Data Science for Causal Inference

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2024-07-15

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About Me

- Associate Prof of Government
  (American University)
- Associate Director, Center for Data Science
  (American University)
- Senior Social Scientist
  (The Lab @ DC)
- Fellow in Methodology
  (US Office of Evaluation Sciences: “OES”)

About Me

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- Associate Director, Center for Data Science (American University)
- Senior Social Scientist (The Lab @ DC)
- Fellow in Methodology (US Office of Evaluation Sciences: "OES")
- Research agenda: political methodology, causal inference, experimental design, experiments in public policy

About You!

- Name?

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- Interests?

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- Olympic sport you look forward to?

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    - Models

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  - Heterogeneous treatment effects

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  - Multiple time periods

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  - Calloway-Sant'Anna approach

Data Science in Causal Inference

Causal Inference Approaches

The “potential outcomes” framework:

Causal Inference Approaches

The "potential outcomes" framework:

Citizen	Canvass?	Would Enroll if Canvass?	Would Enroll if No Canvass?	Enroll
1	Yes	Yes		Yes
2	Yes			Yes
3	No			No
4	No			No

Causal Inference Approaches

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Causal Inference Approaches

The "potential outcomes" framework, more abstractly:

Unit i	Treatment T	$Y(1)$	$Y(0)$	Y^{obs}	True τ $Y(1) - Y(0)$
1	1	10		10	
2	1	20		20	
3	0		15	15	
4	0		5	5	

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				$\widehat{ATE} = \hat{\bar{\tau}} =$	$15 - 10 = 5$

Causal Inference Approaches

The "potential outcomes" framework, notation:

- Units indexed by i
- Treatment T_i or D_i or Z_i
- Outcome if treated $Y_i(1)$
- Outcome if control $Y_i(0)$
- True treatment effect $\tau_i = Y_i(1) - Y_i(0)$
- True average treatment effect $\bar{\tau} = \frac{1}{n} \sum_{i=1}^{n} (Y_i(1) - Y_i(0))$
- Pre-treatment covariates $\mathbf{X}$

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(and we'll draw some DAG's, too)

Data Science Approaches

Three tasks of data science:

- Description

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Models/algorithms central to all three.

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Models/algorithms central to all three.

Hernán, Hsu, and Healy (2019)

Data Science Approaches

Description

- Identifying patterns, etc.

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- Identifying patterns, etc.
- E.g., clustering to discover groups

Data Science Approaches

Prediction

- Components

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  - Inputs/outputs (predictors/outcomes, features/responses, ...)

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- With these, model machine learning does the work
- E.g., regression, random forests, neural networks, ...

Data Science Approaches

Causal Inference

- Potential outcomes/counterfactual/interventionist perspective

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  - T v. $\mathbf{X}$ – very different!
  - (the more knowledge, the better!)
  - (alternative: solve fundamental problem of causal inference!)
- E.g., experiments, observational causal designs, ...

Causal Inference with Machine Learning

Causal Inference with Machine Learning

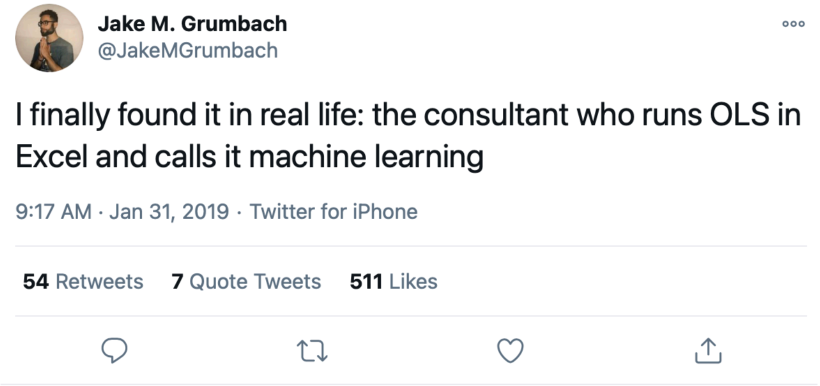
Jake M. Grumbach
@JakeMGrumbach

I finally found it in real life: the consultant who runs OLS in Excel and calls it machine learning

9:17 AM · Jan 31, 2019 · Twitter for iPhone

54 Retweets **7** Quote Tweets **511** Likes

Causal Inference with Machine Learning



(OK, not "machine learning", perhaps, but *models* at least ...)

