# STATS 413 Hw5

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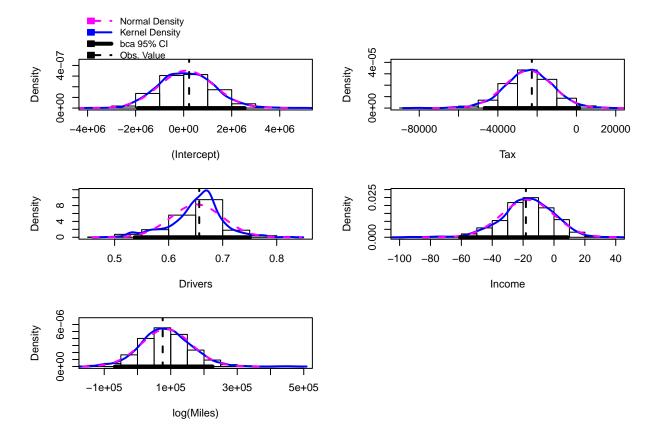
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### Exercise 7.1

The estimate of coefficients, standard errors, F-tests are the same between Sue's and Joe's analyses. However, the  $\sigma^2$  of Joe's analysis is two times of Sue's.

### Exercise 7.10

```
(7.10.1)
fuel2001<-read.csv("fuel2001.csv")</pre>
model_OLS <- lm(FuelC ~ Tax+Drivers+Income+log(Miles), data = fuel2001)</pre>
#bootstrap
boot1 <- Boot(model_OLS, R=999)</pre>
confint(boot1, type="bca")
## Bootstrap bca confidence intervals
##
##
                        2.5 %
                                    97.5 %
## (Intercept) -1.905686e+06 2.544796e+06
               -4.675186e+04 1.388159e+03
## Drivers
                5.373065e-01 7.503208e-01
               -6.077791e+01 8.737136e+00
## Income
## log(Miles) -6.775023e+04 2.258179e+05
# Compare with normal
confint(model_OLS)
##
                        2.5 %
                                    97.5 %
## (Intercept) -2.226912e+06 2.681625e+06
## Tax
               -5.160861e+04 6.208566e+03
## Drivers
               6.123492e-01 7.008500e-01
## Income
               -5.331132e+01 1.691998e+01
## log(Miles) -9.536430e+04 2.469525e+05
(7.10.2)_{-}
hist(boot1)
```



>ISLR:

## Exercise 8

### Part a)

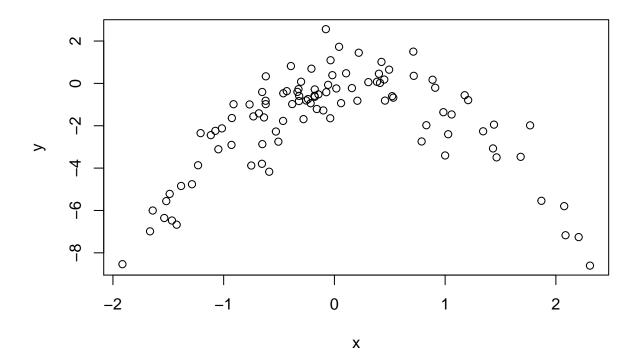
```
set.seed(1)
y <- rnorm(100)
x <- rnorm(100)
y <- x - 2*x^2 + rnorm(100)</pre>
```

n = 100 are observations

p=2 are features

$$Y = X - 2X^2 + \epsilon$$

### Part b)



There is a quadratic relationship between x and y,

```
Part c)
set.seed(1)
df <- data.frame(y, x, x2=x^2, x3=x^3, x4=x^4)
fit1 <- glm(y ~ x, data=df)</pre>
cv.err1 <- cv.glm(df, fit1)</pre>
cv.err1$delta
## [1] 5.890979 5.888812
fit2 <- glm(y \sim x + x2, data=df)
cv.err2 <- cv.glm(df, fit2)</pre>
cv.err2$delta
## [1] 1.086596 1.086326
fit3 <- glm(y \sim x + x2 + x3, data=df)
cv.err3 <- cv.glm(df, fit3)</pre>
cv.err3$delta
## [1] 1.102585 1.102227
fit4 \leftarrow glm(y \sim x + x2 + x3 + x4, data=df)
cv.err4 <- cv.glm(df, fit4)</pre>
cv.err4$delta
## [1] 1.114772 1.114334
Part d)
```

```
set.seed(2020)
df \leftarrow data.frame(y, x, x2=x^2, x3=x^3, x4=x^4)
fit1 <- glm(y ~ x, data=df)</pre>
cv.err1 <- cv.glm(df, fit1)</pre>
cv.err1$delta
## [1] 5.890979 5.888812
fit2 <- glm(y \sim x + x2, data=df)
cv.err2 <- cv.glm(df, fit2)</pre>
cv.err2$delta
## [1] 1.086596 1.086326
fit3 <- glm(y \sim x + x2 + x3, data=df)
cv.err3 <- cv.glm(df, fit3)</pre>
cv.err3$delta
## [1] 1.102585 1.102227
fit4 \leftarrow glm(y \sim x + x2 + x3 + x4, data=df)
cv.err4 <- cv.glm(df, fit4)</pre>
cv.err4$delta
```

