Stat Computing HW1

Michael Ackerman

September 8th

```
gender <- c('M','M','F','M','F','F','M','F','M')</pre>
age \leftarrow c(34, 64, 38, 63, 40, 73, 27, 51, 47)
smoker <- c('no','yes','no','no','yes','no','no','no','yes')</pre>
exercise <- factor(c('moderate','frequent','some','some','moderate','none','moderate','moderate'</pre>
                    levels=c('none','some','moderate','frequent'), ordered=TRUE
)
los \leftarrow c(4,8,1,10,6,3,9,4,8)
x <- data.frame(gender, age, smoker, exercise, los)
##
     gender age smoker exercise los
## 1
        M 34 no moderate
## 2
          M 64
                   yes frequent
                                   8
## 3
         F 38
                  no
                            some
                                  1
## 4
          M 63
                                  10
                            some
          F 40
## 5
                   yes moderate
                                  6
          F 73
## 6
                    no
                            none
                                   3
          M 27
## 7
                   no
                            none
                                  9
          F 51
## 8
                   no moderate
                                   4
## 9
          M 47
                   yes moderate
Model:
model <- lm(los ~ gender + age + smoker + exercise, dat=x)
1) It appears that has being a male has the greatest effect on your length of stay with a value of 4.509.
```

2)

```
mod <- lm(los~gender)
summary(mod)
```

```
##
## Call:
## lm(formula = los ~ gender)
##
## Residuals:
##
     Min
             1Q Median
                           3Q
                                 Max
##
    -3.8
           -0.5
                   0.2
                                 2.5
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
                 3.500
                            1.099
                                    3.186
                                           0.0154 *
## (Intercept)
## genderM
                 4.300
                            1.474
                                    2.917
                                           0.0224 *
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 2.197 on 7 degrees of freedom
## Multiple R-squared: 0.5487, Adjusted R-squared: 0.4842
## F-statistic: 8.51 on 1 and 7 DF, p-value: 0.02243
3)
mod$coef
                    genderM
## (Intercept)
           3.5
                        4.3
##
4)
sqrt(diag(vcov(mod)))
## (Intercept)
                    genderM
      1.098701
                   1.474061
5)
mod <- lm(los ~ gender, dat=x)</pre>
mod.c <- coef(summary(mod))</pre>
teststat <- mod.c[,1]/mod.c[,2]</pre>
2*pt(teststat['genderM'], 7, lower.tail = FALSE)
##
      genderM
## 0.02243214
6)
fitted(mod)-predict(mod)
##
                              2
                                             3
                                                            4
               1
## -5.329071e-15 -1.776357e-15 -1.332268e-15 -1.776357e-15 -1.332268e-15
                              7
## -1.332268e-15 -1.776357e-15 -1.332268e-15 -1.776357e-15
It looks like the functions work a tiny bit different, yet create essentially the same vector. 7)
newdata <- data.frame(gender=c('F','M','F'))</pre>
predict(mod,newdata)
   1 2
## 3.5 7.8 3.5
8)
```

```
residuals <- fitted(mod)- x$los</pre>
residuals
##
                 3
                      4
                            5
                                 6
                                      7
    3.8 -0.2 2.5 -2.2 -2.5 0.5 -1.2 -0.5 -0.2
9)
residuals (mod)
##
            2
                            5
                                 6
                                                  9
                 3
                                    7
## -3.8 0.2 -2.5 2.2 2.5 -0.5 1.2 0.5 0.2
Same result in absolute value.
10)
sum(residuals^2) - deviance(mod)
## [1] 0
These functions do the same thing.
11)
sqrt(deviance(mod)/df.residual(mod))
## [1] 2.197401
This is the same as the Residual Standard Error shown by the original model.
12)
xmen <- x[gender== "M",]</pre>
women <- x[gender=="F",]</pre>
X-Men is the proper labeling.
13)
var(xmen$los)
## [1] 5.2
var(women$los)
## [1] 4.333333
14)
```

```
t.test(women$los, xmen$los)
##
##
    Welch Two Sample t-test
##
## data: women$los and xmen$los
## t = -2.9509, df = 6.8146, p-value = 0.02205
\#\# alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -7.7647486 -0.8352514
## sample estimates:
## mean of x mean of y
##
         3.5
                   7.8
t.test(women$los, xmen$los, var.equal = T)
##
##
    Two Sample t-test
##
## data: women$los and xmen$los
## t = -2.9171, df = 7, p-value = 0.02243
\#\# alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -7.7856014 -0.8143986
## sample estimates:
## mean of x mean of y
##
         3.5
                   7.8
The equal variance assumption causes that p-value in the t-test comparison to be the same as the full model
with the genderM variable.
##this is nice and consice.
t.test(los ~ gender, dat=x, var.equal=TRUE)
##
   Two Sample t-test
##
## data: los by gender
## t = -2.9171, df = 7, p-value = 0.02243
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
## -7.7856014 -0.8143986
## sample estimates:
## mean in group F mean in group M
                                7.8
##
               3.5
```