Design-based problem solving

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Hertie School
Data Science Lab

What are we doing?

1. Take data as given

CausalML

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2. Derive better ways to use that data

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Problem:

> *To consult the statistician after an experiment is finished is often merely to ask him to conduct a post mortem examination. He can perhaps say what the experiment died of.*
>
> *Ronald Fisher*

Design-based inference

Suppose data is n tuples of (Y, A, X)

Y: Outcome, $Y = AY(1) + (1 - A)Y(0)$

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Many Examples: Abadie et al. [2022], Lin [2013], Aronow and Middleton [2013], Sävje et al. [2021], Samii and Aronow [2012]

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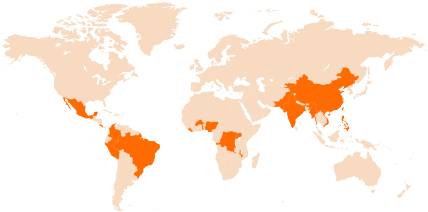
- Solution: Partition the network so that members of a cluster are mainly connected to *other* members of that cluster, assign treatment based on clusters
- "Graph-cluster randomization" Ugander et al. [2013], Eckles et al. [2017], Ugander and Yin [2023]

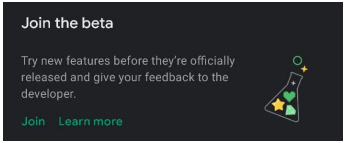
Design-based generalization

[Phan et al., 2021]

Motivation



(a) The Metaketa Initiative's study sites



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Experimental samples in practice:

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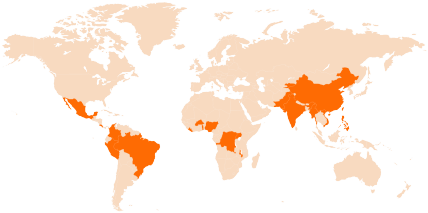

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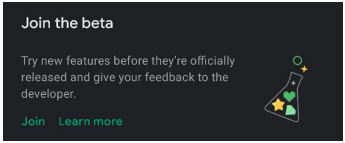

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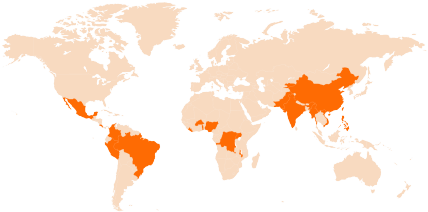

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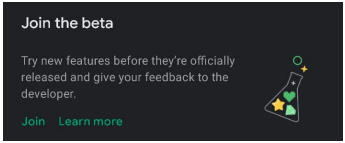

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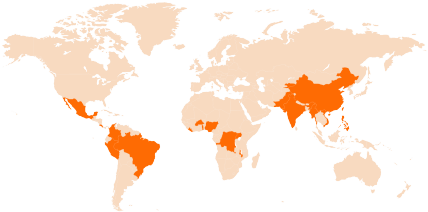

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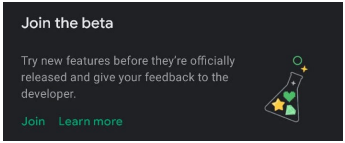

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Key Question: How can we **design** experiments on our sample that will **generalize**?

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- Make the average observed features in the Treatment and Control similar ("balance")
  - **Source Balance**: make the users balance according to the Source (*status quo*)
  - **Target Balance**: using importance weights, make the users balance according to the Target $\rightarrow$ *reduces variance and achieves lower variance than Source Balance*.

Weighted Rerandomization-based Design

With a rejection threshold α, define the balance condition:

$$\phi^{\alpha}(\mathbf{x}, \mathbf{Z}) = \begin{cases} 1, & \text{if } M(\frac{2}{n}(\mathbf{wx})^T\mathbf{Z}) < a(\mathbf{x}) \\ 0, & \text{otherwise} \end{cases}$$

$$\frac{2}{n}\sum_{Z_i=1} w_i x_i - \frac{2}{n}\sum_{Z_i=-1} w_i x_i = \frac{2}{n}(wx)^T Z.$$

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When weights are all one, you get the standard Mahalanobis distance (i.e. Euclidean scaled by the covariance matrix).

1. Assign A randomly for each person $1, \ldots, n$ such that $\sum_i a_i = n_1$. There are $\binom{n}{n_1}$ ways to choose, each of which is equally likely.

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3. Conduct experiment with treatment assignments, A.

