SUPERMARKET SALES ANALYSIS & FORECASTING

Using Python

In this project we have used a Supermarket data and got insights by asking the right questions, and visualized them for better understanding. This helps to get insights from data, which will help to take further decisions. This predictive model helps customer's next shopping list. The data-set used in this project is available on kaggle.com under opensource licence.

```

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LIBRARIES USED

NUMPY PANDA SEABORN

MATPLOTLIB ARIMA

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

import warnings
warnings.filterwarnings("ignore")
```

Overview

overwiewing the data

```
df=pd.read_csv('supermarket_sales.csv')

df.head()
```

```
    Invoice ID Branch       City Customer type  Gender  \
0  750-67-8428      A     Yangon        Member  Female
1  226-31-3081      C  Naypyitaw        Normal  Female
2  631-41-3108      A     Yangon        Normal    Male
3  123-19-1176      A     Yangon        Member    Male
4  373-73-7910      A     Yangon        Normal    Male

             Product line  Unit price  Quantity   Tax 5%     Total
Date  \
0       Health and beauty       74.69         7  26.1415  548.9715
1/5/2019
1  Electronic accessories       15.28         5   3.8200   80.2200
3/8/2019
2      Home and lifestyle       46.33         7  16.2155  340.5255
3/3/2019
3       Health and beauty       58.22         8  23.2880  489.0480
1/27/2019
4       Sports and travel       86.31         7  30.2085  634.3785
2/8/2019

    Time      Payment    cogs  gross margin percentage  gross income
Rating
0  13:08      Ewallet  522.83                 4.761905       26.1415
9.1
1  10:29         Cash   76.40                 4.761905        3.8200
9.6
2  13:23  Credit card  324.31                 4.761905       16.2155
7.4
3  20:33      Ewallet  465.76                 4.761905       23.2880
8.4
4  10:37      Ewallet  604.17                 4.761905       30.2085
5.3
```

Dimensions

Determining the various dimensions

```
df.shape
```

```
(1000, 17)
```

```
df.describe()
```

```
        Unit price     Quantity       Tax 5%        Total         cogs
\
count  1000.000000  1000.000000  1000.000000  1000.000000  1000.00000

mean     55.672130     5.510000    15.379369   322.966749   307.58738

std      26.494628     2.923431    11.708825   245.885335   234.17651

min      10.080000     1.000000     0.508500    10.678500    10.17000

25%      32.875000     3.000000     5.924875   124.422375   118.49750

50%      55.230000     5.000000    12.088000   253.848000   241.76000

75%      77.935000     8.000000    22.445250   471.350250   448.90500

max      99.960000    10.000000    49.650000  1042.650000   993.00000


       gross margin percentage  gross income      Rating
count             1.000000e+03   1000.000000  1000.00000
mean              4.761905e+00     15.379369     6.97270
std               6.131498e-14     11.708825     1.71858
min               4.761905e+00      0.508500     4.00000
25%               4.761905e+00      5.924875     5.50000
50%               4.761905e+00     12.088000     7.00000
75%               4.761905e+00     22.445250     8.50000
max               4.761905e+00     49.650000    10.00000
```

Applying cleaning of data eleminating duplicate values, changing of data types and more.

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 17 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Invoice ID               1000 non-null   object 
 1   Branch                   1000 non-null   object 
 2   City                     1000 non-null   object 
 3   Customer type            1000 non-null   object 
 4   Gender                   1000 non-null   object 
 5   Product line             1000 non-null   object 
 6   Unit price               1000 non-null   float64
 7   Quantity                 1000 non-null   int64  
 8   Tax 5%                   1000 non-null   float64
 9   Total                    1000 non-null   float64
 10  Date                     1000 non-null   object 
 11  Time                     1000 non-null   object 
 12  Payment                  1000 non-null   object 
 13  cogs                     1000 non-null   float64
 14  gross margin percentage  1000 non-null   float64
 15  gross income             1000 non-null   float64
 16  Rating                   1000 non-null   float64
dtypes: float64(7), int64(1), object(9)
memory usage: 132.9+ KB

#no null values are present in the dataset
#Date,Time ARE string so these need to be changed

df.isnull().sum()

Invoice ID                 0
Branch                     0
City                       0
Customer type              0
Gender                     0
Product line               0
Unit price                 0
Quantity                   0
Tax 5%                     0
Total                      0
Date                       0
Time                       0
Payment                    0
cogs                       0
gross margin percentage    0
gross income               0
Rating                     0
dtype: int64
```

```
df=df.drop(['Invoice ID'],axis=1)
#dropping Invoice ID column as it is not useful in our analysis

df['gross margin percentage'].unique()

array([4.76190476])

df.duplicated().value_counts()

False    1000
dtype: int64
```

Since we do not have anu null values or duplicates we can go ahead and convert the column values into thier corresponding datatypes.

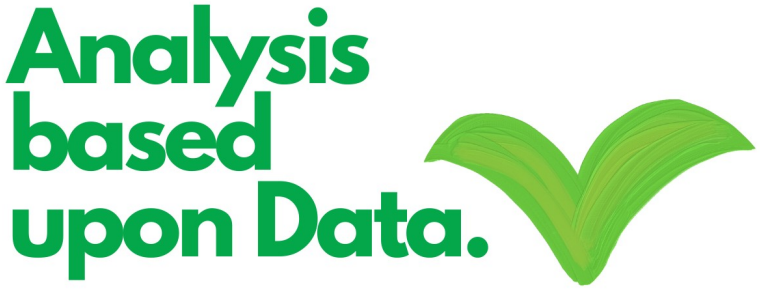
```
df['Date']=pd.to_datetime(df['Date'])

df['Time']=pd.to_datetime(df['Time'])

df.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Branch                   1000 non-null   object
 1   City                     1000 non-null   object
 2   Customer type            1000 non-null   object
 3   Gender                   1000 non-null   object
 4   Product line             1000 non-null   object
 5   Unit price               1000 non-null   float64
 6   Quantity                 1000 non-null   int64
 7   Tax 5%                   1000 non-null   float64
 8   Total                    1000 non-null   float64
 9   Date                     1000 non-null   datetime64[ns]
 10  Time                     1000 non-null   datetime64[ns]
 11  Payment                  1000 non-null   object
 12  cogs                     1000 non-null   float64
 13  gross margin percentage  1000 non-null   float64
 14  gross income             1000 non-null   float64
 15  Rating                   1000 non-null   float64
dtypes: datetime64[ns](2), float64(7), int64(1), object(6)
memory usage: 125.1+ KB
```

Now our Data is Cleaned and ready to be used in Analysis.



It evaluates exploratory data analysis based upon data and provides us powerfull insights.

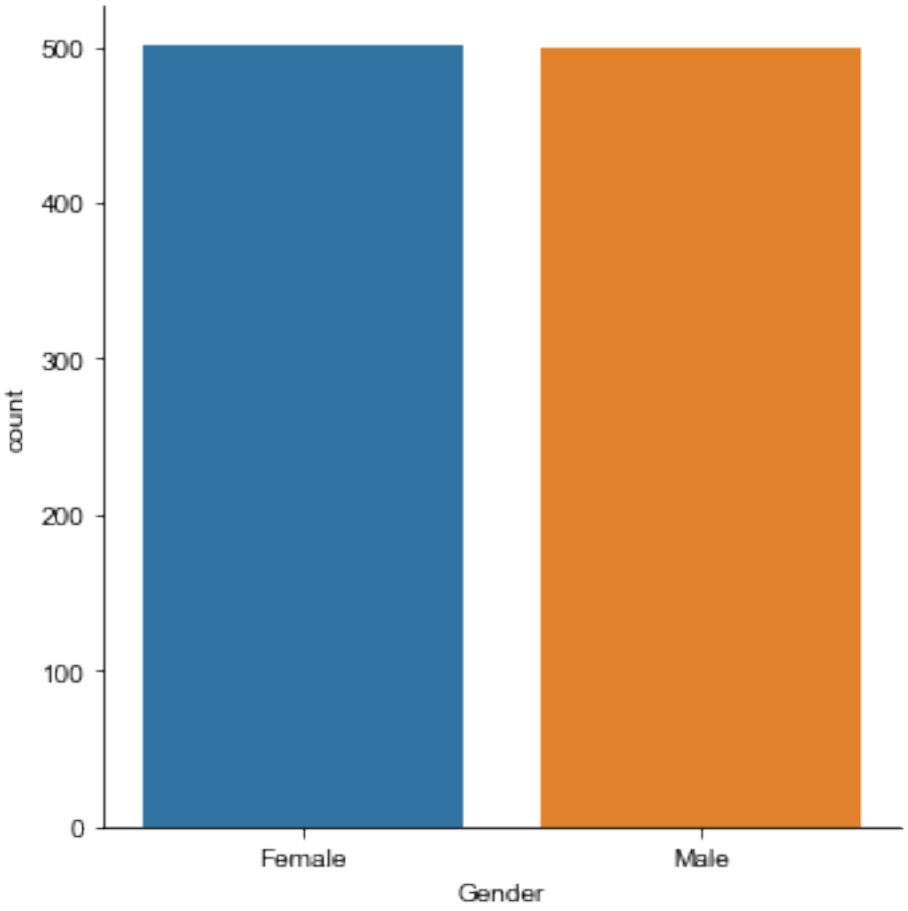
..

```
df['Gender'].value_counts()
```

```
Female    501
Male      499
Name: Gender, dtype: int64
```

Checking if the store is more popular to a particular gender or not

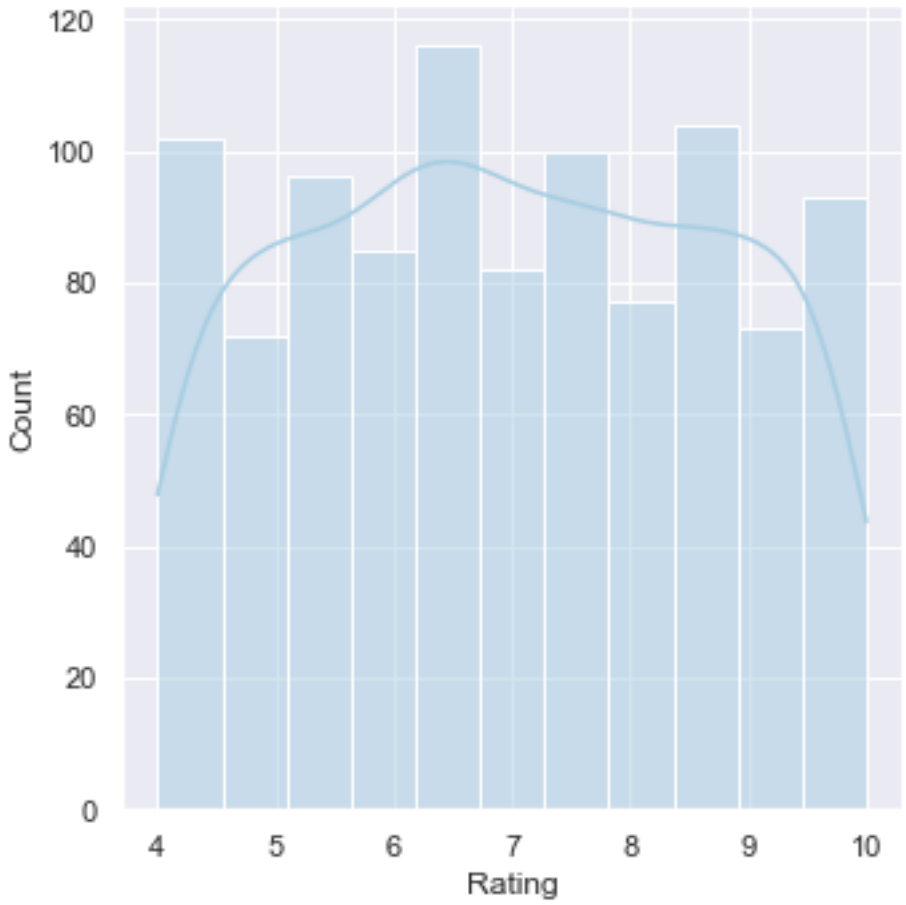
```
sns.catplot(x='Gender',kind='count',data= df)
sns.set(rc={'figure.figsize':(5,7)},palette='Paired')
```



There is no difference in the amount of female and male customers visiting the store.

Analyzing the customer rating column

```
sns.displot(x='Rating',data=df,kde=True)
plt.show()
```



The distribution seems to be almost uniform with a slight deviation from the normal.Lets check the skewness of the distribution using skew function of pandas library

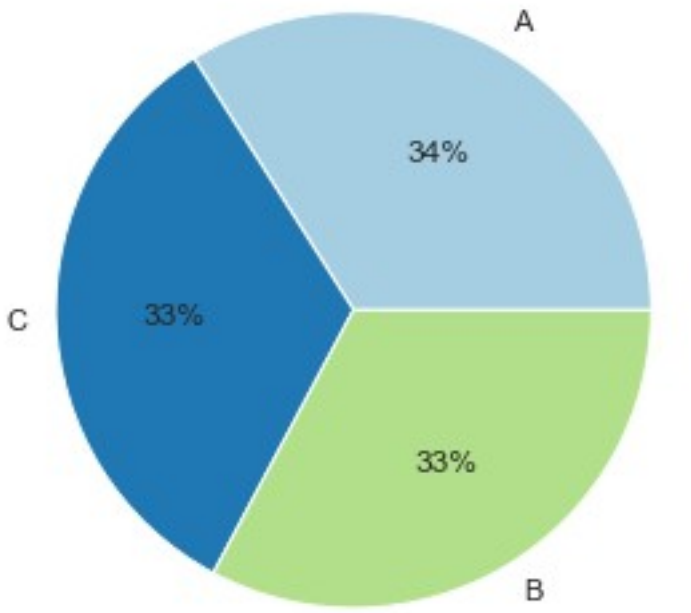
```
df['Rating'].skew()
```

```
0.00900964876573073
```

A skewnwss of 0.009 is very low and so the distribution can be said to be unskewed.

Now i want to check the aggregate sales across the branches

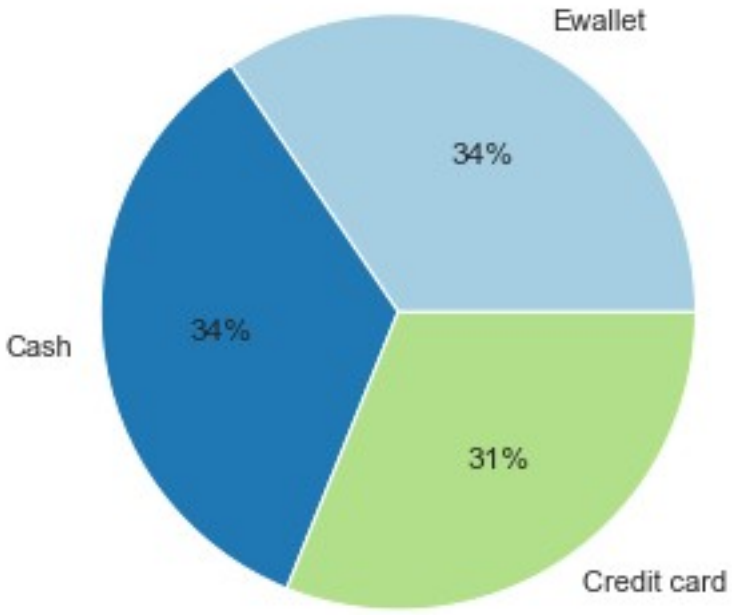
```
plt.pie(df['Branch'].value_counts(),labels=df['Branch'].unique(),autop
ct='%0.0f%%')
plt.show()
```



The pie chart represents the relative amount of total sales happening across branches A,B AND C.All three of these branches seem to be fairing well in thier respective locations.

Lets see what is the most popular payment method used by customers

```
plt.pie(df['Payment'].value_counts(),labels=df['Payment'].unique(),aut
opct='%0.0f%%')
plt.show()
```



E-wallet and Cash are the most used methods.

Does gross income affect customer rating?

```
sns.lmplot(x='Rating',y='gross income',data=df,col='Customer type')
```

```
<seaborn.axisgrid.FacetGrid at 0x21672bb1df0>
```

The linier model plot gives a scatter plot along with a linier model approximation of the data points .From the plot it seems like there is no relation between customers rating and the income the store generates on the order.

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Untill Now there are no interrelated insights, from which we can conclude or manupulate things upon.

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So, Analysing Data in more ways.

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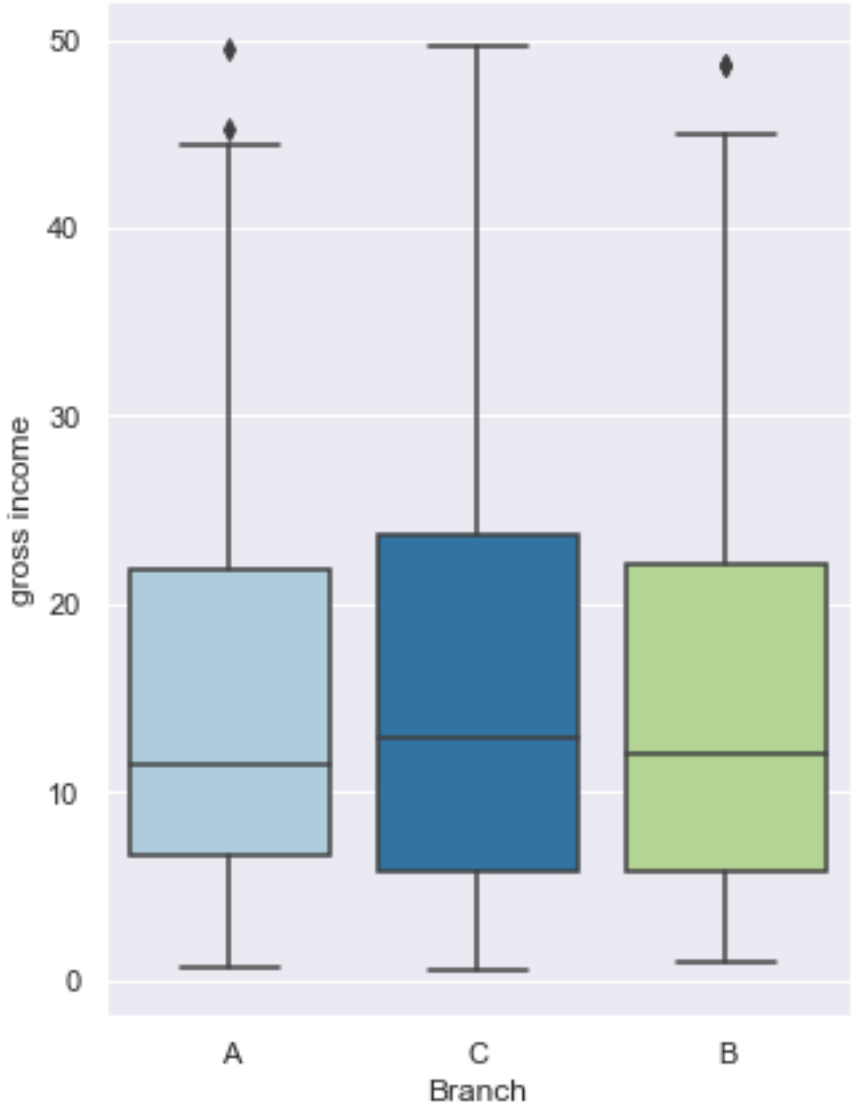
Lets Check ,which is the most profitable branch?

```
sns.boxplot(x=df['Branch'],y=df['gross income'])
```

```
<AxesSubplot:xlabel='Branch', ylabel='gross income'>
```

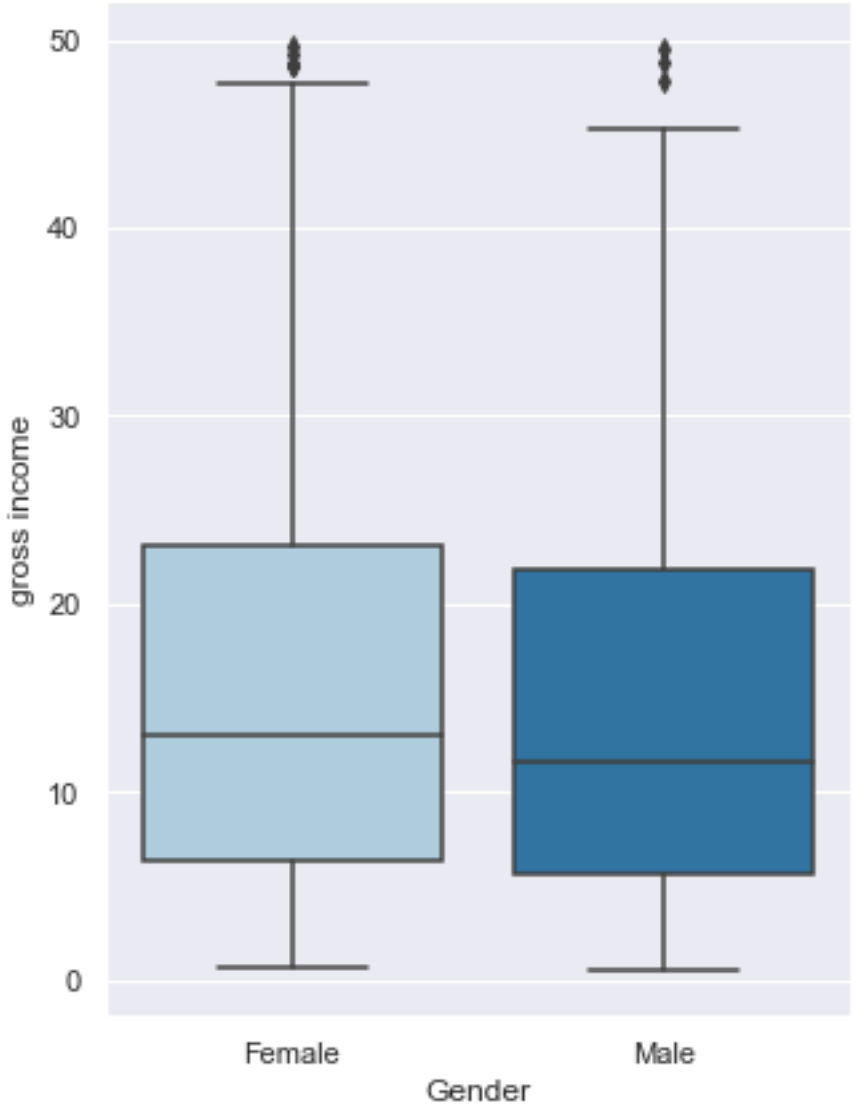


Evidently the branch C is doing the better than the other branches by a small margin.

Relationship between Gender and Gross Income

```
sns.boxplot(x='Gender',y='gross income',data=df)
```

```
<AxesSubplot:xlabel='Gender', ylabel='gross income'>
```

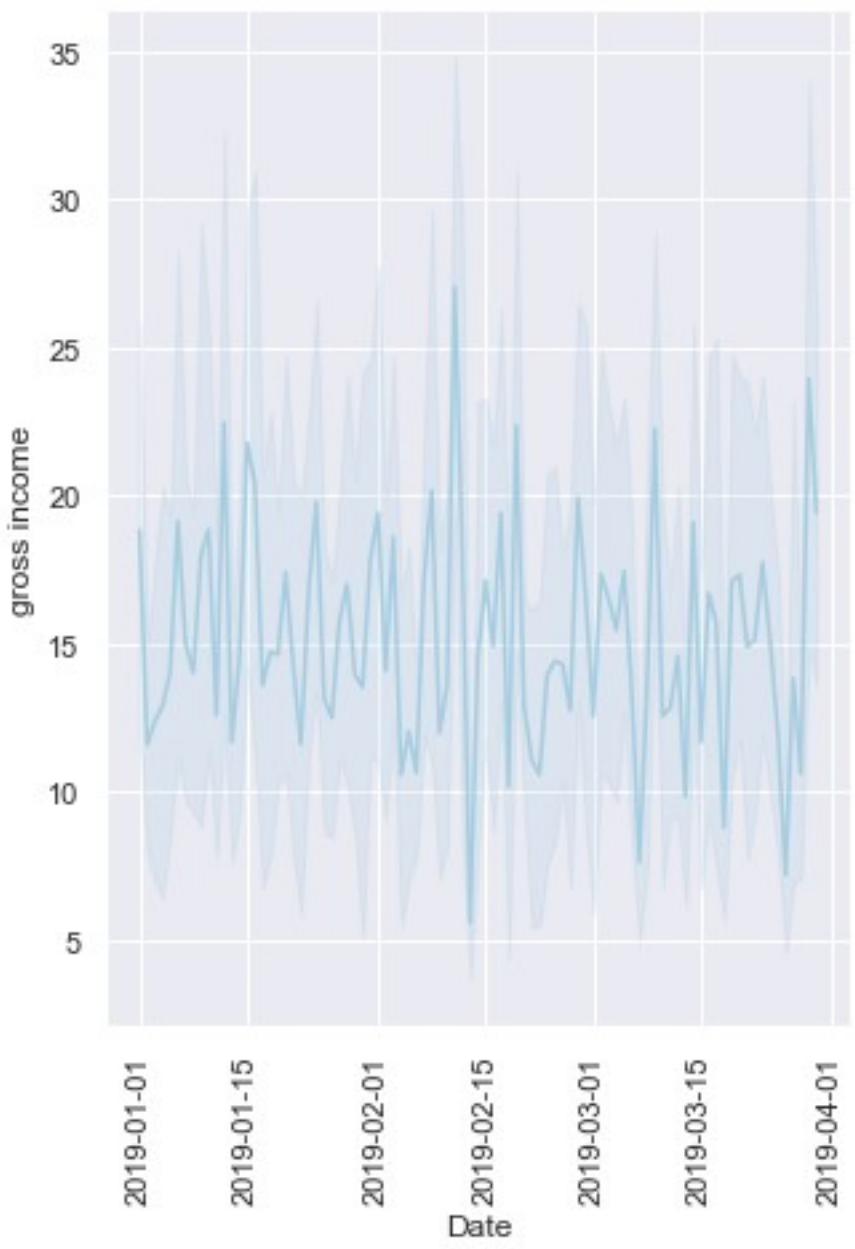


Gross income is similar for both male and female customers but there is a slightly higher mean of income generated from female.

Trend in gross income

```
sns.lineplot(x=df.Date,y=df['gross income'])
plt.xticks(rotation=90)
```

```
(array([17897., 17911., 17928., 17942., 17956., 17970., 17987.]),
 [Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, ''),
  Text(0, 0, '')])
```



As we can see in the plot above,there is no certain trend which the income generated follows depending on the time series of dates provided in the data set.

Which product line generates the most income?

```
df.head()
```

```
  Branch       City Customer type  Gender            Product line
Unit price  \
0      A     Yangon        Member  Female       Health and beauty
74.69
1      C  Naypyitaw        Normal  Female  Electronic accessories
15.28
```

```
2      A     Yangon        Normal    Male      Home and lifestyle
46.33
3      A     Yangon        Member    Male       Health and beauty
58.22
4      A     Yangon        Normal    Male       Sports and travel
86.31

   Quantity   Tax 5%     Total       Date                 Time
Payment  \
0         7  26.1415  548.9715 2019-01-05 2022-05-01 13:08:00
Ewallet
1         5   3.8200   80.2200 2019-03-08 2022-05-01 10:29:00
Cash
2         7  16.2155  340.5255 2019-03-03 2022-05-01 13:23:00  Credit
card
3         8  23.2880  489.0480 2019-01-27 2022-05-01 20:33:00
Ewallet
4         7  30.2085  634.3785 2019-02-08 2022-05-01 10:37:00
Ewallet

     cogs  gross margin percentage  gross income  Rating
0  522.83                 4.761905       26.1415     9.1
1   76.40                 4.761905        3.8200     9.6
2  324.31                 4.761905       16.2155     7.4
3  465.76                 4.761905       23.2880     8.4
4  604.17                 4.761905       30.2085     5.3
```

Which product line helps generate the most income?

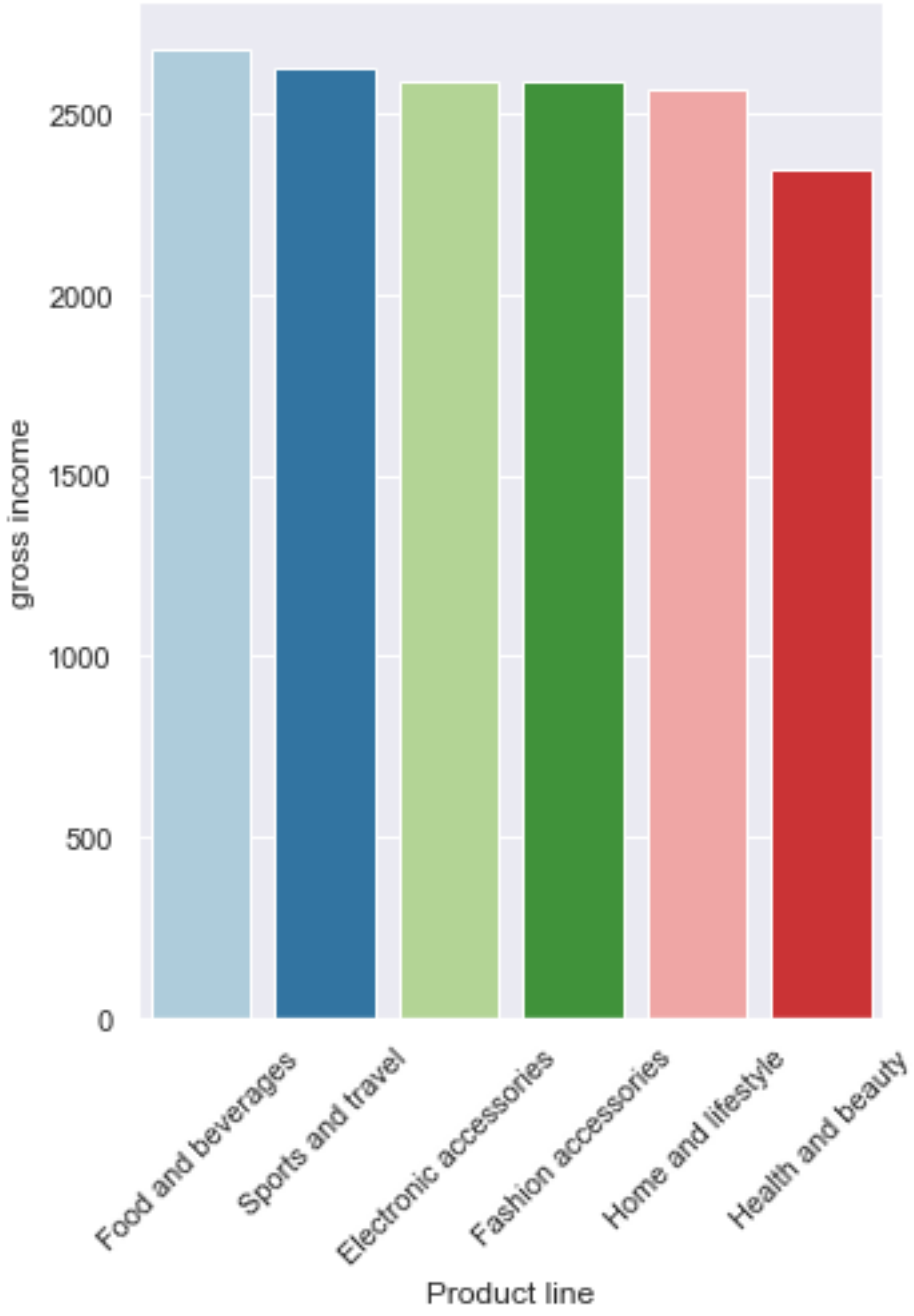
```
totalsales=df[["Product line","gross income"]].groupby(['Product
line'],as_index= False).sum().sort_values(by= 'gross
income',ascending= False)
totalsales
```

```
             Product line  gross income
2      Food and beverages     2673.5640
5       Sports and travel     2624.8965
0  Electronic accessories     2587.5015
1     Fashion accessories     2585.9950
4      Home and lifestyle     2564.8530
3       Health and beauty     2342.5590
```

```
sns.barplot(x='Product line',y='gross income',data=totalsales)
sns.set(rc={'figure.figsize':(10,10)})
plt.xticks(rotation=45)
```

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'Food and beverages'),
  Text(1, 0, 'Sports and travel'),
  Text(2, 0, 'Electronic accessories'),
```

```
  Text(3, 0, 'Fashion accessories'),
  Text(4, 0, 'Home and lifestyle'),
  Text(5, 0, 'Health and beauty')])
```

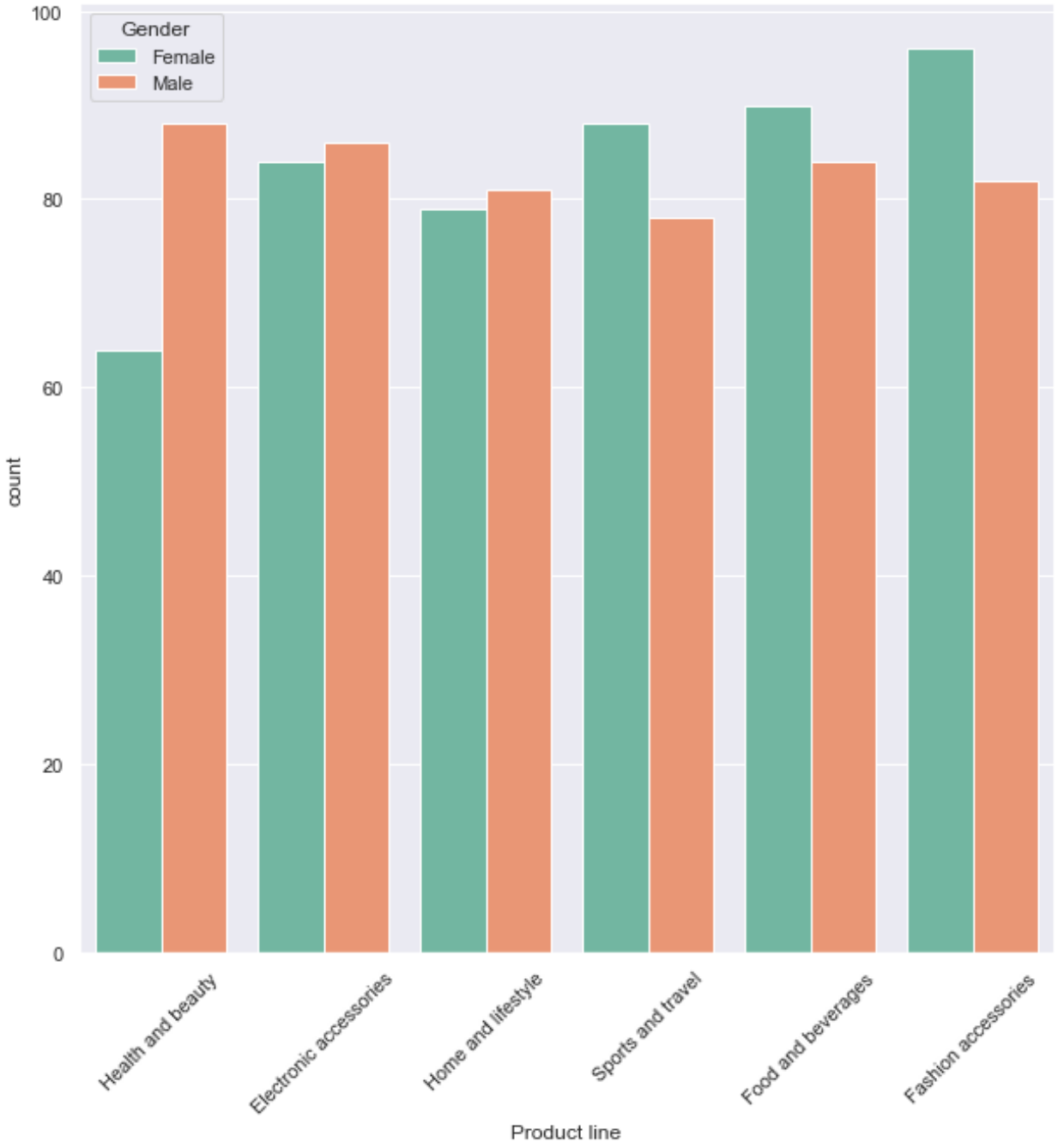


When we calculate the total sum of income generated from each product line ,we see that Food and Beverages AND Sports and Travel has the highest values.

Spending pattern of both males and females(which category do they spend more)

```
sns.countplot(df['Product line'],hue=df.Gender,palette='Set2')
plt.xticks(rotation=45)
```

```
(array([0, 1, 2, 3, 4, 5]),
 [Text(0, 0, 'Health and beauty'),
  Text(1, 0, 'Electronic accessories'),
  Text(2, 0, 'Home and lifestyle'),
  Text(3, 0, 'Sports and travel'),
  Text(4, 0, 'Food and beverages'),
  Text(5, 0, 'Fashion accessories')])
```



Males spend more on Health and Beauty than females .

Females purchase more Fashion accessories and Sports and Travel than males.

Which day of the week has maximum sales?

```
df['day'] = df['Date'].dt.day_name()   #to get the day of the date column
df.head()
```

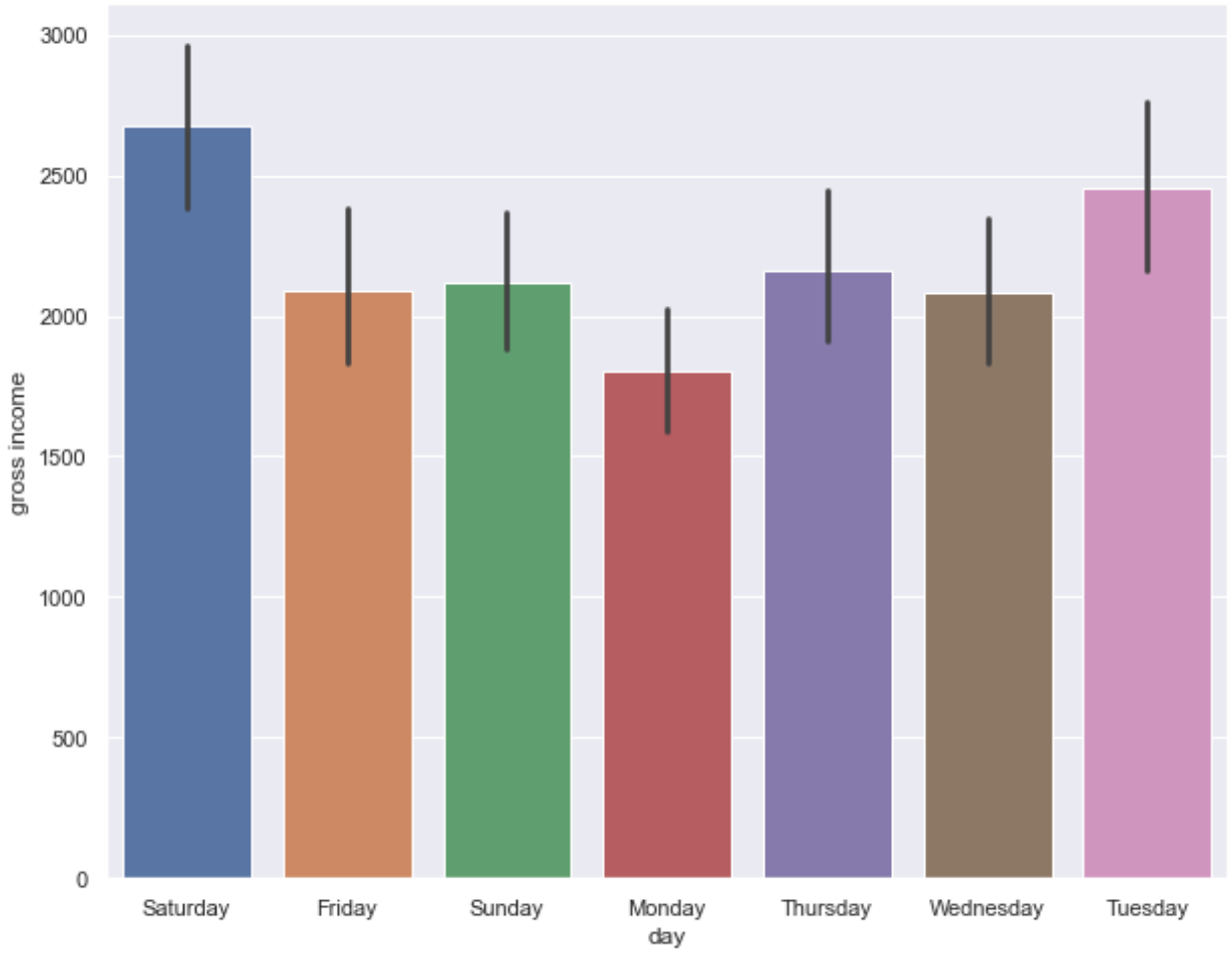
```
  Branch       City Customer type  Gender             Product line
Unit price  \
0      A     Yangon        Member  Female       Health and beauty
74.69
1      C  Naypyitaw        Normal  Female  Electronic accessories
15.28
2      A     Yangon        Normal    Male      Home and lifestyle
46.33
3      A     Yangon        Member    Male       Health and beauty
58.22
4      A     Yangon        Normal    Male       Sports and travel
86.31

   Quantity   Tax 5%     Total       Date                 Time
Payment  \
0         7  26.1415  548.9715 2019-01-05 2022-05-01 13:08:00
Ewallet
1         5   3.8200   80.2200 2019-03-08 2022-05-01 10:29:00
Cash
2         7  16.2155  340.5255 2019-03-03 2022-05-01 13:23:00  Credit
card
3         8  23.2880  489.0480 2019-01-27 2022-05-01 20:33:00
Ewallet
4         7  30.2085  634.3785 2019-02-08 2022-05-01 10:37:00
Ewallet

     cogs  gross margin percentage  gross income  Rating       day
0  522.83                 4.761905       26.1415     9.1  Saturday
1   76.40                 4.761905        3.8200     9.6    Friday
2  324.31                 4.761905       16.2155     7.4    Sunday
3  465.76                 4.761905       23.2880     8.4    Sunday
4  604.17                 4.761905       30.2085     5.3    Friday
```

```
plt.figure(figsize=(10,8))
sns.barplot(x='day',y='gross income',data=df,estimator=sum)
#using estimator=sum parameter to get the total gross income for each
day in our plot rather than the mean of gross income .
```

```
<AxesSubplot:xlabel='day', ylabel='gross income'>
```



Sales is highest on Saturday followed by Sunday and it was lowest on monday.Hence we can say that sales are higher on weekends and lower on weekdays.

Now lets check which hour of the day is the busiest

```
df['Hour']=df['Time'].dt.hour
df.head()
```

```
  Branch       City Customer type  Gender            Product line
Unit price  \
0      A     Yangon        Member  Female       Health and beauty
74.69
1      C  Naypyitaw        Normal  Female  Electronic accessories
15.28
2      A     Yangon        Normal    Male      Home and lifestyle
46.33
3      A     Yangon        Member    Male       Health and beauty
58.22
4      A     Yangon        Normal    Male       Sports and travel
86.31
```

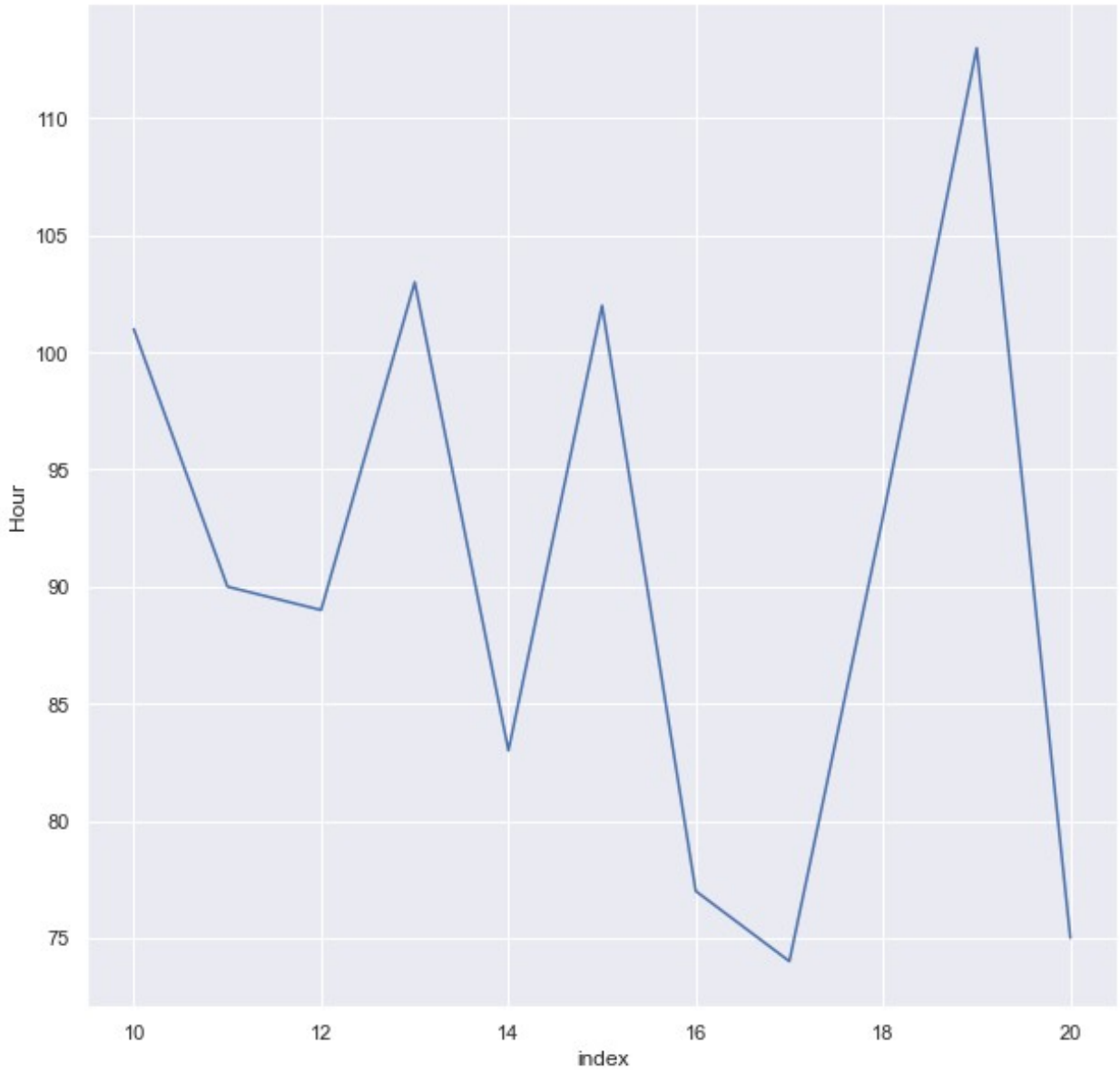
```
   Quantity   Tax 5%     Total       Date                 Time
Payment  \
0         7  26.1415  548.9715 2019-01-05 2022-05-01 13:08:00
Ewallet
1         5   3.8200   80.2200 2019-03-08 2022-05-01 10:29:00
Cash
2         7  16.2155  340.5255 2019-03-03 2022-05-01 13:23:00  Credit
card
3         8  23.2880  489.0480 2019-01-27 2022-05-01 20:33:00
Ewallet
4         7  30.2085  634.3785 2019-02-08 2022-05-01 10:37:00
Ewallet

     cogs  gross margin percentage  gross income  Rating       day
Hour
0  522.83                4.761905       26.1415     9.1  Saturday
13
1   76.40                4.761905        3.8200     9.6    Friday
10
2  324.31                4.761905       16.2155     7.4    Sunday
13
3  465.76                4.761905       23.2880     8.4    Sunday
20
4  604.17                4.761905       30.2085     5.3    Friday
10
```

```
hourly_customer=df['Hour'].value_counts().reset_index()
hourly_customer
```

```
    index  Hour
0      19   113
1      13   103
2      15   102
3      10   101
4      18    93
5      11    90
6      12    89
7      14    83
8      16    77
9      20    75
10     17    74
```

```
sns.lineplot(x='index',y='Hour',data=hourly_customer)
sns.set(rc={'figure.figsize':(14,7)})
```



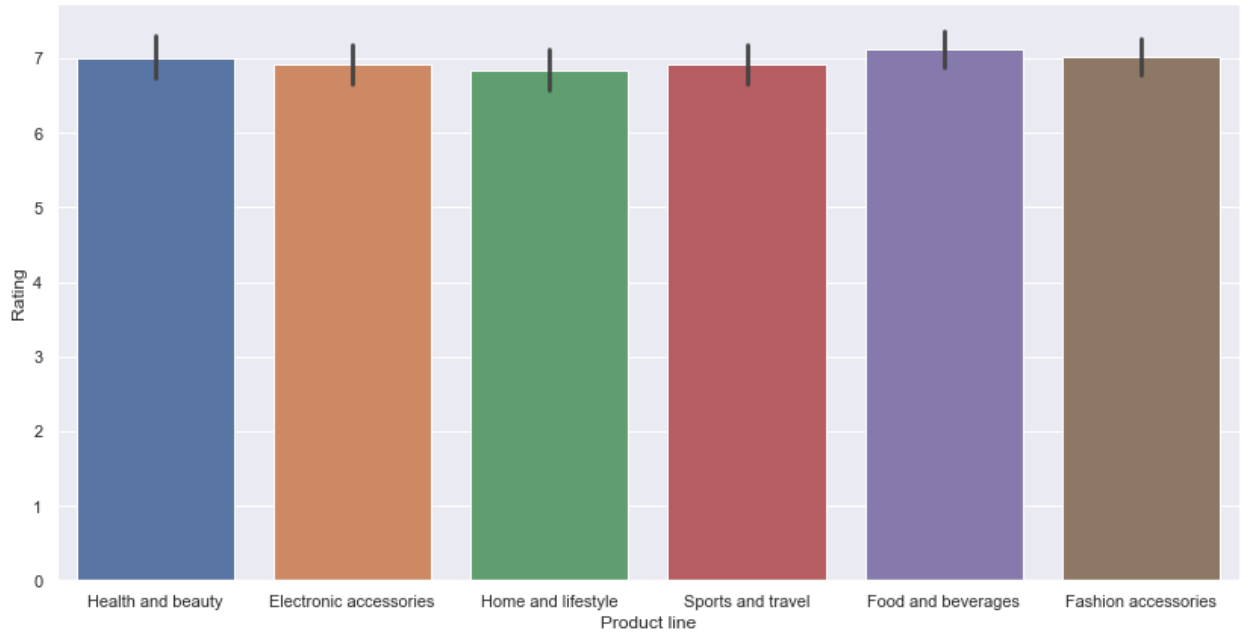
Looks like the 19th hour,that is 7PM IN THE EVENING IS THE BUSIEST HOUR OF THE DAY WITH THE MOST AMOUNT OF CUSTOMERS PURCHASING ITEMS.

What product line should the supermarket focus on?

HERE WE CAN HAVE TWO APPROCHES by which we can ANSWER THIS QUESTION. 1)By looking for the highest rated product line 2)By looking for the most sold products

```
sns.barplot(x='Product line',y='Rating',data=df)
plt.figure(figsize=(12,10))
```

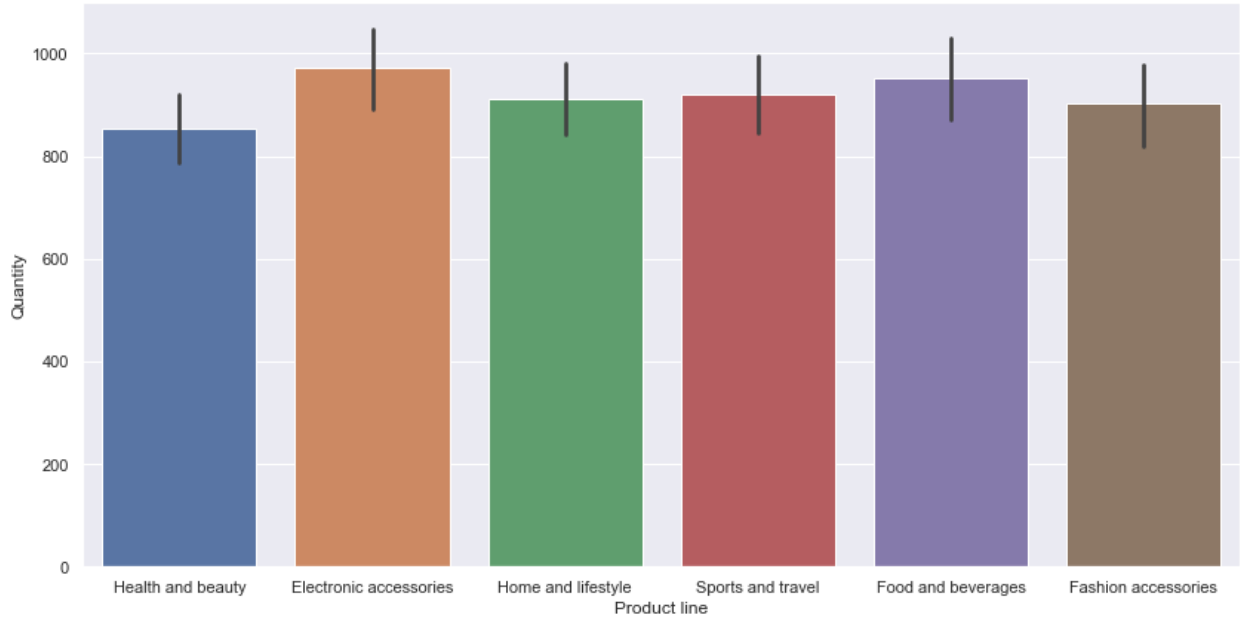
```
<Figure size 864x720 with 0 Axes>
```




```
<Figure size 864x720 with 0 Axes>
```

```
sns.barplot(x='Product line',y='Quantity',data=df,estimator=sum)
```

```
<AxesSubplot:xlabel='Product line', ylabel='Quantity'>
```

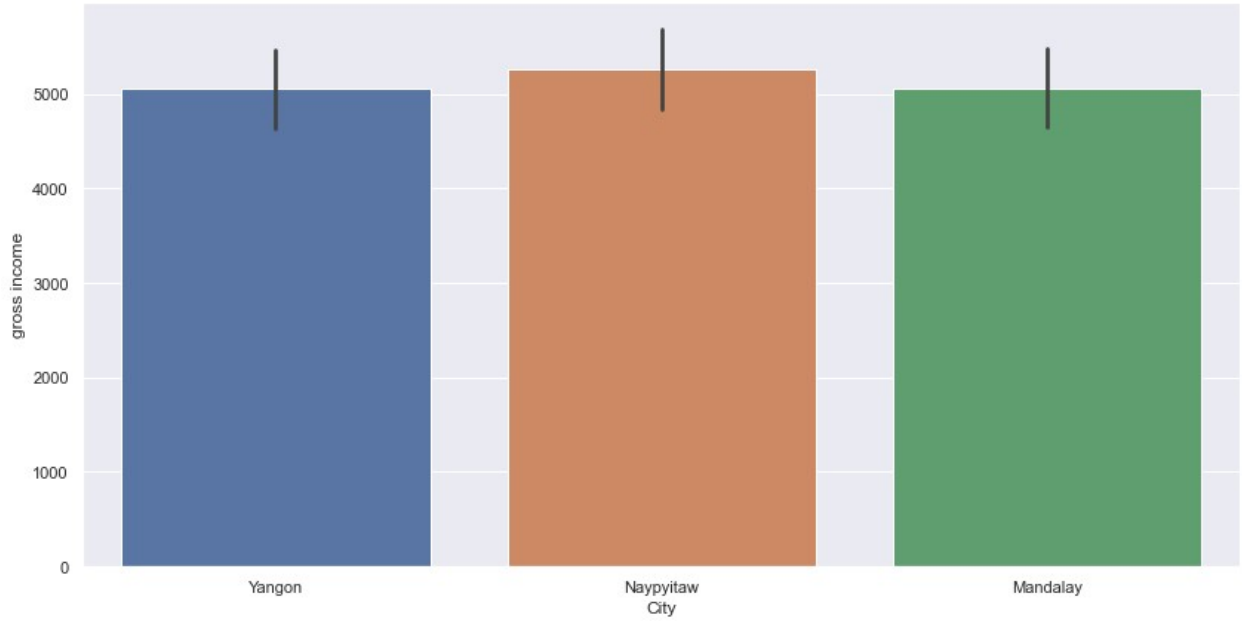


Rating for Fashion Accessories AND Food and Beverages is high but we can see that quantity purchased is high for Electronic accessories AND Food and Beverages.SO IN ORDER TO MEET THE DEMAND,Electronic accessories and Food and Beverages need to be on top priority.

Now lets check where can we open a new store for expansion of the buisness

```
sns.barplot(x='City',y='gross income',data=df,estimator=sum)
```

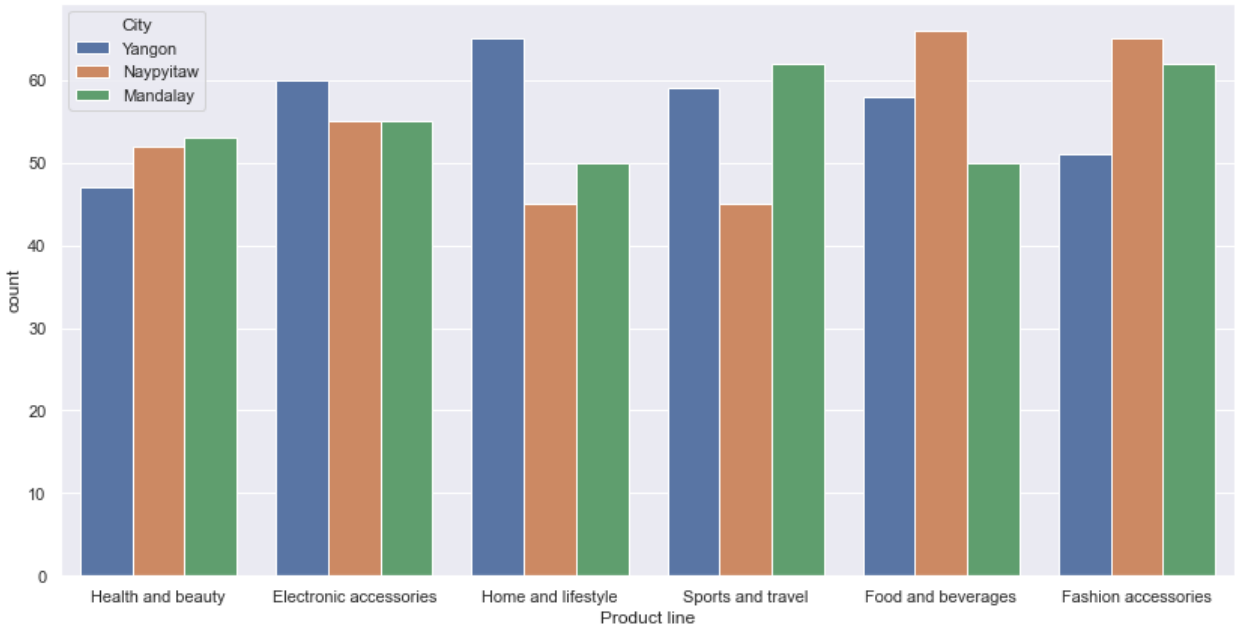
```
<AxesSubplot:xlabel='City', ylabel='gross income'>
```



Since the city NAYPYITAW has the highest mean gross income we should plan on expansion of branches in that city.

```
sns.countplot(df['Product line'],hue=df['City'])
```

```
<AxesSubplot:xlabel='Product line', ylabel='count'>
```



Since the product lines of Fashion accessories and Food and Beverages are the most popular it will be benificial if those two product lines are given higher priority over other product lines in terms of stocking,logistics,quality and other aspects.

```
d=pd.read_csv('supermarket_sales.csv')
print("Dataset contains {} row and {}
colums".format(d.shape[0],d.shape[1]))
```

```
Dataset contains 1000 row and 17 colums
```

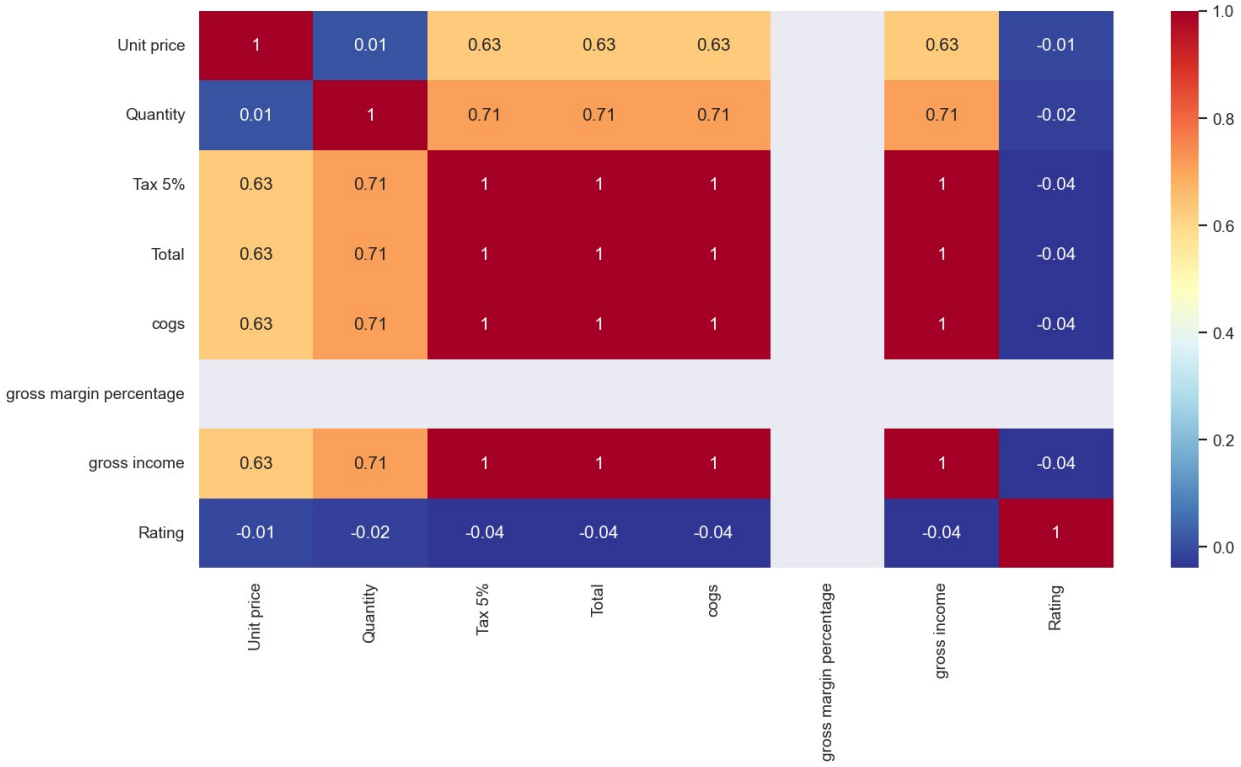
```
np.round(d.corr(),2)
```

```
                        Unit price  Quantity  Tax 5%  Total  cogs  \
Unit price                    1.00      0.01    0.63   0.63  0.63
Quantity                      0.01      1.00    0.71   0.71  0.71
Tax 5%                        0.63      0.71    1.00   1.00  1.00
Total                         0.63      0.71    1.00   1.00  1.00
cogs                          0.63      0.71    1.00   1.00  1.00
gross margin percentage        NaN       NaN     NaN    NaN   NaN
gross income                  0.63      0.71    1.00   1.00  1.00
Rating                       -0.01     -0.02   -0.04  -0.04 -0.04

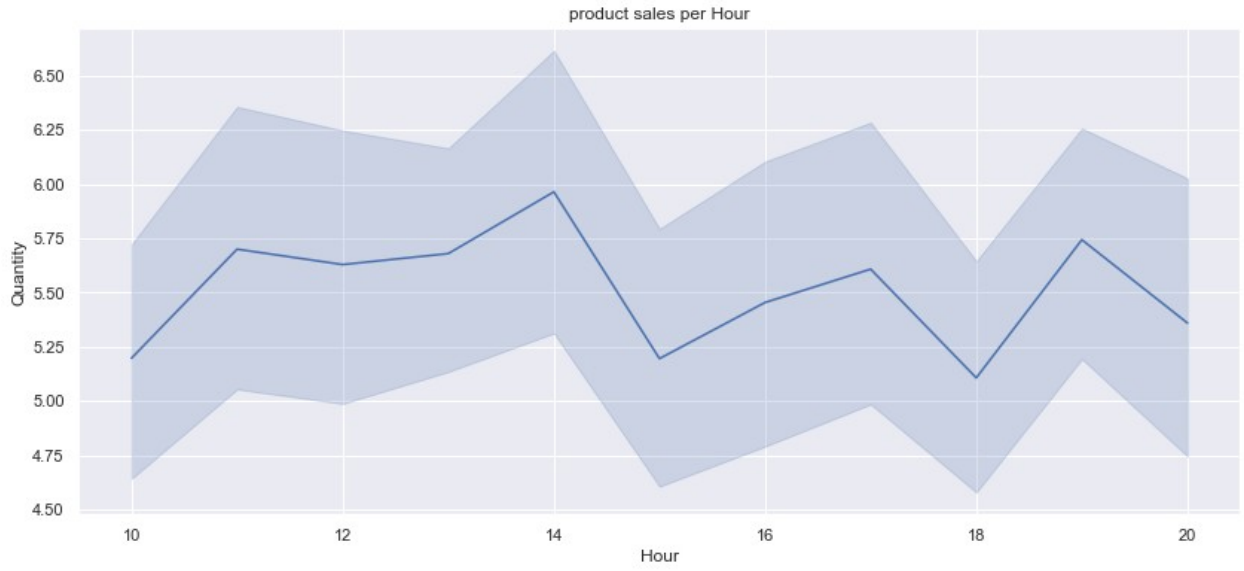
                        gross margin percentage  gross income  Rating
Unit price                                  NaN          0.63   -0.01
Quantity                                    NaN          0.71   -0.02
Tax 5%                                      NaN          1.00   -0.04
```

```
Total                                 NaN          1.00    -0.04
cogs                                  NaN          1.00    -0.04
gross margin percentage               NaN           NaN      NaN
gross income                          NaN          1.00    -0.04
Rating                                NaN         -0.04     1.00
```

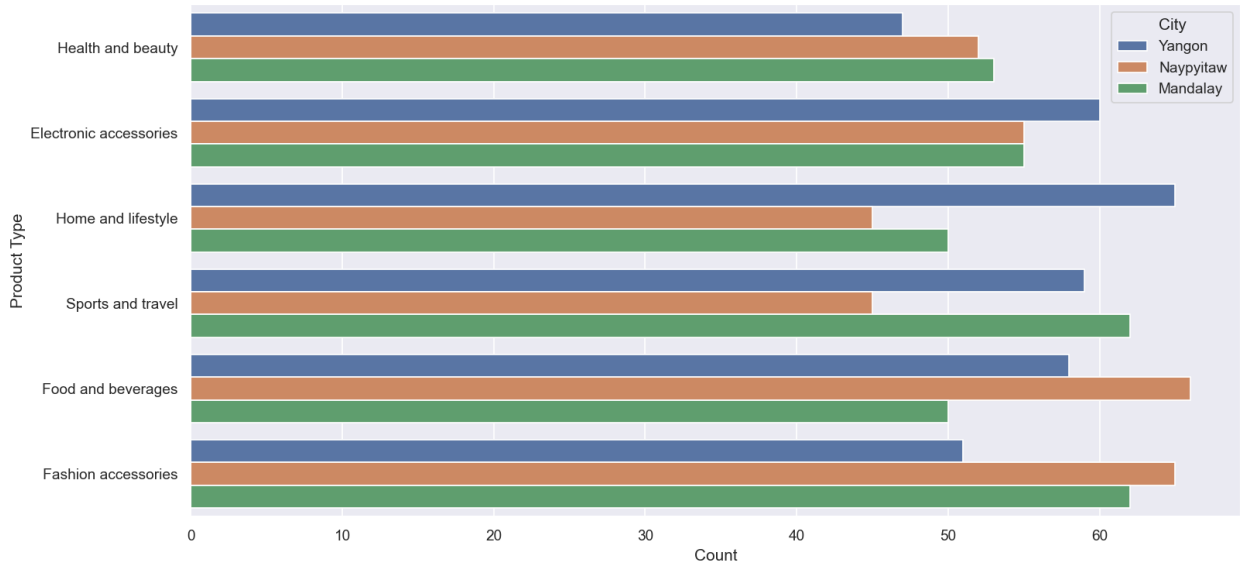
```
plt.figure(dpi=125)
sns.heatmap(np.round(d.corr(),2),annot=True,cmap='RdYlBu_r')
plt.show()
```




```
d["Time"]= pd.to_datetime(d["Time"])
d["Hour"]= (d["Time"]).dt.hour
plt.figure(figsize=(14,6))
SalesTime = sns.lineplot(x="Hour", y ="Quantity", data =
d).set_title("product sales per Hour")
```




```
plt.figure(dpi=125)
sns.countplot(y ='Product line', hue = "City", data = d)
plt.xlabel('Count')
plt.ylabel('Product Type')
plt.show()
```



analysis based upon gender

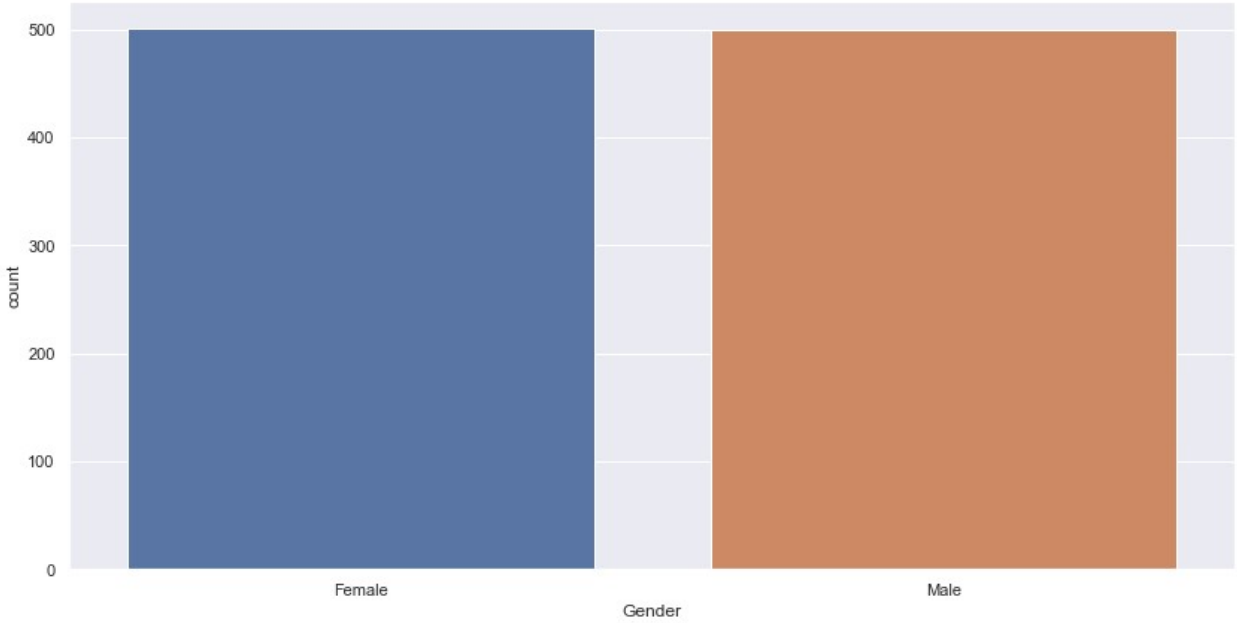
```
print(df.shape)
df['Gender'].value_counts()
```

```
(1000, 18)
```

```
Female    501
Male      499
Name: Gender, dtype: int64
```

```
sns.countplot('Gender',data=df)
```

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




```
gender_dummies=pd.get_dummies(df['Gender'])
gender_dummies.head()
```

```
   Female  Male
0       1     0
1       1     0
2       0     1
3       0     1
4       0     1
```

```
df=pd.concat([df,gender_dummies],axis=1)
df.head()
```

```
  Branch       City Customer type  Gender            Product line
Unit price  \
0      A     Yangon        Member  Female       Health and beauty
74.69
1      C  Naypyitaw        Normal  Female  Electronic accessories
15.28
2      A     Yangon        Normal    Male      Home and lifestyle
46.33
3      A     Yangon        Member    Male       Health and beauty
```

```
58.22
4      A     Yangon         Normal    Male       Sports and travel
86.31

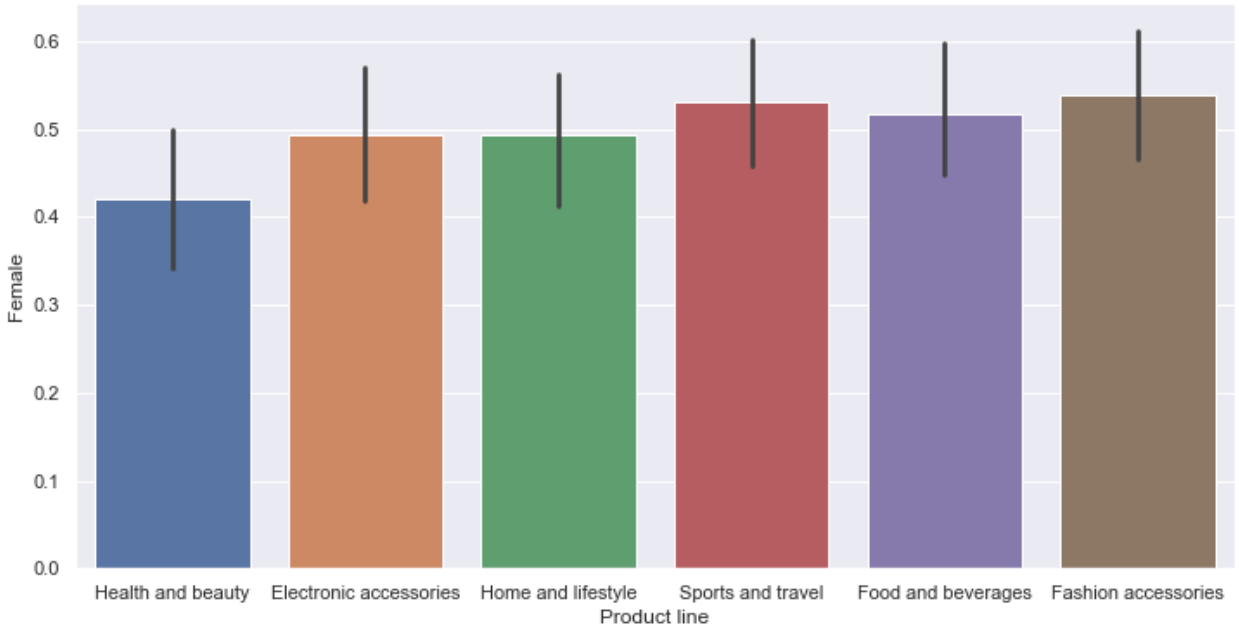
   Quantity   Tax 5%     Total       Date                Time
Payment  \
0         7  26.1415  548.9715 2019-01-05 2022-05-01 13:08:00
Ewallet
1         5   3.8200   80.2200 2019-03-08 2022-05-01 10:29:00
Cash
2         7  16.2155  340.5255 2019-03-03 2022-05-01 13:23:00  Credit
card
3         8  23.2880  489.0480 2019-01-27 2022-05-01 20:33:00
Ewallet
4         7  30.2085  634.3785 2019-02-08 2022-05-01 10:37:00
Ewallet

     cogs  gross margin percentage  gross income  Rating       day
Hour  \
0  522.83                 4.761905       26.1415     9.1  Saturday
13
1   76.40                 4.761905        3.8200     9.6    Friday
10
2  324.31                 4.761905       16.2155     7.4    Sunday
13
3  465.76                 4.761905       23.2880     8.4    Sunday
20
4  604.17                 4.761905       30.2085     5.3    Friday
10

   Female  Male
0       1     0
1       1     0
2       0     1
3       0     1
4       0     1

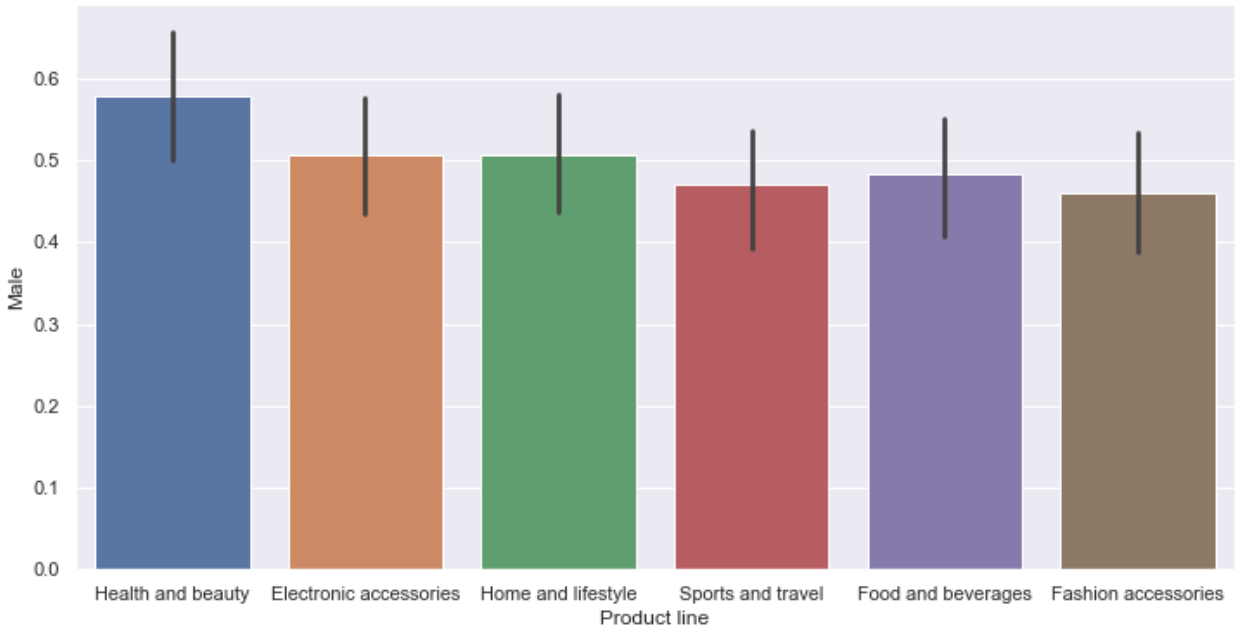
plt.figure(figsize=(12,6))
sns.barplot(x="Product line",y="Female", data = df)

<AxesSubplot:xlabel='Product line', ylabel='Female'>
```




```
plt.figure(figsize=(12,6))
sns.barplot(x="Product line",y="Male", data = df)
```

```
<AxesSubplot:xlabel='Product line', ylabel='Male'>
```



..

conclusions & actions to be taken.

conclusions, scope of improvement & actions to be taken

C brach has highest profit among all and females contribute to larger part of profit in all three branches.

Food and Sports gives supermarket most sales whereas health gives less sales.

males are more interested in healthcare products and least interested in fashion products

females are spending more on fashion and least in sports.

- As, we concluded earlier supermarket sales are least in healthcare but males are most interested in healthcare products. so this means if volume of male customers increases, the healthcare section of supermarkets can see a rise.

On mondays, sales are least & highest on saturday followed by tuesday.

- So, by means like sale events or any other attracting strategy organized on low sale-scoring days like mondays can improve sales and profits.

7 PM is the busiest hour of the day

- Arranging more staff around 19th hour colud help in fluency and hassle free shopping experience.

Health section have highest ratings yet lowest sales.

- To improve this we have to attract more male customers.

Yangon branch have highest sales in electronics and home supplies

Mandalay branch have highest sales in sports and fashion

Napatlay branch have highest sales in food and fashion

- Supermarket needs to focus on other categories that are not popular in any of three branches like healthcare and lifestyle section

We can conclude that healthcare and lifestyle sector are'nt doing well.

..

we make test cases using arima library and sarimax library and furthermore predicting the sales for upcoming one month.

```
#   (ii)if p value<0.05 then we will reject null hypothesis and accept
the alternate hypothesis which say data is stationary
from statsmodels.tsa.stattools import adfuller
dftest=adfuller(df['cogs'], autolag='AIC')
dfoutput=pd.Series(dftest[0:4], index=['Test Statistic','p-
value','Lags Used','Number of Observations Used'])
for key,value in dftest[4].items():
    dfoutput['Critical Value (%s)'%key] = value
print(dfoutput)
```

```
Test Statistic                  -30.603524
p-value                           0.000000
Lags Used                         0.000000
Number of Observations Used     999.000000
Critical Value (1%)              -3.436913
Critical Value (5%)              -2.864437
Critical Value (10%)             -2.568313
dtype: float64
```

```
from pmdarima.arima import auto_arima
stepwise_model = auto_arima(df["cogs"], start_p=1, start_q=1,
                            max_p=3, max_q=3, m=12,
                            start_P=0, seasonal=True,
                            d=1, D=1, trace=True,
                            error_action='ignore',
                            suppress_warnings=True,
                            stepwise=True)
print(stepwise_model.aic())
```

```
Performing stepwise search to minimize aic
 ARIMA(1,1,1)(0,1,1)[12]             : AIC=inf, Time=1.25 sec
```

```
 ARIMA(0,1,0)(0,1,0)[12]             : AIC=14953.532, Time=0.04 sec
 ARIMA(1,1,0)(1,1,0)[12]             : AIC=14374.028, Time=0.41 sec
 ARIMA(0,1,1)(0,1,1)[12]             : AIC=inf, Time=0.63 sec
 ARIMA(1,1,0)(0,1,0)[12]             : AIC=14647.800, Time=0.06 sec
 ARIMA(1,1,0)(2,1,0)[12]             : AIC=14232.963, Time=0.77 sec
 ARIMA(1,1,0)(2,1,1)[12]             : AIC=inf, Time=2.30 sec
 ARIMA(1,1,0)(1,1,1)[12]             : AIC=inf, Time=0.88 sec
 ARIMA(0,1,0)(2,1,0)[12]             : AIC=14518.302, Time=0.25 sec
 ARIMA(2,1,0)(2,1,0)[12]             : AIC=14125.114, Time=1.02 sec
 ARIMA(2,1,0)(1,1,0)[12]             : AIC=14267.955, Time=0.52 sec
 ARIMA(2,1,0)(2,1,1)[12]             : AIC=inf, Time=2.89 sec
 ARIMA(2,1,0)(1,1,1)[12]             : AIC=inf, Time=1.33 sec
 ARIMA(3,1,0)(2,1,0)[12]             : AIC=14072.650, Time=1.26 sec
 ARIMA(3,1,0)(1,1,0)[12]             : AIC=14209.035, Time=0.60 sec
 ARIMA(3,1,0)(2,1,1)[12]             : AIC=inf, Time=3.16 sec
 ARIMA(3,1,0)(1,1,1)[12]             : AIC=inf, Time=1.67 sec
 ARIMA(3,1,1)(2,1,0)[12]             : AIC=inf, Time=2.81 sec
 ARIMA(2,1,1)(2,1,0)[12]             : AIC=inf, Time=2.48 sec
 ARIMA(3,1,0)(2,1,0)[12] intercept   : AIC=14074.650, Time=2.90 sec

Best model:  ARIMA(3,1,0)(2,1,0)[12]
Total fit time: 27.243 seconds
14072.650231476935
```

```
#importing Sarimax and passing the parameters
from statsmodels.tsa.statespace.sarimax import SARIMAX
m=SARIMAX(df['cogs'], order=(3,1,0),seasonal_order=(2,1,0,12))
res=m.fit()

df['arima_predict']=res.fittedvalues



forecast=res.predict(start=len(df),end=len(df)+35)

forecast
```

```
1000     545.795261
1001     358.519118
1002     353.130318
1003     529.710285
1004     275.063525
1005     333.480107
1006     761.341884
1007     483.866080
1008     893.202382
1009     348.586395
1010     244.032465
1011     539.594297
1012     693.200426
1013     513.367148
```

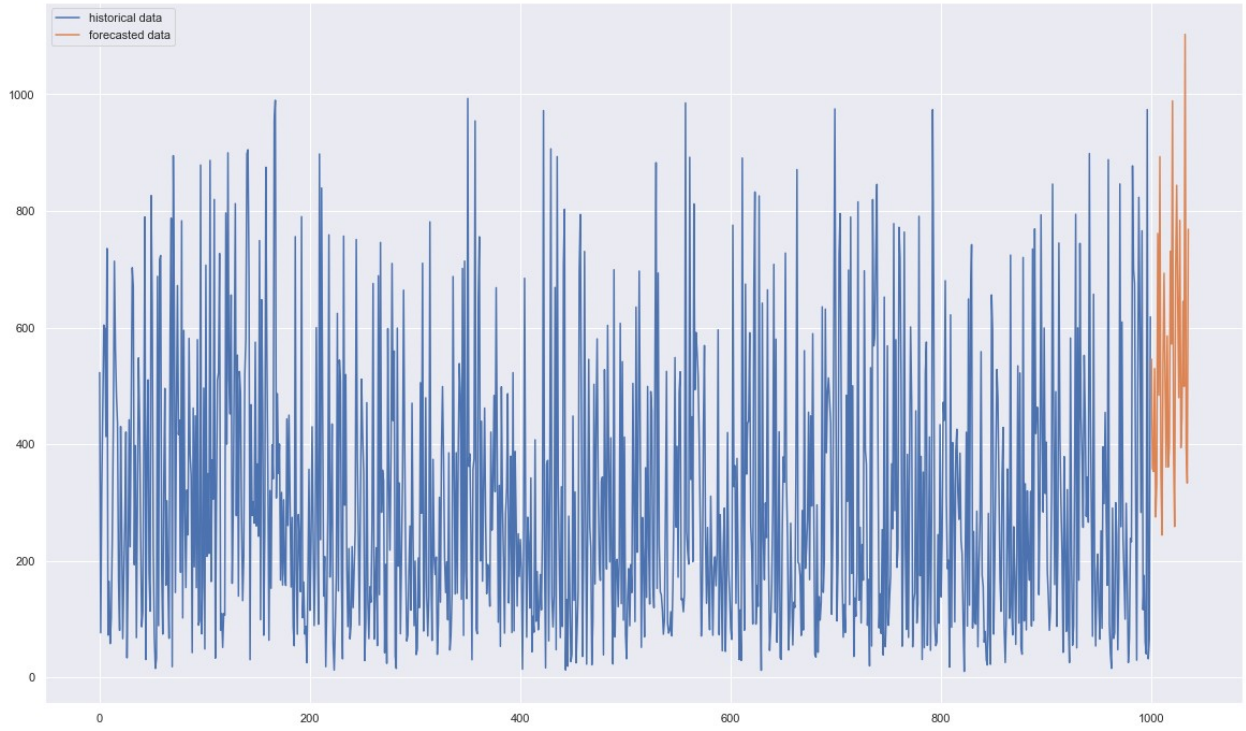
```
1014     360.717997
1015     585.574656
1016     360.912858
1017     395.999716
1018     730.854893
1019     571.780439
1020     988.699719
1021     386.711232
1022     258.624513
1023     698.700796
1024     844.007462
1025     646.914869
1026     479.733734
1027     783.951654
1028     393.789945
1029     445.016781
1030     644.911292
1031     498.910620
1032    1102.829220
1033     394.442188
1034     333.280131
1035     768.583495
Name: predicted_mean, dtype: float64
```

```
df['cogs'].append(forecast)
```

```
0         522.830000
1          76.400000
2         324.310000
3         465.760000
4         604.170000
            ...
1031     498.910620
1032    1102.829220
1033     394.442188
1034     333.280131
1035     768.583495
Length: 1036, dtype: float64
```

```
#plot between historical data and forecasted data
plt.figure(figsize=(20, 12))
plt.plot(df['cogs'],label="historical data")
plt.plot(forecast,label="forecasted data")
plt.legend()
```

```
<matplotlib.legend.Legend at 0x2169b6819a0>
```



From this we can clearly see Supermarket's sales are going in uptrend according to prediction for upcoming next 30 days.

This model will help Supermarket to improve thier profits, eliminate thier mistakes.

with help of EDA and Predicting libraries we have analysed data in such a way that it asks important questions and helps us in making necessary decesions based upon the fact of analysed data.

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Thank you.