In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import statsmodels.formula.api as smf
import matplotlib.pyplot as plt
from sklearn import linear_model
```

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

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

In [3]:
```
df.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]:
```
df.describe()
```

Out[4]:

	Delivery Time	Sorting Time
count	21.000000	21.000000
mean	16.790952	6.190476
std	5.074901	2.542028
min	8.000000	2.000000
25%	13.500000	4.000000
50%	17.830000	6.000000
75%	19.750000	8.000000
max	29.000000	10.000000

In [38]:
```
df.dtypes
```

Out[38]:
```
Delivery Time       float64
Sorting Time          int64
Deliverd_predict    float64
dtype: object
```

In [39]:
```
df.isnull()
```

Out[39]:

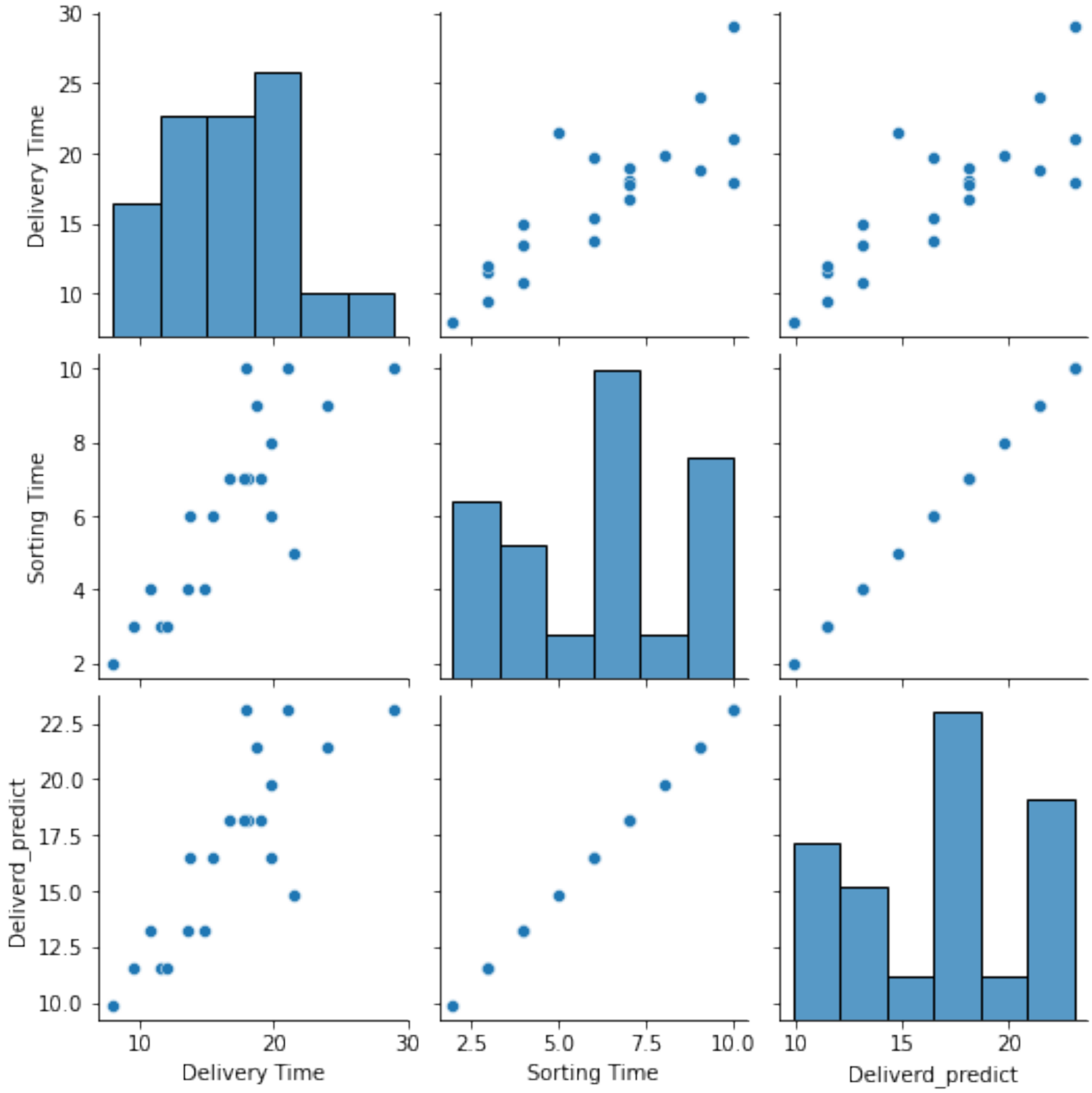
	Delivery Time	Sorting Time	Deliverd_predict
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
5	False	False	False
6	False	False	False
7	False	False	False
8	False	False	False
9	False	False	False
10	False	False	False
11	False	False	False
12	False	False	False
13	False	False	False
14	False	False	False
15	False	False	False
16	False	False	False
17	False	False	False
18	False	False	False
19	False	False	False
20	False	False	False

