**Name : Tushar Shirsath**

**Roll No : 220940325083**

# Q.2

In [1]:
```
# Importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df = pd.read_excel(r'C:\Users\Dell\Desktop\ML_Module_Exam\Data\data_final.xlsx')
df
```

Out[2]:

| | observation | feature | price |
|---|---|---|---|
| **0** | 0.44 | 0.68 | 511.14 |
| **1** | 0.99 | 0.23 | 717.10 |
| **2** | 0.84 | 0.29 | 607.91 |
| **3** | 0.28 | 0.45 | 270.40 |
| **4** | 0.07 | 0.83 | 289.88 |
| **...** | ... | ... | ... |
| **95** | 0.99 | 0.13 | 636.22 |
| **96** | 0.28 | 0.46 | 272.12 |
| **97** | 0.87 | 0.36 | 696.65 |
| **98** | 0.23 | 0.87 | 434.53 |
| **99** | 0.77 | 0.36 | 593.86 |

100 rows × 3 columns

### Data Understanding

In [3]:
```
df.shape
```

Out[3]:
```
(100, 3)
```

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 3 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   observation  100 non-null    float64
 1   feature      100 non-null    float64
 2   price        100 non-null    float64
dtypes: float64(3)
memory usage: 2.5 KB
```

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

Out[5]:

| | observation | feature | price |
|---|---|---|---|
| **count** | 100.000000 | 100.000000 | 100.000000 |
| **mean** | 0.550300 | 0.501700 | 554.214600 |
| **std** | 0.293841 | 0.307124 | 347.312796 |
| **min** | 0.010000 | 0.000000 | 42.080000 |
| **25%** | 0.300000 | 0.230000 | 278.172500 |
| **50%** | 0.570000 | 0.485000 | 514.285000 |
| **75%** | 0.822500 | 0.760000 | 751.752500 |
| **max** | 1.000000 | 0.990000 | 1563.820000 |

In [6]:
```
df.head()
```

Out[6]:

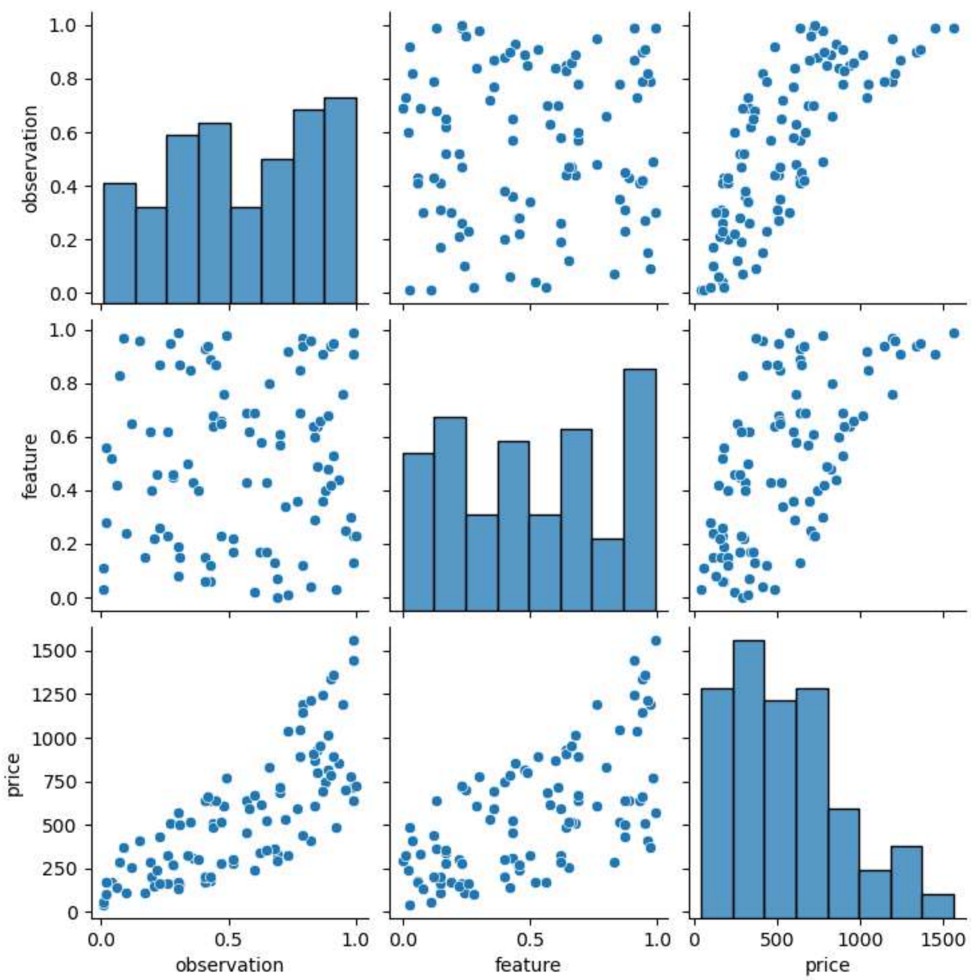
| | observation | feature | price |
|---|---|---|---|
| **0** | 0.44 | 0.68 | 511.14 |
| **1** | 0.99 | 0.23 | 717.10 |
| **2** | 0.84 | 0.29 | 607.91 |
| **3** | 0.28 | 0.45 | 270.40 |
| **4** | 0.07 | 0.83 | 289.88 |

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

Out[7]:
```
observation    0
feature        0
price          0
dtype: int64
```

In [8]:
```
sns.pairplot(df)
```

Out[8]:
```
<seaborn.axisgrid.PairGrid at 0x1cb47678400>
```




In [9]:
```
df.corr()
```

Out[9]:

| | observation | feature | price |
|---|---|---|---|
| **observation** | 1.000000 | 0.041766 | 0.764315 |
| **feature** | 0.041766 | 1.000000 | 0.627476 |
| **price** | 0.764315 | 0.627476 | 1.000000 |

In [10]:
```
# Dataset has Two independent Variabale and One dependent variable
```

In [11]:
```
x = df.drop('price', axis=1)
x
```

Out[11]:

| | observation | feature |
|---|---|---|
| **0** | 0.44 | 0.68 |
| **1** | 0.99 | 0.23 |
| **2** | 0.84 | 0.29 |
| **3** | 0.28 | 0.45 |
| **4** | 0.07 | 0.83 |
| **...** | ... | ... |
| **95** | 0.99 | 0.13 |
| **96** | 0.28 | 0.46 |
| **97** | 0.87 | 0.36 |
| **98** | 0.23 | 0.87 |
| **99** | 0.77 | 0.36 |

100 rows × 2 columns

In [12]:
```
y = df.price
y
```

Out[12]:
```
0     511.14
1     717.10
2     607.91
3     270.40
4     289.88
       ...
95    636.22
96    272.12
97    696.65
98    434.53
99    593.86
Name: price, Length: 100, dtype: float64
```

In [13]:
```
x.shape, y.shape
```

Out[13]:
```
((100, 2), (100,))
```

In [14]:
```
# Train and Test Data
```

In [15]:
```
from sklearn.model_selection import train_test_split
```

In [16]:
```
x_train, x_test, y_train, y_test = train_test_split(x, y, train_size=0.8, random_state=42)
```

In [17]:
```
x_train.shape, x_test.shape, y_train.shape, y_test.shape
```

Out[17]:
```
((80, 2), (20, 2), (80,), (20,))
```

In [ ]:

**As number of independent feature are more than one so we will go with Multiple Linear Regression Model**

## Multiple Linear Regression Model

In [18]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression()
model.fit(x_train, y_train)
```

