Problem Statement 1:

Importing Libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

Importing Dataset

```
df = pd.read_csv('data.csv')
```

```
df.head()
```

```
      F     N  Prprice per square foot
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
```

```
df.shape
```

```
(100, 3)
```

```
df.info()
```

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

```
df.describe()
```

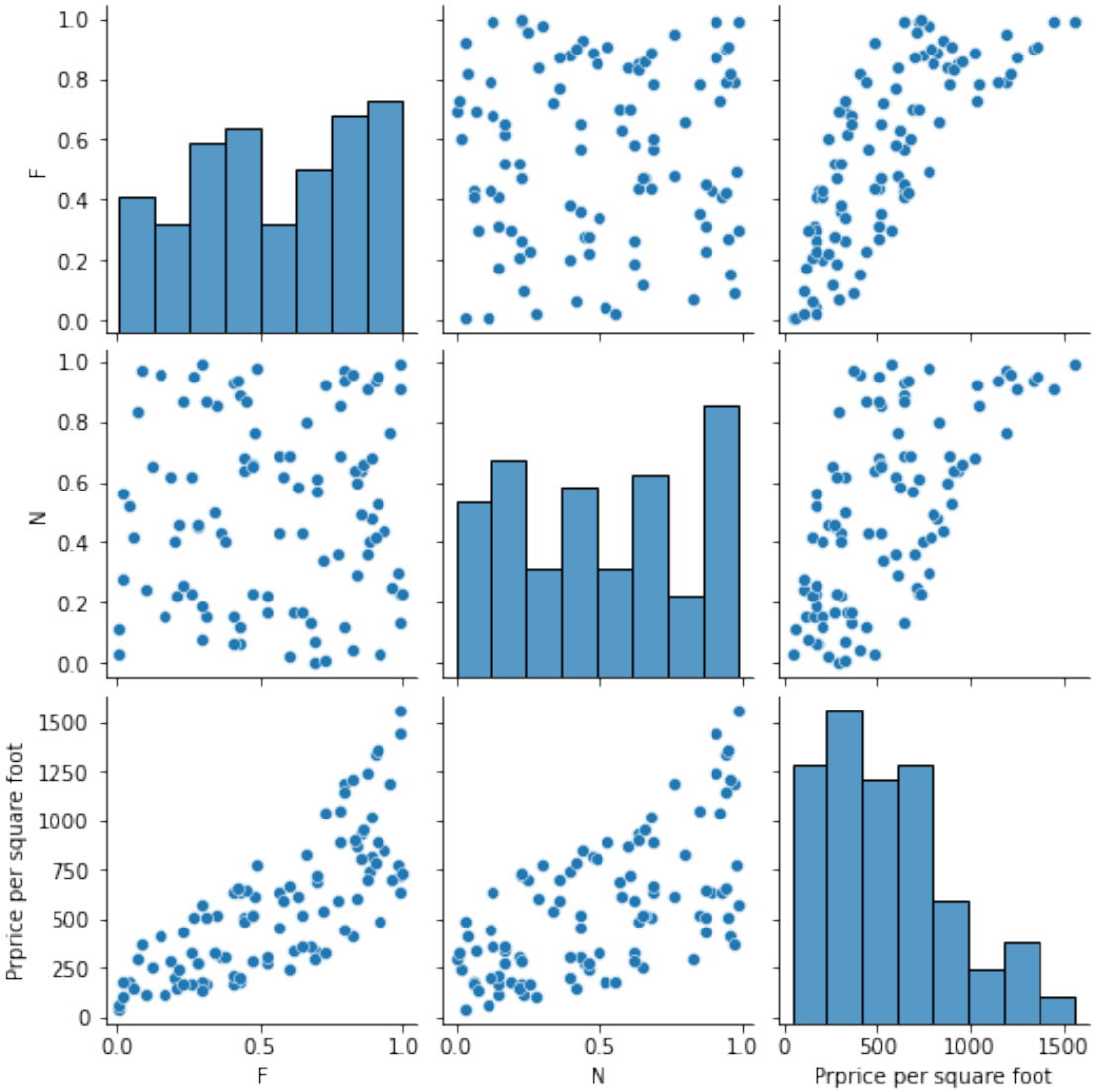
```
                F           N  Prprice per square foot
count  100.000000  100.000000               100.000000
mean     0.550300    0.501700               554.214600
std      0.293841    0.307124               347.312796
min      0.010000    0.000000                42.080000
25%      0.300000    0.230000               278.172500
50%      0.570000    0.485000               514.285000
75%      0.822500    0.760000               751.752500
max      1.000000    0.990000              1563.820000
```

```
df.isnull().sum()
```

```
F                            0
N                            0
Prprice per square foot      0
dtype: int64
```

```
sns.pairplot(df)
```

```
<seaborn.axisgrid.PairGrid at 0x21cef090850>
```




```
# Independent and Dependent variables
```

```
X = df.iloc[:,:-1].values
```

```
y = df.iloc[:,-1].values
```

```
X.shape , y.shape
```

```
((100, 2), (100,))
```

```
#Train and Test Data

from sklearn.model_selection import train_test_split
X_train , X_test , y_train , y_test =
train_test_split(X,y,test_size=0.33,random_state=0)
```

```
X_train.shape , X_test.shape , y_train.shape , y_test.shape
```

```
((67, 2), (33, 2), (67,), (33,))
```

Multiple Linerar Regression Model Building

```
from sklearn.linear_model import LinearRegression
reg = LinearRegression()
reg.fit(X_train,y_train)
```

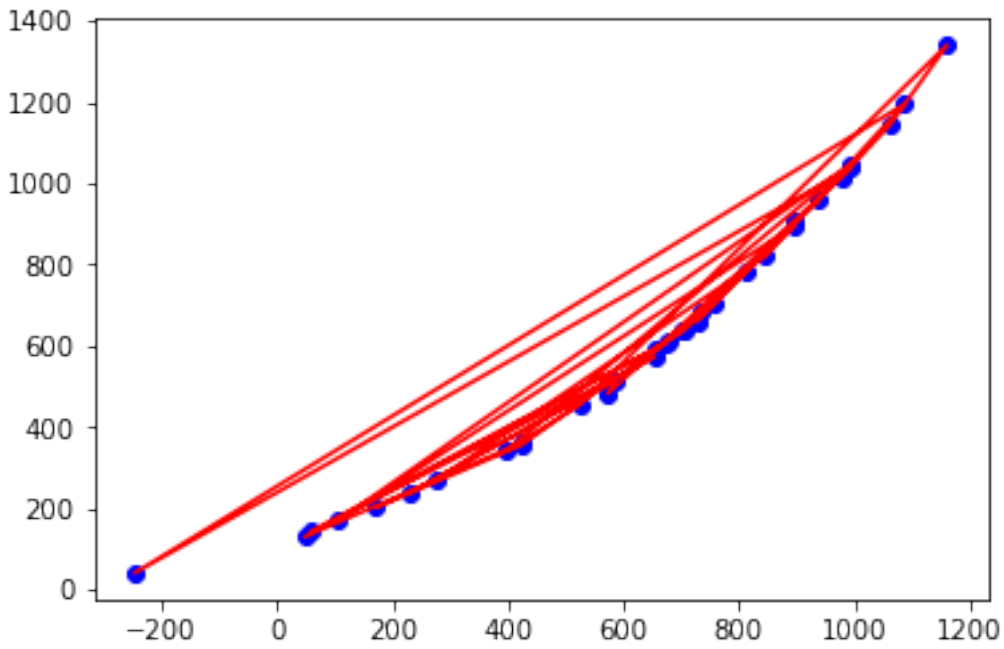
```
LinearRegression()
```

```
y_pred = reg.predict(X_test)
y_pred
```

```
array([ 422.81092199,   47.3117882 ,  673.47663105,   57.68448711,
        653.51497592,  228.41131427,  586.76861722,  572.31598687,
        677.55656248,  701.96695506,  754.89073698,  978.30316384,
       1061.45374137, 1160.50910794,  523.60276016,  395.42701601,
        992.49454662,  106.29015537,  896.38962812,  703.96467422,
        422.44211598,  170.43180667,  275.77994073,  845.07169401,
       1085.62595172, -247.14204568,  994.10039444,  657.07241222,
        733.93022227,  937.96491688,  897.62666993,  814.10728639,
        728.26750836])
```

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

```
[<matplotlib.lines.Line2D at 0x21cef78d0d0>]
```



1 = 180.38

2 = 1312.07

3 = 440.13

4 = 343.72

```
reg.predict([[0.34,0.68]])
```

```
array([483.02633098])
```

```
reg.predict([[0.33,0.19]])
```

```
array([147.60419658])
```

```
from sklearn import metrics as sm

# Model Performance
print("Regressor model performance:")
print("Mean absolute error(MAE) =",
round(sm.mean_absolute_error(y_test, y_pred), 2))
print("Mean squared error(MSE) =", round(sm.mean_squared_error(y_test,
y_pred), 2))
print("Median absolute error =",
round(sm.median_absolute_error(y_test, y_pred), 2))
print("Explain variance score =",
round(sm.explained_variance_score(y_test, y_pred), 2))
```

```
Regressor model performance:
Mean absolute error(MAE) = 64.79
Mean squared error(MSE) = 6893.9
```

```
Median absolute error = 63.21
Explain variance score = 0.94
```

Polynomial Regression Model Building

```
from sklearn.preprocessing import PolynomialFeatures
poly_reg = PolynomialFeatures(degree = 3)
X_poly = poly_reg.fit_transform(X_train)
lg1 = LinearRegression()
lg1.fit(X_poly,y_train)
```

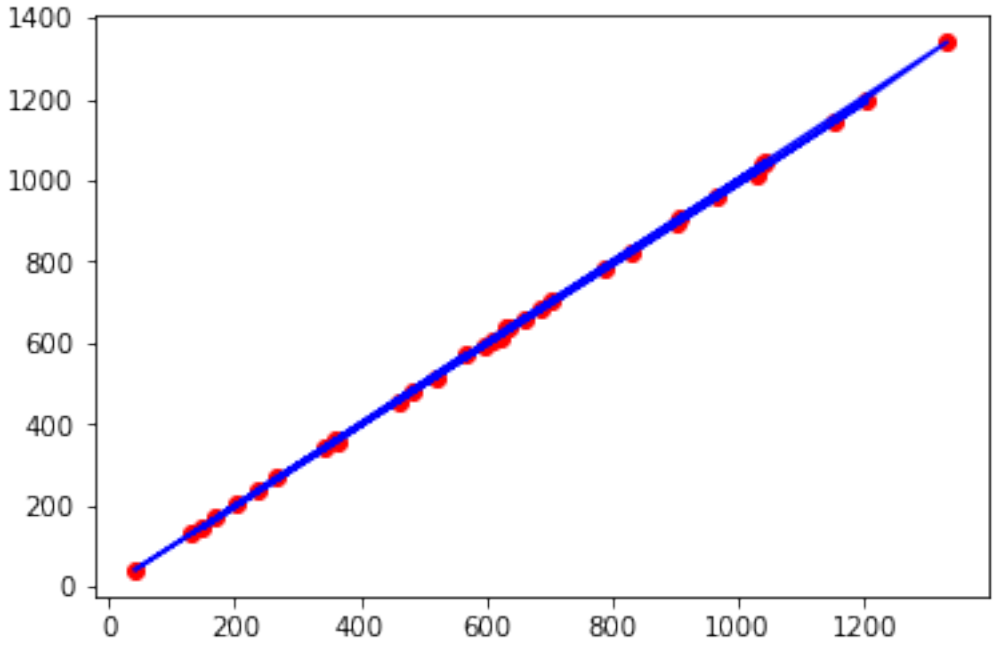
```
LinearRegression()
```

```
y_pred1 = lg1.predict(poly_reg.fit_transform(X_test))
y_pred1
```

```
array([ 359.75976199,  131.68218142,  610.25321634,  149.21839813,
        565.70476871,  237.32776414,  520.95984491,  484.01063981,
        620.99264658,  631.87647431,  704.04970819, 1027.89797017,
       1151.40826113, 1331.94059362,  461.42089638,  341.20348876,
       1042.75661496,  170.30867277,  904.41563338,  635.41490761,
        362.40482444,  204.12101516,  266.88411561,  831.11222225,
       1205.59511066,   41.00053444, 1039.87078205,  595.13955572,
        687.50938689,  965.50286138,  905.63644023,  787.83921136,
        659.7042353 ])
```

```
plt.scatter(y_pred1,y_test,color='red')
plt.plot(y_pred1,y_test,color='blue')
```

```
[<matplotlib.lines.Line2D at 0x21cef913ca0>]
```



Conclusion

1. I have used Multiple Linear regression model and Polynomial Regression model. As I have plotted scatter-plot for these two models , it is seen that Polynomial regression model gives best regression line.

2. Almost all the points are on the regression line,hence Polynomial regression model is best to decide "price per square foot" .

3. Hence, for these DataSet ,Polynomial Regression model is more accurate than Multiple Linear regression model

Problem Statement 2

Importing Dataset

```
data = {'Id':[1,2,3,4,5,6,7,8,9,10,11,12,13,14],
'Age':['<21','<21','21-35','>35','>35','>35','21-
35','<21','<21','>35','<21','21-35','21-35','>35'],
'Income':
['High','High','High','Medium','Low','Low','Low','Medium','Low','Mediu
m','Medium','Medium','High','Medium'],
'Gender':
['Male','Male','Male','Male','Female','Female','Female','Male','Female
','Female','Female','Male','Female','Male'],
'MaritalStatus':
['Single','Married','Single','Single','Single','Married','Married','Si
ngle','Married','Single','Married','Married','Single','Married'],
'Buys':
['No','No','Yes','Yes','Yes','No','Yes','No','Yes','Yes','Yes','Yes','
Yes','No']}

df2 =
pd.DataFrame(data,columns=['Id','Age','Income','Gender','MaritalStatus
','Buys'])

df2 = df2.drop('Id', axis=1)

df2.head()
```

	Age	Income	Gender	MaritalStatus	Buys
0	<21	High	Male	Single	No
1	<21	High	Male	Married	No
2	21-35	High	Male	Single	Yes
3	>35	Medium	Male	Single	Yes
4	>35	Low	Female	Single	Yes

```
df2.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 5 columns):
```

```
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Age            14 non-null     object 
 1   Income         14 non-null     object 
 2   Gender         14 non-null     object 
 3   MaritalStatus  14 non-null     object 
 4   Buys           14 non-null     object 
dtypes: object(5)
memory usage: 688.0+ bytes
```

```
df2.shape
```

```
(14, 5)
```

```
df2.describe()
```

```
        Age  Income Gender MaritalStatus Buys
count    14      14     14            14   14
unique    3       3      2             2    2
top     <21  Medium   Male        Single  Yes
freq      5       6      7             7    9
```

```
df2["Buys"].value_counts()
```

```
Yes    9
No     5
Name: Buys, dtype: int64
```

```
df2.isnull().sum()
```

```
Age              0
Income           0
Gender           0
MaritalStatus    0
Buys             0
dtype: int64
```

```
# Preprocessing

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df2 = df2.apply(le.fit_transform)
df2
```

```
    Age  Income  Gender  MaritalStatus  Buys
0     1       0       1              1     0
1     1       0       1              0     0
2     0       0       1              1     1
3     2       2       1              1     1
4     2       1       0              1     1
5     2       1       0              0     0
6     0       1       0              0     1
```

```
7     1       2       1               1     0
8     1       1       0               0     1
9     2       2       0               1     1
10    1       2       0               0     1
11    0       2       1               0     1
12    0       0       0               1     1
13    2       2       1               0     0
```

```
#Independent and Dependent variables

X = df2.iloc[:,:-1].values

y = df2.iloc[:,-1].values

#Train and Test Data

from sklearn.model_selection import train_test_split
X_train , X_test , y_train , y_test =
train_test_split(X,y,train_size=0.3,random_state=0)

X_train.shape , X_test.shape , y_train.shape , y_test.shape

((4, 4), (10, 4), (4,), (10,))
```

Descision Tree Model Building

```
#Model Building

from sklearn.tree import DecisionTreeClassifier
classifier = DecisionTreeClassifier(criterion='entropy' ,
random_state=0)
classifier.fit(X_train,y_train)

DecisionTreeClassifier(criterion='entropy', random_state=0)

y_pred = classifier.predict(X_test)
y_pred

array([0, 1, 0, 1, 1, 1, 1, 0, 1, 1])

from sklearn.metrics import confusion_matrix , accuracy_score ,
classification_report

#Confusion Matrix
cm = confusion_matrix(y_test , y_pred)
cm

array([[1, 2],
       [2, 5]], dtype=int64)

print(classification_report(y_test , y_pred))
```

```
              precision    recall  f1-score   support

           0       0.33      0.33      0.33         3
           1       0.71      0.71      0.71         7

    accuracy                           0.60        10
   macro avg       0.52      0.52      0.52        10
weighted avg       0.60      0.60      0.60        10
```

```
classifier.predict([[0,0,1,1]])
```

```
array([1])
```

```
classifier.predict([[1,1,0,0]])
```

```
array([0])
```

Conclusion

1. Root Node for the decision tree is 'Age'
2. Predicted class for input [Age>21 , Income = Low , Gender = Female , Marital Status = Married] i. e. [1,1,0,0] is No[0]
3. The accuracy for this model is 60%.