Causality and Statistical Learning

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1. Different questions, different approaches

- Forward causal inference:
  - What might happen if we do X?
  - Effects of smoking on health
  - Effects of schooling on knowledge
  - Effects of campaigns on election outcomes
- Reverse causal inference:
  - What causes Y?
  - Why do more attractive people earn more money?
  - Why do poor people in India turn out to vote at a higher rate than the middle class and rich?
  - Why are health care costs going up so fast?

Different perspectives on causal inference

- Humans: reverse causal reasoning
- Macro: state-space models
- Applied micro: forward casual inference
- Statisticians: fitting models
- Political scientists: no single dominant framework
- Computer scientists: modeling everyday reasoning (traveling salesman story)

Spectrum of attitudes toward causal reasoning

- (Most conservative) Heckman and Deaton: experiments are no gold standard, you need a substantive model
- Angrist and Pischke, labor economics: identification is all
- Epidemiologists: causal inference from observational data using statistical models
- Social psychologists: structural equation models
- (most permissive) Cognitive scientists: causal *structure* can be estimated from purely observational data

2. Difficulties with the regression paradigm

- Big data set, lots of background variables
- Associating a regression model with an underlying utility model

Cautionary example: death sentences and crime

- Deterrent effect of capital punishment
- Historically, when death penalty comes, crime rates go down
- Data show this at national and state levels
- Death penalty typically goes with other crime-fighting measures
- Regression predicting crime rate from death-sentencing rate and other predictors ...
- ... utility model of the choices of potential murderers

Deterrent effect of the death penalty

From New York Times article, 18 Nov 2007:

> *To many economists, then, it follows inexorably that there will be fewer murders as the likelihood of execution rises.*
>
> *"I am definitely against the death penalty on lots of different grounds," said Joanna M. Shepherd, a law professor at Emory with a doctorate in economics who wrote or contributed to several studies. "But I do believe that people respond to incentives."... The recent studies are, some independent observers say, of good quality, given the limitations of the available data.*
>
> *"These are sophisticated econometricians who know how to do multiple regression analysis at a pretty high level," Professor Weisberg of Stanford said.*

Faith in “sophisticated econometricians”

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Curriculum Vitae

Biography

Faculty Co-Director, Stanford Criminal Justice Center

Robert Weisberg '79 works primarily in the field of criminal justice, writing and teaching in the areas of criminal law, criminal procedure, white collar crime, and sentencing policy. He also founded and now serves as faculty co-director of the Stanford Criminal Justice Center (SCJC), which promotes and coordinates research and public policy programs on criminal law and the criminal justice system, including institutional examination of the police and correctional systems. Professor Weisberg was a consulting attorney for the NAACP Legal Defense Fund and the California Appellate Project, where he worked on death penalty litigation in the state and federal courts. In addition, he served as a law clerk to Justice Potter Stewart of the U.S. Supreme Court and Judge J. Skelly Wright of the U.S. Court of Appeals for the District of Columbia Circuit. In 1979, Professor Weisberg received his J.D. from Stanford Law School, where he served as President of the Stanford Law Review. Professor Weisberg is a two-time winner of the law school's John Bingham Hurlbut Award for Excellence in Teaching.

Before joining the Stanford Law School faculty in 1981, Professor Weisberg received a PhD in English at Harvard and was a tenured English professor at

Education

BA, City College of New York, 1966

MA, 1967; PhD (English), 1971, Harvard University Graduate School of Arts and Sciences

JD, Stanford Law School, 1979

Model of death penalty deterrence

From "Deterrence versus Brutalization," by Joanna M. Shepherd:

For technically-inclined readers, I express the system symbolically:

$$M_{i,t} = \alpha_i + \beta_1 Pa_{i,t} + \beta_2 Ps \mid a_{i,t} + \beta_3 SD_i Pe \mid s_{i,t} + \gamma_1 Z_{i,t} + \gamma_2 TD_t + \varepsilon_{i,t}, \quad (1)$$

$$Pa_{i,t} = \phi_{1,i} + \phi_2 M_{i,t} + \phi_3 PE_{i,t} + \phi_4 TD_t + \varsigma_{i,t}, \quad (2)$$

$$Ps \mid a_{i,t} = \theta_{1,i} + \theta_2 M_{i,t} + \theta_3 JE_{i,t} + \theta_4 PI_{i,t} + \theta_5 PA_{i,t} + \theta_6 TD_t + \xi_{i,t}, \quad (3)$$

$$Pe \mid s_{i,t} = \psi_{1,i} + \psi_2 M_{i,t} + \psi_3 JE_{i,t} + \psi_4 PI_{i,t} + \psi_5 TD_t + \zeta_{i,t}, \quad (4)$$