In [41]:
```
df.isnull().sum()
```

Out[41]:
```
Delivery Time       0
Sorting Time        0
Deliverd_predict    0
dtype: int64
```

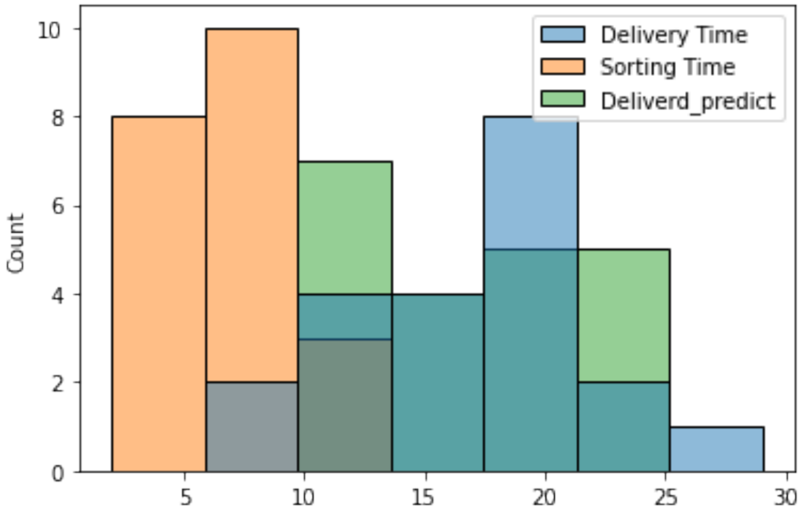
In [42]:
```
sns.pairplot(data = df)
```

