

### Exercise

⑧  $\mathbb{E}[\hat{\theta}_e | \theta_0] = \mathbb{E}[\bar{y}] = \frac{1}{n} \sum_{i=1}^n \mathbb{E}[y_i] = \frac{1}{n} \sum \theta = \theta$   
 $\hat{\theta}_e$  is unbiased.

$$\mathbb{E}[\hat{\theta}_b | \theta_0] = \mathbb{E}[w\bar{y} + (1-w)\mu_0]$$
$$\boxed{w\theta + (1-w)\mu_0}$$

If  $\mu_0 \neq \theta_0$  then  $\hat{\theta}_b$  is biased.

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Which has lower variance?

$$\begin{aligned} \mathbb{V}(\hat{\theta}_e | \theta_0) &= \mathbb{V}(\bar{y}) = \mathbb{V}\left(\frac{1}{n} \sum y_i\right) = \frac{1}{n^2} \sum \mathbb{V}(y_i) \\ &= \frac{1}{n^2} \sum \sigma^2 = \boxed{\frac{1}{n} \cdot \sigma^2} \end{aligned}$$

$$\begin{aligned} \mathbb{V}(\hat{\theta}_b | \theta_0) &= \mathbb{V}(w\bar{y} + (1-w)\mu_0) \\ &= \mathbb{V}(w\bar{y}) \\ &= w^2 \mathbb{V}(\bar{y}) \\ &= \boxed{\frac{w^2 \cdot \sigma^2}{n}} \end{aligned}$$

$\hat{\theta}_b$  has smaller variance.

$$MSE = E[(\hat{\theta} - \theta_0)^2 | \theta_0] \quad (\star)$$

$$= \text{var}(\hat{\theta} | \theta_0) + \text{Bias}^2(\hat{\theta} | \theta_0)$$

$$\boxed{MSE(\hat{\theta}_e | \theta_0) = \frac{\text{var} + \text{bias}}{n} = \frac{\sigma^2}{n} + O^2}$$

$$MSE(\hat{\theta}_w | \theta_0)$$

$$\boxed{\text{TRICK}} \quad \theta_0 = w\theta_0 + (1-w)\theta_0$$

$$w/(\star) : E[(w(\bar{y} - \theta_0) + \frac{(1-w)(\mu_0 - \theta_0)}{1})^2]$$

$$= E\left[\underbrace{w^2(\bar{y} - \theta_0)^2}_{\text{var } \bar{y}} + 2w(\bar{y} - \theta_0)(1-w)(\mu_0 - \theta_0) + (1-w)^2(\mu_0 - \theta_0)^2\right]$$

$$\boxed{w^2 \cdot \frac{\sigma^2}{n} + 0 + (1-w)^2(\mu_0 - \theta_0)^2}$$

$$\text{MSE} [\hat{\theta}_b | \theta_0] < \text{MSE} [\hat{\theta}_e | \theta_0] \quad \text{when}$$

$$(M_0 - \theta_0)^2 < \frac{\sigma^2}{n} \frac{1+w}{1-w}$$

$$= \sigma^2 \left( \frac{1}{n} + \frac{2}{K_0} \right)$$

Rule of thumb: if prior guess of  $M_0$  is within 2 sd of  $\theta_0$  & we pick  $K_0 = 1$  then Bayes estimator probably has lower MSE.



$$MSE(\hat{\theta}|\theta_0) = \mathbb{E}[\underbrace{(\hat{\theta} - \theta_0)^2}_{\substack{\uparrow \\ \text{mean squared error}}}]$$

$$\text{let } m = \mathbb{E}[\hat{\theta}|\theta_0]$$

TRICK:

$$MSE(\hat{\theta}|\theta_0) = \mathbb{E}[(\hat{\theta} - m + m - \theta_0)^2 | \theta_0]$$

$$= \mathbb{E}[(\hat{\theta} - m)^2 + 2(\hat{\theta} - m)(m - \theta_0) + (m - \theta_0)^2 | \theta_0]$$

$$\underbrace{\mathbb{E}[(\hat{\theta} - m)^2]}_{\text{Var}(\hat{\theta}|\theta_0)} + \underbrace{2\mathbb{E}[(\hat{\theta} - m)(m - \theta_0)]}_0 + \underbrace{\mathbb{E}[(m - \theta_0)^2 | \theta_0]}_{\substack{(m - \theta_0)^2 \\ \text{Bias}^2(\hat{\theta}|\theta_0)}}$$

## Frequentist risk

How well does  $\hat{\theta}$  perform on avg across different datasets?

$$R(\theta, \hat{\theta}) = \mathbb{E}[L(\theta, \hat{\theta})^2 | \theta]$$

↓ function of  $y$

If  $L(\theta, \hat{\theta}) = (\hat{\theta} - \theta)^2$  then  $R(\theta, \hat{\theta}) = \text{MSE}(\theta, \hat{\theta})$ .