

DATA**SCIENCES**ALON
NEW YORK

Causal Design Patterns



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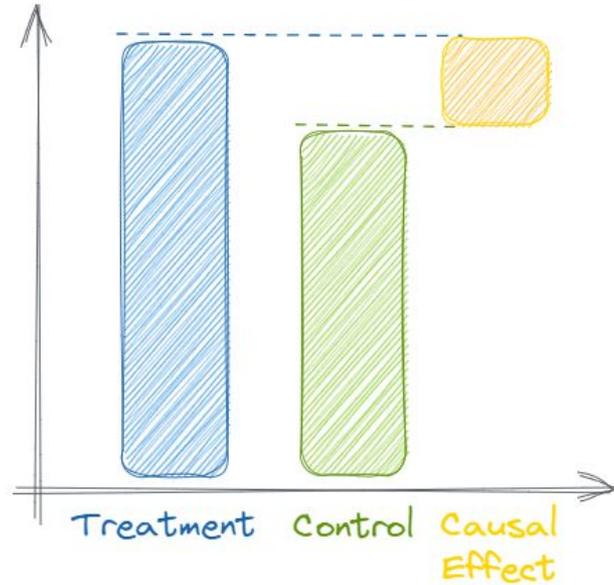
Causal Design Patterns

Emily Riederer
DSS Salon NYC
June 7, 2023

Randomized experiments allow for credible measurement

X X X X X \rightarrow T T C T T C C T C C

Using the *spark of randomization*,
assign *treatment* and *control* groups
to measure a credible *causal effect*
by comparing their outcomes



Randomized experiments are not always practical



Not feasible

- *Customer experience*
- *Ethics*



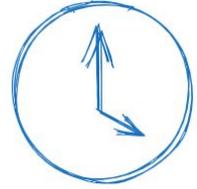
Not easy

- *Randomization bugs*
- *Treatment isolation*



Not cheap

- *Direct costs*
- *Opportunity costs*



Not fast

- *Long-term endpoints*
- *Historical variants*

Causal inference helps recreate the 'spark' with historical data

semi-random variation

Using the ~~spark of randomization~~,

+ data & context

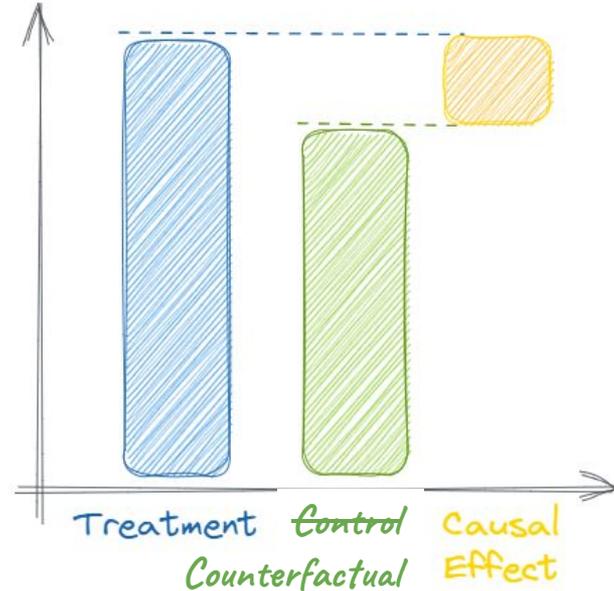
identify those who received the

~~assign~~ **treatment** and ~~control~~ groups

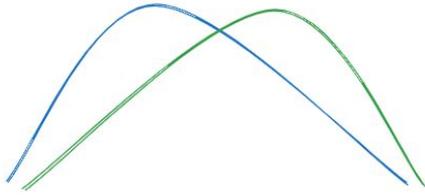
construct a **counterfactual 'control'**

to measure a credible **causal effect**

by comparing their outcomes

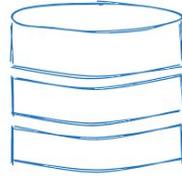


Industry has distinct advantages when applying causal methods



Semi-random Variation

- Segmentation
- Timing
- Execution
- Natural experiments!



Rich Historical Data

- Individual-level
- Integrated, multimodal
- Longitudinal
- Out-of-time



Domain-Driven Assumptions

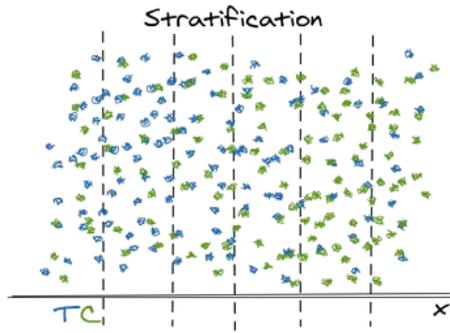
- Context / rationale for decisions, treatment assignments
- Proxies for validation

Agenda

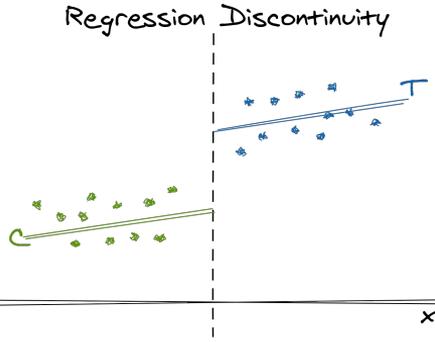
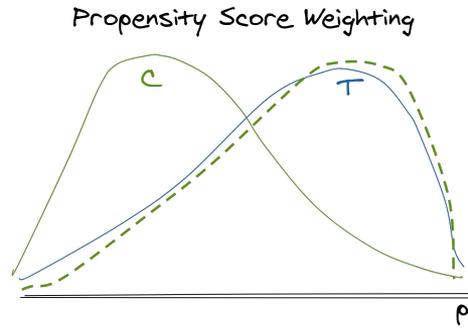
- *Common design patterns*
- *Patterns as building blocks*
- *Prerequisites for success*
- *Resources to learn more*

