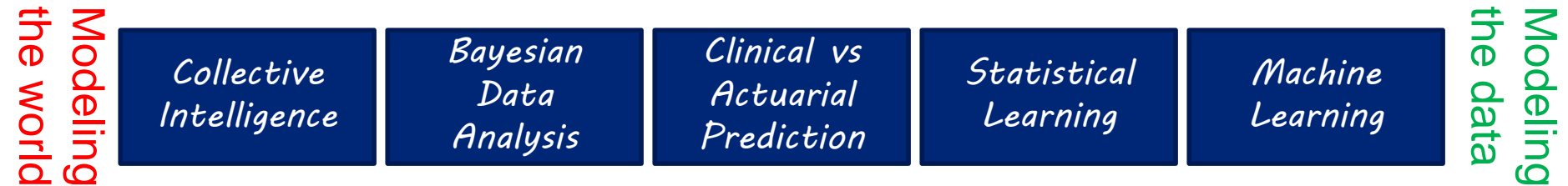
*-- D.J. Patil
LinkedIn*



Points on a curve

Explaining variation in “data science”

- “Data science” is an umbrella term
- It spans multiples disciplines and statistical / computer science paradigms
- A continuum of paradigms



- Some fall more naturally within “actuarial science” than others
- Ok to embrace fuzzy concepts – as long as we remember they are fuzzy
- (“What happens in vagueness stays in vagueness”)

The second machine age

Collective Intelligence

Bayesian Data Analysis

Clinical vs Actuarial Prediction

Statistical Learning

Machine Learning



The second machine age

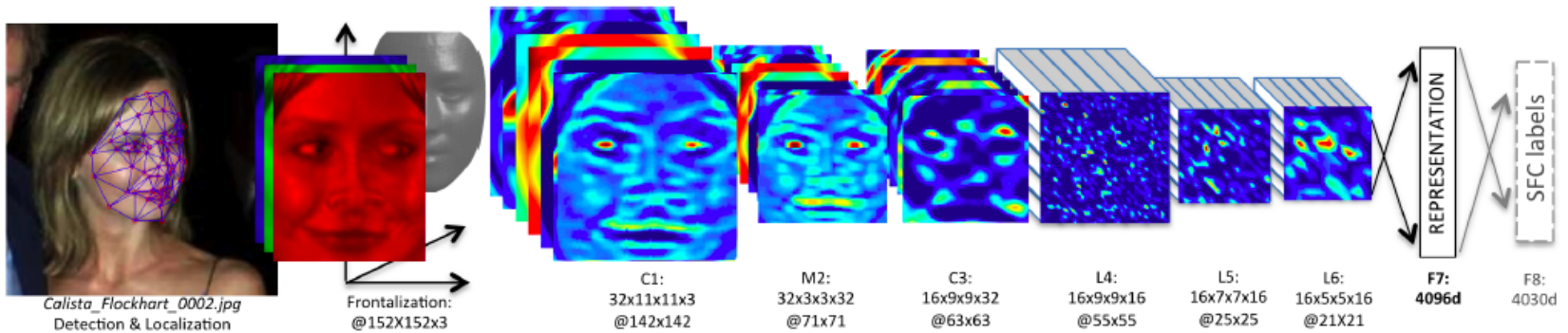
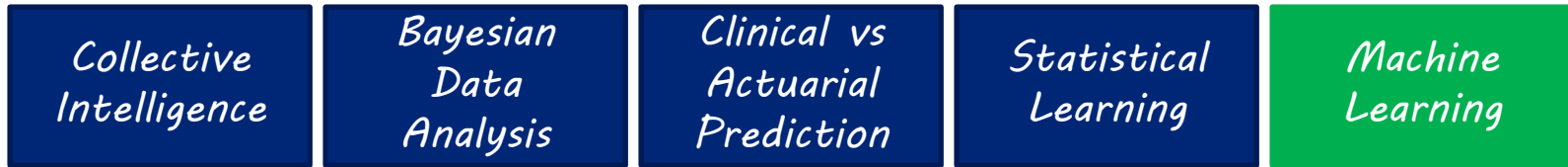


Figure 2. Outline of the *DeepFace* architecture. A front-end of a single convolution-pooling-convolution filtering on the rectified input, followed by three locally-connected layers and two fully-connected layers. Colors illustrate outputs for each layer. The net includes more than 120 million parameters, where more than 95% come from the local and fully connected layers.

