customer-purchase-behavior

August 31, 2023

1 A company has provided the data of its top most customers who have purchased products from the company. It wants to know patterns in the data to understand its potential customer and also wants to know the areas which it needs to stress to increase its selling.

Major takeaways frrom the analysis:
1. The data is prepared for the analysis by following numerous checks such as null value check, duplicate rows check, outlier check, erroneous data standardization etc. 2. Data has been derived from the existing columns when and where required. 3. The list of top customers have been found and shown. 4. The age group of 26-35 by far exceeds the amount of purchasing compared to other age groups. 5. The frequency of purchase and total purchase by individual users are highly correlated. 6. The net purchase amounts are highly skewed towards Male. The number of purchase by male and female are exactly same but the amount of purchase is quite small for females. The retail company might want to think about tapping the potential buyers in females and design products as well as marketing and pricing strategy accordingly 7. Customers who have come to the city in last one year have purchased the most which, by far exceeds the purchase amounts of others in the category. Further City_Category B has given the most purchases to the company. 8. Occupation levels 4,0,and 7 are the most spender who bought the products where as occupation level 8 is the least spender 9. product category number 1 has been purchased the most whereas purchases from products of product categories 7, 9, 12 &18 are quite small comparatively. 10. P00025442, P00110742 and P00255842 are the top three purchased products 11. P00353042, P00309042 and P00091742 are the top three least selling products

[23]:
```
#Importing the necessary libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[94]:
```
#loading the data into a dataframe
df = pd.read_csv('C:/Users/Vinod Jha/Desktop/Data Analysis Projects/Black␣
↪Friday Sale/train.csv')
```

[3]:
```
#checking first 5 entries in all the columns of
df.head(40)
```

```
#Takeaways: One user ha ordered multiple products. There are many NULL values␣
↪in product_category_3 and prodduct_category_2
```

[3]:

```
    User_ID Product_ID Gender   Age  Occupation City_Category  \
0   1000001  P00069042      F  0-17          10             A
1   1000001  P00248942      F  0-17          10             A
2   1000001  P00087842      F  0-17          10             A
3   1000001  P00085442      F  0-17          10             A
4   1000002  P00285442      M   55+          16             C
5   1000003  P00193542      M 26-35          15             A
6   1000004  P00184942      M 46-50           7             B
7   1000004  P00346142      M 46-50           7             B
8   1000004   P0097242      M 46-50           7             B
9   1000005  P00274942      M 26-35          20             A
10  1000005  P00251242      M 26-35          20             A
11  1000005  P00014542      M 26-35          20             A
12  1000005  P00031342      M 26-35          20             A
13  1000005  P00145042      M 26-35          20             A
14  1000006  P00231342      F 51-55           9             A
15  1000006  P00190242      F 51-55           9             A
16  1000006   P0096642      F 51-55           9             A
17  1000006  P00058442      F 51-55           9             A
18  1000007  P00036842      M 36-45           1             B
19  1000008  P00249542      M 26-35          12             C
20  1000008  P00220442      M 26-35          12             C
21  1000008  P00156442      M 26-35          12             C
22  1000008  P00213742      M 26-35          12             C
23  1000008  P00214442      M 26-35          12             C
24  1000008  P00303442      M 26-35          12             C
25  1000009  P00135742      M 26-35          17             C
26  1000009  P00039942      M 26-35          17             C
27  1000009  P00161442      M 26-35          17             C
28  1000009  P00078742      M 26-35          17             C
29  1000010  P00085942      F 36-45           1             B
30  1000010  P00118742      F 36-45           1             B
31  1000010  P00297942      F 36-45           1             B
32  1000010  P00266842      F 36-45           1             B
33  1000010  P00058342      F 36-45           1             B
34  1000010  P00032442      F 36-45           1             B
35  1000010  P00105942      F 36-45           1             B
36  1000010  P00182642      F 36-45           1             B
37  1000010  P00186942      F 36-45           1             B
38  1000010  P00155442      F 36-45           1             B
39  1000010  P00221342      F 36-45           1             B

   Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                           2               0                   3
```

1	2	0	1
2	2	0	12
3	2	0	12
4	4+	0	8
5	3	0	1
6	2	1	1
7	2	1	1
8	2	1	1
9	1	1	8
10	1	1	5
11	1	1	8
12	1	1	8
13	1	1	1
14	1	0	5
15	1	0	4
16	1	0	2
17	1	0	5
18	1	1	1
19	4+	1	1
20	4+	1	5
21	4+	1	8
22	4+	1	8
23	4+	1	8
24	4+	1	1
25	0	0	6
26	0	0	8
27	0	0	5
28	0	0	5
29	4+	1	2
30	4+	1	5
31	4+	1	8
32	4+	1	5
33	4+	1	3
34	4+	1	5
35	4+	1	5
36	4+	1	2
37	4+	1	5
38	4+	1	1
39	4+	1	1

	Product_Category_2	Product_Category_3	Purchase
0	NaN	NaN	8370
1	6.0	14.0	15200
2	NaN	NaN	1422
3	14.0	NaN	1057
4	NaN	NaN	7969
5	2.0	NaN	15227

```
6             8.0              17.0     19215
7            15.0               NaN     15854
8            16.0               NaN     15686
9             NaN               NaN      7871
10           11.0               NaN      5254
11            NaN               NaN      3957
12            NaN               NaN      6073
13            2.0               5.0     15665
14            8.0              14.0      5378
15            5.0               NaN      2079
16            3.0               4.0     13055
17           14.0               NaN      8851
18           14.0              16.0     11788
19            5.0              15.0     19614
20           14.0               NaN      8584
21            NaN               NaN      9872
22            NaN               NaN      9743
23            NaN               NaN      5982
24            8.0              14.0     11927
25            8.0               NaN     16662
26            NaN               NaN      5887
27           14.0               NaN      6973
28            8.0              14.0      5391
29            4.0               8.0     16352
30           11.0               NaN      8886
31            NaN               NaN      5875
32            NaN               NaN      8854
33            4.0               NaN     10946
34            NaN               NaN      5152
35            NaN               NaN      7089
36            4.0               9.0     12909
37           12.0               NaN      8770
38           11.0              15.0     15212
39            2.0               5.0     15705
```

[4]:
```python
df.describe()
```

[4]:
```
            User_ID     Occupation  Marital_Status  Product_Category_1  \
count  5.500680e+05  550068.000000   550068.000000       550068.000000
mean   1.003029e+06       8.076707        0.409653            5.404270
std    1.727592e+03       6.522660        0.491770            3.936211
min    1.000001e+06       0.000000        0.000000            1.000000
25%    1.001516e+06       2.000000        0.000000            1.000000
50%    1.003077e+06       7.000000        0.000000            5.000000
75%    1.004478e+06      14.000000        1.000000            8.000000
max    1.006040e+06      20.000000        1.000000           20.000000
```

