In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.formula.api as smf
```

In [2]:

```
dataset=pd.read_csv('delivery_time.csv')
dataset.head()
```

Out[2]:

	Delivery Time	Sorting Time
0	21.00	10
1	13.50	4
2	19.75	6
3	24.00	9
4	29.00	10

In [3]:

```
#Null value and data types check
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21 entries, 0 to 20
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Delivery Time  21 non-null     float64
 1   Sorting Time   21 non-null     int64  
dtypes: float64(1), int64(1)
memory usage: 464.0 bytes
```

In [4]:

```
#rename the Delivery Time column as delivery_time and Sorting Time Column as sorting_time
dataset1= dataset.rename({'Delivery Time': 'DT','Sorting Time': 'ST'}, axis=1)
dataset1.head()
```

Out[4]:

	DT	ST
0	21.00	10
1	13.50	4
2	19.75	6
3	24.00	9
4	29.00	10

In [5]:

```
#Print the duplicated rows if present inside the data set
dataset1[dataset1.duplicated(keep = False)]
```

Out[5]:

DT	ST

Hence as per above process we found that there is no duplicate values are present inside the data set

In [6]:

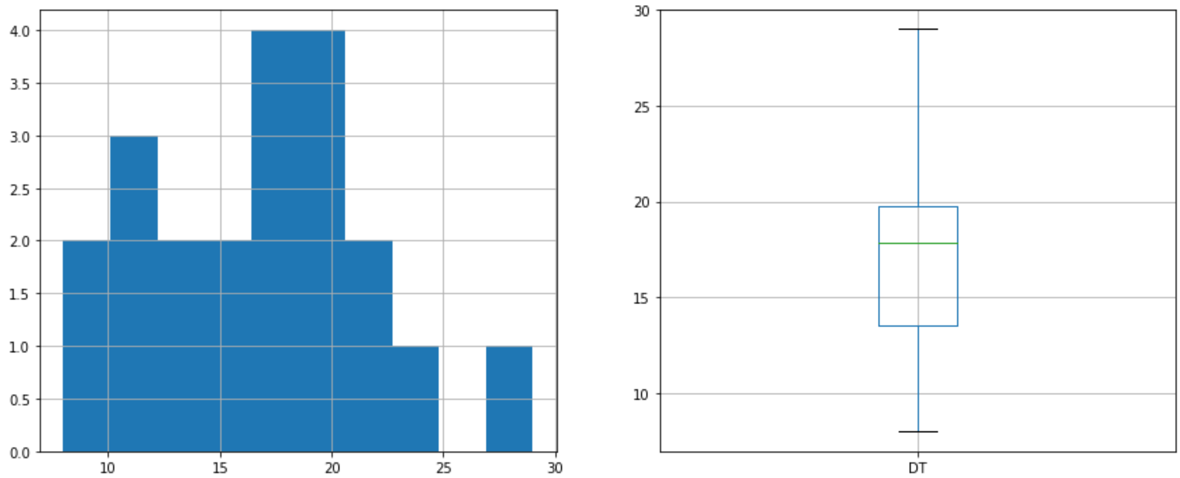
```
#Correlation
dataset1.corr()
```

Out[6]:

	DT	ST
DT	1.000000	0.825997
ST	0.825997	1.000000

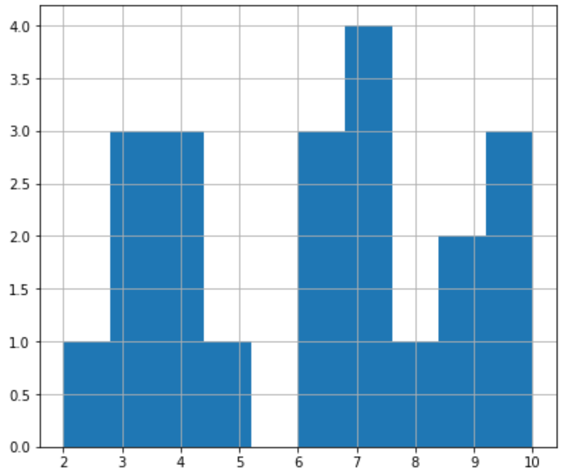
In [7]:

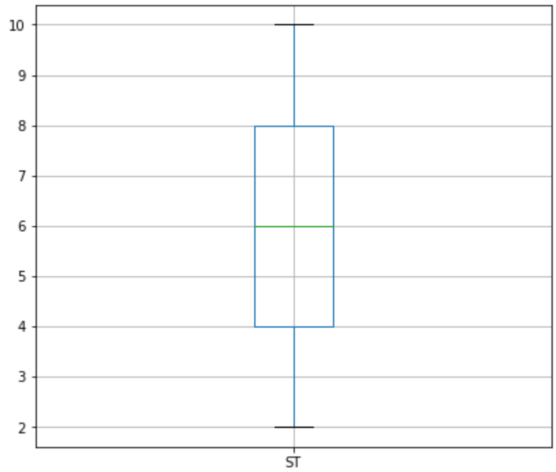
```
#Outlier checking
plt.figure(figsize = (15,6))
plt.subplot(1,2,1)
dataset1['DT'].hist()
plt.subplot(1,2,2)
dataset1.boxplot(column=['DT'])

