ADVENTURER EXPLORER TRAILBLAZER REBEL PIONEER CREATOR DEFENDER ADVENTURER EXPLORER TRAILBLAZER

REBEL PIONEER CREATOR DEFENDER ADVENTURER EXPLORER TRAILBLAZER REBEL PIONEER CREATOR DEFENDER ADVENTURER EXPLORER TRAILBLAZER REBEL PIONEER CREATOR DEFENDER

Manitoba Centre for Health Policy

Inverse Propensity Score Weights or IPTWs

University of Manitoba

EST. 1877

- Describe Different Types of Treatment Effects
  - Average Treatment Effect
  - Average Treatment Effect among Treated
  - Average Treatment Effect among Untreated
- Introduce different Weights using Propensity Score

FUNDAMENTAL PROBLEM OF CAUSAL INFERENCE

- Cannot Observe…

  The same person under both conditions

Average Effects

- Effects vary from individual to individual

- Average effect tells us…

  “the effect for a person--at random-- from our group.”

How do we get this “average effect”?

Compare average outcomes

Average Effects

- One state: the group **receives** the Full Day Kindergarten
- One state: the group **does not receive** the Full Day Kindergarten
- Difference in average outcomes between the two is the average effect of Full Day Kindergarten

FUNDAMENTAL PROBLEM OF CAUSAL INFERENCE

CANNOT OBSERVE GROUP under BOTH STATES

- Groups that we can actually observe
  - Those that really did receive FDK
  - Those that did not receive FDK
- Ask: Are these two groups comparable?
  - Minimize possibility that observed differences are due to confounding
- Strategies to deal with confounding:
  - Multiple Regression
  - Matching
  - **Propensity Score Methods**

EXPLORER INNOVATOR PIONEER ADVENTURER VISIONARY TRAILBLAZER

The Propensity Score—Review

- The Propensity Score: Probability that unit is exposed:
  The probability that the person receives FDK

The Propensity Score--Review

- If probability (aka propensity score) is close to 1
  - —VERY LIKELY to receive FDK given observed covariates
- If probability (aka propensity score) is close to 0
  - —VERY UNLIKELY to receive FDK given observed covariates

- Use propensity score to make and compare comparable groups

Weight Population to Estimate Treatment Effects

- Analytic Sample: Everyone Eligible to receive FDK:

- Treatment Effects

  - What is the average effect of the FDK among all of the children who could to receive FDK?

  - What is the effect of FDK among the children who ACTUALLY received FDK?

  - What would the effect of the FDK be for those who were eligible to receive it, but (for whatever reason) did not?

Weight Population to Estimate Treatment Effects

- Analytic Sample: Everyone Eligible to receive FDK:

- Treatment Effects

  - What is the average effect of the FDK among all of the children who could to receive FDK? **ATE**

  - What is the effect of FDK among the children who ACTUALLY received FDK? **ATT**

  - What would the effect of the FDK be for those who were eligible to receive it, but (for whatever reason) did not? **ATU**

Weight Population to Estimate Treatment Effects

- Treatment Effects—What question does each answer…

  Analytic Sample: Target Population for FDK

  - **ATE:** What is the effect among the target population?
  - **ATT:** Ok, we did not reach everyone in our target population… what is the effect among those that we *did* reach?
  - **ATU:** Ok, we did not reach everyone in our target population… what would the effect have been among those that we *did not* reach?

Treatment Effects: What are the comparison groups?

– **Average Treatment Effect** for FDK:

We take EVERYONE in the TARGET POPULATION…

- Imagine if EVERY CHILD **receives** FDK
  COMPARED WITH…
- Imagine if EVERY CHILD **does not receive** FDK

Treatment Effects: What are the comparison groups?

– **Average Treatment Effect Among the Treated**

Limit analyses to dyads WHO LOOK LIKE the dyads that ACTUALLY RECEIVED the benefit

- EVERYONE who **actually received** FDK

  COMPARED WITH

- EVERYONE who **looks like** those **who received** FDK but **did not**

Treatment Effects: What are the comparison groups?

– **Average Treatment Effect Among the Untreated** for FDK

Limit analyses to childrens WHO LOOK LIKE children that ACTUALLY DID NOT RECEIVE FDK

- EVERYONE who **actually did not receive** FDK

  COMPARED WITH

- EVERYONE who **looks like** those who **did not receive** FDK **but actually did**

Weights– Setting Up the Weights

Let

- FDK represent indicator for receiving Healthy Baby Benefit:
  - FDK=1 Person ACTUALLY RECEIVED FDK
  - FDK=0 Person ACTUALLY DID NOT RECEIVE FDK

- PS represent propensity score (probability of receiving FDK):
  - PS ranges between 0 and 1
  - PS close to 0 Based on observed covariates, dyad LOOKS LIKE they DID NOT receive FDK
  - PS close to 1 Based on observed covariates, dyad LOOKS LIKE they DID receive FDK

Weights: ATE

- **Average Treatment Effect** :

  Imagine we take EVERYONE in the TARGET POPULATION…

  – EVERYONE **receives** FDK

  COMPARED WITH…

  – EVERYONE **does not receive** FDK

$$WEIGHT_{Average\ Treatment\ Effect} = FDK * \frac{1}{PS} + (1 - FDK) * \frac{1}{1 - PS}$$

Manitoba Centre for Health Policy | University of Manitoba

Weights: ATT

- **Average Treatment Effect Among the Treated**

  Limit analyses to dyads WHO LOOK LIKE the dyads that ACTUALLY RECEIVED the benefit

  - EVERYONE who **actually received** FDK

    COMPARED WITH

  - EVERYONE who **looks like** those **who received** FDK but **did not**

$$ATT = FDK + (1 - FDK) * \frac{PS}{1 - PS}$$

EXPLORER INNOVATOR PIONEER ADVENTURER VISIONARY TRAILBLAZER

Weights: ATU

- **Average Treatment Effect Among the Untreated** for FDK

Limit analyses to children WHO LOOK LIKE children that ACTUALLY DID NOT RECEIVE FDK

- EVERYONE who **actually did not receive** FDK

  COMPARED WITH

- EVERYONE who **looks like** children who **did not receive** FDK **but actually did**

$$ATU = FDK * \frac{1 - PS}{PS} + (1 - FDK)$$

Manitoba Centre for Health Policy

University of Manitoba

Articles for More Information

- Hirano K, Imbens G. Estimation of Causal Effects using Propensity Score Weighting: An Application to Data on Right Heart Catheterization. 2001.
- Hirano K, Imbens G. Efficient Estimation of Average Treatment Effects Using the Estimated Propensity Score. 2003.
- McCaffrey D, Ridgeway G, Morral AR. Propensity Score Estimation with Boosted Regression for Causal Effects in Observational Studies. 2004.