Marketing Analytics

For

E-Commerce Market Place Company

In [1]:
```
import numpy as np
import pandas as pd
from itertools import combinations
from collections import Counter
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
```

In [2]:
```
# import files:
cust = pd.read_csv('CUSTOMERS.csv')
order_pay = pd.read_csv('ORDER_PAYMENTS.csv')
geo = pd.read_csv('GEO_LOCATION.csv')
order_items = pd.read_csv('ORDER_ITEMS.csv')
order_review = pd.read_csv('ORDER_REVIEW_RATINGS.csv')
orders = pd.read_csv('ORDERS.csv')
products = pd.read_csv('PRODUCTS.csv')
sellers = pd.read_csv('SELLERS.csv')
```

In [3]:
```
# merging the datasets as per requirements based on flow chart:
cust_order =pd.merge(left=cust, right=orders, how="inner", on="customer_ic

```

In [4]:
```
a=pd.merge(left=cust_order, right=order_items, how="right", on="order_id")

```

In [5]:
```
b=pd.merge(left=a, right=order_pay, how="inner", on="order_id")

```

In [6]:
```
c=pd.merge(left=b, right=products, how="left", on="product_id")

```

In [7]:
```
d=pd.merge(left=c, right=order_review, how="left", on="order_id")
```

In [8]:
```
# final dataframe
df = pd.merge(left=d, right=sellers, how="left", on="seller_id")
df.head()
```

Out[8]:

	customer_id	customer_unique_id	customer_zip_code_pı
0	3ce436f183e68e07877b285a838db11a	871766c5855e863f6eccc05f988b23cb	28
1	f6dd3ec061db4e3987629fe6b26e5cce	eb28e67c4c0b83846050ddfb8a35d051	15
2	6489ae5e4333f3693df5ad4372dab6d3	3818d81c6709e39d06b2738a8d3a2474	35
3	d4eb9395c8c0431ee92fce09860c5a06	af861d436cfc08b2c2ddefd0ba074622	12
4	58dbd0b2d70206bf40e62cd34e84d795	64b576fb70d441e8f1b2d7d446e483c5	13

5 rows × 37 columns

In [9]:
```
df.columns
```

Out[9]:
```
Index(['customer_id', 'customer_unique_id', 'customer_zip_code_prefix',
       'customer_city', 'customer_state', 'order_id', 'order_status',
       'order_purchase_timestamp', 'order_approved_at',
       'order_delivered_carrier_date', 'order_delivered_customer_date',
       'order_estimated_delivery_date', 'order_item_id', 'product_id',
       'seller_id', 'shipping_limit_date', 'price', 'freight_value',
       'payment_sequential', 'payment_type', 'payment_installments',
       'payment_value', 'product_category_name', 'product_name_lenght',
       'product_description_lenght', 'product_photos_qty', 'product_weight_
g',
       'product_length_cm', 'product_height_cm', 'product_width_cm',
       'review_id', 'review_score', 'review_creation_date',
       'review_answer_timestamp', 'seller_zip_code_prefix', 'seller_city',
       'seller_state'],
      dtype='object')
```

In [10]:
```
# drop extra not usefull columns
df=df.drop(columns=['order_approved_at','order_delivered_carrier_date','or
                    'order_delivered_customer_date','shipping_limit_date'
                    'product_description_lenght','product_weight_g','proc
                    'product_height_cm','product_width_cm','review_creat:
```

In [11]:
```
# treating with missing data using UDF:

def missing_var(x):
    if ((x.dtype == 'float') or (x.dtype == 'int')):
        x = x.fillna(x.median())

    elif x.dtype == 'object':
        x = x.fillna(x.mode()[0])

    else:
        x
    return (x)
```

In [12]:
```
df = df.apply(missing_var)
```

In [13]:
```
df.isna().sum()
```

Out[13]:
```
customer_id                 0
customer_unique_id          0
customer_zip_code_prefix    0
customer_city               0
customer_state              0
order_id                    0
order_status                0
order_purchase_timestamp    0
order_item_id               0
product_id                  0
seller_id                   0
price                       0
freight_value               0
payment_sequential          0
payment_type                0
payment_installments        0
payment_value               0
product_category_name       0
product_photos_qty          0
review_id                   0
review_score                0
seller_zip_code_prefix      0
seller_city                 0
seller_state                0
dtype: int64
```

In [14]:
```
# change datatype of date:
df['order_purchase_timestamp'] = pd.to_datetime(df['order_purchase_timesta
```

1. Perform Detailed exploratory analysis

a. Define & calculate high level metrics like (Total Revenue, Total quantity, Total products, Total categories, Total sellers, Total