It continues:

> *The first equation measures the response of the behavior of criminals to the deterrent factors while controlling for a series of other factors found in the series . . .*

Don't take the choice model too seriously

- Death penalty affects incentives of potiential murderers
- Also affects incentives of ...
  - Judges
  - Juries
  - Prosecutors
  - General population
- Thinking like a statistician frees you to think like a social scientist

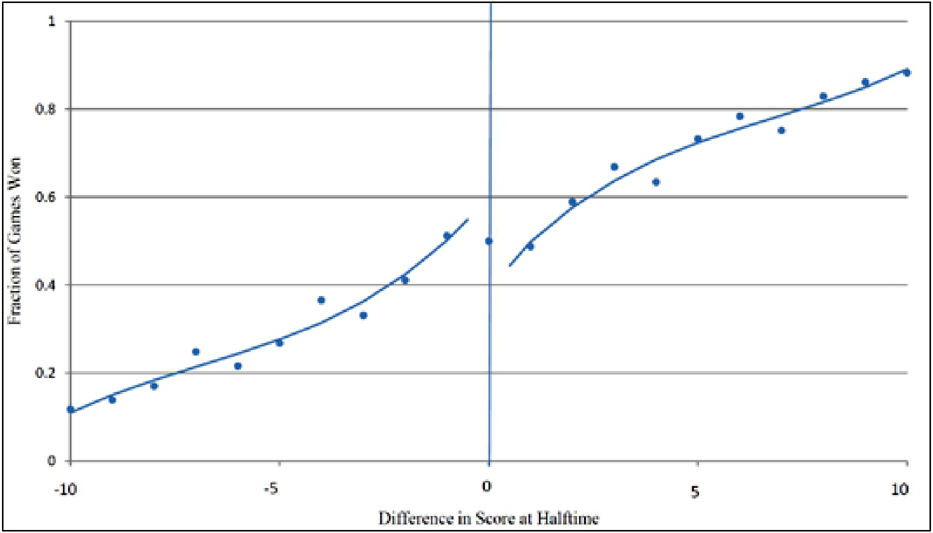
3. Understanding natural experiments

- Levitt study of policing and crime rates
- In cities with mayoral election years:
  - More cops on the street
  - Crime rate goes down
- Can interpret the joint outcome without worrying about IV assumptions

Halftime motivation in basketball

- Economists Jonah Berger and Devin Pope:
  "Analysis of over 6,000 collegiate basketball games illustrates that being slightly behind increases a team's chance of winning. Teams behind by a point at halftime, for example, actually win more often than teams ahead by one. This increase is between 5.5 and 7.7 percentage points . . ."
- But . . . in their data, teams that were behind at halftime by 1 point won 51.3% of the time
- Approx 600 such games; thus, std. error is $0.5/\sqrt{600} = 0.02$
- Estimate ± 1 se is $[0.513 \pm 0.02] = [0.49, 0.53]$
- So where did they get "5.5 and 7.7 percentage points"??

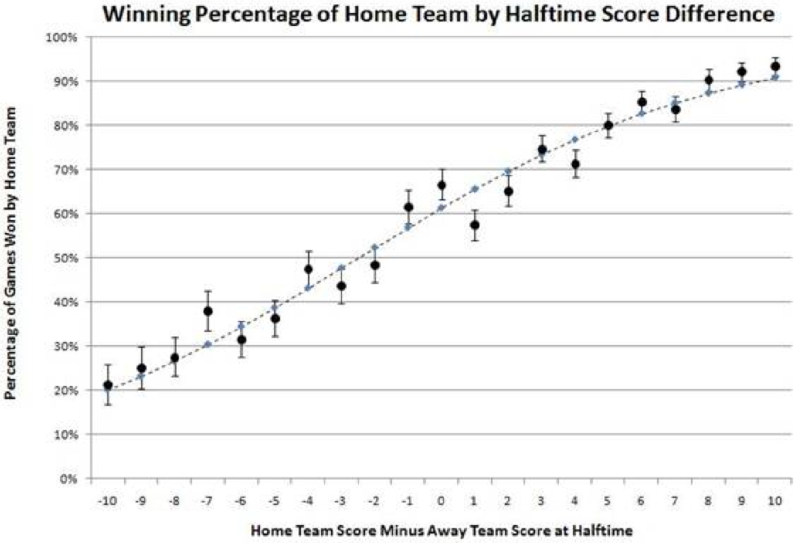
Halftime motivation in basketball: the data



