

200340325053

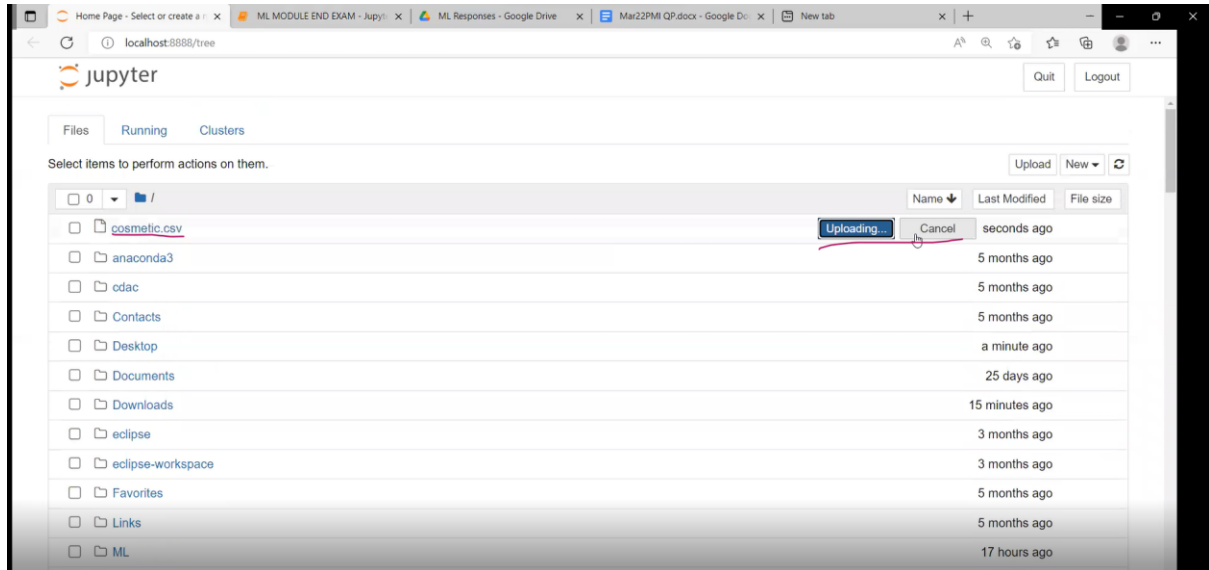
## Module End Exam -Machine Learning seat no:220340325053

### Q2

Importing required libraries

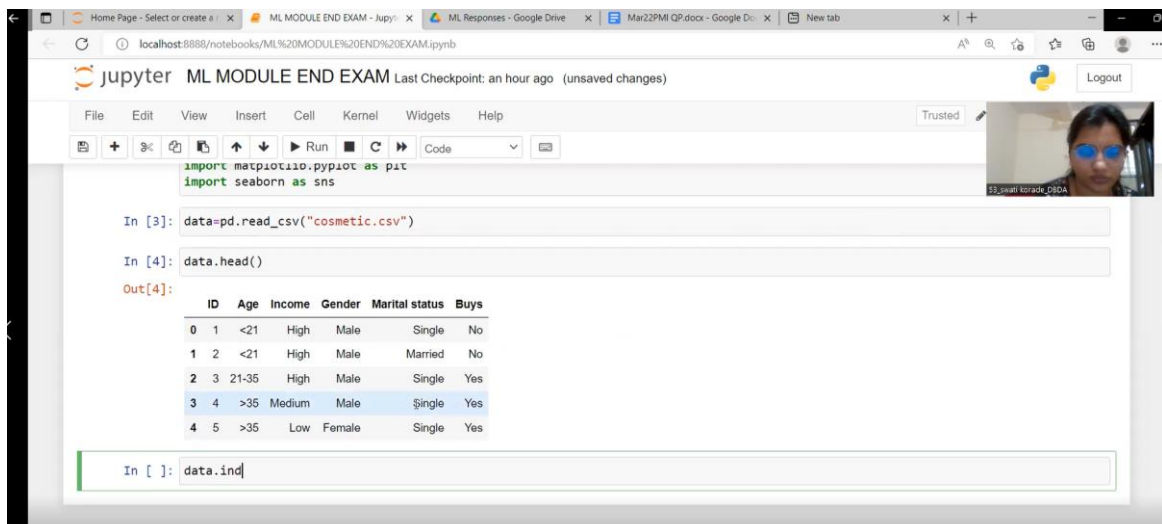
```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

### Upload csv file in jupyter



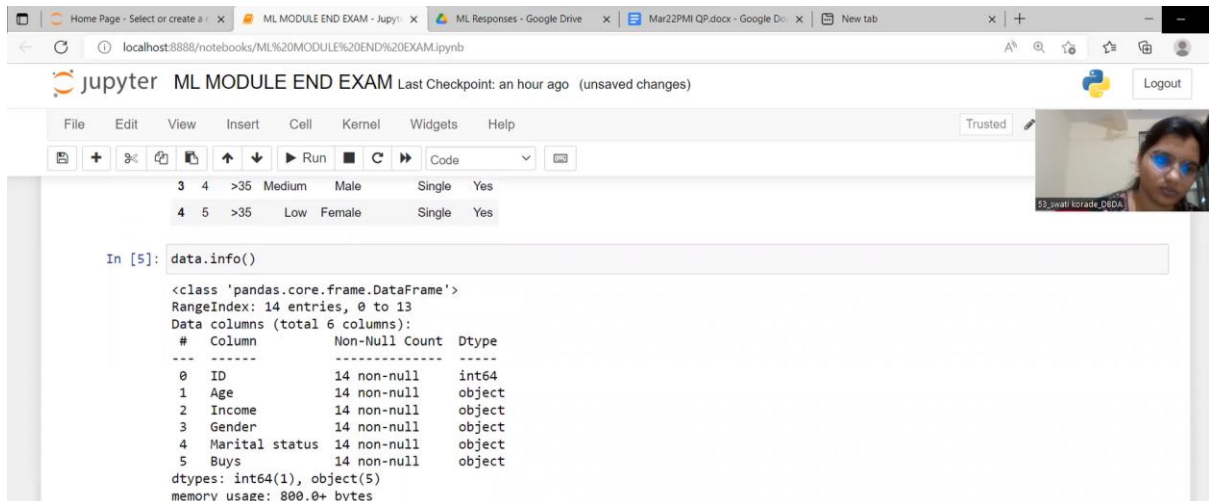
### EDA

### #Loading and show some records in data



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#show info about data

A screenshot of a Jupyter Notebook interface. The browser tabs at the top include 'Home Page - Select or create a...', 'ML MODULE END EXAM - Jupyter', 'ML Responses - Google Drive', 'Mar22PM QP.docx - Google Do...', and 'New tab'. The notebook title is 'ML MODULE END EXAM' with a note 'Last Checkpoint: an hour ago (unsaved changes)'. The menu bar shows 'File', 'Edit', 'View', 'Insert', 'Cell', 'Kernel', 'Widgets', and 'Help'. The toolbar has icons for file operations and a 'Run' button. A video feed in the top right corner shows a person. The code cell contains 'data.info()' and the output shows the DataFrame structure with 14 entries and 6 columns: ID, Age, Income, Gender, Marital status, and Buys. The output also shows the data types and memory usage.

```
In [5]: data.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14 entries, 0 to 13
Data columns (total 6 columns):
#   Column          Non-Null Count  Dtype  
---  -
0    ID              14 non-null    int64  
1    Age             14 non-null    object  
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(1), object(5)
memory usage: 880.0+ bytes
```

#drop unnecceracy column and check missing values

```
data=data.drop('ID',axis=1)      #id column is not required so i will drop it
data.head()
```

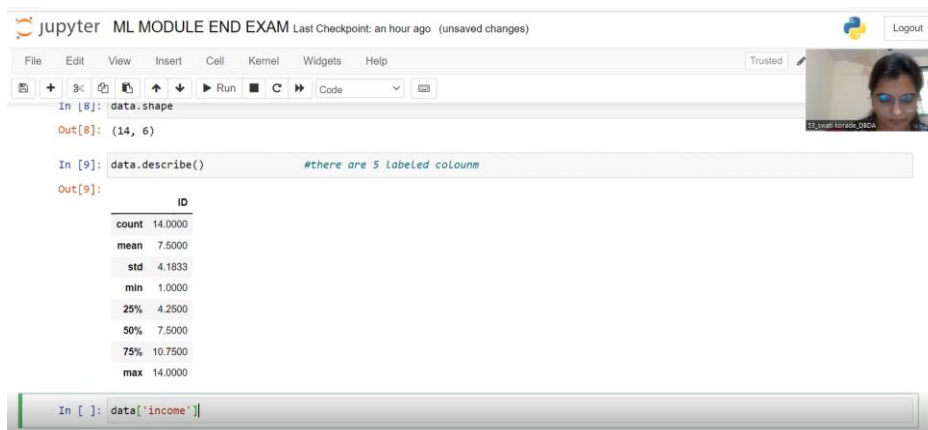
	Age	Income	Gender	Marital status	Buys
0	<21	High	Male	Single	No
1	<21	High	Male	Married	No
2	21-35	High	Male	Single	Yes
3	>35	Medium	Male	Single	Yes
4	>35	Low	Female	Single	Yes

```
data.isnull().sum()      # checking null values in the data set or not

Age          0
Income       0
Gender       0
Marital status  0
Buys        0
dtype: int64
```

from above we can say that there is no null values in the data

# check statistics about data

A screenshot of a Jupyter Notebook interface. The browser tabs at the top include 'Home Page - Select or create a...', 'ML MODULE END EXAM - Jupyter', 'ML Responses - Google Drive', 'Mar22PM QP.docx - Google Do...', and 'New tab'. The notebook title is 'ML MODULE END EXAM' with a note 'Last Checkpoint: an hour ago (unsaved changes)'. The menu bar shows 'File', 'Edit', 'View', 'Insert', 'Cell', 'Kernel', 'Widgets', and 'Help'. The toolbar has icons for file operations and a 'Run' button. A video feed in the top right corner shows a person. The code cell contains 'data.shape' and 'data.describe()'. The output for 'data.shape' is '(14, 6)'. The output for 'data.describe()' shows statistics for the 'ID' column, including count, mean, std, min, 25%, 50%, 75%, and max.

```
In [8]: data.shape
Out[8]: (14, 6)

In [9]: data.describe()      #there are 5 labeled coloumn
Out[9]:
```

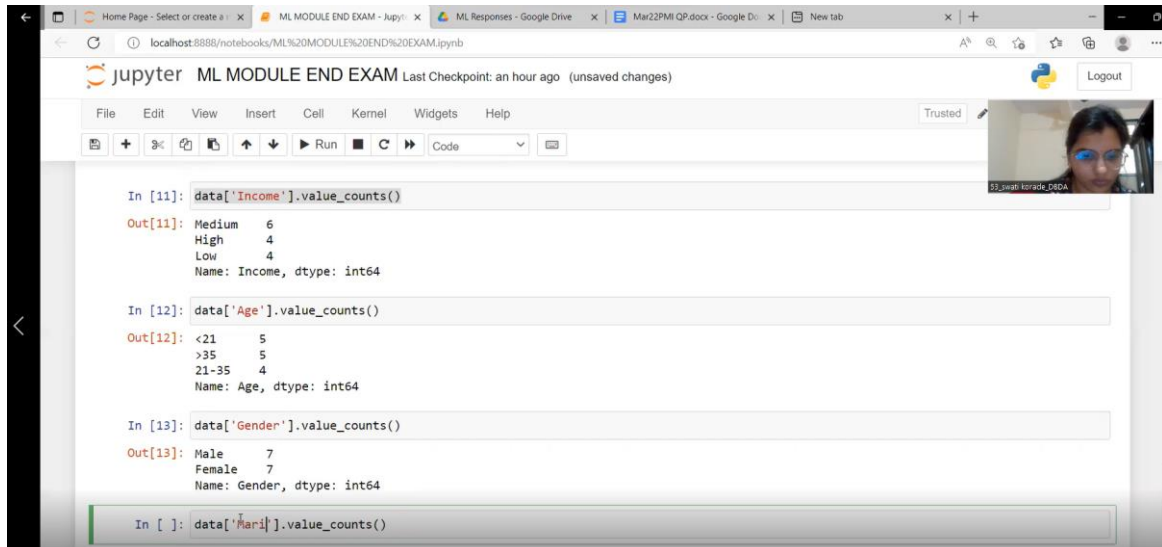
	ID
count	14.0000
mean	7.5000
std	4.1833
min	1.0000
25%	4.2500
50%	7.5000
75%	10.7500
max	14.0000

```
In [ ]: data['income']
```

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But here all data in terms of categorical form so need to label it.

# count the number of observation in each group of variables



The screenshot shows a Jupyter Notebook interface with the title 'ML MODULE END EXAM'. The notebook contains three code cells. The first cell calculates the value counts for the 'Income' variable, showing counts for Medium (6), High (4), and Low (4). The second cell calculates the value counts for the 'Age' variable, showing counts for <21 (5), >35 (5), and 21-35 (4). The third cell calculates the value counts for the 'Gender' variable, showing counts for Male (7) and Female (7). A fourth cell is partially visible, showing the start of a value count calculation for the 'Married' variable.

```
In [11]: data['Income'].value_counts()
Out[11]: Medium    6
         High      4
         Low       4
         Name: Income, dtype: int64

In [12]: data['Age'].value_counts()
Out[12]: <21      5
         >35     5
         21-35   4
         Name: Age, dtype: int64

In [13]: data['Gender'].value_counts()
Out[13]: Male      7
         Female    7
         Name: Gender, dtype: int64

In [ ]: data['Married'].value_counts()
```

Target Variable

```
: data['Buys'].value_counts() # buys is target binary variable

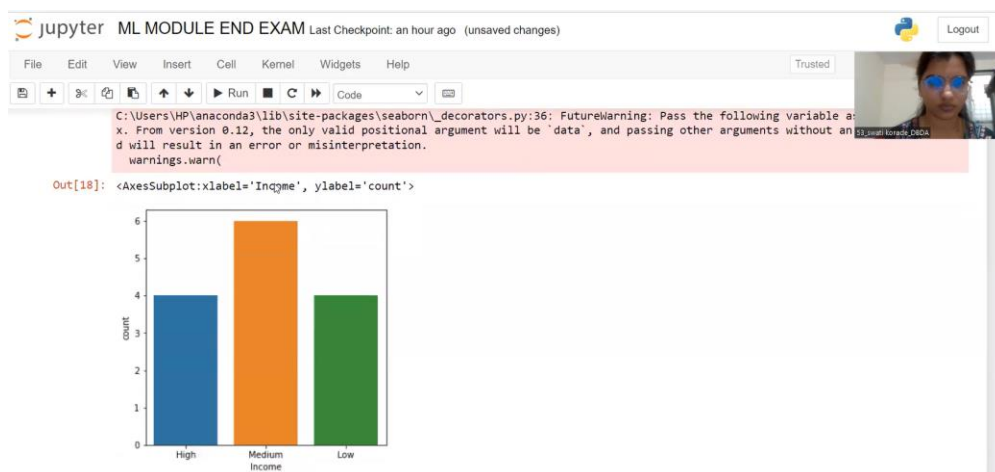
: Yes    9
  No     5
  Name: Buys, dtype: int64
```

Countplot for each categorical variable

```
: plt.figure(figsize=(5,5))
  sns.countplot(data['Income'])

C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg:
x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword
d will result in an error or misinterpretation.
  warnings.warn(

: <AxesSubplot:xlabel='Income', ylabel='count'>
```



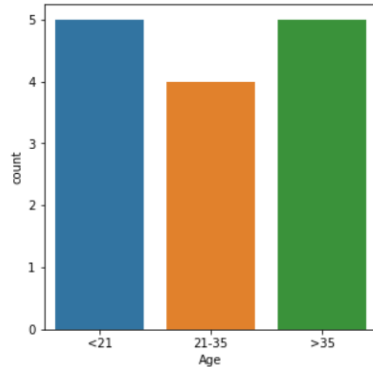
Conclusion : most of the people having medium income.

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```
plt.figure(figsize=(5,5))
sns.countplot(data['Age'])
```

C:\Users\HP\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.  
warnings.warn(

<AxesSubplot:xlabel='Age', ylabel='count'>

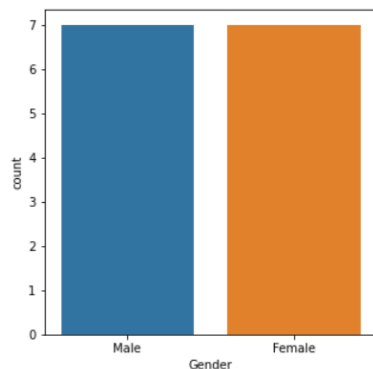


**Conclusion: There are most of the people are having age less than 21 and greater than 35.**

```
: plt.figure(figsize=(5,5))
sns.countplot(data['Gender'])
```

C:\Users\HP\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.  
warnings.warn(

: <AxesSubplot:xlabel='Gender', ylabel='count'>



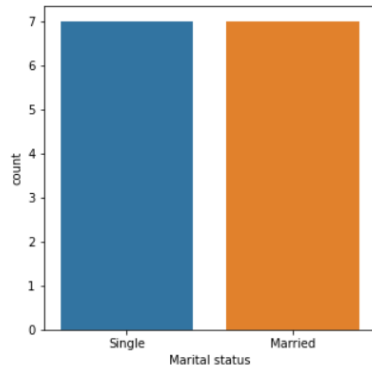
**Conclusion: In the data set equal no of male and female.**

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```
plt.figure(figsize=(5,5))
sns.countplot(data['Marital status'])
```

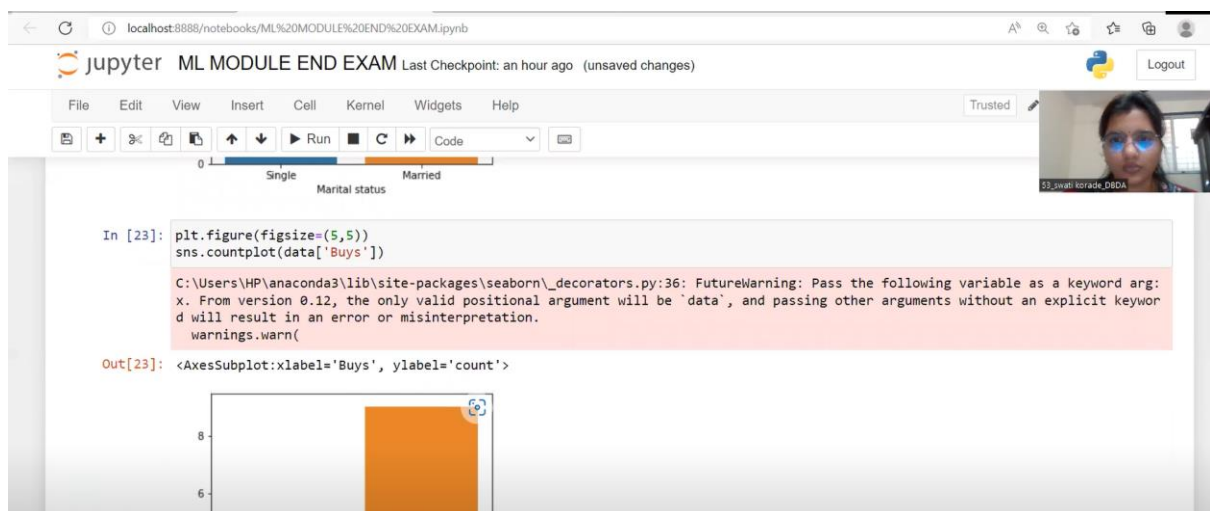
C:\Users\HP\anaconda3\lib\site-packages\seaborn\\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.  
warnings.warn(

<AxesSubplot:xlabel='Marital status', ylabel='count'>



Conclusion: same no of married and unmarried peoples.

## # checking Imbalance data



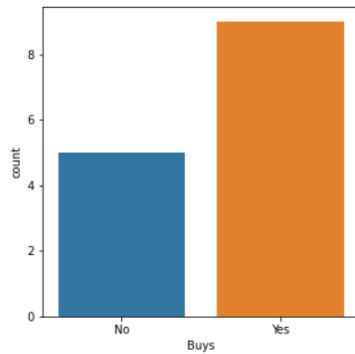
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## checking of Balance data

```
In [8]: plt.figure(figsize=(5,5))
sns.countplot(data['Buys'])

C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg:
x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword
d will result in an error or misinterpretation.
  warnings.warn(

Out[8]: <AxesSubplot:xlabel='Buys', ylabel='count'>
```



Here we can say that count of buys cosmetics is greater than not buying.

here buys is our target variable and praportion of both is not balance it may be possible that data is imbalance in some extend 64 % data in yes category and remaining in no category.

## PREPROCESSING:

### Label the data

Preprocessing

```
In [9]: # convert categorical data into numerical data

from sklearn.preprocessing import LabelEncoder
label=LabelEncoder()
data=data.apply(label.fit_transform)
```

```
In [219]: print(data)
```

	Age	Income	Gender	Marital status	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

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Home Page - Select or create a notebook | ML MODULE END EXAM - Jupyter | +

localhost:8888/notebooks/ML%20MODULE%20END%20EXAM.ipynb

Jupyter ML MODULE END EXAM Last Checkpoint: a few seconds ago (autosaved)

File Edit View Insert Cell Kernel Widgets Help

Not Trusted Python 3 (ipykernel)

11	0	2	1	0	1
12	0	0	0	1	1
13	2	2	1	0	0

### Independent and dependent variables

```
In [10]: x=data.drop('Buys',axis=1) # independent
         y=data['Buys']           # dependent
```

### split data into train and test data

```
In [11]: 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=12)
         print(x_train.shape)
         print(x_test.shape)
         print(y_train.shape)
         print(y_test.shape)

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

Home Page - Select or create a notebook | ML MODULE END EXAM - Jupyter | +

localhost:8888/notebooks/ML%20MODULE%20END%20EXAM.ipynb

Jupyter ML MODULE END EXAM Last Checkpoint: a minute ago (unsaved changes)

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Not Trusted Python 3 (ipykernel)

### Build Model

```
In [12]: #build decision tree model

from sklearn.tree import DecisionTreeClassifier
classifier=DecisionTreeClassifier(criterion='entropy',random_state=12)
classifier.fit(x,y)

Out[12]: DecisionTreeClassifier(criterion='entropy', random_state=12)
```

### Prediction from test data

```
In [13]: y_pred=classifier.predict(x_test)

In [14]: y_pred

Out[14]: array([0, 1, 1, 0])
```

### Prediction for given values of test data

```
In [26]: x_test=np.array([1,1,0,0])
         y_pred=classifier.predict([[1,1,0,0]])

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

In [27]: print(x_test,y_pred)

[1 1 0 0] [1] — 425
```

for given data [Age < 21, Income = Low, Gender = Female, Marital Status = Married] prection is buying cosmetic

localhost:8888/notebooks/ML%20MODULE%20END%20EXAM.ipynb#Q1

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Run Code

### Model Evaluation

```
In [230]: from sklearn.metrics import confusion_matrix, accuracy_score
con_m=confusion_matrix(y_test,y_pred)
con_m
```

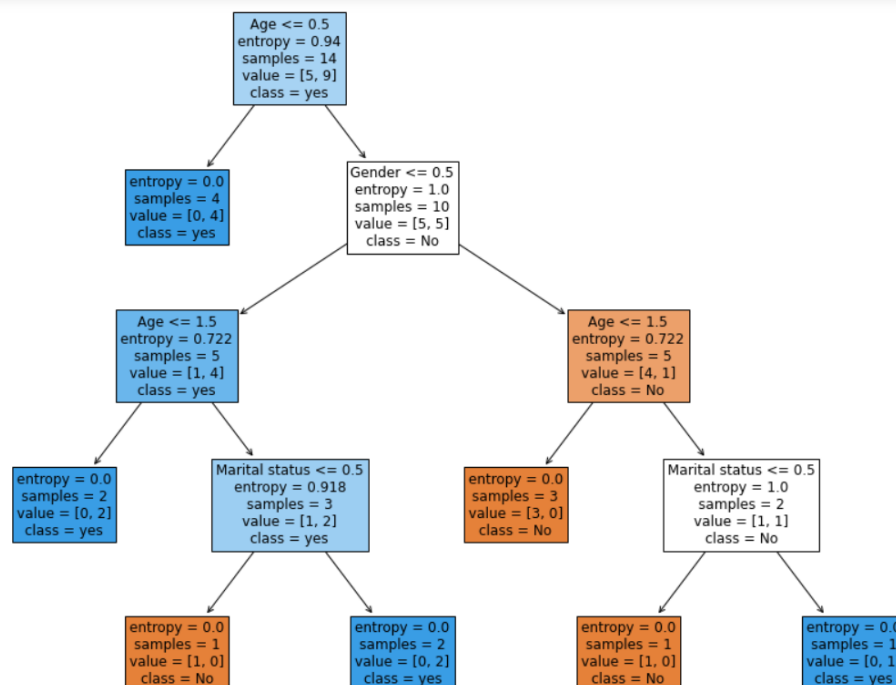
```
Out[230]: array([[2, 0],
               [0, 2]], dtype=int64)
```

```
In [231]: accuracy_score(y_test,y_pred)
```

```
Out[231]: 1.0
```

```
In [242]: from sklearn.tree import plot_tree

import matplotlib.pyplot as plt
fig = plt.figure(figsize=(16,12))
a = plot_tree(classifier, feature_names=x.columns, fontsize=12, filled=True,
              class_names=['No', 'yes'])
```



## Overall conclusion:

from the conclusion matrix and accuracy score we can say that there are all observations are correctly predicted. But there might be possibility of overfitting due to some imbalance data



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Q.1

The image displays two screenshots of a Jupyter Notebook interface, likely from a web browser. The top screenshot shows the notebook titled "ML MODULE END EXAM" with a "Q1" section. The "Import libraries" section contains the following code:

```
In [174]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

The "Import dataset" section is also visible. The bottom screenshot shows the same notebook with the code executed to load a CSV file:

```
In [175]: data=pd.read_csv("data.csv")
data.head()
```

The output of the code is displayed as follows:

```
Out[175]:
```

	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

The bottom screenshot also shows the output of the following code:

```
In [152]: data.shape
```

```
Out[152]: (100, 3)
```

And the output of the following code:

```
In [153]: data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 3 columns):
#   Column              Non-Null Count  Dtype
#   ...
```

In [177]: `data.info()` *#to check info about data*

```
<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
```

In [178]: `data.isnull().sum()` *#to check missing values in data set*

```
Out[178]: F          0
          N          0
          Prprice per square foot  0
          dtype: int64
```

In [179]: `data.describe()` *# statistics about data*

```
Out[179]:
```

	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

**Jupyter ML MODULE END EXAM** Last Checkpoint: 30 minutes ago (unsaved changes) Logout

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Run Code

In [181]: *# splitting data into independent and dependent values*

```
x=data.iloc[:,0:2].values
y=data.iloc[:, -1].values
```

### Split data training and testing

In [182]: `from sklearn.model_selection import train_test_split`  
`x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.2,random_state=12)`

In [172]: `print(x_train.shape)`  
`print(x_test.shape)`  
`print(y_train.shape)`  
`print(y_test.shape)`

```
(80, 2)
(20, 2)
(80,)
(20,)
```

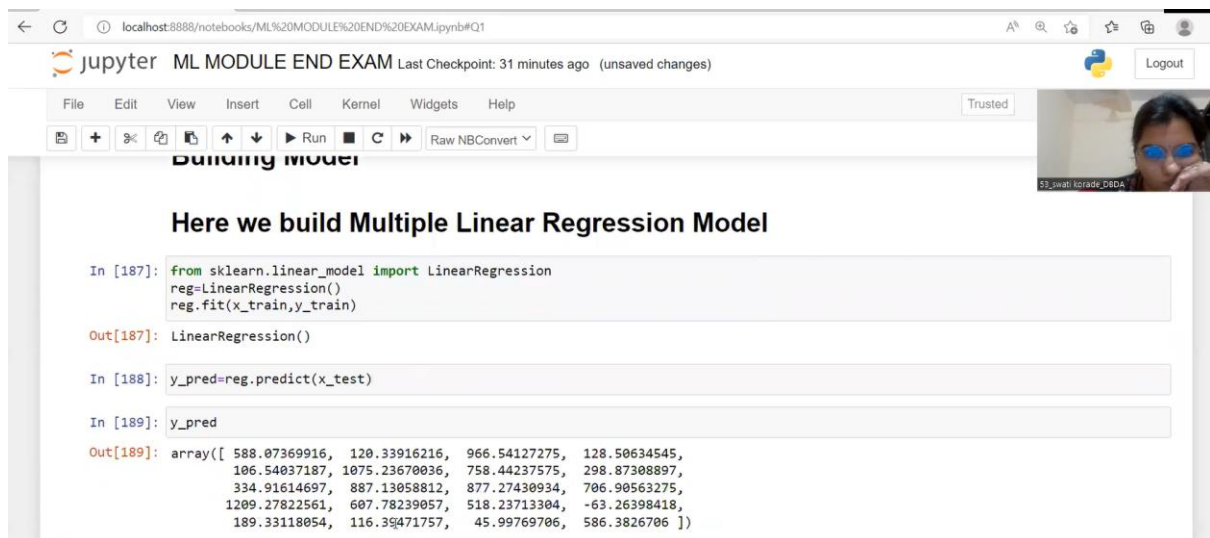
**Building Model**

### Here we build Multiple Linear Regression Model

In [184]: `from sklearn.linear_model import LinearRegression`  
`reg=LinearRegression()`  
`reg.fit(x_train,y_train)`

Out[184]: `LinearRegression()`

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The screenshot shows a Jupyter Notebook titled "ML MODULE END EXAM" with a "Last Checkpoint: 31 minutes ago (unsaved changes)". The notebook is running on a local host. The code in the notebook is as follows:

```
In [187]: from sklearn.linear_model import LinearRegression
reg=LinearRegression()
reg.fit(x_train,y_train)

Out[187]: LinearRegression()

In [188]: y_pred=reg.predict(x_test)

In [189]: y_pred

Out[189]: array([ 588.07369916, 120.33916216, 966.54127275, 128.50634545,
106.54037187, 1075.23670036, 758.44237575, 298.87308897,
334.91614697, 887.13058812, 877.27430934, 706.90563275,
1209.27822561, 607.78239057, 518.23713304, -63.26398418,
189.33118054, 116.39471757, 45.99769706, 586.3826706 ])
```

## Predcition from test data

```
] y_pred=reg.predict(x_test)
```

```
] y_pred
```

```
] array([ 588.07369916, 120.33916216, 966.54127275, 128.50634545,
106.54037187, 1075.23670036, 758.44237575, 298.87308897,
334.91614697, 887.13058812, 877.27430934, 706.90563275,
1209.27822561, 607.78239057, 518.23713304, -63.26398418,
189.33118054, 116.39471757, 45.99769706, 586.3826706 ])
```

```
] reg.intercept_
```

```
] -269.95594596725823
```

```
] reg.coef_
```

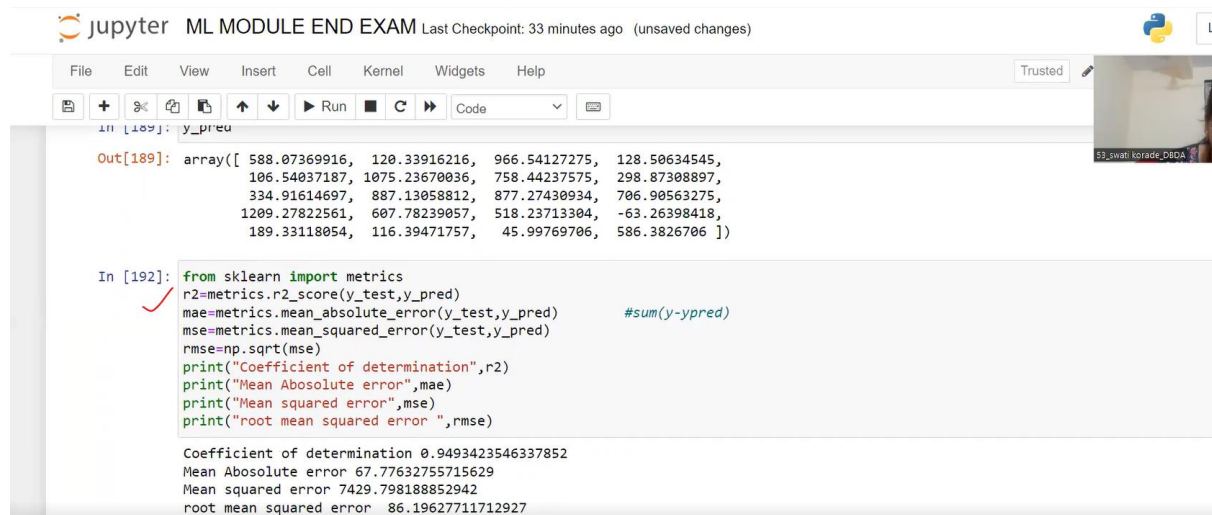
```
] array([872.9570765 , 675.83150092])
```

Multiple linear equation is :

Perpreice square foot: y

$$Y = -269.9559 + (872.9570 * F) + (675.8315 * N)$$

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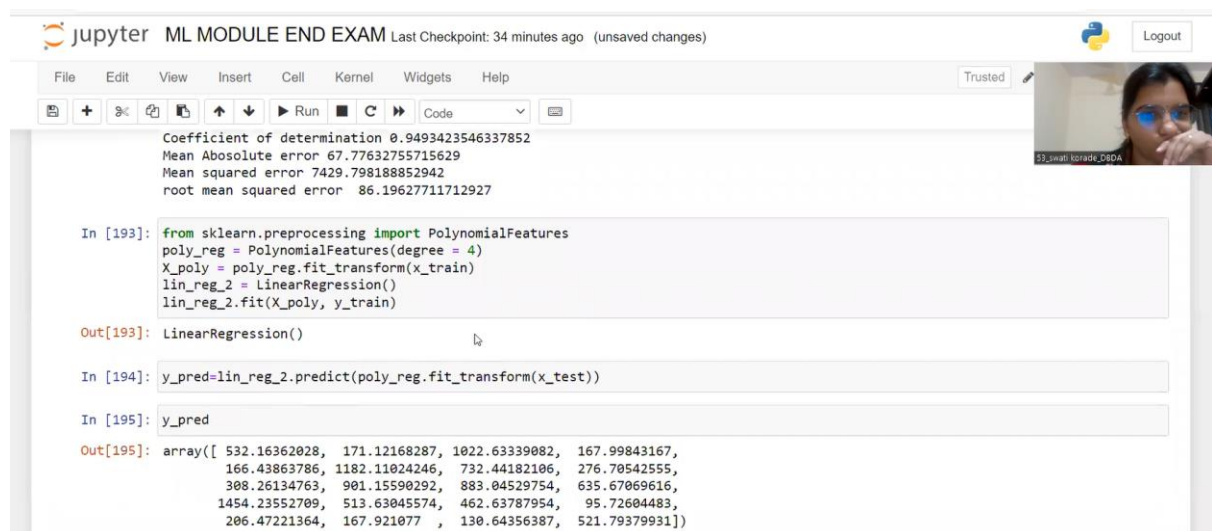
The screenshot shows a Jupyter Notebook interface with the title 'ML MODULE END EXAM'. The top bar indicates 'Last Checkpoint: 33 minutes ago (unsaved changes)'. The notebook has a menu bar with 'File', 'Edit', 'View', 'Insert', 'Cell', 'Kernel', 'Widgets', and 'Help'. Below the menu is a toolbar with icons for file operations, running, and code execution. The main area contains two code cells. The first cell, labeled 'In [189]:', shows a NumPy array of predicted values. The second cell, labeled 'In [192]:', imports metrics from sklearn and prints several performance metrics. The output of the second cell shows a high R-squared value but relatively high error metrics.

```
Out[189]: array([ 588.07369916, 120.33916216, 966.54127275, 128.50634545,
 106.54037187, 1075.23670036, 758.44237575, 298.87308897,
 334.91614697, 887.13058812, 877.27430934, 706.90563275,
 1209.27822561, 607.78239057, 518.23713304, -63.26398418,
 189.33118054, 116.39471757, 45.99769706, 586.3826706 ])
```

```
In [192]: from sklearn import metrics
r2=metrics.r2_score(y_test,y_pred)
mae=metrics.mean_absolute_error(y_test,y_pred) #sum(y-ypred)
mse=metrics.mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
print("Coefficient of determination",r2)
print("Mean Absolute error",mae)
print("Mean squared error",mse)
print("root mean squared error ",rmse)

Coefficient of determination 0.9493423546337852
Mean Absolute error 67.77632755715629
Mean squared error 7429.798188852942
root mean squared error 86.19627711712927
```

If we see r2 is good but error is larger so we try to fit another model polynomial regression for better accuracy and minimize the error



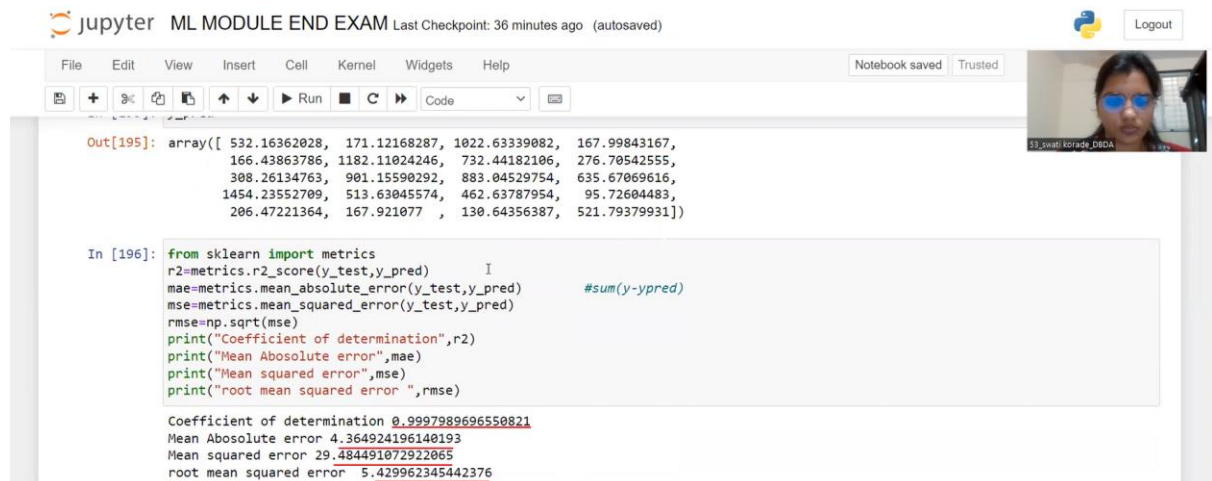
The screenshot shows the same Jupyter Notebook interface, now with 'Last Checkpoint: 34 minutes ago (unsaved changes)'. The notebook contains three code cells. The first cell repeats the performance metrics from the previous screenshot. The second cell, labeled 'In [193]:', imports PolynomialFeatures from sklearn.preprocessing and fits a polynomial regression model of degree 4 to the training data. The third cell, labeled 'In [194]:', uses the fitted polynomial model to predict values for the test data. The output of the third cell shows a new set of predicted values.

```
Out[193]: LinearRegression()
```

```
In [194]: y_pred=lin_reg_2.predict(poly_reg.fit_transform(x_test))

In [195]: y_pred

Out[195]: array([ 532.16362028, 171.12168287, 1022.63339082, 167.99843167,
 166.43863786, 1182.11024246, 732.44182106, 276.70542555,
 308.26134763, 901.15590292, 883.04529754, 635.67069616,
 1454.23552709, 513.63045574, 462.63787954, 95.72604483,
 206.47221364, 167.921077 , 130.64356387, 521.79379931])
```



The screenshot shows the Jupyter Notebook interface with 'Last Checkpoint: 36 minutes ago (autosaved)'. The notebook contains two code cells. The first cell, labeled 'Out[195]:', shows the predicted values from the polynomial regression model. The second cell, labeled 'In [196]:', imports metrics from sklearn and prints performance metrics for the polynomial regression model. The output shows a significantly higher R-squared value and lower error metrics compared to the linear regression model.

```
Out[195]: array([ 532.16362028, 171.12168287, 1022.63339082, 167.99843167,
 166.43863786, 1182.11024246, 732.44182106, 276.70542555,
 308.26134763, 901.15590292, 883.04529754, 635.67069616,
 1454.23552709, 513.63045574, 462.63787954, 95.72604483,
 206.47221364, 167.921077 , 130.64356387, 521.79379931])
```

```
In [196]: from sklearn import metrics
r2=metrics.r2_score(y_test,y_pred)
mae=metrics.mean_absolute_error(y_test,y_pred) #sum(y-ypred)
mse=metrics.mean_squared_error(y_test,y_pred)
rmse=np.sqrt(mse)
print("Coefficient of determination",r2)
print("Mean Absolute error",mae)
print("Mean squared error",mse)
print("root mean squared error ",rmse)

Coefficient of determination 0.9997989696550821
Mean Absolute error 4.364924196140193
Mean squared error 29.484491072922065
root mean squared error 5.429962345442376
```

## Overall conclusion :

if we compare both the data set then accuracy for polynomial regression is better than multiple linear regression aslo mean absolute error also reduce much in case of polynomial regression

so from the model we can suggest that anil has to choose polynomial regression for his prediction