Theory

- The importance-weighted estimator with Target Balance results in an unbiased estimator of the target distribution's ATE
- Target Balance reduces the variance and achieves a lower variance than Source Balance.
- Among all balance criteria with rejection probability at most α (including Source Balance), Target Balance achieves the optimal variance reduction

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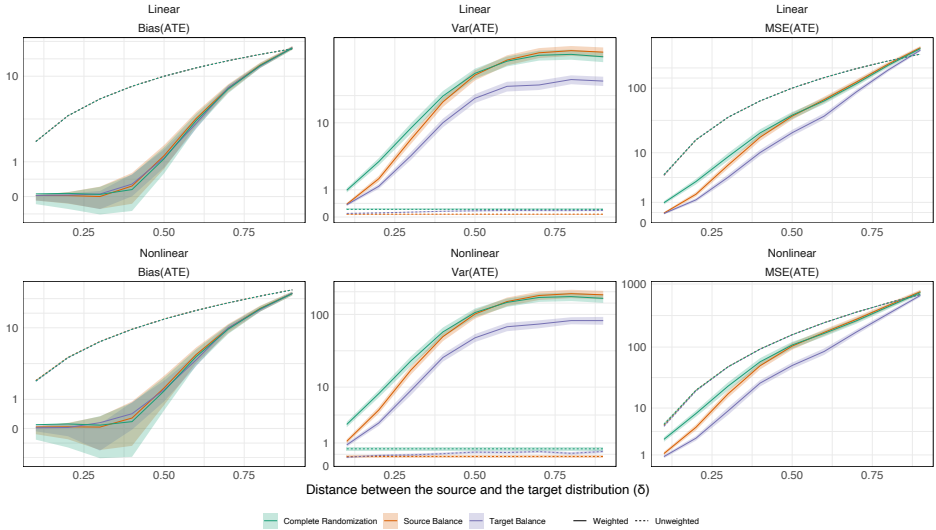
Simulations



Design-based HTE estimation

[Arbour et al., 2021a]

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Approaches:

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Estimation of HTE

The HTE for x is: $Y^{A=1}(x) - Y^{A=0}(x)$, $x \in X$.

We focus on the following kernel-weighted estimator:

$$\hat{f}(x_i) = \sum_{j}^{N} \frac{\mathbb{1}(a_i \neq a_j) k(x_i, x_j) y_j}{\sum_m^N \mathbb{1}(a_i \neq a_m) k(x_i, x_m)} \tag{1}$$

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Fixing observed outcomes leads to the transductive inference estimator of Zhu et al. [2003].

Similar to singular kernels analyzed in benign overfitting literature [Belkin et al., 2018].

Defining the optimization problem for the HTE

Minimize the sum of absolute errors in each response surface:

$$\min_{A} \sum_{i}^{N} \left| \sum_{j} \frac{\mathbb{1}(a_i \neq a_j) w_{ij} y_j}{\sum_k \mathbb{1}(a_i \neq a_k) w_{ik}} - \tilde{y}_i \right| \tag{3}$$

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- w_{sum}: sum of weights
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Intuition: There is irreducible error from the counterfactual, and reducible error from assignment to treatment which is minimized by maximizing $\sum_{i,j} \mathbb{1}(a_i \neq a_j) w_{ij}$: MAXCUT

SoftBlock Algorithm

input : $X \in \mathbb{R}^D$

output: Assignments A, Spanning Tree T

1 $G \leftarrow$ Similarity matrix constructed from X

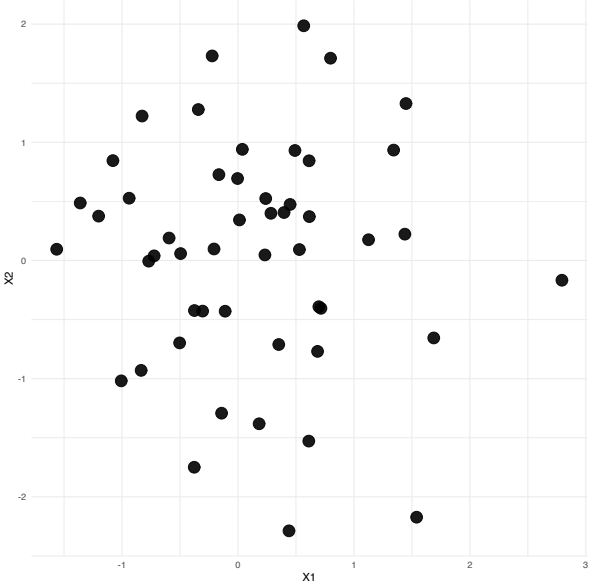
2 $T \leftarrow$ Maximum Spanning Tree(G)

3 $A \leftarrow$ MAXCUT(T)

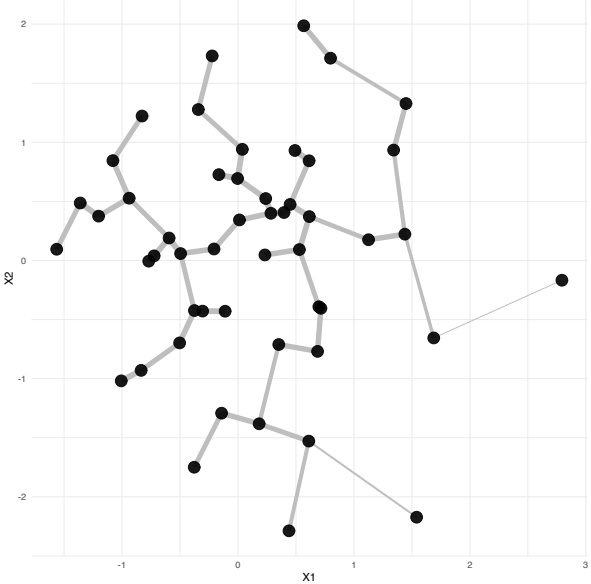
Algorithm: Friedman-Rafsky Minimizing Design