Causal Inference with Models

Loaded two datasets:

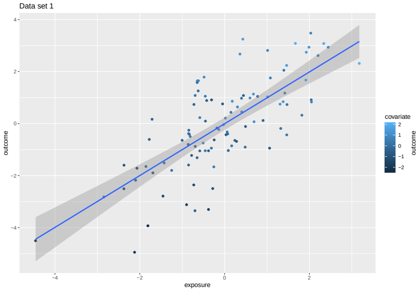
```
str(df1)
```

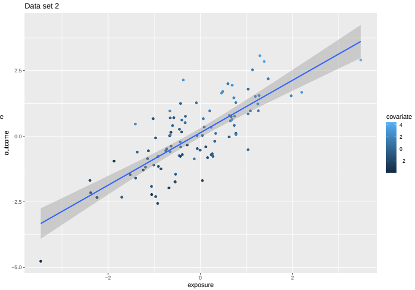
```
tibble [100 x 3] (S3: tbl_df/tbl/data.frame)
 $ covariate: num [1:100] -0.622 1.137 -0.238 1.529 -0.154
 $ exposure : num [1:100] 0.0332 0.3627 0.2422 1.4633 0.779
 $ outcome  : num [1:100] -0.429 2.675 -0.647 2.238 1.044
```

```
str(df2)
```

```
tibble [100 x 3] (S3: tbl_df/tbl/data.frame)
 $ exposure : num [1:100] 0.4862 0.0653 -1.4021 -0.546 -0.4
 $ outcome  : num [1:100] 1.706 0.669 -1.597 -1.733 0.617
 $ covariate: num [1:100] 2.24 0.924 -0.999 -2.343 0.207 ..
```

Causal Inference with Models





Causal Inference with Models

Model each

```r
lm_df1 <- lm(outcome ~ exposure, data = df1)
lm_df2 <- lm(outcome ~ exposure, data = df2)
```

```
# A tibble: 4 x 4
  data  term        estimate std.error
  <chr> <chr>          <dbl>     <dbl>
1 df1   (Intercept) -0.00671    0.120
2 df1   exposure     0.996      0.0927
3 df2   (Intercept)  0.133      0.0890
4 df2   exposure     1.00       0.0841
```

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- Both cases: effect of exposure ≈ 1.

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- Both cases: effect of exposure ≈ 1.
- Is this good?
- What if we adjust for covariate?

Causal Inference with Models

```r
lm_df1_adj <- lm(outcome ~ exposure + covariate, data = df1
lm_df2_adj <- lm(outcome ~ exposure + covariate, data = df2
```

```
# A tibble: 4 x 4
  data  term       estimate std.error
  <chr> <chr>         <dbl>     <dbl>
1 df1   exposure      0.501    0.108
2 df1   covariate     0.970    0.147
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```

- Both cases: effect of exposure ≈ 0.5.

Causal Inference with Models

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- Both cases: effect of exposure ≈ 0.5.
- Is this good?
- Which is correct? $\beta = 1$? $\beta = 0.5$?
- *Should* we adjust for covariate?

Causal Inference with Models

There is nothing in the data that tells us.

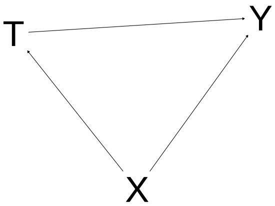
Causal Inference with Models

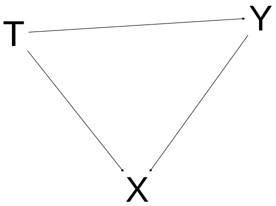
There is nothing in the data that tells us. ☹

Causal Inference with Models

There is nothing in the data that tells us. ☹

Here are the true structures:





Causal Inference with Models

When know structures, adjustment sets for unbiasedness differ:

- `df1`: confounding $\Rightarrow$ **adjust for** X
- `df2`: collider $\Rightarrow$ **do not adjust for** X