plt.show()
```



In [8]:

```
plt.figure(figsize = (15,6))
plt.subplot(1,2,1)
dataset1['ST'].hist()
plt.subplot(1,2,2)
dataset1.boxplot(column=['ST'])

plt.show()
```





From the above histogrms and boxplots, we found that there is no outleirs present inside the Delivery Time and Sorting Time variable.

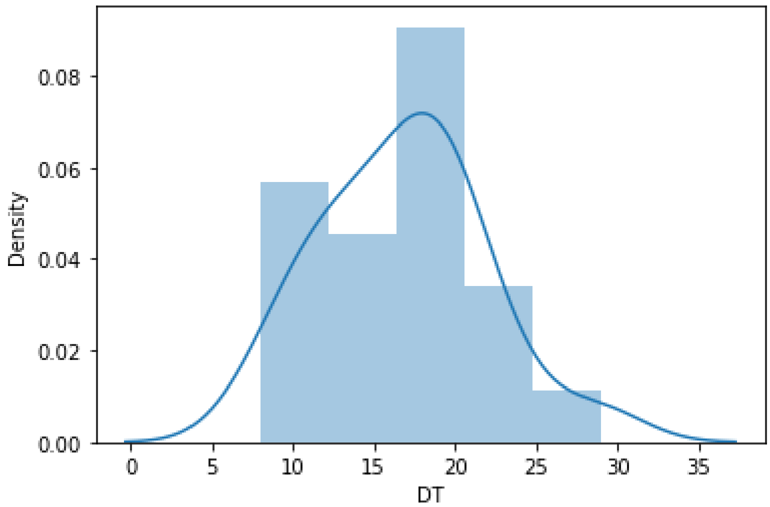
In [9]:

```
#Cheking of distribution of data using distplot
sns.distplot(dataset1['DT'])
```

```
C:\Users\sowmya sandeep\anaconda3\lib\site-packages\seaborn\distributions.p
y:2619: FutureWarning: `distplot` is a deprecated function and will be remov
ed in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-level f
unction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[9]:

```
<AxesSubplot:xlabel='DT', ylabel='Density'>
```



