

Tools and Techniques for ML Homework 2

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1 Complete case mean - unbiased or what

1.1

2 Regression imputation with $E[Y|X = x]$

2.1

$$\begin{aligned} E(\hat{\mu}_{\hat{f}\text{-full}}) &= E\left(\frac{1}{n} \sum_{i=1}^n \hat{f}(X_i)\right) \\ &= \frac{1}{n} \sum_{i=1}^n E(\hat{f}(X_i)) \\ &= \frac{1}{n} \sum_{i=1}^n E(E(Y|X = X_i)) \\ &= \frac{1}{n} \sum_{i=1}^n E(Y) \text{ (by Adam's law)} \\ &= E(Y). \end{aligned}$$

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2.2

$$\begin{aligned}
E\left[\frac{1}{n} \sum_{i=1}^n [R_i Y_i + (1 + R_i) \hat{f}(X_i)]\right] &= E\left[E\left[\frac{1}{n} \sum_{i=1}^n [R_i Y_i + (1 + R_i) \hat{f}(X_i)] \middle| X_1, \dots, X_n\right] \middle| X_1, \dots, X_n\right] \\
&= E\left[\frac{1}{n} \sum_{i=1}^n E[R_i | X_i] E[Y_i | X_i] + (1 - E[R_i | X_i]) E[\hat{f}(X_i) | X_i] \middle| X_1, \dots, X_n\right] \\
&= E\left[\frac{1}{n} \sum_{i=1}^n E[R_i | X_i] E[Y_i | X_i] + (1 - E[R_i | X_i]) E[Y_i | X_i] \middle| X_1, \dots, X_n\right] \\
&= E\left[\frac{1}{n} \sum_{i=1}^n E[Y_i | X_i] \middle| X_1, \dots, X_n\right] \\
&= E[E[Y] | X] \\
&= E[Y].
\end{aligned}$$

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3 A family of simple AIPW estimators

3.1

$$\hat{\mu}_{\text{ipw}-a} = \hat{\mu}_{\text{ipw}}(\mathcal{D} + a) - a = \frac{1}{n} \sum_{i=1}^n \frac{R_i Y_i}{\pi(X_i)} + \frac{a}{n} \sum_{i=1}^n \frac{R_i}{\pi(X_i)} - a,$$

so the control variate is $\frac{a}{n} \sum_{i=1}^n \frac{R_i}{\pi(X_i)}$ with expectation a .

3.2

We want to minimize the variance of $\hat{\mu}_{\text{ipw}-a}$.

$$\begin{aligned}
\text{Var}(\hat{\mu}_{\text{ipw}-a}) &= \text{Var}\left(\frac{RY}{\pi(X)} + \frac{aR}{\pi(X)} - a\right) \\
&= \text{Var}\left(\frac{RY}{\pi(X)} + a^2 \text{Var}\left(\frac{R}{\pi(X)}\right) + 2a \text{Cov}\left(\frac{RY}{\pi(X)}, \frac{R}{\pi(X)}\right)\right).
\end{aligned}$$

Thus to minimize $\text{Var}(\hat{\mu}_{\text{ipw}-a})$, we can set

$$a < -\frac{2\text{Cov}\left(\frac{RY}{\pi(X)}, \frac{R}{\pi(X)}\right)}{\text{Var}\left(\frac{R}{\pi(X)}\right)}.$$

4 Election forecasting

4.1 Fitting the regression

4.1.1

4.1.2

$$\frac{1}{n} \sum_{i=1}^n \frac{P(Y_i, X_i | T = 1)}{P(Y_i, X_i | R = 1)} l(f(X_i), Y_i)$$

4.2 Using our regression to forecast the election

4.2.1

$$\begin{aligned} E[f(x)|T = 1] &= E[f(x)|T = 1, X = x] \\ &= 1 \times P(Y = 1|T = 1, X = x) + 0 \times P(Y = 0|T = 1, X = x) \\ &= P(Y = 1|T = 1, X = x) \\ &= P(Y = 1|T = 1). \end{aligned}$$

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$$\begin{aligned} E[Tf(X)] &= E[E[Tf(X)|X]] \\ &= E[E[T|X]E[f(X)|X]] \\ &= E[P(T = 1|X)E[f(X)|T = 1, X]] \\ &= P(T = 1)E[f(X)|T = 1]. \end{aligned}$$

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$$\begin{aligned} \frac{E[\pi_t(X)f(X)]}{P(T = 1)} &= \frac{E[E[T|X]f(X)]}{P(T = 1)} \\ &= \frac{E[f(X)]E[T]}{P(T = 1)} \\ &= E[f(X)] \\ &= E[E[Y|X, T]] \\ &= E[Y|T]. \end{aligned}$$

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$$\begin{aligned} E[\pi_t(X)] &= E[E[T|X]] \\ &= E[T] \\ &= P(T = 1). \end{aligned}$$

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