Q. Build a simple linear regression model by performing EDA and do necessary transformations and select the best model using R or Python.

2) Salary_hike -> Build a prediction model for Salary_hike

1. Import Necessary Libraries ¶

In [38]:

```
import pandas as pd

import seaborn as sns
from matplotlib import pyplot as plt

import warnings
warnings.filterwarnings("ignore")

from sklearn.linear_model import LinearRegression
import statsmodels.formula.api as smf

from sklearn.metrics import mean_squared_error,mean_absolute_error
```

2. Import Data

In [2]:

```
salary_data = pd.read_csv("E:\Data Science by John\Assignments\Assignment 4- Simple Linear Regression\Salary_Data.csv")
salary_data
```

Out[2]:

	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
5	2.9	56642.0
6	3.0	60150.0
7	3.2	54445.0
8	3.2	64445.0
9	3.7	57189.0
10	3.9	63218.0
11	4.0	55794.0
12	4.0	56957.0
13	4.1	57081.0
14	4.5	61111.0
15	4.9	67938.0
16	5.1	66029.0
17	5.3	83088.0
18	5.9	81363.0
19	6.0	93940.0
20	6.8	91738.0
21	7.1	98273.0
22	7.9	101302.0
23	8.2	113812.0

	YearsExperience	Salary
24	8.7	109431.0
25	9.0	105582.0
26	9.5	116969.0
27	9.6	112635.0
28	10.3	122391.0
29	10.5	121872.0

3. Data Understanding

3.1 Perform Initial Analysis

In [3]:
```
salary_data.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 [4]:
```
salary_data.shape
```

Out[4]:
```
(30, 2)
```

In [5]:
```
salary_data.describe()
```

Out[5]:

	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 [6]:
```
salary_data.isna().sum()
```

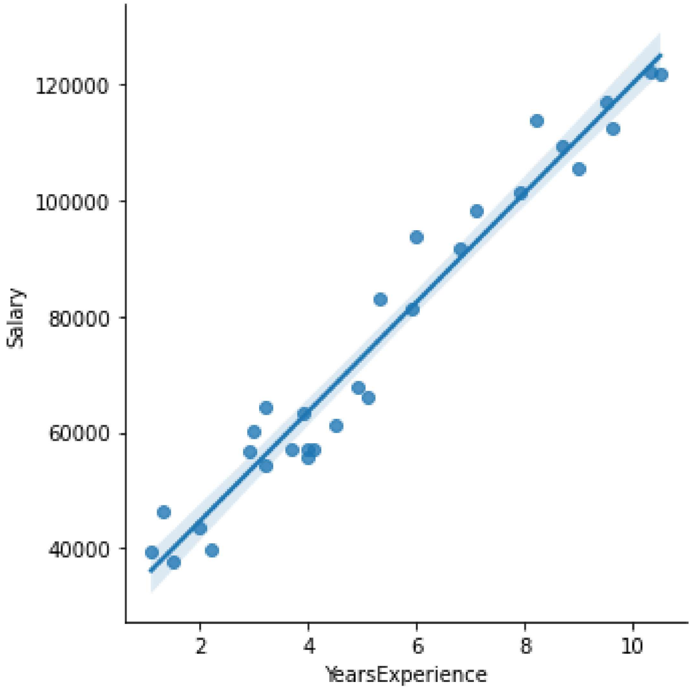
Out[6]:
```
YearsExperience    0
Salary             0
dtype: int64
```

3.2 Assumptions Check

1. Linearity Check

In [7]:

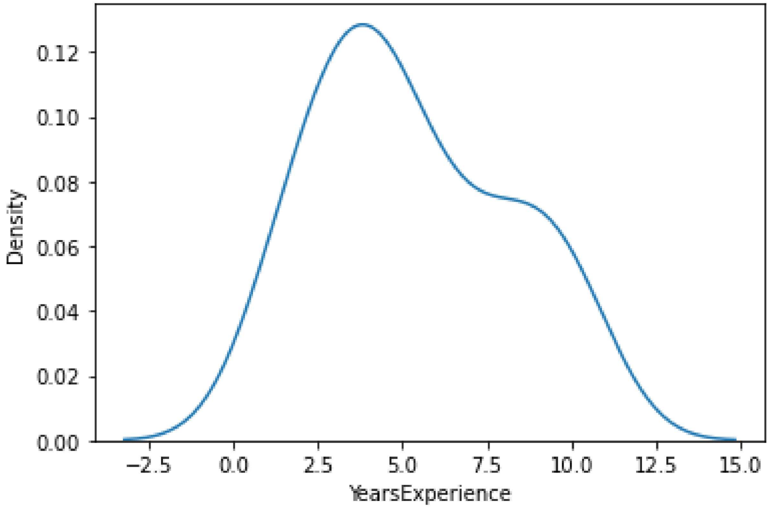
```
sns.lmplot(x="YearsExperience", y="Salary", data=salary_data)
plt.xlabel("YearsExperience")
plt.ylabel("Salary")
plt.show()
```



Linearity Test is passed

2. Normality Check

```
In [8]: sns.distplot(a= salary_data['YearsExperience'], hist = False)
        plt.show()
```



Normality Test is Failed

3. Multicollinearity || 4. Autoregression

These test are passed because we have only one input so No Multicollinearity & We don't have datetime datatype of our data

4. Data Preparation

Already in required format so no need to any changes

5. Model Building || 6. Model Training

Using Sklearn

In [9]:

```
x = salary_data[['YearsExperience']]
y = salary_data[['Salary']]
```

In [10]:

```
linear_model = LinearRegression()
```

In [11]:

```
linear_model_sk = linear_model.fit(x,y)
```

In [12]:

```
linear_model.coef_
```

Out[12]:

```
array([[9449.96232146]])
```

In [13]:

```
linear_model.intercept_
```

Out[13]:

```
array([25792.20019867])
```

7. Model Testing

Manual Prediction

In [14]:

```
# y = mx+c
# If x = 2, y = ??
(9449.96232146 * 2) + 25792.20019867
```

Out[14]:

```
44692.124841590005
```

In [15]:

```
# y = mx+c
# If x = 5, y = ??
(9449.96232146 * 5) + 25792.20019867
```

Out[15]:

```
73042.01180597
```

In [16]:
```
# y = mx+c
# If x = 6.5, y = ??
(9449.96232146 * 6.5) + 25792.20019867
```

Out[16]:
```
87216.95528816
```

In [17]:
```
# y = mx+c
# If x = 8, y = ??
(9449.96232146 * 8) + 25792.20019867
```

Out[17]:
```
101391.89877035
```

In [18]:
```
# y = mx+c
# If x = 10, y = ??
(9449.96232146 * 10) + 25792.20019867
```

Out[18]:
```
120291.82341327
```

Automatic Prediction

In [19]:
```
y.head()
```

Out[19]:

	Salary
0	39343.0
1	46205.0
2	37731.0
3	43525.0
4	39891.0

In [20]:

```
X_test = pd.DataFrame(data={'YearsExperience':[2,5,6.5,8,10]})
X_test
```

Out[20]:

	YearsExperience
0	2.0
1	5.0
2	6.5
3	8.0
4	10.0

In [21]:

```
linear_model_sk.predict(X_test)
```

Out[21]:

```
array([[ 44692.12484158],
       [ 73042.01180594],
       [ 87216.95528813],
       [101391.89877031],
       [120291.82341322]])
```

In [22]:
```
y_pred = linear_model_sk.predict(x)
y_pred
```

Out[22]:
```
array([[ 36187.15875227],
       [ 38077.15121656],
       [ 39967.14368085],
       [ 44692.12484158],
       [ 46582.11730587],
       [ 53197.09093089],
       [ 54142.08716303],
       [ 56032.07962732],
       [ 56032.07962732],
       [ 60757.06078805],
       [ 62647.05325234],
       [ 63592.04948449],
       [ 63592.04948449],
       [ 64537.04571663],
       [ 68317.03064522],
       [ 72097.0155738 ],
       [ 73987.00803809],
       [ 75877.00050238],
       [ 81546.97789525],
       [ 82491.9741274 ],
       [ 90051.94398456],
       [ 92886.932681  ],
       [100446.90253816],
       [103281.8912346 ],
       [108006.87239533],
       [110841.86109176],
       [115566.84225249],
       [116511.83848464],
       [123126.81210966],
       [125016.80457395]])
```

8. Model Evaluation

In [23]:

```
error = y - y_pred
error
```

Out[23]:

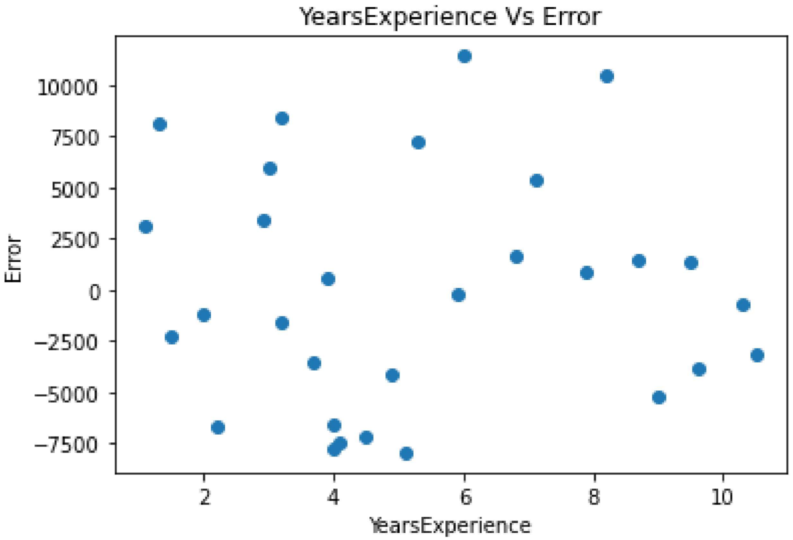
```
          Salary
 0   3155.841248
 1   8127.848783
 2  -2236.143681
 3  -1167.124842
 4  -6691.117306
 5   3444.909069
 6   6007.912837
 7  -1587.079627
 8   8412.920373
 9  -3568.060788
10    570.946748
11  -7798.049484
12  -6635.049484
13  -7456.045717
14  -7206.030645
15  -4159.015574
16  -7958.008038
17   7210.999498
18   -183.977895
19  11448.025873
20   1686.056015
21   5386.067319
22    855.097462
23  10530.108765
```

	Salary
24	1424.127605
25	-5259.861092
26	1402.157748
27	-3876.838485
28	-735.812110
29	-3144.804574

.....back to Assumption Check

5. Homoscedasticity Check

In [24]:
```
plt.scatter(x= salary_data['YearsExperience'], y=error)
plt.title('YearsExperience Vs Error')
plt.xlabel('YearsExperience')
plt.ylabel('Error')
plt.show()
```

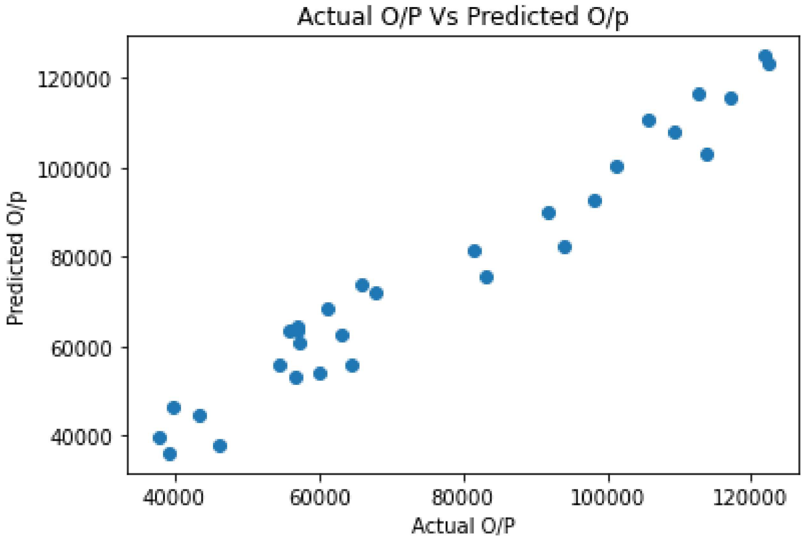


Homoscedasticity Check is Passed

6. Zero Residual Mean across the Fitted Line.

In [25]:

```
plt.scatter(x=salary_data['Salary'],y=y_pred)
plt.title('Actual O/P Vs Predicted O/p')
plt.xlabel('Actual O/P')
plt.ylabel('Predicted O/p')
plt.show()
```



Zero Residual Mean Test is Passed

Build Linear Model using StatsModels

Model Building || Model Training

In [27]:
```
salary_data.head()
```

Out[27]:

	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 [29]:
```
linear_model_stats = smf.ols(formula = 'Salary~YearsExperience', data = salary_data).fit()
linear_model_stats
```

Out[29]:
```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x20bed656ac0>
```

In [30]:
```
linear_model_stats.params
```

Out[30]:
```
Intercept          25792.200199
YearsExperience     9449.962321
dtype: float64
```

8.1 Evaluation Metrics of Linear Regression

In [31]:

```
print('R2Score     :',linear_model_stats.rsquared.round(4)) #Overall Contribution of Predictors
print('Adj.R2Score :',linear_model_stats.rsquared_adj.round(4)) #Overall Contribution of Predictors
print('AIC Value   :',linear_model_stats.aic.round(4)) #Error Impurity
print('BIC Value   :',linear_model_stats.bic.round(4)) #Error Impurity
print('P-Value   \n:',linear_model_stats.pvalues)
```

```
R2Score     : 0.957
Adj.R2Score : 0.9554
AIC Value   : 606.8823
BIC Value   : 609.6847
P-Value
: Intercept          5.511950e-12
YearsExperience    1.143068e-20
dtype: float64
```

In [39]:

```
mean_squared_error(y,y_pred)
```

Out[39]:

```
31270951.722280968
```

In [40]:

```
mean_absolute_error(y,y_pred)
```

Out[40]:

```
4644.2012894435375
```

In [33]:

```
y_pred_stats = linear_model_stats.predict(x)
y_pred_stats
```

Out[33]:

```
0      36187.158752
1      38077.151217
2      39967.143681
3      44692.124842
4      46582.117306
5      53197.090931
6      54142.087163
7      56032.079627
8      56032.079627
9      60757.060788
10     62647.053252
11     63592.049484
12     63592.049484
13     64537.045717
14     68317.030645
15     72097.015574
16     73987.008038
17     75877.000502
18     81546.977895
19     82491.974127
20     90051.943985
21     92886.932681
22    100446.902538
23    103281.891235
24    108006.872395
25    110841.861092
26    115566.842252
27    116511.838485
28    123126.812110
29    125016.804574
dtype: float64
```

In [42]:

```
error_stats = salary_data['Salary'] - y_pred_stats
error_stats
```

Out[42]:

```
0       3155.841248
1       8127.848783
2      -2236.143681
3      -1167.124842
4      -6691.117306
5       3444.909069
6       6007.912837
7      -1587.079627
8       8412.920373
9      -3568.060788
10       570.946748
11     -7798.049484
12     -6635.049484
13     -7456.045717
14     -7206.030645
15     -4159.015574
16     -7958.008038
17      7210.999498
18      -183.977895
19     11448.025873
20      1686.056015
21      5386.067319
22       855.097462
23     10530.108765
24      1424.127605
25     -5259.861092
26      1402.157748
27     -3876.838485
28      -735.812110
29     -3144.804574
dtype: float64
```