```
       Product_Category_2  Product_Category_3       Purchase
count       376430.000000       166821.000000  550068.000000
mean             9.842329           12.668243    9263.968713
std              5.086590            4.125338    5023.065394
min              2.000000            3.000000      12.000000
25%              5.000000            9.000000    5823.000000
50%              9.000000           14.000000    8047.000000
75%             15.000000           16.000000   12054.000000
max             18.000000           18.000000   23961.000000
```

[5]:
```python
df.shape
```

[5]:
```
(550068, 12)
```

[6]:
```python
df.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
```

Since one user has purchased multiple times, it will be beter to have a user specific dataframe and many columns are user specific One derived metric "number_purchases" has to be vreated which will keep the track of number of purchases made my a single user

Before going for standardization of the data,it is needed to treat the missing values and wrong entries if any. the unique values of the categorical variables is being checked:

[7]:
```python
df.Gender.unique()
#it has 2 unique values as shown below
```

[7]:
```
array(['F', 'M'], dtype=object)
```

[82]:
```
df.Stay_In_Current_City_Years.unique()
```

[82]:
```
array(['2', '4+', '3', '1', '0'], dtype=object)
```

[8]:
```
df.Age.unique()
#It has 7 unique entries each pertaining to a range of ages of customers
```

[8]:
```
array(['0-17', '55+', '26-35', '46-50', '51-55', '36-45', '18-25'],
      dtype=object)
```

[9]:
```
df.City_Category.unique()
```

[9]:
```
array(['A', 'C', 'B'], dtype=object)
```

[10]:
```
df.Marital_Status.unique()
```

[10]:
```
array([0, 1], dtype=int64)
```

[11]:
```
df.Product_Category_1.unique()
```

[11]:
```
array([ 3,  1, 12,  8,  5,  4,  2,  6, 14, 11, 13, 15,  7, 16, 18, 10, 17,
        9, 20, 19], dtype=int64)
```

[12]:
```
df.Product_Category_2.unique()
```

[12]:
```
array([nan,  6., 14.,  2.,  8., 15., 16., 11.,  5.,  3.,  4., 12.,  9.,
       10., 17., 13.,  7., 18.])
```

[13]:
```
df.Product_Category_3.unique()
```

[13]:
```
array([nan, 14., 17.,  5.,  4., 16., 15.,  8.,  9., 13.,  6., 12.,  3.,
       18., 11., 10.])
```

[14]:
```
#This column has already been standerdized and convered to numeric
df.Occupation.unique()
```

[14]:
```
array([10, 16, 15,  7, 20,  9,  1, 12, 17,  0,  3,  4, 11,  8, 19,  2, 18,
        5, 14, 13,  6], dtype=int64)
```

[15]:
```
df.User_ID.unique().shape
#So there are 5891 unique users who have purchased items ate various instances.␣
 ↪To know about their repeated behaiviour of purchasing a product it is␣
 ↪necessary to keep this coloumn
#
```

[15]:
```
(5891,)
```

[16]:
```
df.Product_ID.unique().shape
#There are 3631 different products available with the superstore. To knoe if␣
 ↪the user has repeated the product or not,
#this column will be required.
```

[16]:
```
(3631,)
```

[17]:
```
df.head(10)
```

[17]:
```
   User_ID Product_ID Gender   Age  Occupation City_Category  \
0  1000001  P00069042      F  0-17          10             A
1  1000001  P00248942      F  0-17          10             A
2  1000001  P00087842      F  0-17          10             A
3  1000001  P00085442      F  0-17          10             A
4  1000002  P00285442      M   55+          16             C
5  1000003  P00193542      M 26-35          15             A
6  1000004  P00184942      M 46-50           7             B
7  1000004  P00346142      M 46-50           7             B
8  1000004   P0097242      M 46-50           7             B
9  1000005  P00274942      M 26-35          20             A

  Stay_In_Current_City_Years  Marital_Status  Product_Category_1  \
0                          2               0                   3
1                          2               0                   1
2                          2               0                  12
3                          2               0                  12
4                         4+               0                   8
5                          3               0                   1
6                          2               1                   1
7                          2               1                   1
8                          2               1                   1
9                          1               1                   8

   Product_Category_2  Product_Category_3  Purchase
0                 NaN                 NaN      8370
1                 6.0                14.0     15200
2                 NaN                 NaN      1422
3                14.0                 NaN      1057
4                 NaN                 NaN      7969
5                 2.0                 NaN     15227
6                 8.0                17.0     19215
7                15.0                 NaN     15854
8                16.0                 NaN     15686
9                 NaN                 NaN      7871
```

Further one productID is listed in all three categories. This is possible as some products can be listed in more than one categories e.g. a refrigerator can be listed in Electronics as well as home accessories. To know the exact reason, the Product columns will be explored more

[191]:
```
df2 = df[['Product_ID',␣
↪'Product_Category_1','Product_Category_2','Product_Category_3','Purchase']]
df2
```

[191]:
```
        Product_ID  Product_Category_1  Product_Category_2  Product_Category_3  \
0        P00069042                   3                 NaN                 NaN
1        P00248942                   1                 6.0                14.0
2        P00087842                  12                 NaN                 NaN
3        P00085442                  12                14.0                 NaN
4        P00285442                   8                 NaN                 NaN
…              …                   …                   …                   …
550063   P00372445                  20                 NaN                 NaN
550064   P00375436                  20                 NaN                 NaN
550065   P00375436                  20                 NaN                 NaN
550066   P00375436                  20                 NaN                 NaN
550067   P00371644                  20                 NaN                 NaN

         Purchase
0            8370
1           15200
2            1422
3            1057
4            7969
…             …
550063        368
550064        371
550065        137
550066        365
550067        490

[550068 rows x 5 columns]
```

[19]:
```
df2.loc[df2.Product_ID=='P00069042']
```

[19]:
```
        Product_ID  Product_Category_1  Product_Category_2  Product_Category_3
0        P00069042                   3                 NaN                 NaN
825      P00069042                   3                 NaN                 NaN
3314     P00069042                   3                 NaN                 NaN
4224     P00069042                   3                 NaN                 NaN
5864     P00069042                   3                 NaN                 NaN
…              …                   …                   …                   …
539484   P00069042                   3                 NaN                 NaN
540849   P00069042                   3                 NaN                 NaN
543419   P00069042                   3                 NaN                 NaN
544454   P00069042                   3                 NaN                 NaN
```