Key Design Patterns

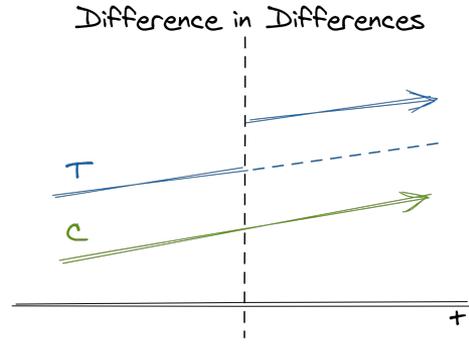
Four basic strategies for causal inference



Variation in treatment *distribution* within a population

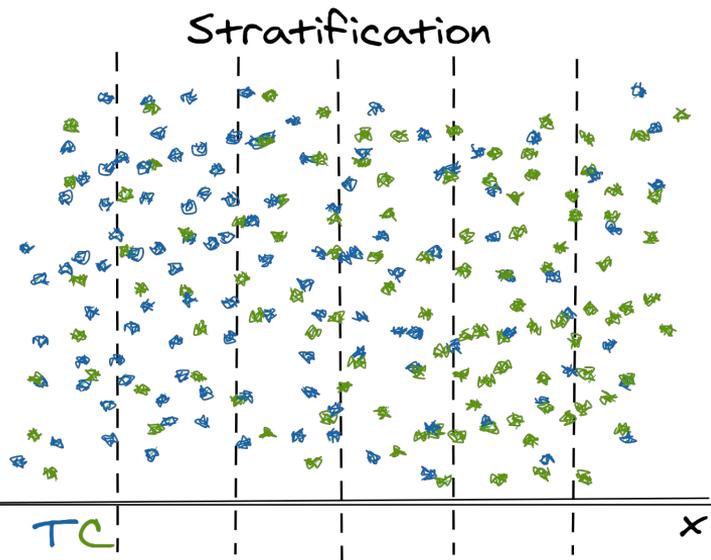


Variation across *distinct groups*



Variation across *groups & time*

When we have imbalance...



When you have:

- “similar” treated and untreated individuals
- different distributions
- on few relevant dimensions

Tries to:

Bin comparisons into comparable subgroups

★ Spark from untreated data and rich featureset ★

Stratification pattern

Recipe:

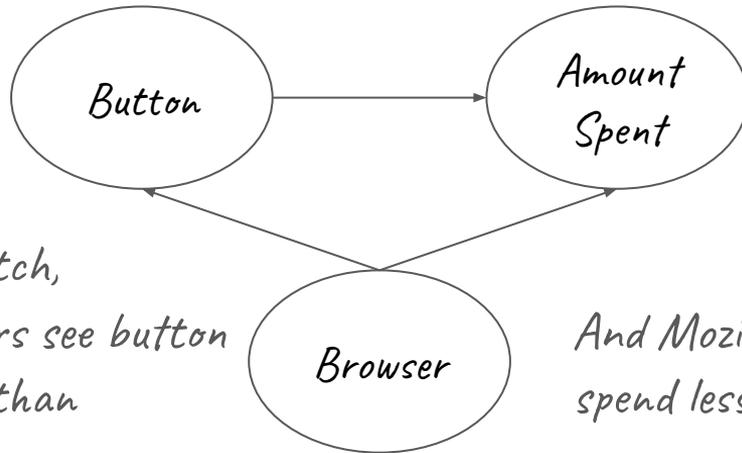
- Bin population by subgroups
- Calculate average effect by group
- Weight average across groups

Assumption:

- All *common causes* of treatment and outcome are observed
- All observations have *positive probability* of treatment
- Few variables need adjustment

Stratification application

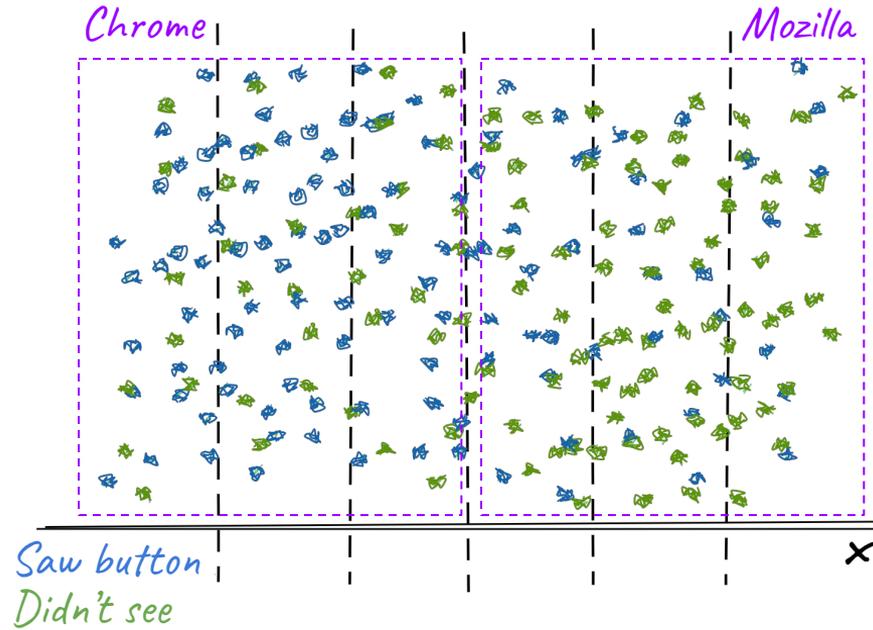
Attempt to A/B test "one-click instant checkout" on Black Friday



