MATCHING FOR EE AND DR IMPACTS

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A Proposal

- Always use matching
  - Non-parametric preprocessing to reduce model dependence
  - Decrease bias and variance
  - Better understand your data
  - EE, DR
    - Quasi-Experiment
    - Randomized Experiment

Agenda

- Review current best practice for impact evaluation
- Review some matching methods
- Matching example

Impact Estimation

- Best Practice
  - RCT + Model (to reduce bias and variance)
  - Quasi-experiment + Matching + Model

Methods

- Model
  - Difference-in-Difference
  - Linear Fixed Effects
  - Lagged Dependent Variable
- Match
  - Propensity Score
  - Mahalanobis Distance
  - Coarsened Exact
  - Matching Frontier

Feeling Lucky?

- Randomized experiments are guaranteed to be unbiased over repeated experiments
  - There is only **one** actual experiment
  - How sure can we be that this one is unbiased?
    - Check the balance of treatment versus control
  - What can we do?
    - Match to reduce imbalance
    - Model to correct for dependence on known and (fixed) unknown covariates

Applying the Rubin Causal Model

For a particular unit, the causal effect of a treatment at time t is the difference between what would have happened at time t if the unit was exposed to the treatment and what would have happened at time t if the unit was not exposed to the treatment.

Applying the Rubin Causal Model

- The customer cannot be simultaneously exposed to the treatment and not exposed to the treatment
- We need to make some assumptions
  - SUTVA
  - Ignorable treatment assignment

Ignorable treatment assignment

- Model
  - Parametrically adjust for the effect of covariates
- Match
  - Non-parametrically improve balance of all included covariates
- Both also usually reduce variance
- Matching yields insight into the data

Matching Procedure

1. Select a distance measure
2. Select and implement a matching method
3. Assess balance, return to 1 or 2 as necessary
4. Use the matched data to perform analysis

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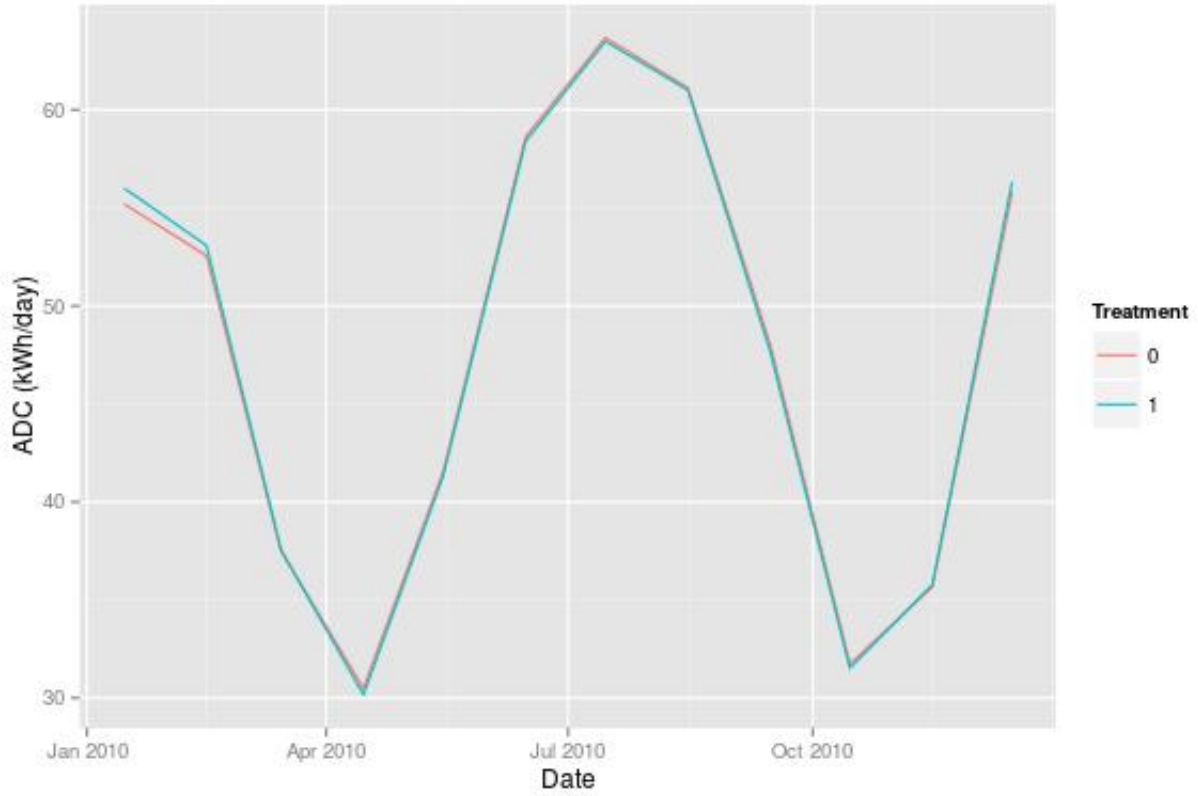
Matching Procedure - Considerations

- Choice of treatment effect (ITT, ATE, ATT, SATT, FSATT, etc.)
- Choice of variables to include in matching
- Choice of matching method
  - Choice of model in distance metric for Propensity Score matching
  - Choice of balance checks

Example

- Home energy report program with an RCT design



Matching Methods

- Exact
- K nearest neighbors
- Coarsened Exact
- Matching Frontier
- Many others

Balance Checks

- Difference in Means
  - Check all variables (don't use statistical significance)
- Average Mahalanobis Imbalance
  - Mean Mahalanobis distance between all matched pairs
- Median L1 Distance
  - Distance between multivariate histograms

When Matching Doesn't Help

- Coincident non-treatment changes
  - Some whole-house programs
- Missing information about treatment assignment
  - Opt-in bias?
- Modeling doesn't help either

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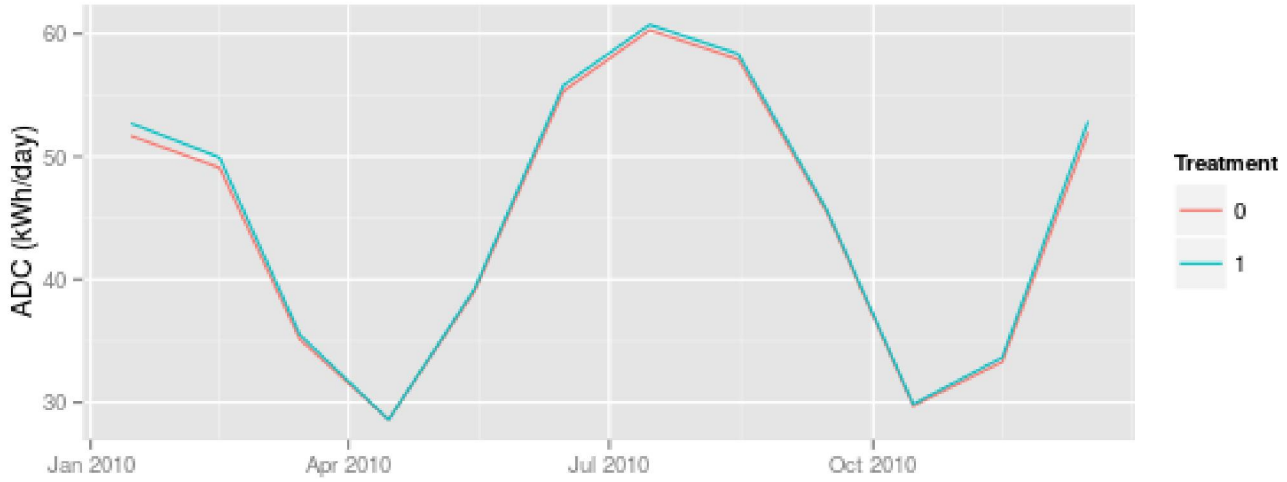
Coarsened Exact

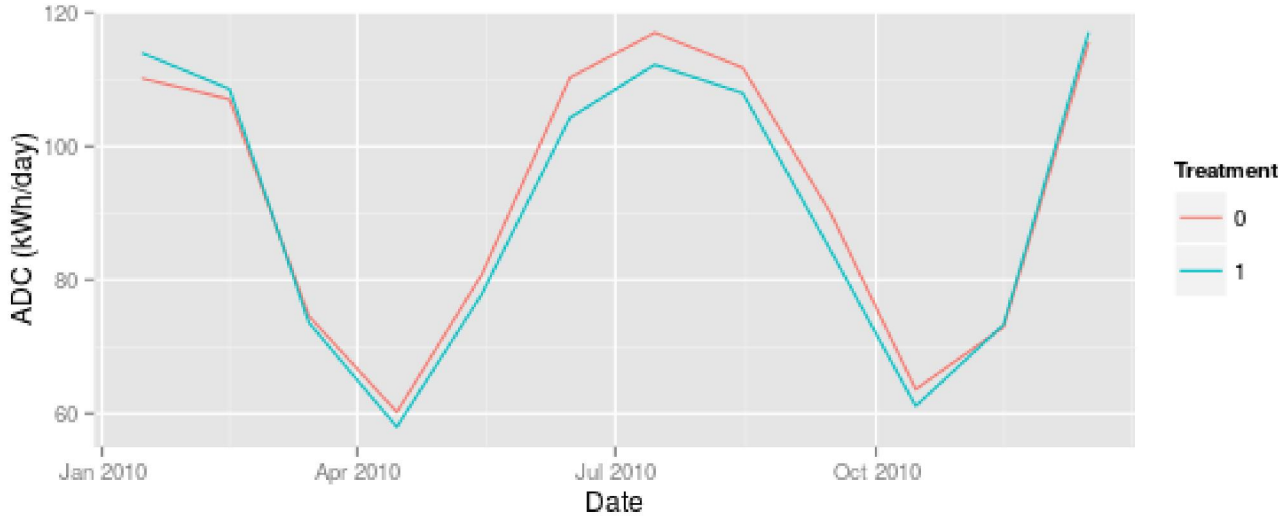
- N = 9,408, Nc = 9,355
- Median L1 distance: 0.09
  - Much better
- Average mean distance: 0.37 kWh/day
  - Somewhat worse