- (2) is calculated in $\mathcal{O}(n^2 \log n)$.
- (3) is calculated in $\mathcal{O}(n)$ on a tree.
- An additional algorithm (GreedyNeighbors) based on the nearest neighbor graph simply substitutes (2) for constructing the nearest neighbor graph.

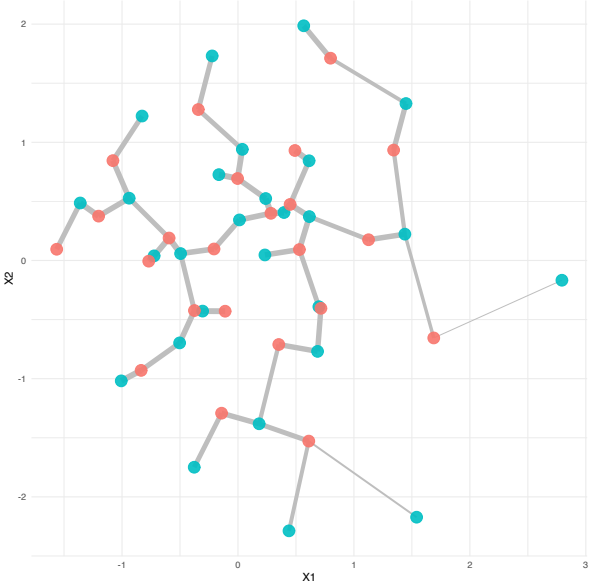
Take a point-cloud in $\mathbb{R}^2$



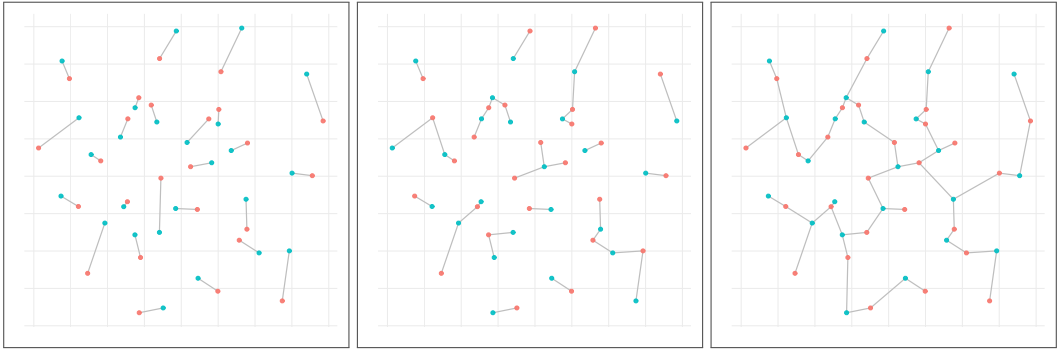
Find the maximum spanning tree



Greedily assign adjacent nodes alternating treatments



Three Designs on the Same Data in $\mathbb{R}^2$



Matched Pairs GreedyNeighbors SoftBlock

Design-based sequential balance

[Arbour et al., 2022]

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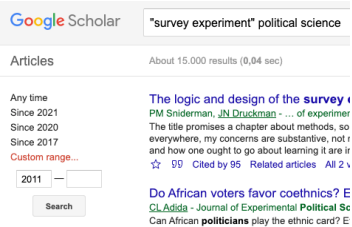

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(b) A criminally under-cited paper

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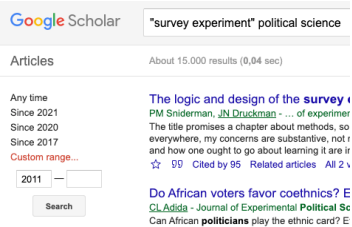

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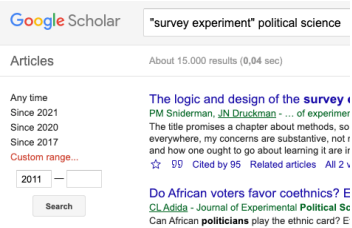

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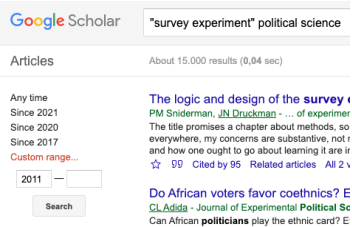

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Methods Question: How can we guarantee balance with highly efficient designs?

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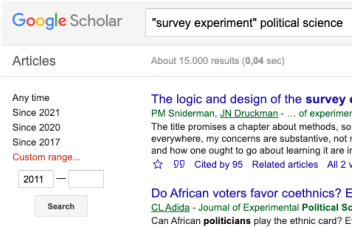


(a) We run a lot of survey experiments

(b) A criminally under-cited paper

Design of survey experiments in practice:

- Just flip a coin, it's fine!
- Slow balancing designs (either offline or with poor time complexity)

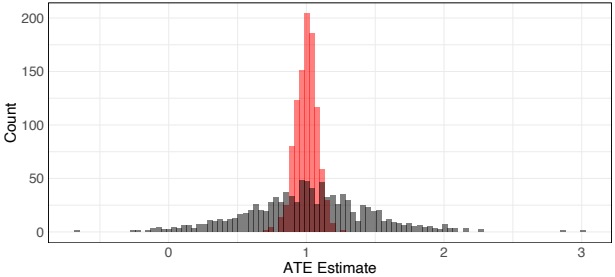
Methods Question: How can we guarantee balance with highly efficient designs?

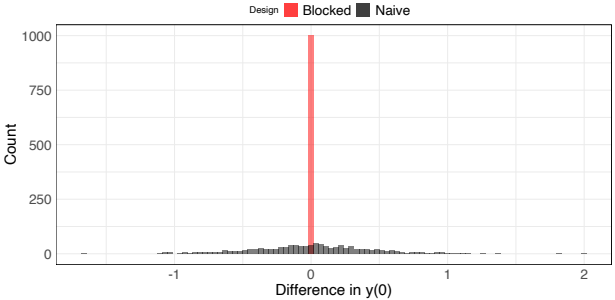
Software Question: How can we make it easy to run balancing designs on sequential data?

What makes good sequential experimental design?

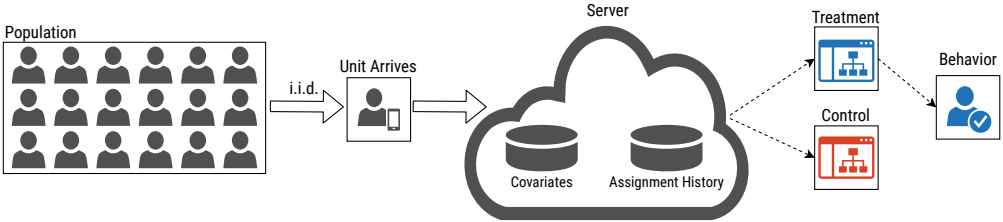
1. Balances Covariates

- Effective at minimizing imbalance
  - Better than coin-flipping
  - Ideally with theoretical guarantees



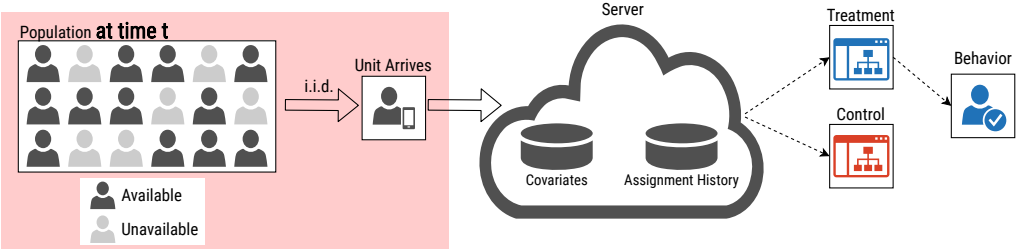


Idealized Sequential Experiment



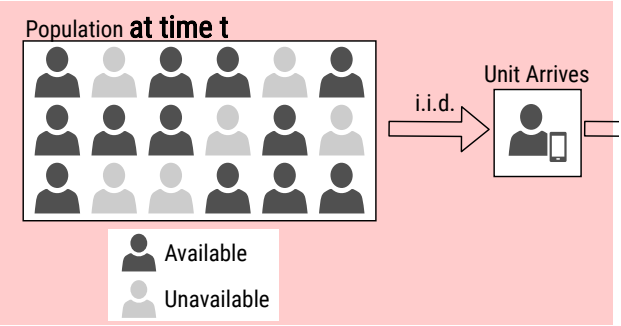
Sampling frames vary over time

More Realistic Sequential Experiment



2. Incorporates randomization to improve robustness

- Appropriate to the data generating process
- Not easily “exploitable” by an adversary
- Ideally, we would be able to turn a dial like [Harshaw et al., 2020].



How can we formalize this?

(At least) three approaches:

- i.i.d. Stochastic arrivals / SRS from population

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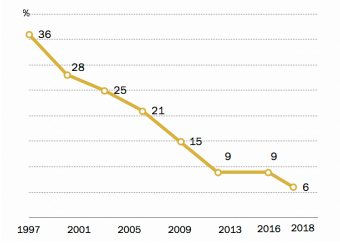
  - This work.

3. Doesn't assign units who won't actually show up.

- Focuses design on respondents.

After brief plateau, telephone survey response rates have fallen again

Response rate by year (%)



Note: Response rate is AAPOR RR3. Only landlines sampled 1997-2006. Rates are typical for surveys conducted in each year.
Source: Pew Research Center telephone surveys conducted 1997-2018.

PEW RESEARCH CENTER

4. Fast

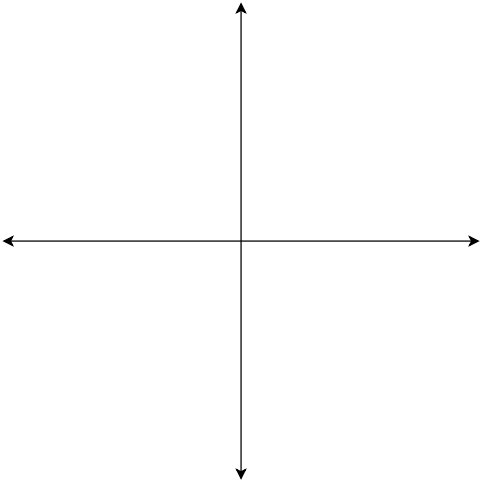
- Single-pass (i.e. must work online)
- Ideally constant-time in each iteration (i.e. overall $\mathcal{O}(n)$)

using covariate-adaptive randomization for large surveys, I have estimated
dents, the 4,000th respondent takes 5 seconds on average to assign. This es
`eqblock` on a Macbook Pro and might not be fully reflective of how the al

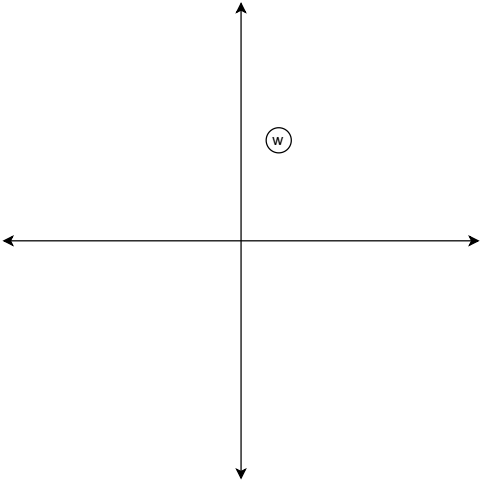
Cavaille [2018] on Moore and Moore [2017]

The algorithm

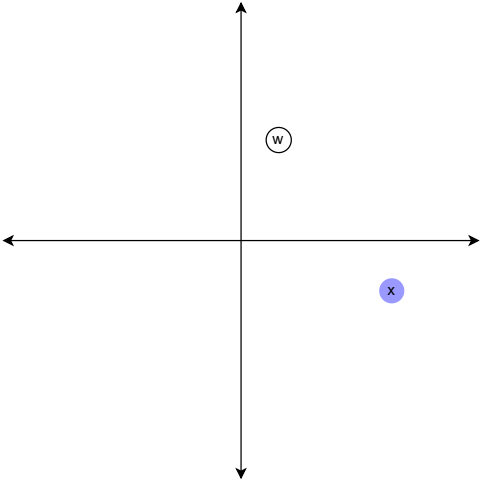
A covariate space



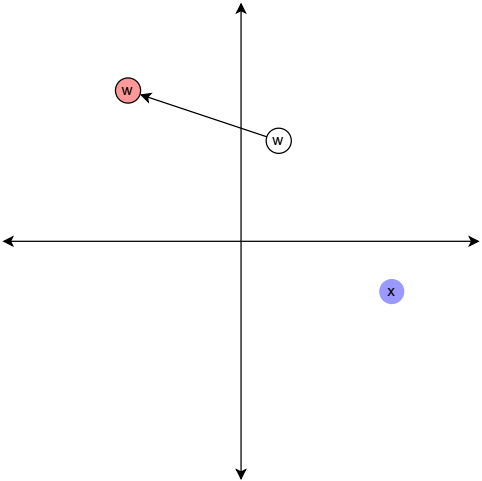
Current imbalance



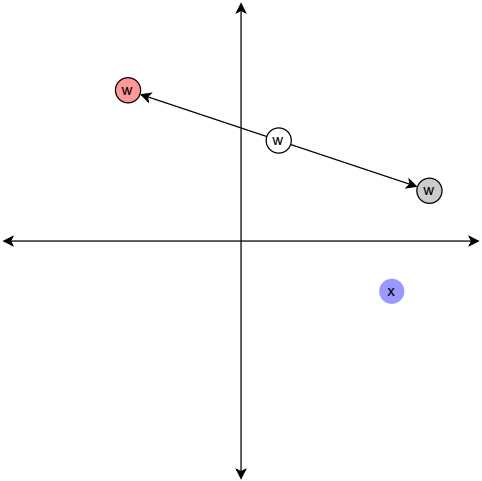
New unit arrives



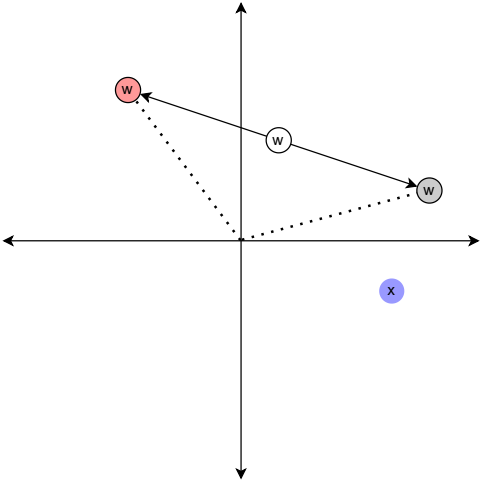
Could assign the new unit to control



Or could assign the new unit to treatment

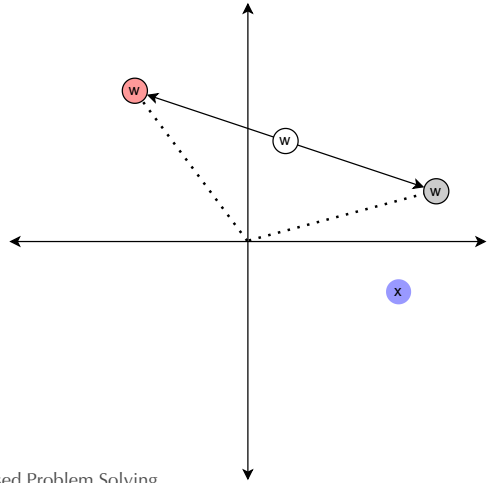


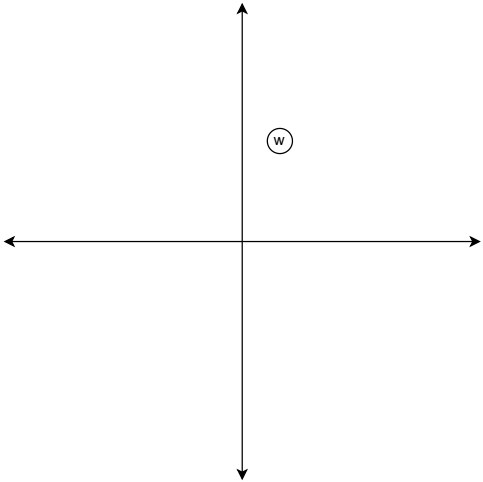
Either treatment results in similar levels imbalance



Repeating the exercise

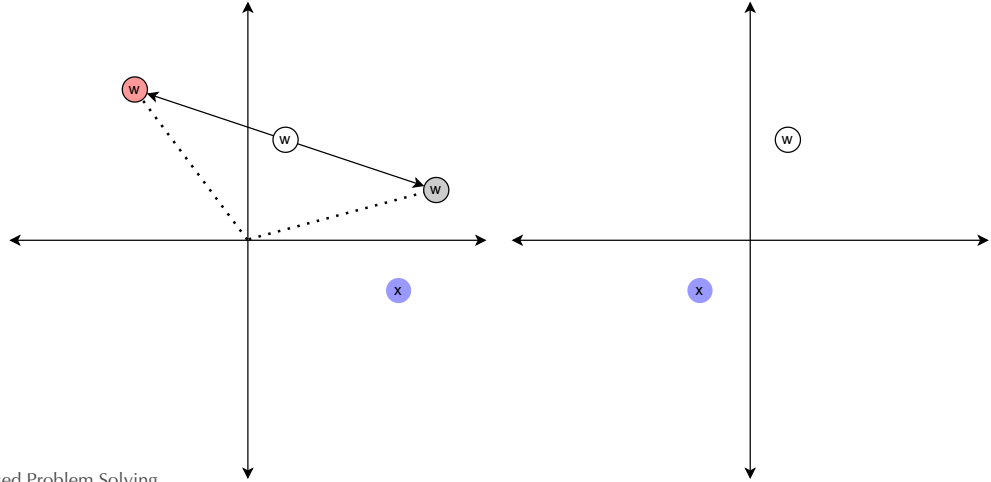
Assignment doesn't matter much





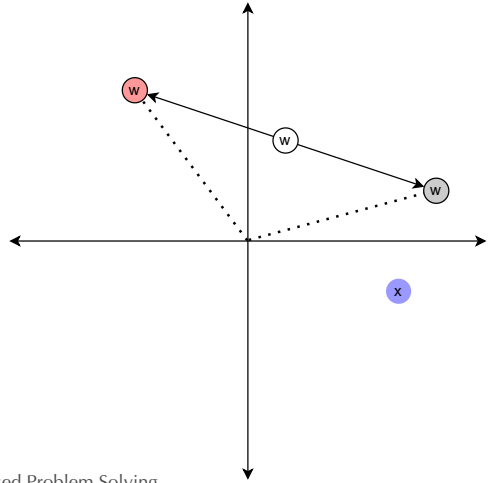
What if a different unit had arrived?