Due to a glitch,
Chrome users see button
more often than
Mozilla users

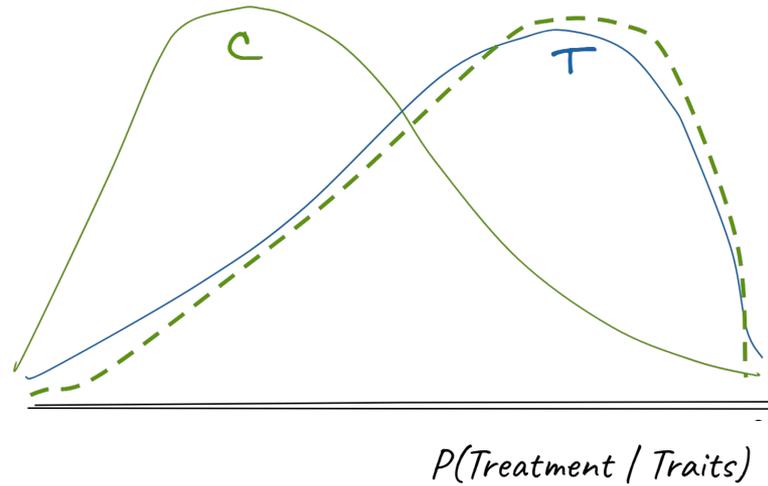
And Mozilla users tend to
spend less on average

Stratification application



When we have imbalance across many dimensions...

Propensity Score Weighting



When you have:

- “similar” treated and untreated individuals
- different distributions
- on many dimensions

Tries to:

Rebalance to make groups more comparable

★ Spark from untreated data and rich featureset ★

Propensity Score Weighting pattern

Recipe:

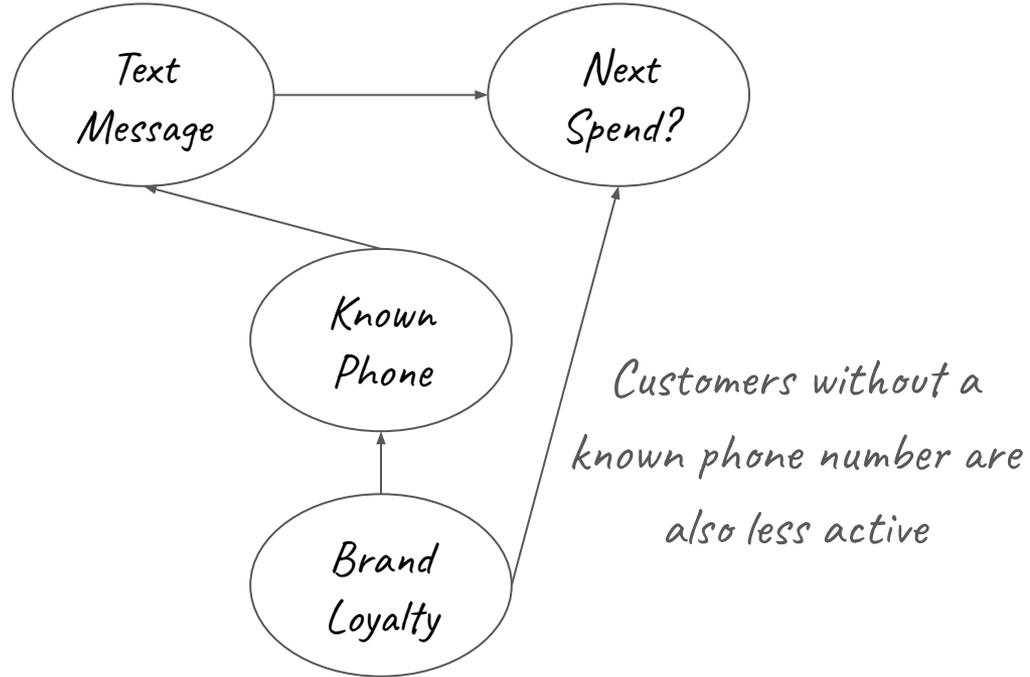
- Model the $P(\text{Treatment} \mid \text{Traits})$
- Derive weights from predictions
- Calculate average outcome by treatment using weights

Assumption:

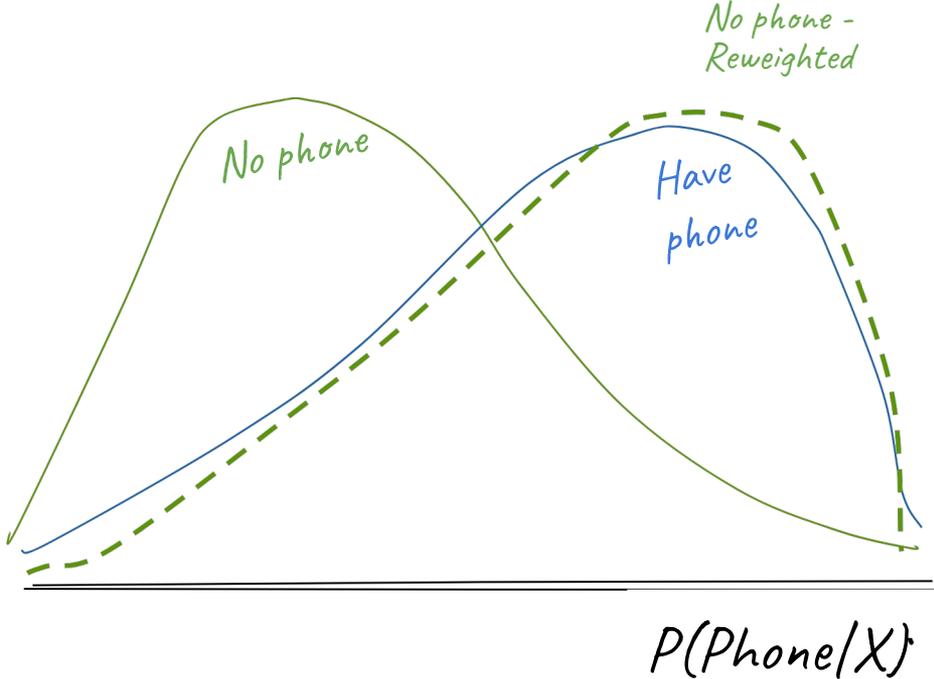
- All *common causes* of treatment and outcome are accounted for
- All observations have *positive probability* of treatment