Coarsened Exact

Feasible Group



Non-Feasible Group



Coarsened Exact

- FSATT (N_f=9,408, N_c=9,355) savings = 4.3%
- NFSATT (N_{nf}=592, N_c=644) savings = 9.6%
- Weighted SATT (N=N_c=10,000) savings = 4.6%
- Full Sample SATT (N=N_c=10,000) savings = 4.8%

$$\text{weighted SATT} = \frac{\text{FSATT} \cdot \text{N}_\text{f} + \text{NFSATT} \cdot \text{N}_\text{nf}}{\text{N}}$$

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A Second Proposal

- How do we evaluate what are the best methods/approaches for impact evaluation?
- We need published data and well-defined metrics
- Common Task Method
  - Everyone works on the same problem
  - Method
    - Publish data
    - Define evaluation metrics
    - Periodic public evaluation of methods

For More Information

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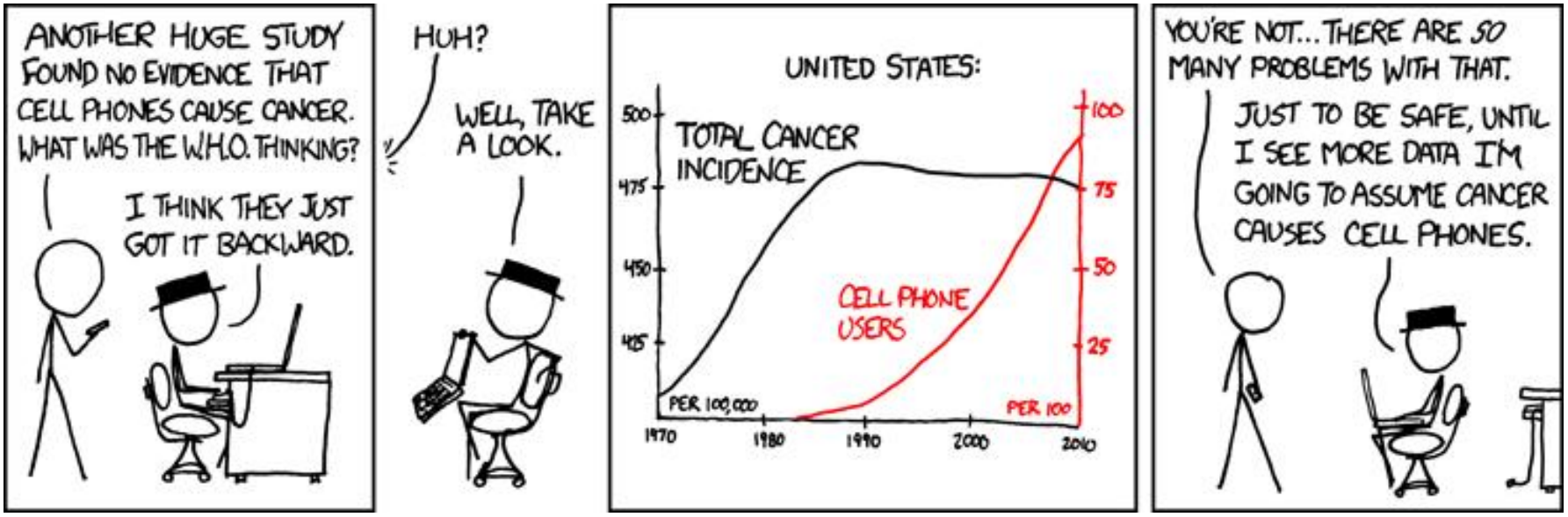
Thank you



xkcd.com/925

Distance Metrics

- Exact
- Propensity Score
- Mahalanobis
  - Euclidian is a special case

Match Anyway

- Methods
  - K nearest neighbors (1:1) with SATT
    - Propensity score distance
    - Mahalanobis distance
  - Coarsened Exact with weighted SATT
    - L1 distance

Balance Metrics

- Treated group N = 10,000
- Comparison group N_c = 10,000
- Average mean difference for the 12 months of the pre-period: 0.03 kWh/day
- Median L1 distance: 0.56

K Nearest Neighbors

- Propensity score metric
  - Simple model with a variable for each month of pre-period usage
  - N = 10,000 and N_c = 5,580
  - Average mean difference: -0.22 kWh/day
  - Balance is a little worse

K Nearest Neighbors

- Mahalanobis distance
  - N = 10,000 and N_c = 5,762
  - Average mean difference: 2.9
  - Balance is much worse