The second machine age

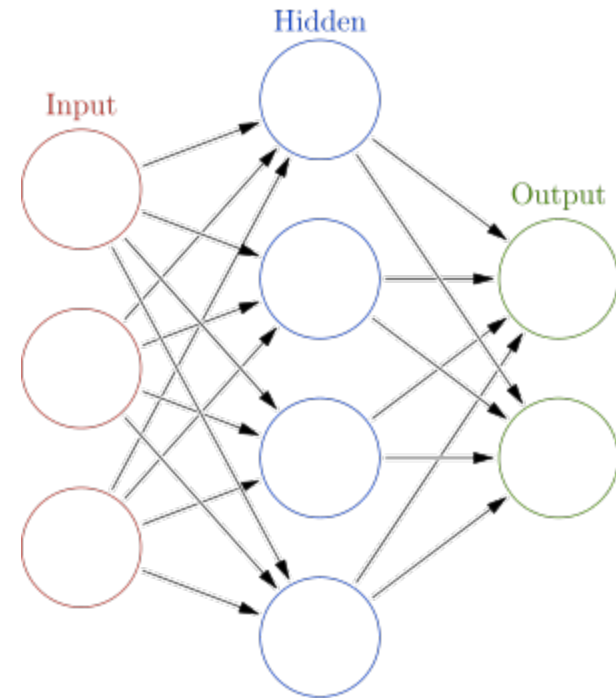
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Intelligence*

*Bayesian
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*Clinical vs
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The second machine age

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Examples:

- Natural language processing and “cognitive computing”
- Deep learning for pattern recognition
- Internet search
- Recommendation algorithms

Sample applications:

- Next-generation precision underwriting, fraud detection
- Image recognition – help adjust claims
- Speech recognition – customer service



Greater statistics – learning from data

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Statistical Science
2001, Vol. 16, No. 3, 199–231

Statistical Modeling: The Two Cultures

Leo Breiman

Abstract. There are two cultures in the use of statistical modeling to reach conclusions from data. One assumes that the data are generated by a given stochastic data model. The other uses algorithmic models and treats the data mechanism as unknown. The statistical community has

been committed to the almost exclusive use of data models. This commitment has led to irrelevant theory, questionable conclusions, and has kept statisticians from working on a large range of interesting current problems. Algorithmic modeling, both in theory and practice, has developed rapidly in fields outside statistics. It can be used both on large complex data sets and as a more accurate and informative alternative to data modeling on smaller data sets. If our goal as a field is to use data to solve problems, then we need to move away from exclusive dependence on data models and adopt a more diverse set of tools.

Greater statistics – learning from data

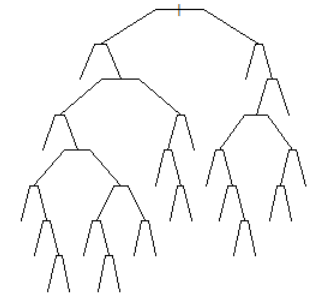
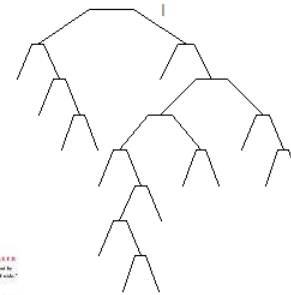
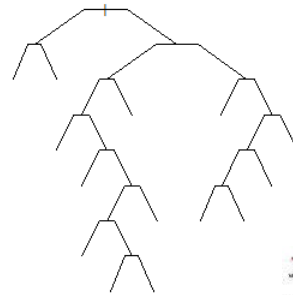
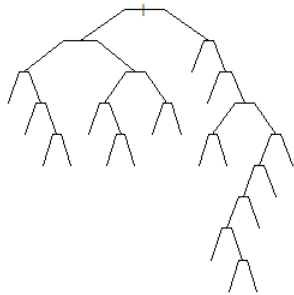
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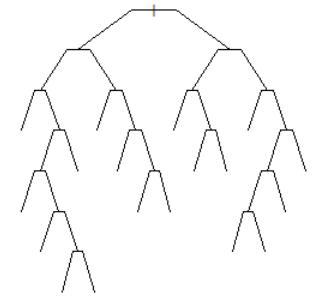
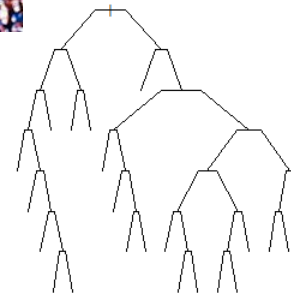
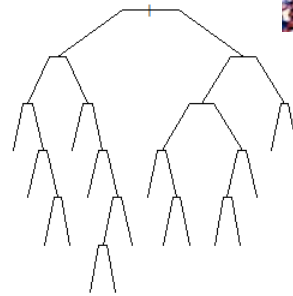
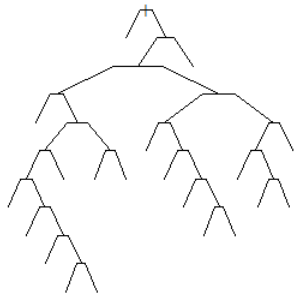