Propensity Score Weighting application

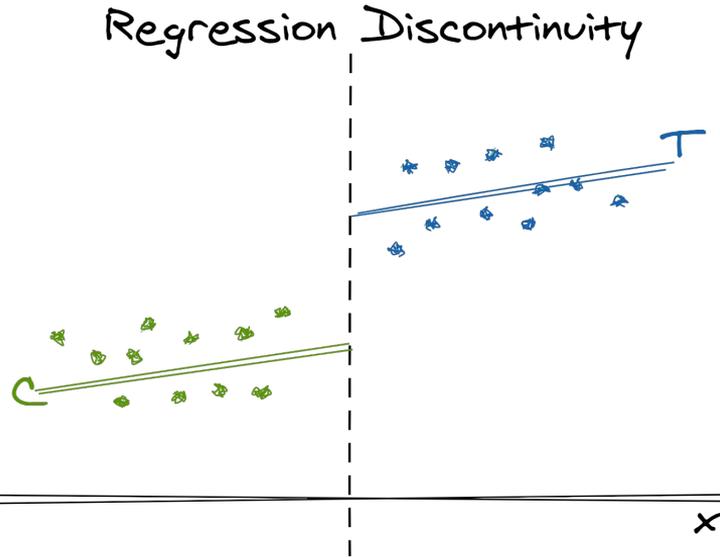
Send *text message* to all customers with a valid phone number on record



Propensity Score Weighting application



When we have no overlap...



When you have:

- disjoint treated and untreated individuals
- separated by sharp cut-off

Tries to:

Exploit arbitrary variation in treatment assignment at cut-off to evaluate local effect

★ Spark from sharp policy cut-off ★

Regression Discontinuity pattern

Recipe:

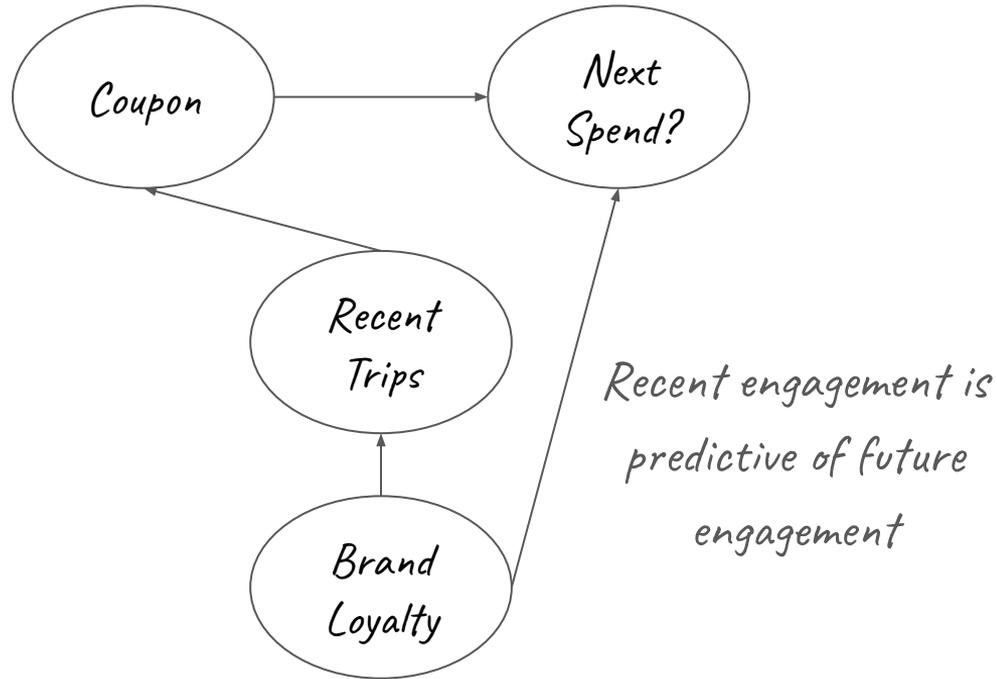
- Model Outcome = $f(\text{running var})$ on each side of cut-off
- Evaluate models at cut-off value
- The local treatment effect is the difference in estimates

Assumption:

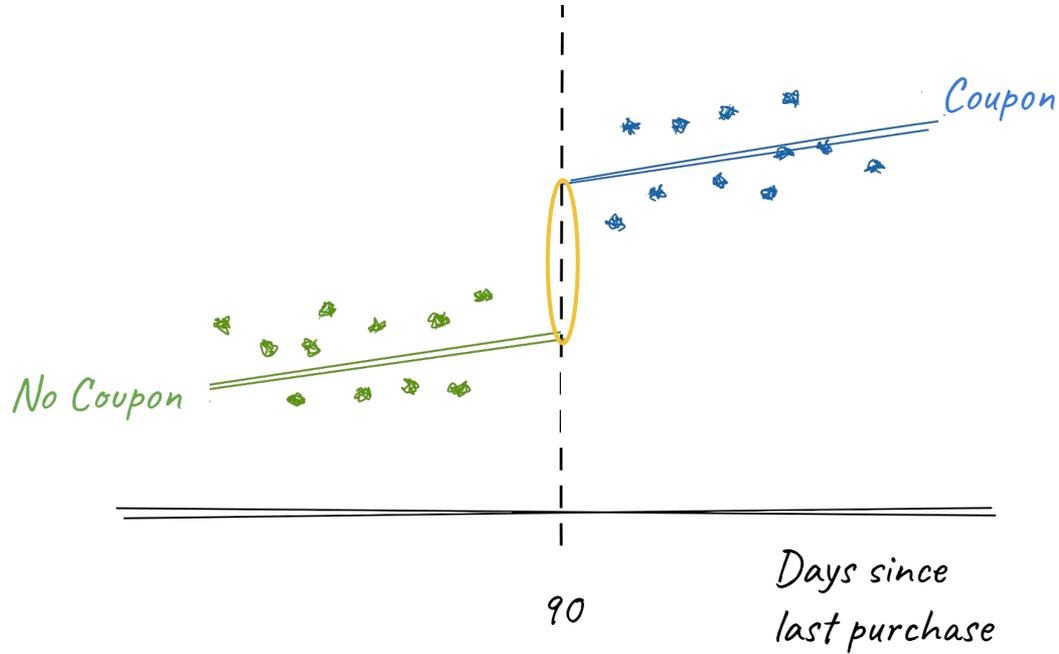
- Assignment rule is *unknown* to individuals (not gameable)
- Outcome is *continuous* function of running variable
- Can fit a reasonably well-specified and *simple* model

Regression Discontinuity application

Send *coupon* to customers who've not purchased in last 90 days

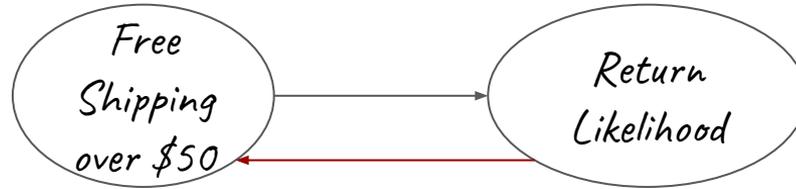


Regression Discontinuity application



Regression Discontinuity breakdown

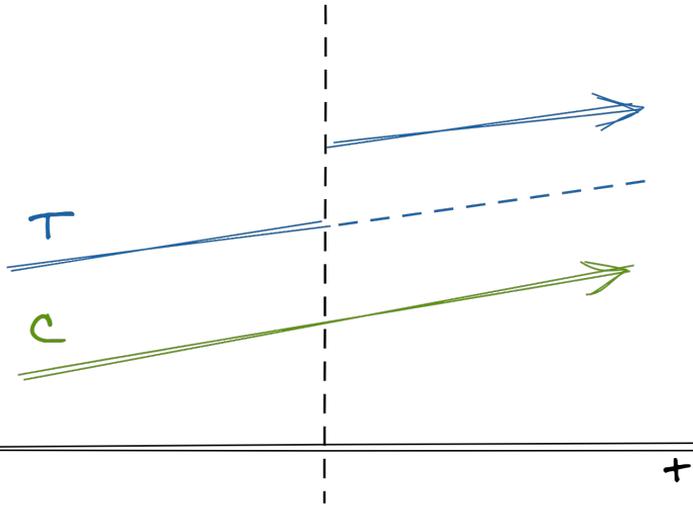
Offer free shipping and returns on purchases over \$50



Customers anticipating returns can *game a known policy*

When we have pre-existing differences...

Difference in Differences



When you have:

- different baselines in comparison groups
- variation across time (pre/post)

Tries to:

Compare how difference in pre/post behavior differs across populations

Difference-in-Differences pattern

Recipe:

- Take the pre/post treatment difference within each group
- Find the difference in differences between groups
- Technically done as a fixed-effects regression

Assumption:

But-for the treatment, groups would have *parallel trends*

- Decision to treat *not influenced* by anticipated outcome
- *No spill-over* between groups