```
545219  P00069042                   3                 NaN                 NaN

[227 rows x 4 columns]
```

[20]:
```python
df2.loc[df2.Product_ID=='P00248942']
```

[20]:
```
       Product_ID  Product_Category_1  Product_Category_2  Product_Category_3
1       P00248942                   1                 6.0                14.0
126     P00248942                   1                 6.0                14.0
405     P00248942                   1                 6.0                14.0
516     P00248942                   1                 6.0                14.0
701     P00248942                   1                 6.0                14.0
…            …                  …                  …                  …
542905  P00248942                   1                 6.0                14.0
544481  P00248942                   1                 6.0                14.0
545091  P00248942                   1                 6.0                14.0
545123  P00248942                   1                 6.0                14.0
545583  P00248942                   1                 6.0                14.0

[581 rows x 4 columns]
```

The above two examples show that the products sometimes belong to multiple category. And therefor category_2 and category_3 are NULL values.and NULL values cannot be replaced by any interpolation in this case checking if other columns have null values

[21]:
```python
df.isna().sum()
```

[21]:
```
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
```

As oberseved earlier, only 2 columns have NULL values. And they are present because many products are listed in only one or two Product category they will be treated for NA values as and when reuqired Lets reduce the size of the dataframe by concatinating the different entries of unique User_ID

[22]:
```python
number_of_purchase = df['User_ID'].value_counts().sort_index()
number_of_purchase
```

[22]:
```
1000001     35
1000002     77
1000003     29
1000004     14
1000005    106
          …
1006036    514
1006037    122
1006038     12
1006039     74
1006040    180
Name: User_ID, Length: 5891, dtype: int64
```

[25]:
```
df_user = df.groupby('User_ID')['Purchase'].sum()
df_user
```

[25]:
```
User_ID
1000001     334093
1000002     810472
1000003     341635
1000004     206468
1000005     821001
              …
1006036    4116058
1006037    1119538
1006038      90034
1006039     590319
1006040    1653299
Name: Purchase, Length: 5891, dtype: int64
```

[35]:
```
prchase_per_user = pd.DataFrame({'User_ID':df_user.index[:
↪],'number_of_purchase':number_of_purchase.values[:],'total_purchase_count':
                                df_user.values[:]})
```

[68]:
```
prchase_per_user=prchase_per_user.
↪sort_values(by='number_of_purchase',ascending=False)
prchase_per_user=prchase_per_user.reset_index(drop=True)
prchase_per_user
#the list of users having done most number of purchases has been shown
```

[68]:

	User_ID	number_of_purchase	total_purchase_count
0	1001680	1026	8699596
1	1004277	979	10536909
2	1001941	898	6817493
3	1001181	862	6387961
4	1000889	823	5499872
…	…	…	…

```
5886   1002111                  7              54536
5887   1005391                  7              60182
5888   1002690                  7              87789
5889   1005608                  7              61628
5890   1000708                  6              58625

[5891 rows x 3 columns]
```

[72]:
```python
#the top 20 users having done the purchase most number of times:
prchase_per_user[:20]
```

[72]:

	User_ID	number_of_purchase	total_purchase_count
0	1001680	1026	8699596
1	1004277	979	10536909
2	1001941	898	6817493
3	1001181	862	6387961
4	1000889	823	5499872
5	1003618	767	5962012
6	1001150	752	4728932
7	1001015	740	6511314
8	1005795	729	5464535
9	1005831	727	6512433
10	1002909	718	7577756
11	1001449	714	5103795
12	1002063	709	5167421
13	1004344	705	5733683
14	1003391	698	6477160
15	1003841	698	6044415
16	1000424	694	6573609
17	1004510	691	5150373
18	1001980	685	5549865
19	1001088	680	5628655

[77]:
```python
#top 20 purchasers according to purchase values
prchase_per_user.sort_values(by='total_purchase_count',ascending=False)[:20]
```

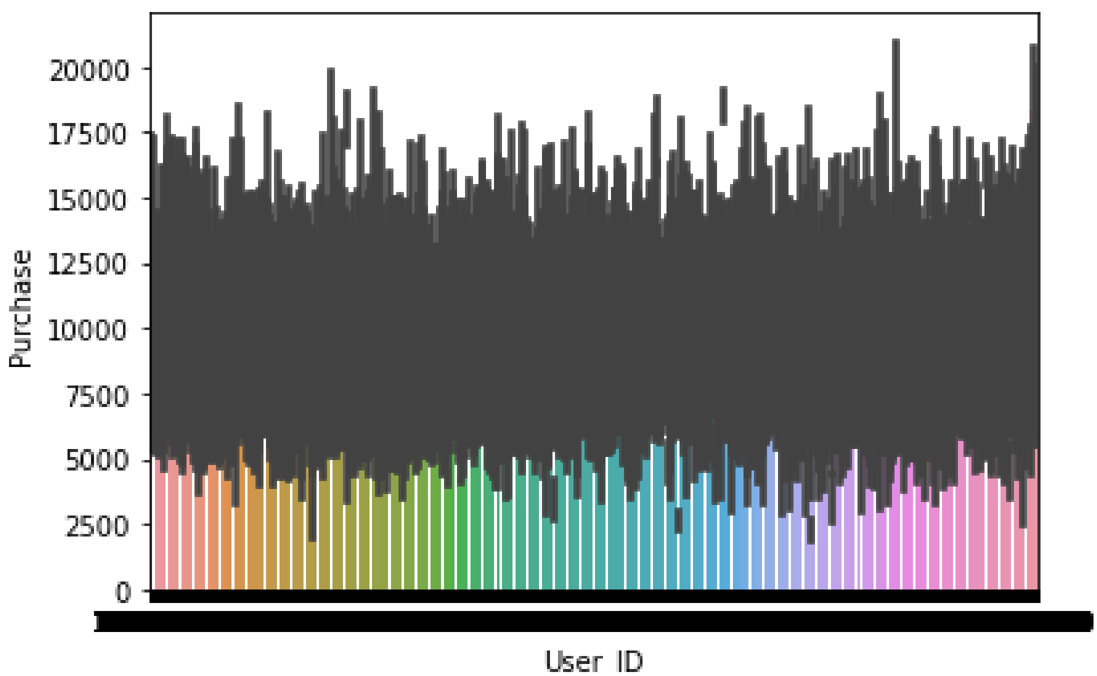
[77]:

	User_ID	number_of_purchase	total_purchase_count
1	1004277	979	10536909
0	1001680	1026	8699596
10	1002909	718	7577756
2	1001941	898	6817493
16	1000424	694	6573609
31	1004448	575	6566245
9	1005831	727	6512433
7	1001015	740	6511314
14	1003391	698	6477160
3	1001181	862	6387961

23	1000549	632	6310723
25	1003539	617	6187094
35	1003032	568	6126540
15	1003841	698	6044415
5	1003618	767	5962012
27	1001285	606	5805379
13	1004344	705	5733683
24	1003224	622	5673106
19	1001088	680	5628655
18	1001980	685	5549865

[79]:
```
sns.barplot(x='User_ID',y='Purchase',data = df)
```

[79]: <AxesSubplot:xlabel='User_ID', ylabel='Purchase'>



[ ]:
```
## This plot doesnt give us much of informations except that there are no␣
↪extreme top purchasers.
```

[81]:
```
#checking for duplicate rows
df.duplicated().sum()

#So we don't have any duplicated entry
```

[81]: 0

[86]:
```
#The data is clean and the entries to each column is logical. The purchase data may contain some outlier.
df.Purchase.sort_values(ascending=False)[:20]
```

[86]:
```
370891    23961
93016     23961
87440     23961
503697    23960
321782    23960
349658    23960
292083    23960
298378    23959
437804    23959
229329    23958
416883    23958
7542      23958
373300    23958
33268     23956
388010    23955
449656    23955
366333    23955
54364     23954
56879     23954
68926     23953
Name: Purchase, dtype: int64
```

[98]:
```
df.Purchase.sort_values(ascending=True)[:20]
```

[98]:
```
549221    12
549477    12
547819    12
548027    12
547538    12
549720    12
546630    12
546398    12
547364    12
549986    12
549095    12
546325    12
547555    12
549989    12
549105    12
547559    12
546747    12
548309    12
549632    12
```

```
548701    12
Name: Purchase, dtype: int64
```

The purchase column does not have any illogical entry as well. So All enries are logical inthe dataframe. The NA values in df will be treated when and where required We can see the top purchasers, and bottom purchasers in the provided data

[116]:
```
df_group_pID=pd.DataFrame(df.groupby('Product_ID')['Purchase'].sum().
    ↪sort_values(ascending=False))
type(df_group_pID)
df_group_pID['Product_ID'] = df_group_pID.index
df_group_pID
```

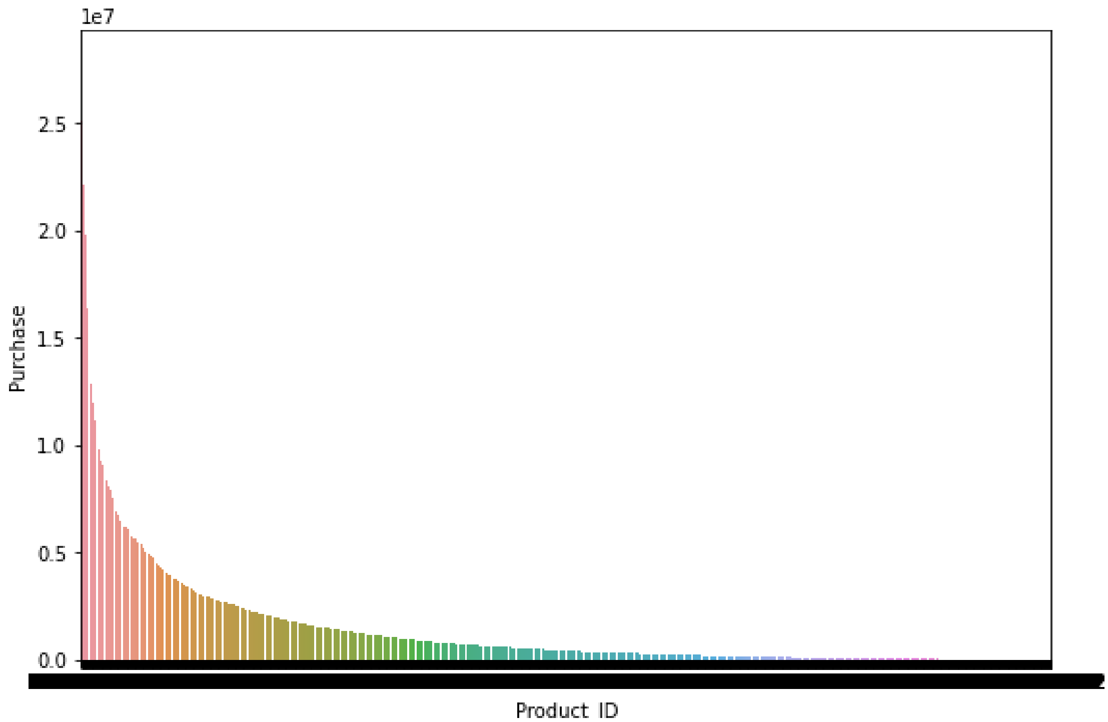
[116]:
```
            Purchase Product_ID
Product_ID
P00025442   27995166  P00025442
P00110742   26722309  P00110742
P00255842   25168963  P00255842
P00059442   24338343  P00059442
P00184942   24334887  P00184942
…                …          …
P00012942       1717  P00012942
P00325342       1656  P00325342
P00353042       1545  P00353042
P00309042        726  P00309042
P00091742        405  P00091742