Out[42]: <seaborn.axisgrid.PairGrid at 0x7fe97035c460>



In [44]:
```
sns.histplot(data = df)
```

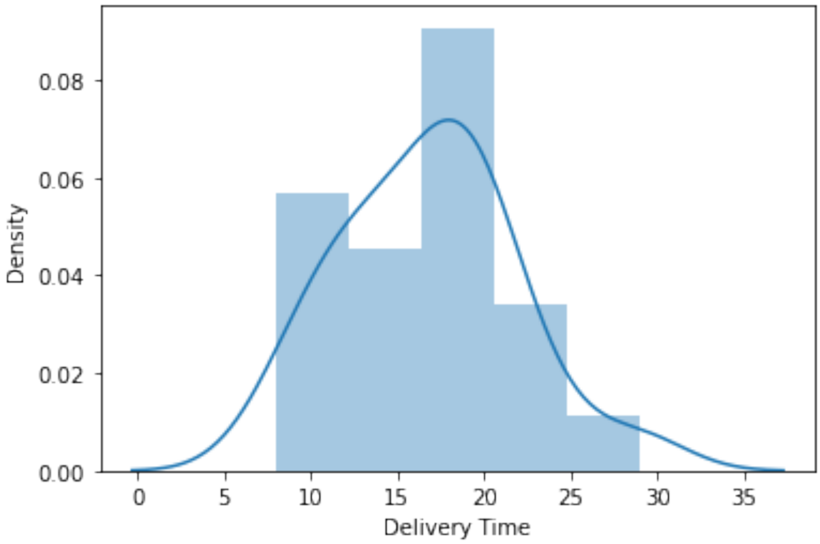
Out[44]: <AxesSubplot:ylabel='Count'>



In [5]:
```
sns.distplot(df['Delivery Time'])
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/distributions.p
y:2619: FutureWarning: `distplot` is a deprecated function and wil
l be removed in a future version. Please adapt your code to use ei
ther `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

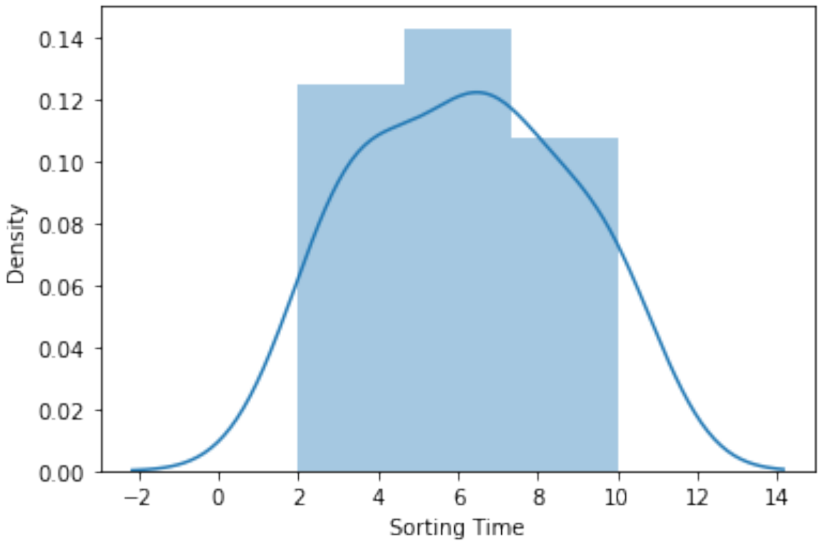
Out[5]: <AxesSubplot:xlabel='Delivery Time', ylabel='Density'>



In [6]:
```
sns.distplot(df['Sorting Time'])
```

```
/opt/anaconda3/lib/python3.9/site-packages/seaborn/distributions.p
y:2619: FutureWarning: `distplot` is a deprecated function and wil
l be removed in a future version. Please adapt your code to use ei
ther `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[6]:
```
<AxesSubplot:xlabel='Sorting Time', ylabel='Density'>
```



In [7]:
```
df.corr()
```

Out[7]:

	Delivery Time	Sorting Time
Delivery Time	1.000000	0.825997
Sorting Time	0.825997	1.000000

In [8]:
```
df['Sorting Time'].describe()
```

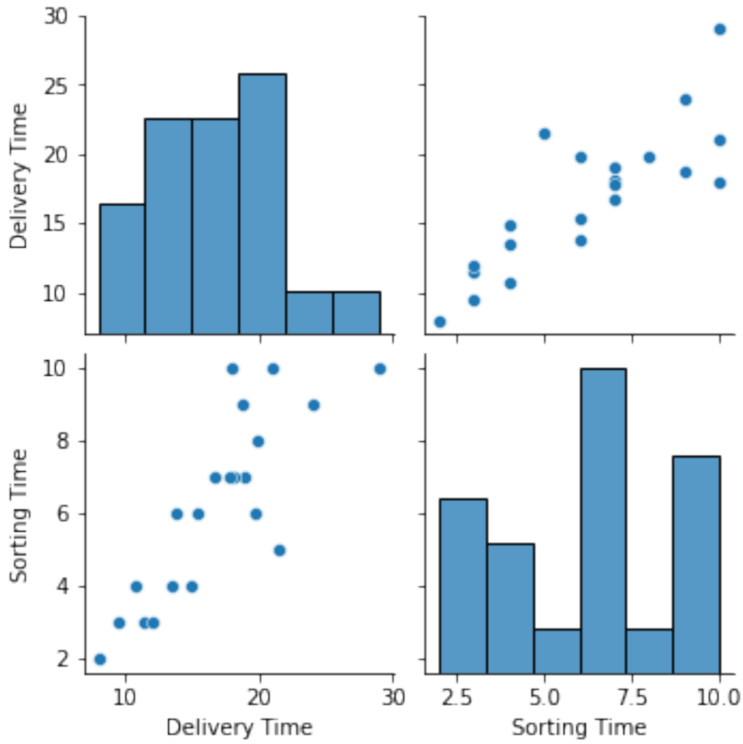
Out[8]:
```
count    21.000000
mean      6.190476
std       2.542028
min       2.000000
25%       4.000000
50%       6.000000
75%       8.000000
max      10.000000
Name: Sorting Time, dtype: float64
```

