20191COM0231

BALLA HARIKRISHNA

5COM4

PRESIDENCY UNIVERSITY

Problem Statement

The head of HR of a certain organization wants to automate their salary hike estimation. The organization consulted an analytics service provider and asked them to build a basic prediction model by providing them with a dataset that contains the data about the number of years of experience and the salary hike given accordingly. Build a Simple Linear Regression model with salary as the target variable.

Definition of Variable -:

Year of Experience (Input) Salary Hike -> Hike in salary (Target)

Approach to Solve the Business Case -:

1 Business Objective - Find Relationship between Salary Hike and Year of Experience 2 Perform EDA on data (Outlier, Missing Values). 3 Understand the relationship between the variable's using Scatter Plot. 4 Apply Simple linear regression with OLE to create base regression model(Vanilla Model) 5 Check the RMSE, R^2 & R values for the model. Compare the Vanilla model with Model with Transformation's to check the best fit model. Transformation used Logarithmic Exponential Polynomial with degree 2 After comparing RMSE, R^2 & R values, Select the best model. Train & Test your data on these model to check the performance of model on test data.

```
#Import Library
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
% matplotlib inline
import statsmodels.formula.api as smf
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19: FutureWarni
```

```
import pandas.util.testing as tm
```

```
#Import the dataset
sal = pd.read_csv("/content/Salary.csv")
```

```
#Check the data
sal.head()
```

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891

```
sal = sal.rename(columns={"Salary":"hike","YearsExperience":"years"})
sal.head(5)
```

	years	hike
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891

```
# Check for Null Data - No Null values
sal.info()
```

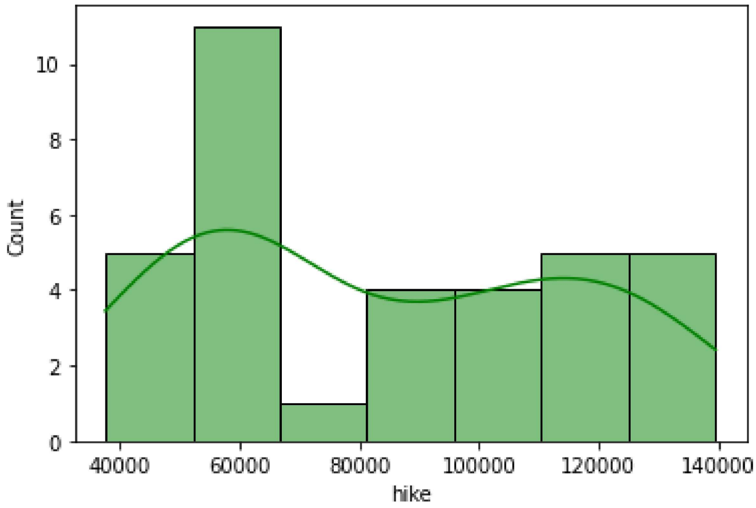
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 35 entries, 0 to 34
Data columns (total 2 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   years   35 non-null     float64
 1   hike    35 non-null     int64  
dtypes: float64(1), int64(1)
memory usage: 688.0 bytes
```

```
sal.describe()
```

	years	hike
count	35.000000	35.000000
mean	6.308571	83945.600000
std	3.618610	32162.673003
min	1.100000	37731.000000
25%	3.450000	57019.000000
50%	5.300000	81363.000000

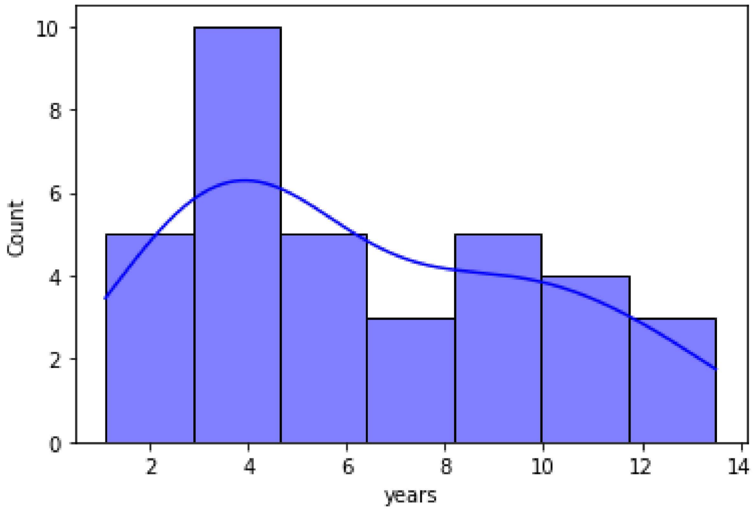
```
#Plot Histogram to view Distribution of data field ( Univariate)
sns.histplot(sal["hike"], color ='green',kde=True)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f212ef8ecd0>



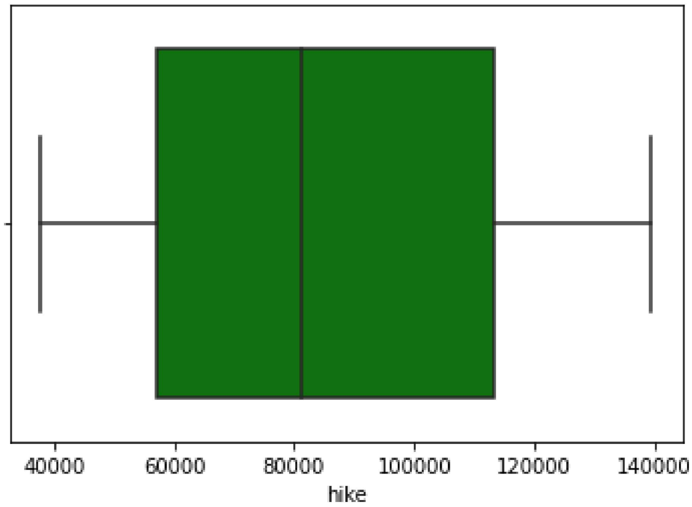

```
#Plot Histogram to view Distribution of data field ( Univariate)
sns.histplot(sal["years"], color ='blue',kde=True)
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f2120b00d10>



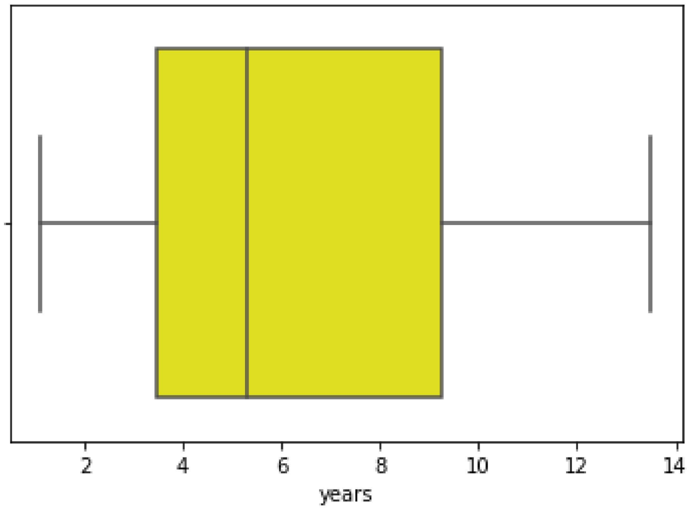

```
sns.boxplot(sal["hike"], color ='green')
# No Outlier found based on the boxplot analysis
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f212064a5d0>
```



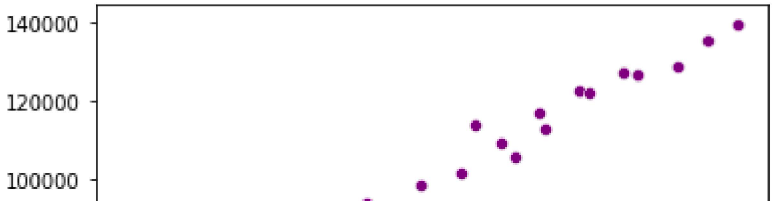

```
sns.boxplot(sal["years"], color ='yellow')
# No Outlier found based on the boxplot analysi
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f21205c70d0>
```




```
#Check the relation between Variable by Scatter Plot & Correlation Coefficient.
sns.scatterplot(y="hike",x="years",data=sal, color = "purple" )
#Relation Type = Linear
#Direction - Positive Correlation
#Strength -Can't Comment
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f2123fe5410>
```




```
# Find the Correlation Coefficient (R) for the relation
# R tells the magnitude of strength of relation between y & x
```


```
np.corrcoef(sal["years"],sal["hike"])
# R value is above 0.85 means Correlation strength is High.
```

```
array([[1.        , 0.98242725],
       [0.98242725, 1.        ]])
```

```
#Use OLS & fit model on data
import statsmodels.formula.api as smf
model1= smf.ols('hike~years',data = sal).fit()
model1.summary()
```

OLS Regression Results

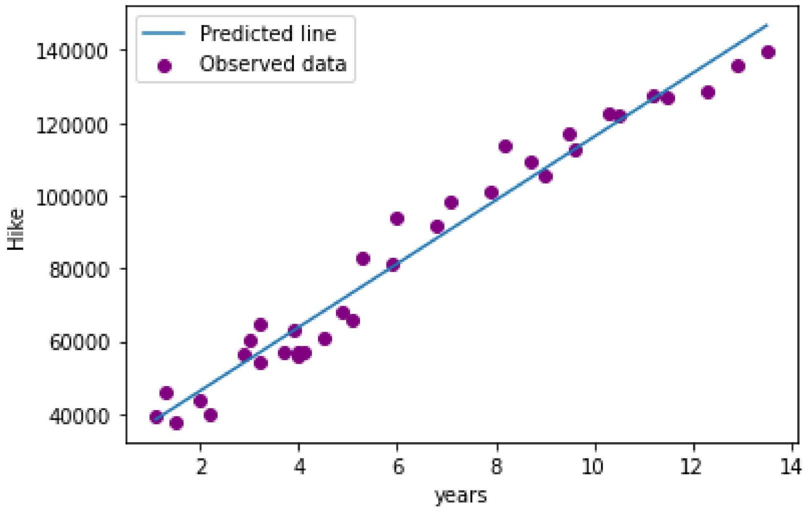
Dep. Variable:	hike	**R-squared:**	0.965
Model:	OLS	**Adj. R-squared:**	0.964
Method:	Least Squares	**F-statistic:**	914.3
Date:	Sat, 30 Oct 2021	**Prob (F-statistic):**	1.23e-25
Time:	16:50:05	**Log-Likelihood:**	-353.66
No. Observations:	35	**AIC:**	711.3
Df Residuals:	33	**BIC:**	714.4
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.886e+04	2092.797	13.790	0.000	2.46e+04	3.31e+04
years	8731.9410	288.783	30.237	0.000	8144.407	9319.475

Omnibus:	1.704	**Durbin-Watson:**	1.284
Prob(Omnibus):	0.426	**Jarque-Bera (JB):**	1.498
Skew:	0.372	**Prob(JB):**	0.473
Kurtosis:	2.313	**Cond. No.**	14.9

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

```
# Predict Regression Line Model1
pred1 = model1.predict(pd.DataFrame(sal['years']))
plt.scatter(x="years",y="hike",data=sal, color = "purple" )
plt.plot(sal['years'],pred1)
plt.legend(['Predicted line', 'Observed data'])
plt.xlabel('years')
plt.ylabel('Hike')
plt.show()
```

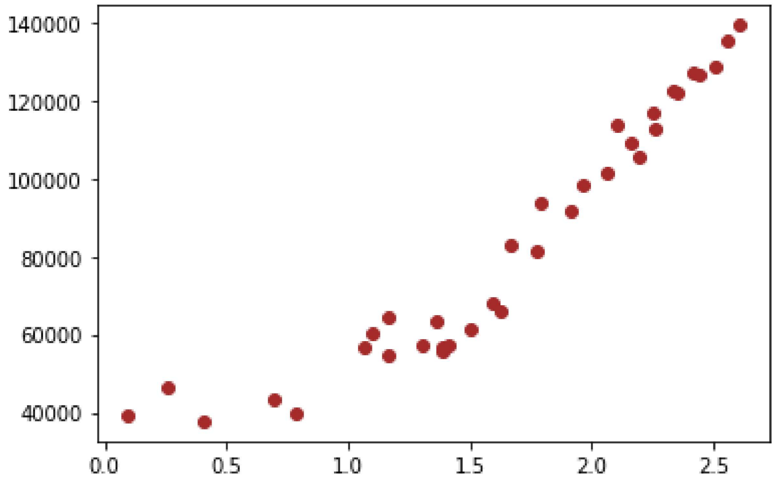



```
# RMSE Error calculation (Model-1)
res1 = sal.hike - pred1
res_sqr1 = res1 * res1
mse1 = np.mean(res_sqr1)
rmse1 = np.sqrt(mse1)
rmse1
```

```
5916.65177221896
```

```
#Check the relation between Variable by Scatter Plot & Correlation Coefficient.
plt.scatter(x = np.log(sal['years']), y = sal['hike'], color = 'brown')
np.corrcoef(np.log(sal['years']),sal['hike'] ) #correlation
```

```
array([[1.        , 0.94275493],
       [0.94275493, 1.        ]])
```




```
#Use OLS & fit model on data
model2= smf.ols('hike ~ np.log(years)',data = sal).fit()
model2.summary()
```

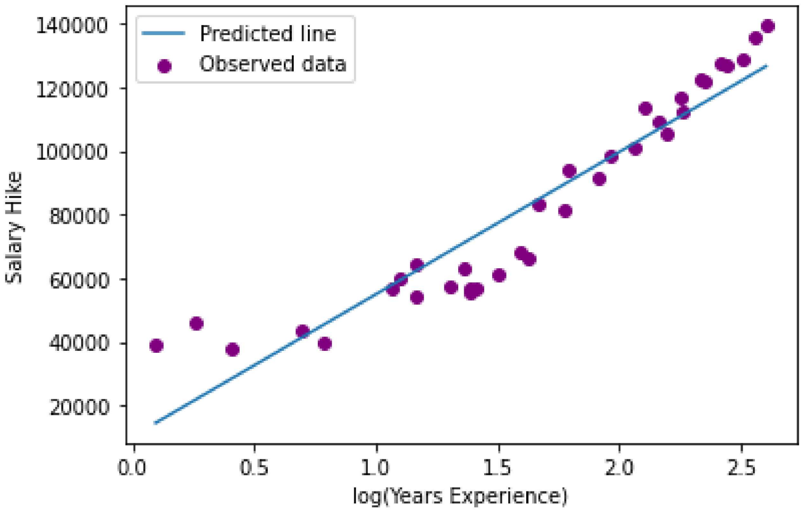
OLS Regression Results

Dep. Variable:	hike	**R-squared:**	0.889
Model:	OLS	**Adj. R-squared:**	0.885
Method:	Least Squares	**F-statistic:**	263.7
Date:	Sat, 30 Oct 2021	**Prob (F-statistic):**	2.66e-17
Time:	16:51:31	**Log-Likelihood:**	-373.97
No. Observations:	35	**AIC:**	751.9
Df Residuals:	33	**BIC:**	755.1
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	1.021e+04	4898.980	2.085	0.045	247.046	2.02e+04
np.log(years)	4.474e+04	2755.115	16.240	0.000	3.91e+04	5.03e+04

Omnibus:	0.448	**Durbin-Watson:**	0.439
Prob(Omnibus):	0.799	**Jarque-Bera (JB):**	0.381
Skew:	0.234	**Prob(JB):**	0.826

```
# Predict Regression Line for Model-2
pred2 = model2.predict(pd.DataFrame(sal['years']))
plt.scatter(x=np.log(sal["years"]),y="hike",data= sal, color = "purple" )
plt.plot(np.log(sal['years']),pred2)
plt.legend(['Predicted line', 'Observed data'])
plt.xlabel('log(Years Experience)')
plt.ylabel('Salary Hike')
plt.show()
```



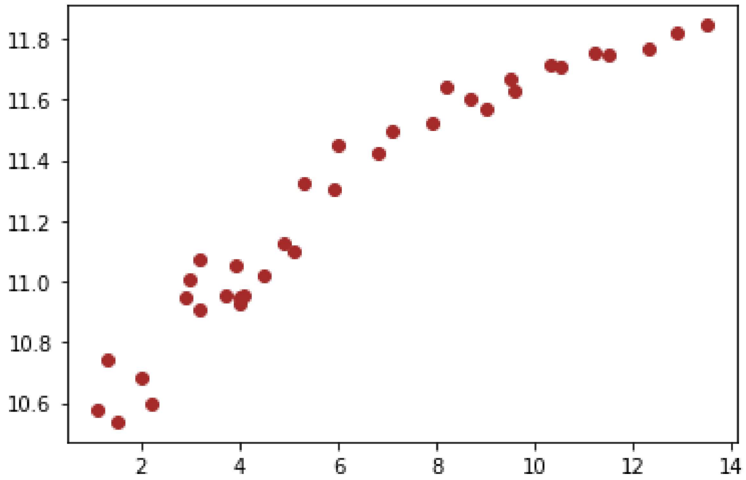

```
# RMSE Error calculation for Model-2
res2 = sal.hike- pred2
res_sqr2 = res2 * res2
mse2 = np.mean(res_sqr2)
rmse2 = np.sqrt(mse2)
rmse2
```

    10571.476134692335

```
#Check the relation between Variable by Scatter Plot & Correlation Coefficient.
plt.scatter(x = sal['years'], y= np.log(sal['hike']), color = 'brown') # Scatter Plot for
```

```
np.corrcoef(sal['years'],np.log(sal['hike']) ) #correlation
```

```
array([[1.        , 0.95969313],
       [0.95969313, 1.        ]])
```




```
#Use OLS & fit model on data
import statsmodels.formula.api as smf
model3= smf.ols('np.log(hike) ~ years',data = sal).fit()
model3.summary()
```

OLS Regression Results

Dep. Variable:	np.log(hike)	**R-squared:**	0.921
Model:	OLS	**Adj. R-squared:**	0.919
Method:	Least Squares	**F-statistic:**	384.8
Date:	Sat, 30 Oct 2021	**Prob (F-statistic):**	9.25e-20
Time:	16:52:45	**Log-Likelihood:**	26.953
No. Observations:	35	**AIC:**	-49.91
Df Residuals:	33	**BIC:**	-46.79
Df Model:	1		
Covariance Type:	nonrobust		

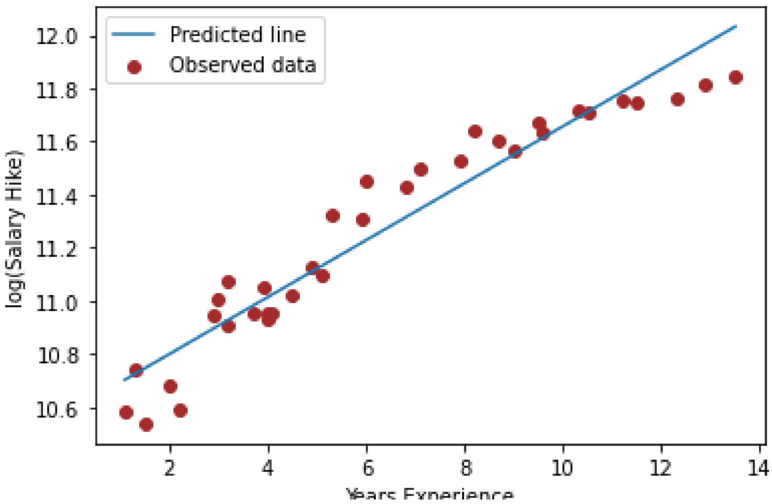
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	10.5849	0.040	267.124	0.000	10.504	10.666
years	0.1073	0.005	19.616	0.000	0.096	0.118

Omnibus:	0.626	**Durbin-Watson:**	0.893
Prob(Omnibus):	0.731	**Jarque-Bera (JB):**	0.687
Skew:	-0.106	**Prob(JB):**	0.709
Kurtosis:	2.347	**Cond. No.**	14.9

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

