PROJECT ON

BLACK FRIDAY SALES USING ML

CS-5710

MACHINE LEARNING

SUBMITTED BY

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Importing set of libraries

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.simplefilter(action="ignore", category=FutureWarning)
```

Reading the csv file which we have downloaded and placing the path below in order to display the dataset.

```
pd.read_csv("C:\\Users\\makut\\Downloads\\black friday sales\\Black-Friday-Sales-Prediction-master\\Data\\BlackFridaySales.csv")
```

head() displays the first 5 rows of the dataset

```
data.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Prod
0	1000001	P00069042	F	0-17	10	A	2	0	3	NaN	
1	1000001	P00248942	F	0-17	10	A	2	0	1	6.0	
2	1000001	P00087842	F	0-17	10	A	2	0	12	NaN	
3	1000001	P00085442	F	0-17	10	A	2	0	12	14.0	
4	1000002	P00285442	M	55+	16	C	4+	0	8	NaN	

shape attribute in pandas is used to get the shape of a DataFrame

```
data.shape
```

```
(550068, 12)
```

info() is used to print the information of a DataFrame

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   User_ID                     550068 non-null  int64  
 1   Product_ID                  550068 non-null  object 
 2   Gender                      550068 non-null  object 
 3   Age                         550068 non-null  object 
 4   Occupation                  550068 non-null  int64  
 5   City_Category               550068 non-null  object 
 6   Stay_In_Current_City_Years  550068 non-null  object 
 7   Marital_Status              550068 non-null  int64  
 8   Product_Category_1          550068 non-null  int64  
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
 11  Purchase                    550068 non-null  int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 50.4+ MB
```

Checking whether if we have any null values in the dataset

```
data.isnull().sum()
```

```
User_ID                            0
Product_ID                         0
Gender                             0
Age                                0
Occupation                         0
City_Category                      0
Stay_In_Current_City_Years         0
Marital_Status                     0
Product_Category_1                 0
Product_Category_2            173638
Product_Category_3            383247
Purchase                           0
dtype: int64
```

Checking null values in percentage for the dataset

```
data.isnull().sum()/data.shape[0]*100
```

```
User_ID                        0.000000
Product_ID                     0.000000
Gender                         0.000000
Age                            0.000000
Occupation                     0.000000
City_Category                  0.000000
Stay_In_Current_City_Years     0.000000
Marital_Status                 0.000000
Product_Category_1             0.000000
Product_Category_2            31.566643
Product_Category_3            69.672659
Purchase                       0.000000
dtype: float64
```

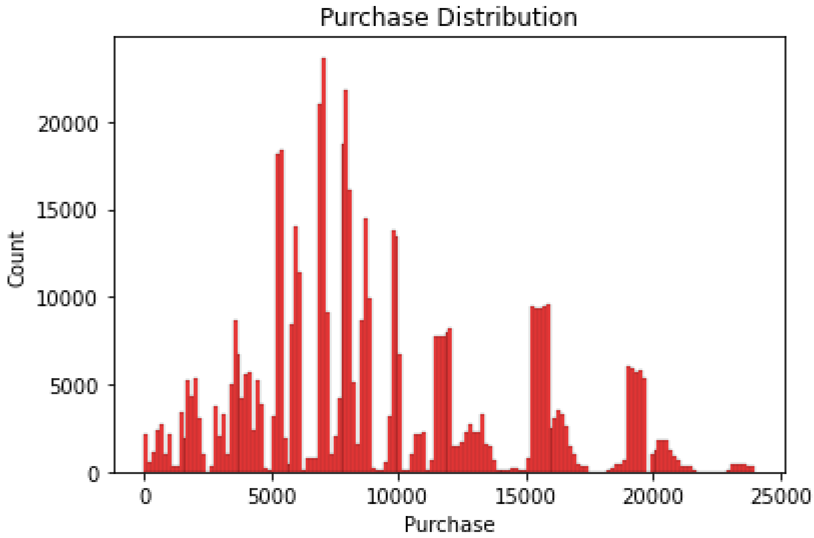
Checking unique values in the elements

```
data.nunique()
```

```
User_ID                        5891
Product_ID                     3631
Gender                            2
Age                               7
Occupation                       21
City_Category                     3
Stay_In_Current_City_Years        5
Marital_Status                    2
Product_Category_1               20
Product_Category_2               17
Product_Category_3               15
Purchase                      18105
dtype: int64
```

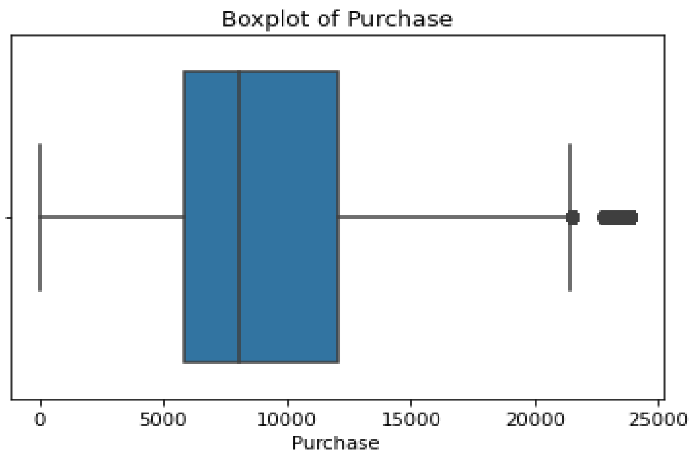
Histogram (histplot()) is used to display the distribution of the data and shows the values of your data in series