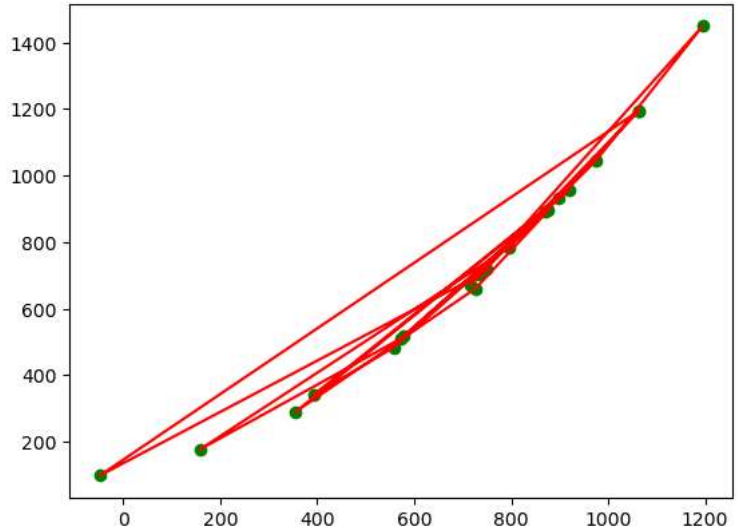
Out[18]:
```
LinearRegression()
```

In [19]:
```
y_pred = model.predict(x_test)
y_pred
```

Out[19]:
```
array([ 749.76896963,  735.98936824,  -48.85992817, 1062.20644707,
        716.69328274, 1194.90581714,  975.78229373,  796.22763539,
        157.64413694,  573.18572683,  897.84604006,  392.4709254 ,
        557.34034613,  876.99318895,  726.73794801,  354.96783965,
        919.53346956,  579.16989129,  870.75451763, 1063.1120833 ])
```

In [20]:
```
# Now we will plot scatter plot

plt.scatter(y_pred, y_test, color = 'green')
plt.plot(y_pred, y_test, color = 'red')
plt.show()
```




In [21]:
```
model.predict([[0.40, 0.65]])
```

```
C:\Users\Dell\anaconda3\lib\site-packages\sklearn\base.py:450: UserWarning: X does not have valid feature names, but LinearRegr
ession was fitted with feature names
  warnings.warn(
```