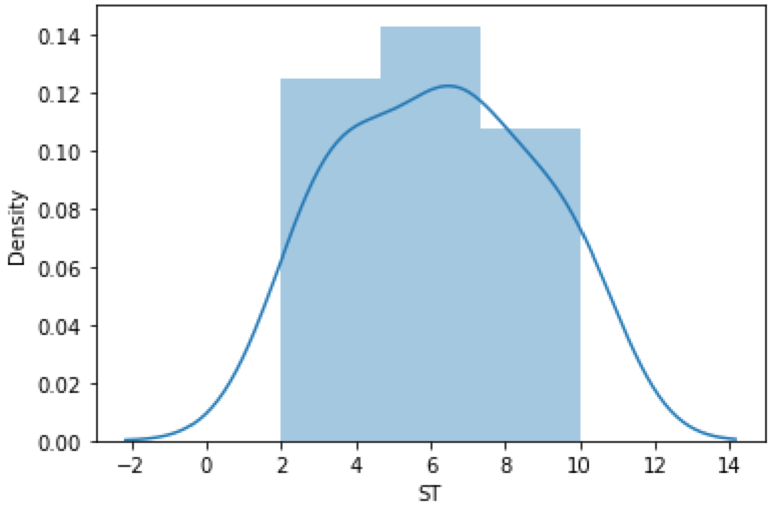
In [10]:

```
sns.distplot(dataset1['ST'])
```

```
C:\Users\sowmya sandeep\anaconda3\lib\site-packages\seaborn\distributions.p
y:2619: FutureWarning: `distplot` is a deprecated function and will be remov
ed in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-level f
unction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[10]:

```
<AxesSubplot:xlabel='ST', ylabel='Density'>
```



#Model1- Predict this model without applying transformation

In [11]:

```
dataset_1 = smf.ols('DT~ST', data = dataset1).fit()
```

In [12]:

```
dataset_1
```

Out[12]:

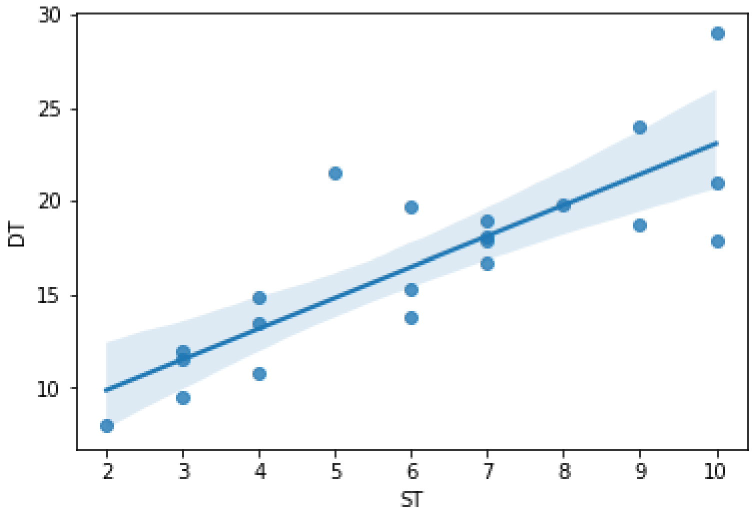
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2535d083a
00>
```

In [14]:

```
#Regresssion Plot
sns.regplot(x="ST", y="DT", data = dataset1 )
```

Out[14]:

```
<AxesSubplot:xlabel='ST', ylabel='DT'>
```



In [15]:

```
#Coefficients
dataset_1.params
```

Out[15]:

```
Intercept    6.582734
ST           1.649020
dtype: float64
```

In [16]:

```
print(dataset_1.tvalues, '\n', dataset_1.pvalues)
```

```
Intercept    3.823349
ST           6.387447
dtype: float64
 Intercept    0.001147
ST           0.000004
dtype: float64
```

In [17]:

```
(dataset_1.rsquared,dataset_1.rsquared_adj)
```

Out[17]:

```
(0.6822714748417231, 0.6655489208860244)
```

In [18]:

```
dataset_1.summary()
```

Out[18]:

OLS Regression Results

Dep. Variable:	DT	**R-squared:**	0.682
Model:	OLS	**Adj. R-squared:**	0.666
Method:	Least Squares	**F-statistic:**	40.80
Date:	Wed, 25 May 2022	**Prob (F-statistic):**	3.98e-06
Time:	16:50:24	**Log-Likelihood:**	-51.357
No. Observations:	21	**AIC:**	106.7
Df Residuals:	19	**BIC:**	108.8
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	6.5827	1.722	3.823	0.001	2.979	10.186
ST	1.6490	0.258	6.387	0.000	1.109	2.189

Omnibus:	3.649	**Durbin-Watson:**	1.248
Prob(Omnibus):	0.161	**Jarque-Bera (JB):**	2.086
Skew:	0.750	**Prob(JB):**	0.352
Kurtosis:	3.367	**Cond. No.**	18.3