```
sns.histplot(data["Purchase"],color='r')
plt.title("Purchase Distribution")
plt.show()
```



(boxplot()) is used to display the groups of the numerical in the form quartiles

```
sns.boxplot(data["Purchase"])
plt.title("Boxplot of Purchase")
plt.show()
```



Skewness of the data which is present in the given axis of the dataframe, it denotes an asymmetric distribution

```
data["Purchase"].skew()
```

```
0.6001400037087128
```

Kurtosis is another method which is used when the data are heavy outliers or light – tailed to normal distribution

```
data["Purchase"].kurtosis()
```

```
-0.3383775655851702
```

Describe() gives the entire details of the dataset

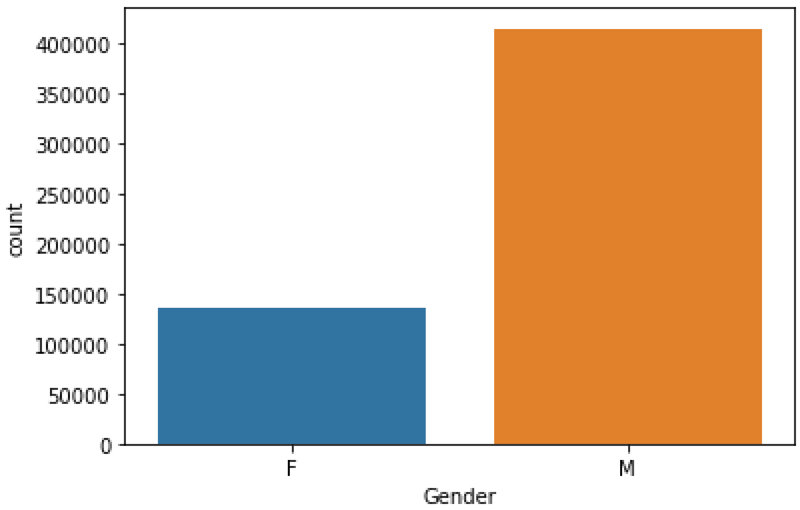
```
data["Purchase"].describe()
```

```
count    550068.000000
mean       9263.968713
std        5023.065394
min          12.000000
25%        5823.000000
50%        8047.000000
75%       12054.000000
max       23961.000000
Name: Purchase, dtype: float64
```

Countplot is used to display the counts of the observations in each category i.e for female and male

Gender

```
sns.countplot(data['Gender'])
plt.show()
```



Displaying the percentage of purchase which were made by both male and female

```
data['Gender'].value_counts(normalize=True)*100
```

```
M    75.310507
F    24.689493
Name: Gender, dtype: float64
```

Groupby is used for gender category so that it can separate the data into groups and mean() is used to get the average of the purchases.

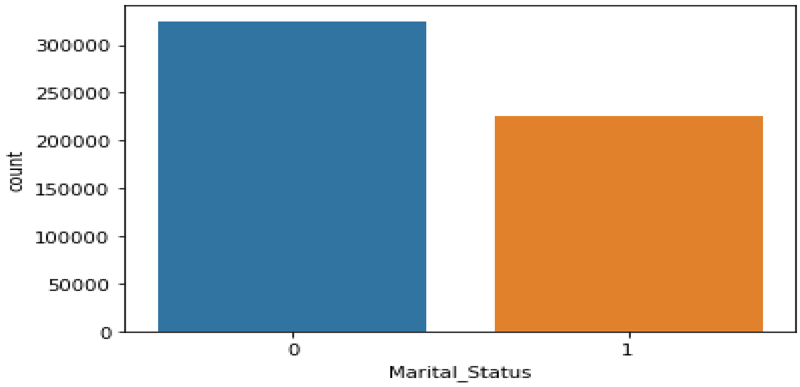
```
data.groupby("Gender").mean()["Purchase"]
```

```
Gender
F     8734.565765
M     9437.526040
Name: Purchase, dtype: float64
```

Countplot is used to display the counts of the observations in each category i.e for married and unmarried

Marital Status

```
sns.countplot(data['Marital_Status'])
plt.show()
```



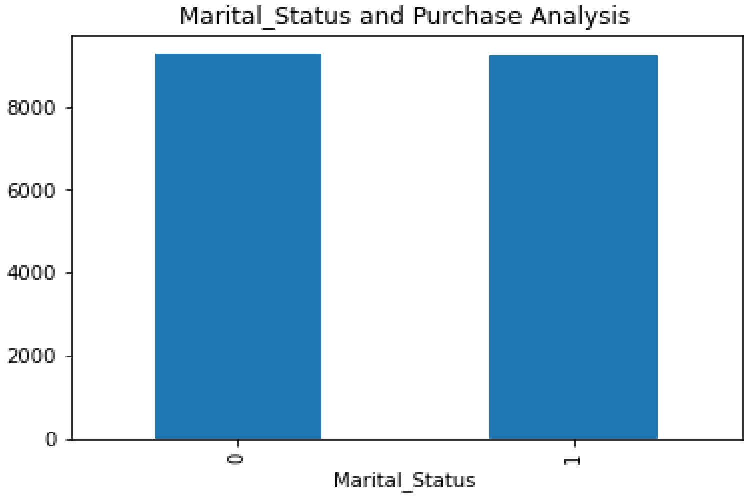
Groupby is used for marital_status so that it can separate the data into groups and mean() is used to get the average of the purchases made by unmarried and married people

