Chapter12 IP weighting and marginal structures models

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Table of Contents

Table of Contents

The causal question

- Goal: Estimate the average causal effect of smoking cessation A weight gain Y
- causal effect := $E(Y^{a=1}) - E(Y^{a=0})$
- $E(Y^{a=1})$: mean weight gain that would have been observed if all individuals in the population had quit smoking before the follow-up visit

The causal question

- Average association effect $:= E(Y|A=1) - E(Y|A=0)$
- L=(sex,age,race,education,intensity and duration of smoking,physical activity in daily life, recreational exercise, weight): Confounder
- $E(Y^{a=1}) - E(Y^{a=0}) \neq E(Y|A=1) - E(Y|A=0)$
- We trying to adjust for these covariates with IP weighting

Table of Contents

Estimating IP weights via modeling

- IP weighting creates a pseudo-population in which the arrow from the covariates L to the treatment A is removed

- Pseudo-population has the following two properties
  1. A and L are statistically independent
  2. $E_{ps}(Y|A = a) = \sum_l E(Y|A = a, L = l)Pr(L = l)$

Estimating IP weights via modeling

- The individual-specific IP weights for treatment $W^A := \frac{1}{f(A|L)}$
- For Dichotomous treatment A , $f(A|L) = Pr(A = 1|L)$
- In section 2.4, We estimated $Pr(A = 1|L)$ nonparametrically
- In this chapter, we estimated $Pr(A = 1|L)$ with logistic regression model

Estimating IP weights via modeling

1. Estimate $Pr(A = 1|L)$ with logistic regression model
2. Create pseudo population by using IP weight
3. Estimate $E_{ps}(Y|A = 1) - E_{ps}(Y|A = 0)$ in pseudo population
4. If there is no confounding for the effect of A in the pseudo-population and the model for $Pr(A = 1|L)$ is correct, association is causation and an unbiased estimator of $E_{ps}(Y|A = 1) - E_{ps}(Y|A = 0)$ in the pseudo-population is also an unbiased estimator of $E(Y^{a=1}) - E(Y^{a=0})$ in the actual population

Estimating IP weights via modeling

- Estimating $E_{ps}(Y|A=1) - E_{ps}(Y|A=0)$ in the pseudo-population is to fit the linear mean model $E(Y|A) = \theta_0 + \theta_1 A$ by weighted Least square
- Find θ_0 and θ_1 such that minimize $\sum_{i=1}^{n}(\hat{W}_i(Y_i - \theta_0 - \theta_1 A))^2$ where $\hat{W}_i = \frac{1}{\hat{P}r(A=1|L)}$ for quiiter , $\hat{W}_i = \frac{1}{1-\hat{P}r(A=1|L)}$ for non-quiiter

Table of Contents

Stabilized IP weights

- Stabilized IP weighing is another way to create a pseudo-population in which A and L are independent
- IP weights $W^A := \frac{1}{f(A|L)}$
- Stabilized IP weights $SW^A := \frac{f(A)}{f(A|L)}$

Stabilized IP weights advantages

- Stabilized IP weights have more narrow confidence interval range than IP weights
- Pseudo population made by stabilized IP weights would be of the same size as the study population

Table of Contents

Marginal structural models

- $E(Y^a) = \beta_0 + \beta_1 a$: Marginal structural mean model , where Y^a :counterfactual
- Causal effect $\beta_1 = E(Y^{a=1}) - E(Y^{a=0})$
- In pseudo population, fit $E(Y|A) = \theta_0 + \theta_1 A$
- In pseudo population, the association is causation
- So, $\hat{\theta}_1$ is consistent estimator of β_1