[3631 rows x 2 columns]
```

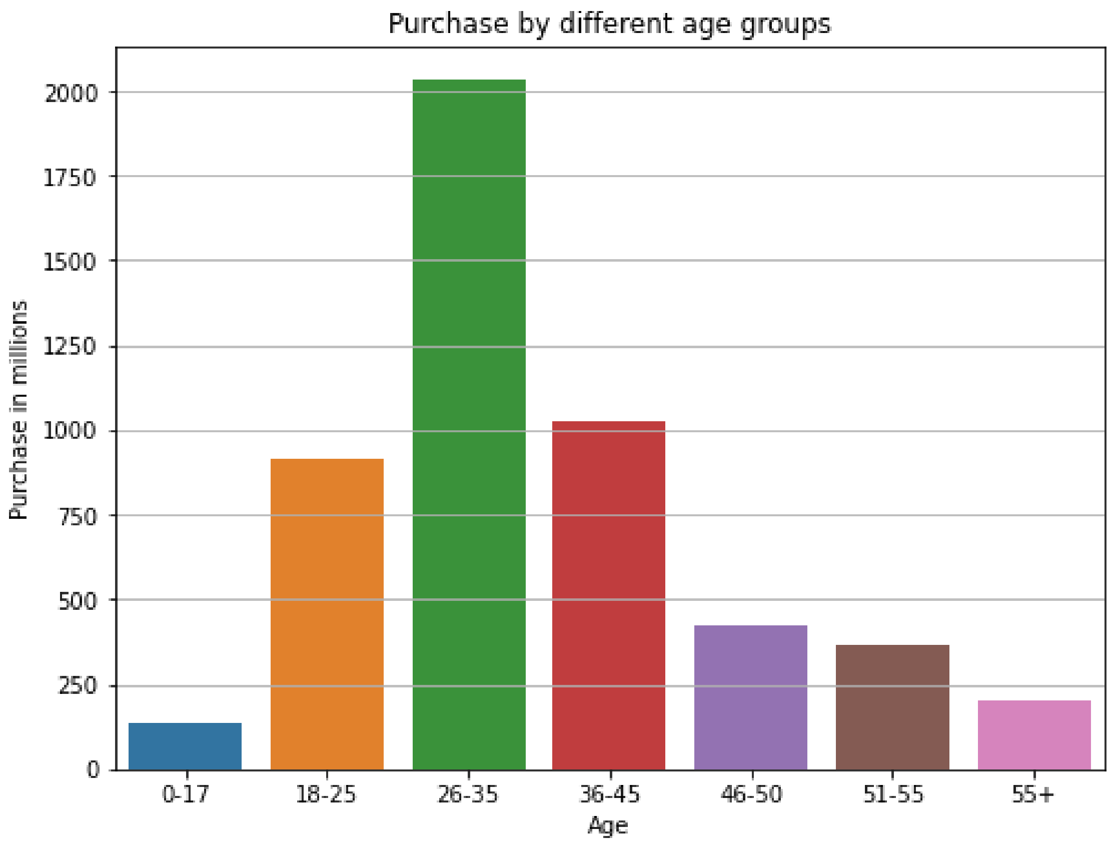
We can see the top products purchased

[117]:
```
#Plotting productwise purchases
plt.figure(figsize=(9,6))
sns.barplot(data=df_group_pID,x='Product_ID',y='Purchase')
plt.title("Amount of purchase Vs Product in decreasing order")
```

[117]:
```
<AxesSubplot:xlabel='Product_ID', ylabel='Purchase'>
```

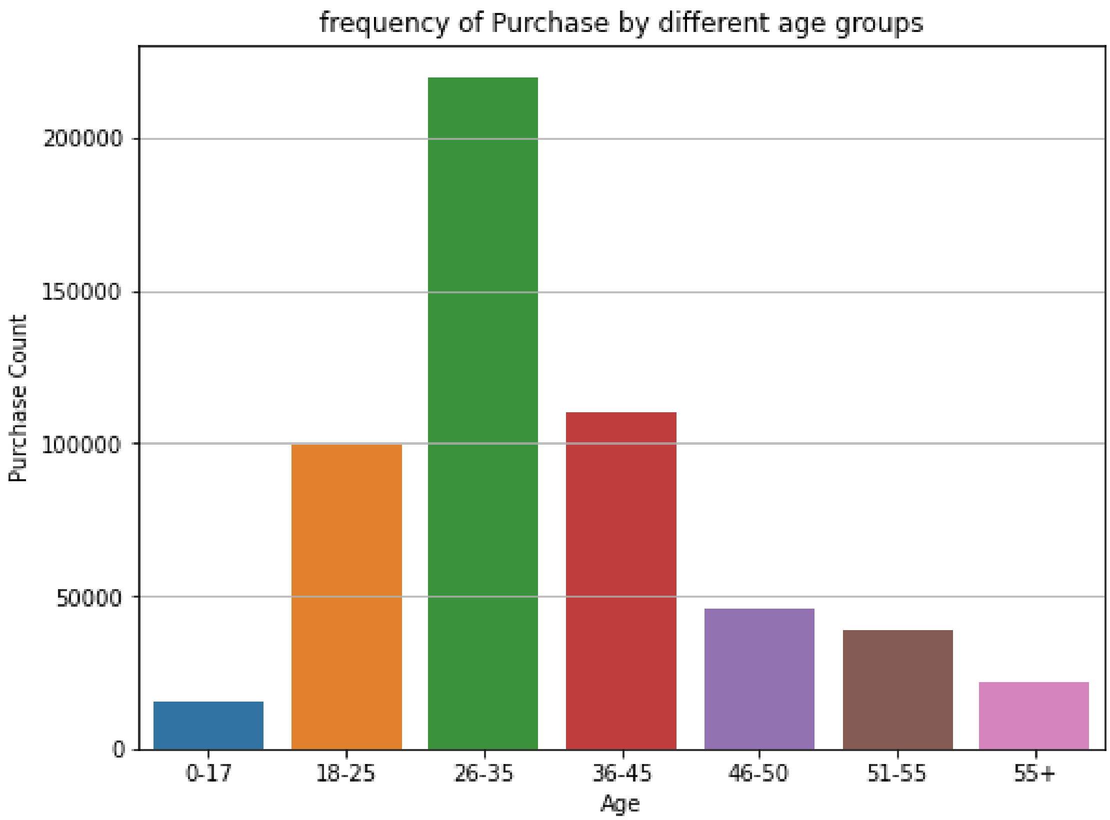


[137]:
```
df_group_age = df.groupby('Age')['Purchase'].sum().reset_index()
df_group_age.Purchase/=1000000
plt.figure(figsize=(8,6))
sns.barplot(x='Age',y='Purchase',data=df_group_age)
plt.ylabel('Purchase in millions')
plt.title("Purchase by different age groups")
plt.grid(True, axis='y')
```



The age group of 26=35 by far exceeds in the amount of purchasing. lets find out the number of times individual age group purchases

[131]:
```
df_group_age_count = df.groupby('Age')['Purchase'].count().reset_index()
plt.figure(figsize=(8,6))
sns.barplot(x='Age',y='Purchase',data=df_group_age_count)
plt.ylabel('Purchase Count')
plt.title("frequency of Purchase by different age groups")
plt.grid(True, axis='y')
```



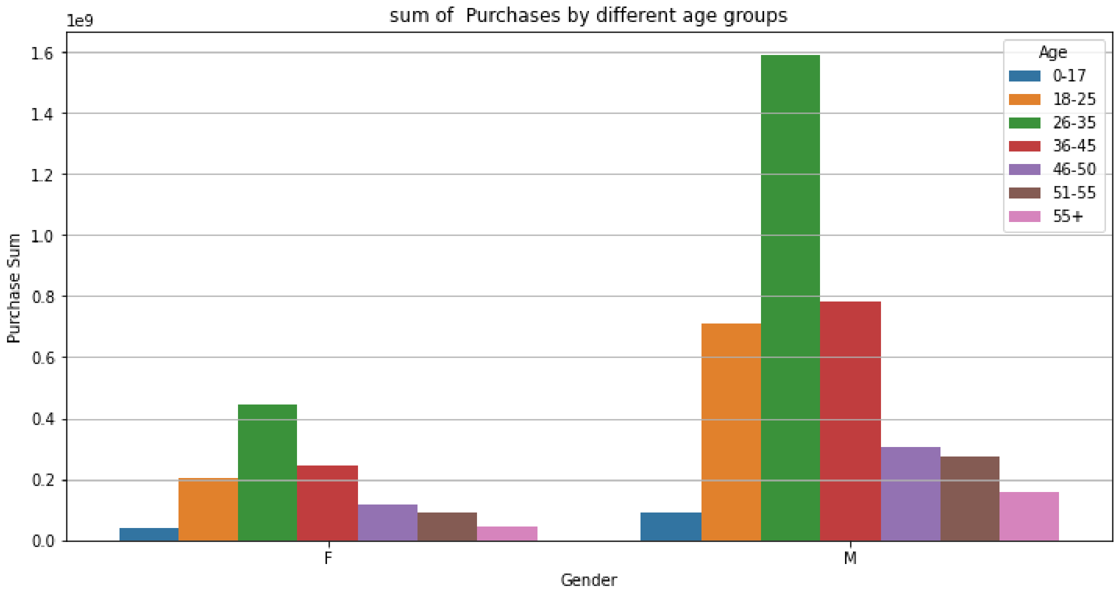
[162]:
```
df_grouped_GA= df.groupby(['Gender', 'Age'])['Purchase'].count().reset_index()
df_grouped_GA
```

[162]:

	Gender	Age	Purchase
0	F	0-17	5083
1	F	18-25	24628
2	F	26-35	50752
3	F	36-45	27170
4	F	46-50	13199
5	F	51-55	9894
6	F	55+	5083
7	M	0-17	10019
8	M	18-25	75032
9	M	26-35	168835
10	M	36-45	82843
11	M	46-50	32502
12	M	51-55	28607
13	M	55+	16421

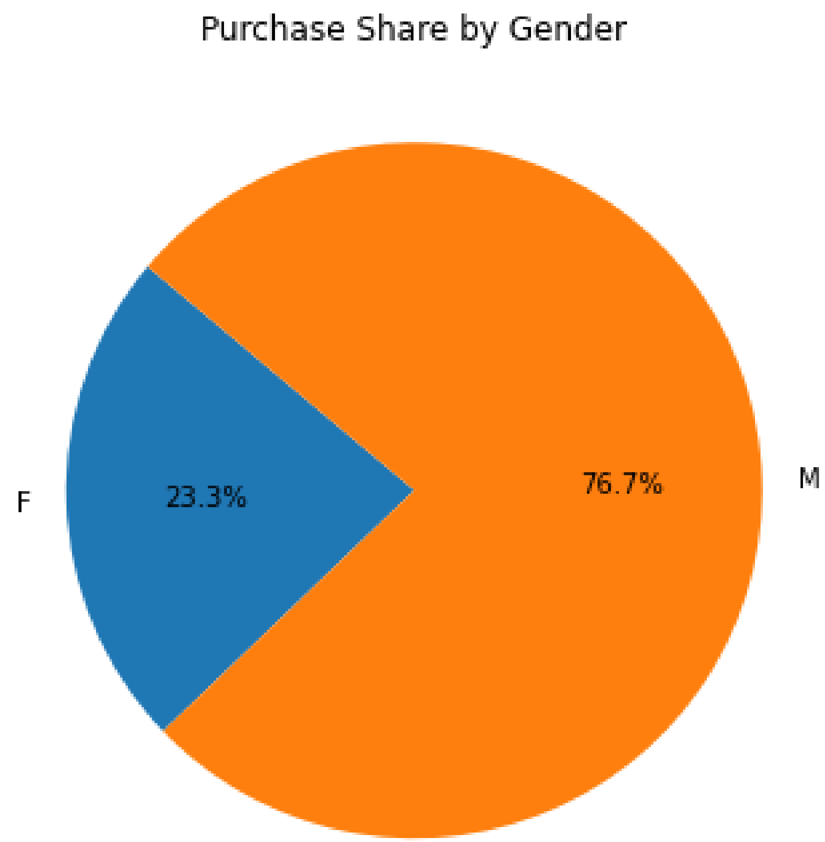
The count and total purchase plots are highly correlated. We will explore the gender dependece on purchases as well

[170]:
```
df_grouped_GA= df.groupby(['Gender', 'Age'])['Purchase'].sum().
 ↪reset_index()#aggregating by the sum
plt.figure(figsize=(12,6))
sns.barplot(x='Gender', y='Purchase', hue='Age', data=df_grouped_GA)
plt.ylabel('Purchase Sum')