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Here from above OLS regression results R-Squared value is 0.682 which is not greater than 0.85 hence we cannot say this model1 is good for predict Delivery TIme. Here p value is less than 0.05, it is significant

In [19]:

```
def RMSE(predict, actual):
    return np.sqrt(((predict - actual) ** 2).mean())
```

In [20]:

```
#Checking the RMSE value
value_1= dataset_1.predict(dataset1.ST)
```

In [21]:

```
value_1
```

Out[21]:

```
0     23.072933
1     13.178814
2     16.476853
3     21.423913
4     23.072933
5     16.476853
6     18.125873
7     11.529794
8     23.072933
9     21.423913
10    19.774893
11    13.178814
12    18.125873
13    11.529794
14    11.529794
15    13.178814
16    16.476853
17    18.125873
18     9.880774
19    18.125873
20    14.827833
dtype: float64
```

In [22]:

```
actual = dataset1.DT
```

In [23]:

```
RMSE(value_1,actual)
```

Out[23]:

```
2.7916503270617654
```

Model2 - We will try to apply Transformation on variables to get higher R-squared value as to predict better model

In [24]:

```
#Applying Logarithim Transformation and predict a new model
dataset_2 = smf.ols('DT~np.log(ST)', data = dataset1).fit()
```

In [25]:

```
#Coefficients
dataset_2 .params
```

Out[25]:

```
Intercept     1.159684
np.log(ST)    9.043413
dtype: float64
```

In [26]:

```
dataset_2.summary()
```

Out[26]:

OLS Regression Results

Dep. Variable:	DT	**R-squared:**	0.695
Model:	OLS	**Adj. R-squared:**	0.679
Method:	Least Squares	**F-statistic:**	43.39
Date:	Wed, 25 May 2022	**Prob (F-statistic):**	2.64e-06
Time:	16:50:34	**Log-Likelihood:**	-50.912
No. Observations:	21	**AIC:**	105.8
Df Residuals:	19	**BIC:**	107.9
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.1597	2.455	0.472	0.642	-3.978	6.297
np.log(ST)	9.0434	1.373	6.587	0.000	6.170	11.917

Omnibus:	5.552	**Durbin-Watson:**	1.427
Prob(Omnibus):	0.062	**Jarque-Bera (JB):**	3.481
Skew:	0.946	**Prob(JB):**	0.175
Kurtosis:	3.628	**Cond. No.**	9.08

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Here as per above result in this case R-squared value is 0.695 which is greater than our model1 but not greater than 0.85. We can say model2 is better than model1 . But not the best fit model to predict Delivery_time

In [27]:

```
#Checking of RMSE value
value_2= dataset_2.predict(dataset1.ST)
value_2
```

Out[27]:

```
0     21.982913
1     13.696517
2     17.363305
3     21.030094
4     21.982913
5     17.363305
6     18.757354
7     11.094889
8     21.982913
9     21.030094
10    19.964933
11    13.696517
12    18.757354
13    11.094889
14    11.094889
15    13.696517
16    17.363305
17    18.757354
18     7.428100
19    18.757354
20    15.714496
dtype: float64
```

In [28]:

```
RMSE(value_2,actual)
```

Out[28]:

```
2.7331714766820663
```

Model3 - As in model2 the R-squared value is not also good. So we need to do another transformation to get better R-squared value.

In [29]:

```
#Applying Exponential transformation and predict a new model
dataset_3 = smf.ols('DT~np.exp(ST)', data = dataset1).fit()
```

In [30]:

```
#Coefficients
dataset_3 .params
```

Out[30]:

```
Intercept     15.083578
np.exp(ST)     0.000393
dtype: float64
```

In [31]:

```
dataset_3.summary()
```

Out[31]:

OLS Regression Results

Dep. Variable:	DT	**R-squared:**	0.361
Model:	OLS	**Adj. R-squared:**	0.327
Method:	Least Squares	**F-statistic:**	10.74
Date:	Wed, 25 May 2022	**Prob (F-statistic):**	0.00396
Time:	16:50:44	**Log-Likelihood:**	-58.691
No. Observations:	21	**AIC:**	121.4
Df Residuals:	19	**BIC:**	123.5
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	15.0836	1.047	14.406	0.000	12.892	17.275
np.exp(ST)	0.0004	0.000	3.277	0.004	0.000	0.001

Omnibus:	2.426	**Durbin-Watson:**	1.676
Prob(Omnibus):	0.297	**Jarque-Bera (JB):**	1.151
Skew:	-0.087	**Prob(JB):**	0.562
Kurtosis:	1.866	**Cond. No.**	1.01e+04

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The condition number is large, 1.01e+04. This might indicate that there are
strong multicollinearity or other numerical problems.

Here as per above result in this case R-squared value is 0.361 which is lesser than 0.85. We cannot take this model to predict Delivery_time

In [32]:

```
#Checking of RMSE value
value_3= dataset_3.predict(dataset1.ST)
value_3
```

Out[32]:

```
0     23.739082
1     15.105033
2     15.242109
3     18.267760
4     23.739082
5     15.242109
6     15.514510
7     15.091471
8     23.739082
9     18.267760
10    16.254973
11    15.105033
12    15.514510
13    15.091471
14    15.091471
15    15.105033
16    15.242109
17    15.514510
18    15.086482
19    15.514510
20    15.141898
dtype: float64
```

In [33]:

```
RMSE(value_3,actual)
```

Out[33]:

```
3.958615702523664
```

Model4 - We need to do another transformation to get better R-squared value.

In [34]:

```
#Applying Reciprocal transformation and predict a new model
dataset_4 = smf.ols('DT~np.reciprocal(ST)', data = dataset1).fit()
```

In [35]:

```
#Coefficients
dataset_4.params
```

Out[35]:

```
Intercept            16.790952
np.reciprocal(ST)     0.000000
dtype: float64
```

In [36]:

```
dataset_4.summary()
```

```
C:\Users\sowmya sandeep\anaconda3\lib\site-packages\statsmodels\regression\l
inear_model.py:1860: RuntimeWarning: divide by zero encountered in double_sc
alars
  return np.sqrt(eigvals[0]/eigvals[-1])
```

Out[36]:

OLS Regression Results

Dep. Variable:	DT	**R-squared:**	0.000
Model:	OLS	**Adj. R-squared:**	0.000
Method:	Least Squares	**F-statistic:**	nan
Date:	Wed, 25 May 2022	**Prob (F-statistic):**	nan
Time:	16:50:51	**Log-Likelihood:**	-63.396
No. Observations:	21	**AIC:**	128.8
Df Residuals:	20	**BIC:**	129.8
Df Model:	0		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	16.7910	1.107	15.162	0.000	14.481	19.101
np.reciprocal(ST)	0	0	nan	nan	0	0

Omnibus:	0.864	**Durbin-Watson:**	1.720
Prob(Omnibus):	0.649	**Jarque-Bera (JB):**	0.374
Skew:	0.327	**Prob(JB):**	0.829
Kurtosis:	2.974	**Cond. No.**	inf

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
[2] The smallest eigenvalue is 0. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.

In [37]:

```
#Checking of RMSE value
value_4= dataset_4.predict(dataset1.ST)
value_4
```

Out[37]:

```
0     16.790952
1     16.790952
2     16.790952
3     16.790952
4     16.790952
5     16.790952
6     16.790952
7     16.790952
8     16.790952
9     16.790952
10    16.790952
11    16.790952
12    16.790952
13    16.790952
14    16.790952
15    16.790952
16    16.790952
17    16.790952
18    16.790952
19    16.790952
20    16.790952
dtype: float64
```

In [38]:

```
RMSE(value_4,actual)
```

Out[38]:

```
4.952596149170659
```

Model5 - We need to do another transformation to get better R-squared value.

In [39]:

```
#Applying squareroot transformation and predict a new model
dataset_5 = smf.ols('DT~np.sqrt(ST)', data = dataset1).fit()
```

In [40]:

```
#Coefficients
dataset_5.params
```

Out[40]:

```
Intercept     -2.518837
np.sqrt(ST)    7.936591
dtype: float64
```

In [41]:

```
dataset_5.summary()
```

Out[41]:

OLS Regression Results

Dep. Variable:	DT	**R-squared:**	0.696
Model:	OLS	**Adj. R-squared:**	0.680
Method:	Least Squares	**F-statistic:**	43.46
Date:	Wed, 25 May 2022	**Prob (F-statistic):**	2.61e-06
Time:	16:50:53	**Log-Likelihood:**	-50.900
No. Observations:	21	**AIC:**	105.8
Df Residuals:	19	**BIC:**	107.9
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	-2.5188	2.995	-0.841	0.411	-8.788	3.751
np.sqrt(ST)	7.9366	1.204	6.592	0.000	5.417	10.456

Omnibus:	4.658	**Durbin-Watson:**	1.318
Prob(Omnibus):	0.097	**Jarque-Bera (JB):**	2.824
Skew:	0.865	**Prob(JB):**	0.244
Kurtosis:	3.483	**Cond. No.**	13.7

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

In [42]:

```
value_5= dataset_5.predict(dataset1.ST)
value_5
```

Out[42]:

```
0     22.578867
1     13.354345
2     16.921761
3     21.290936
4     22.578867
5     16.921761
6     18.479409
7     11.227742
8     22.578867
9     21.290936
10    19.929232
11    13.354345
12    18.479409
13    11.227742
14    11.227742
15    13.354345
16    16.921761
17    18.479409
18     8.705198
19    18.479409
20    15.227920
dtype: float64
```

In [43]:

```
RMSE(value_5,actual)
```

Out[43]:

```
2.731543210091211
```

Model6 - We need to do another transformation to get better R-squared value.

In [44]:

```
#Applying exponential transformation in other way and predict a new model
dataset_6 = smf.ols('np.log(DT)~ST', data = dataset1).fit()
```

In [45]:

```
#Coefficients
dataset_6.params
```

Out[45]:

```
Intercept    2.121372
ST           0.105552
dtype: float64
```

In [46]:

```
dataset_6.summary()
```

Out[46]:

OLS Regression Results

Dep. Variable:	np.log(DT)	**R-squared:**	0.711
Model:	OLS	**Adj. R-squared:**	0.696
Method:	Least Squares	**F-statistic:**	46.73
Date:	Wed, 25 May 2022	**Prob (F-statistic):**	1.59e-06
Time:	16:50:54	**Log-Likelihood:**	7.7920
No. Observations:	21	**AIC:**	-11.58
Df Residuals:	19	**BIC:**	-9.495
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.1214	0.103	20.601	0.000	1.906	2.337
ST	0.1056	0.015	6.836	0.000	0.073	0.138

Omnibus:	1.238	**Durbin-Watson:**	1.325
Prob(Omnibus):	0.538	**Jarque-Bera (JB):**	0.544
Skew:	0.393	**Prob(JB):**	0.762
Kurtosis:	3.067	**Cond. No.**	18.3

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

Here as per above result in this case R-squared value is 0.711. p- values is less than 0.05, it is significant

In [47]:

```
#Checking RMSE value and predict delivery time
value_6= np.exp(dataset_6.predict(dataset1.ST))
value_6
```

Out[47]:

```
0     23.972032
1     12.725123
2     15.716034
3     21.570707
4     23.972032
5     15.716034
6     17.465597
7     11.450423
8     23.972032
9     21.570707
10    19.409927
11    12.725123
12    17.465597
13    11.450423
14    11.450423
15    12.725123
16    15.716034
17    17.465597
18    10.303411
19    17.465597
20    14.141728
dtype: float64
```

In [48]:

```
RMSE(value_6 ,actual)
```

Out[48]:

```
2.9402503230562007
```

CONCLUSION - Comparing between all models , model6 has higher R-squared value i.e. 0.711 as comapare to others. From the above data we know higher R-squred value and lower RMSE value gives better model. Hence the Model-6 is better model to predict delivery_time

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```