Statistics Research and Careers

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Where do I want to be, and what might it look like?

Jobs You're Considering (Statistically Speaking)

1. Statistics PhD

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2. Data Scientist

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4. Software
5. Other

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Energy Modeling at E3

- A mix of econometrics, engineering, and consulting roles
- "Predict the profit stream from this potential transmission line so we can decide if it's worth building"
- "Compile a dossier on environmental threats to the electric grid"

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Electric Grid Optimization

Minimize total energy cost given demand time series, subject to these constraints:

- generator output $\in \{0\} \cup [250, 500] GW$
- transmission line capacity $\in [-250, 500] GW$
- generator startup cost $= 250,000$
- excess production cost $= 1000/GW$

Mixed integer-linear program is NP hard, need to balance accuracy vs. compute

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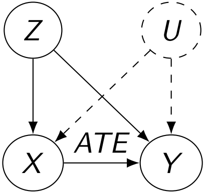
- Which block group and county was a home sale in? "Spatial join" home lat/lon with geographic polygons (`sf::st_join`)
- Filter data to remove misleading transactions without biasing results (`dplyr::filter`)
- Compute county- and block group-level sale averages (`dplyr::group_by`, `dplyr::summarize`)

Statistics PhD Research

Causal Inference

Given a causal graph:



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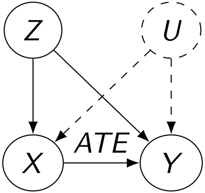

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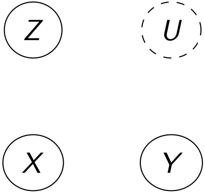
Causal Discovery

Given variables of interest and observational data,
fill in the graph:



Application: Causal Fairness in Peer Review

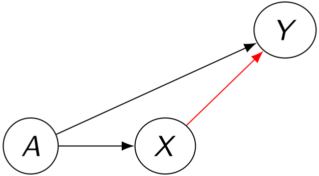
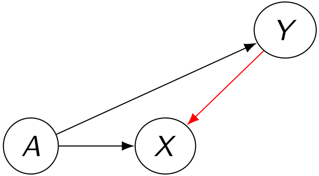


Figure: Forward review procedure



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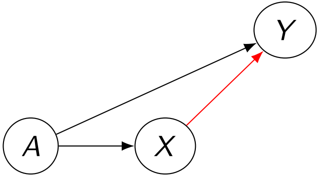

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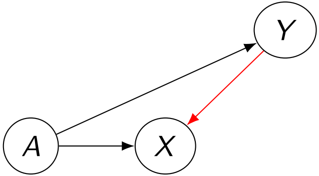

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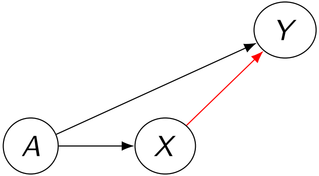

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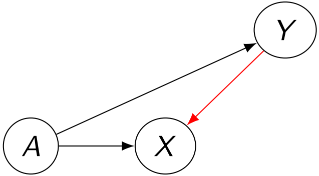

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Goal: estimate direct effect of A (race) on Y (overall score) in the presence of X (criterion score)

- Fit $Y = \beta_0 + \beta_A A + \beta X + \epsilon$; β_A is direct effect of race under forward procedure
- Under backward procedure, however, need to fit $Y = \beta_0 + \beta_A A + \epsilon$ for β_A to be direct effect

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4. What if the models aren't nested and you want to quantify how plausible each model is given some data $\{X, Y\}_n$?

Use Bayes' Rule! $\mathrm{P}(M_k|\{X, Y\}_n) = \frac{\mathrm{P}(\{X,Y\}_n|M_k)\mathrm{P}(M_k)}{\mathrm{P}(\{X,Y\}_n)}$
We make an *assumption* about how cause and effect are related (a "model"), but the models M_k describe causal relationships.

(Nonlinear) Additive Noise Models (ANMs)

Identification

Suppose (WLOG)

$$
\begin{aligned}
&Y = f(X) + \epsilon, \\
&\epsilon \perp\!\!\!\perp X, \\
&f \text{ nonlinear.}
\end{aligned}
$$

Then $\nexists g, \eta$ such that

$$
\begin{aligned}
&X = g(Y) + \eta \\
&\eta \perp\!\!\!\perp Y
\end{aligned}
$$

(Hoyer et al. 2009).

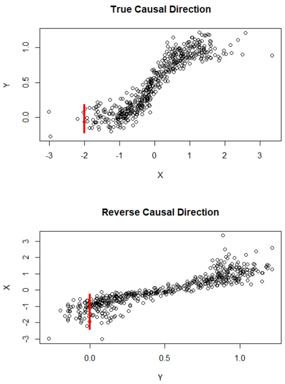

Figure: Data generated from a logistic ANM with Gaussian noise.

Nonlinearity and Identifiability

$\gamma\backslash\sigma_Y$	0.5	1	2
1/3	1.0 (11.4)	0.85 (2.2)	0.77 (0.9)
1/2	1.0 (8.2)	0.81 (1.4)	0.68 (0.6)
1	0.50 (0.1)	0.57 (0.0)	0.54 (0.1)
2	0.99 (14.8)	0.93 (3.8)	0.54 (0.3)
3	1.0 (31.0)	1.0 (8.5)	0.68 (0.8)

Table: Correct causal discovery rates (log average Bayes Factor) for Bayesian ANM over 100 replications and $n = 100$.

- For linear Gaussian model, Bayes Factors close to zero as expected
- For nonlinear models, greater nonlinearity and smaller noise yield higher Bayes Factors and greater accuracy
- Small sample size and model misspecification don't destroy ability to learn plausibility of identification assumption under each model

How do I decide? How do I get there?

General Advice

- There is a (partial) trade-off between *learning* new stuff, and *producing* new stuff. You may be eager to do the latter, but I recommend pushing harder on the former. You have plenty of time to produce stuff, but learning stuff gets harder.

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- The world will show you what you're good at—you get to *help* decide. 5 years ago, I thought I would be a great mathematician. Turns out, I'm better at making statistics transparent and accessible.

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- "It all sounds good/I'm not sure": give yourself the chance to find out what you're good at. This may take time, money, or commitment—1 year at a job may not be enough (it wasn't for me), a PhD is a 5-year commitment, and a Master's degree isn't cheap.

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Master’s degrees:

- Expensive ($100K or more for 2 years)
- Useful for progressing in salary/level in industry
- Useful for improving grad school resume, particularly for international students (UW Stats master’s explicitly preps you for PhD applications)