```
data.groupby("Marital_Status").mean()["Purchase"]
```

```
Marital_Status
0     9265.907619
1     9261.174574
Name: Purchase, dtype: float64
```

Plotting a graph for the grouped data of marital_status and mean of purchases

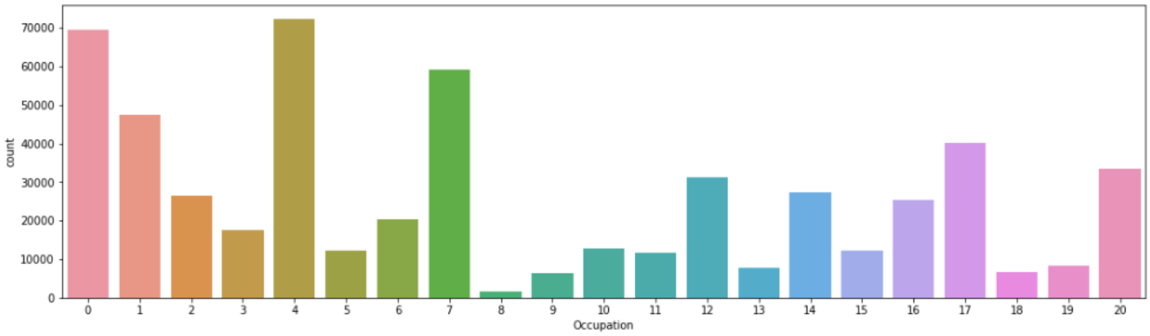
```
data.groupby("Marital_Status").mean()["Purchase"].plot(kind='bar')
plt.title("Marital_Status and Purchase Analysis")
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for occupation data

Occupation

```
plt.figure(figsize=(18,5))
sns.countplot(data['Occupation'])
plt.show()
```



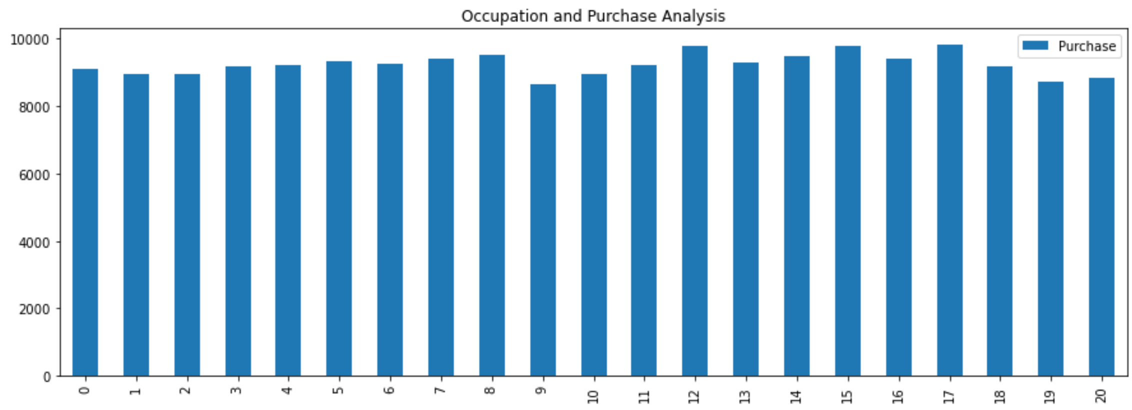
Groupby is used for occupation data so that it can separate the data into groups and mean() is used to get the average of the purchase of each occupation

```
occup = pd.DataFrame(data.groupby("Occupation").mean()["Purchase"])
occup
```

Occupation	Purchase
0	9124.428588
1	8953.193270
2	8952.481683
3	9178.593088
4	9213.980251
5	9333.149298
6	9256.535691
7	9425.728223
8	9532.592497
9	8637.743761
10	8959.355375
11	9213.845848
12	9796.640239
13	9306.351061