A NEW YORK TIMES BUSINESS BESTSELLER
"An entertaining and thought-provoking read. The Tipping Point by Malcolm Gladwell... 'The Wisdom of Crowds' is not only..."
—The Boston Globe

**THE WISDOM
OF CROWDS**

**JAMES
SUROWIECKI**

WITH A NEW AFTERWORD BY THE AUTHOR



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Examples:

- Tree-based modeling
- Ensembles
- Bagging, boosting
- GLM, regularized regression (lasso, ridge, ...)
- Support vector machines
- Unsupervised learning
- ...

Sample applications:

- Ratemaking, price optimization
- analysis of “sparse” digital breadcrumbs
- Credit scoring
- Analysis of telematics data
- Precision marketing, customer segmentation
- Setting case reserves

Playing Moneyball

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Science 31 March 1989:
Vol. 243 no. 4899 pp. 1668-1674
DOI: 10.1126/science.2648573

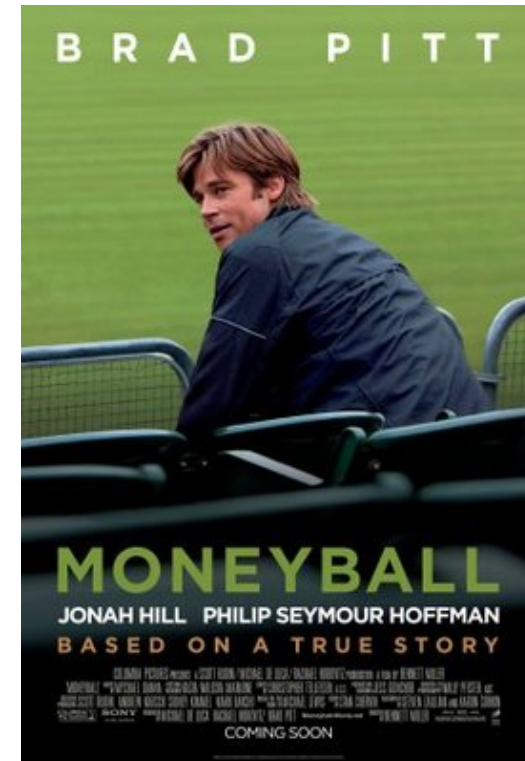
Clinical versus actuarial judgment

RM Dawes, D Faust and PE Meehl

[±](#) Author Affiliations

ABSTRACT

Professionals are frequently consulted to diagnose and predict human behavior; optimal treatment and planning often hinge on the consultant's judgmental accuracy. The consultant may rely on one of two contrasting approaches to decision-making--the clinical and actuarial methods. Research comparing these two approaches shows the actuarial method to be superior. Factors underlying the greater accuracy of actuarial methods, sources of resistance to the scientific findings, and the benefits of increased reliance on actuarial approaches are discussed.



Playing Moneyball

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“Whatever else it produces, an organization is a factory that manufactures judgments and decisions.”

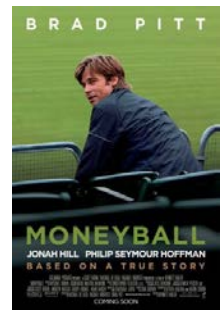
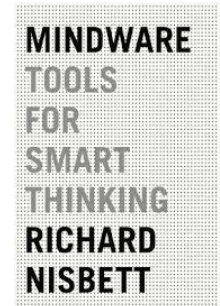
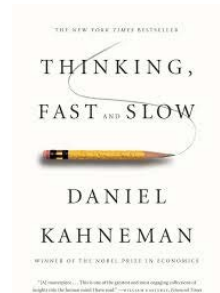
– Daniel Kahneman, *Thinking, Fast and Slow*

“Human judges are not merely worse than optimal regression equations; they are worse than almost any regression equation.”

– Richard Nisbett and Lee Ross, *Human Inference*

“The market for baseball players was so inefficient... that superior management could still run circles around taller piles of cash.”

– Michael Lewis, *Moneyball*



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- Kahneman: thinking fast (Type 1) vs thinking slow (Type 2)
- Type 1 is terrible at statistics
- Leads to inefficient markets a la Moneyball
- Research dating back to Paul Meehl in the 1950s
- ~~equations~~ → ~~experts~~
- (experts + equations) > experts

Sample applications:

- Underwriting complex risks
- Claims triage
- Fraud investigation
- Premium audit
- Predictive hiring
- Risk management, safety analytics

Statistics' "first culture"

Collective Intelligence

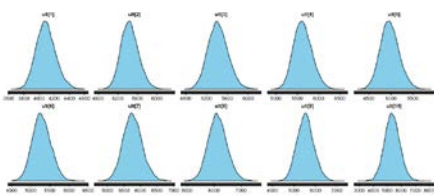
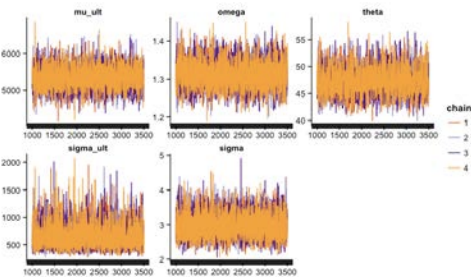
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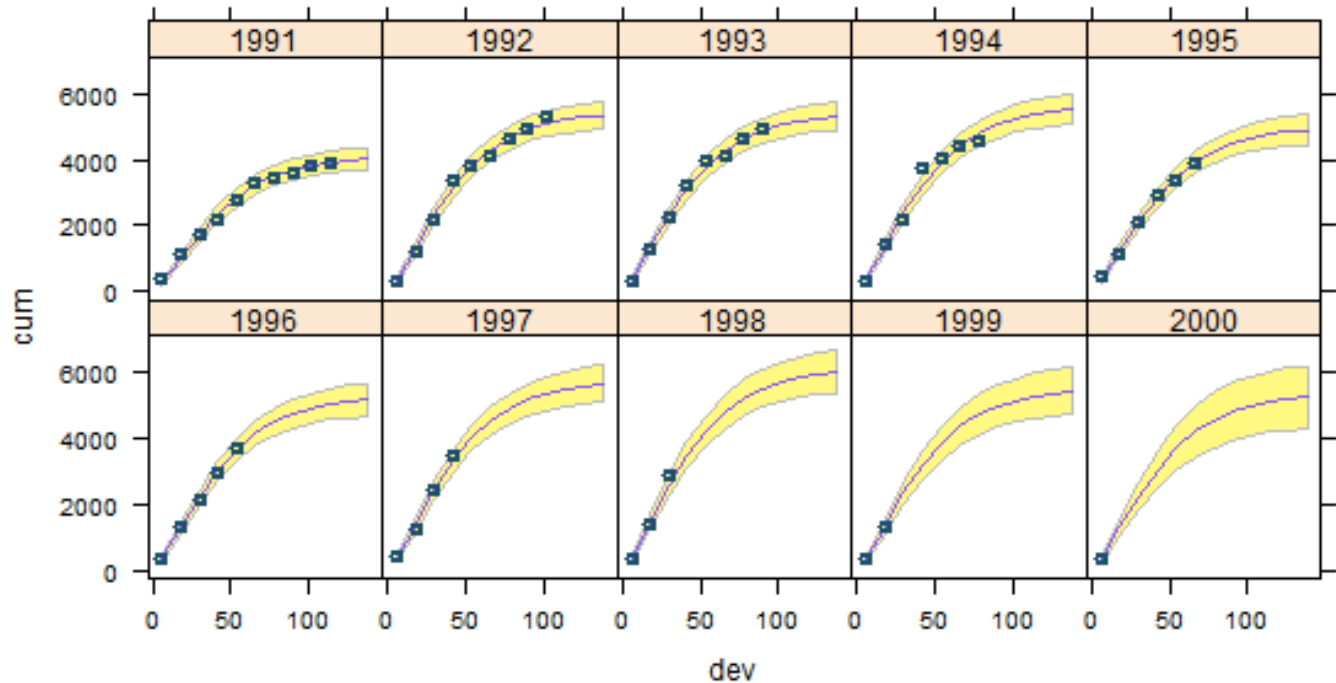
Machine Learning

Bayesian loss reserving example

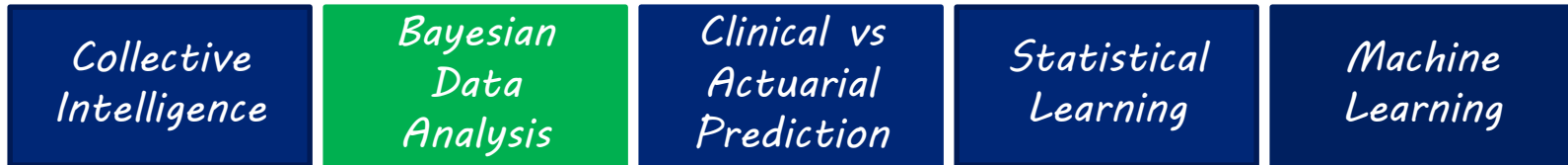


Weibull Growth Curve with Random Effect

◇ Observation 95% Prediction credible interval
 — Mean Estimate



Statistics' "first culture"



- Rather than just model the data we model the process that generates the data
- Appreciation for model risk
- Appreciation for parameter risk
- Necessary when you're in a situation where the data is useful but doesn't contain all of the information needed for predictions/inferences/forecasts

Sample applications:

- Bayesian loss reserving
- Loss model analysis, VaR
- Precision medicine
- Social science research

I think we all agree about the opposite of groupthink

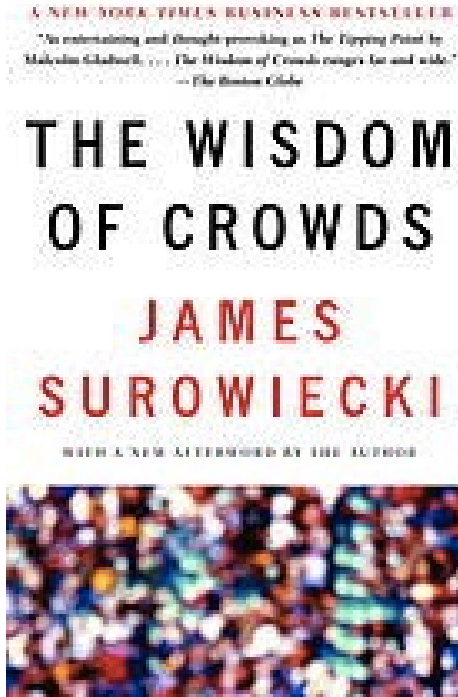
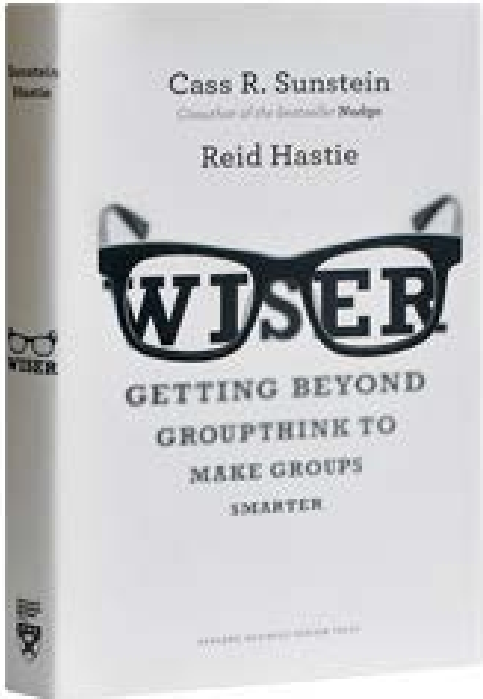
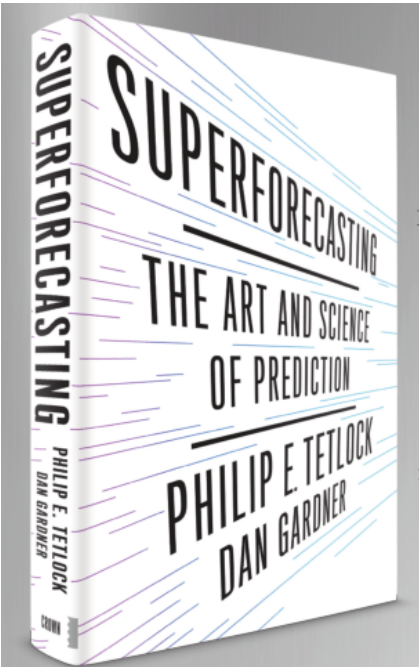
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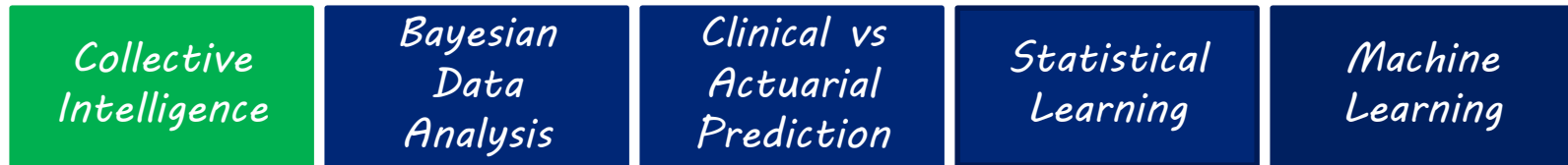
Clinical vs Actuarial Prediction