#### ## [1] 1.114772 1.114334

The results are the same. Since the LOOCV methods uses all the other methods as the reference for prediction.

#### Part e

Model (ii) using X and  $X^2$  had the lowest error, which shows that our prediction is correct. Since the true model was generated using a quadratic formula.

#### Part f)

```
fit0 <- lm(y ~ poly(x,4))
summary(fit0)</pre>
```

```
##
## Call:
## lm(formula = y \sim poly(x, 4))
##
## Residuals:
      Min
             1Q Median
                              ЗQ
                                     Max
## -2.8914 -0.5244 0.0749 0.5932 2.7796
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.8277
                       0.1041 -17.549 <2e-16 ***
                          1.0415 2.224
## poly(x, 4)1 2.3164
                                          0.0285 *
## poly(x, 4)2 -21.0586
                         1.0415 -20.220
                                          <2e-16 ***
## poly(x, 4)3 -0.3048
                          1.0415 -0.293
                                           0.7704
## poly(x, 4)4 -0.4926
                          1.0415 -0.473
                                          0.6373
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.041 on 95 degrees of freedom
## Multiple R-squared: 0.8134, Adjusted R-squared: 0.8055
## F-statistic: 103.5 on 4 and 95 DF, p-value: < 2.2e-16
```

Summary shows that only X and  $X^2$  are statistically significant predictors. Which agrees with our cross-validation results in part (e).

## Exercise 9

```
Part a)
data(Boston)
mu <- mean(Boston$medv)</pre>
## [1] 22.53281
Part b)
sd <- sd(Boston$medv)/sqrt(nrow(Boston))</pre>
## [1] 0.4088611
The standard error of the sample mean is equal to the standard deviation of the dataset divided by the
number of observations. Part c)
set.seed(1)
mean.fn <- function(var, id) {</pre>
  return(mean(var[id]))
boot.res <- boot(Boston$medv, mean.fn, R=200)</pre>
boot.res
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = Boston$medv, statistic = mean.fn, R = 200)
##
##
## Bootstrap Statistics :
       original
                     bias
                              std. error
## t1* 22.53281 0.04741601
                               0.3971741
From bootstrap with R=200, our estimation of the std.err is 0.43, which is close to 0.41.
boot.res$t0 - 2*sd(boot.res$t) # lower bound
## [1] 21.73846
boot.res$t0 + 2*sd(boot.res$t) # upper bound
## [1] 23.32715
t.test(Boston$medv)
##
##
    One Sample t-test
## data: Boston$medv
```

```
## t = 55.111, df = 505, p-value < 2.2e-16
## alternative hypothesis: true mean is not equal to 0
## 95 percent confidence interval:
## 21.72953 23.33608
## sample estimates:
## mean of x
## 22.53281
The 95% confidence interval of the t-test result is approximately equal to the lower and upper bound found
by bootstrap. Part e)
median <- median(Boston$medv)</pre>
median
## [1] 21.2
Part f)
set.seed(1)
median.fn <- function(var, id) {</pre>
  return(median(var[id]))
}
boot.res <- boot(Boston$medv, median.fn, R=100)</pre>
boot.res
##
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
## boot(data = Boston$medv, statistic = median.fn, R = 100)
##
##
## Bootstrap Statistics :
       original bias
                          std. error
           21.2 -0.029 0.3461316
Estimated standard error is 0.3461 with r = 100.
Part g)
mu0.1 <- quantile(Boston$medv, 0.1)</pre>
mu0.1
##
    10%
## 12.75
Part h)
set.seed(1)
quantile10 <- function(var, id) {</pre>
  return(quantile(var[id], 0.1))
(boot.res <- boot(Boston$medv, quantile10, R=100))</pre>
## ORDINARY NONPARAMETRIC BOOTSTRAP
##
##
## Call:
```

```
## boot(data = Boston$medv, statistic = quantile10, R = 100)
##
##
## Bootstrap Statistics :
## original bias std. error
## t1* 12.75 0.008 0.5370477
```

Estimated standard error is 0.537