In [9]:
```
df['Delivery Time'].describe()
```

Out[9]:
```
count    21.000000
mean     16.790952
std       5.074901
min       8.000000
25%      13.500000
50%      17.830000
75%      19.750000
max      29.000000
Name: Delivery Time, dtype: float64
```

In [10]:
```
sns.pairplot(df)
```

Out[10]: <seaborn.axisgrid.PairGrid at 0x7fe96f79bdf0>



In [11]:
```
model = smf.ols("df['Delivery Time']~df['Sorting Time']",data = df)
```

In [12]:
```
model.summary()
```

Out[12]:

OLS Regression Results

Dep. Variable:	df['Delivery Time']	**R-squared:**	0.682
Model:	OLS	**Adj. R-squared:**	0.666
Method:	Least Squares	**F-statistic:**	40.80
Date:	Thu, 01 Dec 2022	**Prob (F-statistic):**	3.98e-06
Time:	02:01:40	**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
df['Sorting Time']	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.

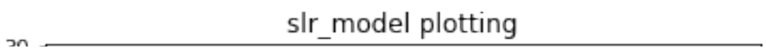
In [13]:
```
print(model.summary())
prediction = model.predict(df.iloc[:,1])
```

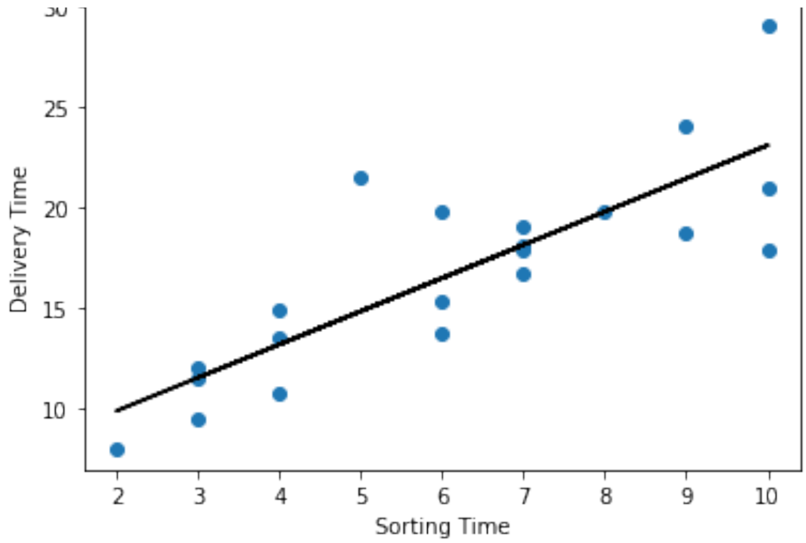
```
                            OLS Regression Results
==============================================================================
Dep. Variable:     df['Delivery Time']   R-squared:
0.682
Model:                             OLS   Adj. R-squared:
0.666
Method:                  Least Squares   F-statistic:
40.80
Date:                 Thu, 01 Dec 2022   Prob (F-statistic):
3.98e-06
Time:                         02:01:40   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
df['Sorting Time']    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 error
s is correctly specified.
```

In [14]:
```
slr_model=smf.ols("df['Delivery Time']~df['Sorting Time']",data=df)
print(slr_model.summary())
predict=slr_model.predict(df.iloc[:,1])
import matplotlib.pylab as plt
```

```
plt.scatter(x=df['Sorting Time'],y=df['Delivery Time'])
plt.plot(df['Sorting Time'],predict,color='black')
plt.xlabel("Sorting Time")
plt.ylabel("Delivery Time")
plt.title("slr_model plotting")
plt.show()
```

```
                              OLS Regression Results
==================================================================
=============
Dep. Variable:     df['Delivery Time']   R-squared:
0.682
Model:                             OLS   Adj. R-squared:
0.666
Method:                  Least Squares   F-statistic:
40.80
Date:                 Thu, 01 Dec 2022   Prob (F-statistic):
3.98e-06
Time:                         02:01:40   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
df['Sorting Time']     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 error
s is correctly specified.
```

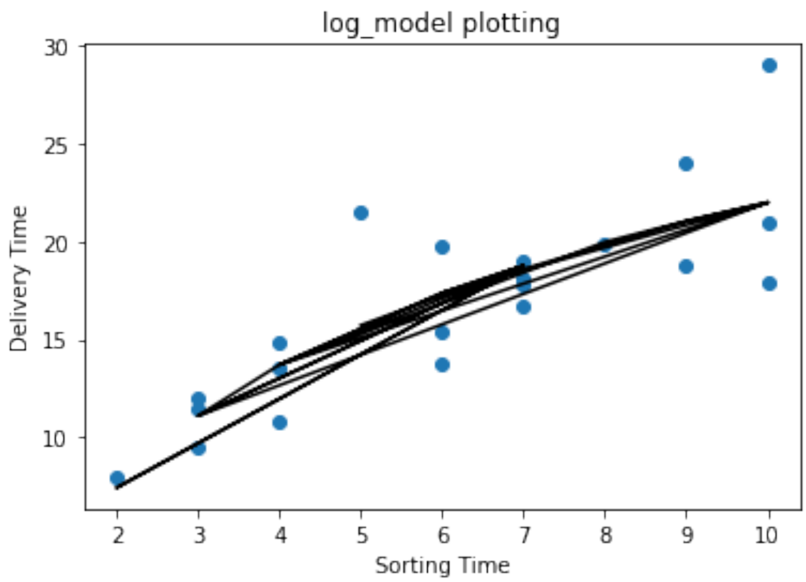




In [15]:
```
log_model=smf.ols("df['Delivery Time']~np.log(df['Sorting Time'])",
print(log_model.summary())
log_predict=log_model.predict(pd.DataFrame(df['Sorting Time']))

import matplotlib.pylab as plt
%matplotlib inline
plt.scatter(x=df['Sorting Time'],y=df['Delivery Time'])
plt.plot(df['Sorting Time'],log_predict,color='black')
plt.xlabel("Sorting Time")
plt.ylabel("Delivery Time")
plt.title("log_model plotting")
plt.show()
```

```
                             OLS Regression Results
==================================================================
==============
Dep. Variable:     df['Delivery Time']   R-squared:
0.695
Model:                             OLS   Adj. R-squared:
0.679
Method:                  Least Squares   F-statistic:
43.39
Date:                 Thu, 01 Dec 2022   Prob (F-statistic):
2.64e-06
Time:                         02:01:41   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]
------------------------------------------------------------------
```

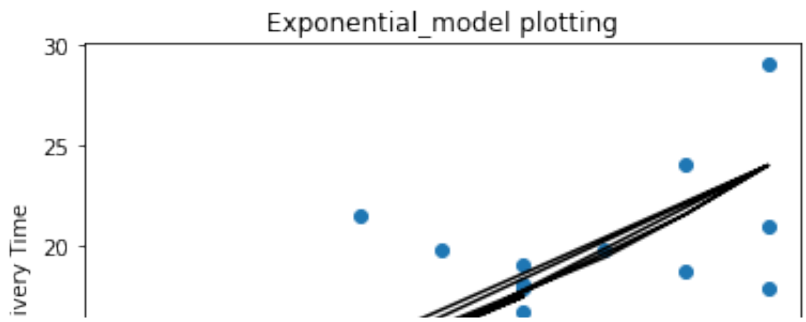
```
----------------------------
Intercept                      1.1597      2.455      0.472      0
.642      -3.978       6.297
np.log(df['Sorting Time'])     9.0434      1.373      6.587      0
.000       6.170      11.917
==================================================================
============
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 error
s is correctly specified.
```

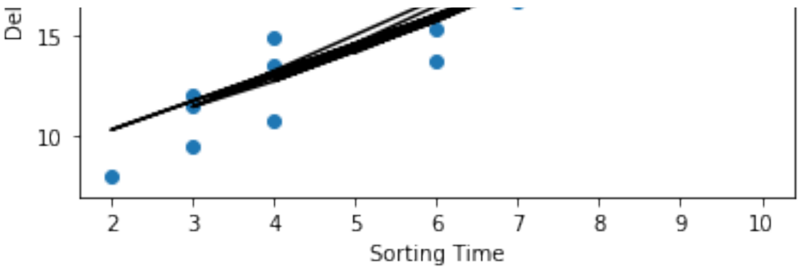


In [16]:
```
exp_model=smf.ols("np.log(df['Delivery Time'])~(df['Sorting Time'])
print(exp_model.summary())
predict_exp=exp_model.predict(pd.DataFrame(df['Sorting Time']))
pred_exp=np.exp(predict_exp)

import matplotlib.pylab as plt
%matplotlib inline
plt.scatter(x=df['Sorting Time'],y=df['Delivery Time'])
plt.plot(df['Sorting Time'],np.exp(predict_exp),color='black')
plt.title("Exponential_model plotting")
plt.xlabel("Sorting Time")
plt.ylabel("Delivery Time")
plt.show()
```

```
                         OLS Regression Results
```

```
                            OLS Regression Results
==============================================================================
=====================
Dep. Variable:     np.log(df['Delivery Time'])   R-squared:
0.711
Model:                                     OLS   Adj. R-squared:
0.696
Method:                          Least Squares   F-statistic:
46.73
Date:                         Thu, 01 Dec 2022   Prob (F-statistic
):             1.59e-06
Time:                                 02:01:41   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
df['Sorting Time']    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 error
s is correctly specified.
```





In [20]:
```
np.sqrt(np.mean((df['Delivery Time']-predict)**2))
```
Out[20]: 2.7916503270617654

In [22]:
```
np.sqrt(np.mean((df['Delivery Time']-predict_exp)**2))
```
Out[22]: 14.795516941016686

In [24]:
```
np.sqrt(np.mean((df['Delivery Time']-log_predict)**2))
```
Out[24]: 2.733171476682066

In [25]:
```
from sklearn.linear_model import LinearRegression
linear_model = LinearRegression()
```

In [26]:
```
linear_model=smf.ols("df['Delivery Time']~df['Sorting Time']",data
```

In [27]:
```
linear_model=linear_model.fit()
```

In [28]:
```
linear_model.params
```
Out[28]:
```
Intercept             6.582734
df['Sorting Time']    1.649020
dtype: float64
```

In [29]:
```
predicteddata = linear_model.predict(df)
predicteddata
```

Out[29]:
```
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 [30]:
```
print(model.tvalues, '\n', model.pvalues)
```

```
Intercept             3.823349
df['Sorting Time']    6.387447
dtype: float64
 Intercept             0.001147
df['Sorting Time']    0.000004
dtype: float64
```

In [31]:
```
#R squared values
(model.rsquared,model.rsquared_adj)
```

Out[31]:
```
(0.6822714748417231, 0.6655489208860244)
```

In [32]:
```
model.summary()
```

Out[32]:

OLS Regression Results

Dep. Variable:	df['Delivery Time']	**R-squared:**	0.682
Model:	OLS	**Adj. R-squared:**	0.666
Method:	Least Squares	**F-statistic:**	40.80
Date:	Thu, 01 Dec 2022	**Prob (F-statistic):**	3.98e-06
Time:	02:04:15	**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
df['Sorting Time']	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.

In [33]:
```
Deliverd =  model.predict()
Deliverd
```

Out[33]:
```
array([23.07293294, 13.17881356, 16.47685335, 21.42391304, 23.0729
3294,
       16.47685335, 18.12587325, 11.52979366, 23.07293294, 21.4239
1304,
       19.77489315, 13.17881356, 18.12587325, 11.52979366, 11.5297
9366,
       13.17881356, 16.47685335, 18.12587325,  9.88077377, 18.1258
7325,
       14.82783346])
```

In [34]:
```
Deliverd_predict=pd.DataFrame(Deliverd, columns=['Salary_hike'])
Deliverd_predict
```

Out[34]:

	Salary_hike
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

In [35]:
```
Deliverd_predict=pd.DataFrame(Deliverd, columns=['Salary_hike'])
Deliverd_predict
```

Out[35]:

	Salary_hike
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

In [36]:
```
df['Deliverd_predict'] = Deliverd_predict
df
```

Out[36]:

	Delivery Time	Sorting Time	Deliverd_predict
0	21.00	10	23.072933
1	13.50	4	13.178814
2	19.75	6	16.476853
3	24.00	9	21.423913
4	29.00	10	23.072933
5	15.35	6	16.476853
6	19.00	7	18.125873
7	9.50	3	11.529794
8	17.90	10	23.072933
9	18.75	9	21.423913
10	19.83	8	19.774893
11	10.75	4	13.178814
12	16.68	7	18.125873
13	11.50	3	11.529794
14	12.03	3	11.529794
15	14.88	4	13.178814
16	13.75	6	16.476853
17	18.11	7	18.125873
18	8.00	2	9.880774
19	17.83	7	18.125873
20	21.50	5	14.827833

In [ ]:

In [ ]: