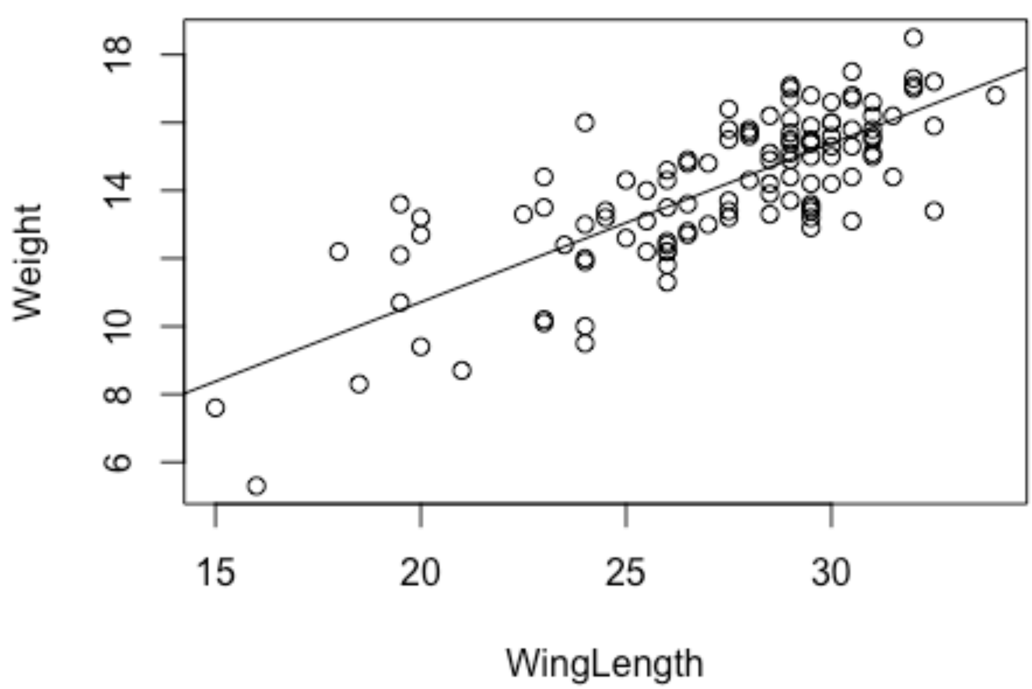
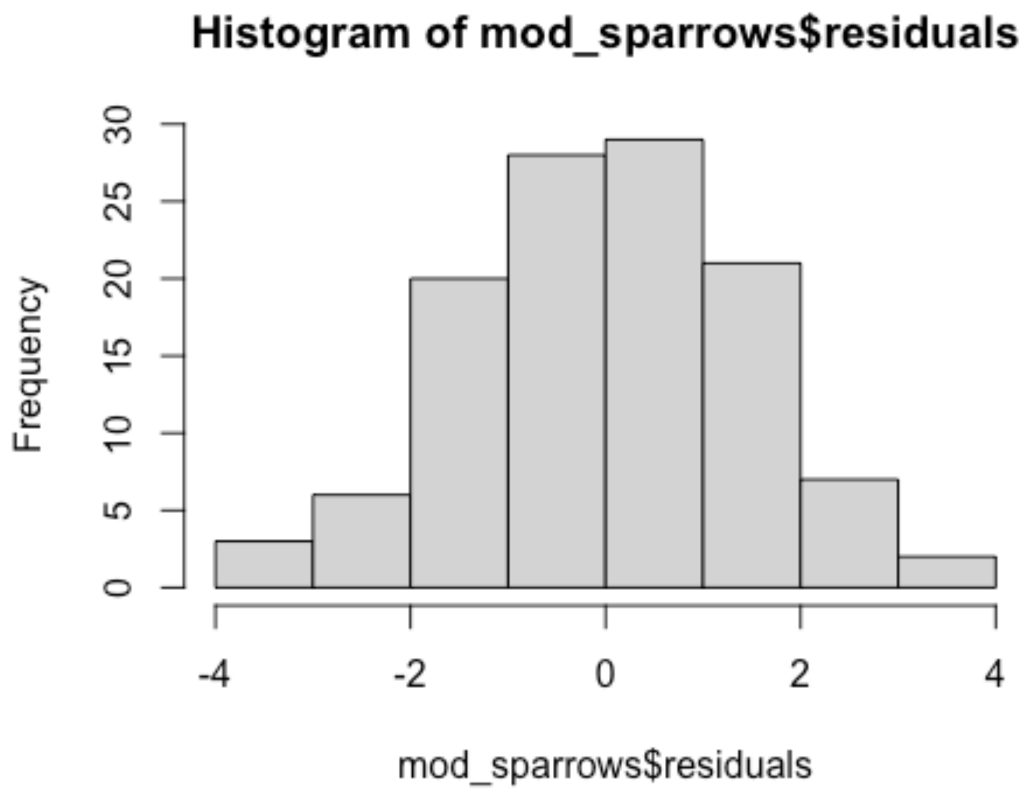
STOR 455 Extra Credit HW. Due 04/30 11:55pm. Submit through Sakai Assignments.

```r
library(Stat2Data)
data("FranticFingers")

# Chapter 1 Exercises
# 3, 5, 23, 27, 31, 47

#3
data("Sparrows")
head(Sparrows)

##   Treatment Weight WingLength
## 1   control   14.9       29.0
## 2   control   15.0       31.0
## 3   control   14.3       25.0
## 4   control   17.0       29.0
## 5   control   16.0       30.0
## 6   control   16.2       31.5

mod_sparrows=lm(Weight~WingLength,data=Sparrows)
summary(mod_sparrows)

##
## Call:
## lm(formula = Weight ~ WingLength, data = Sparrows)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.5440 -0.9935  0.0809  1.0559  3.4168
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  1.36549    0.95731   1.426    0.156
## WingLength   0.46740    0.03472  13.463   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.4 on 114 degrees of freedom
## Multiple R-squared:  0.6139, Adjusted R-squared:  0.6105
## F-statistic: 181.3 on 1 and 114 DF,  p-value: < 2.2e-16

#To extract the intercept
B1=summary(mod_sparrows)$coefficients[2,1]
B1

## [1] 0.467404
```