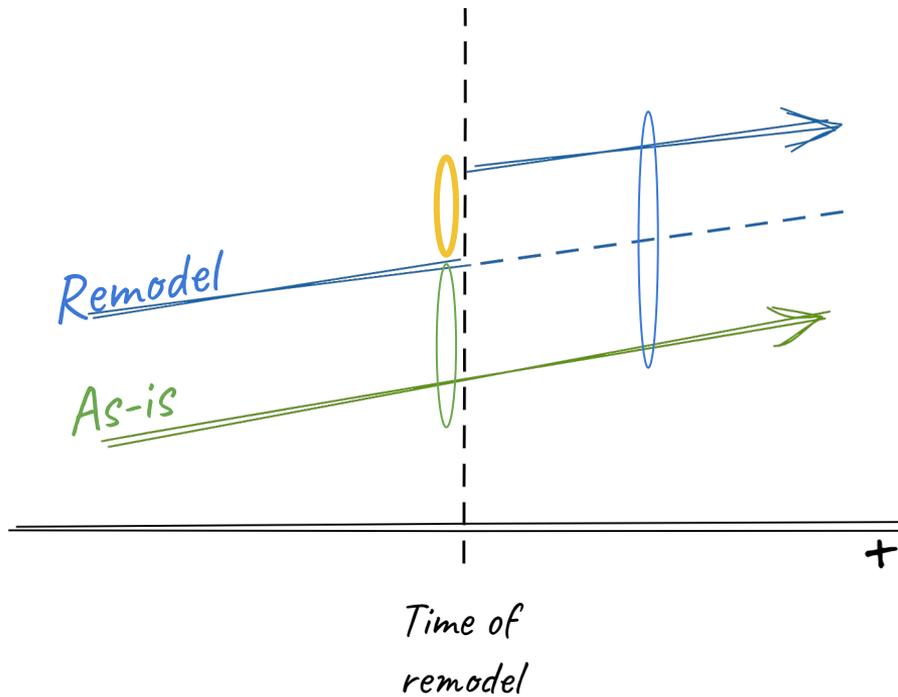
Difference-in-Differences application

Remodel store and want to measure effect on store traffic



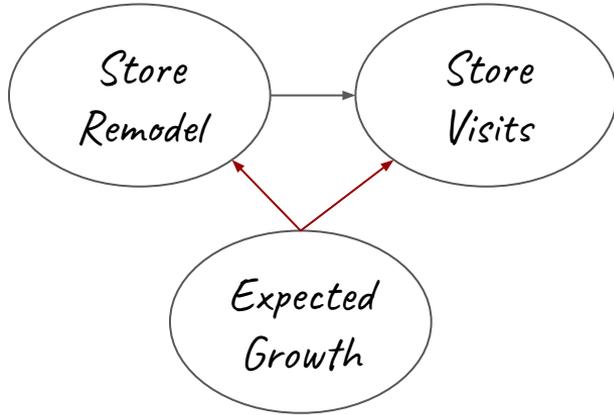
*Too capital intensive
to experiment!*

Difference-in-Differences application

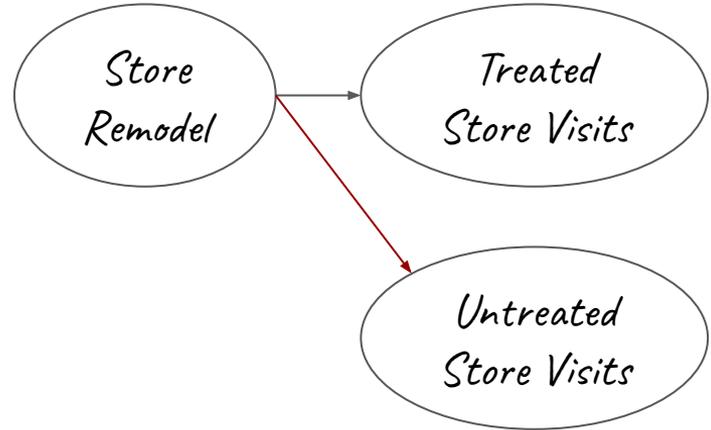


Difference-in-Differences breakdowns

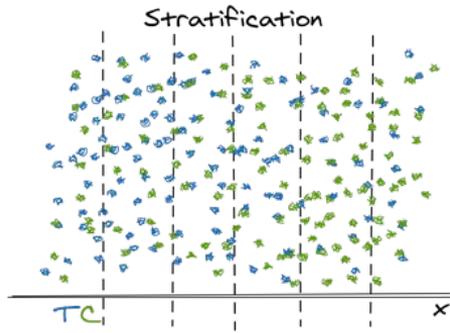
Decision to Treat



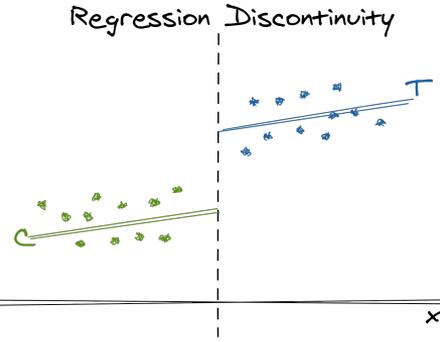
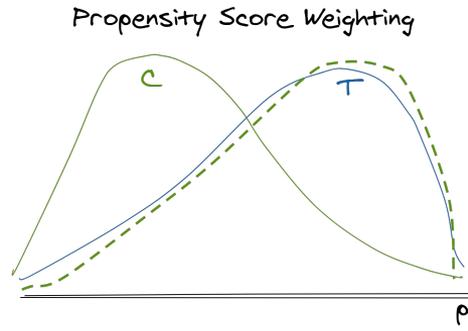
Spillover



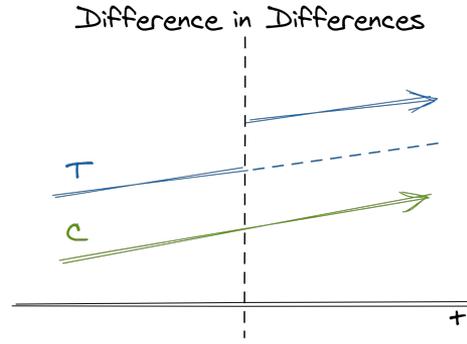
Four basic strategies for causal inference



Variation in treatment *distribution* within a population



Variation across *distinct groups*

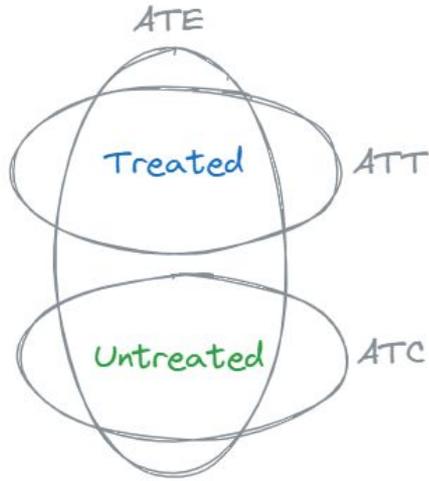


Variation across *groups & time*

Extensions

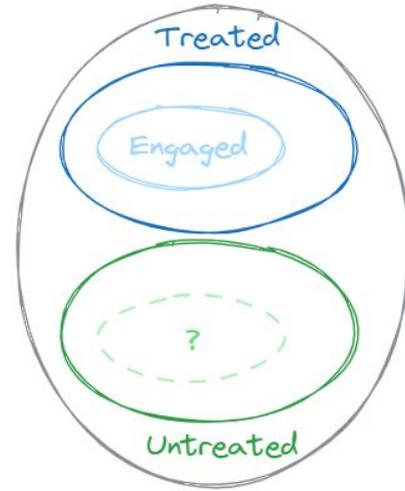
Propensity scores to measure different effects

Different Subgroups



Map propensity scores to different weights for different populations

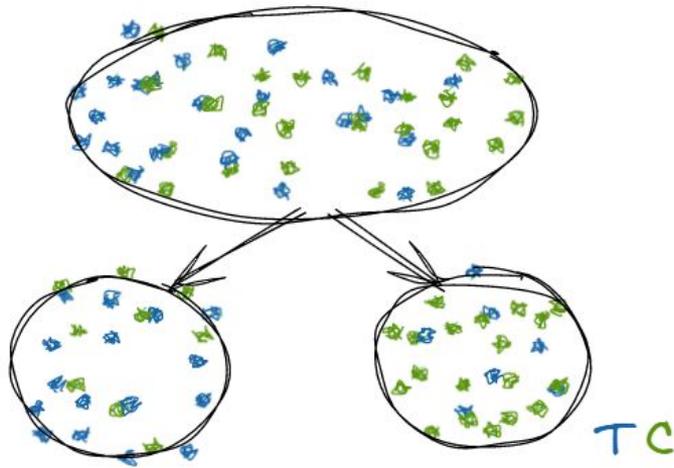
Different Points of Randomization



Create counterfactuals for narrower subgroups like campaign opt-ins

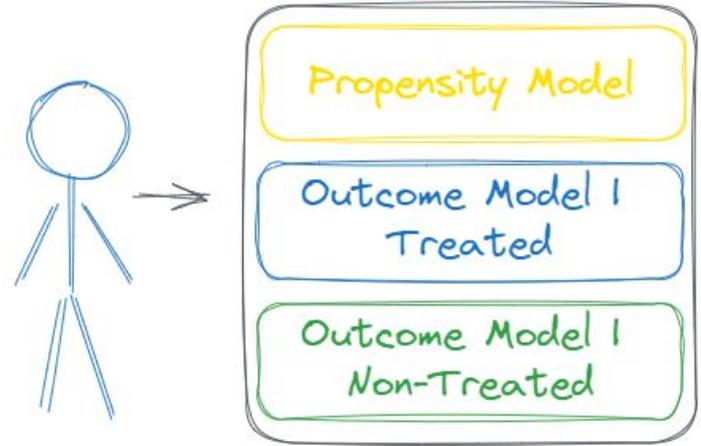
Propensity scores to estimate individual effects

Causal Forests



Create balanced experiment within tree nodes

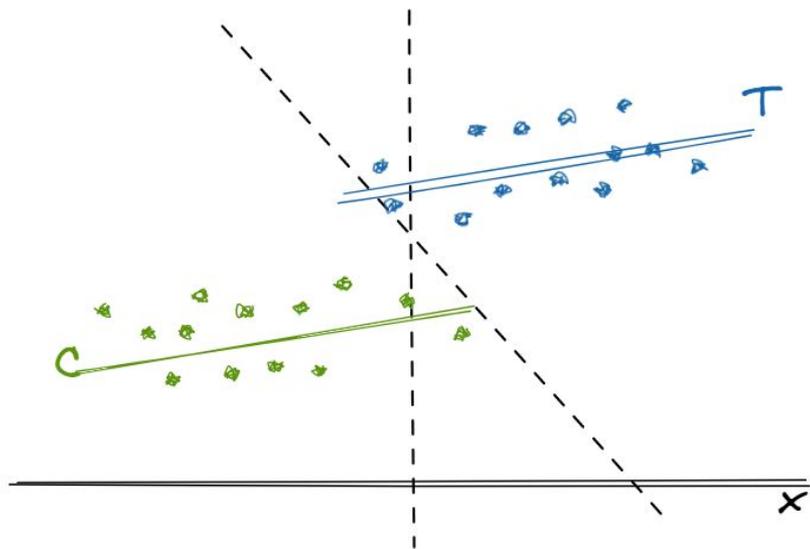
Doubly Robust Methods (e.g. AIPTW)



*Combine treatment and outcome models-
even if one is mis-specified!*

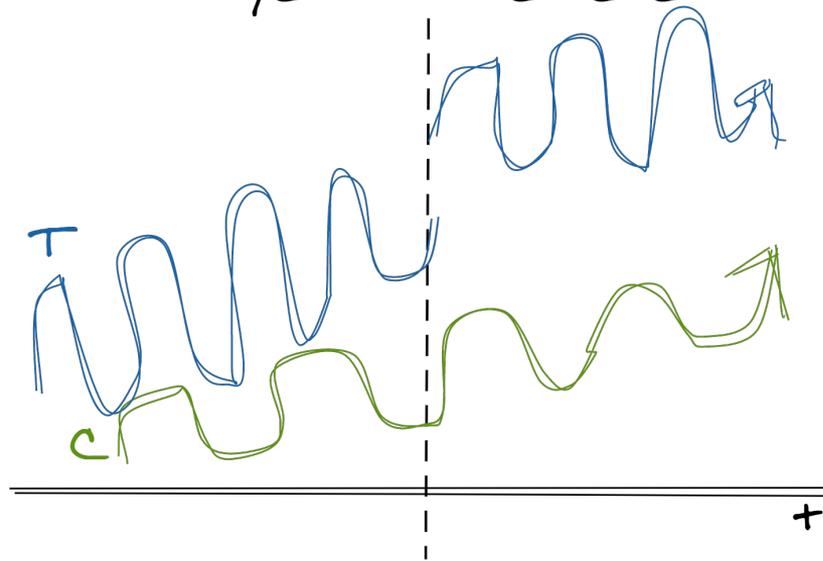
Relaxing RD and Diff-in-Diff assumptions

Fuzzy Regression Discontinuity



Regression discontinuity with imprecise cut-off

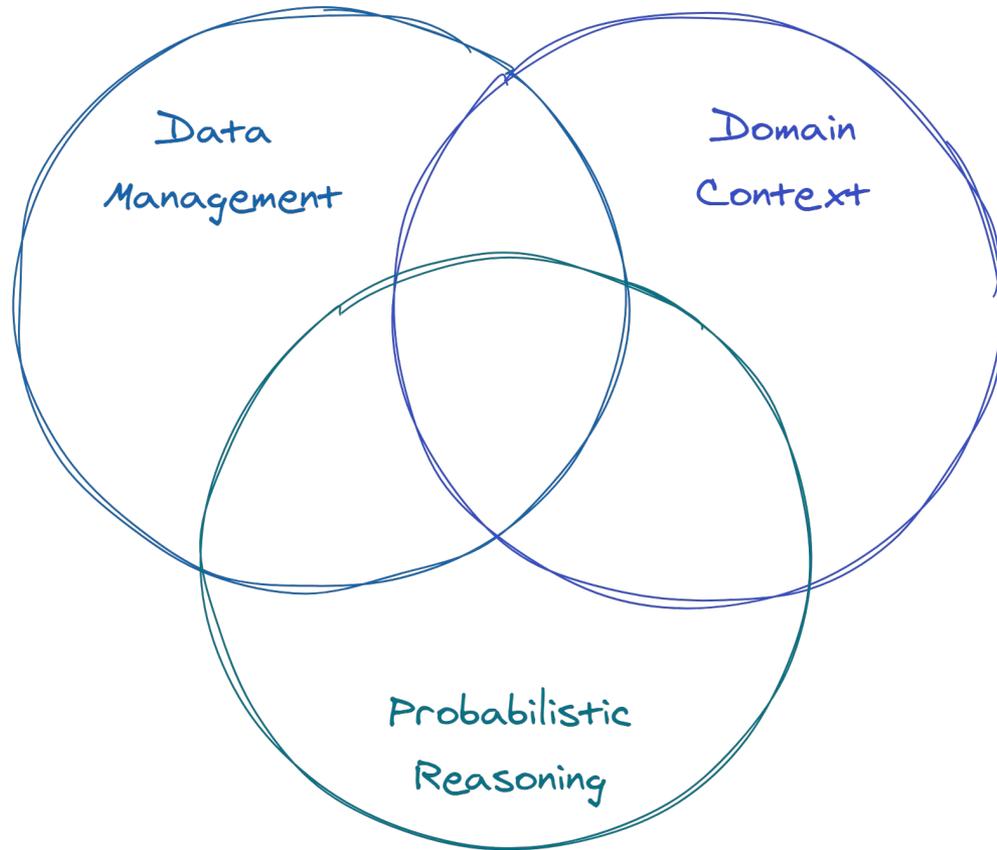
Bayesian Time Series



Diff-in-diff extension for richer time series

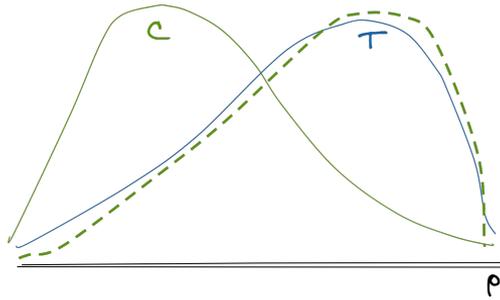
Org Implications

Successful causal inference requires a mix of skills & capabilities



Holistic data management can help us find the 'sparks' we need

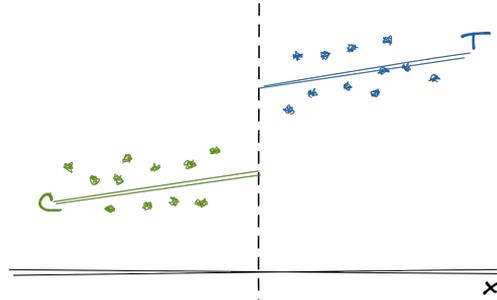
Propensity Score Weighting



Data Management

Behavioral data
Digital data
Operational data

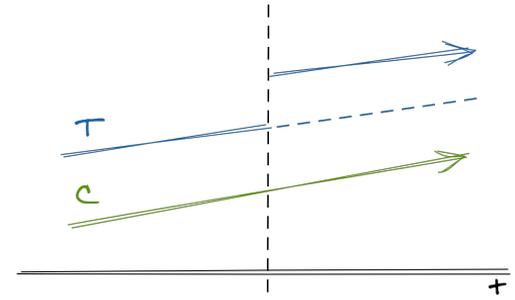
Regression Discontinuity



Metadata Management

Segmentations
Strategies
Offers & Targeting

Difference in Differences



Knowledge Management

Decisions to enact policy
Rollout/launch dates

Resources

Questions?

↓ *Get in touch* ↓

@emilyriederer on Web / Twitter / GitHub / LinkedIn / Gmail

↓ *Related blog posts* ↓

Causal design patterns

Causal inference resource roundup

↓ *Open access books* ↓

The Effect: an Introduction to Research Design and Causality by Nick Huntington-Klein

Causal Inference: the Mixtape by Scott Cunningham

Causal Inference: What If? by Miguel Hernan

Introduction to Causal Inference by Brady Neal

Causal Inference for the Brave and True by Matheus Alves

Thank you!