Out[21]: `array([519.25718884])`

**Result with error calculation and Performance of Model**

In [22]:
```
from sklearn import metrics
```

**Mean Absolute error**

In [23]:
```
round(metrics.mean_absolute_error(y_test, y_pred),2)
```

Out[23]: `68.25`

**Mean Squared Error**

In [24]:
```
round(metrics.mean_squared_error(y_test, y_pred) ,2)
```

Out[24]: `7901.48`

**Median Absolute Error**

In [25]:
```
round(metrics.median_absolute_error(y_test, y_pred),2)
```

Out[25]: `56.08`

**Explained Varience Score**

In [26]:
```
round(metrics.explained_variance_score(y_test, y_pred),2)
```

Out[26]: `0.94`

**OLS Summary Report**

In [27]:
```
import statsmodels.api as sm
constant = sm.add_constant(x_train)
op = sm.OLS(y_train, constant).fit()
op.summary()
```

Out[27]:

OLS Regression Results

| | | | |
|---|---|---|---|
| **Dep. Variable:** | price | **R-squared:** | 0.935 |
| **Model:** | OLS | **Adj. R-squared:** | 0.933 |
| **Method:** | Least Squares | **F-statistic:** | 553.4 |
| **Date:** | Mon, 23 Jan 2023 | **Prob (F-statistic):** | 2.04e-46 |
| **Time:** | 17:38:06 | **Log-Likelihood:** | -468.52 |
| **No. Observations:** | 80 | **AIC:** | 943.0 |
| **Df Residuals:** | 77 | **BIC:** | 950.2 |
| **Df Model:** | 2 | | |
| **Covariance Type:** | nonrobust | | |

| | coef | std err | t | P>\|t\| | [0.025 | 0.975] |
|---|---|---|---|---|---|---|
| **const** | -249.7765 | 24.830 | -10.059 | 0.000 | -299.219 | -200.334 |
| **observation** | 855.8957 | 33.498 | 25.550 | 0.000 | 789.192 | 922.600 |
| **feature** | 656.4236 | 31.261 | 20.998 | 0.000 | 594.174 | 718.673 |

| | | | |
|---|---|---|---|
| **Omnibus:** | 33.673 | **Durbin-Watson:** | 1.755 |
| **Prob(Omnibus):** | 0.000 | **Jarque-Bera (JB):** | 60.429 |
| **Skew:** | 1.656 | **Prob(JB):** | 7.55e-14 |
| **Kurtosis:** | 5.675 | **Cond. No.** | 5.16 |

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

In [28]:
```
# From above report we can see that R-squared value is 0.935 .
```

In [29]:
```
# Now we will build model using Polynomial Regression
```

## Polynomial Regression Model Building

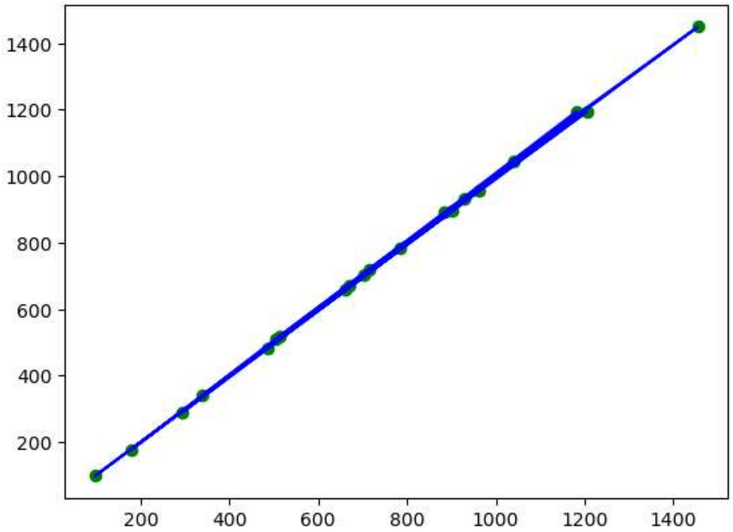
In [30]:
```
from sklearn.preprocessing import PolynomialFeatures
model = PolynomialFeatures(degree=3)
x_poly = model.fit_transform(x_train)
lg = LinearRegression()
lg.fit(x_poly, y_train)
```

Out[30]:
```
LinearRegression()
```

In [31]:
```
y_pred1 = lg.predict(model.fit_transform(x_test))
y_pred1
```

Out[31]:
```
array([ 716.52240373,  704.37562725,   97.24650833, 1204.76400021,
        669.68357104, 1455.2008966 , 1040.15954211,  785.86534227,
        178.57434028,  504.97788554,  929.36965021,  339.75359125,
        486.26458087,  902.35416128,  659.78240988,  294.35425077,
        962.79883875,  512.84840805,  884.0971578 , 1181.89303059])
```

In [32]:
```
# We will see it on scatter plot
plt.scatter(y_pred1, y_test, color = 'green')
plt.plot(y_pred1, y_test, color='blue')
plt.show()
```




In [33]:
```
metrics.r2_score(y_test, y_pred1)
```

Out[33]:
```
0.9997458144373799
```

In [ ]:

## Conclusion

**Here i have build two different models . One using Multiple Regression and Second using Polynomial Regression. From this two model i can conclude that Polynomial Regression model is more accurate tahn Multiple linear regression model**

In [ ]: