

# Green Collar Agritech Solutions Private Limited

Data Science internship

**Submitted By:**

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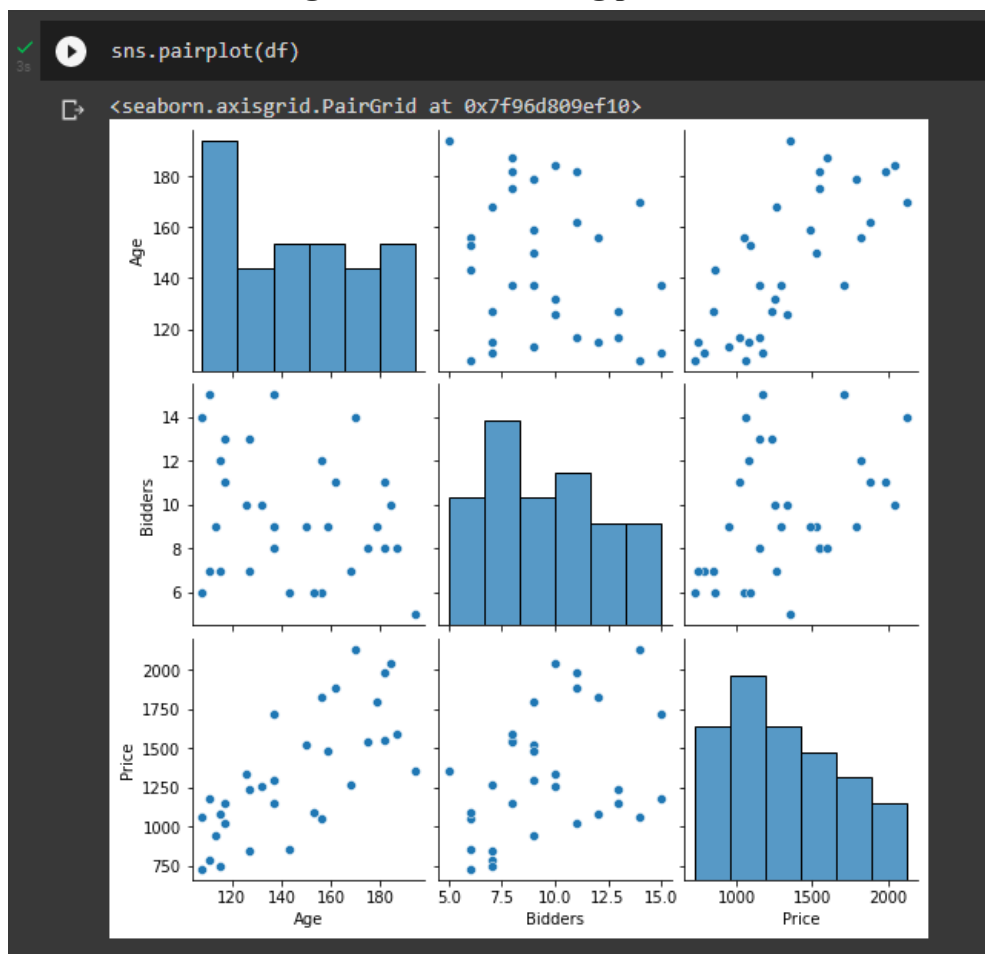
The clock prices data set contains the selling Price (in pounds Stirling) of 32 antique grandfather clocks in different auctions, along with the Age of the clocks in years and the number of Bidders participating in that auction.

## VARIABLES

1. Age - Age of the clock (years)
2. Bidders - Number of individuals participating in the bidding
3. Price - Selling price (pounds Stirling)

We're interested in modeling the Price (Dependent Variable) based on Age and Bidders.

**1. Graphically analyze the data and comment on how the age of the clock and the number of bidders are affecting the auctioned selling price.**

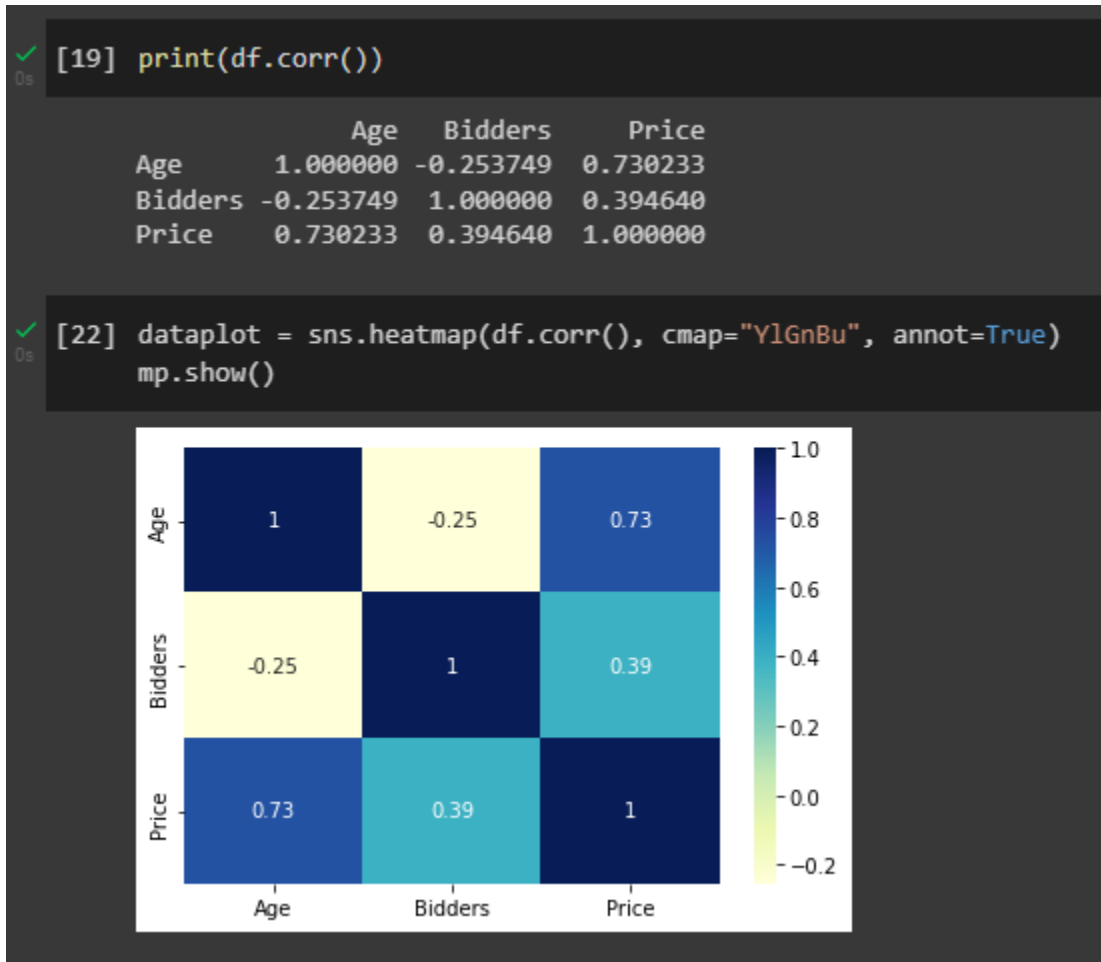


Looking at the above visualization, we can say that,

1. Price of the Clock seems to be linearly related to the Age of the Clock.

2. The Price of the Clock seems to be linearly related to the Number of Bidders on the Clock.
3. Age of the Clock and Number of Bidders don't seem to have a strong correlation between each other.

Lets look at the Correlation between the different Variables.



The correlation Matrix simply confirms our inferences from the visual inspection of plots.

## 2. Fit a first order multiple regression model to the data and answer the following based on this model :

we proceed with fitting a Full First Order Model, to explain the relationship between Price of the Clock and Age of the Clock and/or Number of Bidders for the Clock.

```
#OLS Regression

import statsmodels.api as sm

X = df_EV[["Age", "Bidders"]]
y = df_DV["Price"]

X = sm.add_constant(X)
model = sm.OLS(y, X).fit()

# Print out the statistics
model.summary()
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tsa/tsatools.
x = pd.concat(x[::order], 1)

OLS Regression Results

Dep. Variable: Price      R-squared: 0.893
Model: OLS              Adj. R-squared: 0.885
Method: Least Squares   F-statistic: 120.7
Date: Mon, 22 Aug 2022  Prob (F-statistic): 8.77e-15
Time: 19:07:30          Log-Likelihood: -200.35
No. Observations: 32    AIC: 406.7
Df Residuals: 29        BIC: 411.1
Df Model: 2
Covariance Type: nonrobust

               coef    std err          t      P>|t|   [0.025   0.975]
const -1336.7221  173.356   -7.711  0.000 -1691.275 -982.169
Age    12.7362    0.902   14.114  0.000  10.891  14.582
Bidders 85.8151    8.706    9.857  0.000  68.010 103.620

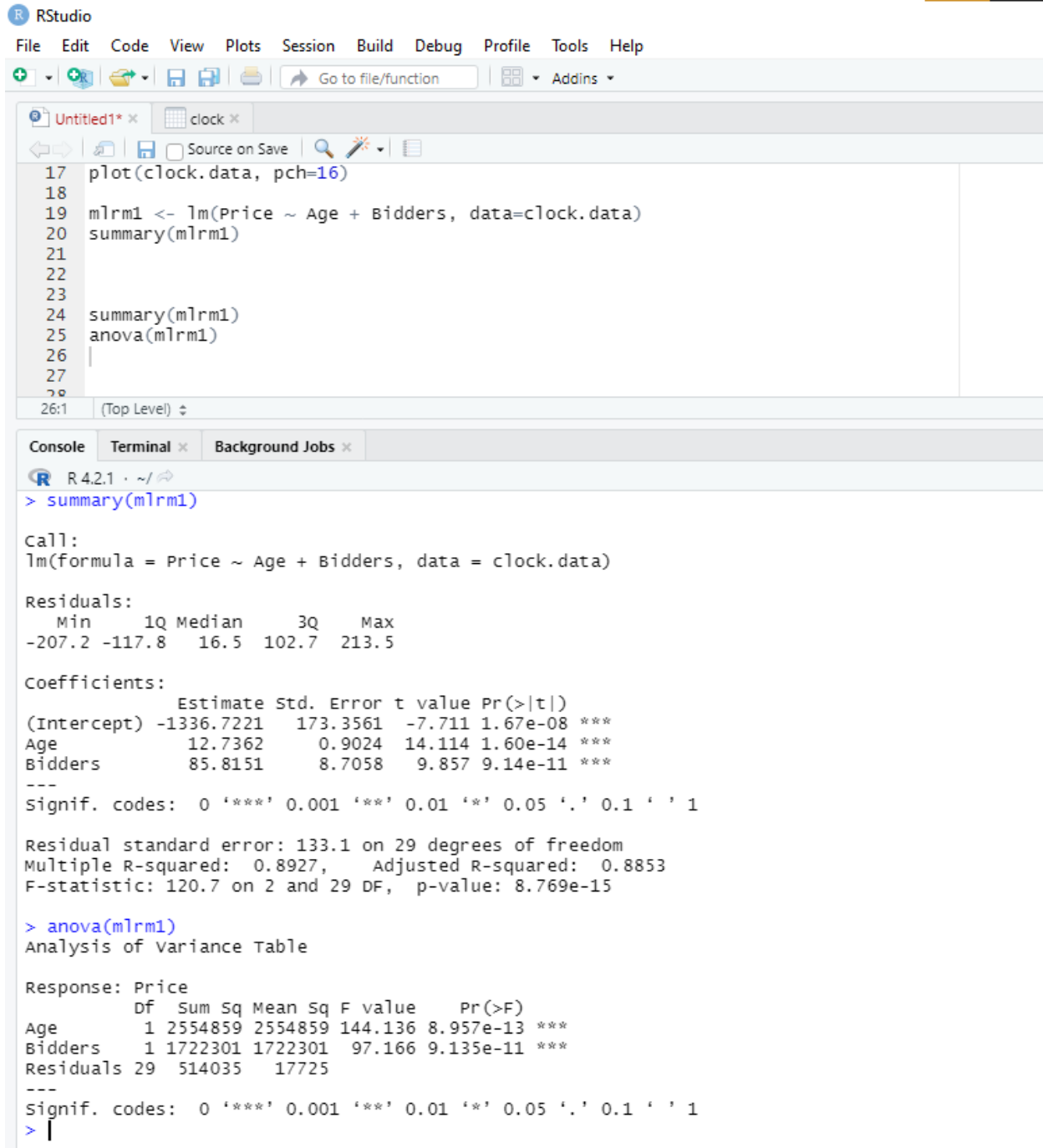
Omnibus: 6.587   Durbin-Watson: 1.864
Prob(Omnibus): 0.037   Jarque-Bera (JB): 2.018
Skew: 0.040    Prob(JB): 0.365
Kurtosis: 1.772    Cond. No.    1.09e+03
```

Notes:

1. Standard Errors assume that the covariance matrix of the errors is correctly specified.
2. The condition number is large, 1.09e+03. This might indicate that there are strong multicollinearity or other numerical problems.
3. As can be observed from the R sq. value, the Model with both Age of the Clock and Number of Bidders is explaining **89.30%** of the variability in Price.

(From now onwards I am using R Software for the further analysis)

### a. Is the Model useful?



The screenshot shows the RStudio environment. The script editor contains the following R code:

```
17 plot(clock.data, pch=16)
18
19 mlrm1 <- lm(Price ~ Age + Bidders, data=clock.data)
20 summary(mlrm1)
21
22
23
24 summary(mlrm1)
25 anova(mlrm1)
26 |
27
28
```

The console shows the output of the `summary(mlrm1)` command:

```
> summary(mlrm1)

Call:
lm(formula = Price ~ Age + Bidders, data = clock.data)

Residuals:
    Min       1Q   Median       3Q      Max
-207.2  -117.8   16.5   102.7   213.5

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) -1336.7221    173.3561  -7.711 1.67e-08 ***
Age           12.7362     0.9024  14.114 1.60e-14 ***
Bidders       85.8151     8.7058   9.857 9.14e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 133.1 on 29 degrees of freedom
Multiple R-squared:  0.8927,    Adjusted R-squared:  0.8853
F-statistic: 120.7 on 2 and 29 DF,  p-value: 8.769e-15

> anova(mlrm1)

Analysis of Variance Table

Response: Price
      Df Sum Sq Mean Sq F value    Pr(>F)
Age     1 2554859 2554859 144.136 8.957e-13 ***
Bidders 1 1722301 1722301  97.166 9.135e-11 ***
Residuals 29 514035 17725
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
> |
```

The low p-values observed for both  $\beta_0$  and  $\beta_1$  is quite low allowing us to conclude that both the values are significant.

We can also proceed with creation of ANOVA Table that allows us to infer if  $R^2$  obtained is significant or not.

As can be seen, p-values for both Age and Bidders is nearly 0, allowing us to conclude that both  $\beta_0$  and  $\beta_1$  are both significant.

**Therefore, we can conclude that the following Model that has been fitted is useful :**

$$\text{Price} = -1336.7221 + 12.7362(\text{Age}) + 85.8151(\text{Bidders})$$

**b. Given the age of a clock, by what amount can one expect the selling price to go up for one more person participating in the auction?**

Using the fitted Model described above, we can say that for a Clock with given age, an increase of 1 Bidder in the number of Bidders, is associated with an increase of 85.8151 in the Mean Price of the Clock.

**c. An auction house has acquired several grandfather clocks each 100 years old paying an average price of £500 per clock. From the past experience it has found that such auctions (for antique grandfather clocks) typically attract about 10-12 bidders. What can be said about its expected profit per clock with 95% confidence?**

We need to find 95% Confidence Interval for the Price \$ 500 for a clock that is 100 years old and has 10 Bidders.

Effectively we are finding  $E(\text{Price}|\text{Age} = 100, \text{Bidders} = 10)$ ,  $E(\text{Price}|\text{Age} = 100, \text{Bidders} = 11)$ , and  $E(\text{Price}|\text{Age} = 100, \text{Bidders} = 12)$ .

```

24 summary(m1rm1)
25 anova(m1rm1)
26
27
28 #For Bidders = 10
29 exp.value <- predict(m1rm1, newdata = data.frame(Age = 100, Bidders = 10), interval = "confidence", level = .95)
30 exp.value[2]-500
31
32 #For Bidders = 11
33 exp.value <- predict(m1rm1, newdata = data.frame(Age = 100, Bidders = 11), interval = "confidence", level = .95)
34 exp.value[2]-500
35
36 #For Bidders = 12
37 exp.value <- predict(m1rm1, newdata = data.frame(Age = 100, Bidders = 12), interval = "confidence", level = .95)
38 exp.value[2]-500
39
40
41
42

```

38:17 (Top Level) ↕

Console Terminal Background Jobs

```

R 4.2.1 ~ /
> anova(m1rm1)
Analysis of Variance Table

Response: Price
          Df Sum Sq Mean Sq F value    Pr(>F)
Age         1 2554859 2554859 144.136 8.957e-13 ***
Bidders      1 1722301 1722301  97.166 9.135e-11 ***
Residuals   29  514035    17725
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

> #For Bidders = 10
> exp.value <- predict(m1rm1, newdata = data.frame(Age = 100, Bidders = 10), interval = "confidence", level = .95)
> exp.value[2]-500
[1] 200.6368
>
> #For Bidders = 11
> exp.value <- predict(m1rm1, newdata = data.frame(Age = 100, Bidders = 11), interval = "confidence", level = .95)
> exp.value[2]-500
[1] 287.1706
>
> #For Bidders = 12
> exp.value <- predict(m1rm1, newdata = data.frame(Age = 100, Bidders = 12), interval = "confidence", level = .95)
> exp.value[2]-500
[1] 370.3602
>

```

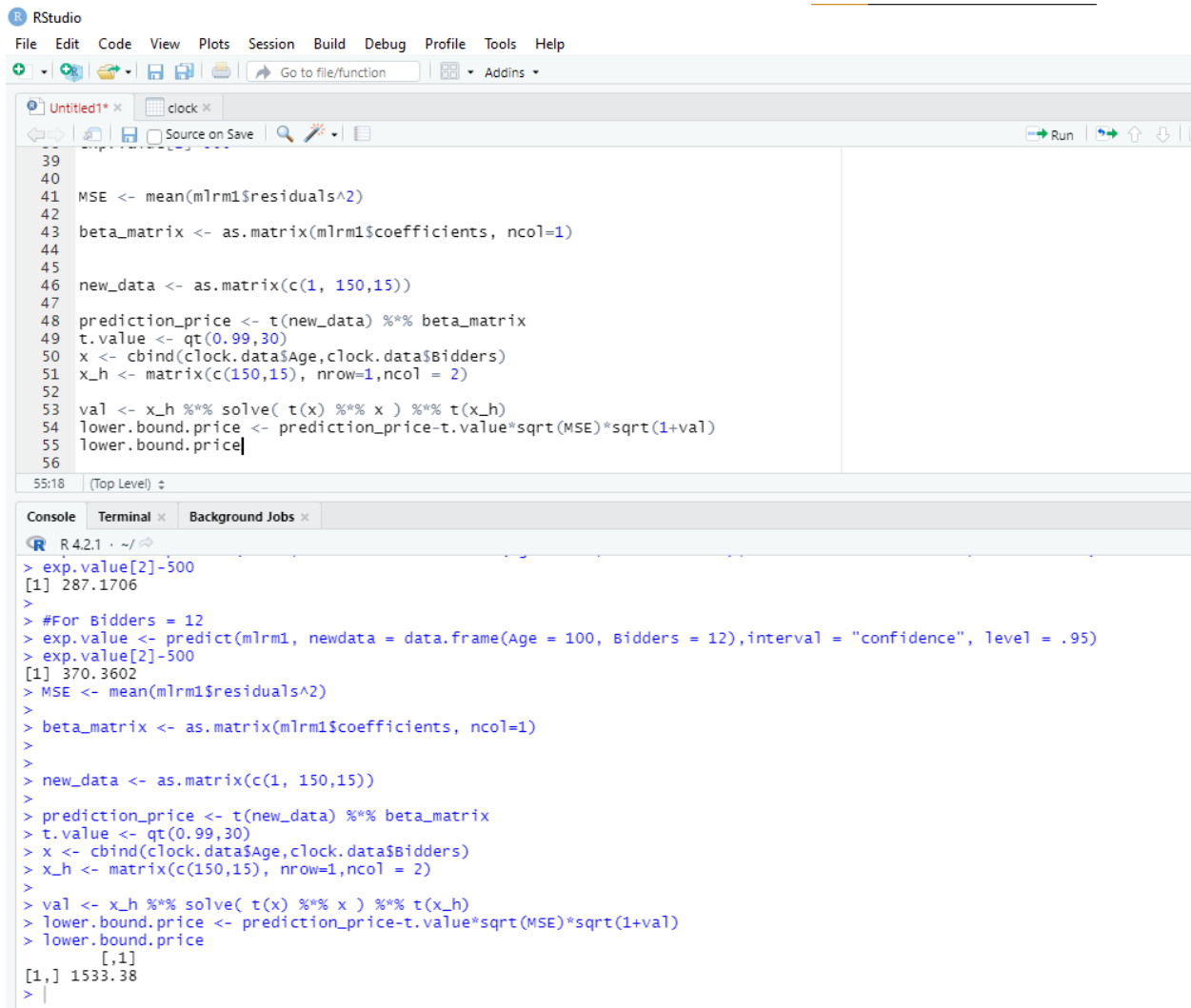
The Expected Profit per Clock that is 100 years old and has 10 Bidders, with 95% confidence is 200.6368?

The Expected Profit per Clock that is 100 years old and has 11 Bidders, with 95% confidence is 287.1706?

The Expected Profit per Clock that is 100 years old and has 10 Bidders, with 95% confidence is 370.3602?

**d. You walk into an auction selling an antique 150 year old grandfather clock and find that there are 15 bidders (including yourself) participating in the auction. You are extremely keen in acquiring the clock. At least what amount should you bid for the clock, so that, you are 99% certain that nobody else can out-bid you?**

For this, we need to predict a lower bound for a Predicted value of Y ( $\hat{Y}$ ) for the given values of Age = 150 years and Bidders = 15.



```

39
40
41 MSE <- mean(mlrm1$residuals^2)
42
43 beta_matrix <- as.matrix(mlrm1$coefficients, ncol=1)
44
45
46 new_data <- as.matrix(c(1, 150,15))
47
48 prediction_price <- t(new_data) %>% beta_matrix
49 t.value <- qt(0.99,30)
50 x <- cbind(clock.data$Age,clock.data$Bidders)
51 x_h <- matrix(c(150,15), nrow=1,ncol = 2)
52
53 val <- x_h %>% solve( t(x) %>% x ) %>% t(x_h)
54 lower.bound.price <- prediction_price-t.value*sqrt(MSE)*sqrt(1+val)
55 lower.bound.price
56
55:18 (Top Level)

```

```

R 4.2.1 ~ /
> exp.value[2]-500
[1] 287.1706
>
> #For Bidders = 12
> exp.value <- predict(mlrm1, newdata = data.frame(Age = 100, Bidders = 12),interval = "confidence", level = .95)
> exp.value[2]-500
[1] 370.3602
> MSE <- mean(mlrm1$residuals^2)
>
> beta_matrix <- as.matrix(mlrm1$coefficients, ncol=1)
>
>
> new_data <- as.matrix(c(1, 150,15))
>
> prediction_price <- t(new_data) %>% beta_matrix
> t.value <- qt(0.99,30)
> x <- cbind(clock.data$Age,clock.data$Bidders)
> x_h <- matrix(c(150,15), nrow=1,ncol = 2)
>
> val <- x_h %>% solve( t(x) %>% x ) %>% t(x_h)
> lower.bound.price <- prediction_price-t.value*sqrt(MSE)*sqrt(1+val)
> lower.bound.price
      [,1]
[1,] 1533.38
>

```

From the above calculations, we can say that if we bid at a Price higher than 1533.38, we can be 99% certain that no one else can out-bid us.

e. In presence of the other, which of the two factors, age of the clock or the number of bidders, is more important in determining the selling price of a clock?

To answer this, we first build a standardized First Order Linear Model as follows :



```

58 std.clock <- clock.data
59
60 std.clock$Price <- (clock.data$Price - mean(clock.data$Price))/sd(clock.data$Price)
61 std.clock$Age <- (clock.data$Age - mean(clock.data$Age))/sd(clock.data$Age)
62 std.clock$Bidders <- (clock.data$Bidders - mean(clock.data$Bidders))/sd(clock.data$Bidders)
63
64 standard.model <- lm(Price ~ -1 + Age + Bidders,data = std.clock)
65 summary(standard.model)
66 vcov(standard.model)
67 val <- (0.88752-0.61985)/sqrt(2*(0.0038223614-0.0009699208))
68 p.val <- 2*(1-pt(val,30))
69 cat("p-value for Statistical significance between Coefficients of Age and Bidders",p.val)

```

69:90 (Top Level) ↓

Console Terminal Background Jobs

```

R 4.2.1 ~ /
>
> summary(standard.model)

```

Call:  
lm(formula = Price ~ -1 + Age + Bidders, data = std.clock)

Residuals:

Min	1Q	Median	3Q	Max
-0.52699	-0.29976	0.04196	0.26121	0.54305

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
Age	0.88752	0.06183	14.36	5.60e-15 ***
Bidders	0.61985	0.06183	10.03	4.31e-11 ***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.333 on 30 degrees of freedom  
Multiple R-squared: 0.8927, Adjusted R-squared: 0.8856  
F-statistic: 124.8 on 2 and 30 DF, p-value: 2.872e-15

```

> vcov(standard.model)
           Age      Bidders
Age  0.0038223614 0.0009699208
Bidders 0.0009699208 0.0038223614
>
> val <- (0.88752-0.61985)/sqrt(2*(0.0038223614-0.0009699208))
> p.val <- 2*(1-pt(val,30))
> cat("p-value for Statistical significance between Coefficients of Age and Bidders",p.val)
p-value for Statistical significance between Coefficients of Age and Bidders 0.001314188
>

```

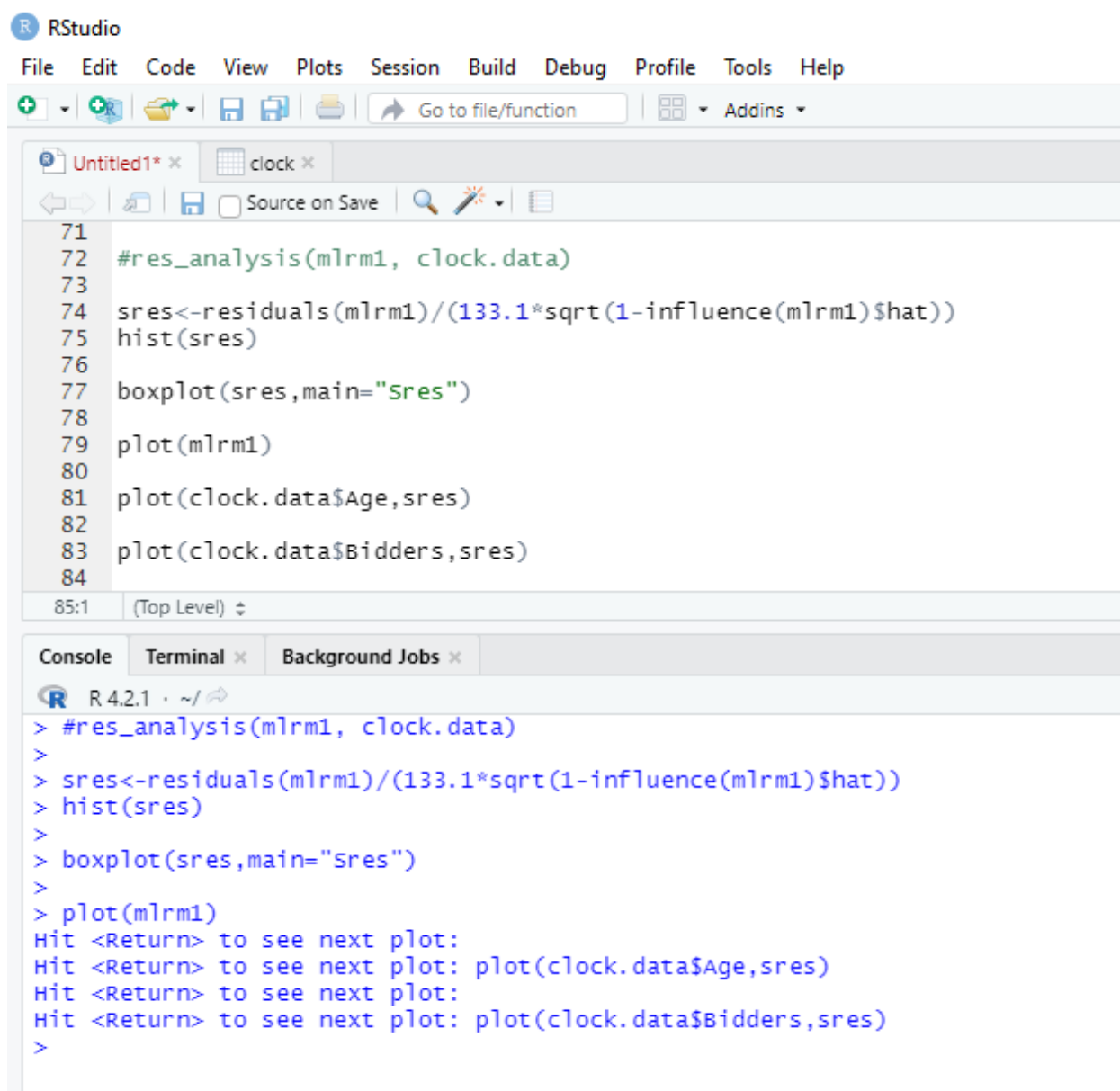
As can be observed from the calculations above, coefficient of standardized Age of the Clock is higher than the coefficient of standardized Number of Bidders for the Clock. The difference between the two values is also significant as indicated by a p-value of 0.001314. (Considering  $\alpha = 5\%$ )

**We can conclude that Age of the Clock is more important in determining the selling price of the Clock compared to Number of Bidders.**

**3. Is the first order model acceptable? Fit as appropriate a model as possible for the auctioned selling price of grandfather clocks, based on the information on the age of the clock and the number of bidders, and then based on this model answer the same questions as in 2. b, c, and d above.**

To answer whether a Model is acceptable or not, we proceed with plotting the residuals obtained after fitting the model.

For the 1st Order Model we fitted earlier :

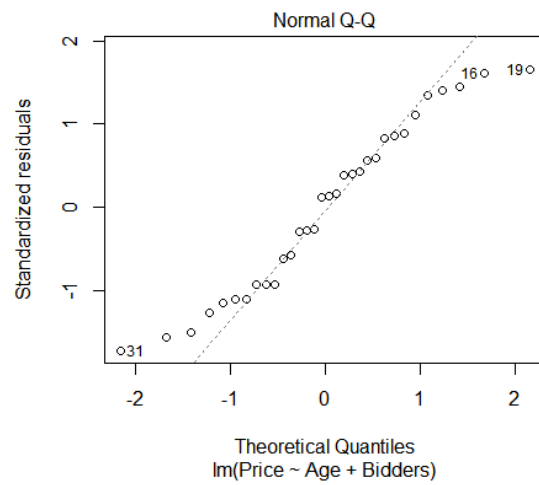
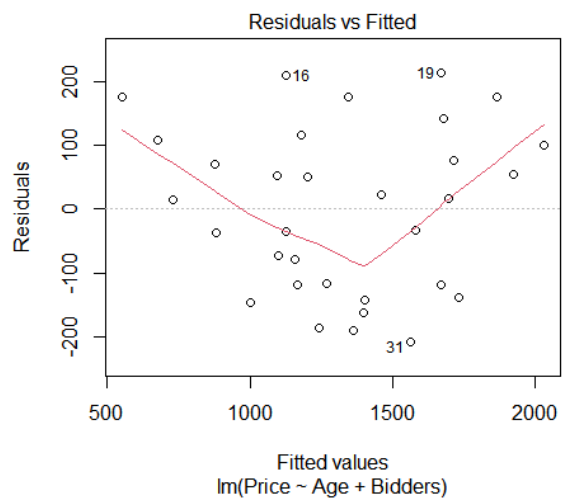
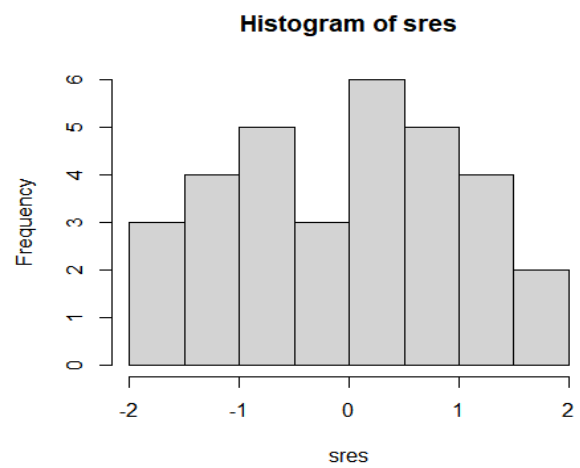
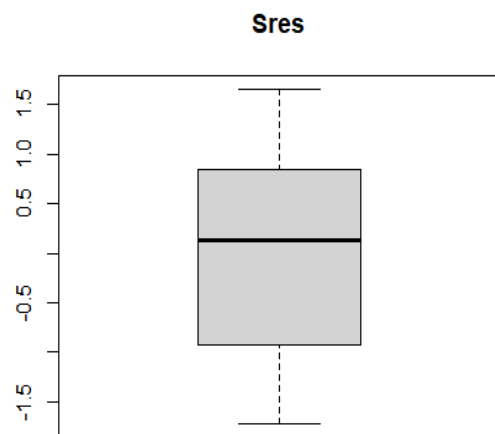


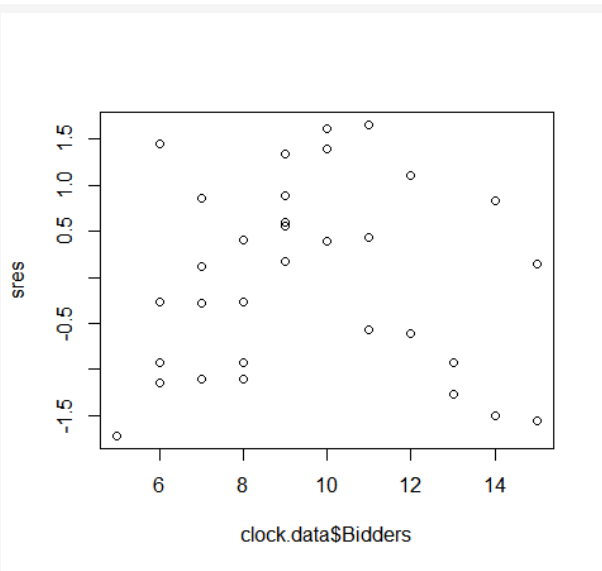
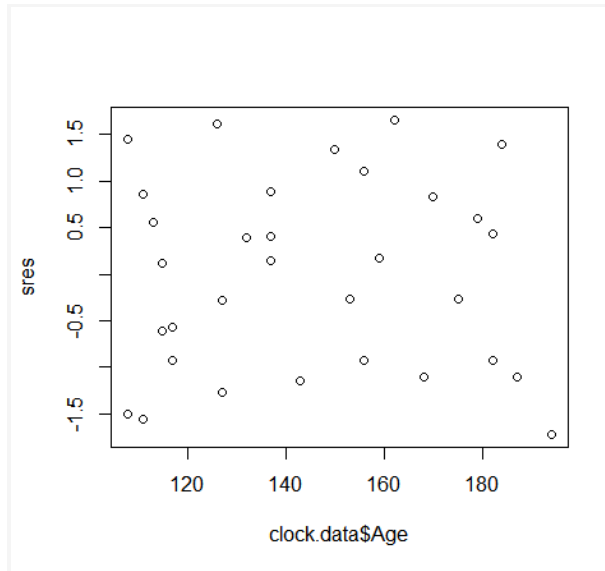
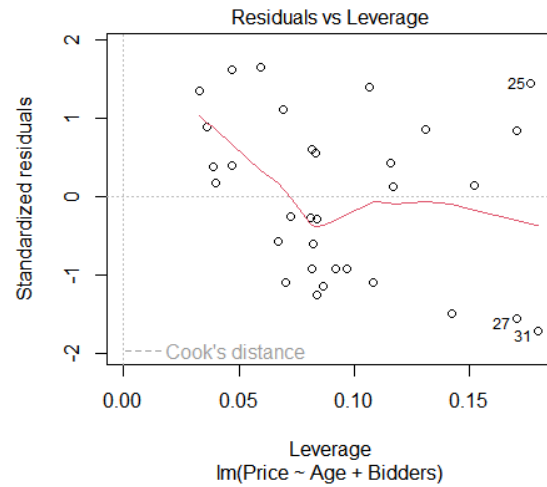
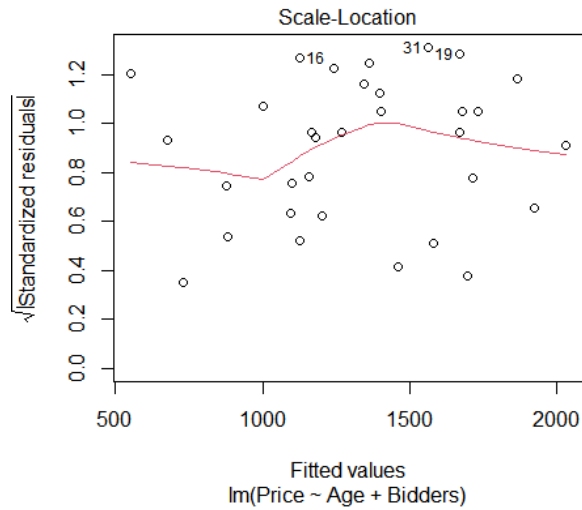
The screenshot shows the RStudio environment. The top menu bar includes File, Edit, Code, View, Plots, Session, Build, Debug, Profile, Tools, and Help. Below the menu is a toolbar with icons for file operations and a search bar labeled 'Go to file/function'. The main editor window displays a script with the following R code:

```
71
72 #res_analysis(mlrm1, clock.data)
73
74 sres<-residuals(mlrm1)/(133.1*sqrt(1-influence(mlrm1)$hat))
75 hist(sres)
76
77 boxplot(sres,main="Sres")
78
79 plot(mlrm1)
80
81 plot(clock.data$Age,sres)
82
83 plot(clock.data$Bidders,sres)
84
```

The console window at the bottom shows the execution of the code, with prompts for the next plot:

```
R 4.2.1 · ~/
> #res_analysis(mlrm1, clock.data)
>
> sres<-residuals(mlrm1)/(133.1*sqrt(1-influence(mlrm1)$hat))
> hist(sres)
>
> boxplot(sres,main="Sres")
>
> plot(mlrm1)
Hit <Return> to see next plot:
Hit <Return> to see next plot: plot(clock.data$Age,sres)
Hit <Return> to see next plot:
Hit <Return> to see next plot: plot(clock.data$Bidders,sres)
>
```