Assignment doesn't matter much

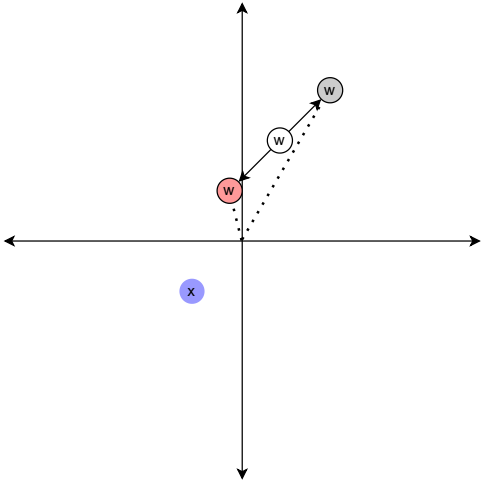


If a different unit had arrived, assignment would matter a lot

Assignment doesn't matter much

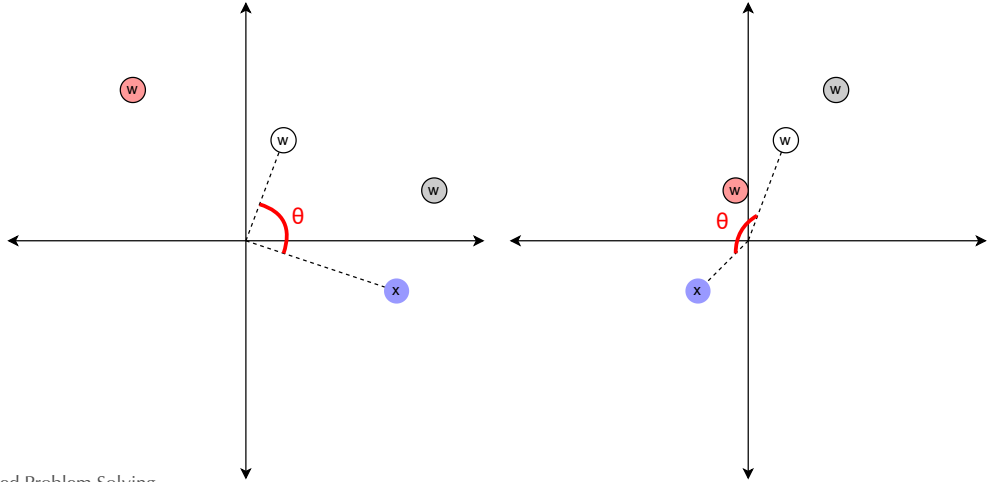


Assignment matters a lot

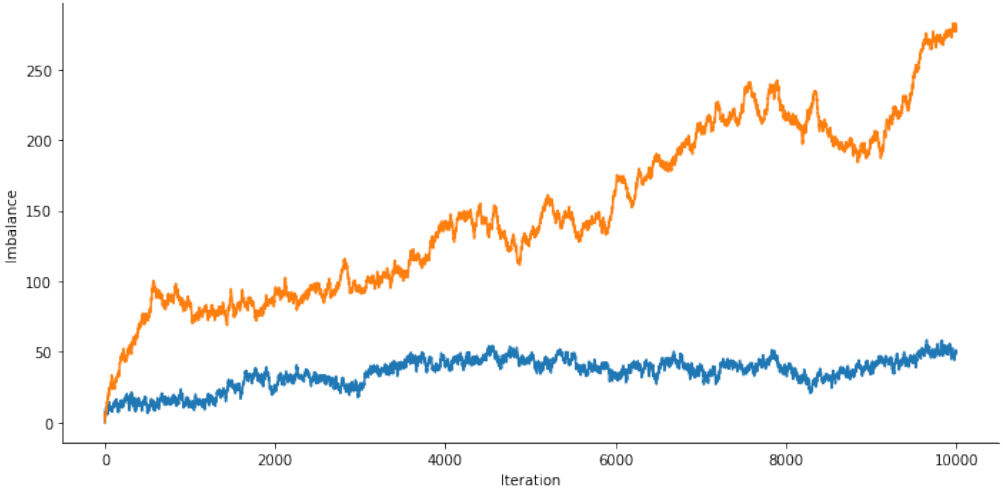


This motivates the algorithm: The Balancing Walk Design (BWD)

$\therefore$ Assign based on $\cos\theta$.

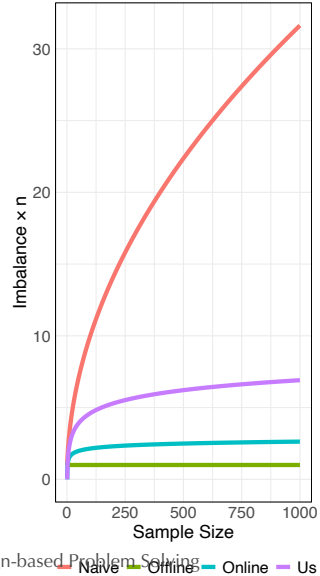


A self-balancing random walk of imbalance (drifts back towards zero)



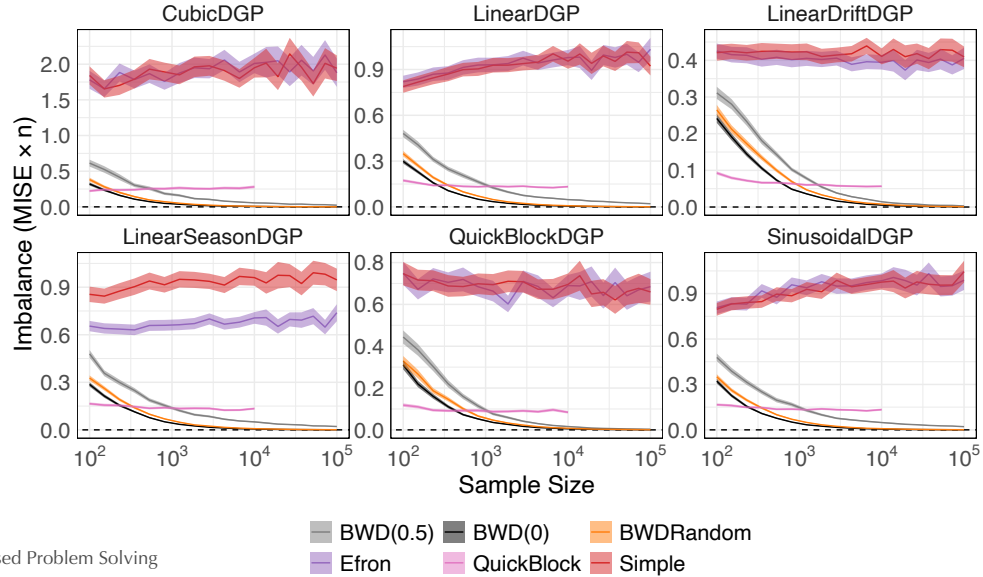
Blue: the Balancing Walk Design (BWD)

Total imbalance is small

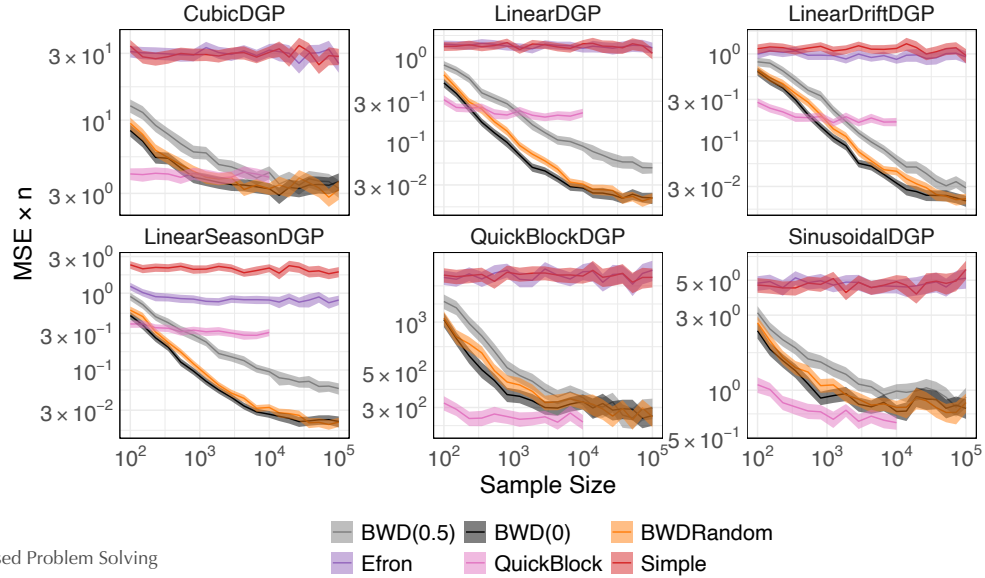


- Total imbalance: $\|\sum_i a_i \mathbf{x}_i - \sum_i (1 - a_i)\mathbf{x}_i\|_\infty$
- Our method (BWD): $\log(n/\delta)$
  - Pure randomization: $\sqrt{n}$
  - Optimal (online) rate: $\sqrt{\log n}$
  - Offline optimal rate [Harshaw et al., 2020]: 1
- A knob controls how much to prioritize imbalance versus robustness, as in Harshaw et al. [2020].
- Will be better than post-hoc covariate adjustment.
- Inference is (mostly) standard.

Two balanced treatments - L_2 norm



Two balanced treatments - causal MSE



Summary and future direction

- Better design is a huge opportunity.
- Must consider the social science context.
- But how can we change the practice of experimentation?
  - Software

Thank You!

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