plt.title("sum of  Purchases by different age groups")
plt.grid(True, axis='y')
```



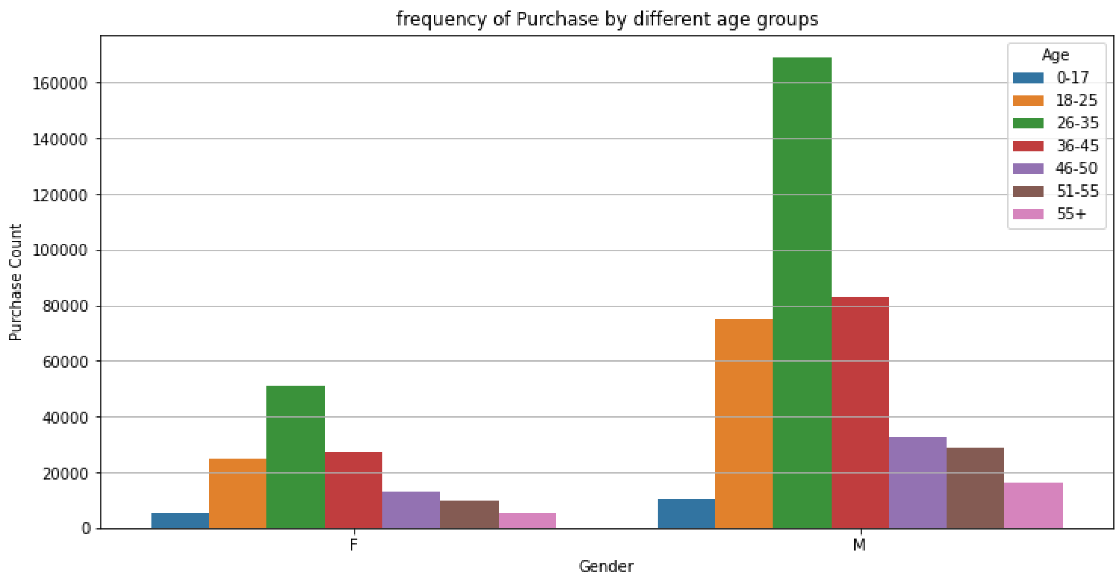
[177]:
```
df_group_gender = df_grouped_GA.groupby('Gender')['Purchase'].sum()
plt.figure(figsize=(6, 6))
plt.pie(df_group_gender, labels=df_group_gender.index, autopct='%1.1f%%',␣
 ↪startangle=140)
plt.title('Purchase Share by Gender')
```

[177]: Text(0.5, 1.0, 'Purchase Share by Gender')



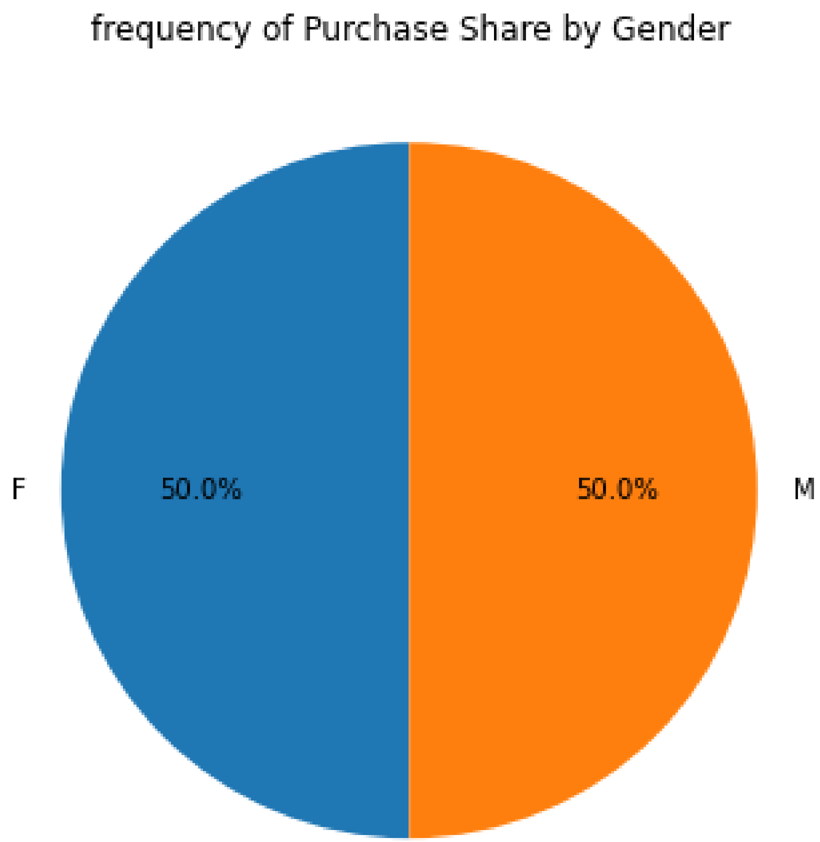
It can be seen that the purchases are highly skewed towards Male. The retail company might want to think about tapping the potential buyers in females and design prodcuts as well as marketting strategy accordingly

[172]:
```
df_grouped_GA1= df.groupby(['Gender', 'Age'])['Purchase'].count().
    ↪reset_index()#aggregating by the sum
plt.figure(figsize=(12,6))
sns.barplot(x='Gender', y='Purchase', hue='Age', data=df_grouped_GA1)
plt.ylabel('Purchase Count')
plt.title("frequency of Purchase by different age groups")
plt.grid(True, axis='y')
```



[175]:
```
df_group_gender1 = df_grouped_GA.groupby('Gender')['Purchase'].count() #through␣
↪count
plt.figure(figsize=(6, 6))
plt.pie(df_group_gender1, labels=df_group_gender1.index, autopct='%1.1f%%',␣
↪startangle=90)
plt.title('frequency of Purchase Share by Gender')
```

[175]:
```
Text(0.5, 1.0, 'frequency of Purchase Share by Gender')
```



Strangely, The frequnecy of purchase is same for male and female. That means women are buying cheaper products then men. Or the products of the company for men are costlier than women on average.

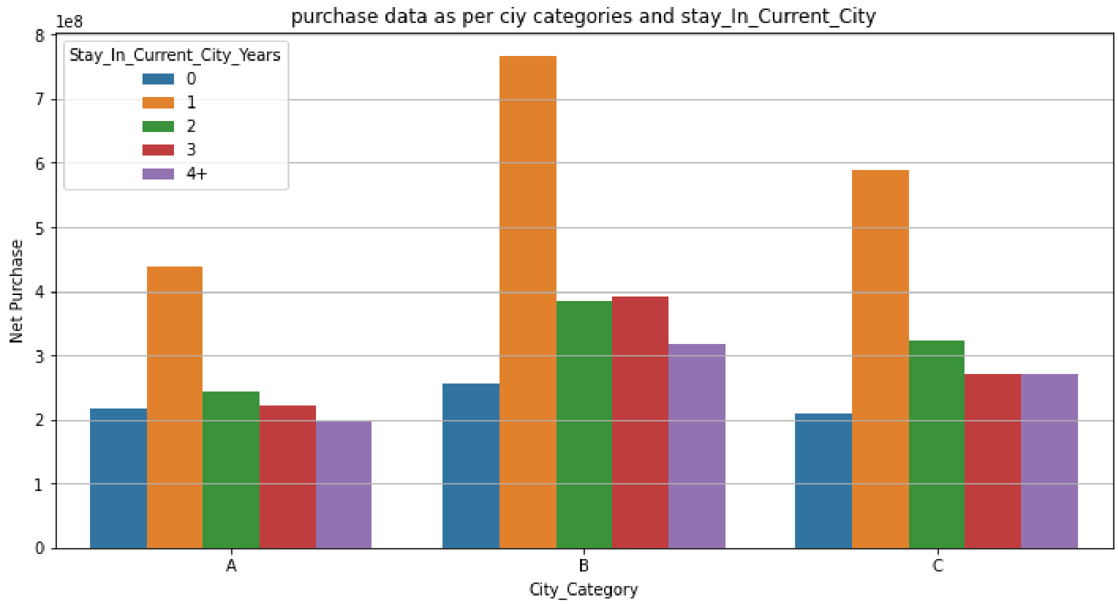
[173]:
```
df_grouped_city=df.
  ↪groupby(['City_Category','Stay_In_Current_City_Years'])['Purchase'].count().
  ↪reset_index()
df_grouped_city
```

[173]:

	City_Category	Stay_In_Current_City_Years	Purchase
0	A	0	24178
1	A	1	49305
2	A	2	27114
3	A	3	24804
4	A	4+	22319
5	B	0	28687
6	B	1	83413
7	B	2	41772