Methodological conservatism

- What about that 5th-degree polynomial?
- Berger and Pope write:
  "While the regression discontinuity methods we use in the paper (including the 5th degree polynomial) are standard in economics (see for example the 2009 working paper on R&D implementation by David Lee and Thomas Lemiuex) we respect that your may find a different approach to the problem to be more useful. . . ."

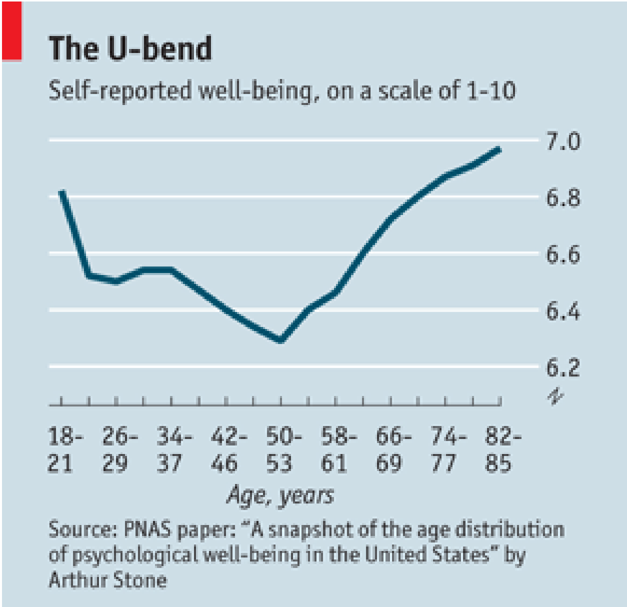
The data without the 5th-degree polynomial



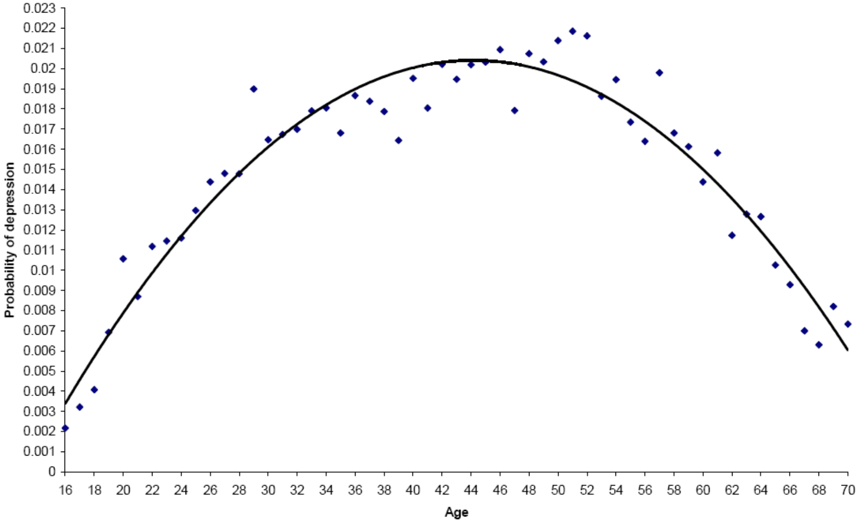
4. The importance of data and measurement

- A key principle in applied statistics is that you should be able to connect between the raw data, your model, your methods, and your conclusions

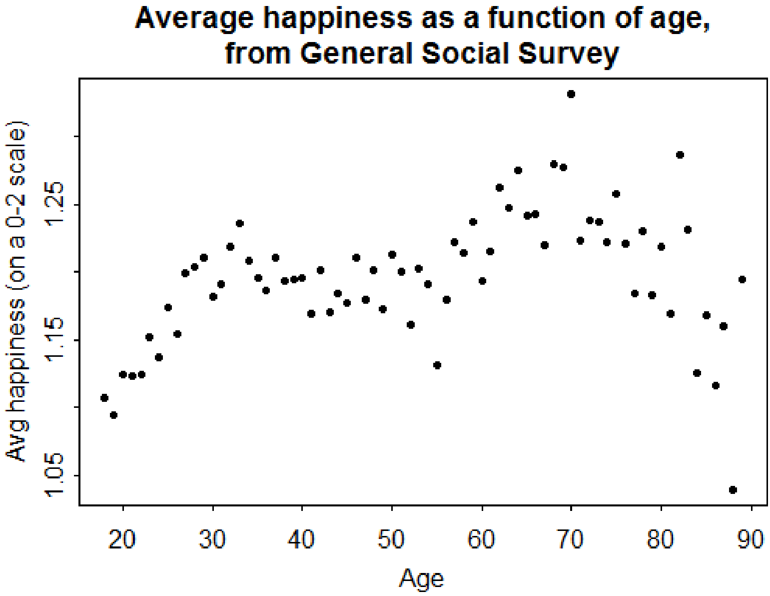
Age and happiness and



Data!


Probability of depression
0.023
0.022
0.021
0.02
0.019
0.018
0.017
0.016
0.015
0.014
0.013
0.012
0.011
0.01
0.009
0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0
16 18 20 22 24 26 28 30 32 34 36 38 40 42 44 46 48 50 52 54 56 58 60 62 64 66 68 70
Age

More data


Average happiness as a function of age,
from General Social Survey
Avg happiness (on a 0-2 scale)
1.05
1.15
1.25
20
30
40
50
60
70
80
90
Age

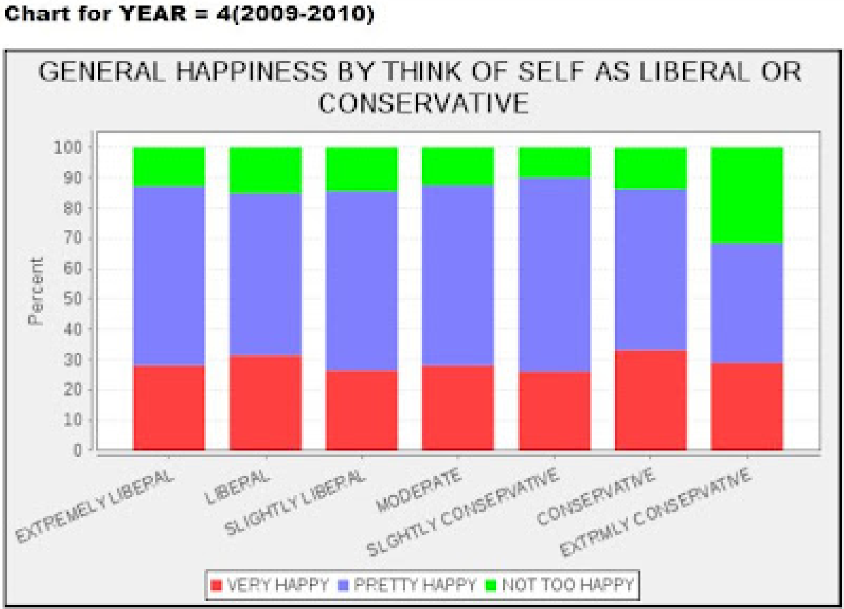
Those happy Tea Party protesters

Arthur “not David” Brooks in the *New York Times*:

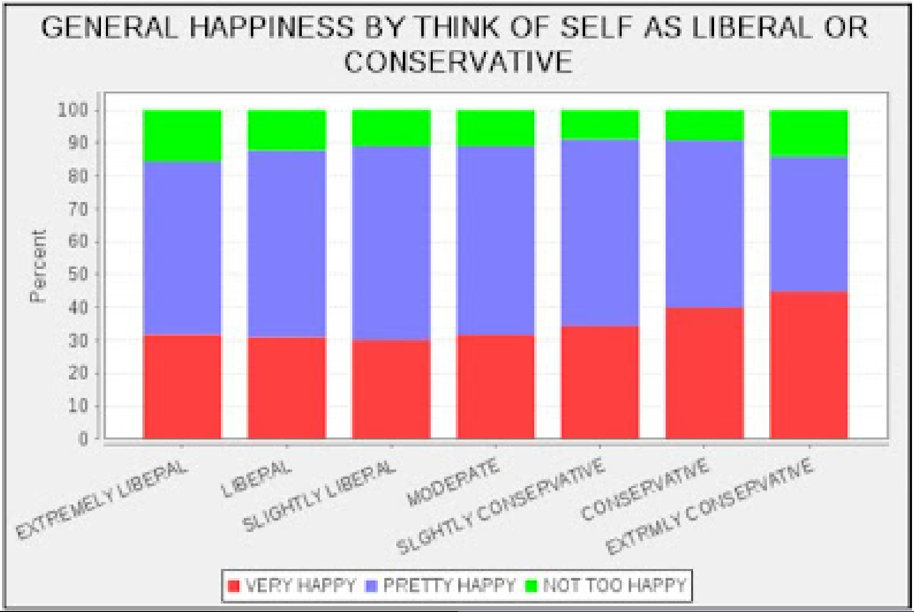
> *“People at the extremes are happier than political moderates. . . . none, it seems, are happier than the Tea Partiers . . . ”*

Jay Livingston (sociology, Montclair State University) looks up the data in the General Social Survey . . .

“None, it seems, are happier than the Tea Partiers . . . ”



Data since 1972



5. Difficulties with the research program of learning causal structure

- For example: income, religion, religions attendance, and vote choice in different reasons of the country
- No true zeros
- I respect that some social scientists find it useful to frame their research in terms of conditional independence and the testing of null effects, but I dont generally find this approach helpful—and I certainly dont believe it *necessary* to think in terms of conditional independence in order to study causality

Challenges of causal reasoning are not going away

From a recent book by a cognitive scientist:

If two of the variables are dependent, say, intelligence and socioeconomic status, but conditionally independent given the third variable [beer consumption], then either they are related by one of two chains:

(Intelligence → Amount of beer consumed → Socioeconomic status)

(Socioeconomic status → Amount of beer consumed → Intelligence)

or by a fork:

$$\text{Amount of beer consumed} \begin{array}{l} \nearrow \text{Socioeconomic status} \\ \searrow \text{Intelligence} \end{array}$$

and then we must use some other means [other than observational data] to decide between these three possibilities. In some cases, common sense may be sufficient, but we can also, if necessary, run an experiment. If we intervene and vary the amount of beer consumed and see that we affect intelligence, that implies that the second or third model is possible; the first one is not. Or course, all this assumes that there aren't other variables mediating between the ones shown that provide alternative explanations of the depen-

The problem understanding the world using "stylized facts"

- Problems with is-it-there-or-is-it-not models of correlations and effects
- Problems with the concept of "false positives"
- Accepting variation (as distinct from measurement error)
- Don't fool yourself!

Our brains can do causal inference, so why can't social scientists?

- Humans do (model-based) everyday causal inference all the time
- We rarely use experimental data, certainly not the double-blind stuff that is considered the gold standard
- But . . .
  - The sorts of inferences used as examples by the proponents of "everyday causal reasoning" look much less precise than the sorts of inferences we demand in science (or even social science).
  - Also, everyday causal reasoning is not purely observational
  - We use informal experimentation in our ordinary lives is to resolve some of the causal questions left open by models and observational inference

6. Story time

- When the data go to bed, the stories come out . . .
- Ole Rogeberg:

> *The puzzle that we try to explain is this frequent disconnect between high-quality, sophisticated work in some dimensions, and almost incompetently argued claims about the real world on the other*

"A Raise Won't Make You Work Harder"

- Economist Ray Fisman writing in *Slate*:
  - Students were employed in a six-hour data-entry job for \$12/hour. Half the students were actually paid this amount. The other half were paid \$20/hour.
  - At first, the \$20-per-hour employees were more productive than the \$12-an-hour employees. But by the end the two groups were working at the same pace.
- Conclusions:
  - "The goodwill of high wages took less than three hours to evaporate completely—hardly a prescription for boosting long-term productivity."
  - "A raise won't make you work harder."
- Conflict between internal and external validity:
  - "All participants were told that this was a one-time job—otherwise, the higher-paid group might work harder in hopes of securing another overpaying library gig."

Summary 1: Perspectives

- Controlled experiments are the gold standard, but I never do them!
- (Some) computer scientists' view: we don't need controlled experiments; we can automatically learn from observational data
- Psychologists' view: each causal question requires its own experiment
- Observational scientist's version: each causal question requires its own data analysis

Summary 2: Working together

- Experimenters can learn from:
  - Sample surveys (for the problem of extending from sample to population)
  - Descriptive observational research (for the problem of modeling complex interactions and response surfaces)
- Observational researchers (i.e., most empirical social scientists, including me) should model our biases and connect our work to experimental research wherever possible