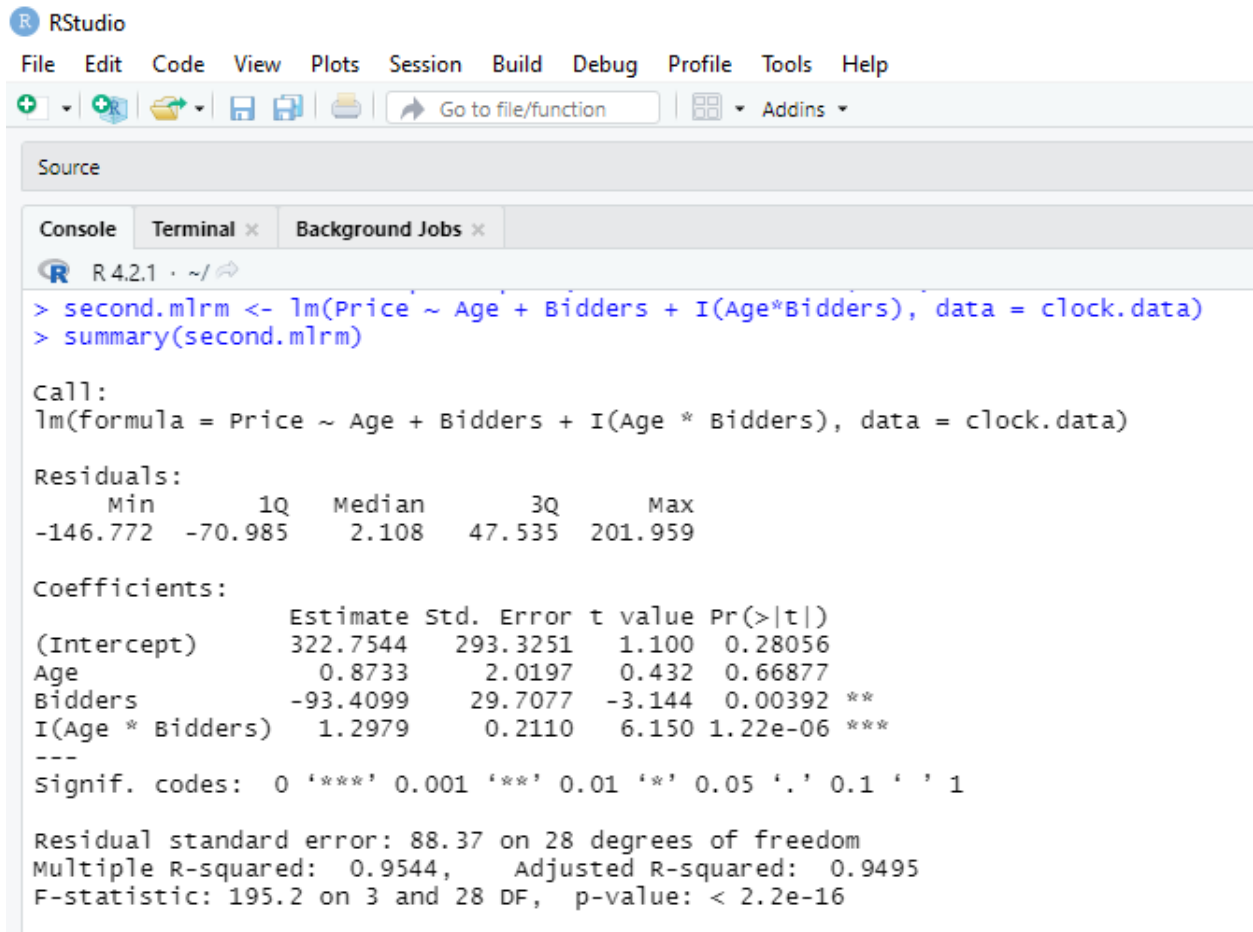




As can be seen from the Residual plots, there are no visible patterns in the Residuals obtained from the fitted model.

Based on the above, we can conclude that the First Order Model we have fitted is Acceptable.

We believe that a second order Model might be able to explain the variance in Prices better than the First Order Model already fitted. We can check this by fitting a Second Order Model as follows :



RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

Go to file/function Addins

Source

Console Terminal x Background Jobs x

```
R 4.2.1 ~/  
> second.mlrm <- lm(Price ~ Age + Bidders + I(Age*Bidders), data = clock.data)  
> summary(second.mlrm)
```

Call:  
lm(formula = Price ~ Age + Bidders + I(Age \* Bidders), data = clock.data)

Residuals:

	Min	1Q	Median	3Q	Max
	-146.772	-70.985	2.108	47.535	201.959

Coefficients:

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	322.7544	293.3251	1.100	0.28056
Age	0.8733	2.0197	0.432	0.66877
Bidders	-93.4099	29.7077	-3.144	0.00392 **
I(Age * Bidders)	1.2979	0.2110	6.150	1.22e-06 ***

---  
Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 88.37 on 28 degrees of freedom  
Multiple R-squared: 0.9544, Adjusted R-squared: 0.9495  
F-statistic: 195.2 on 3 and 28 DF, p-value: < 2.2e-16

RStudio

File Edit Code View Plots Session Build Debug Profile Tools Help

Go to file/function Addins

clock x

Source on Save

```

113
114 ))
115
116 round(tab, 2)|
117
118
119
120
116:14 (Top Level)

```

Console Terminal x Background Jobs x

R 4.2.1 · ~/

```

>
> #fit <- lm(formula = Price ~ Age + Bidders + I(Age*Bidders),data = clock.data)
> fit.aov <- anova(second.mlrm)
> tab <- as.table(cbind(
+   'SS' = c("SSR(x1, x2, x3)" = sum(fit.aov[1:3, 2]),
+     "SSR(x1)" = fit.aov[1, 2],
+     "SSR(x2|x1)" = fit.aov[2, 2],
+     "SSR(x3|x1, x2)" = fit.aov[3, 2],
+     "SSE" = fit.aov[4, 2],
+     "Total" = sum(fit.aov[, 2])),
+   'Df' = c(
+     sum(fit.aov[1:3, 1]),
+     fit.aov[1, 1],
+     fit.aov[2, 1],
+     fit.aov[3, 1],
+     fit.aov[4, 1],
+     sum(fit.aov$Df)),
+   'MS' = c(
+     sum(fit.aov[1:3, 2]) / sum(fit.aov[1:3, 1]),
+     fit.aov[1, 3],
+     fit.aov[2, 3],
+     fit.aov[3, 3],
+     fit.aov[4, 3],
+     NA)
+ ))
>
> round(tab, 2)

```

	SS	Df	MS
SSR(x1, x2, x3)	4572547.99	3.00	1524182.66
SSR(x1)	2554859.01	1.00	2554859.01
SSR(x2 x1)	1722300.69	1.00	1722300.69
SSR(x3 x1, x2)	295388.28	1.00	295388.28
SSE	218646.23	28.00	7808.79
Total	4791194.22	31.00	

```

> |

```

**As can be seen from the R Sq. value obtained, this Model is able to explain 95.44% of the variance in Price.**

**b. Given the age of a clock, by what amount can one expect the selling price to go up for one more person participating in the auction?**

We can write the fitted Model as :

$$E(\text{Price}) = 322.7544 + 0.8733(\text{Age}) - 93.4099(\text{Bidders}) + 1.2979(\text{Age} * \text{Bidders})$$

This can be re-written as :

$$E(\text{Price}) = 322.7544 + 0.8733(\text{Age}) + (-93.4099 + 1.2979 \times \text{Age}) \times \text{Bidders}$$

For a given Age, the Expected selling Price of a Clock will go up by  $(-93.4099 + 1.2979 \times \text{Age})$  where Age will be a constant given to us.

**c. An auction house has acquired several grandfather clocks each 100 years old paying an average price of £500 per clock. From the past experience it has found that such auctions (for antique grandfather clocks) typically attract about 10-12 bidders. What can be said about its expected profit per clock with 95% confidence?**

We need to find 95% Confidence Interval for the  $(\text{Price} - 500)$ ? for a clock that is 100 years old and has 10 to 12 Bidders.

Effectively we are finding  $E(\text{Price}|\text{Age} = 100, \text{Bidders} = 10)$ ,  $E(\text{Price}|\text{Age} = 100, \text{Bidders} = 11)$ , and  $E(\text{Price}|\text{Age} = 100, \text{Bidders} = 12)$ .

```

119
120 #For Bidders = 10
121 exp.value1 <- predict(second.mlrm, newdata = data.frame(Age = 100, Bidders = 10), interval = "confidence", level = .95)
122 exp.value1[2] - 500
123
124 #For Bidders = 11
125 exp.value2 <- predict(second.mlrm, newdata = data.frame(Age = 100, Bidders = 11), interval = "confidence", level = .95)
126 exp.value2[2] - 500
127
128 #For Bidders = 12
129 exp.value3 <- predict(second.mlrm, newdata = data.frame(Age = 100, Bidders = 12), interval = "confidence", level = .95)
130 exp.value3[2] - 500
131
132
133

```

	SSR(x2 x1)		SSR(x3 x1, x2)	
SSR(x2 x1)	1722300.69	1.00	1722300.69	
SSR(x3 x1, x2)	295388.28	1.00	295388.28	
SSE	218646.23	28.00	7808.79	
Total	4791194.22	31.00		

```

> #For Bidders = 10
> exp.value1 <- predict(second.mlrm, newdata = data.frame(Age = 100, Bidders = 10), interval = "confidence", level = .95)
> exp.value1[2] - 500
[1] 210.7254
>
> #For Bidders = 11
> exp.value2 <- predict(second.mlrm, newdata = data.frame(Age = 100, Bidders = 11), interval = "confidence", level = .95)
> exp.value2[2] - 500
[1] 243.6869
>
> #For Bidders = 12
> exp.value3 <- predict(second.mlrm, newdata = data.frame(Age = 100, Bidders = 12), interval = "confidence", level = .95)
> exp.value3[2] - 500
[1] 271.1562
>

```

The Expected Profit per Clock that is 100 years old and has 10 Bidders, with 95% confidence is 210.7254.

The Expected Profit per Clock that is 100 years old and has 11 Bidders, with 95% confidence is 243.6869.

The Expected Profit per Clock that is 100 years old and has 12 Bidders, with 95% confidence is 271.1562.

d. You walk into an auction selling an antique 150 year old grandfather clock and find that there are 15 bidders (including yourself) participating in the auction. You are extremely keen in acquiring the clock. At least what amount should you bid for the clock, so that, you are 99% certain that nobody else can out-bid you?

For this, we need to predict a lower bound for a Predicted value of  $Y$  ( $\hat{Y}$ ) for the given values of Age = 150 years and Bidders = 15.



The image shows the RStudio interface with a script editor and a console. The script editor contains R code for calculating a lower bound price. The console shows the execution of the code, including the calculation of the Mean Squared Error (MSE), the beta matrix, the new data matrix, the prediction price, the t-value, the x matrix, the val, and the final lower bound price.

```

138 beta_matrix
139
140 new_data <- as.matrix(c(1, 150,15, 2250))
141 new_data
142
143 prediction_price <- t(new_data) %%% beta_matrix
144 t.value <- qt(0.99,30) #df = 30
145 x <- cbind(clock.data$Age,clock.data$Bidders, clock.data$Age*clock.data$Bidders)
146 x_h <- matrix(c(150,15,2250), nrow=1,ncol = 3)
147
148 val <- x_h %%% solve( t(x) %%% x ) %%% t(x_h)
149 lower.bound.price <- prediction_price-t.value*sqrt(MSE)*sqrt(1+val)
150 lower.bound.price
151

```

```

150:18 (Top Level) ↕

```

```

Console Terminal Background Jobs
R 4.2.1 ~ /
> MSE <- mean(second.mlrm$residuals^2)
>
> beta_matrix <- as.matrix(second.mlrm$coefficients, ncol=1)
> beta_matrix
              [,1]
(Intercept) 322.7543531
Age          0.8732878
Bidders      -93.4099199
I(Age * Bidders) 1.2978983
>
> new_data <- as.matrix(c(1, 150,15, 2250))
> new_data
      [,1]
[1,]    1
[2,]   150
[3,]    15
[4,]  2250
>
> prediction_price <- t(new_data) %%% beta_matrix
> t.value <- qt(0.99,30) #df = 30
> x <- cbind(clock.data$Age,clock.data$Bidders, clock.data$Age*clock.data$Bidders)
> x_h <- matrix(c(150,15,2250), nrow=1,ncol = 3)
>
> val <- x_h %%% solve( t(x) %%% x ) %%% t(x_h)
> lower.bound.price <- prediction_price-t.value*sqrt(MSE)*sqrt(1+val)
> lower.bound.price
      [,1]
[1,] 1750.339
>

```

From the above calculations, we can say that if we bid at a Price higher than **1750.339**, we can be 99% certain that no one else can out-bid us.