```
# Predict Regression Line for Model-3
pred3 = model3.predict(pd.DataFrame(sal['years']))
pred3_exp = np.exp(pred3)
plt.scatter(x =(sal['years']), y = np.log(sal['hike']), color = 'brown')
plt.plot(sal['years'],pred3)
plt.legend(['Predicted line', 'Observed data'])
plt.xlabel('Years Experience')
```

```
plt.ylabel('log(Salary Hike)')
plt.show()
```




```
# RMSE Error calculation
res3 = sal.hike - pred3_exp
res_sqr3 = res3 * res3
mse3 = np.mean(res_sqr3)
rmse3 = np.sqrt(mse3)
rmse3
```

```
10200.516603204116
```

```
#Use OLS & fit model on data
model4 = smf.ols('hike ~ years + I(years*years)', data = sal).fit()
model4.summary()
```

OLS Regression Results

Dep. Variable:	hike	**R-squared:**	0.970
Model:	OLS	**Adj. R-squared:**	0.968
Method:	Least Squares	**F-statistic:**	519.0
Date:	Sat, 30 Oct 2021	**Prob (F-statistic):**	4.10e-25
Time:	16:53:39	**Log-Likelihood:**	-350.99
No. Observations:	35	**AIC:**	708.0
Df Residuals:	32	**BIC:**	712.6
Df Model:	2		
Covariance Type:	nonrobust		

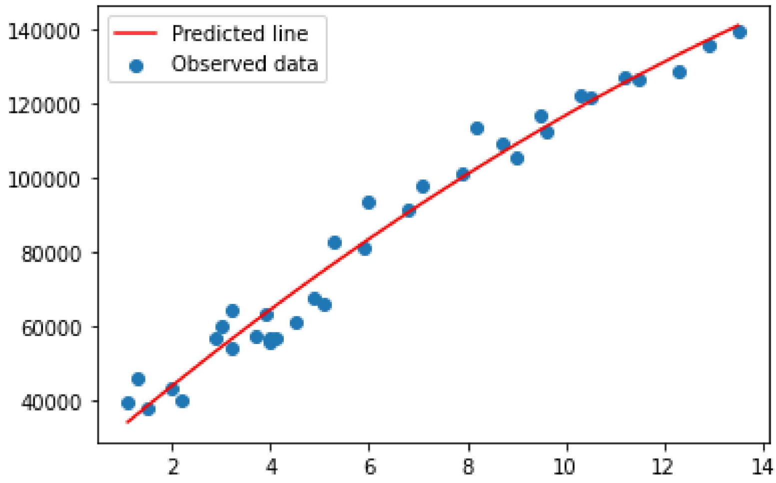
	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.186e+04	3630.803	6.019	0.000	1.45e+04	2.93e+04
years	1.146e+04	1217.275	9.411	0.000	8976.863	1.39e+04
I(years * years)	-193.9004	84.449	-2.296	0.028	-365.917	-21.884

Omnibus:	0.820	**Durbin-Watson:**	1.492
Prob(Omnibus):	0.664	**Jarque-Bera (JB):**	0.813
Skew:	0.157	**Prob(JB):**	0.666
Kurtosis:	2.322	**Cond. No.**	290.

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

```
pred4 = model4.predict(pd.DataFrame(sal))
X = sal.iloc[:, 0:1].values


plt.scatter(sal.years,sal.hike)
plt.plot(X, pred4, color = 'red')
plt.legend(['Predicted line', 'Observed data'])
plt.show()
```




```
# Error calculation
res4 = sal.hike - pred4
res_sqr4 = res4 * res4
mse4 = np.mean(res_sqr4)
rmse4 = np.sqrt(mse4)
rmse4
```

    5482.262467661961

```
# Choose the best model using RMSE
data = {"MODEL":pd.Series(["SLR", "Log model", "Exp model", "Poly model"]), "RMSE":pd.Seri
table_rmse = pd.DataFrame(data)
table_rmse
```

	MODEL	RMSE
0	SLR	5916.651772
1	Log model	10571.476135
2	Exp model	10200.516603
3	Poly model	5482.262468

```
#Althought the R^2 & RMSE value is higher for Polynomial model but it is having p value hi
#Our Best model is Base Model with No transfomation.( Vanilla Model)
```

4.Best Model Selection from 4 Model tested Based on R ,

S.No.	Model	R	R^2	RMSE	Equation	Comments
1	Simple Linear Regression	0.9782	0.831	5592.043609	y=9449.9623x + 2.579*10^4	Best model, Lowest RMSE & Highest R^2
2	Logarithmic Model	0.924	0.854	10302	y=40580(log(x))+14934	RMSE higher than base Model
3	Exponential Method	0.965	0.932	7213	log(y) = -0.0014x+6.6383	RMSE higher than base Model
4	Polynomial of Degree 2 (Quadratic Equation)	-	0.957	5590.8414	y= 0.0005(x^2)-1.7371x+1647.0116	p value for X^2 is higher than 5% hence neglecting this Model

4.1. BEST MODEL - Vanilla Model (y=mx+c,No Tranformation)

5. Train & Test your data on the Best model to check the performance of model on test data

```
from sklearn.model_selection import train_test_split

train, test = train_test_split(sal, test_size = 0.25,random_state=6)

finalmodel = smf.ols('hike ~ years', data = train).fit()
finalmodel.summary()
```

OLS Regression Results

Dep. Variable:	hike	**R-squared:**	0.973
Model:	OLS	**Adj. R-squared:**	0.972
Method:	Least Squares	**F-statistic:**	877.7
Date:	Sat, 30 Oct 2021	**Prob (F-statistic):**	2.06e-20
Time:	16:58:12	**Log-Likelihood:**	-259.54
No. Observations:	26	**AIC:**	523.1
Df Residuals:	24	**BIC:**	525.6
Df Model:	1		
Covariance Type:	nonrobust		

	coef	**std err**	**t**	**P>|t|**	**[0.025**	**0.975]**
Intercept	2.764e+04	2216.766	12.471	0.000	2.31e+04	3.22e+04
years	8692.7201	293.409	29.627	0.000	8087.154	9298.287

Omnibus:	8.006	**Durbin-Watson:**	1.830
Prob(Omnibus):	0.018	**Jarque-Bera (JB):**	2.218
Skew:	0.219	**Prob(JB):**	0.330
Kurtosis:	1.638	**Cond. No.**	15.9

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

```
# Prediction on train data
train_pred = finalmodel.predict(pd.DataFrame(train))
```

```
train_pred
```

```
33    139780.315313
5      52853.113957
22     96316.714635
24    103270.890744
18     78931.274364
32    134564.683232
2      40683.305767
8      55460.929998
21     89362.538527
4      46768.209862
14     66761.466174
12     62415.106106
26    110225.066852
29    118917.786988
30    125002.691083
11     62415.106106
1      38944.761740
25    105878.706784
16     71977.098256
31    127610.507123
15     70238.554228
13     63284.378120
34    144995.947394
20     86754.722486
9      59807.290066
10     61545.834093
dtype: float64
```

```
# Model Evaluation on train data
train_res = train.hike - train_pred
train_sqrs = train_res * train_res
train_mse = np.mean(train_sqrs)
train_rmse = np.sqrt(train_mse)
train_rmse
```

```
5235.575922893785
```

```
# Predict on test data
test_pred = finalmodel.predict(pd.DataFrame(test))
test_pred
```

```
7      55460.929998
27    111094.338866
23     98924.530676
0      37206.217713
17     73715.642283
28    117179.242961
3      45029.665835
19     79800.546378
6      53722.385971
dtype: float64
```

```
# Model Evaluation on Test data
test_res = test.hike - test_pred
test_sqrs = test_res * test_res
```

```
test_mse = np.mean(test_sqrs)
test_rmse = np.sqrt(test_mse)
test_rmse
```

```
8083.68880767068
```

6 Final Observation

Although Train data is giving better result than test data hence it looks like an overfit model. But since the RMSE value of Train & Test data is very Close, it can be Inferred Model will perform well in real life scenario with Unknown Data. Hence, we can predict the Salary Hike with higher accuracy based on Year's of Experience data.

Final R^2 Value = 97.3%

✓ 0s completed at 10:29 PM