# Designing Transportable Experiments Under S-Admissability

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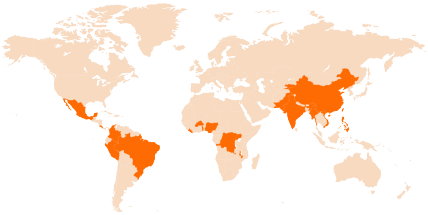
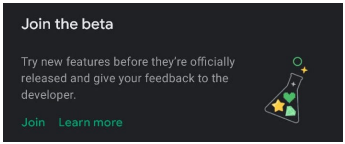
# Motivation



**(a)** The Metaketa Initiative's study sites




**(b)** Google Play's Beta program

Experimental samples in practice:

- Distinct from the population of interest, e.g., tests can be performed in **one country** and we wish to generalize to the whole world
- A subpopulation of the population of interest, e.g., **beta testers** of a product

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

# Setting

- Two populations
  - Source population ($p_S$) - where we can experiment
  - Target population ($p_T$) - where we want to understand effects
- Design Phase. Given covariates $\mathbf{X}$ from the Source , we are free to assign treatments, $A$
- Run the experiment in the Source
- Analysis Phase.
  - Observe outcomes $Y$ from the Source
  - Estimate the average treatment effect (ATE) in the Target

# Novelty

- Previous works: do not consider the Target distribution in the design phase.
- Our work: considers the Target distribution in the design phase.

# Assumptions

**Assumption**

$p_S(Y|X) = p_T(Y|X)$.

The above assumption corresponds to $S$-admissibility.

**Assumption**

$$Y^1 = X^T\beta_1 + noise \qquad Y^0 = X^T\beta_0 + noise$$

**Assumption**
*Overlap between source and target distributions, i.e.,* $p_T(X) > 0 \implies p_S(X) > 0$.

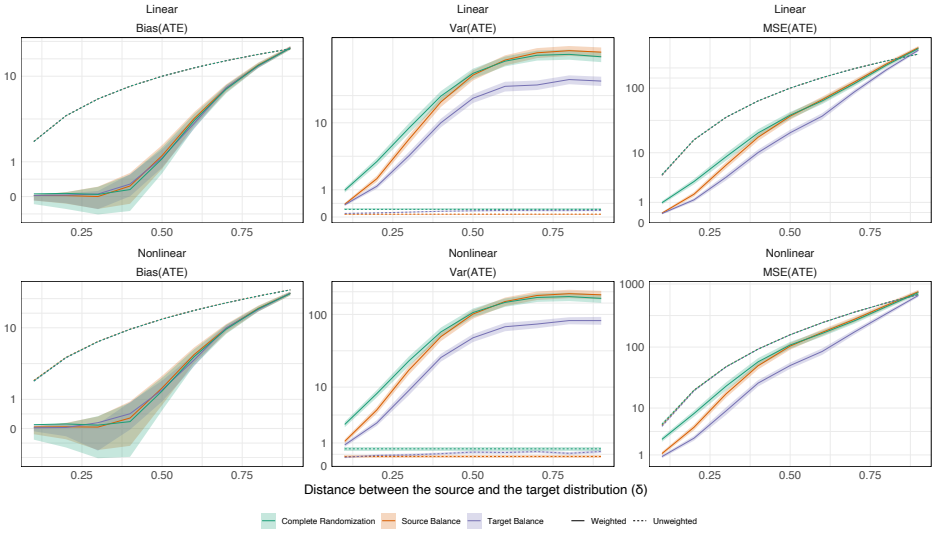
**Assumption**
*The density ratio (weight)* $p_T(X)/p_S(X)$ *is known.*

# Estimation via Posthoc Weighting and Target Balance

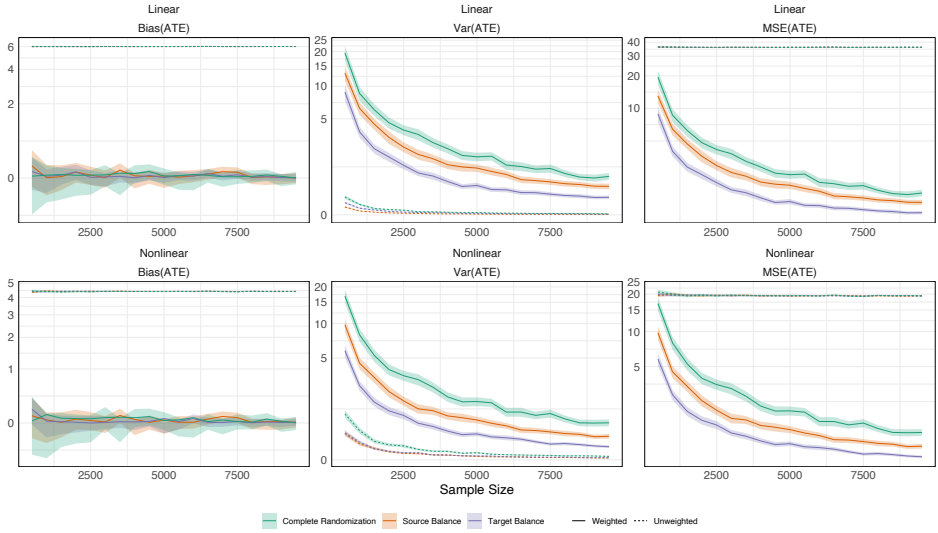
- Rerandomization:
  - Repeatedly randomize treatment assignments until a criteria (balance) is satisfied
- Importance-weighted estimator $\rightarrow$ unbiased estimator for the Target's ATE.
- Make the average observed features in the Treatment and Control similar ("balance")
  - Source Balance: make the users balance according to the Source
  - Target Balance: using importance weights, make the users balance according to the Target $\rightarrow$ reduces variance and achieves lower variance than Source Balance.

# Simulations

# Distance between source and target



# Sample size


Linear
Bias(ATE)
Linear
Var(ATE)
Linear
MSE(ATE)
Nonlinear
Bias(ATE)
Nonlinear
Var(ATE)
Nonlinear
MSE(ATE)
Sample Size
Complete Randomization
Source Balance
Target Balance
Weighted
Unweighted

# Thank You!

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