# $HW2\_ISYE6414\_ashish\_dhiman$

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```
library(ggplot2)
```

### Part 1

### Read Data and Summary

```
head -5 ./6414\-HW2\-taxes.csv
## "The following data are sale price, y ($10,000) and taxes, x ($10,000). ",
## Sale Price, Taxes
## 25.9,4.9176
## 29.5,5.0208
## 27.9,4.5429
Since the first line does not have data we should skip it, also both the data columns are in 10k USD scale.
df_tax = read.table(file ="./6414-HW2-taxes.csv",skip=1, sep=",",header=TRUE)
head(df_tax)
##
    Sale.Price Taxes
## 1
           25.9 4.9176
## 2
          29.5 5.0208
## 3
          27.9 4.5429
## 4
           25.9 4.5573
## 5
           29.9 5.0597
## 6
           29.9 3.8910
dim(df_tax)
## [1] 26 2
summary(df_tax)
##
      Sale.Price
                        Taxes
## Min. :25.90 Min.
                           :3.891
## 1st Qu.:29.90 1st Qu.:5.057
```

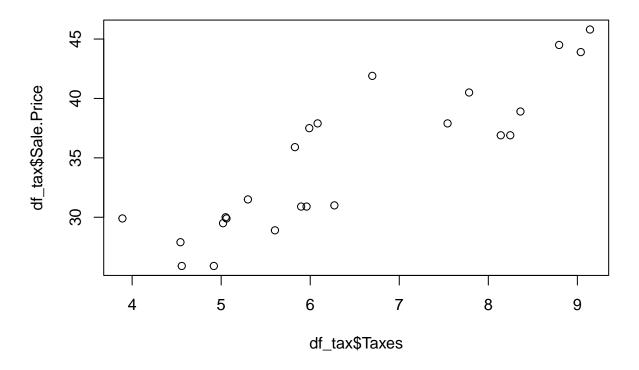
```
##
    Median :33.70
                    Median :5.974
##
           :34.61
                    Mean
                            :6.405
    Mean
    3rd Qu.:38.15
                     3rd Qu.:7.873
           :45.80
                            :9.142
##
    Max.
                     Max.
    NA's
           :2
                     NA's
df_tax = df_tax[1:(nrow(df_tax)-2),] #Remove last two empty rows
dim(df tax)
```

## [1] 24 2

### Question 1: Scatter Plot

```
title_i = "Sales Price vs Annual Taxes (both in 10k USD)"
plot(x=df_tax$Taxes, y=df_tax$Sale.Price, type ="p",main = title_i)
```

# Sales Price vs Annual Taxes (both in 10k USD)



From the above plot, a linear realationship between Sales Price and Taxes is apparent. The strength of the linear realtionship can also be tested with corealtion between x and y.

```
print (paste("Corealtion on full data:",round(cor(df_tax$Taxes,df_tax$Sale.Price),2)))
```

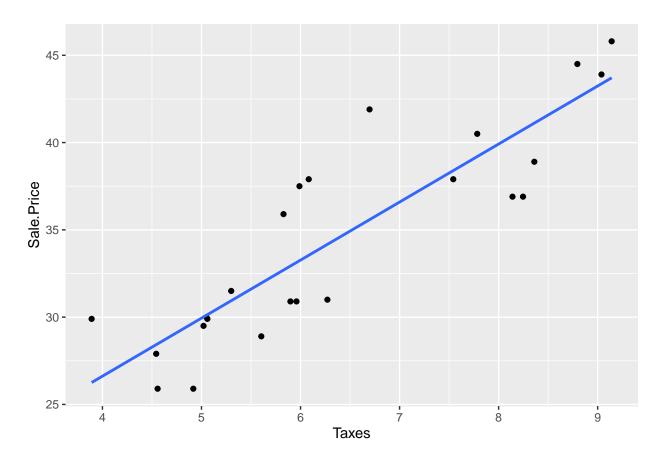
## [1] "Corealtion on full data: 0.88"

A corelation of 0.88 is pretty significant and supports strong linear realtionship between x and y.

### Question 2: Fit SLR

```
#Fit SLR
model0 <- lm(Sale.Price ~ Taxes, data = df_tax)</pre>
model0
##
## Call:
## lm(formula = Sale.Price ~ Taxes, data = df_tax)
## Coefficients:
## (Intercept)
                      Taxes
                       3.324
##
        13.320
#Superpositioning regression line on
ggplot(df_{tax}, aes(Taxes, Sale.Price)) + #aes(x,y)
  geom_point() +
  stat_smooth(method = lm, se = FALSE)
```

## 'geom\_smooth()' using formula 'y ~ x'



From above, we have :  $\hat{\beta}_0 := Intecept = 13.320,$ 

$$\hat{\beta}_1 := Slope = 3.324, \ and$$
 
$$\hat{y} = \hat{\beta}_0 + \hat{\beta}_1 * x = 13.320 + 3.324 * x$$

# Question 3: Meaning of beta1 $(\hat{\beta}_1)$ :

 $\hat{\beta}_1$  implies the slope of the SLR line we have fit to the data. In other words, it tells us, the change recorded in y (on average) for every one unit of change in x.

In this case, this implies for every 10k USD change in Taxes, the Price goies up by 3,324 USD (on average).

# Question 4: Meaning of beta0 $(\hat{\beta}_0)$ :

 $\hat{\beta}_0$  implies the predicted value of y given x is zero.

In this case, this implies for 0 USD in taxes (let's assume), the the expected prices is 13,320 USD

### Question 5: value of s, $s^2$ and SSE:

```
s and s^2
```

```
s_squared = sum(sapply(model0["residuals"], function(x) x^2))/(nrow(df_tax)-2)
s_squared
```

## [1] 8.767753

```
s_squared^0.5
```

## [1] 2.961039

#### SSE from fitted values

```
SSE = \sum_{i \in all \ data \ points} ([y_i - \hat{y}_i]^2)
```

```
y_hat = fitted(model0)
y_act = df_tax$Sale.Price

sse = sum((y_act - y_hat)^2)
print (paste("sse is",sse))
```

## [1] "sse is 192.89056494381"

```
sse/(nrow(df_tax)-2)
```

## [1] 8.767753

### Part 2

### Question 6: Least Square Estimate of beta0, beta1:

$$\hat{\beta}_1 = \frac{\left(\sum_i x_i y_i\right) - n\overline{x}\overline{y}}{\sum_i x_i^2 - n\overline{x}^2},$$

$$we \ have:$$

$$\sum_i x_i y_i = 1697.8,$$

$$n\overline{x}\overline{y} = n * \frac{\sum_i x_i}{n} * \frac{\sum_i y_i}{n},$$

$$\sum_i x_i^2 = 157.42,$$

$$n\overline{x}^2 = n * \frac{\sum_i x_i}{n} = \sum_i x_i = 14 * (43/14)^2$$

```
num = 1697.8 - (14 * (43/14) * (572/14))
num
```

## [1] -59.05714

```
denom = 157.42 - (14*(43/14)^2)
denom
```

## [1] 25.34857

```
beta1 = num/denom
print (paste("Intecept (or beta0)",beta1))
```

## [1] "Intecept (or beta0) -2.32980162308386"

$$\hat{\beta}_0 = \overline{y} - \hat{\beta}_1 \overline{x}$$

```
beta0 = (572/14) - beta1*(43/14)
print (paste("Intecept (or beta0)",beta0))
```

## [1] "Intecept (or beta0) 48.0129621280433"

### Question 7: Calculate SSE

$$SSE = SS_{yy} - \hat{\beta}_1 SS_{xy},$$

$$SS_{yy} = \sum_i (y_i - \overline{y})^2 = \sum_i y_i^2 - n\overline{y}^2$$

$$SS_{xy} = (\sum_i x_i y_i) - n\overline{xy}$$

```
SS_yy = 23530 - 14 *((572/14))^2
SS_xy = num #from ques7
SSE = SS_yy - beta1 * SS_xy
sigma2 = SSE/(14-2)
print (paste("Sigma squared is", sigma2))
```

## [1] "Sigma squared is 1.84357153591864"

### Question 8: y for x = 3.7

```
y_act = 46.1
y_hat = beta0 + beta1 * 3.7
residual = y_act - y_hat
print (paste("Predicted Y value is",y_hat))

## [1] "Predicted Y value is 39.392696122633"

print (paste("Corresponding Residual is",y_hat))
```

## [1] "Corresponding Residual is 39.392696122633"