# STA206 Fall 2022: Take Home Quiz (Solution)

#### **Instruction**:

- In this quiz, you will be asked to perform some tasks in R
- You should submit a .html (preferred format) or .docx file

In Quiz\_data.Rdata you will find a data set called data with three variables: Y and X1, X2. For the following, you should use the original data and no standardization should be applied.

• (a). Load the data into the R workspace. How many observations are there in this data?

```
#(Type your code in the space below)
load("Quiz_data.Rdata")
cat("There are", dim(data)[1], "observations in the data.")
```

- ## There are 100 observations in the data.
  - (b). What is the type of each variable? For each variable, draw one plot to depict its distribution. Arrange these plots into one overall graph.

```
#(Type your code in the space below)
sapply(data, class)

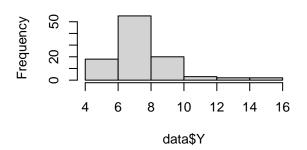
## Y X1 X2

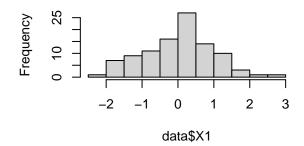
## "numeric" "numeric" "numeric"

par(mfrow=c(2,2))
hist(data$Y)
hist(data$X1)
hist(data$X2)
par(mfrow=c(1,1))
```

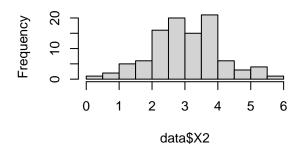
## Histogram of data\$Y

## Histogram of data\$X1





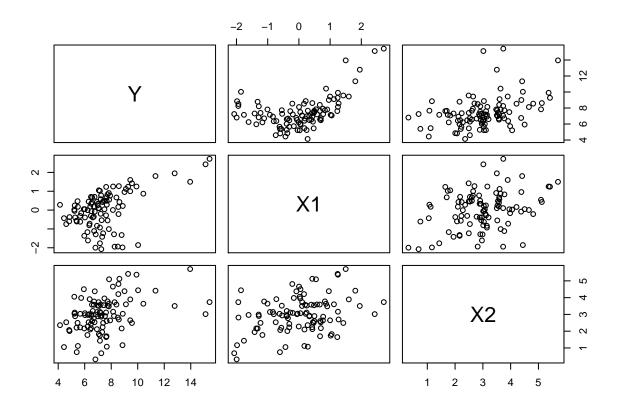
### Histogram of data\$X2



(Type your answer here): All three variables are of numeric type.

• (c). Draw the scatter plot matrix and obtain the correlation matrix for these three variables. Briefly describe how Y appears to be related to X1 and X2.

# (Type your code in the space below)
plot(data) ## alternatively: pairs(data)



#### cor(data)

```
## Y X1 X2
## Y 1.0000000 0.4872571 0.3987890
## X1 0.4872571 1.0000000 0.3236289
## X2 0.3987890 0.3236289 1.0000000
```

Y is positively related to  $X_1$  and  $X_2$ . The relationship between Y and  $X_2$  appears to be linear, but there appears to be a nonlinear relationship between Y and  $X_1$ .

(Type your answer here):

• (d). Fit a first-order model with Y as the response variable and X1, X2 as the predictors (referred to as Model 1). How many regression coefficients are there in Model 1?

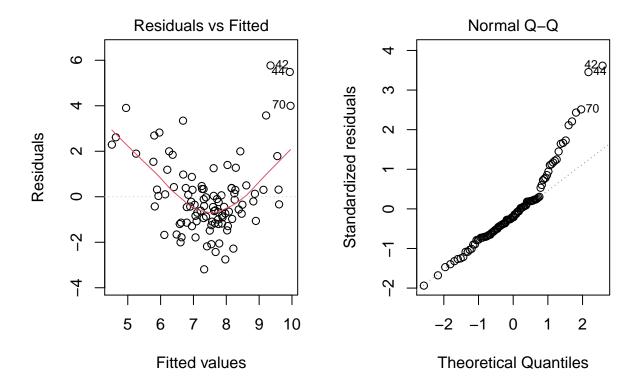
```
# (Type your code in the space below)
fit1=lm(Y~X1+X2, data=data) ## alternatively: lm(Y~., data=data)
```

(Type your answer here):

There are 3 regression coefficients (including the intercept) in Model 1.

• (e). Conduct model diagnostics for Model 1 and comment on how well model assumptions hold.

```
# (Type your code in the space below)
par(mfrow=c(1,2))
plot(fit1, which=1:2)
```



### par(mfrow=c(1,1))

(Type your answer here):

There is a nonlinear trend in the residuals vs. fitted values plot, which indicates the linearity assumption does not hold well. Moreover, the residuals Q-Q plot deviates from a straight line pattern. This might indicate that the normal error assumption is violated, but it could also be due to nonlinearity.

• (f). Fit a 2nd-order polynomial regression model with Y as the response variable and X1, X2 as the predictors (referred to Model 2). Calculate the variance inflation factors for this model. Does there appears to be strong multicollinearity? Explain briefly.

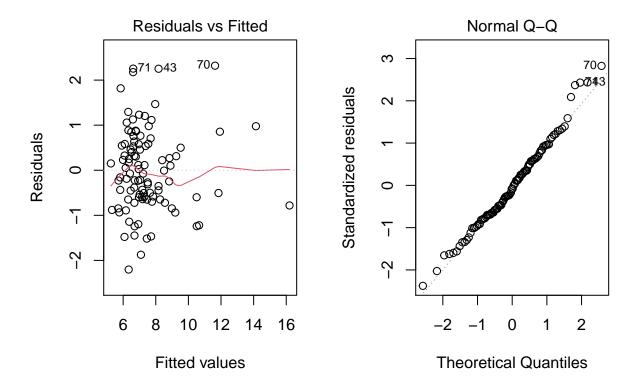
```
# (Type your code in the space below)
fit2=lm(Y~X1+I(X1^2)+X2+I(X2^2)+X1:X2,data=data)
diag(solve(cor(model.matrix(fit2)[,-1]))) ## alternatively, set up design matrix manually
##
          X1
               I(X1^2)
                              Х2
                                    I(X2^2)
                                                X1:X2
              1.251545 27.499045 27.772480 13.464178
## 12.942934
## alternatively
library(car)
## Warning: package 'car' was built under R version 4.0.5
## Loading required package: carData
## Warning: package 'carData' was built under R version 4.0.5
vif(fit2)
               I(X1^2)
                                    I(X2^2)
##
          X1
                              X2
                                                X1:X2
```

## 12.942934 1.251545 27.499045 27.772480 13.464178

(Type your answer here): The maximum VIF is 27 and greater than 10, which indicates fairly high multi-collinearity among Model 2 X variables.

• (g). Conduct model diagnostics for Model 2. Do model assumptions appear to hold better under Model 2 compared to under Model 1? Explain briefly.

```
# (Type your code in the space below)
par(mfrow=c(1,2))
plot(fit2, which=1:2)
```



```
par(mfrow=c(1,1))
```

(Type your answer here):

Compared to residuals plots under Model 1, model assumptions appear to hold better under Model 2 as there is no obvious nonlinear trend in the residuals vs. fitted values plot and the residuals Q-Q plot follows a straight line pattern quite well.

• (h). Under Model 2, obtain the 99% confidence interval for the mean response when X1=X2=0.

```
#(Type your code in the space below)
x.new=data.frame(X1=0,X2=0)
predict.lm(fit2, x.new, level=0.99, interval="confidence")
## fit lwr upr
```

## 1 5.258508 3.41719 7.099826

(Type your answer here): The confidence interival is [3.41719, 7.099826].

• (i). At the significance level 0.01, test whether or not all terms involving X2 may be simultaneously dropped out of Model 2. State your conclusion.

```
#(Type your code in the space below)
fit3 = lm(Y \sim X1 + I(X1^2), data = data)
anova(fit3, fit2)
## Analysis of Variance Table
##
## Model 1: Y ~ X1 + I(X1^2)
## Model 2: Y ~ X1 + I(X1^2) + X2 + I(X2^2) + X1:X2
               RSS Df Sum of Sq
    Res.Df
                                           Pr(>F)
                                      F
## 1
         97 117.899
## 2
         94 82.541 3
                          35.358 13.422 2.307e-07 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## alternatively
aov2=anova(fit2)
SSR.2.1=sum((aov2$'Sum Sq')[3:5])
Fstar=(SSR.2.1/3)/aov2$`Mean Sq`[6]
Fstar
## [1] 13.42233
1-pf(Fstar, 3,94)
```

## [1] 2.307253e-07

## ---

(Type your answer here): The p-value is 2.307e - 07 and is smaller than 0.01, so we can **not** simultaneously drop all terms involving X2 out of Model 2.

