Simple Linear Regression Assignment

Data Set : Salary_Data Building a Prediction Model for Salary Hike

1. Import Necessary libraries

```
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')
```

1. Import Data

```
salary_details = pd.read_csv('/content/Salary_Data (2).csv')
salary_details
```

```
    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
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
```

1. Data Understanding

a) Initial Analysis:

```
salary_details.head()
```

```
   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
```

```
salary_details.shape
```

```
(30, 2)
```

```
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
```

```
salary_details.isna().sum()
```

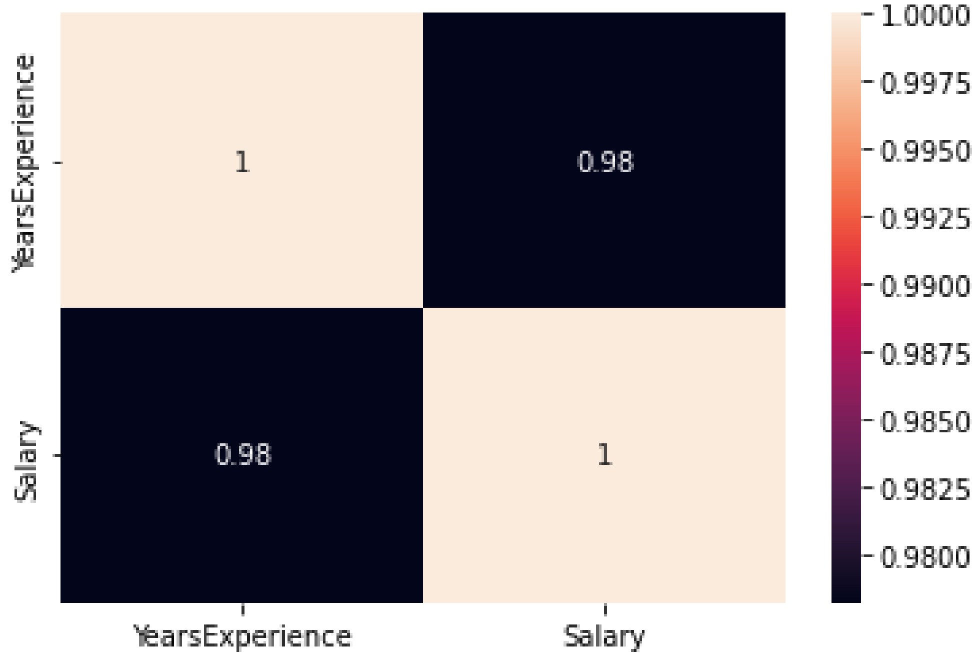
```
YearsExperience    0
Salary             0
dtype: int64
```

b) Correlation Matrix :

```
corr_matrix = salary_details.corr()
corr_matrix
```

```
                 YearsExperience    Salary
YearsExperience         1.000000  0.978242
Salary                  0.978242  1.000000
```

```
sns.heatmap(data = corr_matrix,annot = True)
plt.show()
```

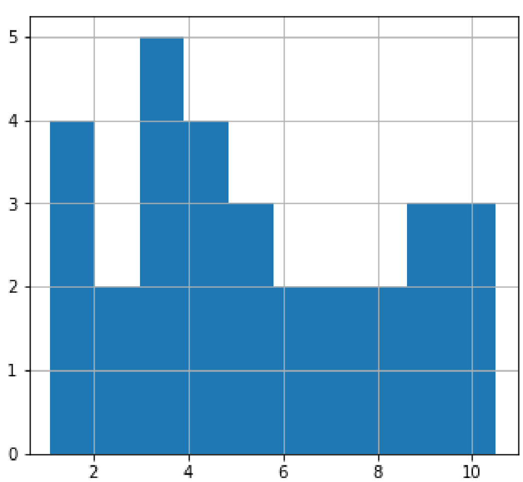


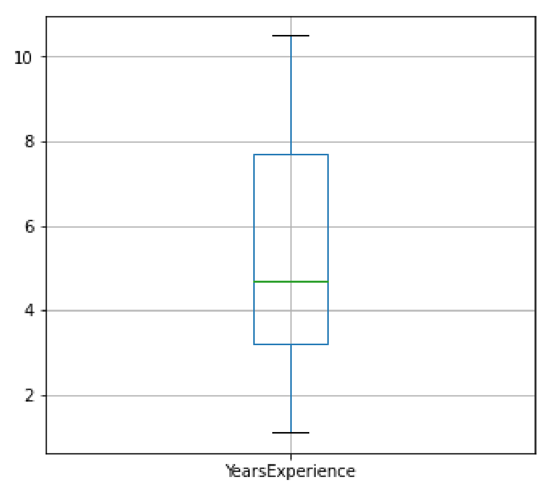
1. Perform Assumption Check

a) Outlier Test Using Box Plot :

```
plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
salary_details['YearsExperience'].hist()
plt.subplot(1,2,2)
salary_details.boxplot(column = ['YearsExperience'])

plt.show()
```

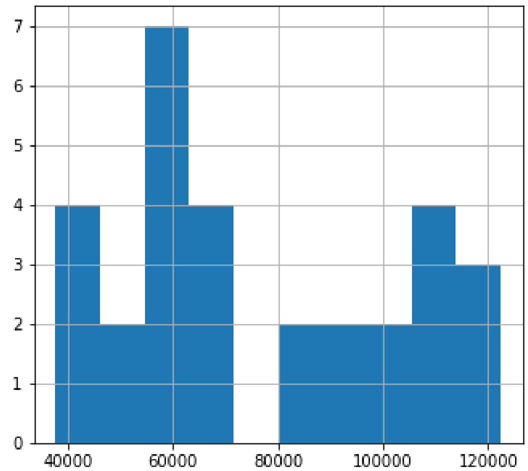


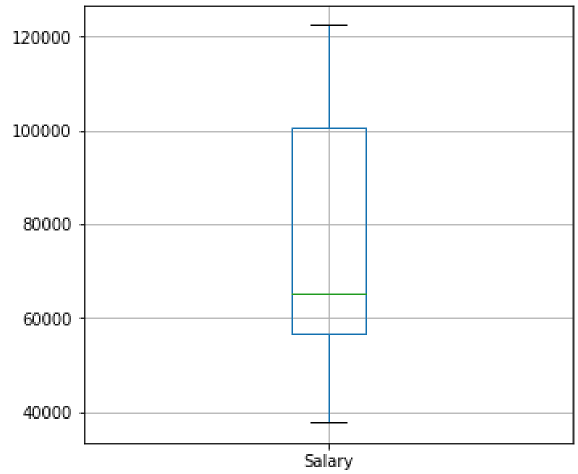



```
plt.figure(figsize = (12,5))
plt.subplot(1,2,1)
salary_details['Salary'].hist()
```

```
plt.subplot(1,2,2)
salary_details.boxplot(column = ['Salary'])

plt.show()
```

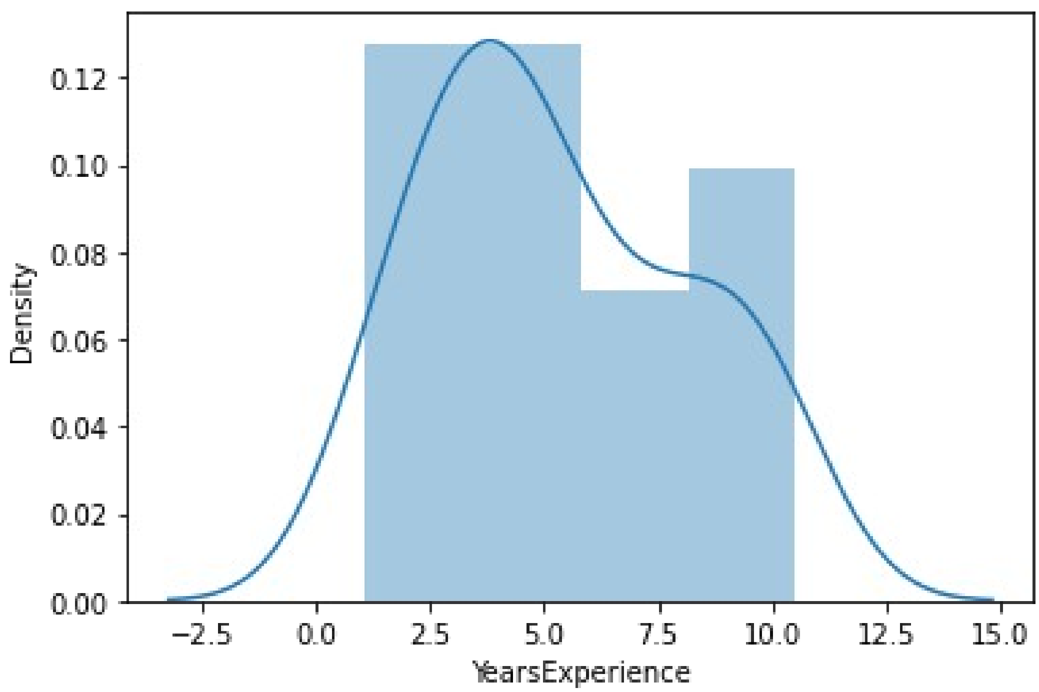




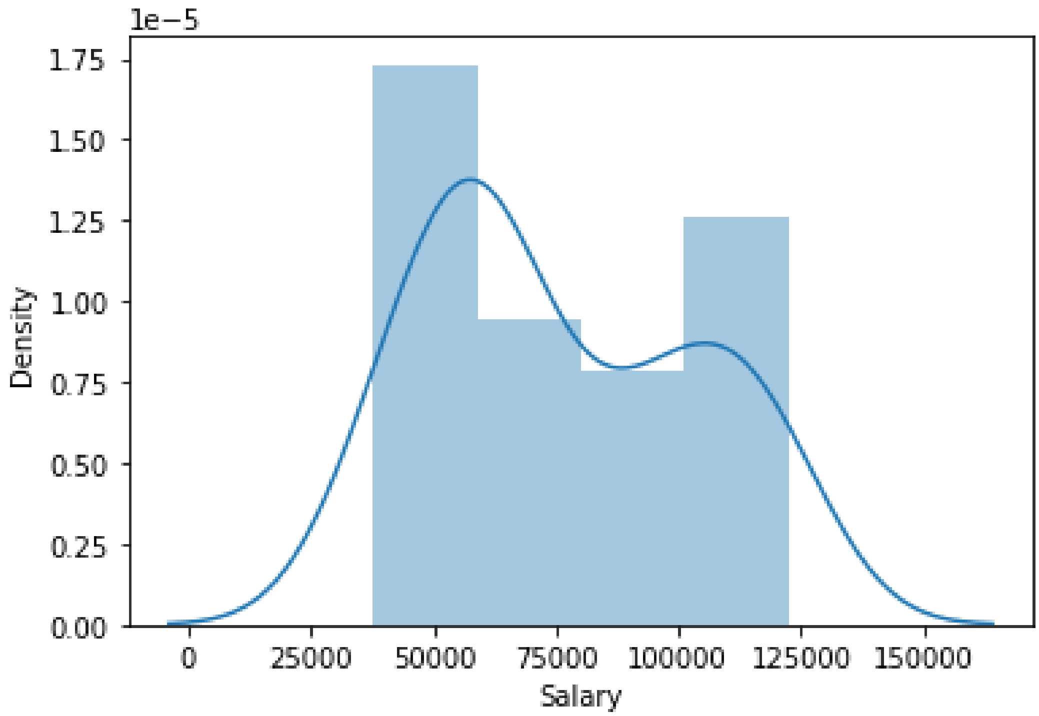
From the above histogrms and boxplots, we found that there is no outleirs present inside the YearsExperience and Salary data.

b) Normality / Distribution Test Using Distplot :

```
sns.distplot(salary_details['YearsExperience'])
plt.show()
```



```
sns.distplot(salary_details['Salary'])
plt.show()
```



Normality Test Failed

7. Model Building || 8. Model Training

Now Try to fit Model for Salary Hike

Model 1: Without Applying any Transformation

Using Statsmodel

```
model_1 = smf.ols(formula = 'YearsExperience~Salary', data = 
salary_details).fit()
model_1
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at 
0x7fdcb5b4bdf0>
```

```
#coefficient
model_1.params
```

```
Intercept   -2.383161
Salary       0.000101
dtype: float64
```

```
model_1.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:        YearsExperience   R-squared:
0.957
Model:                            OLS   Adj. R-squared:
0.955
Method:                 Least Squares   F-statistic:
622.5
Date:                Fri, 20 Jan 2023   Prob (F-statistic):
1.14e-20
Time:                        17:28:01   Log-Likelihood:
-26.168
No. Observations:                  30   AIC:
56.34
Df Residuals:                      28   BIC:
59.14
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
Intercept     -2.3832      0.327     -7.281      0.000      -3.054
-1.713
Salary         0.0001   4.06e-06     24.950      0.000     9.3e-05
0.000
======================================================================
========
Omnibus:                        3.544   Durbin-Watson:
1.587
Prob(Omnibus):                  0.170   Jarque-Bera (JB):
2.094
Skew:                          -0.412   Prob(JB):
0.351
Kurtosis:                       2.003   Cond. No.
2.41e+05
======================================================================
========

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

```
[2] The condition number is large, 2.41e+05. This might indicate that
there are
strong multicollinearity or other numerical problems.
"""
```

From the Above OLS Regression Result the R-Squared value is 0.957 > 0.75 and we can say that this Model is good to Predict Salary_hike and p-value < 0.05 and it is significant model

Model 2: Apply Log Transformation of Y

```
model_2 = smf.ols(formula = 'Salary~np.log(YearsExperience)',data =
salary_details).fit()
model_2
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at
0x7fdcb5b72250>
```

```
model_2.params
```

```
Intercept                  14927.97177
np.log(YearsExperience)    40581.98796
dtype: float64
```

```
model_2.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                 Salary   R-squared:
0.854
Model:                            OLS   Adj. R-squared:
0.849
Method:                 Least Squares   F-statistic:
163.6
Date:                Fri, 20 Jan 2023   Prob (F-statistic):
3.25e-13
Time:                        17:29:24   Log-Likelihood:
-319.77
No. Observations:                  30   AIC:
643.5
Df Residuals:                      28   BIC:
646.3
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
=====================
```

```
                              coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
---------------------
Intercept                1.493e+04   5156.226      2.895      0.007
4365.921    2.55e+04
np.log(YearsExperience)  4.058e+04   3172.453     12.792      0.000
3.41e+04    4.71e+04
======================================================================
========
Omnibus:                        1.094   Durbin-Watson:
0.512
Prob(Omnibus):                  0.579   Jarque-Bera (JB):
0.908
Skew:                           0.156   Prob(JB):
0.635
Kurtosis:                       2.207   Cond. No.
5.76
======================================================================
========

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

Model 3: Apply Log Transformation of X

```
model_3 = smf.ols(formula = 'np.log(Salary)~YearsExperience',data =
salary_details).fit()
model_3
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at
0x7fdccef66940>
```

```
model_3.params
```

```
Intercept          10.507402
YearsExperience     0.125453
dtype: float64
```

```
model_3.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:         np.log(Salary)   R-squared:
0.932
```

```
Model:                            OLS   Adj. R-squared:
0.930
Method:                 Least Squares   F-statistic:
383.6
Date:                Fri, 20 Jan 2023   Prob (F-statistic):
7.03e-18
Time:                        17:30:10   Log-Likelihood:
28.183
No. Observations:                  30   AIC:
-52.37
Df Residuals:                      28   BIC:
-49.56
Df Model:                           1

Covariance Type:            nonrobust

======================================================================
=============
                      coef    std err          t      P>|t|
[0.025      0.975]
----------------------------------------------------------------------
-------------
Intercept          10.5074      0.038    273.327      0.000
10.429      10.586
YearsExperience     0.1255      0.006     19.585      0.000
0.112       0.139
======================================================================
========
Omnibus:                        0.826   Durbin-Watson:
1.438
Prob(Omnibus):                  0.661   Jarque-Bera (JB):
0.812
Skew:                           0.187   Prob(JB):
0.666
Kurtosis:                       2.286   Cond. No.
13.2
======================================================================
========

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

Model 4: Apply Log Transformation of X and Y

```
model_4 = smf.ols(formula =
'np.log(Salary)~np.log(YearsExperience)',data = salary_details).fit()
model_4
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at
0x7fdcb5b6b9a0>
```

```
model_4.params
```

```
Intercept                   10.328043
np.log(YearsExperience)      0.562089
dtype: float64
```

```
model_4.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            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:                Fri, 20 Jan 2023   Prob (F-statistic):
7.40e-16
Time:                        17:30:56   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.
"""
```

Model 5: Apply Square Root Transformation

```
model_5 = smf.ols(formula = 'Salary~np.sqrt(YearsExperience)',data =
salary_details).fit()
model_5
```

```
<statsmodels.regression.linear_model.RegressionResultsWrapper at
0x7fdcb5aef4f0>
```

```
model_5.params
```

```
Intercept                  -16055.769117
np.sqrt(YearsExperience)    41500.680583
dtype: float64
```

```
model_5.summary()
```

```
<class 'statsmodels.iolib.summary.Summary'>
"""
                            OLS Regression Results

======================================================================
========
Dep. Variable:                 Salary   R-squared:
0.931
Model:                            OLS   Adj. R-squared:
0.929
Method:                 Least Squares   F-statistic:
377.8
Date:                Fri, 20 Jan 2023   Prob (F-statistic):
8.57e-18
Time:                        17:33:21   Log-Likelihood:
-308.52
No. Observations:                  30   AIC:
621.0
Df Residuals:                      28   BIC:
623.8
Df Model:                           1
```

```
Covariance Type:            nonrobust

==============================================================================
======================
                              coef    std err          t      P>|t|
[0.025      0.975]
------------------------------------------------------------------------------
----------------------
Intercept                -1.606e+04   4921.599     -3.262      0.003
-2.61e+04   -5974.331
np.sqrt(YearsExperience)   4.15e+04   2135.122     19.437      0.000
3.71e+04    4.59e+04
==============================================================================
========
Omnibus:                        0.588   Durbin-Watson:
1.031
Prob(Omnibus):                  0.745   Jarque-Bera (JB):
0.638
Skew:                           0.011   Prob(JB):
0.727
Kurtosis:                       2.286   Cond. No.
9.97
==============================================================================
========

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

CONCLUSION = Comparing between all Models we got to know that without applying any transformation for the Model_1 we got the Higher R-squared Value i.e. 0.957 as comapare to all Model.

Hence the Model_1 is better model to predict Salary_hike