```
8          B      3   42691
9          B     4+   34610
10         C      0   21533
11         C      1   61103
12         C      2   32952
13         C      3   27790
14         C     4+   27797
```

[155]:
```
plt.figure(figsize=(12,6))
sns.barplot(x='City_Category', y='Purchase', hue='Stay_In_Current_City_Years',␣
↪data=df_grouped_city)
plt.ylabel('Net Purchase')
plt.title("purchase data as per ciy categories and stay_In_Current_City")
plt.grid(True, axis='y')
```



Customers who have come to the city in last one year have purchased the most. This quntity as shown in above plot, by far exceeds the others, who have mmore or less same distribution Further City_Category B has given the most purchases to the company.

[187]:
```
df.groupby('Occupation')['Purchase'].sum().sort_values()[:5]
```

[187]:
```
Occupation
8      14737388
9      54340046
18     60721461
13     71919481
19     73700617
```

```
Name: Purchase, dtype: int64
```

[188]:
```
df.groupby('Occupation')['Purchase'].sum().sort_values(ascending = False)[:5]
```

[188]:
```
Occupation
4     666244484
0     635406958
7     557371587
1     424614144
17    393281453
Name: Purchase, dtype: int64
```

Occupation levels 4,0,and 7 are the most spender who bought the prodcts where as occupation level 8 is the least spender

Now we will see which type of products have got more purchase we had created a df named df2 consiting of all details about products

[194]:
```
df2.head(20)
```

[194]:
```
   Product_ID  Product_Category_1  Product_Category_2  Product_Category_3  \
0   P00069042                   3                 NaN                 NaN
1   P00248942                   1                 6.0                14.0
2   P00087842                  12                 NaN                 NaN
3   P00085442                  12                14.0                 NaN
4   P00285442                   8                 NaN                 NaN
5   P00193542                   1                 2.0                 NaN
6   P00184942                   1                 8.0                17.0
7   P00346142                   1                15.0                 NaN
8    P0097242                   1                16.0                 NaN
9   P00274942                   8                 NaN                 NaN
10  P00251242                   5                11.0                 NaN
11  P00014542                   8                 NaN                 NaN
12  P00031342                   8                 NaN                 NaN
13  P00145042                   1                 2.0                 5.0
14  P00231342                   5                 8.0                14.0
15  P00190242                   4                 5.0                 NaN
16   P0096642                   2                 3.0                 4.0
17  P00058442                   5                14.0                 NaN
18  P00036842                   1                14.0                16.0
19  P00249542                   1                 5.0                15.0

    Purchase
0       8370
1      15200
2       1422
3       1057
4       7969
```

```
5       15227
6       19215
7       15854
8       15686
9        7871
10       5254
11       3957
12       6073
13      15665
14       5378
15       2079
16      13055
17       8851
18      11788
19      19614
```

Product_Category_1 is the primary category and one product may belong to more than one category #So if we have to find category wise Purchase, we need to see three columns together. There are total 20 product category

[219]:
```
x= df.Product_Category_1.unique() #All product categories
y= np.zeros(df.Product_Category_1.unique().shape[0]) #purchases made from the␣
↪categories
k=-1
#df2.loc['Product_Category_1'] = df2.loc['Product_Category_1'].astype('float64')
for i in x:
    k=k+1
    for j in range(df2.shape[0]):
        if df2.Product_Category_1[j] ==i or df2.Product_Category_2[j]==i or df2.
↪Product_Category_1[j] ==i:
            y[k]+= df2.Purchase[j]

print(x,y)
```

```
[ 3  1 12  8  5  4  2  6 14 11 13 15  7 16 18 10 17  9 20 19] [2.36487490e+08
1.91001375e+09 4.38922560e+07 1.51271146e+09
 1.17868013e+09 2.89675973e+08 9.38820050e+08 5.13567779e+08
 4.11571635e+08 2.40157280e+08 1.05983985e+08 4.85036218e+08
 6.52065430e+07 5.90460334e+08 3.51964610e+07 1.48456385e+08
 1.31374099e+08 4.77983240e+07 9.44727000e+05 5.93780000e+04]
```

sum of y values will not match with the sum of total purchases. y represents the total purchase corresponding the product category in X

[225]:
```
pp=pd.DataFrame({'Product_ID': x, 'Purchase': y})
pp['Purchase']=pp['Purchase']/1000000
pp
```

[225]:

	Product_ID	Purchase
0	3	236.487490
1	1	1910.013754
2	12	43.892256
3	8	1512.711455
4	5	1178.680128
5	4	289.675973
6	2	938.820050
7	6	513.567779
8	14	411.571635
9	11	240.157280
10	13	105.983985
11	15	485.036218
12	7	65.206543
13	16	590.460334
14	18	35.196461
15	10	148.456385
16	17	131.374099
17	9	47.798324
18	20	0.944727
19	19	0.059378

[232]:

```
plt.figure(figsize=(14,6))
sns.barplot(data=pp,x='Product_ID',y='Purchase',color = 'red')
plt.title('Purchase vs Product categories')
plt.ylabel('Net Purchasein millions')
```

[232]: Text(0, 0.5, 'Net Purchasein millions')

Now its clear which category has been purchased the most and whch categories aren't contributing

[233]:
```
#lets find out the individual products purchase pattern:
df.groupby('Product_ID')['Purchase'].sum().sort_values(ascending=False).
↪reset_index()
```

[233]:

	Product_ID	Purchase
0	P00025442	27995166
1	P00110742	26722309
2	P00255842	25168963
3	P00059442	24338343
4	P00184942	24334887
…	…	…
3626	P00012942	1717
3627	P00325342	1656
3628	P00353042	1545
3629	P00309042	726
3630	P00091742	405

[3631 rows x 2 columns]

Now it is clear which products are getting sold the most and which products are heating the selves only.

[ ]:
```

```