Plotting a graph for the grouped data of occupation and mean of purchases

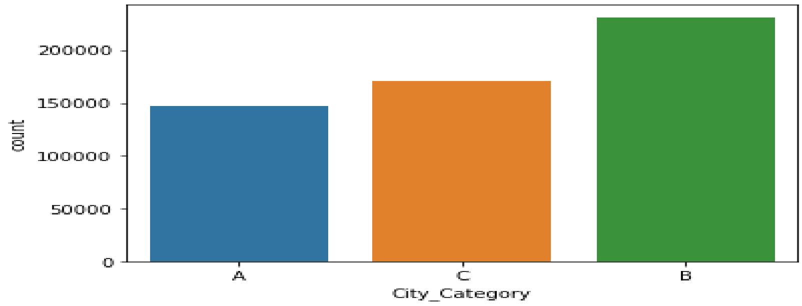
```
occup.plot(kind='bar',figsize=(15,5))
plt.title("Occupation and Purchase Analysis")
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for City_Category data

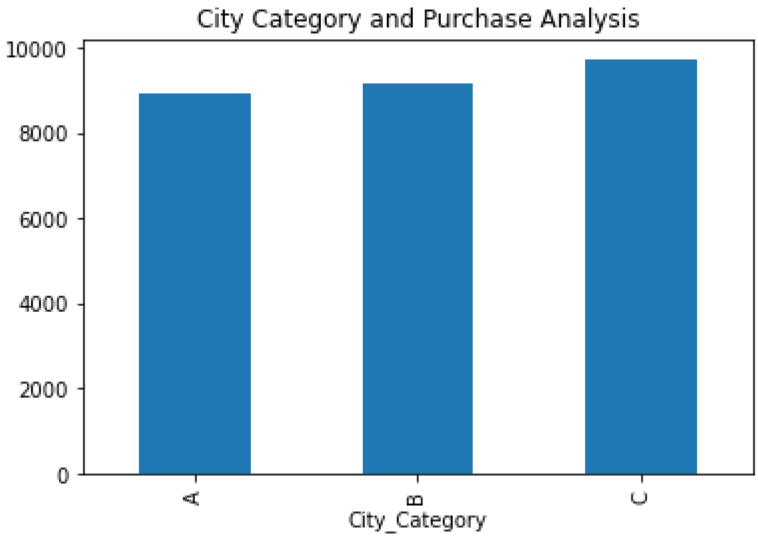
City_Category

```
sns.countplot(data['City_Category'])
plt.show()
```



Groupby is used for city_category data so that it can separate the data into groups and mean() is used to get the average of the purchase

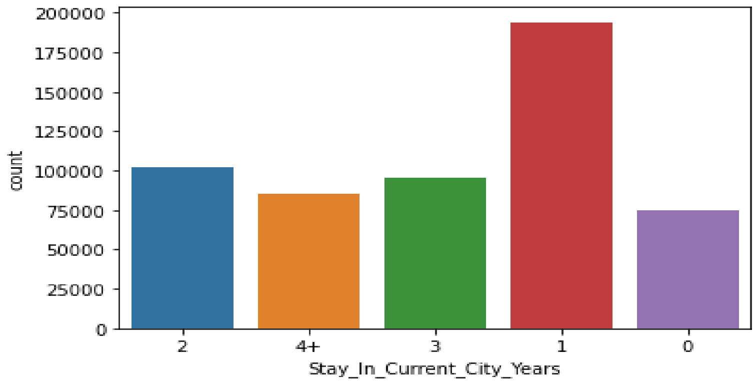
```
data.groupby("City_Category").mean()["Purchase"].plot(kind='bar')
plt.title("City Category and Purchase Analysis")
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for stay_in_current_city_years.

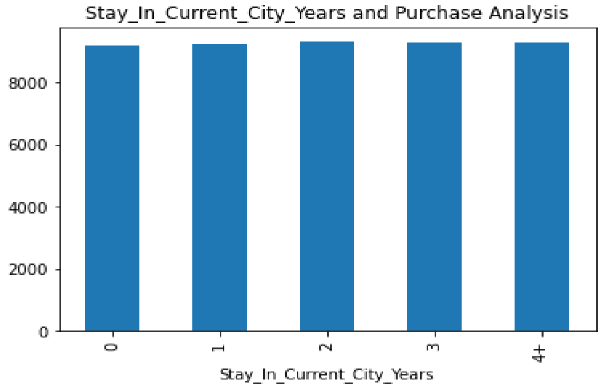
Stay_In_Current_City_Years

```
sns.countplot(data['Stay_In_Current_City_Years'])
plt.show()
```



Groupby is used for Stay_In_Current_City_Years data so that it can separate the data into groups and mean() is used to get the average of the purchase

