Simple Linear Regression Assignment

Data Set : delivery_time

Q = Predict delivery time using sorting time

1. Import Necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
import seaborn as sns

import statsmodels.formula.api as smf

from sklearn.metrics import mean_squared_error
from math import sqrt

import warnings
warnings.filterwarnings('ignore')
```

2. Import Data

In [2]:
```
time_pickup = pd.read_csv('delivery_time.csv')
time_pickup
```

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
5	15.35	6
6	19.00	7
7	9.50	3
8	17.90	10
9	18.75	9
10	19.83	8
11	10.75	4
12	16.68	7
13	11.50	3
14	12.03	3
15	14.88	4
16	13.75	6
17	18.11	7
18	8.00	2
19	17.83	7
20	21.50	5

3. Data Understanding

a) Initial Analysis :

In [3]:
```
time_pickup.head()
```

Out[3]:

	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 [4]:
```
time_pickup.shape
```

Out[4]:
```
(21, 2)
```

In [5]:
```
time_pickup.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 [6]:
```
time_pickup.isna().sum()
```

Out[6]:
```
Delivery Time    0
Sorting Time     0
dtype: int64
```

In [7]:
```
time_pickup.dtypes
```

Out[7]:
```
Delivery Time    float64
Sorting Time       int64
dtype: object
```

There is no Null value present in this data set and also the data types are appropriate in all attributes

In [8]:
```
time_pickup_1 = time_pickup.rename({'Delivery Time':'DT','Sorting Time':'ST'},axis = 1)
time_pickup_1
```

Out[8]:

	DT	ST
0	21.00	10
1	13.50	4
2	19.75	6
3	24.00	9
4	29.00	10
5	15.35	6
6	19.00	7
7	9.50	3
8	17.90	10
9	18.75	9
10	19.83	8
11	10.75	4
12	16.68	7
13	11.50	3
14	12.03	3
15	14.88	4
16	13.75	6
17	18.11	7
18	8.00	2
19	17.83	7
20	21.50	5

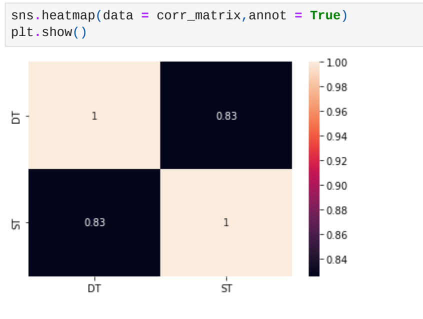
b) Correlation Matrix :

In [9]:
```
corr_matrix = time_pickup_1.corr()
corr_matrix
```

Out[9]:

	DT	ST
DT	1.000000	0.825997
ST	0.825997	1.000000

In [10]:
```
sns.heatmap(data = corr_matrix,annot = True)
plt.show()
```

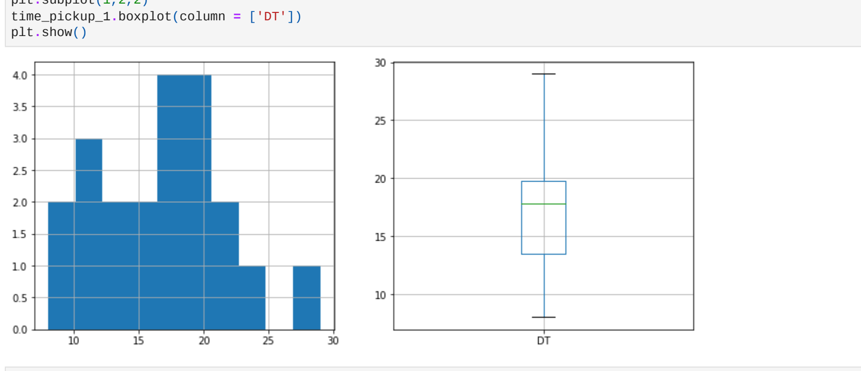


|r| > 0.8, hence there is a strong positive relation between Delivery Time and Sorting Time

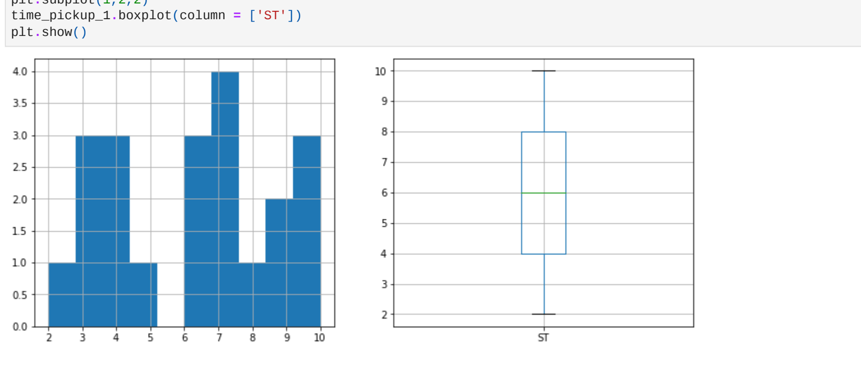
5. Perform Assumption Check

a) Outlier Test Using Box Plot :

In [11]:
```
plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
time_pickup_1['DT'].hist()
plt.subplot(1,2,2)
time_pickup_1.boxplot(column = ['DT'])
plt.show()
```



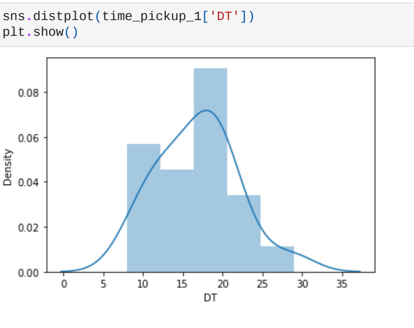
In [12]:
```
plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
time_pickup_1['ST'].hist()
plt.subplot(1,2,2)
time_pickup_1.boxplot(column = ['ST'])
plt.show()
```



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

b) Normality / Distribution Test Using Distplot :

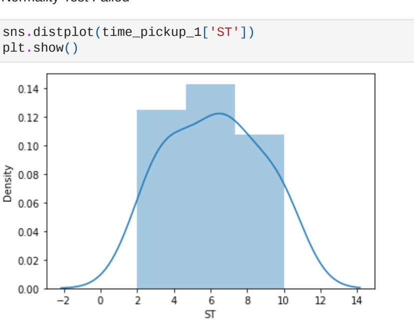
In [13]:
```
sns.distplot(time_pickup_1['DT'])
plt.show()
```



DT is a Positive Skew & Asymmetrical Distribution

Normality Test Failed

In [14]:
```
sns.distplot(time_pickup_1['ST'])
plt.show()
```



ST is a Zero Skew & Symmetrical Distribution

7. Model Building || 8. Model Training

Now Try To Fit Model For Delivery Time [DT] Because It Is a Asymmetrical Distribution

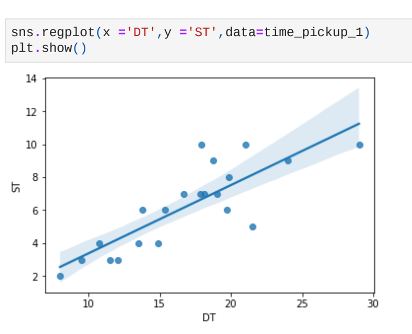
Model 1: Without Applying any Transformation

Using Statsmodel

In [15]:
```
time_model_1 = smf.ols(formula = 'DT~ST',data = time_pickup_1).fit()
time_model_1
```

Out[15]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d64ac76fa0>
```

In [16]:
```
sns.regplot(x ='DT',y ='ST',data=time_pickup_1)
plt.show()
```



In [17]:
```
#coefficient
time_model_1.params
```

Out[17]:
```
Intercept    6.582734
ST           1.649020
dtype: float64
```

In [18]:
```
time_model_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:	Sat, 24 Sep 2022	Prob (F-statistic):	3.98e-06
Time:	00:32:40	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.

From the Above OLS Regression Result the R-Squared value is 0.682 < 0.75 and this Model is Not Good to Predict Delivery Time [DT] and p-value < 0.05

9. Model Testing

In [19]:
```
pred_1 = time_model_1.predict(time_pickup_1.ST)
pred_1
```

Out[19]:
```
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 [20]:
```
actual_1 = time_pickup_1.DT
```

In [21]:
```
rmse = sqrt(mean_squared_error(actual_1,pred_1))
print(rmse)
```

```
2.7916503270617654
```

Model 2: Apply Exponential Transformation

In [22]:
```
time_model_2 = smf.ols(formula = 'DT~np.exp(ST)',data = time_pickup_1).fit()
time_model_2
```

Out[22]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d64aa2c3d0>
```

In [23]:
```
time_model_2.params
```

Out[23]:
```
Intercept     15.083578
np.exp(ST)     0.000393
dtype: float64
```

In [24]:
```
time_model_2.summary()
```

Out[24]:

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:	Sat, 24 Sep 2022	Prob (F-statistic):	0.00396
Time:	00:32:43	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.

Model 3: Apply Reciprocal Transformation

In [25]:
```
time_model_3 = smf.ols(formula = 'DT~np.reciprocal(ST)',data = time_pickup_1).fit()
time_model_3
```

Out[25]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d644b6c940>
```

In [26]:
```
time_model_3.params
```

Out[26]:
```
Intercept            16.790952
np.reciprocal(ST)     0.000000
dtype: float64
```

In [27]:
```
time_model_3.summary()
```

Out[27]:

OLS Regression Results

Dep. Variable:	DT	R-squared:	0.000
Model:	OLS	Adj. R-squared:	0.000
Method:	Least Squares	F-statistic:	nan
Date:	Sat, 24 Sep 2022	Prob (F-statistic):	nan
Time:	00:32:45	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.

Model 4: Apply Square Transformation

In [28]:
```
time_model_4 = smf.ols(formula = 'DT~np.square(ST)',data = time_pickup_1).fit()
time_model_4
```

Out[28]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d64acc3550>
```

In [29]:
```
time_model_4.params
```

Out[29]:
```
Intercept        11.237205
np.square(ST)     0.124870
dtype: float64
```

In [30]:
```
time_model_4.summary()
```

Out[30]:

OLS Regression Results

Dep. Variable:	DT	R-squared:	0.630
Model:	OLS	Adj. R-squared:	0.611
Method:	Least Squares	F-statistic:	32.39
Date:	Sat, 24 Sep 2022	Prob (F-statistic):	1.74e-05
Time:	00:32:47	Log-Likelihood:	-52.948
No. Observations:	21	AIC:	109.9
Df Residuals:	19	BIC:	112.0
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	11.2372	1.196	9.399	0.000	8.735	13.740
np.square(ST)	0.1249	0.022	5.691	0.000	0.079	0.171

Omnibus:	1.531	Durbin-Watson:	1.248
Prob(Omnibus):	0.465	Jarque-Bera (JB):	0.772
Skew:	0.469	Prob(JB):	0.680
Kurtosis:	3.050	Cond. No.	94.3

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

Model 5: Apply Square Root Transformation

In [31]:
```
time_model_5 = smf.ols(formula = 'DT~np.sqrt(ST)',data = time_pickup_1).fit()
time_model_5
```

Out[31]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d64aaedca0>
```

In [32]:
```
time_model_5.params
```

Out[32]:
```
Intercept     -2.518837
np.sqrt(ST)    7.936591
dtype: float64
```

In [33]:
```
time_model_5.summary()
```

Out[33]:

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:	Sat, 24 Sep 2022	Prob (F-statistic):	2.61e-06
Time:	00:32:48	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.

Model 6: Apply Log Transformation of Y

In [34]:
```
time_model_6 = smf.ols(formula = 'DT~np.log(ST)',data = time_pickup_1).fit()
time_model_6
```

Out[34]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d64aae6fd0>
```

In [35]:
```
time_model_6.params
```

Out[35]:
```
Intercept     1.159684
np.log(ST)    9.043413
dtype: float64
```

In [36]:
```
time_model_6.summary()
```

Out[36]:

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:	Sat, 24 Sep 2022	Prob (F-statistic):	2.64e-06
Time:	00:32:50	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.

Model 7: Apply Log Transformation of X

In [37]:
```
time_model_7 = smf.ols(formula = 'np.log(DT)~ST',data = time_pickup_1).fit()
time_model_7
```

Out[37]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d64a2cafa0>
```

In [38]:
```
time_model_7.params
```

Out[38]:
```
Intercept    2.121372
ST           0.105552
dtype: float64
```

In [39]:
```
time_model_7.summary()
```

Out[39]:

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:	Sat, 24 Sep 2022	Prob (F-statistic):	1.59e-06
Time:	00:32:51	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.

Model 8: Apply Log Transformation of X & Y

In [40]:
```
time_model_8 = smf.ols(formula = 'np.log(DT)~np.log(ST)',data = time_pickup_1).fit()
time_model_8
```

Out[40]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x1d644b6c5e0>
```

In [41]:
```
time_model_8.params
```

Out[41]:
```
Intercept     1.741987
np.log(ST)    0.597522
dtype: float64
```

In [42]:
```
time_model_8.summary()
```

Out[42]:

OLS Regression Results

Dep. Variable:	np.log(DT)	R-squared:	0.772
Model:	OLS	Adj. R-squared:	0.760
Method:	Least Squares	F-statistic:	64.39
Date:	Sat, 24 Sep 2022	Prob (F-statistic):	1.60e-07
Time:	00:32:53	Log-Likelihood:	10.291
No. Observations:	21	AIC:	-16.58
Df Residuals:	19	BIC:	-14.49
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.7420	0.133	13.086	0.000	1.463	2.021
np.log(ST)	0.5975	0.074	8.024	0.000	0.442	0.753

Omnibus:	1.871	Durbin-Watson:	1.322
Prob(Omnibus):	0.392	Jarque-Bera (JB):	1.170
Skew:	0.577	Prob(JB):	0.557
Kurtosis:	2.916	Cond. No.	9.08

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

CONCLUSION = Comparing between all Models , model_8 has Higher R-squared Value i.e. 0.772 as comapare to other Models.

Hence the Model_8 is better Model to Predict Delivery_Time

THE END