```
g_conf <- dagitty("dag{ x -> y ; x <- c -> y }")
g_coll <- dagitty("dag{ x -> y ; x -> c <- y }")

adjustmentSets(g_conf, "x", "y")
```

```
{ c }
```

```
adjustmentSets(g_coll, "x", "y")
```

```
 {}
```

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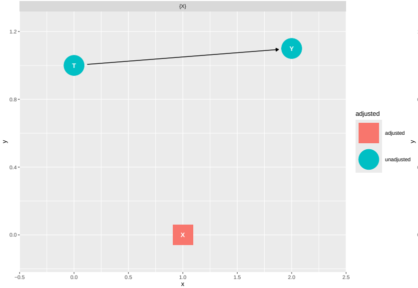

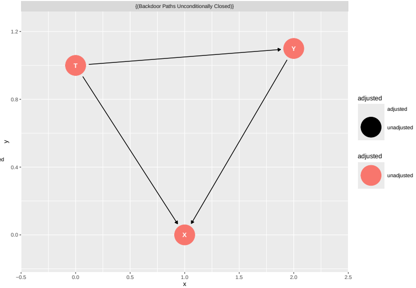

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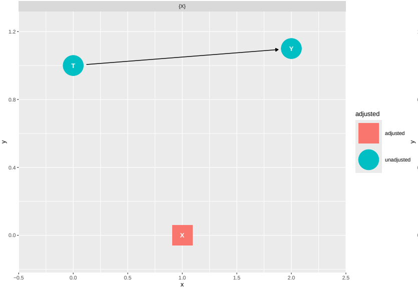

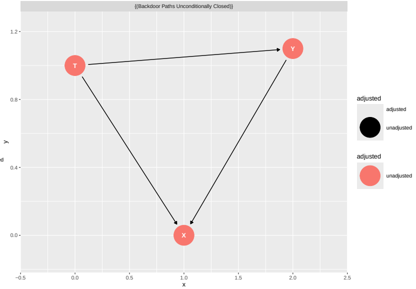

(Data from D'Agostino McGowan (2023))

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- Importance of identifying "pre-treatment covariates", "proper covariates"; doing "design before analysis"

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- Importance of identifying "pre-treatment covariates", "proper covariates"; doing "design before analysis"
- Importance of experiments: strong knowledge about (part of) causal structure
- Causal inference is critical to scientific questions, and separate from prediction
- Though, methods from prediction can aid causal inference
- (A perspective on "causal euphimisms": Hernán (2018))

Approaches of Prediction and Causal Inference

Two Cultures, (Breiman 2001)

- *Data Models*: our "social science modeling"
- *Algorithmic Models*: our "data science algorithms"

Methods for Prediction and Causal Inference

- Cross-validation
- Regression/Decision trees
- Random forests

James et al. (2021)

Cross-validation

k-fold cross-validation

- Randomly partition data into k groups
- Apply method to $k-1$ groups
- Use result to predict for left-out group
- Calculate $\text{MSE}_i = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$
- Calculate test error as average of the k MSE's:

$$CV_{(k)} = \frac{1}{k}\sum_{i=1}^{k}\text{MSE}_i$$

- Select model that minimises $CV_{(k)}$

Regression Trees

- Partition predictor space into regions $R_1, R_2, \ldots, R_J$.
- If unit falls in region R_j, use average outcome in R_j as predicted value – $\hat{y}_{R_j}$
- (For "decision" about discrete outcome, count votes in R_j)
- Goal: minimise residual sum of squares (RSS), just like LS regression:

$$\sum_{j=1}^{J} \sum_{i \in R_j} \left(y_i - \hat{y}_{R_j} \right)$$

Regression Trees

How to define regions R_j?

Regression Trees

How to define regions R_j?

- Top-down, greedy recursive binary split
- At each step, find predictor and cut-point that minimise

$$\sum_{i:x \in R_1(j,s)} \left(y_i - \hat{y}_{R_1(j,s)}\right)^2 + \sum_{i:x \in R_2(j,s)} \left(y_i - \hat{y}_{R_2(j,s)}\right)^2$$

Random Forests

Heterogeneous Treatment Effects

Variable Selection

Slide Title

Material.

Thanks!

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www.ryantmoore.org

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