Quant II

Machine Learning and Optimization

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4/25/2018

Machine learning and optimization in social sciences

- How could machine learning be applied to social sciences?
  - Variable creation: train a model and use it to code data
  - Methods: prediction and heterogeneity
- Optimization has two meanings:
  - Causal inference as an optimization problem
  - Optimize your R code

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- What if it is too expensive? Active learning (Miller et al., 2019)

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- What if we just throw a bunch of variables into the first stage? - Bias in both estimation and inference (Cattaneo et al., 2019)

Example: double selection

```
## Loading required package: hdm
```

```
## [1] 100 100
```

```
## [1] 100   3
```

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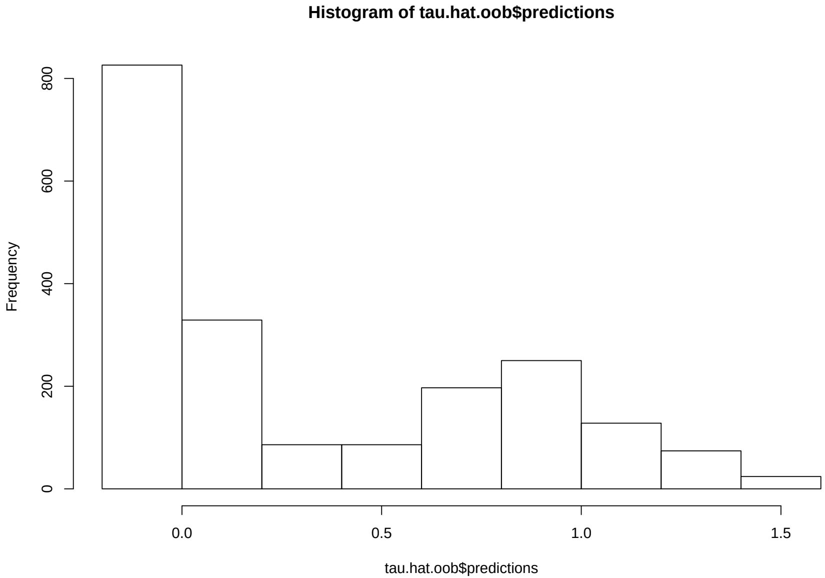
- Example I: Trees and forests
- Example II: X-learner

Example: causal forest

```
## Loading required package: grf
```



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- Repeat until convergence.

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$$
\begin{aligned}
&\min\ f(\mathbf{x}) \\
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- How to solve? Simplex method.

Optimization

Example I: entropy balancing

```
## ##
## ## ebal Package: Implements Entropy Balancing.

## ## See http://www.stanford.edu/~jhain/ for additional in

## Converged within tolerance

## treatment mean

##        x1        x2        x3
## 0.7806424 0.6152861 0.5820738

## weighted control mean

##        x1        x2        x3
## 0.7761886 0.6148558 0.5801141

## unweighted control mean
```

Optimization

Let's do it using convex optimization!

```
## Loading required package: CVXR

##
## Attaching package: 'CVXR'

## The following object is masked from 'package:stats':
##
##     power

## treatment mean

##        x1        x2        x3
## 0.8122392 0.4125846 0.5765168

## weighted control mean

##        x1        x2        x3
## 0.8122392 0.4125846 0.5765168
```

Optimization

- Example II: optimal bandwidth of RD

$$\hat{\tau} = \sum_{i=1}^{n} \hat{\gamma}_i Y_i, \quad \hat{\gamma} = \operatorname{argmin}_{\gamma} \left\{ \sum_{i=1}^{n} \gamma_i^2 \sigma_i^2 + I_B^2(\gamma) \right\},$$

$$I_B(\gamma) := \sup_{\mu_0(\cdot), \mu_1(\cdot)} \left\{ \sum_{i=1}^{n} \gamma_i \mu_{W_i}(X_i) - (\mu_1(c) - \mu_0(c)) : |\mu_w''(x)| \leq B \text{ for all } w,\, x \right\}.$$

Optimization

- **Example III**: evolutionary tree

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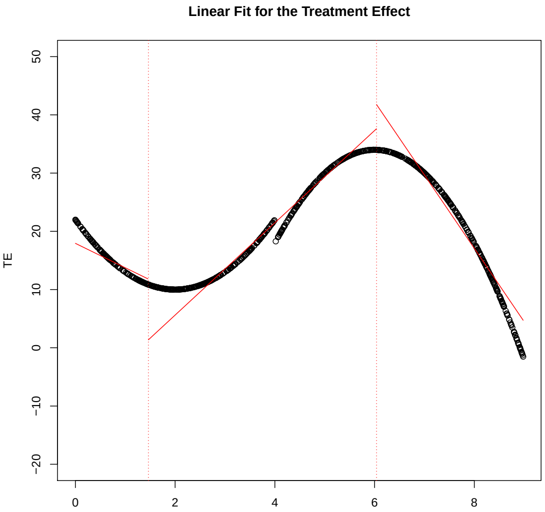
  How to optimally partition an interval?

Optimization

- Example III: evolutionary tree
  How to optimally partition an interval?
  Generate 10,000 partitions and let them "evolve"...



Optimize your R code

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- The R Inferno (Don't grow matrices!)
- Parallel computing
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- NYU clusters

Example: parallel computing

```
## Loading required package: doParallel

## Loading required package: foreach

## Loading required package: iterators

## Loading required package: parallel

## Loading required package: microbenchmark

## Parallel computing with 4 cores...

## Time difference of 4.251918 secs

## Time difference of 0.7286451 secs
```

The End

Good luck with your final!