• (j) Find a model that has less regression coefficients and at the same time a larger adjusted coefficient of multiple determination compared to Model 2. Briefly state how you reach this model.

```
#(Type your code in the space below)
fit4 = lm(Y^{-}.^{2} + I(X1^{2}), data = data) ## Adjusted R-squared: 0.7732
summary(fit4)
##
## lm(formula = Y \sim .^2 + I(X1^2), data = data)
##
## Residuals:
##
        Min
                  1Q
                       Median
                                     3Q
                                             Max
## -2.21958 -0.56348 -0.08906 0.53519 2.50797
##
## Coefficients:
##
               Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.671860
                          0.308676 15.135 < 2e-16 ***
                                      2.760 0.00694 **
## X1
               0.744665
                          0.269843
## X2
               0.590256
                          0.094036
                                      6.277 1.03e-08 ***
## I(X1^2)
               0.991038
                          0.076309
                                     12.987 < 2e-16 ***
## X1:X2
               0.007041
                          0.086669
                                      0.081 0.93542
```

```
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9364 on 95 degrees of freedom
## Multiple R-squared: 0.7824, Adjusted R-squared: 0.7732
## F-statistic: 85.38 on 4 and 95 DF, p-value: < 2.2e-16
summary(fit2) ## Adjusted R-squared: 0.7729
##
## Call:
## lm(formula = Y \sim X1 + I(X1^2) + X2 + I(X2^2) + X1:X2, data = data)
## Residuals:
##
                 1Q
                     Median
                                   3Q
                                           Max
       Min
## -2.20233 -0.60960 -0.07387 0.57877 2.31998
##
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
                          0.70035
                                    7.508 3.39e-11 ***
## (Intercept) 5.25851
                          0.33911
                                    2.761 0.00694 **
## X1
               0.93613
## I(X1^2)
               0.99757
                          0.07668 13.009 < 2e-16 ***
## X2
               0.16454
                          0.46573
                                    0.353 0.72467
## I(X2^2)
               0.06977
                          0.07475
                                    0.933 0.35304
## X1:X2
              -0.05632
                          0.11013 -0.511 0.61031
## Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.9371 on 94 degrees of freedom
## Multiple R-squared: 0.7844, Adjusted R-squared: 0.7729
## F-statistic: 68.38 on 5 and 94 DF, p-value: < 2.2e-16
##alternatively
fit4=lm(Y~X1+I(X1^2)+X2, data=data)
summary(fit4) ##Adjusted R-squared:
                                     0.7756
##
## Call:
## lm(formula = Y \sim X1 + I(X1^2) + X2, data = data)
## Residuals:
                 1Q
                      Median
## -2.22047 -0.56627 -0.08829 0.53604 2.53136
## Coefficients:
##
              Estimate Std. Error t value Pr(>|t|)
## (Intercept) 4.67108
                          0.30693 15.219 < 2e-16 ***
## X1
               0.76504
                          0.09905
                                    7.724 1.09e-11 ***
## I(X1^2)
                          0.06830 14.551 < 2e-16 ***
               0.99374
## X2
               0.59043
                          0.09352
                                    6.313 8.46e-09 ***
## ---
## Signif. codes: 0 '***' 0.001 '**' 0.05 '.' 0.1 ' ' 1
## Residual standard error: 0.9316 on 96 degrees of freedom
## Multiple R-squared: 0.7824, Adjusted R-squared: 0.7756
## F-statistic: 115 on 3 and 96 DF, p-value: < 2.2e-16
```

(Type your answer here): From the scatter plot, there is no evidence that Y and  $X_2$  have any non-linear relationship, so we may drop  $X_2^2$  from Model 2. As a result, the adjusted R-squared is increased from 0.7729 to 0.7732. Another option is to drop both  $X_2^2, X_1 * X_2$  from Model 2. The  $R_a^2$  would be increased to 0.7756.