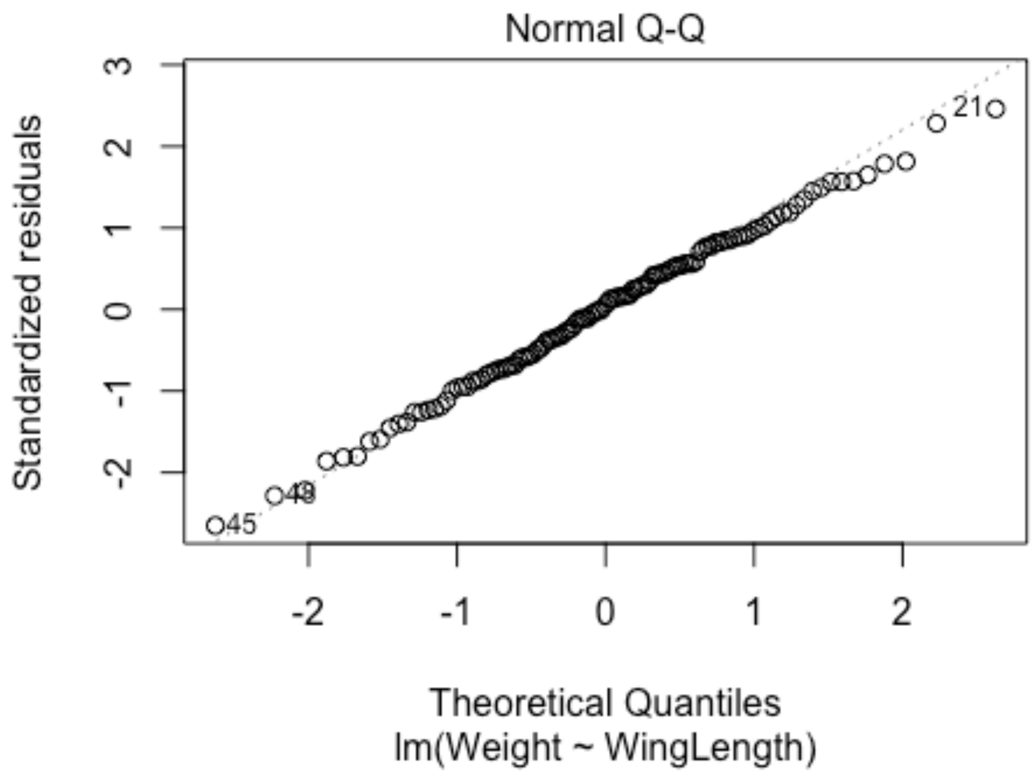
```
#the slope of the least squares regression line for predicting sparrow weight
from wing length is 0.467404

#5
B0=summary(mod_sparrows)$coefficients[1,1]
B0

## [1] 1.36549

#the intercept of the least squares regression line for predicting sparrow
weight from wing length is 1.36549

#23
#a
plot(Weight~WingLength,data=Sparrows)
abline(mod_sparrows)
```



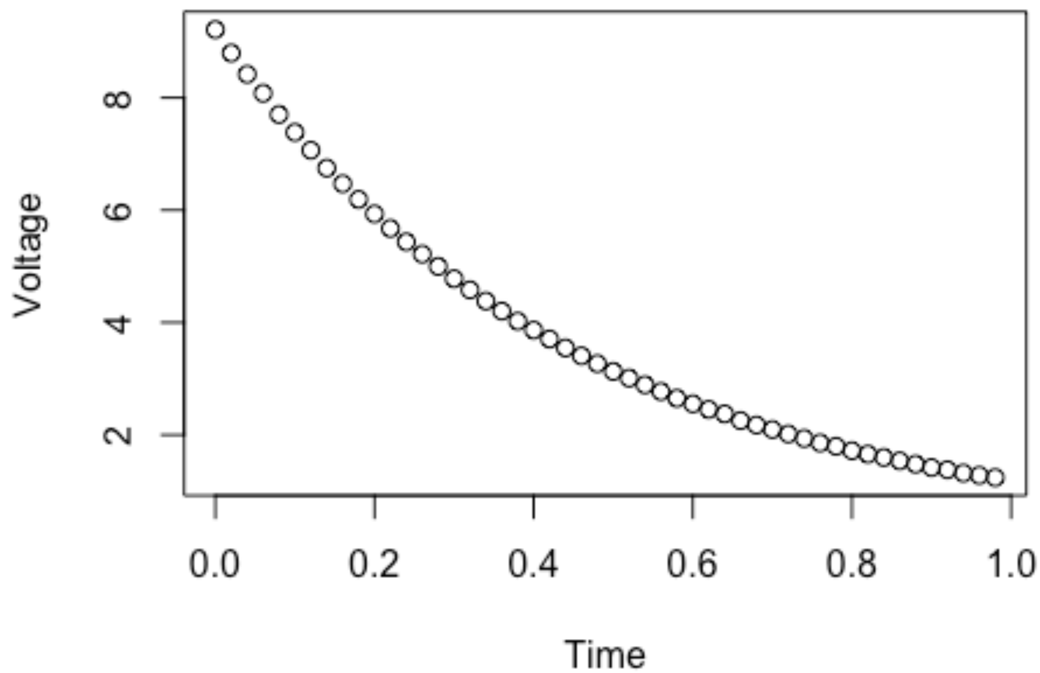

```
#The general fit is pretty good according to the plot and no obvious outliers
or influential points.

#b
hist(mod_sparrows$residuals)
```



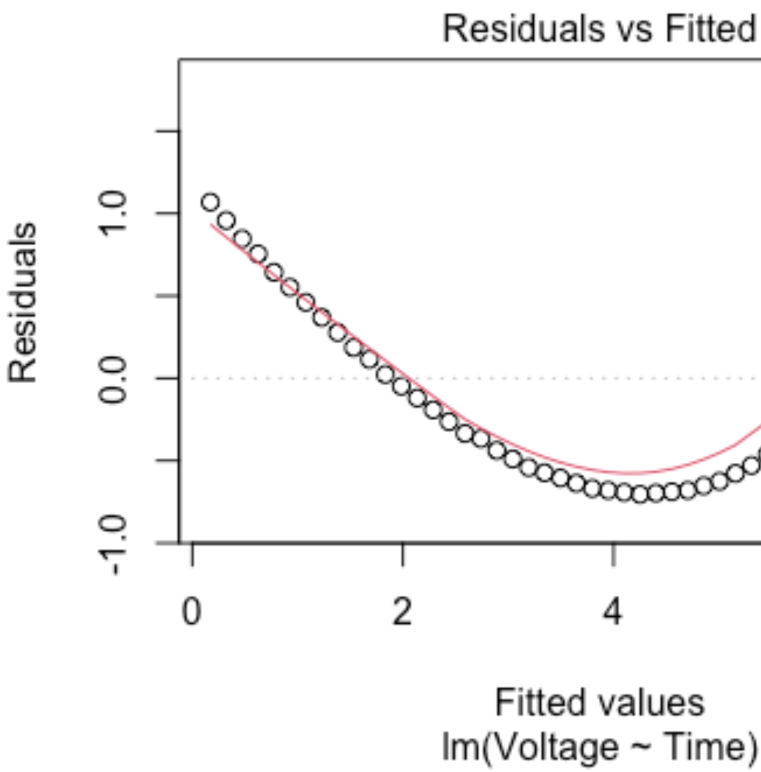

```
#no obvious outlier, the distribution look pretty normal and it's a bell
shape with center at zero.

#c
plot(mod_sparrows,2)
```



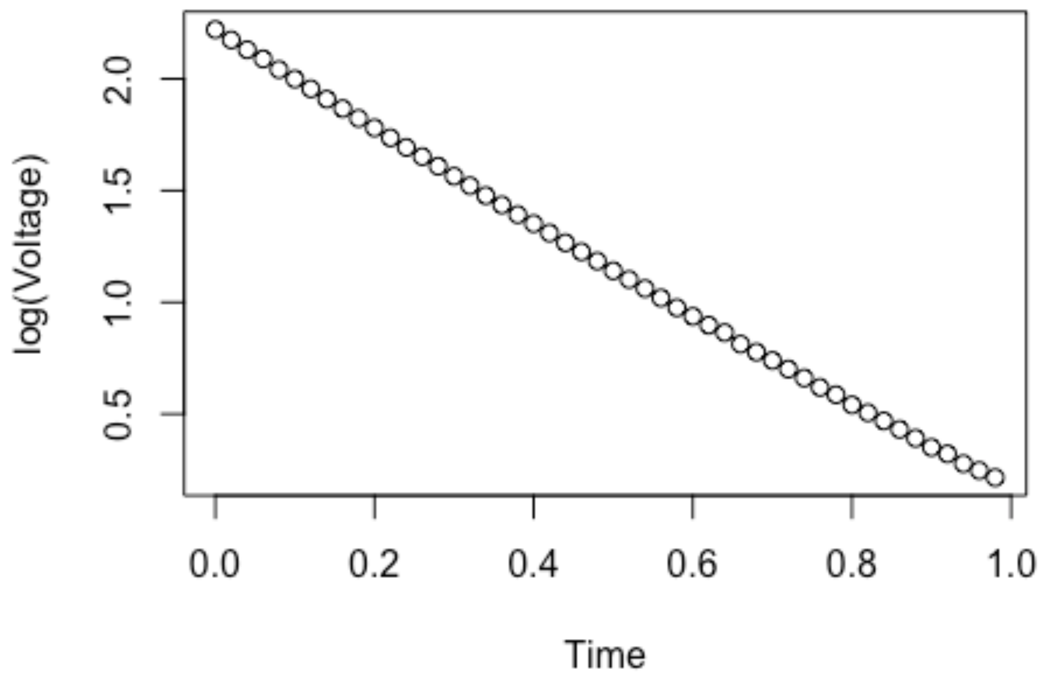

```
#Normal qqplot demonstrates good fit, with very small deviation on the right
tail. Thus the normality condition is good.

#27
#a
data("Volts")
plot(Voltage~Time,data=Volts)
```




```
mod_voltage=lm(Voltage~Time,data=Volts)
#It is showing a negative nonlinear relationship between voltage and time. As
time increasing, voltage is decreasing at a decreasing rate.

#b
plot(mod_voltage,1)
```

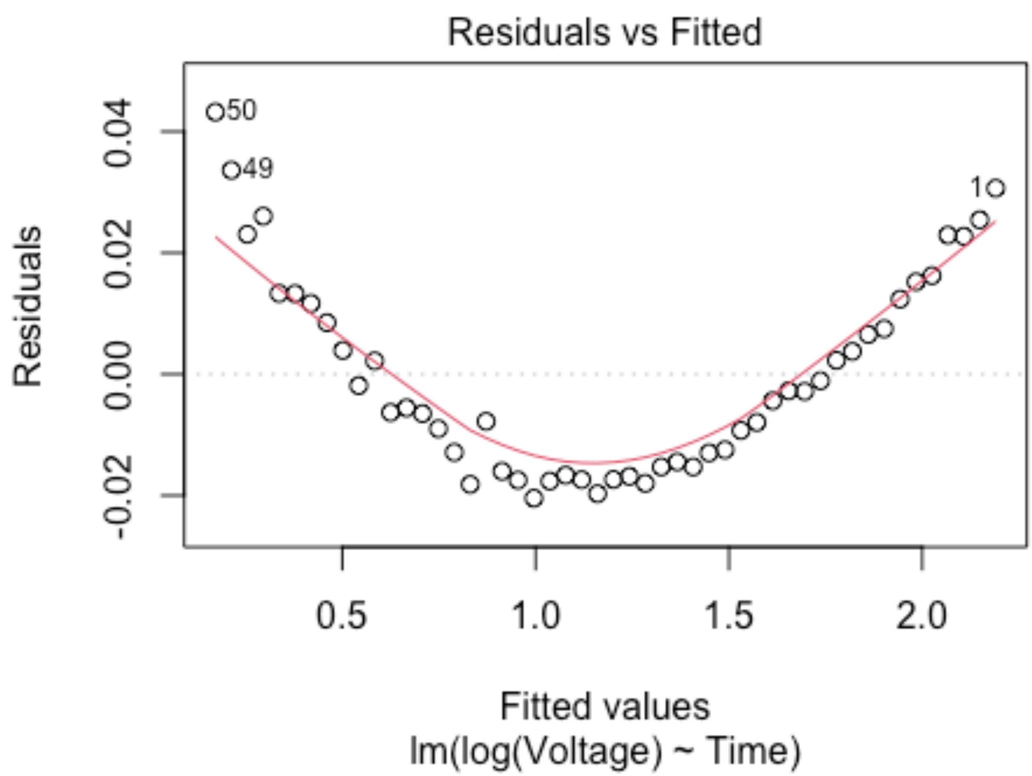



```
#Residual vs. fitted plot is showing big problem with linearity since there
is a clear curved pattern. Thus,it is not a good idea to fit a linear model
to predict Voltage from Time

#c
plot(log(Voltage)~Time,data=Volts)
```

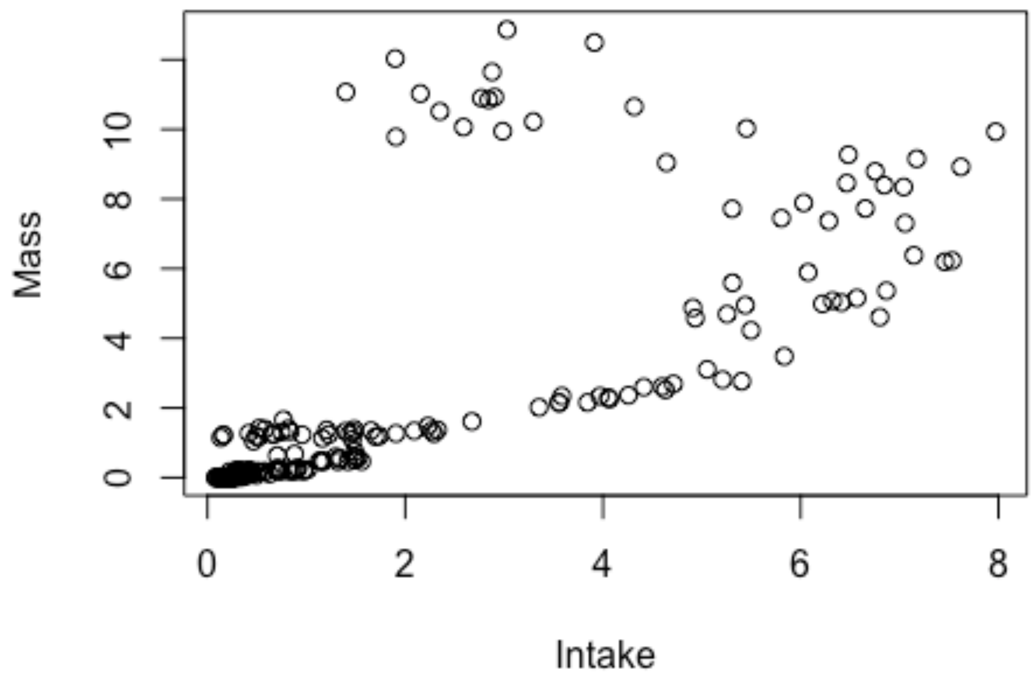



```
#The plot has a very linear pattern for logvoltage and time(linear negative
slope)

#d
mod_voltage_2=lm(log(Voltage)~Time,data=Volts)
summary(mod_voltage_2)

##
## Call:
## lm(formula = log(Voltage) ~ Time, data = Volts)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.020448 -0.015084 -0.003621  0.012190  0.043212
##
## Coefficients:
##              Estimate Std. Error t value Pr(>|t|)
## (Intercept)  2.189945   0.004637   472.3   <2e-16 ***
## Time        -2.059065   0.008154  -252.5   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.01664 on 48 degrees of freedom
```

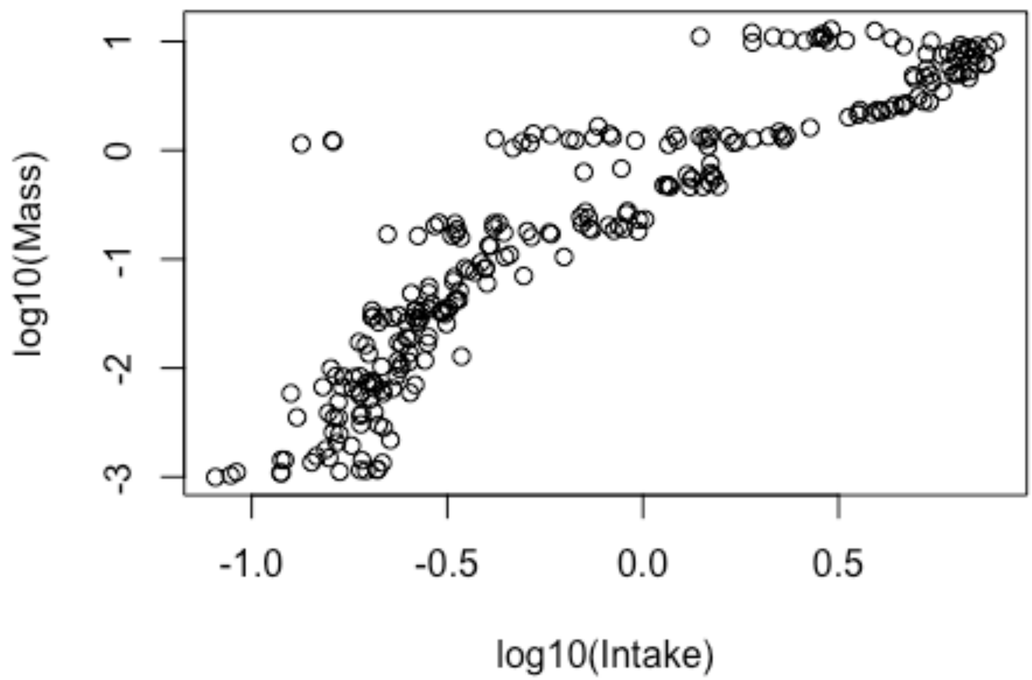
```
## Multiple R-squared:  0.9992, Adjusted R-squared:  0.9992
## F-statistic: 6.377e+04 on 1 and 48 DF,  p-value: < 2.2e-16

#Prediction equation: log(Voltage)=2.18994-2.059065*Time

#e
plot(mod_voltage_2,1)
```




```
#Though there is still a curved pattern(nonlinear), but from the value of y-
axis(residuals), the magnitude of residuals are much smaller than the
previous one(part b, before the transformation)

#31
#a
data("Caterpillars")
plot(Mass~Intake,data=Caterpillars)
```



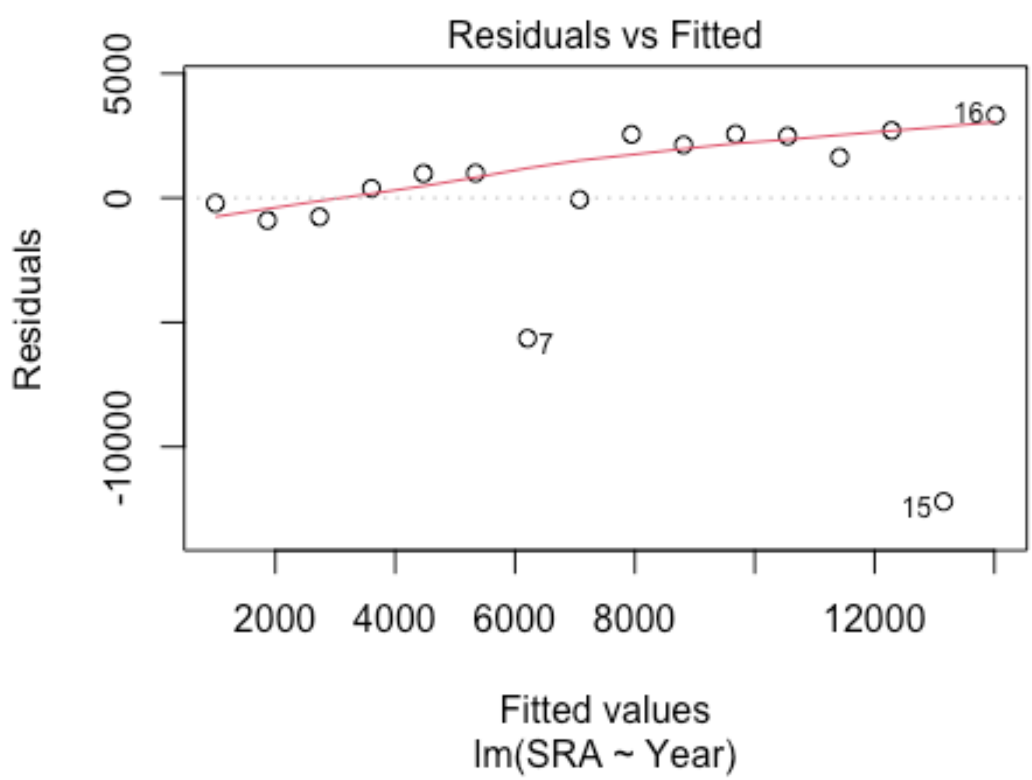

```
#the plot is showing there is a nonlinear relationship between Mass and
Intake

#b
plot(log10(Mass)~log10(Intake),data=Caterpillars)
```




```
#The plot is showing a positive relationship between log10(Mass) and
log10(Intake). But there are also some deviations and a slight curved
pattern(nonlinear), so the relationship is increasing at a decreasing rate.

#c
#no,linear model should not be used to model either of the relationship in
part a and b because both plots are demonstrating curved patterns, so the
relationship is nonlinear between two variables which means we can't use
linear model to model them. If comparing these two models, the second model's
linearity condition is better than the first model but still not linear
enough.

#47
#a
data("Retirement")
mod_retirement=lm(SRA~Year, data=Retirement)
summary(mod_retirement)

##
## Call:
## lm(formula = SRA ~ Year, data = Retirement)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -12201.0   -350.9    990.2   2503.6   3328.7
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1732400.2   439864.9  -3.938  0.00148 **
## Year           868.0      219.4   3.956  0.00144 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 4046 on 14 degrees of freedom
## Multiple R-squared:  0.5278, Adjusted R-squared:  0.494
## F-statistic: 15.65 on 1 and 14 DF,  p-value: 0.001436
```

```
plot(mod_retirement,1)
```




```
resid(mod_retirement)[7]
```

```
##         7
## -5642.725
```

```
resid(mod_retirement)[15]
```

```
##        15
## -12200.96
```

```
#The fit is SRA=-1732400.2+868.0*Year. The residual for 7th
observation(Year=2003) is -5642.725, and the residual for 15th
obersvation(Year=2011) is -12200.96
rstandard(mod_retirement)[7]
```

```
##         7
## -1.445406
```

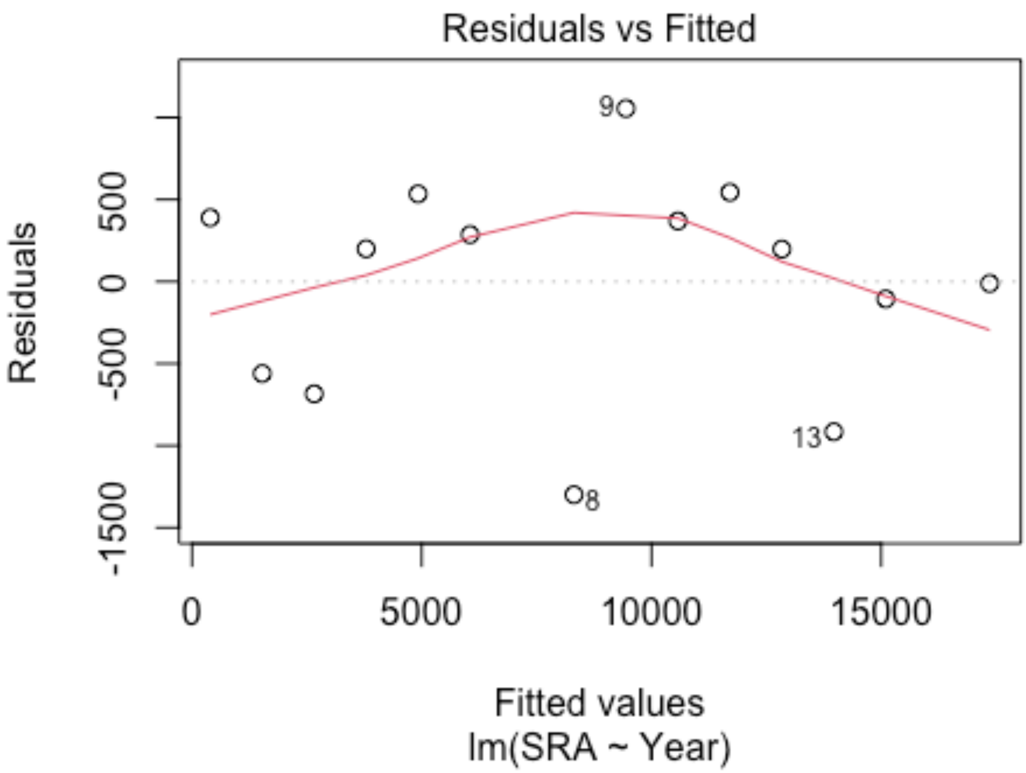
```
rstandard(mod_retirement)[15]
```

```
##        15
## -3.343753
```

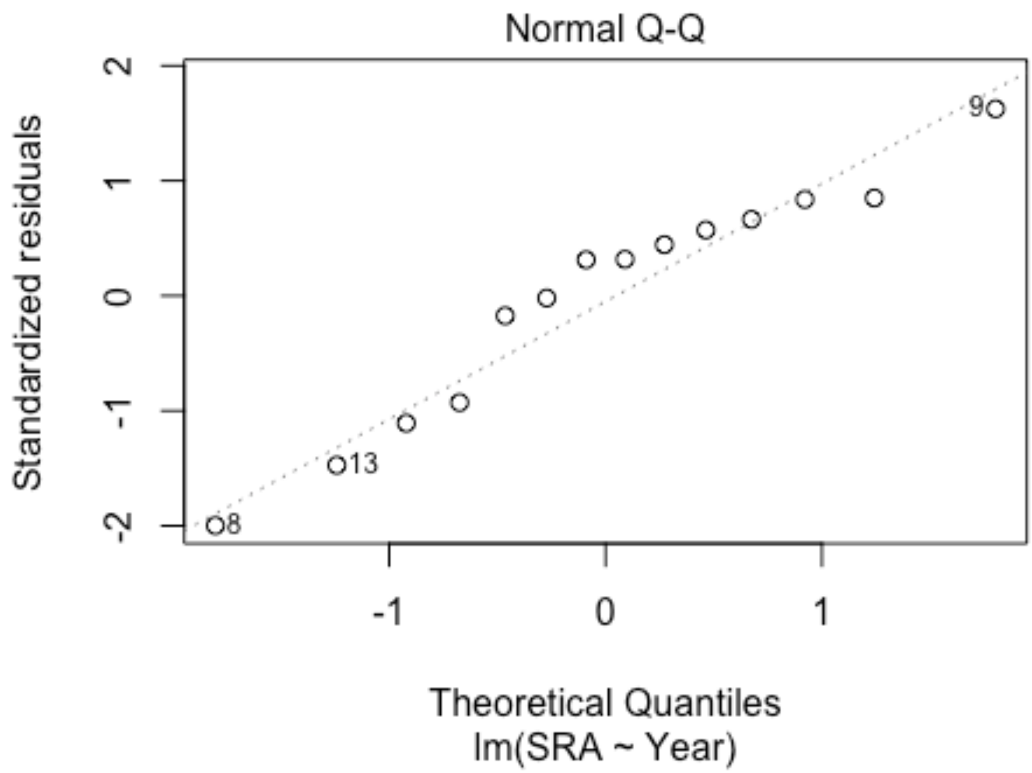
```
#7th obervation(Year=2003) has a standardized residual of -1.445406 which is
within the magnitude of 2 bound, so it is not very significant outlier.
However, 15th observation(Year=2011) has a standardized residual of -3.343753
which is greater than the magnitude of 3 bound, thus it is very significant
and thus it is indeed an outlier.

#b
Retiremen_new=Retirement[c(1:6,8:14,16),]
mod_retirement2=lm(SRA~Year, data = Retiremen_new)
summary(mod_retirement2)
```

```
##
## Call:
## lm(formula = SRA ~ Year, data = Retiremen_new)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -1299.1  -446.8   198.8   384.4  1055.1
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -2.258e+06  7.891e+04  -28.62 2.06e-12 ***
## Year         1.131e+03  3.937e+01   28.72 1.97e-12 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 674.7 on 12 degrees of freedom
## Multiple R-squared:  0.9857, Adjusted R-squared:  0.9845
## F-statistic: 825.1 on 1 and 12 DF,  p-value: 1.97e-12
```

```
plot(mod_retirement2,1:2)
```



Residuals vs Fitted
Residuals
500
0
-500
-1500
0
5000
10000
15000
9
13
8
Fitted values
lm(SRA ~ Year)




```
#The new model indeed provide a better fit for the annual contributions and
the fit is SRA= -2257996.88 + 1130.89*Year. Though there is still a curved
pattern, the residual is much smaller and we can't see any obvious outlier.
Not only the linearity condition is better, the normal qqplot is also showing
that normality condition is good.

# Chapter 2 Exercises
# 15, 17, 23

#15
#a
data("Cereal")
mod_cereal=lm(Calories~Sugar,data=Cereal)
summary(mod_cereal)

##
## Call:
## lm(formula = Calories ~ Sugar, data = Cereal)
##
## Residuals:
##     Min       1Q  Median       3Q      Max
## -37.428  -9.832   0.245   8.909  40.322
##
## Coefficients:
```

```
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  87.4277     5.1627  16.935   <2e-16 ***
## Sugar         2.4808     0.7074   3.507   0.0013 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.27 on 34 degrees of freedom
## Multiple R-squared:  0.2656, Adjusted R-squared:  0.244
## F-statistic:  12.3 on 1 and 34 DF,  p-value: 0.001296
```

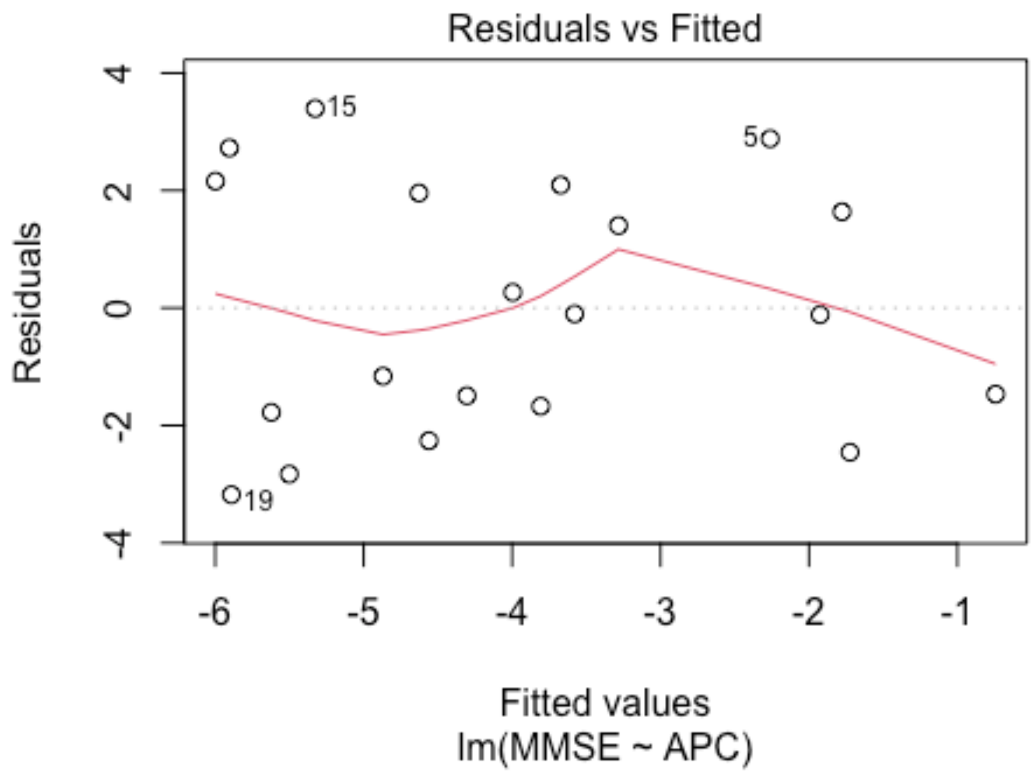
```
#Null hypothesis:The coefficient for sugar is zero(slope(β)=0), Alternative hypothesis: the coefficient for sugar is not zero(β not equal to zero). From the summary table, the t-statistic is 3.507 and the p-value is 0.0013 which is smaller than 0.05, thus we reject the null hypothesis and conclude that there is indeed a linear relationship between calories and sugar.

#b
confint(mod_cereal,level=.95)
```

```
##                  2.5 %    97.5 %
## (Intercept) 76.935859 97.919521
## Sugar        1.043205  3.918421
```

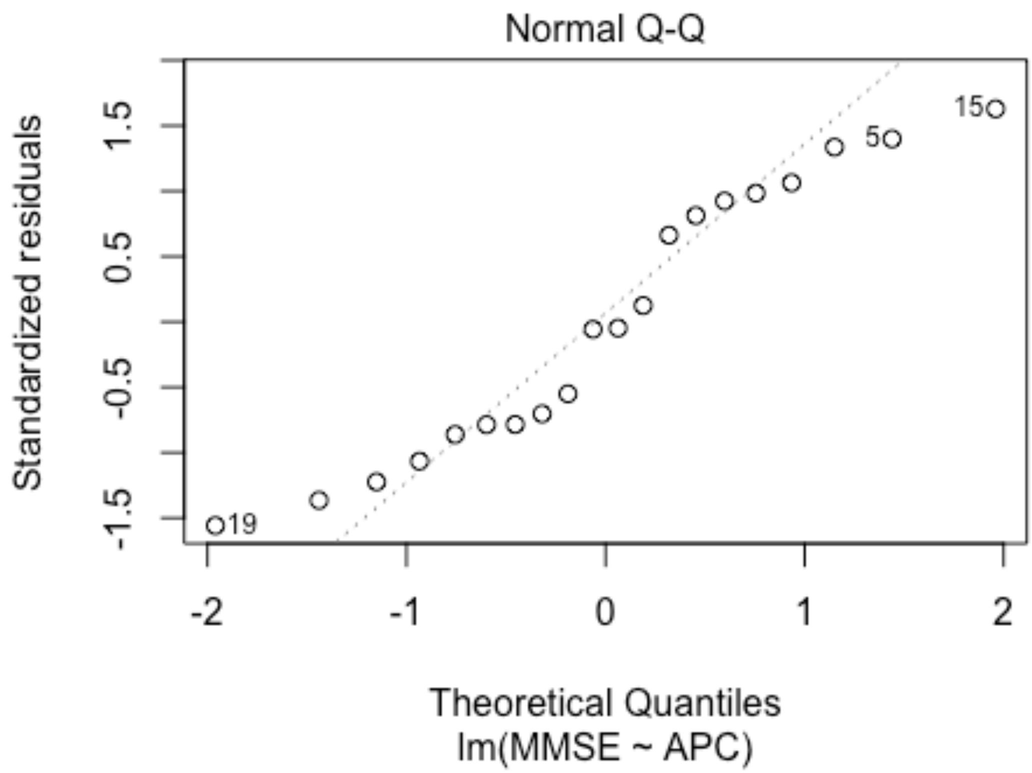
```
#The 95% confidence interval for the slope is (1.043205,3.918421), the slope coefficient means that for each unit change in sugar, calories will increase by 1.043205 to 3.918421

#17
#a
data("LewyDLBad")
mod_dementia=lm(MMSE~APC, data=LewyDLBad)
summary(mod_dementia)
```

```
##
## Call:
## lm(formula = MMSE ~ APC, data = LewyDLBad)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1791 -1.6991 -0.1081  1.9911  3.3963
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -2.4359     0.6858  -3.552  0.00228 **
## APC           1.3444     0.4225   3.182  0.00516 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2.184 on 18 degrees of freedom
## Multiple R-squared:   0.36,  Adjusted R-squared:  0.3245
## F-statistic: 10.13 on 1 and 18 DF,  p-value: 0.005161
```

```r
#Null hypothesis:The coefficient for APC is zero(slope(β)=0), Alternative
hypothesis: the coefficient for APC is not zero(β not equal to zero). From
the summary table, the t statistic is 3.182 and the p-value is 0.00516 which
is smaller than 0.05, thus we reject the null hypothesis and conclude that
there is indeed a statistically significant linear relationship between MMSE
and APC

#b
plot(mod_dementia,1:2)
```



Residuals vs Fitted
Residuals
4
2
0
-2
-4
15
5
19
-6
-5
-4
-3
-2
-1
Fitted values
lm(MMSE ~ APC)




```
#From the residual vs. fitted plot, the linearity condition is pretty good
and constant variance is decent too. However, from the normal qqplot, there
is a slight curved pattern and two short tails, but the overall, the normal
qqplot is not bad thus the normality condition is somewhat satisfied

#c
summary(mod_dementia)

##
## Call:
## lm(formula = MMSE ~ APC, data = LewyDLBad)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -3.1791 -1.6991 -0.1081  1.9911  3.3963
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  -2.4359     0.6858  -3.552  0.00228 **
## APC           1.3444     0.4225   3.182  0.00516 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
```

```
## Residual standard error: 2.184 on 18 degrees of freedom
## Multiple R-squared:   0.36,  Adjusted R-squared:  0.3245
## F-statistic: 10.13 on 1 and 18 DF,  p-value: 0.005161

#from the summary table, estimated slope=1.3444 and standard error=0.4225

#d
confint(mod_dementia,level=.9)

##                      5 %      95 %
## (Intercept) -3.6251781 -1.246683
## APC          0.6117672  2.076951

#The 90% confidence interval for the slope is (0.6117672,2.076951), the slope
coefficient means with 90% confidence the MMSE increase between 0.6117672 and
2.076951 with one unit increase in APC
#My interval does not contain zero, the interval again shows that there is a
statistically significant linear relationship between MMSE and APC which is
what we conclude for part (a)

#23
#a
data("USstamps")
USstamps_new=USstamps[c(5:25),]
USstamps_new

##    Year Price
## 5  1958     4
## 6  1963     5
## 7  1968     6
## 8  1971     8
## 9  1974    10
## 10 1975    13
## 11 1978    15
## 12 1981    18
## 13 1981    20
## 14 1985    22
## 15 1988    25
## 16 1991    29
## 17 1995    32
## 18 1999    33
## 19 2001    34
## 20 2002    37
## 21 2006    39
## 22 2007    41
## 23 2008    42
## 24 2009    44
## 25 2012    45

mod_stamp=lm(Price~Year, data = USstamps_new)
summary(mod_stamp)
```

```
##
## Call:
## lm(formula = Price ~ Year, data = USstamps_new)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9232 -0.9478  0.1195  1.1899  4.5325
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.647e+03  4.686e+01  -35.15   <2e-16 ***
## Year         8.410e-01  2.357e-02   35.68   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.737 on 19 degrees of freedom
## Multiple R-squared:  0.9853, Adjusted R-squared:  0.9845
## F-statistic:  1273 on 1 and 19 DF,  p-value: < 2.2e-16
```

```
#98.53% of variation in postal rates is explained by Year.

#b
summary(mod_stamp)
```

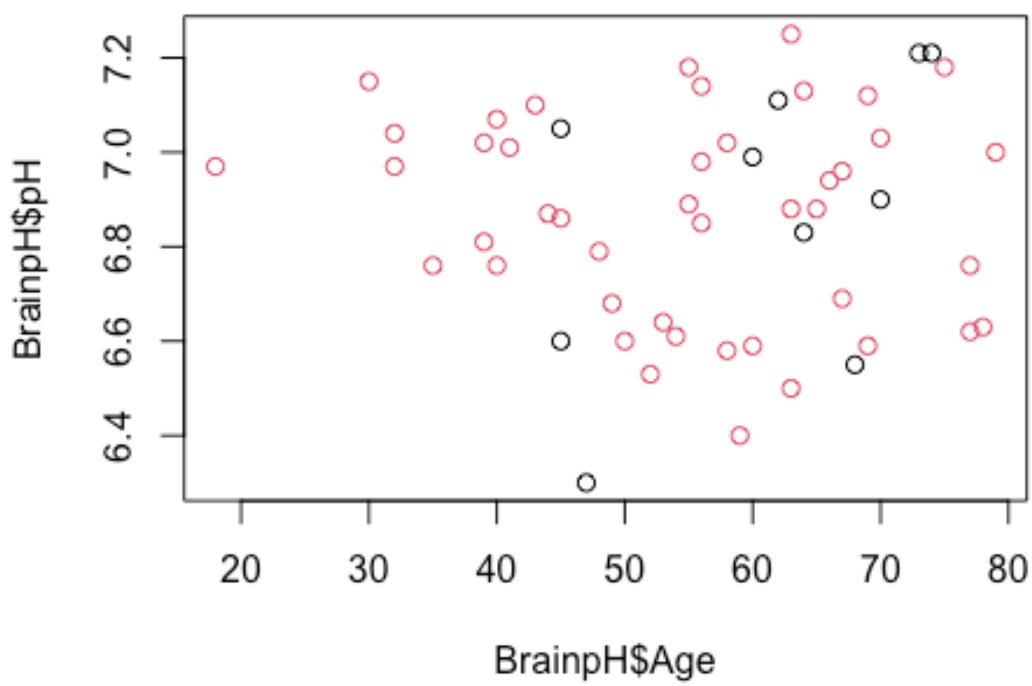
```
##
## Call:
## lm(formula = Price ~ Year, data = USstamps_new)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -2.9232 -0.9478  0.1195  1.1899  4.5325
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.647e+03  4.686e+01  -35.15   <2e-16 ***
## Year         8.410e-01  2.357e-02   35.68   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1.737 on 19 degrees of freedom
## Multiple R-squared:  0.9853, Adjusted R-squared:  0.9845
## F-statistic:  1273 on 1 and 19 DF,  p-value: < 2.2e-16
```

```
#Null hypothesis:The coefficient for Year is zero(slope(β)=0), Alternative
hypothesis: the coefficient for Year is not zero(β not equal to zero). From
the summary table, the t statistic is 35.68 and the p-value is almost zero,
thus we reject the null hypothesis and conclude that there is indeed a
statistically significant linear relationship between Price and Year.
```

```
#c
anova(mod_stamp)

## Analysis of Variance Table
##
## Response: Price
##           Df Sum Sq Mean Sq F value    Pr(>F)
## Year       1 3841.2  3841.2  1273.1 < 2.2e-16 ***
## Residuals 19   57.3     3.0
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#Year has a F-value of 1273.1 and its p-value is almost zero, thus again, we
can conclude that year indeed has a significant impact on price.

# Chapter 3 Exercises
# 21, 23, 29, 31, 35

#21
#a
data("MathEnrollment")
MathEnrollment_new=MathEnrollment[c(1:2,4:11),]
mod_math=lm(Spring~Fall+AYear, data=MathEnrollment_new)
summary(mod_math)

##
## Call:
## lm(formula = Spring ~ Fall + AYear, data = MathEnrollment_new)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.1945  -9.3982   0.3212   5.8503  18.2036
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.172e+04  2.686e+03  -4.361  0.00331 **
## Fall        -1.007e+00  2.041e-01  -4.933  0.00169 **
## AYear        6.107e+00  1.337e+00   4.566  0.00258 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.37 on 7 degrees of freedom
## Multiple R-squared:  0.871,  Adjusted R-squared:  0.8342
## F-statistic: 23.64 on 2 and 7 DF,  p-value: 0.0007704

#from the summary table, Multiple R-squared= 0.871, thus 87.1% variability in
spring enrollment is explained by the multiple regression model based on fall
enrollment and academic year

#b
#From the summary table, the size of the typical error for this multiple
```

```
regression model is 13.37

#c
nullmodel<- lm(Spring~1, data=MathEnrollment_new)
anova(nullmodel,mod_math)

## Analysis of Variance Table
##
## Model 1: Spring ~ 1
## Model 2: Spring ~ Fall + AYear
##   Res.Df    RSS Df Sum of Sq      F    Pr(>F)
## 1      9 9697.6
## 2      7 1250.7  2    8446.9 23.638 0.0007704 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

#Null hypothesis: The regression coefficients(betas) of Fall and AYear are
both zeros.Alternative hypothesis: At least one of the regression
coefficients(betas) of Fall and AYear is not zero. From the anova table, F-
value is 23.638 and p-value 0.0007704 which is extremely small, thus we
reject the null hypothesis and conclude that there is indeed a significant
relationship between response and at least one of the predictor

#d
summary(mod_math)

##
## Call:
## lm(formula = Spring ~ Fall + AYear, data = MathEnrollment_new)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -16.1945  -9.3982   0.3212   5.8503  18.2036
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept) -1.172e+04  2.686e+03  -4.361  0.00331 **
## Fall        -1.007e+00  2.041e-01  -4.933  0.00169 **
## AYear        6.107e+00  1.337e+00   4.566  0.00258 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 13.37 on 7 degrees of freedom
## Multiple R-squared:  0.871,  Adjusted R-squared:  0.8342
## F-statistic: 23.64 on 2 and 7 DF,  p-value: 0.0007704

#For Fall variable: Null hypothesis:The coefficient for Fall is
zero(slope(β)=0), Alternative hypothesis: the coefficient for Fall is not
zero(β not equal to zero). From the summary table, the t statistic is -4.933
and the p-value is 0.00169, thus we reject the null hypothesis and conclude
that there is indeed a statistically significant linear relationship between
```

```
Spring and Fall.
#For AYear variable: Null hypothesis:The coefficient for AYear is
zero(slope(β)=0), Alternative hypothesis: the coefficient for AYear is not
zero(β not equal to zero). From the summary table, the t statistic is 4.566
and the p-value is 0.00258, thus we reject the null hypothesis and conclude
that there is indeed a statistically significant linear relationship between
Spring and AYear.

#23
#a
data("BrainpH")
plot(BrainpH$Age,BrainpH$pH,col=BrainpH$Sex)
```




```
#There does not seem to have a linear relationship among the variables

#b
mod_brainph=lm(pH~Age,data = BrainpH)
summary(mod_brainph)

##
## Call:
## lm(formula = pH ~ Age, data = BrainpH)
##
## Residuals:
```

```
##      Min       1Q   Median       3Q      Max
## -0.56976 -0.21781  0.02032  0.16801  0.38649
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.8881113  0.1321194   52.13   <2e-16 ***
## Age         -0.0003905  0.0022944   -0.17    0.866
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.235 on 52 degrees of freedom
## Multiple R-squared:  0.0005566,  Adjusted R-squared:  -0.01866
## F-statistic: 0.02896 on 1 and 52 DF,  p-value: 0.8655
```

```
#Null hypothesis:The coefficient for Age is zero(slope(β)=0), Alternative
hypothesis: the coefficient for Age is not zero(β not equal to zero). From
the summary table, the t statistic is -0.17 and the p-value is 0.866, thus we
fail to reject the null hypothesis and conclude that there is not a
statistically significant linear relationship between pH and Age.

#c
mod_brainph2=lm(pH~Age+Sex,data = BrainpH)
summary(mod_brainph2)
```

```
##
## Call:
## lm(formula = pH ~ Age + Sex, data = BrainpH)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.58126 -0.21456  0.02306  0.16722  0.38942
##
## Coefficients:
##               Estimate Std. Error t value Pr(>|t|)
## (Intercept)  6.9025758  0.1613711  42.775   <2e-16 ***
## Age         -0.0004535  0.0023499  -0.193    0.848
## SexM        -0.0134258  0.0843155  -0.159    0.874
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.2372 on 51 degrees of freedom
## Multiple R-squared:  0.001053,   Adjusted R-squared:  -0.03812
## F-statistic: 0.02689 on 2 and 51 DF,  p-value: 0.9735
```

```
b1=summary(mod_brainph2)$coefficients[2,1]
b1
```

```
## [1] -0.0004535487
```

```
#slope for age is -0.0004535487
slope <- b1
```

```
BrainpHfemale=subset(BrainpH,Sex=="F")
intercept_female <- mean(BrainpHfemale$pH) - slope * mean(BrainpHfemale$Age)
intercept_female

## [1] 6.902576

#the best fit line for female is pH=6.902576-0.0004535487*Age
BrainpHmale=subset(BrainpH,Sex=="M")
intercept_male <- mean(BrainpHmale$pH) - slope * mean(BrainpHmale$Age)
intercept_male

## [1] 6.88915

#the best fit line for female is pH=6.88915-0.0004535487*Age

# Chapter 4 Exercises
# 13, 15
#13
data("NCbirths")
White=117.87
White

## [1] 117.87

#the coefficients for fitted model: the 1st coefficient which is the baseline
group and the corresponding mother's race is white, and the predicted birth
weights(in ounces) of the babies is 117.87 ounces if the mother's race is
white.
Black=White-7.31*1
Black

## [1] 110.56

#-7.31 means that if the mother is Black, then the predicted birth weights(in
ounces) of the babies will decrease by 7.31. Thus,the predicted birth
weights(in ounces) of the babies is 117.87-7.31 = 110.56 ounces if the
mother's race is black.
Hispanic=White+0.65*1
Hispanic

## [1] 118.52

#0.65 means that if the mother is Hispanic, then the predicted birth
weights(in ounces) of the babies will increase by 0.65. Thus,the predicted
birth weights(in ounces) of the babies is 117.87+0.65 = 118.52 ounces if the
mother's race is hispanic.
Other=White-0.73*1
Other

## [1] 117.14

#-0.73 means that if the mother is Other race, then the predicted birth
weights(in ounces) of the babies will decrease by 0.73. Thus,the predicted
```

```
birth weights(in ounces) of the babies is 117.87-0.73 = 117.14 ounces if the
mother's race is Other race.

# Chapter 5 Exercises
# 27, 37, 45

# Chapter 8 Exercises
# 3, 51, 55

# Chapter 9 Exercises
# 21, 33
```