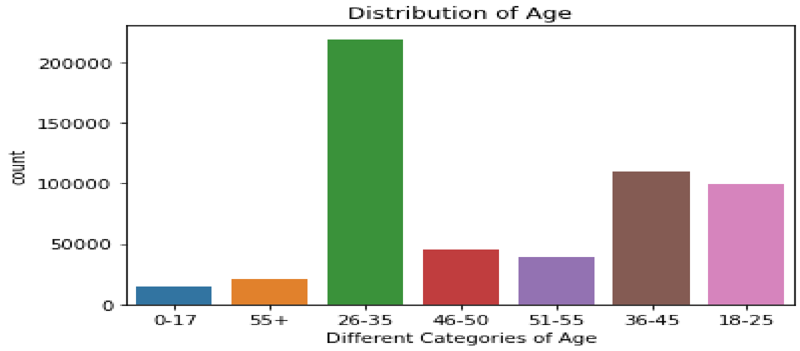
```
data.groupby("Stay_In_Current_City_Years").mean()["Purchase"].plot(kind='bar')
plt.title("Stay_In_Current_City_Years and Purchase Analysis")
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for diff age groups

Age

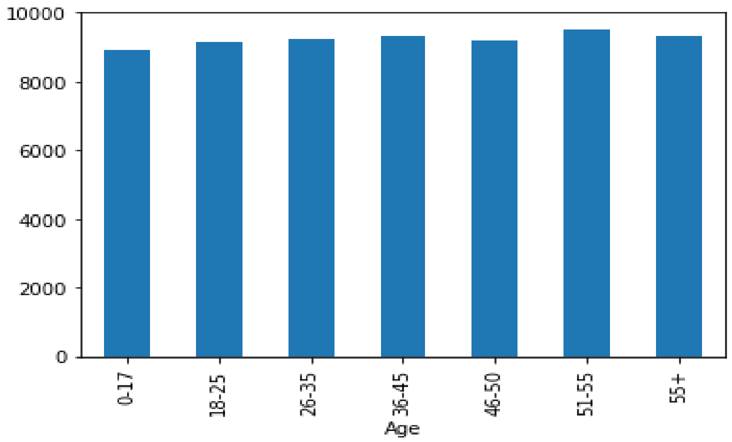
```
sns.countplot(data['Age'])
plt.title('Distribution of Age')
plt.xlabel('Different Categories of Age')
plt.show()
```



Groupby is used for Age data so that it can separate the data into groups and mean() is used to get the average of the purchase

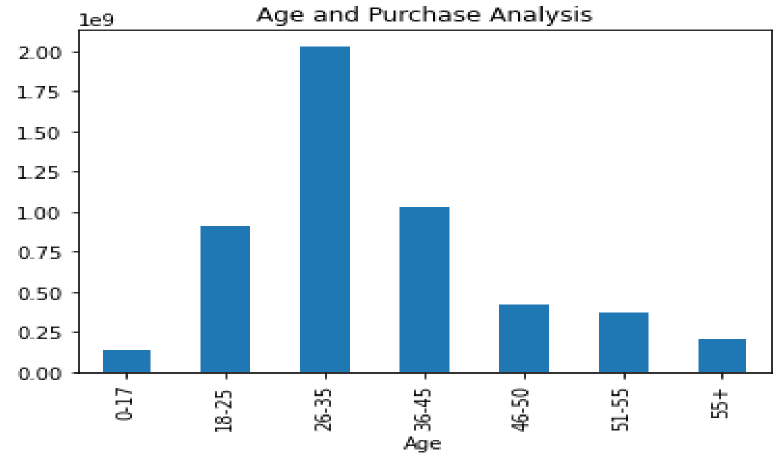
```
data.groupby("Age").mean()["Purchase"].plot(kind='bar')
```

<AxesSubplot:xlabel='Age'>



Groupby is used for Age data so that it can separate the data into groups and sum() is used to get the sum of the purchase of the items

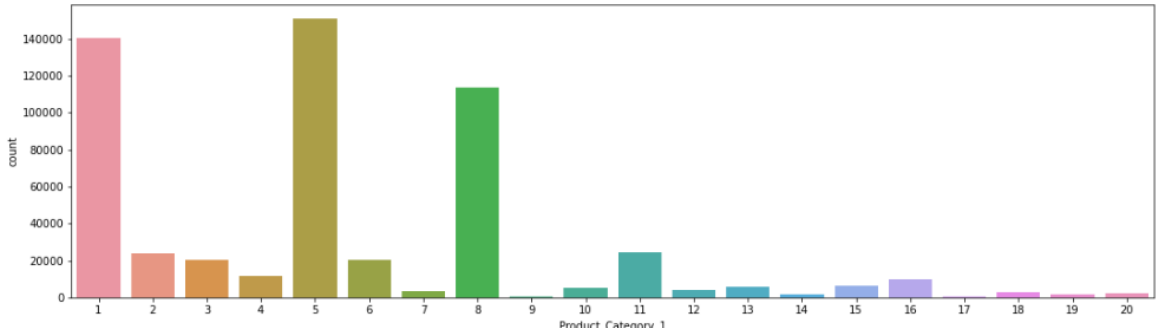
```
data.groupby("Age").sum()['Purchase'].plot(kind="bar")
plt.title("Age and Purchase Analysis")
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for product_category_1

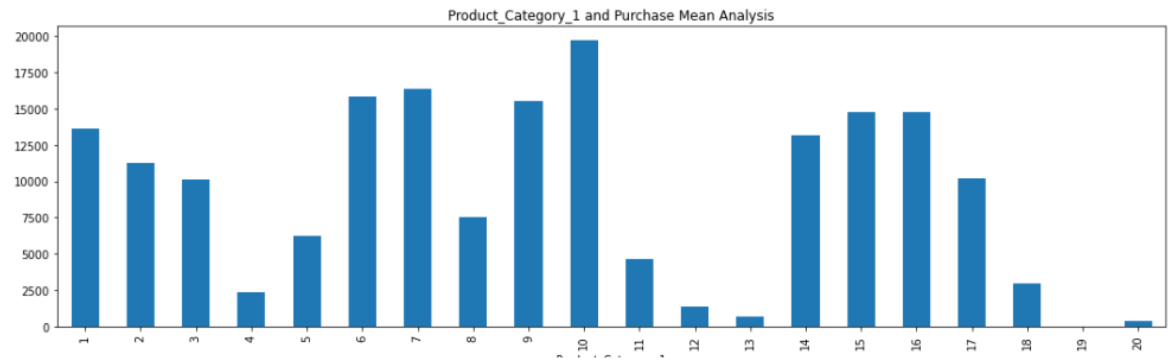
Product_Category_1

```
plt.figure(figsize=(18,5))
sns.countplot(data['Product_Category_1'])
plt.show()
```



