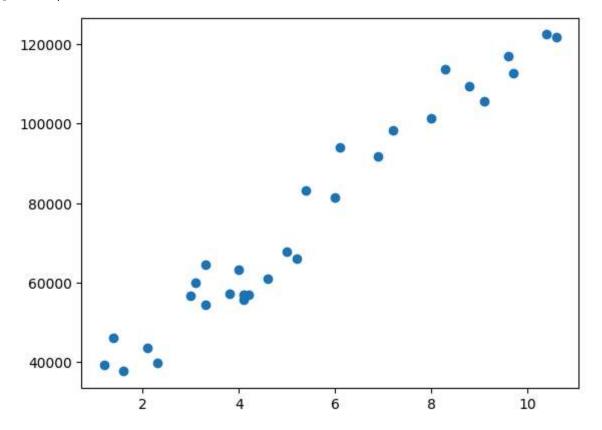
```
In [1]: # import libraries
import pandas as pd
import matplotlib.pyplot as plt
from math import sqrt

In [3]: # read data into a DataFrame
data = pd.read_csv('Salary_dataset.csv', index_col=0)
# Renaming the Columns
data.columns = ['Experience','Salary']
data
```

Out[3]:		Experience	Salary
	0	1.2	39344.0
	1	1.4	46206.0
	2	1.6	37732.0
	3	2.1	43526.0
	4	2.3	39892.0
	5	3.0	56643.0
	6	3.1	60151.0
	7	3.3	54446.0
	8	3.3	64446.0
	9	3.8	57190.0
	10	4.0	63219.0
	11	4.1	55795.0
	12	4.1	56958.0
	13	4.2	57082.0
	14	4.6	61112.0
	15	5.0	67939.0
	16	5.2	66030.0
	17	5.4	83089.0
	18	6.0	81364.0
	19	6.1	93941.0
	20	6.9	91739.0
	21	7.2	98274.0
	22	8.0	101303.0
	23	8.3	113813.0
	24	8.8	109432.0
	25	9.1	105583.0
	26	9.6	116970.0
	27	9.7	112636.0
	28	10.4	122392.0
	29	10.6	121873.0

In [4]: # visualize the relationship between the features and the response using scatterplo
plt.scatter(data['Experience'], data['Salary'])

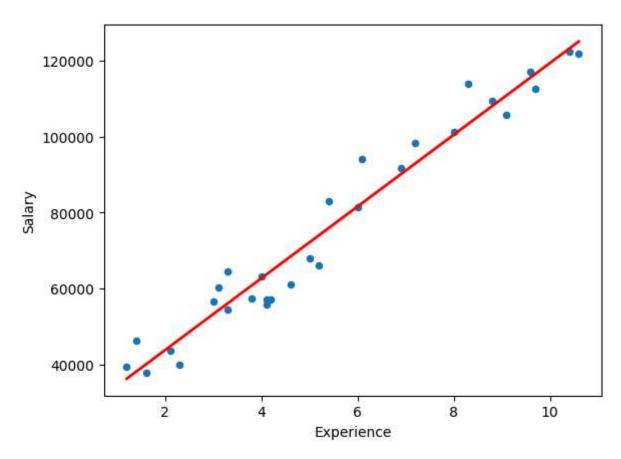
Out[4]: <matplotlib.collections.PathCollection at 0x1a673536710>



```
In [5]: # create X and y
X = data[['Experience']] #DataFrame
y = data.Salary #Series (data['Sales']) / NP Array
print(X)
print(y)
```

0 1.2 1 1.4 2 1.6 3 2.1 4 2.3 5 3.0 6 3.1 7 3.3 8 3.3 9 3.8 10 4.0 11 4.1 12 4.1 13 4.2 14 4.6 15 5.0 16 5.2 17 5.4 18 6.0 19 6.1 20 6.9 21 7.2 22 8.0 23 8.3 24 8.8 25 9.1 26 9.6 27 9.7 28 10.4 29 10.6 0 39344.0 1 46206.0 2 37732.0 3 43526.0 4 39892.0 5 56643.0		Experience
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23 113813.024 109432.0		

```
25
             105583.0
        26 116970.0
        27 112636.0
        28 122392.0
        29
             121873.0
        Name: Salary, dtype: float64
 In [7]: # follow the usual sklearn pattern: import, instantiate, fit
         from sklearn.linear_model import LinearRegression
         lm = LinearRegression()
         lm.fit(X, y) # Lm.fit(DataFrame, Series/Array)
         # print intercept and coefficients
         print("Intercept-",lm.intercept )
         print("Coeffcient-",lm.coef )
        Intercept- 24848.203966523208
        Coeffcient- [9449.96232146]
 In [9]: # you have to create a DataFrame since the predict method expects it
         X_new = pd.DataFrame({'Experience': [2.3]})
         print("Predicted salary-",lm.predict(X_new))
        Predicted salary- [46583.11730587]
In [10]: # create a DataFrame with the minimum and maximum values of Experience
         X_new = pd.DataFrame({'Experience': [data['Experience'].min(), data['Experience'].m
         X_new.head()
Out[10]:
            Experience
                   1.2
         0
                  10.6
In [12]: # make predictions for those x values and store them
         preds = lm.predict(X_new) # Need a DataFrame
         print("predicitions-",preds)
        predicitions- [ 36188.15875227 125017.80457395]
In [13]: # first, plot the observed data
         data.plot(kind='scatter', x='Experience', y='Salary')
         # then, plot the least squares line
         plt.plot(X_new, preds, c='red', linewidth=2)
Out[13]: [<matplotlib.lines.Line2D at 0x1a67d663b50>]
```



```
In [16]: from sklearn.metrics import r2_score, mean_squared_error
predictions = lm.predict(X)

# RMSE form training data
print("RMSE-", sqrt(mean_squared_error(y, predictions)))

# R2 Score
print("R-squared value-", r2_score(y, predictions))
```

RMSE- 5592.043608760661 R-squared value- 0.9569566641435086