Importing the Libraries

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

Import the dataset

```
In [2]: dataset=pd.read_csv("C:/Users/navna/Downloads/Data_lab_exam.csv")
```

In [3]: dataset

	features	observ_features	price_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

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

In [4]: dataset.shape

(100, 3)

```
In [5]:
         dataset.info()
          <class 'pandas.core.frame.DataFrame'>
          RangeIndex: 100 entries, 0 to 99
          Data columns (total 3 columns):
               Column
                                   Non-Null Count Dtype
                                    -----
              features
                                   100 non-null
                                                  float64
           1 observ_features
                                   100 non-null
                                                  float64
           price_per_square_foot 100 non-null
                                                  float64
          dtypes: float64(3)
          memory usage: 2.5 KB
In [6]:
         dataset.isna()
```

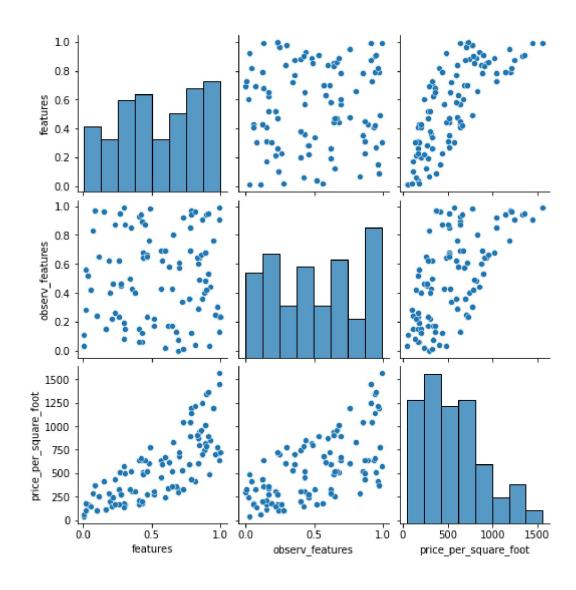
	features	observ_features	price_per_square_foot
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
95	False	False	False
96	False	False	False
97	False	False	False
98	False	False	False
99	False	False	False

100 rows × 3 columns

	features	observ_features	price_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

In [9]: sns.pairplot(dataset)

<seaborn.axisgrid.PairGrid at 0x2516e6b9370>



Conclusion:-

As the number of features and its respective observed_features are incresed then the price is also increases respectively.

```
In [10]: # Independent Variable
    X=dataset.iloc[:,:-1].values

# Dependent Variable
    y=dataset.iloc[:,-1].values
```

```
In [11]: #Check the values of Independent Variable print(X)
```

[[0.44 0.68] [0.99 0.23] [0.84 0.29] [0.28 0.45] [0.07 0.83] [0.66 0.8] [0.73 0.92] [0.57 0.43] [0.43 0.89] [0.27 0.95] [0.43 0.06] [0.87 0.91] [0.78 0.69] [0.9 0.94] [0.41 0.06] [0.52 0.17] [0.47 0.66] [0.65 0.43] [0.85 0.64] [0.93 0.44] [0.41 0.93] [0.36 0.43] [0.78 0.85] [0.69 0.07] [0.04 0.52] [0.17 0.15] [0.68 0.13] [0.84 0.6] [0.38 0.4] [0.12 0.65] [0.62 0.17] [0.79 0.97] [0.82 0.04] [0.91 0.53] [0.35 0.85]

[0.57 0.69]

- [0.52 0.22]
- [0.31 0.15]
- [0.6 0.02]
- [0.99 0.91]
- [0.48 0.76]
- [0.3 0.19]
- [0.58 0.62]
- [0.65 0.17]
- [0.6 0.69]
- [0.95 0.76]
- [0.47 0.23]
- [0.15 0.96]
- [0.01 0.03]
- [0.26 0.23]
- [0.01 0.11]
- [0.45 0.87]
- [0.09 0.97]
- [0.96 0.25]
- [0.63 0.58]
- [0.06 0.42]
- [0.1 0.24]
- [0.26 0.62]
- [0.41 0.15]
- [0.91 0.95]
- [0.83 0.64]
- [0.44 0.64]
- [0.2 0.4]
- [0.43 0.12]
- [0.21 0.22]
- [0.88 0.4]
- [0.31 0.87]
- [0.99 0.99]
- [0.23 0.26]
- [0.79 0.12]
- [0.02 0.28]
- [0.89 0.48]
- [0.02 0.56]
- [0.92 0.03]
- [0.72 0.34]
- [0.3 0.99]
- [0.86 0.66]

- [0.47 0.65]
- [0.79 0.94]
- [0.82 0.96]
- [0.9 0.42]
- [0.19 0.62]
- [0.7 0.57]
- [0.7 0.61]
- [0.69 0.]
- [0.98 0.3]
- [0.3 0.08]
- [0.85 0.49]
- [0.73 0.01]
- [1. 0.23]
- [0.42 0.94]
- [0.49 0.98]
- [0.89 0.68]
- [0.22 0.46]
- [0.34 0.5]
- [0.99 0.13]
- [0.28 0.46]
- [0.87 0.36]
- [0.23 0.87]
- [0.77 0.36]]

localhost:8888/notebooks/PML/ML Lab Assignment.ipynb

```
#Check the values of dependent Variable print(y)
```

```
[ 511.14 717.1
                607.91 270.4
                              289.88 830.85 1038.09
                                                    455.19 640.17
 511.06 177.03 1242.52 891.37 1339.72 169.88 276.05 517.43 522.25
 932.21 851.25 640.11 308.68 1046.05 332.4
                                             171.85 109.55 361.97
        303.7
                256.38 341.2 1194.63 408.6
                                             895.54 518.25 638.75
 301.9
        163.38 240.77 1449.05 609.
                                      174.59 593.45 355.96 671.46
 1193.7
         278.88 411.4
                        42.08 166.19
                                       58.62 642.45
                                                    368.14 702.78
 615.74 143.79 109.
                       328.28 205.16 1360.49 905.83 487.33 202.76
 202.01 148.87 745.3
                       503.04 1563.82 165.21 438.4
                                                      98.47 819.63
 174.44 483.13 534.24 572.31 957.61
                                      518.29 1143.49 1211.31 784.74
         684.38 719.46 292.23 775.68 130.77 801.6
 661.12 771.11 1016.14 237.69 325.89 636.22 272.12 696.65 434.53
 593.86]
```

Splitting the dataset(Training and Testing)

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25, random_state=28)
```

```
In [14]: # Check the values of X_train data

X_train
```

```
array([[0.3 , 0.99],
       [0.47, 0.65],
       [0.42, 0.94],
       [0.27, 0.95],
       [0.31, 0.87],
       [0.19, 0.62],
       [0.41, 0.93],
       [0.89, 0.68],
       [0.01, 0.03],
       [0.86, 0.66],
       [0.06, 0.42],
       [0.26, 0.23],
       [0.87, 0.91],
       [0.93, 0.44],
       [0.34, 0.5],
       [0.63, 0.58],
       [0.88, 0.4],
       [0.96, 0.25],
       [0.3, 0.19],
       [0.98, 0.3],
       [0.23, 0.87],
       [0.79, 0.97],
       [0.7, 0.57],
       [0.84, 0.6],
       [0.6 , 0.02],
       [0.47, 0.66],
       [0.1, 0.24],
       [0.87, 0.36],
       [0.89, 0.48],
       [0.15, 0.96],
       [0.17, 0.15],
       [0.84, 0.29],
       [0.91, 0.95],
       [0.9 , 0.42],
       [0.44, 0.64],
       [0.65, 0.43],
```

- [0.43, 0.06], [0.43, 0.12], [0.7, 0.61], [0.41, 0.15], [0.26, 0.62], [0.73, 0.01], [0.28, 0.46], [0.6, 0.69], [1. , 0.23], [0.69, 0.], [0.07, 0.83], [0.68, 0.13], [0.52, 0.17], [0.38, 0.4], [0.23, 0.26], [0.02, 0.28], [0.31, 0.15], [0.49, 0.98], [0.35, 0.85], [0.83, 0.64], [0.95, 0.76], [0.79, 0.94], [0.77, 0.36], [0.57, 0.43], [0.65, 0.17], [0.04, 0.52], [0.43, 0.89], [0.79, 0.12],[0.22, 0.46], [0.69, 0.07], [0.45, 0.87],[0.21, 0.22], [0.78, 0.69], [0.85, 0.49], [0.28, 0.45], [0.82, 0.04], [0.78, 0.85], [0.66, 0.8], [0.99, 0.23]])
- localhost:8888/notebooks/PML/ML Lab Assignment.ipynb

```
# Check the values of X train data
          y train
           array([ 572.31, 518.29, 661.12, 511.06, 503.04, 283.7, 640.11,
                  1016.14,
                           42.08, 957.61, 143.79, 166.19, 1242.52, 851.25,
                   325.89, 615.74, 745.3, 702.78, 174.59, 775.68, 434.53,
                  1194.63, 684.38, 872.21, 240.77, 517.43, 109. , 696.65,
                   819.63, 411.4, 109.55, 607.91, 1360.49, 784.74, 487.33,
                   522.25, 177.03, 202.01, 719.46, 205.16, 328.28, 323.55,
                   272.12, 671.46, 726.9, 292.23, 289.88, 361.97, 276.05,
                   303.7, 165.21, 98.47, 163.38, 771.11, 518.25, 905.83,
                  1193.7, 1143.49, 593.86, 455.19, 355.96, 171.85, 640.17,
                   438.4 , 237.69, 332.4 , 642.45, 148.87, 891.37, 801.6 ,
                   270.4 , 408.6 , 1046.05 , 830.85 , 717.1 ])
In [16]: y_train
           array([ 572.31, 518.29, 661.12, 511.06, 503.04, 283.7, 640.11,
                  1016.14.
                          42.08, 957.61, 143.79, 166.19, 1242.52, 851.25
                   325.89, 615.74, 745.3, 702.78, 174.59, 775.68, 434.53,
                  1194.63, 684.38, 872.21, 240.77, 517.43, 109. , 696.65
                   819.63, 411.4, 109.55, 607.91, 1360.49, 784.74, 487.33,
```

303.7 , 165.21,

522.25, 177.03, 202.01, 719.46, 205.16, 328.28, 323.55, 272.12, 671.46, 726.9, 292.23, 289.88, 361.97, 276.05,

1193.7 , 1143.49, 593.86, 455.19, 355.96, 171.85, 640.17, 438.4 , 237.69, 332.4 , 642.45, 148.87, 891.37, 801.6 ,

270.4 , 408.6 , 1046.05 , 830.85 , 717.1])

98.47, 163.38, 771.11, 518.25, 905.83,

```
In [17]: y_test

array([1563.82, 169.88, 511.14, 130.77, 1339.72, 932.21, 341.2,
301.9, 368.14, 636.22, 1449.05, 483.13, 895.54, 609.,
534.24, 638.75, 174.44, 256.38, 1038.09, 308.68, 593.45,
1211.31, 58.62, 278.88, 202.76])
```

Splitting the dataset

```
In [18]: from sklearn.model_selection import train_test_split
    X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.25, random_state=28)
In [19]: from sklearn.naive_bayes import GaussianNB
    from sklearn import metrics
    from sklearn.model_selection import train_test_split
```

Problem Statement 2

```
In [21]: data=pd.read_csv("C:/Users/navna/Downloads/Data_cust_problem.csv")
```

In [22]: data

	cust_id	age	income	gender	marital_status	buys
0	1	18	High	male	single	no
1	2	19	High	male	marrid	no
2	3	28	High	male	single	yes
3	4	38	Medium	male	single	yes
4	5	36	Low	female	single	yes
5	6	40	Low	female	marrid	no
6	7	28	Low	female	marrid	yes
7	8	18	Medium	male	single	no
8	9	19	Low	female	marrid	yes
9	10	37	Medium	female	single	yes
10	11	18	Medium	female	marrid	yes
11	12	28	Medium	male	marrid	yes
12	13	28	High	female	single	yes
13	14	39	Medium	male	marrid	no

(14, 6)

```
In [24]: data.info()
```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 6 columns):

#	Column	Non-Null Count	Dtype
0	cust_id	14 non-null	int64
1	age	14 non-null	int64
2	income	14 non-null	object
3	gender	14 non-null	object
4	marital_status	14 non-null	object
5	buys	14 non-null	object

dtypes: int64(2), object(4)
memory usage: 800.0+ bytes

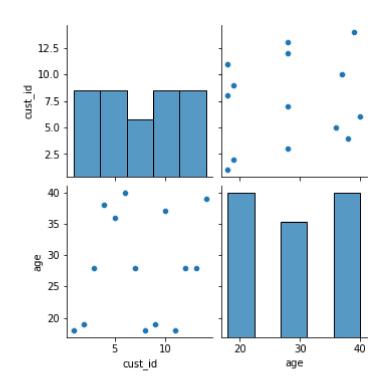
In [25]: data.isna()

	cust_id	age	income	gender	marital_status	buys
0	False	False	False	False	False	False
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
5	False	False	False	False	False	False
6	False	False	False	False	False	False
7	False	False	False	False	False	False
8	False	False	False	False	False	False
9	False	False	False	False	False	False
10	False	False	False	False	False	False
11	False	False	False	False	False	False
12	False	False	False	False	False	False
13	False	False	False	False	False	False

In [26]: data.isna().sum()

cust_id 0
age 0
income 0
gender 0
marital_status 0
buys 0
dtype: int64

<seaborn.axisgrid.PairGrid at 0x2516967abe0>



```
In [29]: data.corr(method = 'pearson')
```

	cust_id	age
cust_id	1.000000	0.174403
age	0.174403	1.000000

In [30]: data.income.count()

14

In [31]: data

	cust_id	age	income	gender	marital_status	buys
0	1	18	High	male	single	no
1	2	19	High	male	marrid	no
2	3	28	High	male	single	yes
3	4	38	Medium	male	single	yes
4	5	36	Low	female	single	yes
5	6	40	Low	female	marrid	no
6	7	28	Low	female	marrid	yes
7	8	18	Medium	male	single	no
8	9	19	Low	female	marrid	yes
9	10	37	Medium	female	single	yes
10	11	18	Medium	female	marrid	yes
11	12	28	Medium	male	marrid	yes
12	13	28	High	female	single	yes
13	14	39	Medium	male	marrid	no

```
In [32]:
          data.columns
           Index(['cust_id', 'age', 'income', 'gender ', 'marital_status', 'buys'], dtype='object')
In [33]:
          data.isna().any()
           cust_id
                            False
                            False
            age
            income
                            False
           gender
                            False
           marital_status
                            False
           buys
                            False
           dtype: bool
          data['income'].unique()
           array(['High', 'Medium', 'Low'], dtype=object)
In [37]:
          data['marital_status'].unique()
           array(['single', 'marrid'], dtype=object)
          data['buys'].unique()
           array(['no ', 'yes'], dtype=object)
```

```
data['income'].value_counts()
           Medium
                    6
           High
                    4
           Low
           Name: income, dtype: int64
In [40]:
          data['marital_status'].value_counts()
           single
           marrid
           Name: marital_status, dtype: int64
          data['buys'].value_counts()
           yes
           no
           Name: buys, dtype: int64
```

```
In [43]: data['gender'].value_counts()
```

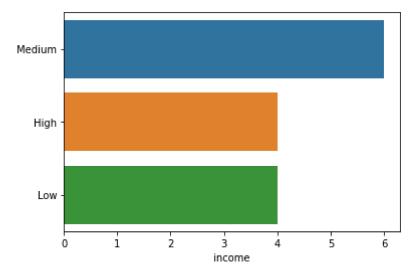
```
KeyError
                                          Traceback (most recent call last)
File C:\Anaconda3\lib\site-packages\pandas\core\indexes\base.py:3621, in Index.get loc(self, key, method, tolerance)
   3620 try:
-> 3621
            return self. engine.get loc(casted key)
   3622 except KeyError as err:
File C:\Anaconda3\lib\site-packages\pandas\_lib\sindex.pyx:136, in pandas. libs.index.IndexEngine.get loc()
File C:\Anaconda3\lib\site-packages\pandas\_lib\sindex.pyx:163, in pandas. libs.index.IndexEngine.get loc()
File pandas\_libs\hashtable_class_helper.pxi:5198, in pandas. libs.hashtable.PyObjectHashTable.get item()
File pandas\_libs\hashtable_class_helper.pxi:5206, in pandas. libs.hashtable.PyObjectHashTable.get item()
KeyError: 'gender'
The above exception was the direct cause of the following exception:
KevError
                                          Traceback (most recent call last)
Input In [43], in <cell line: 1>()
---> 1 data['gender'].value_counts()
File C:\Anaconda3\lib\site-packages\pandas\core\frame.py:3505, in DataFrame. getitem (self, key)
   3503 if self.columns.nlevels > 1:
   3504
            return self. getitem multilevel(key)
-> 3505 indexer = self.columns.get_loc(key)
   3506 if is_integer(indexer):
   3507
           indexer = [indexer]
File C:\Anaconda3\lib\site-packages\pandas\core\indexes\base.py:3623, in Index.get_loc(self, key, method, tolerance)
   3621
            return self._engine.get_loc(casted_key)
   3622 except KeyError as err:
            raise KeyError(key) from err
-> 3623
   3624 except TypeError:
   3625
            # If we have a listlike key, check indexing error will raise
   3626
            # InvalidIndexError. Otherwise we fall through and re-raise
   3627
            # the TypeError.
```

```
3628 self._check_indexing_error(key)
```

KeyError: 'gender'

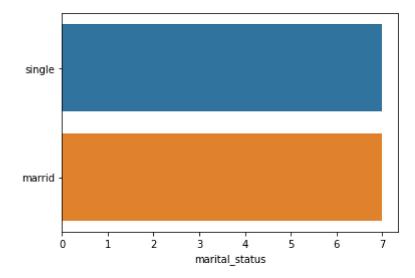
```
income_class=data.income.value_counts()
sns.barplot(y=income_class.index, x=income_class)
```

<AxesSubplot:xlabel='income'>



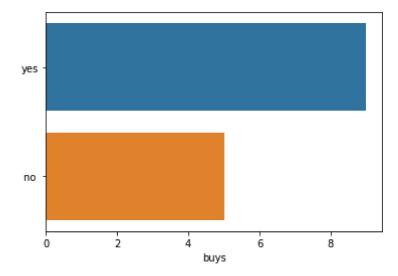
```
marital_status=data.marital_status.value_counts()
sns.barplot(y=marital_status.index, x=marital_status)
```

<AxesSubplot:xlabel='marital_status'>



```
buys=data.buys.value_counts()
sns.barplot(y=buys.index, x=buys)
```

<AxesSubplot:xlabel='buys'>



```
### What is the probability of buy
         probability_of_buy = data['buys']
         probability_of_buy.groupby(probability_of_buy).size()
          buys
          yes
          Name: buys, dtype: int64
         total_cust=data.buys.count()
         total_cust
          14
In [64]:
         total_buy=9
         total_buy
          9
         percent_buy=(total_buy/total_cust)*100
         percent_buy
          64.28571428571429
 In [ ]:
```