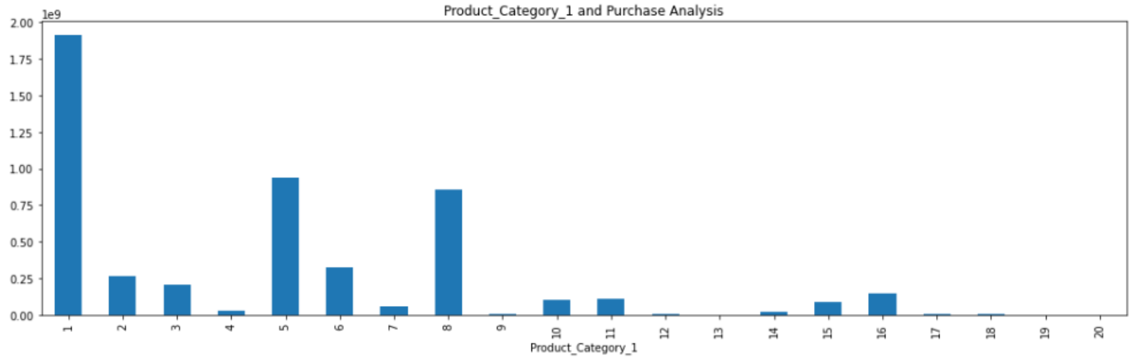
Groupby is used for product_category_1 data so that it can separate the data into groups and mean() is used to get the average of the purchase

```
data.groupby('Product_Category_1').mean()['Purchase'].plot(kind='bar',figsize=(18,5))
plt.title("Product_Category_1 and Purchase Mean Analysis")
plt.show()
```



Groupby is used for product_category_1 data so that it can separate the data into groups and mean() is used to get the sum of the purchase of the item

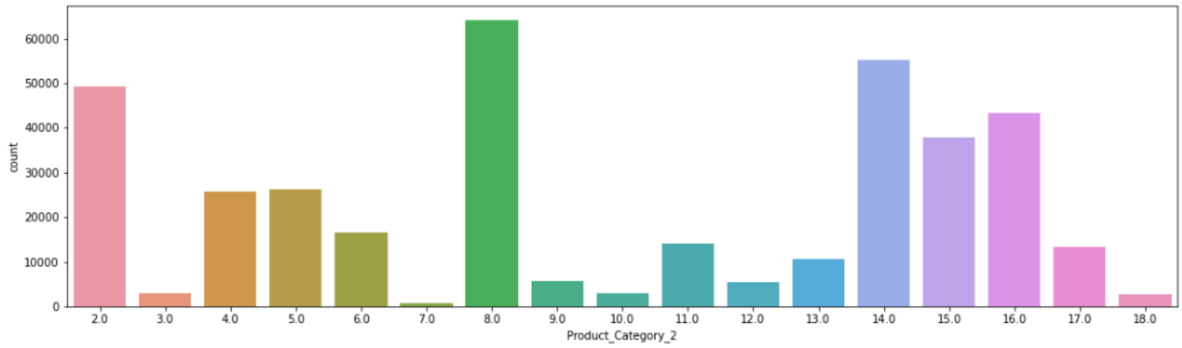
```
data.groupby('Product_Category_1').sum()['Purchase'].plot(kind='bar',figsize=(18,5))
plt.title("Product_Category_1 and Purchase Analysis")
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for product_category_2

Product_Category_2

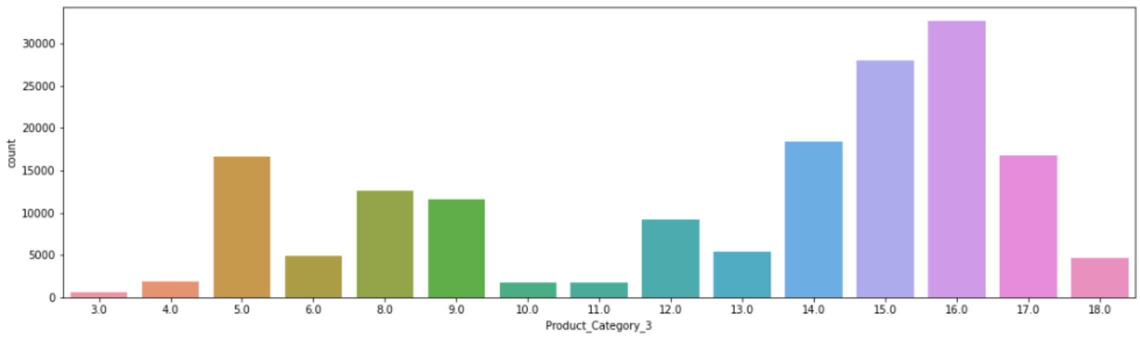
```
plt.figure(figsize=(18,5))
sns.countplot(data['Product_Category_2'])
plt.show()
```



Countplot is used to display the counts of the observations in each category i.e for product_category_3

Product_Category_3

```
]: plt.figure(figsize=(18,5))
sns.countplot(data['Product_Category_3'])
plt.show()
```



corr() is used to find the correlation of each columns in the DataFrame. Nan values were automatically ignored.

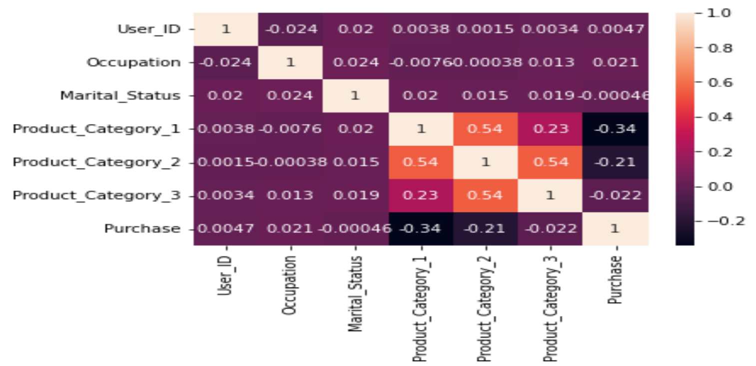
```
data.corr()
```

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
User_ID	1.000000	-0.023971	0.020443	0.003825	0.001529	0.003419	0.004716
Occupation	-0.023971	1.000000	0.024280	-0.007618	-0.000384	0.013263	0.020833
Marital_Status	0.020443	0.024280	1.000000	0.019888	0.015138	0.019473	-0.000463
Product_Category_1	0.003825	-0.007618	0.019888	1.000000	0.540583	0.229678	-0.343703
Product_Category_2	0.001529	-0.000384	0.015138	0.540583	1.000000	0.543649	-0.209918
Product_Category_3	0.003419	0.013263	0.019473	0.229678	0.543649	1.000000	-0.022006
Purchase	0.004716	0.020833	-0.000463	-0.343703	-0.209918	-0.022006	1.000000

HeatMap is used to display the correlation between the different variables in a matrix from ranging from -1 to +1. It displays the various shades of colour for each value.

HeatMap

```
sns.heatmap(data.corr(),annot=True)
plt.show()
```



Displaying the labels of each column below

```
data.columns
```

```
Index(['User_ID', 'Product_ID', 'Gender', 'Age', 'Occupation', 'City_Category',
       'Stay_In_Current_City_Years', 'Marital_Status', 'Product_Category_1',
       'Product_Category_2', 'Product_Category_3', 'Purchase'],
      dtype='object')
```

copy() is used to create a copies of the list

```
df = data.copy()
```

Head() displays the first 5 rows of the dataset

```
: df.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Produc
0	1000001	P00069042	F	0-17	10	A	2	0	3	NaN	
1	1000001	P00248942	F	0-17	10	A	2	0	1	6.0	
2	1000001	P00087842	F	0-17	10	A	2	0	12	NaN	
3	1000001	P00085442	F	0-17	10	A	2	0	12	14.0	
4	1000002	P00285442	M	55+	16	C	4+	0	8	NaN	

Get_dummies is used for manipulating the data

```
#Dummy Variables:
df = pd.get_dummies(df, columns=['Stay_In_Current_City_Years'])
```

Encoding the variables i.e converting set of labels into numeric form and displaying them using head() so that top five data is displayed

Encoding the categorical variables

```
]: from sklearn.preprocessing import LabelEncoder
   lr = LabelEncoder()
```

```
]: df['Gender'] = lr.fit_transform(df['Gender'])
```

```
]: df['Age'] = lr.fit_transform(df['Age'])
```

```
]: df['City_Category'] = lr.fit_transform(df['City_Category'])
```

```
]: df.head()
```

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase	Stay
0	1000001	P00069042	0	0	10	0	0	3	NaN	NaN	8370	
1	1000001	P00248942	0	0	10	0	0	1	6.0	14.0	15200	
2	1000001	P00087842	0	0	10	0	0	12	NaN	NaN	1422	
3	1000001	P00085442	0	0	10	0	0	12	14.0	NaN	1057	
4	1000002	P00285442	1	6	16	2	0	8	NaN	NaN	7969	

fillna() is used to replace the values which are NULL with a specified value and isnull() is used to check whether any null values are present or not

```
df['Product_Category_2'] =df['Product_Category_2'].fillna(0).astype('int64')
df['Product_Category_3'] =df['Product_Category_3'].fillna(0).astype('int64')
```

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

```
User_ID                          0
Product_ID                       0
Gender                           0
Age                              0
Occupation                       0
City_Category                    0
Marital_Status                   0
Product_Category_1               0
Product_Category_2               0
Product_Category_3               0
Purchase                         0
Stay_In_Current_City_Years_0     0
Stay_In_Current_City_Years_1     0
Stay_In_Current_City_Years_2     0
Stay_In_Current_City_Years_3     0
Stay_In_Current_City_Years_4+    0
dtype: int64
```

info() is used to print the information of a DataFrame

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 16 columns):
 #   Column                          Non-Null Count   Dtype
---  ------                          --------------   -----
 0   User_ID                         550068 non-null  int64
 1   Product_ID                      550068 non-null  object
 2   Gender                          550068 non-null  int32
 3   Age                             550068 non-null  int32
 4   Occupation                      550068 non-null  int64
 5   City_Category                   550068 non-null  int32
 6   Marital_Status                  550068 non-null  int64
 7   Product_Category_1              550068 non-null  int64
 8   Product_Category_2              550068 non-null  int64
 9   Product_Category_3              550068 non-null  int64
 10  Purchase                        550068 non-null  int64
 11  Stay_In_Current_City_Years_0    550068 non-null  uint8
 12  Stay_In_Current_City_Years_1    550068 non-null  uint8
 13  Stay_In_Current_City_Years_2    550068 non-null  uint8
 14  Stay_In_Current_City_Years_3    550068 non-null  uint8
 15  Stay_In_Current_City_Years_4+   550068 non-null  uint8
dtypes: int32(3), int64(7), object(1), uint8(5)
memory usage: 42.5+ MB
```

Dropping the irrelevant columns

```
df = df.drop(["User_ID","Product_ID"],axis=1)
```

Splitting data into dependent and independent variables i.e train and test

```
X = df.drop("Purchase",axis=1)
```

```
y=df['Purchase']
```

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=123)
```

A random forest regressor that fits a set of classification decision trees to different samples of data set and used to improve the accuracy of the predictions.

Creating and regressor object called RFregressor.

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error,mean_squared_error, r2_score
# create a regressor object
RFregressor = RandomForestRegressor(random_state = 0)
```

Fit() is used to take the training data as set of parameters and perform set of calculations on the input data

```
RFregressor.fit(X_train, y_train)
```

```
RandomForestRegressor(random_state=0)
```

Declaring a variable as rf_y_pred and using predict() is to predict the values of the data.

MAE(mean_absolute_error) is used to calculate the summation of the absolute difference between the predicted value and the true value

```
: rf_y_pred = RFregressor.predict(X_test)
```

```
: mean_absolute_error(y_test, rf_y_pred)
```

```
: 2222.049109204734
```

MSE(mean_sqaured_error) is used to calculate the average of the square difference between the predicted value and the true value

```
mean_squared_error(y_test, rf_y_pred)
```

```
9310769.87311957
```

R2_score in regression means the proportion of variance of true variable which is explained by estimated variable

```
r2_score(y_test, rf_y_pred)
```

```
0.6309821516972987
```

RMSE means square rooting the value of MSE

```
from math import sqrt
print("RMSE of Random Forest Model is ",sqrt(mean_squared_error(y_test, rf_y_pred)))
```

```
RMSE of Random Forest Model is  3051.35541573242
```

Installing xgboost in order to perform xgboost regressor

```
]: !pip install xgboost
```

```
Collecting xgboost
  Downloading xgboost-1.7.1-py3-none-win_amd64.whl (89.1 MB)
Requirement already satisfied: numpy in c:\users\makut\anaconda3\lib\site-packages (from xgboost) (1.21.5)
Requirement already satisfied: scipy in c:\users\makut\anaconda3\lib\site-packages (from xgboost) (1.7.3)
Installing collected packages: xgboost
Successfully installed xgboost-1.7.1
```

XGBOOST means eXtreme Gradient Boosting which layout parallel tree boosting.

Declaring a variable and initialising the variables with some values and Fit() is used to take the training data as set of parameters and perform set of calculations on the input data

```
]: from xgboost.sklearn import XGBRegressor
```

```
]: xgb_reg = XGBRegressor(learning_rate=1.0, max_depth=6, min_child_weight=40, seed=0)

   xgb_reg.fit(X_train, y_train)
```

```
]: XGBRegressor(base_score=0.5, booster='gbtree', callbacks=None,
                colsample_bylevel=1, colsample_bynode=1, colsample_bytree=1,
                early_stopping_rounds=None, enable_categorical=False,
                eval_metric=None, feature_types=None, gamma=0, gpu_id=-1,
                grow_policy='depthwise', importance_type=None,
                interaction_constraints='', learning_rate=1.0, max_bin=256,
                max_cat_threshold=64, max_cat_to_onehot=4, max_delta_step=0,
                max_depth=6, max_leaves=0, min_child_weight=40, missing=nan,
                monotone_constraints='()', n_estimators=100, n_jobs=0,
                num_parallel_tree=1, predictor='auto', random_state=0, ...)
```

Declaring a variable as xgb_y_pred and using predict() is to predict the values of the data.

MAE(mean_absolute_error) is used to calculate the summation of the absolute difference between the predicted value and the true value

```
xgb_y_pred = xgb_reg.predict(X_test)
```

```
mean_absolute_error(y_test, xgb_y_pred)
```

```
2144.8588298827412
```

MSE(mean_sqaured_error) is used to calculate the average of the square difference between the predicted value and the true value

```
mean_squared_error(y_test, xgb_y_pred)
```

```
8268802.184348016
```

R2_score in regression means the proportion of variance of true variable which is explained by estimated variable

```
r2_score(y_test, xgb_y_pred)
```

```
0.67227891659979
```

RMSE means square rooting the value of MSE

```
: from math import sqrt
  print("RMSE of XGBoost Model is ",sqrt(mean_squared_error(y_test, xgb_y_pred)))
```

```
RMSE of XGBoost Model is  2875.5525007114747
```