BA ASSIGNMENT REGRESSION ANALYTICS

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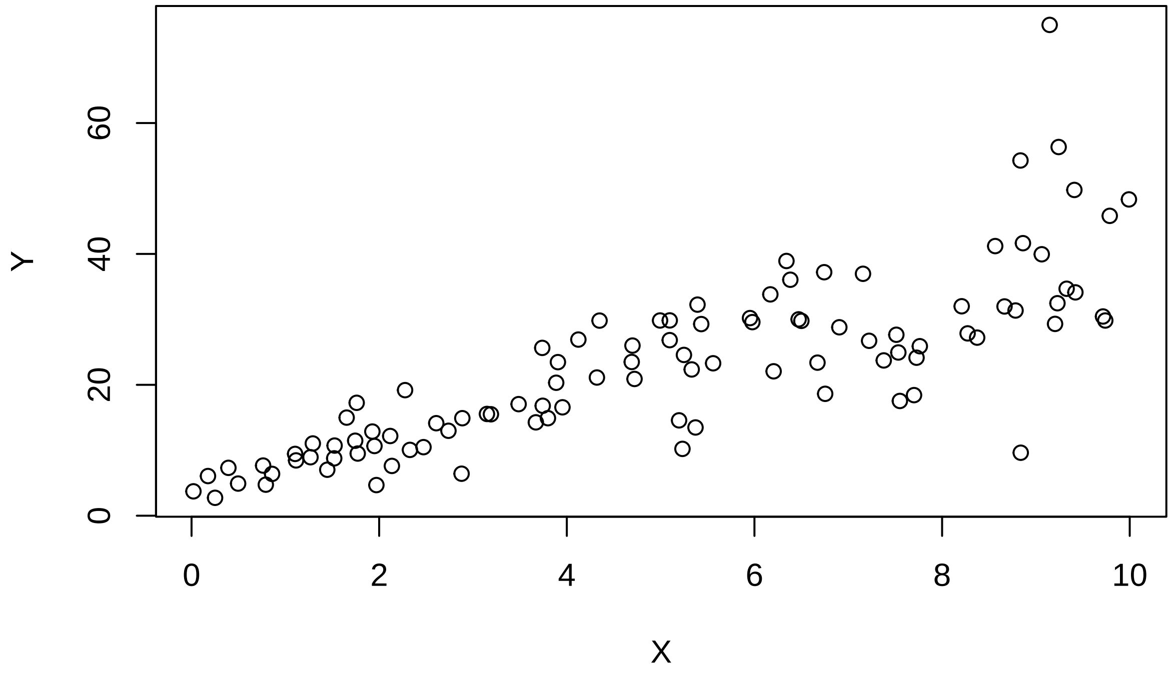
1)

```
set.seed(2017)
X=runif(100)*10
Y=X*4+3.45
Y=rnorm(100)*0.29*Y+Y
## a)
cor(X,Y)
```

```
## [1] 0.807291
```

```
plot(X,Y)
```



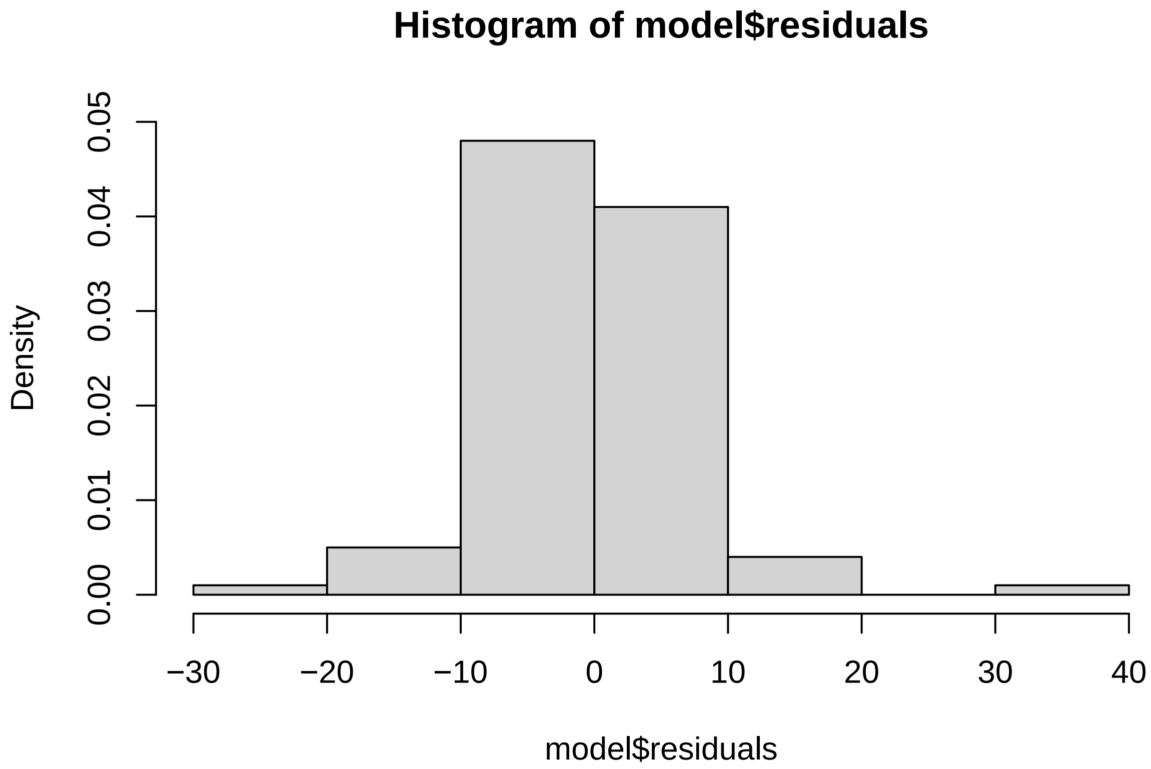
```
##  yes, we can fit a linear model y based on x and has a positive correlation.
## b)
model<-lm(Y~X)
summary(model)
```

```
##
## Call:
## lm(formula = Y ~ X)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -26.755  -3.846  -0.387   4.318  37.503
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   4.4655     1.5537   2.874  0.00497 **
## X             3.6108     0.2666  13.542  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 7.756 on 98 degrees of freedom
## Multiple R-squared:  0.6517, Adjusted R-squared:  0.6482
## F-statistic: 183.4 on 1 and 98 DF,  p-value: < 2.2e-16
```

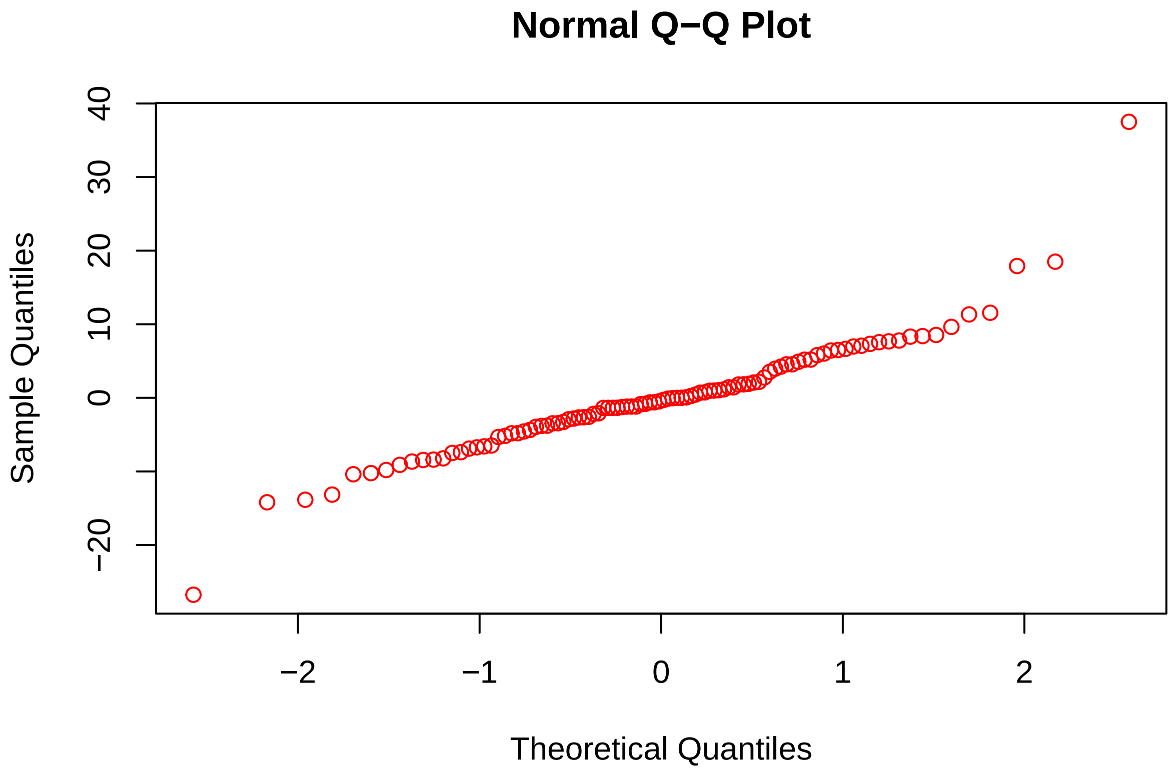
```
##   The accuracy of above linear model is 65.17%, Varability in y can be     explained by x
##    Y=3.6108X+4.4655 is the equation of the model
## c)
(cor(Y,X))^2
```

```
## [1] 0.6517187
```

```
##    square of correlation is multiple r-square.
##    Coefficient of Determination= (Correlation Coefficient)^2
## d)
hist(model$residuals,freq = FALSE,ylim = c(0,0.05))
```



```
qqnorm(model$residuals,col="red")
```



```
##  From the above graph, residuals are normally distrubuted, So the linear model is appropriate.
```

