

# Bios 6301: Assignment 1

*Elizabeth Sigworth*

*due October 10, 2016*

*(informally) Due Thursday, 08 September, 1:00 PM*

50 points total.

This assignment won't be submitted until we've covered Rmarkdown. Place your R code in between the appropriate chunks for each question. Check your output by using the Knit HTML button in RStudio.

## Create a Data Set

A data set in R is called a data.frame. This particular data set is made of three categorical variables, or factors: `gender`, `smoker`, and `exercise`. In addition `exercise` is an ordered factor. `age` and `los` (length of stay) are continuous variables.

```
gender <- c('M','M','F','M','F','F','M','F','M')
age <- c(34, 64, 38, 63, 40, 73, 27, 51, 47)
smoker <- c('no','yes','no','no','yes','no','no','no','yes')
exercise <- factor(c('moderate','frequent','some','some',
                     'moderate','none','none','moderate','moderate'),
                  levels=c('none','some','moderate','frequent'), ordered=TRUE)
)
los <- c(4,8,1,10,6,3,9,4,8)
x <- data.frame(gender, age, smoker, exercise, los)
x
```

```
##   gender age smoker exercise los
## 1      M  34     no moderate   4
## 2      M  64    yes frequent   8
## 3      F  38     no    some    1
## 4      M  63     no    some   10
## 5      F  40    yes moderate   6
## 6      F  73     no     none    3
## 7      M  27     no     none    9
## 8      F  51     no moderate   4
## 9      M  47    yes moderate   8
```

## Create a Model

We can create a model using our data set. In this case I'd like to estimate the association between `los` and all remaining variables. This means `los` is our dependent variable. The other columns will be terms in our model.

The `lm` function will take two arguments, a formula and a data set. The formula is split into two parts, where the vector to the left of `~` is the dependent variable, and items on the right are terms.

```
lm(los ~ gender + age + smoker + exercise, dat=x)
```

```
##
## Call:
## lm(formula = los ~ gender + age + smoker + exercise, data = x)
##
## Coefficients:
## (Intercept)      genderM          age      smokeryes    exercise.L
##    0.588144    4.508675    0.033377    2.966623   -2.749852
## exercise.Q    exercise.C
##   -0.710942    0.002393
```

1. Looking at the output, which coefficient seems to have the highest effect on `los`? (2 points)

Looking at the output, it would appear that `gender` has the highest effect on length of stay, since this variable has the largest coefficient.

This can be tough because it also depends on the scale of the variable. If all the variables are standardized, then this is not the case.

Given that we only have nine observations, it's not really a good idea to include all of our variables in the model. In this case we'd be "over-fitting" our data. Let's only include one term, `gender`.

### Warning

When choosing terms for a model, use prior research, don't just select the variable with the highest coefficient.

2. Create a model using `los` and `gender` and assign it to the variable `mod`. Run the `summary` function with `mod` as its argument. (5 points)

```
mod <- lm(los ~ gender, dat=x)
summary(mod)
```

```
##
## Call:
## lm(formula = los ~ gender, data = x)
##
## Residuals:
##    Min      1Q  Median      3Q     Max
##   -3.8   -0.5    0.2    1.2    2.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.500      1.099   3.186  0.0154 *
## genderM        4.300      1.474   2.917  0.0224 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 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
```

The summary of our model reports the parameter estimates along with standard errors, test statistics, and p-values. This table of estimates can be extracted with the `coef` function.

## Estimates

3. What is the estimate for the intercept? What is the estimate for gender? Use the `coef` function. (3 points)

```
coef(summary(mod))
```

```
##           Estimate Std. Error  t value  Pr(>|t|)
## (Intercept)      3.5    1.098701  3.185581 0.01537082
## genderM          4.3    1.474061  2.917110 0.02243214
```

The estimate for the intercept is 3.5, and the estimate for gender is 4.3.

4. The second column of `coef` are standard errors. These can be calculated by taking the `sqrt` of the `diag` of the `vcov` of the `summary` of `mod`. Calculate the standard errors. (3 points)

```
stderrors <- sqrt(diag(vcov(summary(mod))))
stderrors # standard errors
```

```
## (Intercept)    genderM
##    1.098701    1.474061
```

The third column of `coef` are test statistics. These can be calculated by dividing the first column by the second column.

```
mod <- lm(los ~ gender, data = x)
mod.c <- coef(summary(mod))
mod.c[,1]/mod.c[,2] # test statistics
```

```
## (Intercept)    genderM
##    3.185581    2.917110
```

The fourth column of `coef` are p values. This captures the probability of observing a more extreme test statistic. These can be calculated with the `pt` function, but you will need the degrees-of-freedom. For this model, there are 7 degrees-of-freedom.

5. Use the `pt` function to calculate the p value for gender. The first argument should be the test statistic for gender. The second argument is the degrees-of-freedom. Also, set the `lower.tail` argument to `FALSE`. Finally multiply this result by two. (4 points)

```
pval <- 2*pt(q = 2.917110, df = 7, lower.tail = FALSE)
pval # the p-value for gender
```

```
## [1] 0.02243216
```

## Predicted Values

The estimates can be used to create predicted values.

```
3.5+(x$gender=='M')*4.3
```

```
## [1] 7.8 7.8 3.5 7.8 3.5 3.5 7.8 3.5 7.8
```

6. It is even easier to see the predicted values by passing the model `mod` to the `predict` or `fitted` functions. Try it out. (2 points)

```
predict(object = mod)
```

```
## 1 2 3 4 5 6 7 8 9
## 7.8 7.8 3.5 7.8 3.5 3.5 7.8 3.5 7.8
```

```
fitted(object = mod)
```

```
## 1 2 3 4 5 6 7 8 9
## 7.8 7.8 3.5 7.8 3.5 3.5 7.8 3.5 7.8
```

7. `predict` can also use a new data set. Pass `newdat` as the second argument to `predict`. (3 points)

```
newdat <- data.frame(gender=c('F','M','F'))
predict(mod, newdat)
```

```
## 1 2 3
## 3.5 7.8 3.5
```

## Residuals

The difference between predicted values and observed values are residuals.

8. Use one of the methods to generate predicted values. Subtract the predicted value from the `x$los` column. (5 points)

```
x.res <- x$los-predict(mod)
x.res # residuals
```

```
## 1 2 3 4 5 6 7 8 9
## -3.8 0.2 -2.5 2.2 2.5 -0.5 1.2 0.5 0.2
```

9. Try passing `mod` to the `residuals` function. (2 points)

```
residuals(mod)
```

```
## 1 2 3 4 5 6 7 8 9
## -3.8 0.2 -2.5 2.2 2.5 -0.5 1.2 0.5 0.2
```

10. Square the residuals, and then sum these values. Compare this to the result of passing `mod` to the `deviance` function. (6 points)

```
sqred <- residuals(mod)^2
sum(sqred)
```

```
## [1] 33.8
```

```
deviance(mod)
```

```
## [1] 33.8
```

```
deviance(mod)==sum(sqred) # the sum of the squared residuals is the deviance
```

```
## [1] TRUE
```

Remember that our model object has two items in the formula, `los` and `gender`. The residual degrees-of-freedom is the number of observations minus the number of items to account for in the model formula.

This can be seen by passing `mod` to the function `df.residual`.

```
df.residual(mod) # degrees of freedom of residuals
```

```
## [1] 7
```

11. Calculate standard error by dividing the deviance by the degrees-of-freedom, and then taking the square root. Verify that this matches the output labeled “Residual standard error” from `summary(mod)`. (5 points)

```
sqrt(deviance(mod)/df.residual(mod))
```

```
## [1] 2.197401
```

```
summary(mod)
```

```
##
## Call:
## lm(formula = los ~ gender, data = x)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
##    -3.8    -0.5     0.2     1.2     2.5
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)    3.500     1.099   3.186  0.0154 *
## genderM        4.300     1.474   2.917  0.0224 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 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
```

The two values are equivalent.

Note it will also match this output:

```
predict(mod, se.fit=TRUE)$residual.scale
```

```
## [1] 2.197401
```

## T-test

Let's compare the results of our model to a two-sample t-test. We will compare `los` by men and women.

12. Create a subset of `x` by taking all records where gender is 'M' and assigning it to the variable `men`. Do the same for the variable `women`. (4 points)

```
men <- x[gender=='M',]  
women <- x[gender=='F',]
```

13. By default a two-sampled t-test assumes that the two groups have unequal variances. You can calculate variance with the `var` function. Calculate variance for `los` for the `men` and `women` data sets. (3 points)

```
var(men$los) # variance for los for the men
```

```
## [1] 5.2
```

```
var(women$los) # variance for los for the women
```

```
## [1] 4.333333
```

14. Call the `t.test` function, where the first argument is `los` for women and the second argument is `los` for men. Call it a second time by adding the argument `var.equal` and setting it to `TRUE`. Does either produce output that matches the p value for gender from the model summary? (3 points)

```
t.test(women$los,men$los) # t test not assuming equal variance
```

```
##  
## Welch Two Sample t-test  
##  
## data: women$los and men$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$los,men$los,var.equal=TRUE) # t test assuming equal variance
```

```
##  
## Two Sample t-test  
##  
## data: women$los and men$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 model that assumes equal variance produces the same p-value from the model summary.

An alternative way to call `t.test` is to use a formula.

```
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  
## 3.5 7.8
```

```
# compare p-values  
t.test(los ~ gender, dat=x, var.equal=TRUE)$p.value
```

```
## [1] 0.02243214
```

```
coef(summary(lm(los ~ gender, dat=x)))[2,4]
```

```
## [1] 0.02243214
```