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Collective intelligence



- Prediction markets
- Delphi method
- Combining forecasts
- Philip Tetlock's "Superforecasting"

Sample applications:

- Emerging risks (e.g. cyber security)
- Underwriting one-off risks
- Hiring decisions
- Strategic, investment decisions

“Superforecasting”

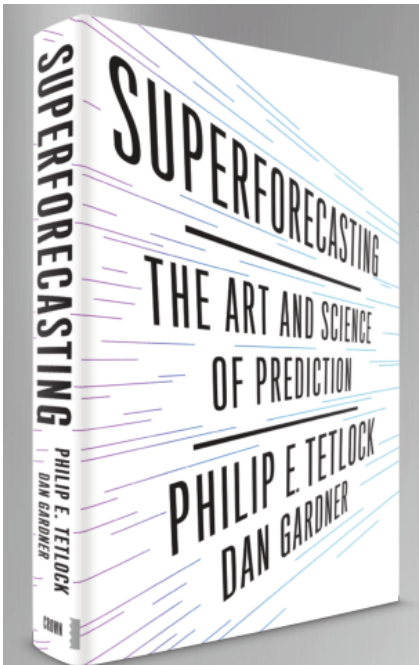
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- “Foxes [not hedgehogs] choose their ideas from a variety of schools of thought.”
- “Reality is infinitely complex”
- “[Be] probabilistic. Judge using many grades of maybe”
- [Be] intellectually curious
- “Beliefs are hypotheses to test, not treasured to be guarded”

“Superforecasting”

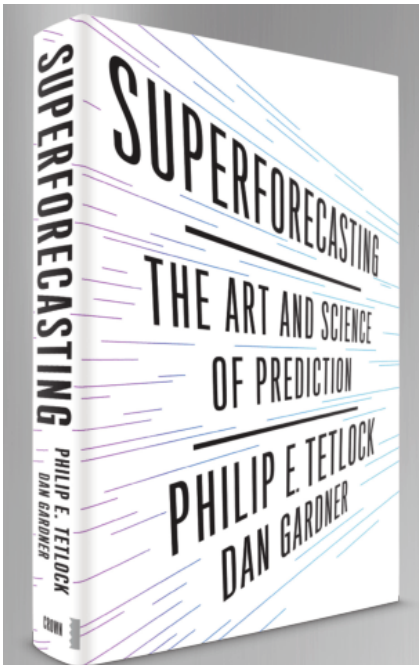
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- “Check thinking for cognitive and emotional biases.”
- “[Be] reflective – introspective and self-critical”
- “Believe it’s possible to get better.”
- “Value diverse views”
- “Be determined to keep at it no matter how long it takes”