2a)

```
head(mtcars)
```

```
##                    mpg cyl disp  hp drat    wt  qsec vs am gear carb
## Mazda RX4         21.0   6  160 110 3.90 2.620 16.46  0  1    4    4
## Mazda RX4 Wag     21.0   6  160 110 3.90 2.875 17.02  0  1    4    4
## Datsun 710        22.8   4  108  93 3.85 2.320 18.61  1  1    4    1
## Hornet 4 Drive    21.4   6  258 110 3.08 3.215 19.44  1  0    3    1
## Hornet Sportabout 18.7   8  360 175 3.15 3.440 17.02  0  0    3    2
## Valiant           18.1   6  225 105 2.76 3.460 20.22  1  0    3    1
```

```
summary(lm(hp~wt,data=mtcars))
```

```
##
## Call:
## lm(formula = hp ~ wt, data = mtcars)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -83.430 -33.596 -13.587   7.913 172.030
##
```

```
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   -1.821     32.325  -0.056    0.955
## wt            46.160      9.625   4.796 4.15e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 52.44 on 30 degrees of freedom
## Multiple R-squared:  0.4339, Adjusted R-squared:  0.4151
## F-statistic:    23 on 1 and 30 DF,  p-value: 4.146e-05
```

```
summary(lm(hp~mpg,data=mtcars))
```

```
##
## Call:
## lm(formula = hp ~ mpg, data = mtcars)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -59.26 -28.93 -13.45  25.65 143.36
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   324.08      27.43  11.813 8.25e-13 ***
## mpg            -8.83       1.31  -6.742 1.79e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 43.95 on 30 degrees of freedom
## Multiple R-squared:  0.6024, Adjusted R-squared:  0.5892
## F-statistic: 45.46 on 1 and 30 DF,  p-value: 1.788e-07
```

```
## chris is correct by seeing the multiple r-squared value, mpg got high r square value 60% compared to
```

2b)

```
summary(model2<-lm(hp~cyl+mpg,data = mtcars))
```

```
##
## Call:
## lm(formula = hp ~ cyl + mpg, data = mtcars)
##
## Residuals:
##    Min     1Q Median     3Q    Max
## -53.72 -22.18 -10.13  14.47 130.73
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   54.067     86.093   0.628  0.53492
## cyl           23.979      7.346   3.264  0.00281 **
## mpg           -2.775      2.177  -1.275  0.21253
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Residual standard error: 38.22 on 29 degrees of freedom
## Multiple R-squared:  0.7093, Adjusted R-squared:  0.6892
## F-statistic: 35.37 on 2 and 29 DF,  p-value: 1.663e-08
```

```
((model2$coefficients[2]*4)+model2$coefficients[1])+(model2$coefficients[3]*22)
```

```
##      cyl
## 88.93618
```

```
predict(model2,data.frame(cyl=4,mpg=22),interval = "prediction",level=0.85)
```

```
##        fit      lwr      upr
## 1 88.93618 28.53849 149.3339
```

3a)

```
library(mlbench)
```

```
## Warning: package ’mlbench’ was built under R version 4.2.2
```

```
data(BostonHousing)
hos<-lm(medv~crim+zn+ptratio+chas,data=BostonHousing)
summary(hos)
```

```
##
## Call:
## lm(formula = medv ~ crim + zn + ptratio + chas, data = BostonHousing)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -18.282  -4.505  -0.986   2.650  32.656
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 49.91868    3.23497  15.431  < 2e-16 ***
## crim        -0.26018    0.04015  -6.480 2.20e-10 ***
## zn           0.07073    0.01548   4.570 6.14e-06 ***
## ptratio     -1.49367    0.17144  -8.712  < 2e-16 ***
## chas1        4.58393    1.31108   3.496 0.000514 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
##
## Residual standard error: 7.388 on 501 degrees of freedom
## Multiple R-squared:  0.3599, Adjusted R-squared:  0.3547
## F-statistic: 70.41 on 4 and 501 DF,  p-value: < 2.2e-16
```

```
## It is not very accurate model because R square value is very low of 36%.
```

3b1)

```r
summary(hos1<-lm(medv~chas,data = BostonHousing))
```

```
##
## Call:
## lm(formula = medv ~ chas, data = BostonHousing)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -17.094  -5.894  -1.417   2.856  27.906
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  22.0938     0.4176  52.902  < 2e-16 ***
## chas1         6.3462     1.5880   3.996 7.39e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 9.064 on 504 degrees of freedom
## Multiple R-squared:  0.03072,    Adjusted R-squared:  0.02879
## F-statistic: 15.97 on 1 and 504 DF,  p-value: 7.391e-05
```

```r
hos1$coefficients
```

```
## (Intercept)       chas1
##   22.093843    6.346157
```

```r
(hos1$coefficients[2]*0)+hos1$coefficients[1]
```

```
##    chas1
## 22.09384
```

```r
(hos1$coefficients[2]*1)+hos1$coefficients[1]
```

```
## chas1
## 28.44
```

```r
## by using the correlation cofficients the house with chas of 1 is more expensive than house without c
```

3b2)

```r
summary(hos2<-lm(medv~ptratio,data = BostonHousing))
```

```
##
## Call:
## lm(formula = medv ~ ptratio, data = BostonHousing)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -18.8342  -4.8262  -0.6426   3.1571  31.2303
##
```

```
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept)   62.345      3.029   20.58   <2e-16 ***
## ptratio       -2.157      0.163  -13.23   <2e-16 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
## 
## Residual standard error: 7.931 on 504 degrees of freedom
## Multiple R-squared:  0.2578, Adjusted R-squared:  0.2564 
## F-statistic: 175.1 on 1 and 504 DF,  p-value: < 2.2e-16
```

```
(hos2$coefficients[2]*15)+hos2$coefficients[1]
```

```
## ptratio 
##  29.987 
```

```
(hos2$coefficients[2]*18)+hos2$coefficients[1]
```

```
##  ptratio 
## 23.51547 
```

```
## By using the correlation coffecients, as the coffecient are negative so if the ptratio increases the
## The price of house whice has ptratio of 15 is high compared to price of house which has a ptratio of
```

3c)

```
summary(hos)
```

```
## 
## Call:
## lm(formula = medv ~ crim + zn + ptratio + chas, data = BostonHousing)
## 
## Residuals:
##     Min      1Q  Median      3Q     Max 
## -18.282  -4.505  -0.986   2.650  32.656 
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 49.91868    3.23497  15.431  < 2e-16 ***
## crim        -0.26018    0.04015  -6.480 2.20e-10 ***
## zn           0.07073    0.01548   4.570 6.14e-06 ***
## ptratio     -1.49367    0.17144  -8.712  < 2e-16 ***
## chas1        4.58393    1.31108   3.496 0.000514 ***
## ---
## Signif. codes:  0 ’***’ 0.001 ’**’ 0.01 ’*’ 0.05 ’.’ 0.1 ’ ’ 1
## 
## Residual standard error: 7.388 on 501 degrees of freedom
## Multiple R-squared:  0.3599, Adjusted R-squared:  0.3547 
## F-statistic: 70.41 on 4 and 501 DF,  p-value: < 2.2e-16
##  A low p-value (< 0.05) indicates that you can reject the null hypothesis Hence from the model summa
```

3d)

```
anova(hos)
```

```
## Analysis of Variance Table
##
## Response: medv
##            Df  Sum Sq Mean Sq F value    Pr(>F)
## crim        1  6440.8  6440.8 118.007 < 2.2e-16 ***
## zn          1  3554.3  3554.3  65.122 5.253e-15 ***
## ptratio     1  4709.5  4709.5  86.287 < 2.2e-16 ***
## chas        1   667.2   667.2  12.224 0.0005137 ***
## Residuals 501 27344.5    54.6
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## by comparing p values
## 1) crim
## 2) ptratio
## 3) zn
## 4)chas
```