Q.No. 1) Delivery_time -> Predict delivery time using sorting time. Build a simple linear regression model by performing EDA and do necessary transformations and select the best model using R or Python.

X-Single & Continous (Independant) and Y-Continous (Dependent)

X-Sorting Time, Y-Delivery Time.

Therefore we go for Simple Linerar Regression Model

Step 1. Import Necessary Libraries:

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

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

Step 2. Import Data/Dataset:

In [3]:
```
delivery_details = pd.read_csv('delivery_time.csv')
delivery_details
```

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
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 [4]:
```
dt_st=delivery_details.rename(columns={'Delivery Time': 'delivery_time','Sorting Time': 'sorting_time'})
dt_st
dt_st.head(5)
```

Out[4]:

	delivery_time	sorting_time
0	21.00	10
1	13.50	4
2	19.75	6
3	24.00	9
4	29.00	10

Step 3. Data Understanding / Performing EDA on Data:

Step 3.1 Initial Analysis:

In [5]:
```
delivery_details.shape
```

Out[5]:
```
(21, 2)
```

In [6]:
```
delivery_details.dtypes
```

Out[6]:
```
Delivery Time    float64
Sorting Time       int64
dtype: object
```

In [7]:
```
delivery_details.isnull().sum()
```

Out[7]:
```
Delivery Time    0
Sorting Time     0
dtype: int64
```

In [8]:
```
delivery_details.info()
```

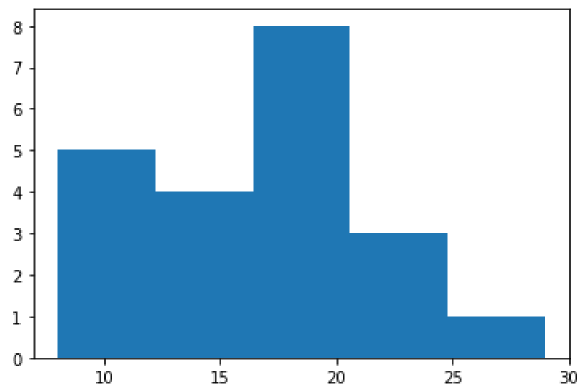
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21 entries, 0 to 20
Data columns (total 2 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Delivery Time  21 non-null     float64
 1   Sorting Time   21 non-null     int64  
dtypes: float64(1),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

In [9]:
```
delivery_details.describe()
```

Out[9]:

	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 [10]:
```
plt.hist(dt_st.delivery_time, bins=5)                    # Hist Plot of Delivery Time
plt.show()
```

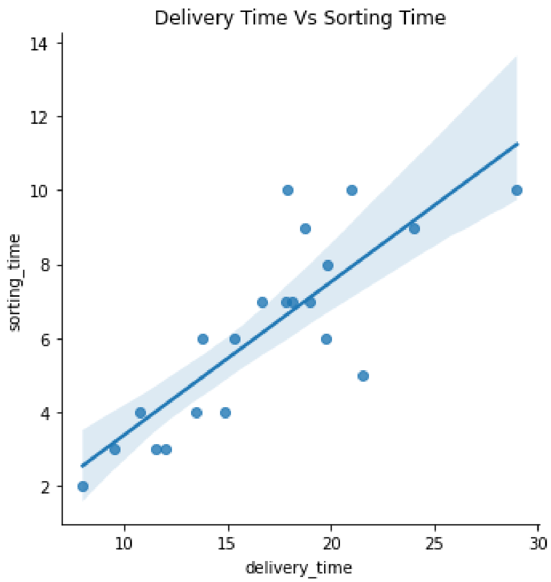


Step 3.2 Perform Assumption Checks:

1. Linearity Test:

In [11]:
```
plt.scatter(x=dt_st.delivery_time, y=dt_st.sorting_time, color='green') #Scatter plot to check the Linerity
plt.title('Delivery Time Vs Sorting Time')
plt.xlabel("Delivery time")
plt.ylabel("Sorting time")
plt.show()
```

In [12]:
```
sns.lmplot(x='delivery_time', y='sorting_time', data=dt_st) #LM plot to check the linerity
plt.title('Delivery Time Vs Sorting Time')
plt.show()
```



Linearity Test is FAILED.

2. Normality Test:

In [13]:
```
sns.distplot(delivery_details['Delivery Time'],hist=False) # Dist plot to check the normal distribution.
plt.title('Delivery Time Distribution')
plt.show()
```

Normality Test is FAILED.

3. No Multicollinearity

Cannot be checked here.

4. No AutoRegression

Here we dont have input features with datetime datatype.

5. Homoscadasticity Check || 6. Zero Residual Mean

This can be performed only after **Model Training.**

Step 3.3 Correlation Study:

In [14]:
```
dt_st.corr() #To check Correaltion between Dependent & Independent Vaiables
```

Out[14]:

	delivery_time	sorting_time
delivery_time	1.000000	0.825997
sorting_time	0.825997	1.000000

See below plot for Visualization of Correlation Between x and y:

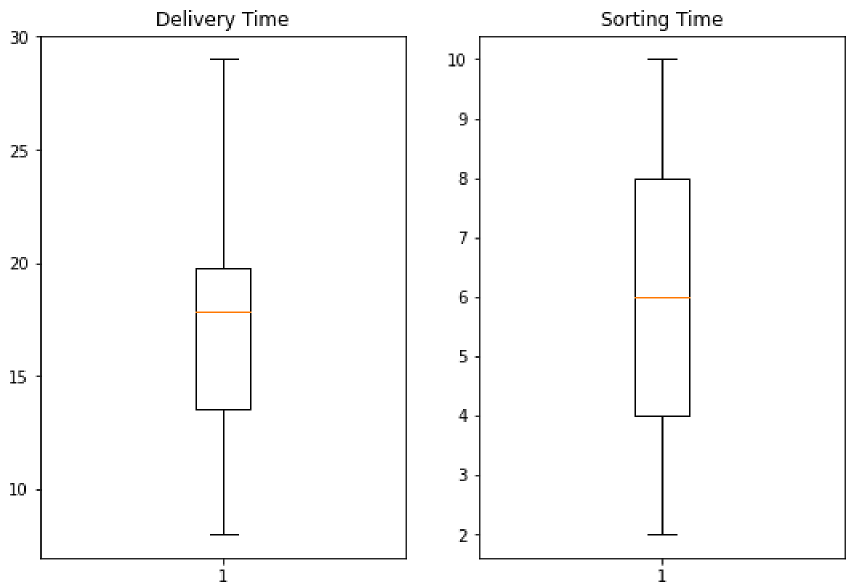
In [15]:
```
sns.regplot(x=dt_st['delivery_time'], y=dt_st['sorting_time']) #regplot = Regression Plot
plt.title('Delivery Time Vs Sorting Time')
plt.show()
```

There is little bit correlation between the two variable.

Score is > 0.8 which is a Good sign.

Step 3.4 Outliers checking:

In [16]:
```
plt.subplots(figsize = (9,6))                     #To check outliers by plotting data:
plt.subplot(121)
plt.boxplot(dt_st['delivery_time'])
plt.title('Delivery Time')
plt.subplot(122)
plt.boxplot(dt_st['sorting_time'])
plt.title('Sorting Time')
plt.show()
```

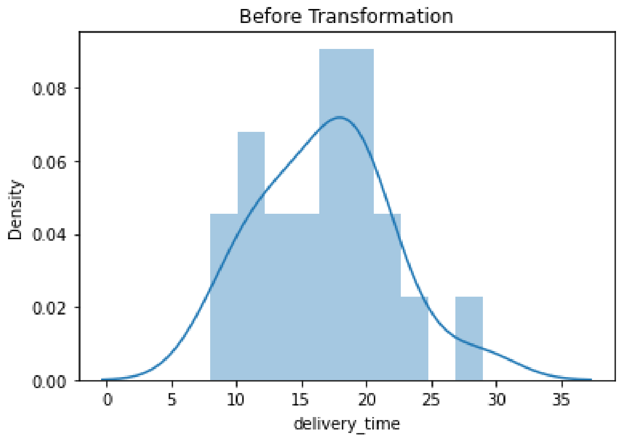


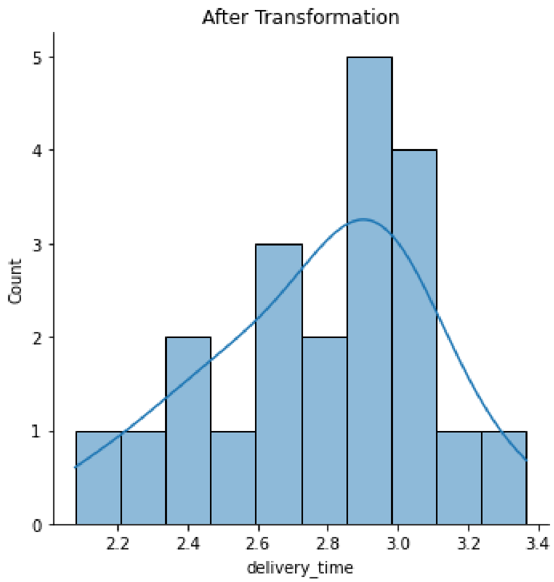
Look at above plots, there are "No Outliers" present in the given dataset

Setp 3.5. Feature Engineering:

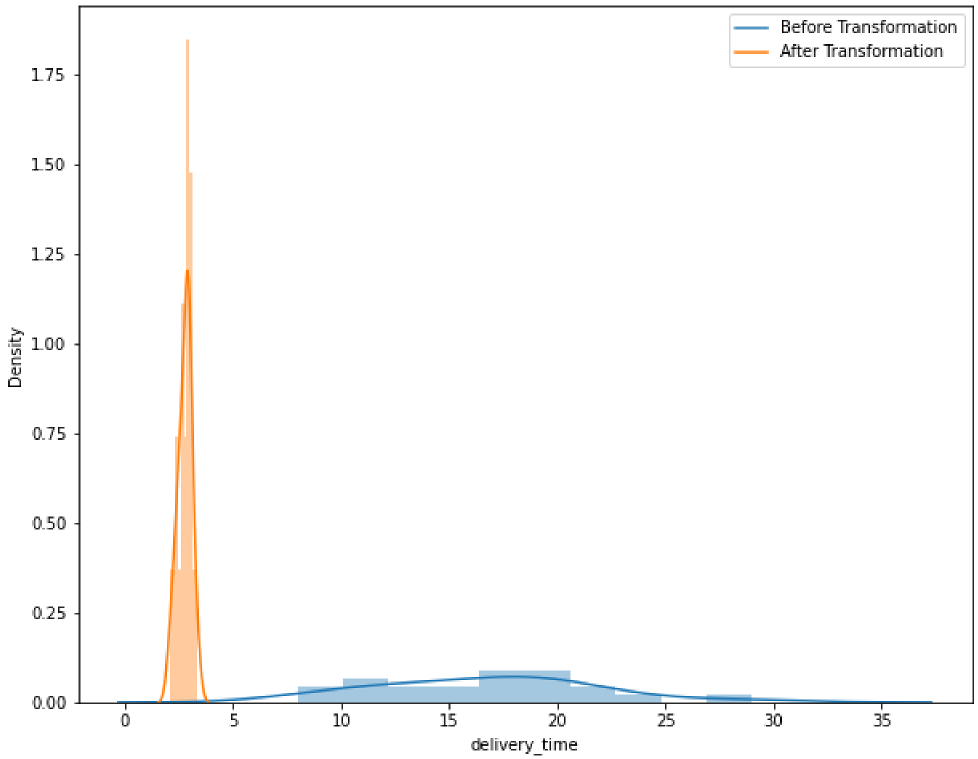
Trying different transformation of data **To estimate normal distribution and **To remove any skewness**

In [17]:
```
sns.distplot(dt_st['delivery_time'], bins = 10, kde = True)
plt.title('Before Transformation')
sns.displot(np.log(dt_st['delivery_time']), bins = 10, kde = True)
plt.title('After Transformation')
plt.show()
```





In [18]:
```
plt.figure(figsize= (10,8))
labels = ['Before Transformation','After Transformation']
sns.distplot(dt_st['delivery_time'], bins = 10, kde = True)
sns.distplot(np.log(dt_st['delivery_time']), bins = 10, kde = True)
plt.legend(labels)
plt.show()
```



4. Data Preparation:

In [19]:
```
dt_st.head(10)
```

Out[19]:

	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

In [20]:
```
dt_st.dtypes
```

Out[20]:
```
delivery_time    float64
sorting_time       int64
dtype: object
```

In [21]:
```
dt_st.isnull().sum()
```

Out[21]:
```
delivery_time    0
sorting_time     0
dtype: int64
```

5. Model Building || 6. Model Training:

Fitting a Linear Regression Model Using Ordinary least squares (OLS) regression.

It is a statistical method of analysis that estimates the relationship between one or more independent variables and a dependent variable; the method estimates the relationship by minimizing the sum of the squares in the difference between the observed and predicted values of the dependent variable configured as a straight line

Linear Regression can be built by using any of the 2 libraries:

1. Statsmodels
2. sklearn

By using Statsmodel

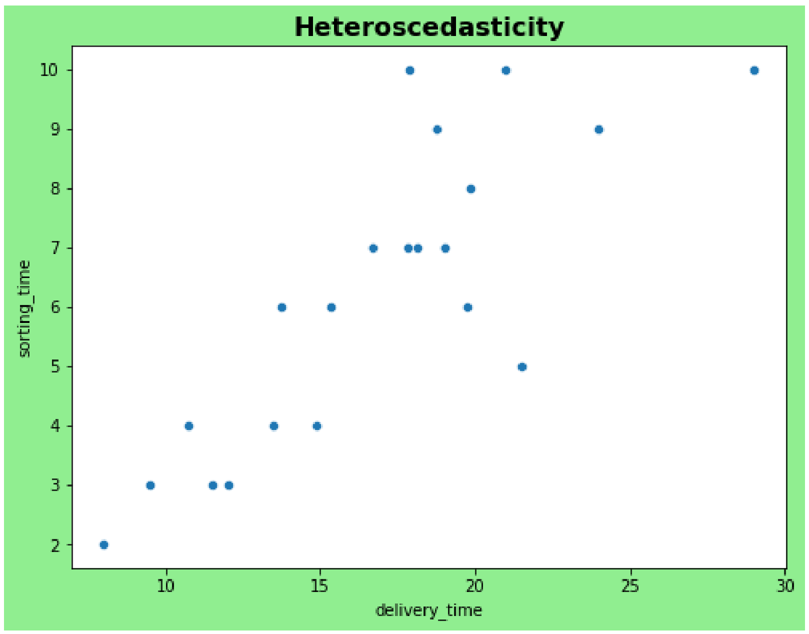
In [22]:
```
lm_1 = smf.ols("delivery_time~sorting_time", data=dt_st).fit()
lm_1
```

Out[22]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2275c51fd30>
```

In [23]:
```
lm_1.params #For finding coefficient parameters: m=1.649020, x=? c=6.582734
```

Out[23]:
```
Intercept       6.582734
sorting_time    1.649020
dtype: float64
```

In [24]:
```
plt.figure(figsize = (8,6), facecolor = 'lightgreen')
sns.scatterplot(x = dt_st['delivery_time'], y = dt_st['sorting_time'])
plt.title('Heteroscedasticity', fontweight = 'bold', fontsize = 16)
plt.show()
```



7. Model Testing:

7.1 Manual Testing / Prediction:

In [25]:
```
# y = mx+c
# If x = 5, y = ??
( 1.649020 * 5) +  6.582734
```

Out[25]:
```
14.827834
```

In [26]:
```
# y = mx+c
# If x = 8, y = ??
( 1.649020 * 8) +  6.582734
```

Out[26]:
```
19.774894
```

In [27]:
```
# y = mx+c
# If x = 10, y = ??
( 1.649020 * 10) +  6.582734
```

Out[27]:
```
23.072933999999997
```

In [28]:
```
lm_1.tvalues, lm_1.pvalues # Here we found t-values and p-values:
```

Out[28]:
```
(Intercept       3.823349
 sorting_time    6.387447
 dtype: float64,
 Intercept       0.001147
 sorting_time    0.000004
 dtype: float64)
```

In [29]:
```
lm_1.summary() # Below we can the see the overall summary:
```

Out[29]:

OLS Regression Results

Dep. Variable:	delivery_time	**R-squared:**	0.682
Model:	OLS	**Adj. R-squared:**	0.666
Method:	Least Squares	**F-statistic:**	40.80
Date:	Thu, 07 Jul 2022	**Prob (F-statistic):**	3.98e-06
Time:	19:47:31	**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
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 [30]:
```
lm_1.conf_int(0.05) # Checking 95% confidence interval:
```

Out[30]:

	0	1
Intercept	2.979134	10.186334
sorting_time	1.108673	2.189367

7.2 Automatic Testing / Prediction:

In [31]:
```
delivery_details.head(5)
```

Out[31]:

	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 [32]:
```
test_model = pd.DataFrame(data={'sorting_time':[5,8,10]})
test_model
```

Out[32]:

	sorting_time
0	5
1	8
2	10

In [33]:
```
lm_1.predict(test_model)
```

Out[33]:
```
0    14.827833
1    19.774893
2    23.072933
dtype: float64
```

8. Model Deployment:

In [34]:
```
from pickle import dump
```

In [35]:
```
dump(lm_1, open('intel.pkl', 'wb'))
```

In [36]:
```
from pickle import load
```

In [37]:
```
loaded_intel_file = load(open('intel.pkl', 'rb'))
loaded_intel_file
```

Out[37]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2275c66a820>
```

In [38]:
```
loaded_intel_file.predict(test_model)
```

Out[38]:
```
0    14.827833
1    19.774893
2    23.072933
dtype: float64
```

==

Q.No. 2) Salary_hike -> Build a prediction model for Salary_hike. Build a simple linear regression model by performing EDA and do necessary transformations and select the best model using R or Python.

y - continuous(Dependent), x - single & continuos (Independent)

1. y - Salary
2. x - YearsExperience

1. Import Necessary Libraries:

In [63]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import statsmodels.formula.api as sm
import statsmodels.formula.api as smf

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

2. Import Data/Dataset:

In [40]:
```
salary_details = pd.read_csv('Salary_data.csv')
salary_details.head(5)
```

Out[40]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

3. Data Understanding / Performing EDA on Data:

Step 3.1 Initial Analysis:

In [41]:
```
salary_details.shape
```

Out[41]:
```
(30, 2)
```

In [42]:
```
salary_details.dtypes
```

Out[42]:
```
YearsExperience    float64
Salary             float64
dtype: object
```

In [43]:
```
salary_details.isnull().sum()
```

Out[43]:
```
YearsExperience    0
Salary             0
dtype: int64
```

In [44]:
```
salary_details.info()
```

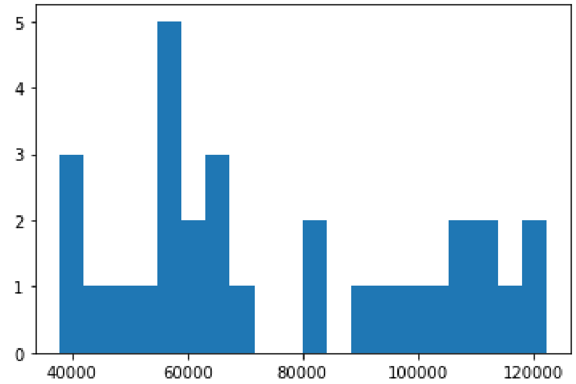
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 30 entries, 0 to 29
Data columns (total 2 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   YearsExperience  30 non-null     float64
 1   Salary           30 non-null     float64
dtypes: float64(2)
memory usage: 608.0 bytes
```

In [45]:
```
salary_details.describe()
```

Out[45]:

	YearsExperience	Salary
count	30.000000	30.000000
mean	5.313333	76003.000000
std	2.837888	27414.429785
min	1.100000	37731.000000
25%	3.200000	56720.750000
50%	4.700000	65237.000000
75%	7.700000	100544.750000
max	10.500000	122391.000000

In [46]:
```
plt.hist(salary_details.Salary, bins=20)                    # Hist Plot of Salary
plt.show()
```



Step 3.2 Perform Assumption Checks:

1. Linearity Test:

In [47]:
```
plt.scatter(x=salary_details.YearsExperience, y=salary_details.Salary, color='green') #Scatter plot to check the linerity
plt.title('Years of Experience Vs Salary')
plt.xlabel('YearsExperience')
plt.ylabel("Salary")
plt.show()
```

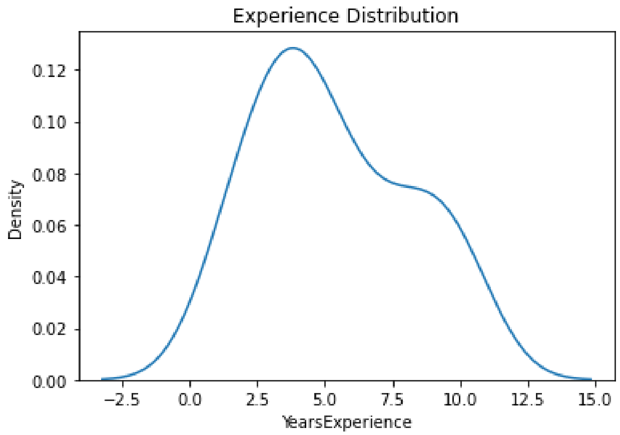
In [48]:
```
sns.lmplot(x='YearsExperience', y='Salary', data=salary_details) #LM plot to check the linerity
plt.title('YearsExperience Vs Salary')
plt.show()
```

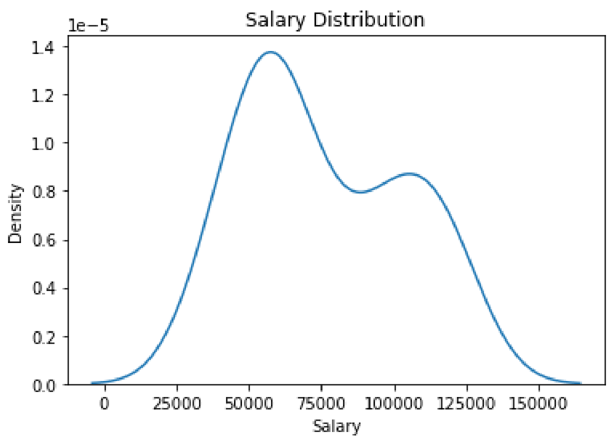
Linearity Test is FAILED.

2. Normality Test:

In [49]:
```
sns.distplot(salary_details['YearsExperience'],hist=False) # Dist plot to check the normal distribution.
plt.title('Experience Distribution')
plt.show()

sns.distplot(salary_details['Salary'],hist=False) # Dist plot to check the normal distribution.
plt.title('Salary Distribution')
plt.show()
```





Normality Test is FAILED.

3. No Multicollinearity

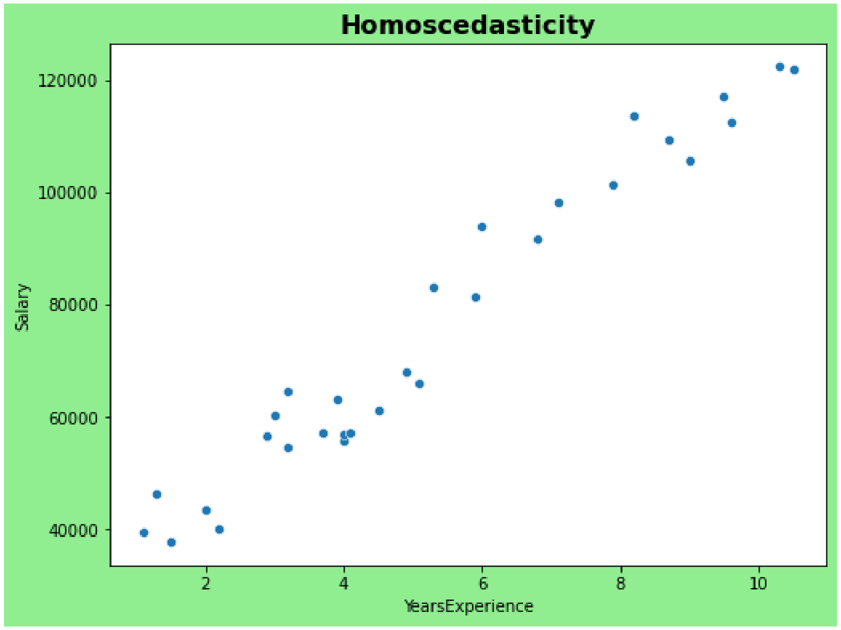
Cannot be checked here.

4. No AutoRegression

Here we dont have input features with datetime datatype.

5. Homoscadasticity Check || 6. Zero Residual Mean

In [50]:
```
plt.figure(figsize = (8,6), facecolor = 'lightgreen')
sns.scatterplot(x = salary_details['YearsExperience'], y = salary_details['Salary'])
plt.title('Homoscedasticity', fontweight = 'bold', fontsize = 16)
plt.show()
```



In [51]:
```
salary_details.var()
```

Out[51]:
```
YearsExperience    8.053609e+00
Salary             7.515510e+08
dtype: float64
```

As Salary Increases, the Years of Experience increases. The data doesn't have any specific pattern in the variation. Hence, we can say it's Homoscedasticity.

Step 3.3 Correlation Study:

In [52]:
```
salary_details.corr() #To check Correaltion between Dependent & Independent Vaiables
```

Out[52]:

	YearsExperience	Salary
YearsExperience	1.000000	0.978242
Salary	0.978242	1.000000

See below plot for Visualization of Correlation Between x and y:

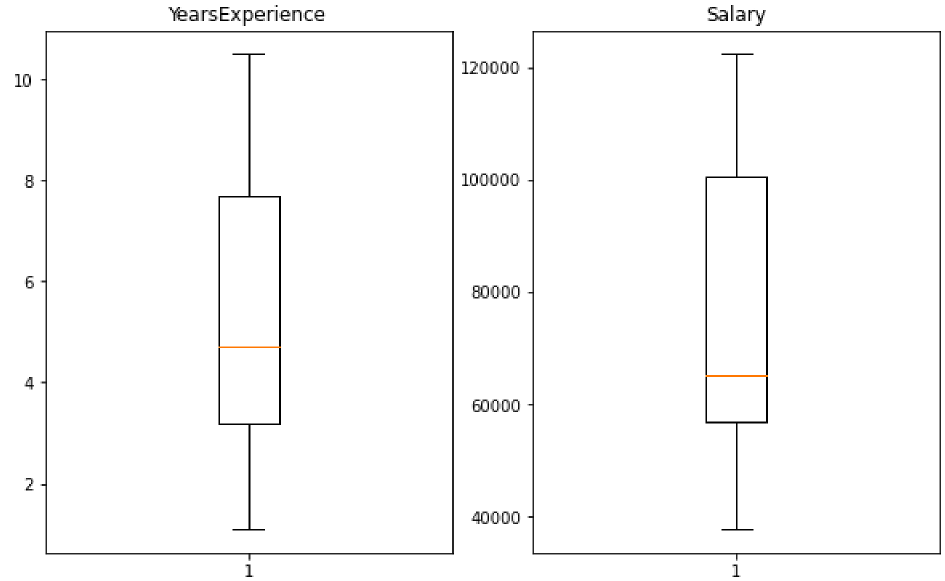
In [53]:
```
sns.regplot(x=salary_details['YearsExperience'], y=salary_details['Salary']) #regplot = Regression Plot
plt.title('YearsExperience Vs Salary')
plt.show()
```

There is GOOD correlation between the two variable.

Score is > 0.8 which is a Good sign.

Step 3.4 Outliers checking:

In [54]:
```
plt.subplots(figsize = (10,6))                          #To check outliers by plotting data:
plt.subplot(121)
plt.boxplot(salary_details['YearsExperience'])
plt.title('YearsExperience')
plt.subplot(122)
plt.boxplot(salary_details['Salary'])
plt.title('Salary')
plt.show()
```

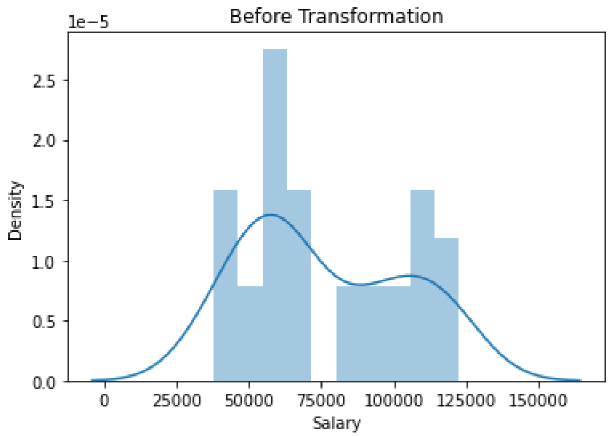


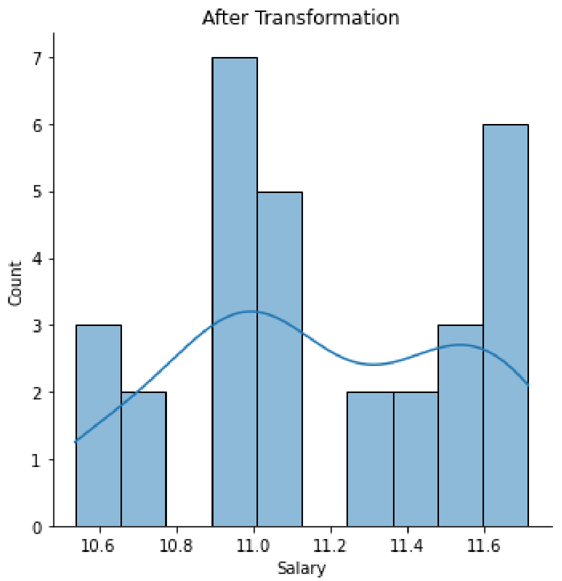
Look at above plots, there are "No Outliers" present in the given dataset

Setp 3.5. Feature Engineering:

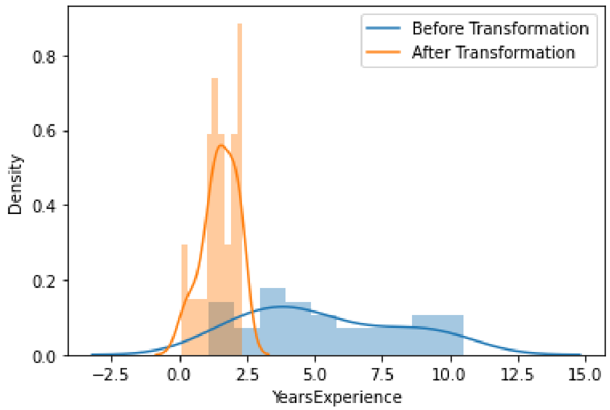
Trying different transformation of data **To estimate normal distribution and **To remove any skewness**

In [55]:
```
sns.distplot(salary_details['Salary'], bins = 10, kde = True)
plt.title('Before Transformation')
sns.displot(np.log(salary_details['Salary']), bins = 10, kde = True)
plt.title('After Transformation')
plt.show()
```





In [56]:
```
labels = ['Before Transformation','After Transformation']
sns.distplot(salary_details['YearsExperience'], bins = 10, kde = True)
sns.distplot(np.log(salary_details['YearsExperience']), bins = 10, kde = True)
plt.legend(labels)
plt.show()
```



4. Data Preparation:

In [57]:
```
salary_details.head(5)
```

Out[57]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

In [58]:
```
salary_details.dtypes
```

Out[58]:
```
YearsExperience    float64
Salary             float64
dtype: object
```

In [59]:
```
salary_details.isnull().sum()
```

Out[59]:
```
YearsExperience    0
Salary             0
dtype: int64
```

5. Model Building || 6. Model Training:

Fitting a Linear Regression Model Using Ordinary least squares (OLS) regression.

It is a statistical method of analysis that estimates the relationship between one or more independent variables and a dependent variable; the method estimates the relationship by minimizing the sum of the squares in the difference between the observed and predicted values of the dependent variable configured as a straight line

Linear Regression can be built by using any of the 2 libraries:

1. Statsmodels
2. sklearn

By using Statsmodel

In [73]:
```
lm_2 = smf.ols("Salary~YearsExperience", data=salary_details).fit()
lm_2
```

Out[73]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2275c58a9a0>
```

In [60]:
```
lm_2.params #For finding coefficient parameters: m=9449.962321, x=? c=25792.200199
```

Out[60]:
```
Intercept          25792.200199
YearsExperience     9449.962321
dtype: float64
```

In [61]:
```
lm_2.summary() #This model has better Accuracy as per R-squared value i.e. 95.7%.
```

Out[61]:

OLS Regression Results

Dep. Variable:	Salary	**R-squared:**	0.957
Model:	OLS	**Adj. R-squared:**	0.955
Method:	Least Squares	**F-statistic:**	622.5
Date:	Thu, 07 Jul 2022	**Prob (F-statistic):**	1.14e-20
Time:	19:40:40	**Log-Likelihood:**	-301.44
No. Observations:	30	**AIC:**	606.9
Df Residuals:	28	**BIC:**	609.7
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.579e+04	2273.053	11.347	0.000	2.11e+04	3.04e+04
YearsExperience	9449.9623	378.755	24.950	0.000	8674.119	1.02e+04

Omnibus:	2.140	**Durbin-Watson:**	1.648
Prob(Omnibus):	0.343	**Jarque-Bera (JB):**	1.569
Skew:	0.363	**Prob(JB):**	0.456
Kurtosis:	2.147	**Cond. No.**	13.2

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

R-squared and Adjusted R-squared scores are above 0.85

(It is a thumb rule to consider Adjusted R-squared to be greater than 0.8 to have a good model for prediction)

F-statitics is quite high and it must to be higher

But log-likelihood is quite very low far away from 0

AIC and BIC score are much higher for this model

Do some data transformation to check whether these scores can get any better than this.

In [64]:
```
# Square Root transformation on data
lm_3 = sm.ols('np.sqrt(Salary)~np.sqrt(YearsExperience)', data = salary_details).fit()
lm_3.summary()
```

Out[64]:

OLS Regression Results

Dep. Variable:	np.sqrt(Salary)	**R-squared:**	0.942
Model:	OLS	**Adj. R-squared:**	0.940
Method:	Least Squares	**F-statistic:**	454.3
Date:	Thu, 07 Jul 2022	**Prob (F-statistic):**	7.58e-19
Time:	19:51:28	**Log-Likelihood:**	-116.52
No. Observations:	30	**AIC:**	237.0
Df Residuals:	28	**BIC:**	239.8
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	103.5680	8.178	12.663	0.000	86.815	120.321
np.sqrt(YearsExperience)	75.6269	3.548	21.315	0.000	68.359	82.895

Omnibus:	0.924	**Durbin-Watson:**	1.362
Prob(Omnibus):	0.630	**Jarque-Bera (JB):**	0.801
Skew:	0.087	**Prob(JB):**	0.670
Kurtosis:	2.219	**Cond. No.**	9.97

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

R-squared and Adjusted R-squared scores are above 0.85 but it is getting less than previous model.

(It is a thumb rule to consider Adjusted R-squared to be greater than 0.8 to have a good model for prediction)

F-statitics getting a little lower for this model than previous.

But log-likelihood got better than before close to 0 higher than previous model

AIC and BIC score are now better for this model.

Again let's try some data transformation to check whether these scores can get any better than this.

In [65]:
```
# Cube Root transformation on data
lm_4 = sm.ols('np.cbrt(Salary)~np.sqrt(YearsExperience)', data = salary_details).fit()
lm_4.summary()
```

Out[65]:

OLS Regression Results

Dep. Variable:	np.cbrt(Salary)	**R-squared:**	0.944
Model:	OLS	**Adj. R-squared:**	0.942
Method:	Least Squares	**F-statistic:**	468.5
Date:	Thu, 07 Jul 2022	**Prob (F-statistic):**	5.06e-19
Time:	19:51:30	**Log-Likelihood:**	-47.882
No. Observations:	30	**AIC:**	99.76
Df Residuals:	28	**BIC:**	102.6
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	24.4757	0.830	29.495	0.000	22.776	26.176
np.sqrt(YearsExperience)	7.7919	0.360	21.644	0.000	7.054	8.529

Omnibus:	1.125	**Durbin-Watson:**	1.474
Prob(Omnibus):	0.570	**Jarque-Bera (JB):**	0.903
Skew:	0.131	**Prob(JB):**	0.637
Kurtosis:	2.191	**Cond. No.**	9.97

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

In [66]:
```
# Log transformation on Data
lm_5 = sm.ols('np.log(Salary)~np.log(YearsExperience)', data = salary_details).fit()
lm_5.summary()
```

Out[66]:

OLS Regression Results

Dep. Variable:	np.log(Salary)	**R-squared:**	0.905
Model:	OLS	**Adj. R-squared:**	0.902
Method:	Least Squares	**F-statistic:**	267.4
Date:	Thu, 07 Jul 2022	**Prob (F-statistic):**	7.40e-16
Time:	19:51:35	**Log-Likelihood:**	23.209
No. Observations:	30	**AIC:**	-42.42
Df Residuals:	28	**BIC:**	-39.61
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	10.3280	0.056	184.868	0.000	10.214	10.442
np.log(YearsExperience)	0.5621	0.034	16.353	0.000	0.492	0.632

Omnibus:	0.102	**Durbin-Watson:**	0.988
Prob(Omnibus):	0.950	**Jarque-Bera (JB):**	0.297
Skew:	0.093	**Prob(JB):**	0.862
Kurtosis:	2.549	**Cond. No.**	5.76

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

7. Model Testing:

7.1 Manual Testing / Prediction:

Checking for first 05 observations of dataset

In [67]:
```
# y = mx+c
# If x = 1.1, y = ??
(  9449.962321 * 1.1) + 25792.200199
```

Out[67]: 36187.158752100004

In [68]:
```
# y = mx+c
# If x = 1.3, y = ??
(  9449.962321 * 1.3) + 25792.200199
```

Out[68]:
```
38077.1512163
```

In [69]:
```
# y = mx+c
# If x = 1.5, y = ??
(  9449.962321 * 1.5) + 25792.200199
```

Out[69]:
```
39967.1436805
```

In [70]:
```
# y = mx+c
# If x = 2.0, y = ??
(  9449.962321 * 2.0) + 25792.200199
```

Out[70]:
```
44692.124841
```

In [ ]:
```
# y = mx+c
# If x = 2.2, y = ??
(  9449.962321 * 2.2) + 25792.200199
```

In [74]:
```
lm_2.tvalues, lm_2.pvalues # Here we found t-values and p-values:
```

Out[74]:
```
(Intercept          11.346940
 YearsExperience    24.950094
 dtype: float64,
 Intercept          5.511950e-12
 YearsExperience    1.143068e-20
 dtype: float64)
```

In [75]:
```
lm_2.summary() # Below we can the see the overall summary:
```

Out[75]:

OLS Regression Results

Dep. Variable:	Salary	**R-squared:**	0.957
Model:	OLS	**Adj. R-squared:**	0.955
Method:	Least Squares	**F-statistic:**	622.5
Date:	Thu, 07 Jul 2022	**Prob (F-statistic):**	1.14e-20
Time:	20:38:11	**Log-Likelihood:**	-301.44
No. Observations:	30	**AIC:**	606.9
Df Residuals:	28	**BIC:**	609.7
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.579e+04	2273.053	11.347	0.000	2.11e+04	3.04e+04
YearsExperience	9449.9623	378.755	24.950	0.000	8674.119	1.02e+04

Omnibus:	2.140	**Durbin-Watson:**	1.648
Prob(Omnibus):	0.343	**Jarque-Bera (JB):**	1.569
Skew:	0.363	**Prob(JB):**	0.456
Kurtosis:	2.147	**Cond. No.**	13.2

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

In [76]:
```
lm_2.conf_int(0.05) # Checking 95% confidence interval:
```

Out[76]:

	0	1
Intercept	21136.061314	30448.339084
YearsExperience	8674.118747	10225.805896

7.2 Automatic Testing / Prediction:

In [77]:
```
salary_details.head(5)
```

Out[77]:

	YearsExperience	Salary
0	1.1	39343.0
1	1.3	46205.0
2	1.5	37731.0
3	2.0	43525.0
4	2.2	39891.0

In [80]:
```
test_model = pd.DataFrame(data={'YearsExperience':[1.1,1.3,1.5,2.0,2.2]})
test_model
```

Out[80]:

	YearsExperience
0	1.1
1	1.3
2	1.5
3	2.0
4	2.2

In [81]:
```
lm_2.predict(test_model)
```

Out[81]:
```
0    36187.158752
1    38077.151217
2    39967.143681
3    44692.124842
4    46582.117306
dtype: float64
```

8. Model Deployment:

In [82]:
```
from pickle import dump
```

In [83]:
```
dump(lm_2, open('intel.pkl', 'wb'))
```

In [84]:
```
from pickle import load
```

In [85]:
```
loaded_intel_file_Salary_model = load(open('intel.pkl', 'rb'))
loaded_intel_file_Salary_model
```

Out[85]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x2275ee33340>
```

In [86]:
```
loaded_intel_file_Salary_model.predict(test_model)
```

Out[86]:
```
0    36187.158752
1    38077.151217
2    39967.143681
3    44692.124842
4    46582.117306
dtype: float64
```

==