

Homework 2 Solutions

Hansen 2.5

a) The mean squared error is given by

$$MSE = E[(e^2 - h(X))^2]$$

b) e^2 is closely related to a measure of the magnitude of how far off our predictions of Y given X are. For example, given X , if we predict a “high” value of e^2 , it would suggest that we expect our predictions to not be too accurate for that value of X .

c) Recall that $\sigma^2(X) = E[e^2|X]$ so that

$$\begin{aligned} MSE &= E[(e^2 - E[e^2|X]) - (h(X) - E[e^2|X])]^2 \\ &= E[(e^2 - E[e^2|X])^2] - 2E[(e^2 - E[e^2|X])(h(X) - E[e^2|X])] + E[(h(X) - E[e^2|X])^2] \end{aligned}$$

Let's consider each of these three terms.

The first term does not depend on $h(X)$ so it is invariant to our choice of h .

The second term is equal to 0 after applying the law of iterated expectations.

The third term is minimized by setting $h(X) = E[e^2|X] = \sigma^2(X)$ which implies that MSE is minimized by $\sigma^2(X)$.

Hansen 2.6

$$\begin{aligned} \text{var}(Y) &= E[\text{var}(Y|X)] + \text{var}(E[Y|X]) \\ &= E[\text{var}(m(X) + e|X)] + \text{var}(E[m(X) + e|X]) \\ &= E[\text{var}(e|X)] + \text{var}(m(X)) \\ &= E[E[e^2|X]] + \text{var}(m(X)) \\ &= E[e^2] + \text{var}(m(X)) \\ &= \sigma^2 + \text{var}(m(X)) \end{aligned}$$

where the first equality holds by the law of total variance (Theorem 2.8 in the textbook), the second equality holds by substituting for Y , the third equality holds because (i) conditional on X the variance of $m(X)$ equals 0, and (ii) $E[m(X) + e|X] = m(X)$, the fourth equality holds because $\text{var}(e|X) = E[e^2|X] - E[e|X]^2$ (by the definition of conditional variance), the fifth equality holds by the law of iterated expectations, and the last equality holds by the definition of σ^2 .

Hansen 2.10

True.

$$E[X^2e] = E[X^2 \underbrace{E[e|X]}_{=0}] = 0$$

Hansen 2.11

False. Here is a counterexample. Suppose that $X = 1$ with probability $1/2$ and that $X = -1$ with probability $1/2$. Importantly, this means that $X^2 = 1$, $X^3 = X$, $X^4 = 1$, and so on; this further implies that $E[X] = 0$, $E[X^2] = 1$, $E[X^3] = 0$ and so on. Also, suppose that $E[e|X] = X^2$. Then, $E[Xe] = E[XE[e|X]] = E[X \cdot X^2] = E[X^3] = 0$. However, $E[X^2e] = E[X^2E[e|X]] = E[X^2 \cdot X^2] = E[X^4] = 1 \neq 0$

Hansen 2.12

False. Here is a counterexample. Suppose that $E[e^2|X]$ depends on X , then e and X are not independent. As a concrete example, $e|X \sim N(0, X^2)$ (that is, conditional on X , e follows a normal distribution with mean 0 and variance X^2).

Hansen 2.13

False. The same counterexample as in 2.11 works here. In that case, $E[Xe] = 0$, but $E[e|X] = X^2$ (in that case $X^2 = 1$, but the main point is that it is not equal to 0 for all values of X).

Hansen 2.14

False. In this case, higher order moments can still depend on X . For example, $E[e^3|X]$ can still depend on X . If it does, then e and X are not independent.

Extra Question

```
# load data
data(Star, package="Ecdat")

# limit data to boys in small or regular class
data <- subset(Star,
               classk %in% c("small.class", "regular") & sex=="boy")

# part (a)
att_a <- mean(subset(data, classk == "small.class")$tmathssk) -
```

```
mean(subset(data, classk=="regular")$tmathssk)
att_a
```

```
## [1] 13.67522
```

```
# part (b)
data <- droplevels(data)           # drop extra factors
X <- model.matrix(~classk, data=data) # get data matrix
Y <- as.matrix(data$tmathssk)      # get outcome
bet <- solve(t(X)%*%X)%*%t(X)%*%Y # estimate beta
att_b <- bet[2]                    # report coefficient on small class
att_b
```

```
## [1] 13.67522
```

```
# part (c)
X <- model.matrix(~classk + totexpk + freelunk, data=data) # X w/ extra vars
bet <- solve(t(X)%*%X)%*%t(X)%*%Y # estimate beta
att_c <- bet[2]                    # report coef. on small
att_c
```

```
## [1] 13.42333
```

The results from parts (a) and (b) are exactly identical. The result from part (c) is similar, but not exactly the same — this is exactly what we would expect.