In [15]:
```python
print('Total Revenue:', df['payment_value'].sum())
print('Total quantity:', df['order_id'].nunique())
print('Total products:', df['product_id'].nunique())
print('Total categories:', df['product_category_name'].nunique())
print('Total sellers:', df['seller_id'].nunique())
print('Total locations:', df['customer_zip_code_prefix'].nunique())
print('Total payment methods:', df['payment_type'].nunique())
```

```
Total Revenue: 20418288.150000002
Total quantity: 98665
Total products: 32951
Total categories: 71
Total sellers: 3095
Total locations: 14976
Total payment methods: 4
```

b. Understanding how many new customers acquired every month

In [16]:
```python
#Extracting months from purchase date:
df['Month'] = df['order_purchase_timestamp'].dt.to_period('M')
```

In [17]:
```python
x = pd.crosstab(df.Month, df.customer_id)

x.sum(axis = 1)
```

Out[17]:
```
Month
2016-09       3
2016-10     386
2016-12       1
2017-01    1023
2017-02    2073
2017-03    3201
2017-04    2864
2017-05    4445
2017-06    3822
2017-07    4887
2017-08    5224
2017-09    5137
2017-10    5617
2017-11    9096
2017-12    6595
2018-01    8603
2018-02    8025
2018-03    8592
2018-04    8273
2018-05    8231
2018-06    7396
2018-07    7356
2018-08    7464
2018-09       1
Freq: M, dtype: int64
```

c. Understand the retention of customers on month on month basis

In [18]:
```
df['customer_id'].nunique()
```

Out[18]:
```
98665
```

d. How the revenues from existing/new customers on month on month basis

In [19]:
```
df.groupby('Month')['payment_value'].sum()
```

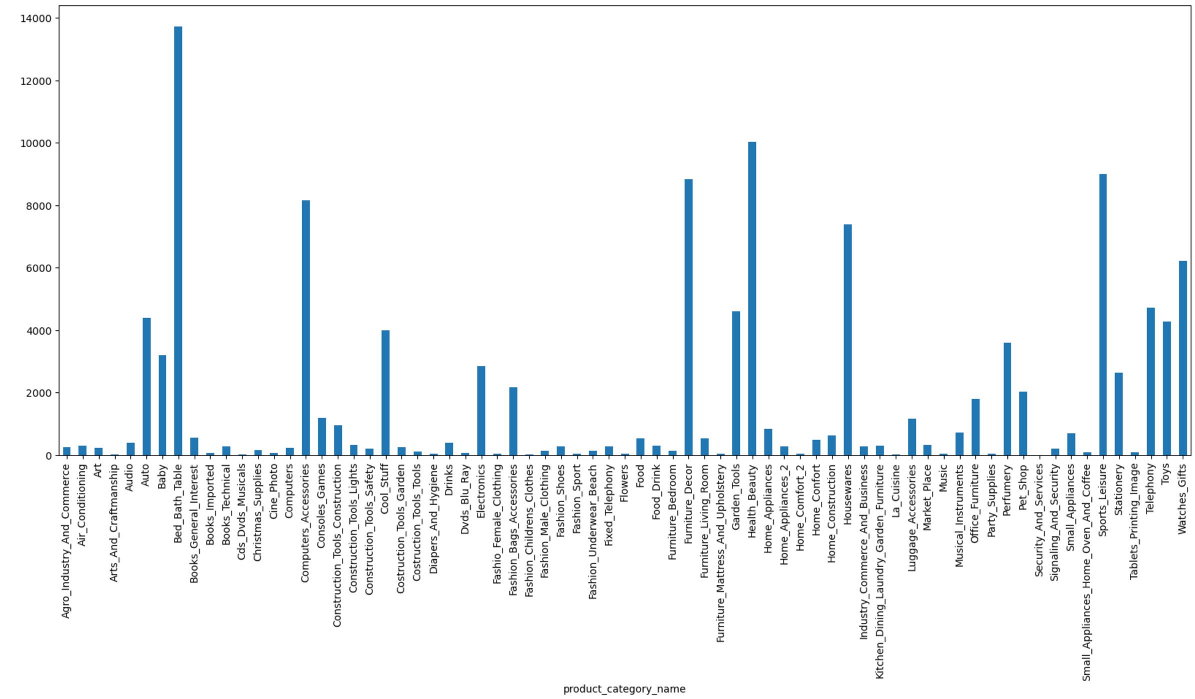
Out[19]:
```
Month
2016-09        347.52
2016-10      74773.54
2016-12         19.62
2017-01     189570.02
2017-02     346280.99
2017-03     529993.27
2017-04     506900.50
2017-05     730912.77
2017-06     605639.30
2017-07     741936.39
2017-08     878027.04
2017-09    1023361.16
2017-10    1035728.78
2017-11    1595006.04
2017-12    1046429.88
2018-01    1418478.51
2018-02    1322340.41
2018-03    1482224.09
2018-04    1499387.74
2018-05    1507872.59
2018-06    1298592.17
2018-07    1354550.94
2018-08    1229748.42
2018-09        166.46
Freq: M, Name: payment_value, dtype: float64
```

e. Understand the trends/seasonality of sales, quantity by category, location, month, week, day, time, channel, payment method etc…

In [20]:

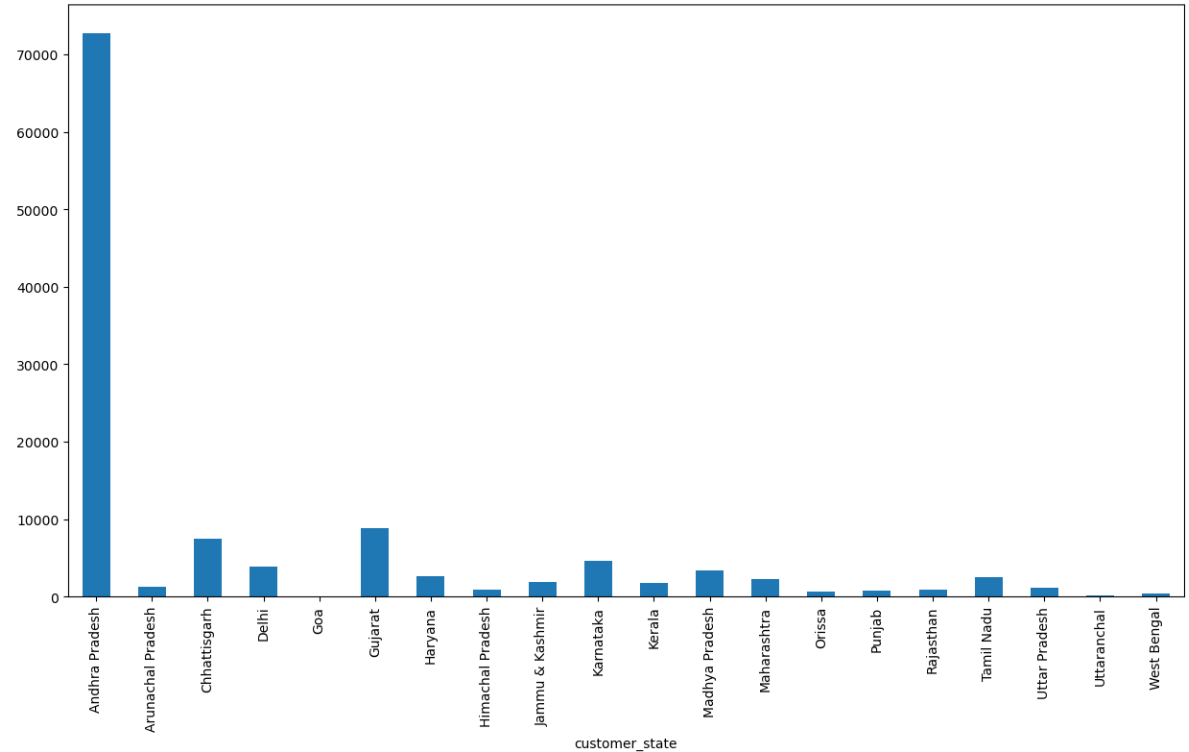
```
#ploting bar chart for prod category name and order id to understand trend
df.groupby('product_category_name')['order_id'].count().plot(kind = 'bar',
```

Out[20]: <AxesSubplot:xlabel='product_category_name'>



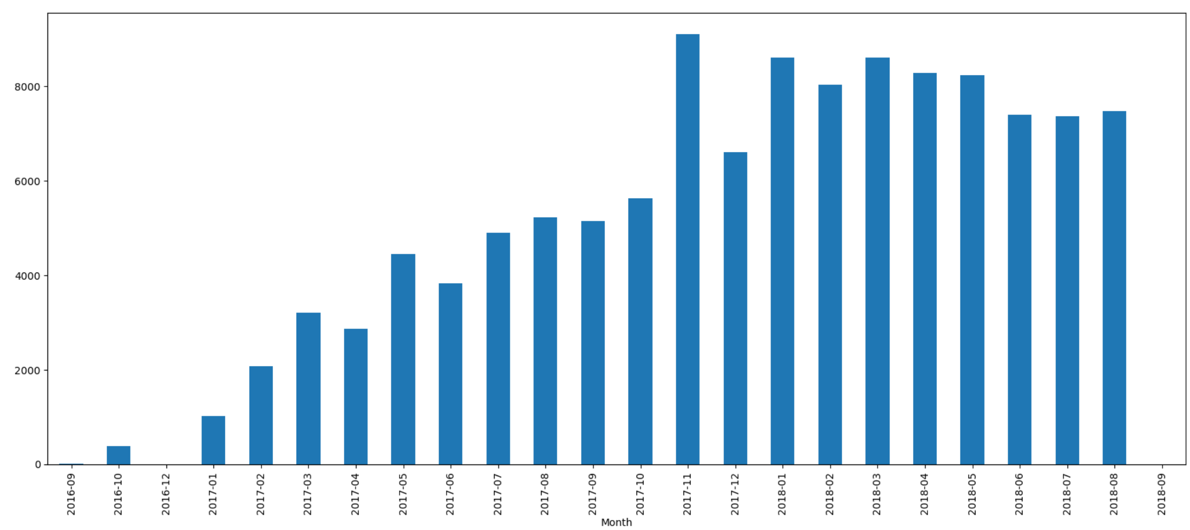
In [21]:
```
1 #ploting bar chart for customer state name and order id to understand tren
2 df.groupby('customer_state')['order_id'].count().plot(kind = 'bar', figsi
```

Out[21]: <AxesSubplot:xlabel='customer_state'>



In [22]:
```
1 #ploting bar chart for time period name and order id to understand trends
2 df.groupby('Month')['order_id'].count().plot(kind = 'bar', figsize= (20,8)
```

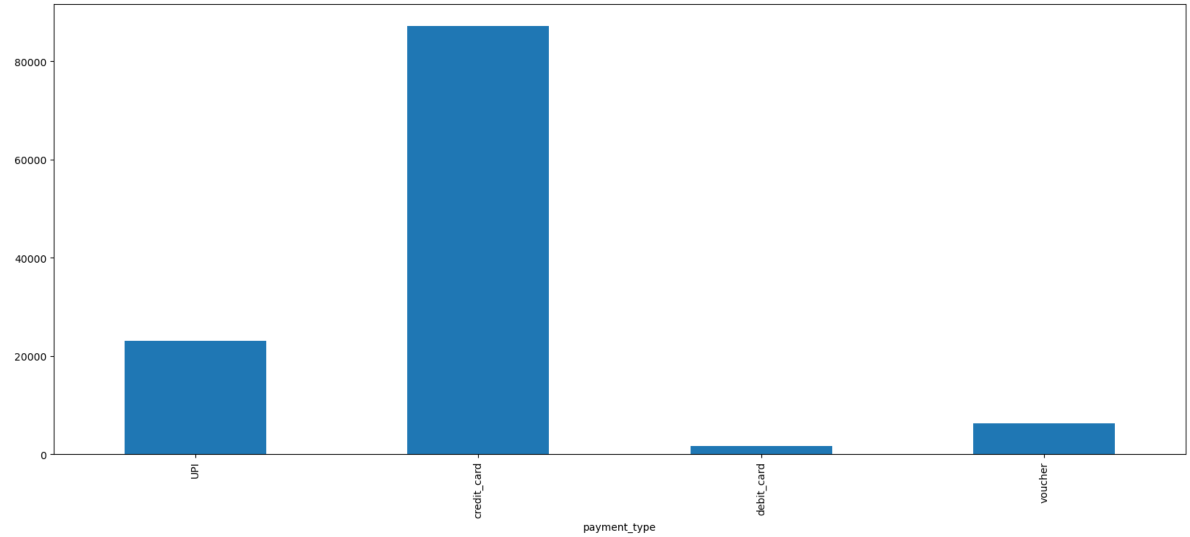
Out[22]: <AxesSubplot:xlabel='Month'>



In [23]:

```
#ploting bar chart for payment method name and order id to understand trer
df.groupby('payment_type')['order_id'].count().plot(kind = 'bar', figsize=
```

Out[23]: <AxesSubplot:xlabel='payment_type'>



f. Popular Products by month, seller, state, category.

In [24]:

```
#popular products on the basis of months
x = df.groupby(['Month',df.product_id.rename('product')]).product_id.count
                                                      ['Month','product_
x = x.groupby('Month').head().reset_index(drop= True)
x
```

Out[24]:

	Month	product	product_id
0	2016-09	c1488892604e4ba5cff5b4eb4d595400	1
1	2016-09	f293394c72c9b5fafd7023301fc21fc2	1
2	2016-09	f3c2d01a84c947b078e32bbef0718962	1
3	2016-10	eba7488e1c67729f045ab43fac426f2e	11
4	2016-10	85b99d83c60cab5b4d8f927ad35212a1	7
...	...	...	...
105	2018-08	73326828aa5efe1ba096223de496f596	56
106	2018-08	19c91ef95d509ea33eda93495c4d3481	32
107	2018-08	2bd9b51a9ab079e095aca987845d3266	29
108	2018-08	a92930c327948861c015c919a0bcb4a8	29
109	2018-09	b98992ea80b467987a7fbb88e7f2076a	1

110 rows × 3 columns

In [25]:
```
#popular products on the basis of sellers
x1 = df.groupby(['seller_id',df.product_id.rename('product')]).product_id.
                                                    ['product_id'],asc
x1 = x1.groupby('seller_id').head().reset_index(drop= True)
x1
```

Out[25]:

	seller_id	product	product_id
0	955fee9216a65b617aa5c0531780ce60	aca2eb7d00ea1a7b8ebd4e68314663af	536
1	4a3ca9315b744ce9f8e9374361493884	99a4788cb24856965c36a24e339b6058	522
2	1f50f920176fa81dab994f9023523100	422879e10f46682990de24d770e7f83d	508
3	1f50f920176fa81dab994f9023523100	389d119b48cf3043d311335e499d9c6b	406
4	1f50f920176fa81dab994f9023523100	368c6c730842d78016ad823897a372db	398
...	...	...	...
10367	70849ca4f400aaabb62cb7462a6f1428	abf460fbe81f4b2741cd059df2925fff	1
10368	702835e4b785b67a084280efca355756	a9c404971d1a5b1cbc2e4070e02731fd	1
10369	70126eecc6aa1274392a1743866e9678	3a96bcbf644a5d390107570628568026	1
10370	70125af26c2d6d4ef401a1d02ae7701f	4ce99ff9dcb7821acd8e599d5d4a6531	1
10371	700f03c207639c22d933381ff60b35c2	527921e5d38d82e839ef2195d6455fc6	1

10372 rows × 3 columns

In [26]:
```
#popular products on the basis of state
x1 = df.groupby(['customer_state',df.product_id.rename('product')]).produc
                                                    ['product_id'],asc
x1 = x1.groupby('customer_state').head().reset_index(drop= True)
x1
```

Out[26]:

	customer_state	product	product_id
0	Andhra Pradesh	aca2eb7d00ea1a7b8ebd4e68314663af	346
1	Andhra Pradesh	99a4788cb24856965c36a24e339b6058	322
2	Andhra Pradesh	422879e10f46682990de24d770e7f83d	302
3	Andhra Pradesh	389d119b48cf3043d311335e499d9c6b	226
4	Andhra Pradesh	53b36df67ebb7c41585e8d54d6772e08	226
...	...	...	...
95	Goa	bfc275f6de912665e4dcd8da32f43c10	1
96	Goa	d9c2eaccfa617895e2720f212e592de1	1
97	Goa	dd231637766e756fd1cf2fd80501fce1	1
98	Goa	b99e4f4fa3f421e0ffbd512d9f152dec	1
99	Goa	a50acd33ba7a8da8e9db65094fa990a4	1

100 rows × 3 columns

In [27]:
```
#popular products on the basis of category
x1 = df.groupby(['product_category_name',df.product_id.rename('product')])
                                                    ['product_id'],asc
x1 = x1.groupby('product_category_name').head().reset_index(drop= True)
x1
```

Out[27]:

	product_category_name	product	product_id
0	Furniture_Decor	aca2eb7d00ea1a7b8ebd4e68314663af	536
1	Bed_Bath_Table	99a4788cb24856965c36a24e339b6058	528
2	Garden_Tools	422879e10f46682990de24d770e7f83d	508
3	Garden_Tools	389d119b48cf3043d311335e499d9c6b	406
4	Garden_Tools	368c6c730842d78016ad823897a372db	398
...	...	...	...
343	Home_Comfort_2	4fb3bad6b502eaca3b6d7d87bc1613a4	1
344	Home_Comfort_2	2072d4792ab7893ddbfc178948e0eb86	1
345	Fashion_Childrens_Clothes	0ab3ab3b2869073aa9afe795fe9151aa	1
346	Fashion_Childrens_Clothes	2b18330ce86ae5c606250b75b499f370	1
347	Fashion_Childrens_Clothes	28ac6af4008a402e5039f3e042a36e13	1

348 rows × 3 columns

g. Popular categories by state, month

In [28]:

```
#popular categories by state:
y = df.groupby(['customer_state',df.product_category_name.rename('cat_name
                                                                          [
y = y.groupby('customer_state').head(5).reset_index(drop=True)
y
```

Out[28]:

	customer_state	cat_name	product_category_name
0	Andhra Pradesh	Bed_Bath_Table	8880
1	Andhra Pradesh	Health_Beauty	6231
2	Andhra Pradesh	Furniture_Decor	5579
3	Andhra Pradesh	Sports_Leisure	5568
4	Andhra Pradesh	Computers_Accessories	5067
...	...	...	...
95	West Bengal	Health_Beauty	45
96	West Bengal	Bed_Bath_Table	40
97	West Bengal	Telephony	34
98	West Bengal	Computers_Accessories	33
99	West Bengal	Sports_Leisure	26

100 rows × 3 columns

In [29]:
```
#popular categories by month:
y = df.groupby(['Month',df.product_category_name.rename('cat_name')]).proc
                                                                          [
y = y.groupby('Month').head(5).reset_index(drop=True)
y
```

Out[29]:

	Month	cat_name	product_category_name
0	2016-09	Furniture_Decor	2
1	2016-09	Telephony	1
2	2016-10	Furniture_Decor	80
3	2016-10	Health_Beauty	50
4	2016-10	Perfumery	36
...	...	...	...
104	2018-08	Bed_Bath_Table	714
105	2018-08	Housewares	650
106	2018-08	Sports_Leisure	481
107	2018-08	Furniture_Decor	461
108	2018-09	Kitchen_Dining_Laundry_Garden_Furniture	1

109 rows × 3 columns

h. List top 10 most expensive products sorted by price

In [30]:
```
df.groupby('product_id')['payment_value'].sum().reset_index().sort_values(
```

Out[30]:

	product_id	payment_value
11352	5769ef0a239114ac3a854af00df129e4	109312.64
24086	bb50f2e236e5eea0100680137654686c	82226.19
8613	422879e10f46682990de24d770e7f83d	80151.10
27039	d1c427060a0f73f6b889a5c7c61f2ac4	70557.90
14068	6cdd53843498f92890544667809f1595	64825.67
...	...	...
10782	5304ff3fa35856a156e1170a6022d34d	12.22
13461	680cc8535be7cc69544238c1d6a83fe8	11.62
1958	0eeeb45e2f5911fd44282e5bb0c624ff	11.56
6388	310dc32058903b6416c71faff132df9e	10.07
9238	46fce52cef5caa7cc225a5531c946c8b	9.59

32951 rows × 2 columns

2. Performing Customers/sellers Segmentation

a. Divide the customers into groups based on the revenue generated

In [31]:
```
#create groups on the basis of payment_value
df['revenue_group'] = np.where(df["payment_value"]<2000,1,(np.where(df["pa
                                                  np.where(df["payment_value"]<6000,3,(
                                                 (np.where(df["payment_value"]<10000,5,
```

In [32]:
```
df.groupby(['revenue_group','customer_id'])['payment_value'].sum()
```

Out[32]:
```
revenue_group  customer_id
1              00012a2ce6f8dcda20d059ce98491703       114.74
               000161a058600d5901f007fab4c27140        67.41
               0001fd6190edaaf884bcaf3d49edf079       195.42
               0002414f95344307404f0ace7a26f1d5       179.35
               000379cdec625522490c315e70c7a9fb       107.01
                                                       ...
4              3fd6777bbce08a352fddd04e4a7cc8f6      6726.66
               c6e2731c5b391845f6800c97401a43a9      6929.31
               ec5b2ba62e574342386871631fafd3fc     29099.52
               f48d464a0baaea338cb25f816991ab1f      6922.21
7              1617b1357756262bfa56ab541c47bc16    109312.64
Name: payment_value, Length: 98670, dtype: float64
```

b. Divide the sellers into groups based on the revenue generated

In [33]:
```
df.groupby(['revenue_group','seller_id'])['payment_value'].sum()
```

Out[33]:
```
revenue_group  seller_id
1              0015a82c2db000af6aaaf3ae2ecb0532      2748.06
               001cca7ae9ae17fb1caed9dfb1094831     48349.22
               001e6ad469a905060d959994f1b41e4f       267.94
               002100f778ceb8431b7a1020ff7ab48f      2478.33
               003554e2dce176b5555353e4f3555ac8       139.38
                                                       ...
4              b37c4c02bda3161a7546a4e6d222d5b2     29099.52
               e3b4998c7a498169dc7bce44e6bb6277      6929.31
               ee27a8f15b1dded4d213a468ba4eb391      6726.66
               f08a5b9dd6767129688d001acafc21e5     36489.24
7              b37c4c02bda3161a7546a4e6d222d5b2    109312.64
Name: payment_value, Length: 3191, dtype: float64
```

3. Cross-Selling (Which products are selling

together)

Hint: We need to find which of the top 10 combinations

In [34]:
```
df.columns
```

Out[34]:
```
Index(['customer_id', 'customer_unique_id', 'customer_zip_code_prefix',
       'customer_city', 'customer_state', 'order_id', 'order_status',
       'order_purchase_timestamp', 'order_item_id', 'product_id', 'seller_i
d',
       'price', 'freight_value', 'payment_sequential', 'payment_type',
       'payment_installments', 'payment_value', 'product_category_name',
       'product_photos_qty', 'review_id', 'review_score',
       'seller_zip_code_prefix', 'seller_city', 'seller_state', 'Month',
       'revenue_group'],
      dtype='object')
```

In [35]:
```
# Assuming the data is available in the Order_Items table with columns 'or

# Group the data at the order level and aggregate the product names as a l
order_items = df.groupby('order_id')['product_category_name'].apply(list)
```

In [36]:
```
# Generate combinations of 2 and 3 products for each order
combinations_2 = order_items.apply(lambda x: list(combinations(x, 2)))
combinations_3 = order_items.apply(lambda x: list(combinations(x, 3)))
```

In [37]:
```
# Count the occurrences of each combination
count_2 = Counter([item for sublist in combinations_2 for item in sublist]
count_3 = Counter([item for sublist in combinations_3 for item in sublist]
```

In [38]:
```
# Get the top 10 combinations
top_10_combinations_2 = count_2.most_common(10)
top_10_combinations_3 = count_3.most_common(10)
```

In [ ]:
```

```

In [39]:
```
# Assuming the data is available at the customer and seller level with col

# Combine revenue from Orders table for each customer
customer_revenue = df.groupby('customer_id')['payment_value'].sum()
```

In [40]:
```
customer_revenue
```

Out[40]:
```
customer_id
00012a2ce6f8dcda20d059ce98491703    114.74
000161a058600d5901f007fab4c27140     67.41
0001fd6190edaaf884bcaf3d49edf079    195.42
0002414f95344307404f0ace7a26f1d5    179.35
000379cdec625522490c315e70c7a9fb    107.01
                                     ...
fffcb937e9dd47a13f05ecb8290f4d3e     91.91
fffecc9f79fd8c764f843e9951b11341     81.36
fffeda5b6d849fbd39689bb92087f431     63.13
ffff42319e9b2d713724ae527742af25    214.13
ffffa3172527f765de70084a7e53aae8     91.00
Name: payment_value, Length: 98665, dtype: float64
```

In [41]:
```
# Divide customers into groups based on revenue using deciles
customer_segments = pd.qcut(customer_revenue, 10, labels=False)
```

In [42]:
```
# Combine revenue from Orders table for each seller
seller_revenue = df.groupby('seller_id')['payment_value'].sum()
```

In [43]:
```
# Divide sellers into groups based on revenue using deciles
seller_segments = pd.qcut(seller_revenue, 10, labels=False)
```

In [44]:
```
seller_segments.head(15)
```

Out[44]:
```
seller_id
0015a82c2db000af6aaaf3ae2ecb0532    6
001cca7ae9ae17fb1caed9dfb1094831    9
001e6ad469a905060d959994f1b41e4f    2
002100f778ceb8431b7a1020ff7ab48f    6
003554e2dce176b5555353e4f3555ac8    1
004c9cd9d87a3c30c522c48c4fc07416    9
00720abe85ba0859807595bbf045a33b    6
00ab3eff1b5192e5f1a63bcecfee11c8    0
00d8b143d12632bad99c0ad66ad52825    1
00ee68308b45bc5e2660cd833c3f81cc    9
00fc707aaaad2d31347cf883cd2dfe10    9
010543a62bd80aa422851e79a3bc7540    5
010da0602d7774602cd1b3f5fb7b709e    7
011b0eaba87386a2ae96a7d32bb531d1    2
01266d4c46afa519678d16a8b683d325    1
Name: payment_value, dtype: int64
```

In [ ]:
```

```

4. Payment Behaviour

a. How customers are paying?

In [45]:
```
df['payment_type'].unique()
```

Out[45]:
```
array(['credit_card', 'UPI', 'voucher', 'debit_card'], dtype=object)
```

b. Which payment channels are used by most customers?

In [46]:
```
df.groupby('payment_type')['customer_id'].count().reset_index().sort_value
```

Out[46]:

	payment_type	customer_id
1	credit_card	87266
0	UPI	23018
3	voucher	6332
2	debit_card	1699

5. Customer satisfaction towards category & product

a. Which categories (top 10) are maximum rated & minimum rated?

In [47]:
```
#top 10 categories maximum rated:
df.groupby('product_category_name')['review_score'].mean().reset_index().s
```

Out[47]:

	product_category_name	review_score
0	Cds_Dvds_Musicals	4.642857
1	Fashion_Childrens_Clothes	4.500000
2	Books_General_Interest	4.431858
3	Books_Imported	4.419355
4	Books_Technical	4.345588
5	Costruction_Tools_Tools	4.333333
6	Small_Appliances_Home_Oven_And_Coffee	4.320513
7	Food_Drink	4.312715
8	Luggage_Accessories	4.290628
9	Fashion_Sport	4.258065

In [48]:
```
#top 10 categories minimum rated:
df.groupby('product_category_name')['review_score'].mean().reset_index().s
```

Out[48]:

	product_category_name	review_score
0	Security_And_Services	2.500000
1	Diapers_And_Hygiene	3.256410
2	Home_Comfort_2	3.387097
3	Office_Furniture	3.516779
4	Fashion_Male_Clothing	3.531034
5	Fixed_Telephony	3.661765
6	Fashio_Female_Clothing	3.780000
7	Furniture_Mattress_And_Upholstery	3.804878
8	Audio	3.824147
9	Construction_Tools_Safety	3.834171

b. Which products (top10) are maximum rated & minimum rated?

In [49]:
```
#top 10 products maximum rated:
df.groupby('product_id')['review_score'].mean().reset_index().sort_values(
```

Out[49]:

	product_id	review_score
0	00066f42aeeb9f3007548bb9d3f33c38	5.0
1	86743ff92eee3d16b7df59cddd583b8c	5.0
2	868ceb027ab706a4dee42e2220006b85	5.0
3	868969d3a93aeeab7bfcd4fc3d3d65de	5.0
4	868766ed2172644fdd977d6bd395a107	5.0
5	8684bd8f93b4f4038d07188a23811e93	5.0
6	867c96d2bb67aba6500a4c509cf76072	5.0
7	867b820367ec206b38a357f2c12454b7	5.0
8	867901d7e8488fb97f1fb538c09d476e	5.0
9	865bfa00c1dad8f4146d3c2765f051ca	5.0

In [50]:
```
#top 10 products minimum rated:
df.groupby('product_id')['review_score'].mean().reset_index().sort_values(
```

Out[50]:

	product_id	review_score
0	592cc6634d2c783d297effc0b828bc37	1.0
1	482c25dc8512547962854dfff5ac057b	1.0
2	e10c5041c0752194622a7a7016d8c9b5	1.0
3	47fafa6908e75ae62b8a36a9eb3b9234	1.0
4	47d85e3e35a3e29f93fdc12b295d520c	1.0
5	47d6209a0b169cc800b0a45a9127d2f2	1.0
6	47cad419b0ad5dc9d2305bf795c3c16f	1.0
7	47b49b876c60eafde72f0e1c602f386d	1.0
8	47b0f8596ee6dafbb4438cac16fa6275	1.0
9	47ac4dcdb04867daeaad647d224389e4	1.0

c. Average rating by location, seller, product, category, month etc.¶

In [51]:
```
#Average rating by Location
df.groupby('customer_city')['review_score'].mean().reset_index().sort_valu
```

Out[51]:

	customer_city	review_score
0	Ghagga	5.0
1	Guru Har Sahai	5.0
2	Gursahaiganj	5.0
3	Singoli	5.0
4	Naranapuram	5.0
...	...	...
4105	Hyderabad	1.0
4106	Hajipur	1.0
4107	Singahi Bhiraura	1.0
4108	Velur	1.0
4109	Kanapaka	1.0

4110 rows × 2 columns

In [52]:
```
#Average rating by seller
df.groupby('seller_id')['review_score'].mean().reset_index().sort_values(
```

Out[52]:

	seller_id	review_score
0	c18309219e789960add0b2255ca4b091	5.0
1	2075d8cd4dd63ff12df0749a5866bb06	5.0
2	40ec8ab6cdafbcc4f544da38c67da39a	5.0
3	4125d9385a25e82d2f72d3a0fd55bc3f	5.0
4	417a1e6c7321084d2a0ae0d023cfad93	5.0
...	...	...
3090	f524ad65d7e0f1daab730ef2d2e86196	1.0
3091	749e7cdabbaf72f16677859e27874ba5	1.0
3092	f5403d3f50089112c4eed37928b7f622	1.0
3093	dadc51ef321949ec9a3ab25cd902e23d	1.0
3094	61c36f0fc4a47f9532e5512b66668e62	1.0

3095 rows × 2 columns

In [53]:
```
#Average rating by products
df.groupby('product_id')['review_score'].mean().reset_index().sort_values(
```

Out[53]:

	product_id	review_score
0	00066f42aeeb9f3007548bb9d3f33c38	5.0
1	86743ff92eee3d16b7df59cddd583b8c	5.0
2	868ceb027ab706a4dee42e2220006b85	5.0
3	868969d3a93aeeab7bfcd4fc3d3d65de	5.0
4	868766ed2172644fdd977d6bd395a107	5.0
...	...	...
32946	984a3b9f9bb4c8feb319da951212696e	1.0
32947	149c06c0927fb59eff16690d31497f12	1.0
32948	628cfb8a45c95a7b796ea06b006e9384	1.0
32949	0a56efd5f050d3f861a04c6f005d1128	1.0
32950	c501923885535aa99ac2dd7a4e0ed7fe	1.0

32951 rows × 2 columns

In [54]:
```
#Average rating by category
df.groupby('product_category_name')['review_score'].mean().reset_index().s
```

Out[54]:

	product_category_name	review_score
0	Cds_Dvds_Musicals	4.642857
1	Fashion_Childrens_Clothes	4.500000
2	Books_General_Interest	4.431858
3	Books_Imported	4.419355
4	Books_Technical	4.345588
...	...	...
66	Fashion_Male_Clothing	3.531034
67	Office_Furniture	3.516779
68	Home_Comfort_2	3.387097
69	Diapers_And_Hygiene	3.256410
70	Security_And_Services	2.500000

71 rows × 2 columns

In [55]:

```
#Average rating by Months
df.groupby('Month')['review_score'].mean().reset_index().sort_values('rev:
```

Out[55]:

	Month	review_score
0	2016-12	5.000000
1	2018-07	4.209897
2	2018-08	4.205520
3	2017-08	4.202527
4	2018-06	4.177258
5	2017-09	4.125560
6	2018-05	4.119670
7	2017-06	4.117216
8	2017-05	4.117210
9	2017-07	4.108042
10	2017-01	4.087977
11	2018-04	4.063218
12	2017-03	4.049360
13	2017-02	4.041003
14	2017-10	4.040947
15	2017-04	3.959497
16	2017-12	3.927824
17	2018-01	3.926072
18	2017-11	3.825638
19	2018-02	3.723863
20	2018-03	3.681448
21	2016-10	3.585492
22	2016-09	1.000000
23	2018-09	1.000000

In [ ]:

In [ ]:

In [ ]:

In [ ]: