Supermarket Sales

We know that the growth of supermarkets in most populated cities and even in the developing towns are increasing day by day and market competitions are also high. The dataset is one of the historical sales of supermarket company which has recorded in 3 different branches for 3 months data.

So, the dataset is basically retrieved from Kaggle. The dataset is potentially able to use Predictive data analytics methods.

The whole data is having 1000 rows and 17 columns. The columns does have nearly all the attributes needed to answer the questions that can decide the behavior of the trending sales.

For further analysis, we'll be using 'Jupyter Notebook' to run the code and vizulaise.

We'll be using several libraries of Python to carve out a meaningful result, like 'Numpy' and 'Pandas' for dealing with numeric values and data cleaning purpose, 'Matplotlib' and 'Seaborn' for 'Data Visualization'.

How to run the code

This is an executable *Jupyter notebook* hosted on Jovian.ml, a platform for sharing data science projects. You can run and experiment with the code in a couple of ways: *using free online resources* (recommended) or *on your own computer*.

Option 1: Running using free online resources (1-click, recommended)

The easiest way to start executing this notebook is to click the "Run" button at the top of this page, and select "Run on Binder". This will run the notebook on mybinder.org, a free online service for running Jupyter notebooks. You can also select "Run on Colab" or "Run on Kaggle".

Option 2: Running on your computer locally

1. Install Conda by following these instructions. Add Conda binaries to your system `PATH`, so you can use the `conda` command on your terminal.
2. Create a Conda environment and install the required libraries by running these commands on the terminal:

```
conda create -n zerotopandas -y python=3.8
conda activate zerotopandas
pip install jovian jupyter numpy pandas matplotlib seaborn opendatasets --upgrade
```

3. Press the "Clone" button above to copy the command for downloading the notebook, and run it on the terminal. This will create a new directory and download the notebook. The command will look something like this:

```
jovian clone notebook-owner/notebook-id
```

4. Enter the newly created directory using `cd directory-name` and start the Jupyter notebook.

```
jupyter notebook
```

You can now access Jupyter's web interface by clicking the link that shows up on the terminal or by visiting http://localhost:8888 on your browser. Click on the notebook file (it has a `.ipynb` extension) to open it.

Downloading the Dataset

In this notebook, we'll analyze the **Supermarket Sales** dataset. The dataset contains historical record of sales data in 3 different supermarkets.

There are several options for getting the dataset into Jupyter:

- Download the CSV manually and upload it via Jupyter's GUI.
- Use the urlretrieve function from the urllib.request to download CSV files from a raw URL.
- Use a helper library, e.g., opendatasets, which contains a collection of curated datasets and provides a helper function for direct download.
- We'll use the opendatasets helper library to download the files.

We'll use the `opendatasets` helper library to download the files.

```
!pip install jovian opendatasets --upgrade --quiet
```

```
dataset_url = 'https://www.kaggle.com/datasets/aungpyaeap/supermarket-sales/download?da
```

```
import opendatasets as od
od.download(dataset_url)
```

```
Skipping, found downloaded files in ".\supermarket-sales" (use force=True to force download)
```

```
data_dir = './supermarket-sales'
```

```
import os
os.listdir(data_dir)
```

```
['.ipynb_checkpoints', 'supermarket_sales.csv']
```

Let us save and upload our work to Jovian before continuing.

```
project_name = "supermarket-sales"
```

```
!pip install jovian --upgrade -q
```

```
import jovian
```

```
jovian.commit(project=project_name)
```

```
[jovian] Updating notebook "deepak-gupta15336/supermarket-sales" on https://jovian.ai/
[jovian] Committed successfully! https://jovian.ai/deepak-gupta15336/supermarket-sales
```

```
'https://jovian.ai/deepak-gupta15336/supermarket-sales'
```

Data Preparation

Though there is a wealth of information in the provided dataset, but still a dataset may have something unwanted that is not beneficial to our analysis. Thus, beforehand, we need to explore our data and make it a bit clean to bring out some unseful insights from it.

Load the dataset in dataframe

Let's load the CSV files using the Pandas library. We'll use the name sales_raw_df for the data frame to indicate this is unprocessed data that we might clean, filter, and modify to prepare a data frame ready for analysis.

```
import pandas as pd
import numpy as np
```

```
sales_raw_df = pd.read_csv('supermarket-sales/supermarket_sales.csv')
sales_raw_df
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019
...	...	...	...	...	...	...	...	...	...	...	...
995	233-67-5758	C	Naypyitaw	Normal	Male	Health and beauty	40.35	1	2.0175	42.3675	1/29/2019
996	303-96-2227	B	Mandalay	Normal	Female	Home and lifestyle	97.38	10	48.6900	1022.4900	3/2/2019
997	727-02-1313	A	Yangon	Member	Male	Food and beverages	31.84	1	1.5920	33.4320	2/9/2019
998	347-56-2442	A	Yangon	Normal	Male	Home and lifestyle	65.82	1	3.2910	69.1110	2/22/2019
999	849-09-3807	A	Yangon	Member	Female	Fashion accessories	88.34	7	30.9190	649.2990	2/18/2019

1000 rows × 17 columns

The dataset have several categories of products being sold in 3 different branches of supermarket. All of the orders do have a unique invoice ID. The customers are even categorised as member who might have taken the membership and normal customers.

Let's view the top 5 rows and bottom 5 rows in the data frame to overview the dataset we'll be working on.

```
sales_raw_df.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date	Ti
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019	13:
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019	10:
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019	13:
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019	20:
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019	10:

```
sales_raw_df.tail()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Date
995	233-67-5758	C	Naypyitaw	Normal	Male	Health and beauty	40.35	1	2.0175	42.3675	1/29/2019
996	303-96-2227	B	Mandalay	Normal	Female	Home and lifestyle	97.38	10	48.6900	1022.4900	3/2/2019
997	727-02-1313	A	Yangon	Member	Male	Food and beverages	31.84	1	1.5920	33.4320	2/9/2019
998	347-56-2442	A	Yangon	Normal	Male	Home and lifestyle	65.82	1	3.2910	69.1110	2/22/2019
999	849-09-3807	A	Yangon	Member	Female	Fashion accessories	88.34	7	30.9190	649.2990	2/18/2019

The meanings of the given columns are mentioned below:

Attribute information

- Invoice id: Computer generated sales slip invoice identification number
- Branch: Branch of supercenter (3 branches are available identified by A, B and C).
- City: Location of supercenters

- Customer type: Type of customers, recorded by Members for customers using member card and Normal for without member card.
- Gender: Gender type of customer
- Product line: General item categorization groups - Electronic accessories, Fashion accessories, Food and beverages, Health and beauty, Home and lifestyle, Sports and travel
- Unit price: Price of each product in Dollar.
- Quantity: Number of products purchased by customer
- Tax: 5% tax fee for customer buying
- Total: Total price including tax
- Date: Date of purchase (Record available from January 2019 to March 2019)
- Time: Purchase time (10am to 9pm)
- Payment: Payment used by customer for purchase (3 methods are available – Cash, Credit card and Ewallet)
- COGS: Cost of goods sold
- Gross margin percentage: Gross margin percentage
- Gross income: Gross income
- Rating: Customer stratification rating on their overall shopping experience (On a scale of 1 to 10)

We can check the data types of the columns given, as shown below:

```
sales_raw_df.dtypes
```

```
Invoice ID                 object
Branch                     object
City                       object
Customer type              object
Gender                     object
Product line               object
Unit price                float64
Quantity                    int64
Tax 5%                    float64
Total                     float64
Date                       object
Time                       object
Payment                    object
cogs                      float64
gross margin percentage   float64
gross income              float64
Rating                    float64
dtype: object
```

```
sales_columns = sales_raw_df.columns
```

It is always preferred to have a copy of the original data and work on it so that the modifications does not affect the original dataframe. To achieve this, let's extract a copy of the data from these columns into a new data frame

sales_df.

```
sales_df = sales_raw_df[sales_columns].copy()
```

Data Exploration and Cleaning

Attribute to check the number of rows and columns available in the dataset.

```
sales_df.shape
```

```
(1000, 20)
```

First of all we need to rename the existing columns as the column's name are having two words in it, that won't be ideal for further analysis.

```
sales_df = sales_df.rename(columns = {' Customer type  ' : ' Customer_Type  ',
                                      'Product line' : 'Product_Line',
                                      'Unit price' : 'Unit_Price',
                                      'gross margin percentage' : 'Gross_
                                       'gross income' : 'Gross_Income'})
```

```
sales_df.keys()
```

```
Index(['Invoice ID', 'Branch', 'City', 'Customer type', 'Gender',
       'Product_Line', 'Unit_Price', 'Quantity', 'Tax 5%', 'Total', 'Date',
       'Time', 'Payment', 'cogs', 'Gross_Margin_Percentage', 'Gross_Income',
       'Rating'],
      dtype='object')
```

Now, we can check the top 5 rows in the dataframe after being renamed to verify the changes done.

```
sales_df.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product_Line	Unit_Price	Quantity	Tax 5%	Total	Date
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019

Invoice Id for an order is always unique, so we can change the index to Invoice ID just for the sake of the attraction of our dataset.

```
sales_df.set_index('Invoice ID', inplace=True)    # index changed to Invoice ID
```

```
sales_df
```

Invoice ID	Branch	City	Customer type	Gender	Product_Line	Unit_Price	Quantity	Tax 5%	Total	Date
750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	1/5/2019
226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	3/8/2019
631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	3/3/2019
123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	1/27/2019
373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2/8/2019
...	...	...	...	...	...	...	...	...	...	...
233-67-5758	C	Naypyitaw	Normal	Male	Health and beauty	40.35	1	2.0175	42.3675	1/29/2019
303-96-2227	B	Mandalay	Normal	Female	Home and lifestyle	97.38	10	48.6900	1022.4900	3/2/2019
727-02-1313	A	Yangon	Member	Male	Food and beverages	31.84	1	1.5920	33.4320	2/9/2019
347-56-2442	A	Yangon	Normal	Male	Home and lifestyle	65.82	1	3.2910	69.1110	2/22/2019
849-09-3807	A	Yangon	Member	Female	Fashion accessories	88.34	7	30.9190	649.2990	2/18/2019

1000 rows × 16 columns

```
# Info method is used to check the datatypes and the no. of non-null values
sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1000 entries, 750-67-8428 to 849-09-3807
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   object
 10  Time                     1000 non-null   object
 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: float64(7), int64(1), object(8)
memory usage: 132.8+ KB
```

There are no null values as non-null count of every column is same as the total number of rows(1000). Only 1 column is detected to be having a numeric value.

```
sales_df['Date']
```

```
Invoice ID
750-67-8428     1/5/2019
226-31-3081     3/8/2019
631-41-3108     3/3/2019
123-19-1176    1/27/2019
373-73-7910     2/8/2019
                  ...
233-67-5758    1/29/2019
303-96-2227     3/2/2019
727-02-1313     2/9/2019
347-56-2442    2/22/2019
849-09-3807    2/18/2019
Name: Date, Length: 1000, dtype: object
```

We have Date and Time as an object, thus, we can change their datatype to date and time using the methods below.

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

```
sales_df['Time'] = pd.to_datetime(sales_df['Time'])
```

Adding day, month, year and hour column

Now, as we do have unique values of date, time, year and hour, we can create new columns respectively to help ourselves in further analysis.

```
sales_df['Day'] = (sales_df['Date']).dt.day
sales_df['Month'] = (sales_df['Date']).dt.month
sales_df['Year'] = (sales_df['Date']).dt.year
sales_df['Hour'] = (sales_df['Time']).dt.hour
```

Let's check if added wisely.

```
sales_df['Hour'].unique()
```

```
array([13, 10, 20, 18, 14, 11, 17, 16, 19, 15, 12], dtype=int64)
```

```
sales_df['Month'].unique()
```

```
array([1, 3, 2], dtype=int64)
```

```
sales_df['Year'].unique()
```

```
array([2019], dtype=int64)
```

```
sales_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 1000 entries, 750-67-8428 to 849-09-3807
Data columns (total 20 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
 16  Day                     1000 non-null   int64
```

```
 17  Month                    1000 non-null   int64
 18  Year                     1000 non-null   int64
 19  Hour                     1000 non-null   int64
dtypes: datetime64[ns](2), float64(7), int64(5), object(6)
memory usage: 196.4+ KB
```

```
sales_df.isnull().sum()
```

```
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
Day                       0
Month                     0
Year                      0
Hour                      0
dtype: int64
```

Exploratory Data Analysis and Visualization

The analysis would help us in answering the questions later by understanding the customer demands or needs better, i.e., the payment method customers prefer, product categories purchased across cities, different branches etc.

It's essential to explore these variables to predict how sales behavior around the supermarket.

Statistical Data

Now, let's view some basic statistics about numeric columns.

```
sales_df.describe()
```

	Unit_Price	Quantity	Tax 5%	Total	cogs	Gross_Margin_Percentage	Gross_Income
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.00000	1.000000e+03	1000.000000
mean	55.672130	5.510000	15.379369	322.966749	307.58738	4.761905e+00	15.379369
std	26.494628	2.923431	11.708825	245.885335	234.17651	6.131498e-14	11.708825
min	10.080000	1.000000	0.508500	10.678500	10.17000	4.761905e+00	0.508500

	Unit_Price	Quantity	Tax 5%	Total	cogs	Gross_Margin_Percentage	Gross_Income
25%	32.875000	3.000000	5.924875	124.422375	118.49750	4.761905e+00	5.924875
50%	55.230000	5.000000	12.088000	253.848000	241.76000	4.761905e+00	12.088000
75%	77.935000	8.000000	22.445250	471.350250	448.90500	4.761905e+00	22.445250
max	99.960000	10.000000	49.650000	1042.650000	993.00000	4.761905e+00	49.650000

We can see that the mean and median does not have much difference, therefore either there is minimum outliers or the values are balanced on both positive and negative side.

Now, let's check the correlation between the numerical or statistical columns.

```
sales_df.corr()
```

	Unit_Price	Quantity	Tax 5%	Total	cogs	Gross_Margin_Percentage	Gross_Inc
Unit_Price	1.000000	0.010778	0.633962	0.633962	0.633962	NaN	0.633
Quantity	0.010778	1.000000	0.705510	0.705510	0.705510	NaN	0.705
Tax 5%	0.633962	0.705510	1.000000	1.000000	1.000000	NaN	1.000
Total	0.633962	0.705510	1.000000	1.000000	1.000000	NaN	1.000
cogs	0.633962	0.705510	1.000000	1.000000	1.000000	NaN	1.000
Gross_Margin_Percentage	NaN	NaN	NaN	NaN	NaN	NaN	
Gross_Income	0.633962	0.705510	1.000000	1.000000	1.000000	NaN	1.000
Rating	-0.008778	-0.015815	-0.036442	-0.036442	-0.036442	NaN	-0.036
Day	0.057021	-0.043347	-0.002515	-0.002515	-0.002515	NaN	-0.002
Month	-0.027387	-0.014524	-0.022301	-0.022301	-0.022301	NaN	-0.022
Year	NaN	NaN	NaN	NaN	NaN	NaN	
Hour	0.008242	-0.007317	-0.002770	-0.002770	-0.002770	NaN	-0.002

We need to round the decimal points to make the data more clear and efficient.

```
sales_corr = np.round(sales_df.corr(),2)
```

```
sales_corr
```

	Unit_Price	Quantity	Tax 5%	Total	cogs	Gross_Margin_Percentage	Gross_Income	Rating	D
Unit_Price	1.00	0.01	0.63	0.63	0.63	NaN	0.63	-0.01	0
Quantity	0.01	1.00	0.71	0.71	0.71	NaN	0.71	-0.02	-0
Tax 5%	0.63	0.71	1.00	1.00	1.00	NaN	1.00	-0.04	-0
Total	0.63	0.71	1.00	1.00	1.00	NaN	1.00	-0.04	-0
cogs	0.63	0.71	1.00	1.00	1.00	NaN	1.00	-0.04	-0
Gross_Margin_Percentage	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
Gross_Income	0.63	0.71	1.00	1.00	1.00	NaN	1.00	-0.04	-0
Rating	-0.01	-0.02	-0.04	-0.04	-0.04	NaN	-0.04	1.00	-0

	Unit_Price	Quantity	Tax 5%	Total	cogs	Gross_Margin_Percentage	Gross_Income	Rating	I
Day	0.06	-0.04	-0.00	-0.00	-0.00	NaN	-0.00	-0.01	1
Month	-0.03	-0.01	-0.02	-0.02	-0.02	NaN	-0.02	-0.04	-0
Year	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
Hour	0.01	-0.01	-0.00	-0.00	-0.00	NaN	-0.00	-0.03	0

The gross margin percentage has NaN value througout the dataset, thus, there is no relation with any other columns.

```
import jovian
jovian.commit()
```

```
[jovian] Updating notebook "deepak-gupta15336/supermarket-sales" on https://jovian.ai/
[jovian] Committed successfully! https://jovian.ai/deepak-gupta15336/supermarket-sales
```

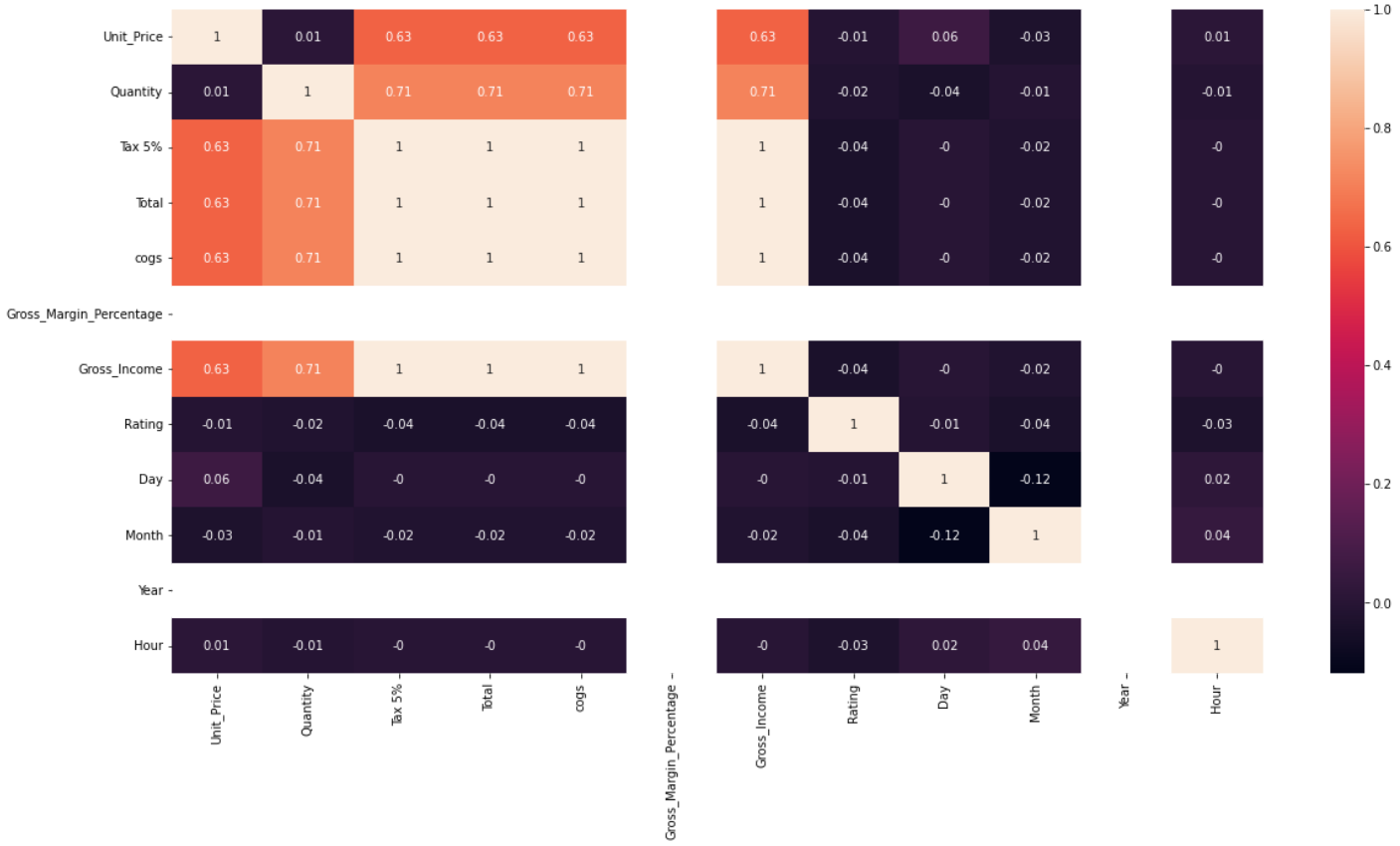
```
'https://jovian.ai/deepak-gupta15336/supermarket-sales'
```

Now, we stand in a position to find the correlation between numeric columns using Heatmaps.

```
%matplotlib inline
import seaborn as sns
import matplotlib
import matplotlib.pyplot as plt
from matplotlib import colors
from matplotlib.ticker import PercentFormatter
```

```
plt.figure(figsize = (20, 10))
sns.heatmap(sales_corr, annot = True)
```

```
<AxesSubplot:>
```



The highest correlation which we can draw from above heatmap is between Quantity and Tax, Quantity and Total Sales, Quantity and Cogs, Quantity and Gross Income. The correlation is 0.71 in each of the above.

```
sales_df.mean()
```

```
C:\Users\deepa\AppData\Local\Temp\ipykernel_5676\2906524947.py:1: FutureWarning:
DataFrame.mean and DataFrame.median with numeric_only=None will include datetime64 and
datetime64tz columns in a future version.
  sales_df.mean()
C:\Users\deepa\AppData\Local\Temp\ipykernel_5676\2906524947.py:1: FutureWarning:
Dropping of nuisance columns in DataFrame reductions (with 'numeric_only=None') is
deprecated; in a future version this will raise TypeError.  Select only valid columns
before calling the reduction.
  sales_df.mean()
```

```
Unit_Price                  55.672130
Quantity                     5.510000
Tax 5%                      15.379369
Total                      322.966749
cogs                       307.587380
Gross_Margin_Percentage      4.761905
Gross_Income                15.379369
Rating                       6.972700
Day                         15.256000
Month                        1.993000
Year                      2019.000000
Hour                        14.910000
dtype: float64
```

The average price of an item in the supermarket is 56 USD. 6 units of such items has been sold with an average profit of 15 USD excluding taxes and with a profit margin of 5%.

```
sales_df.max()
```

```
Branch                                C
City                            Yangon
Customer type                   Normal
Gender                            Male
Product_Line          Sports and travel
Unit_Price                       99.96
Quantity                            10
Tax 5%                           49.65
Total                          1042.65
Date                2019-03-30 00:00:00
Time                2022-11-21 20:59:00
Payment                        Ewallet
cogs                             993.0
Gross_Margin_Percentage       4.761905
Gross_Income                     49.65
Rating                            10.0
Day                                 31
Month                                3
Year                              2019
Hour                                20
dtype: object
```

The most selling items in the supermarket at Branch C is Sports & Travel. It contributes 5% of profit alone and leaving a profit of 40 USD excluding taxes.Mostly purchased by Male and is with a rating of 10.

```
sales_df.min()
```

```
Branch                                   A
City                             Mandalay
Customer type                      Member
Gender                             Female
Product_Line          Electronic accessories
Unit_Price                          10.08
Quantity                                1
Tax 5%                             0.5085
Total                             10.6785
Date                2019-01-01 00:00:00
Time                2022-11-21 10:00:00
Payment                            Cash
cogs                              10.17
Gross_Margin_Percentage        4.761905
Gross_Income                       0.5085
Rating                                4.0
Day                                     1
```

```
Month                                  1
Year                                2019
Hour                                  10
dtype: object
```

The Electronic accessories in the Supermarket at Branch A is not working well. The total units sold is 1 with an income of 0.50 USD excluding taxes.

Distribution of numeric columns

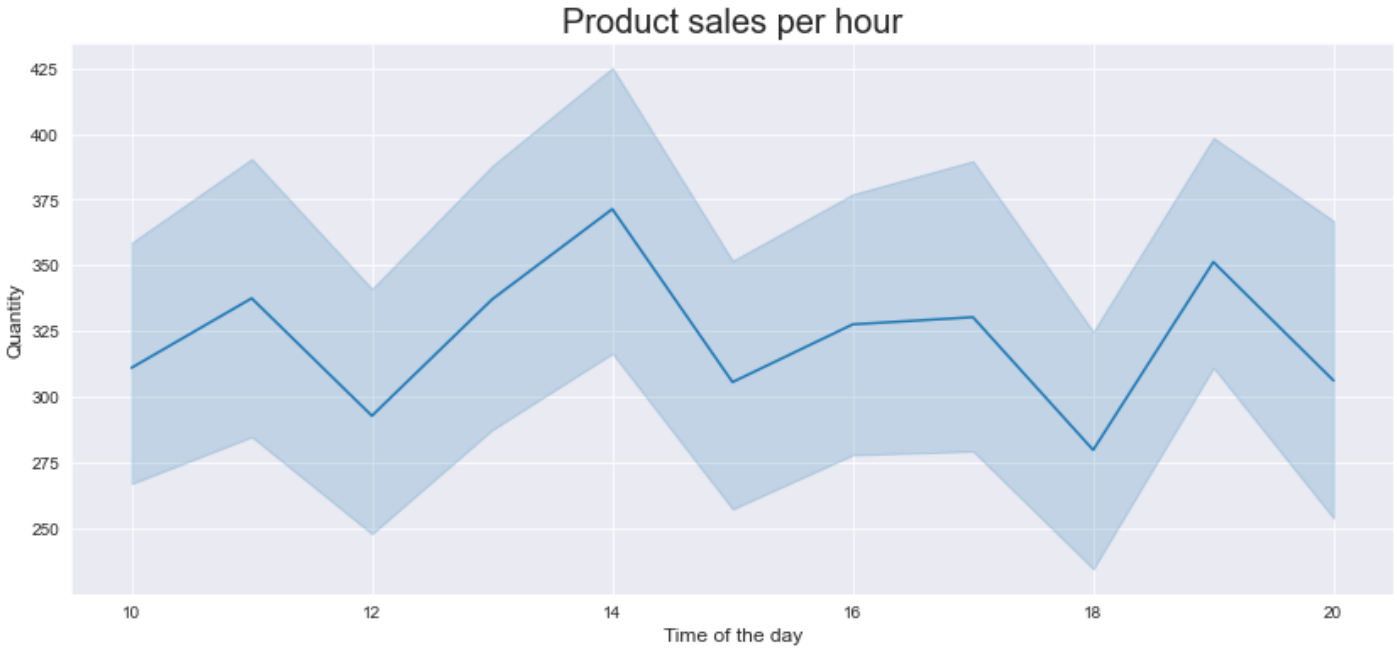
We can explore the data further by checking the distribution of numeric columns using histograms.

Let's begin by importing `matplotlib.pyplot and seaborn` .

Let's plot `Total sales per hour` using LinePlot.

```
plt.figure(figsize = (14, 6))
sns.lineplot(x = 'Hour', y ='Total', data = sales_df)
plt.title('Product sales per hour', fontsize=20)
plt.xlabel('Time of the day', fontsize=12)
plt.ylabel('Quantity', fontsize=12)
```

```
Text(0, 0.5, 'Quantity')
```

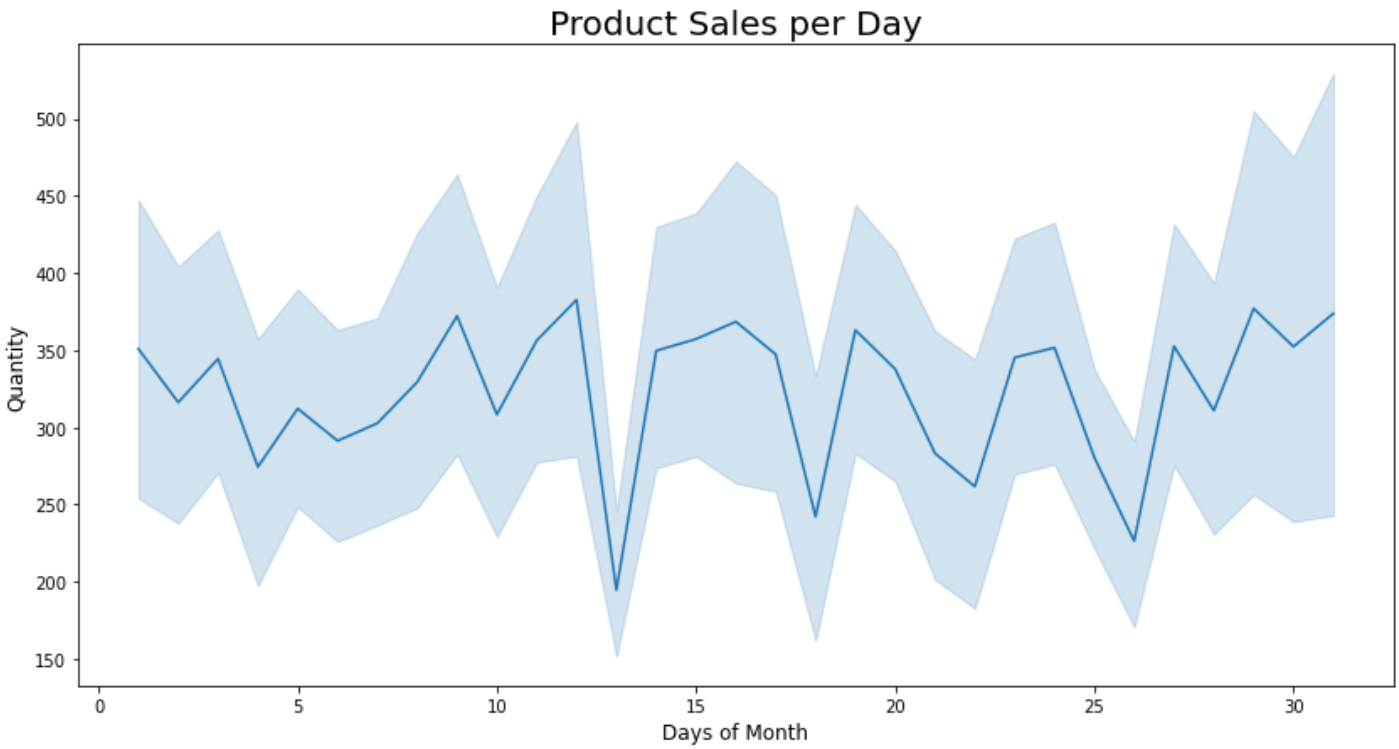


We can see that the sales is highest at 2pm. Good volume of sales is recorded around 5pm and 7pm. The sales is recorded to be the lowest around 12pm, 3pm and 6pm.

We can even check for `Total sales per Day` using Line Plot.

```
plt.figure(figsize = (14, 7))
sns.lineplot(x = 'Day', y = 'Total', data = sales_df)
plt.title('Product Sales per Day', fontsize=20)
plt.xlabel('Days of Month', fontsize=12)
plt.ylabel('Quantity', fontsize=12)
```

```
Text(0, 0.5, 'Quantity')
```



On an average we can see that the sales of products per day is unevenly distributed. There cannot be any pattern drawn.

```
jovian.commit()
```

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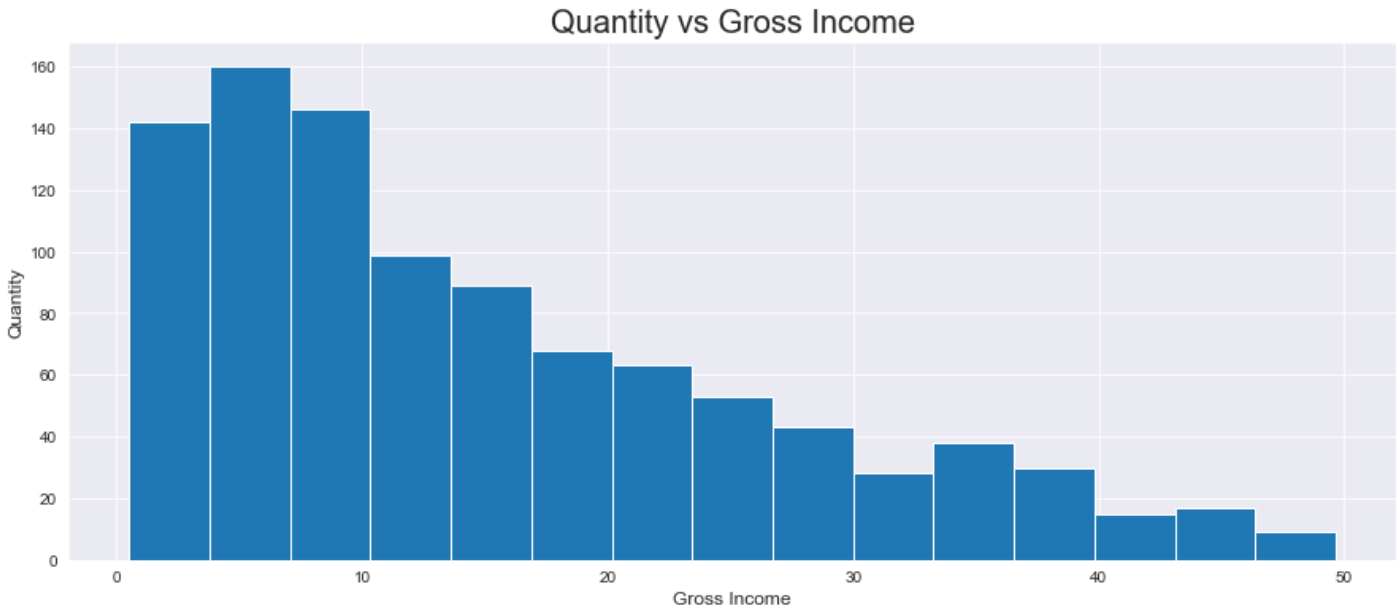
```

```
'https://jovian.ai/deepak-gupta15336/supermarket-sales'
```

```
sns.set_style('darkgrid')
plt.figure(figsize=(15,6))
plt.title('Quantity vs Gross Income', fontsize = 20)
plt.xlabel('Gross Income', fontsize = 12)
plt.ylabel('Quantity', fontsize = 12)
plt.hist(sales_df.Gross_Income, bins = 15, ec = 'White')
```

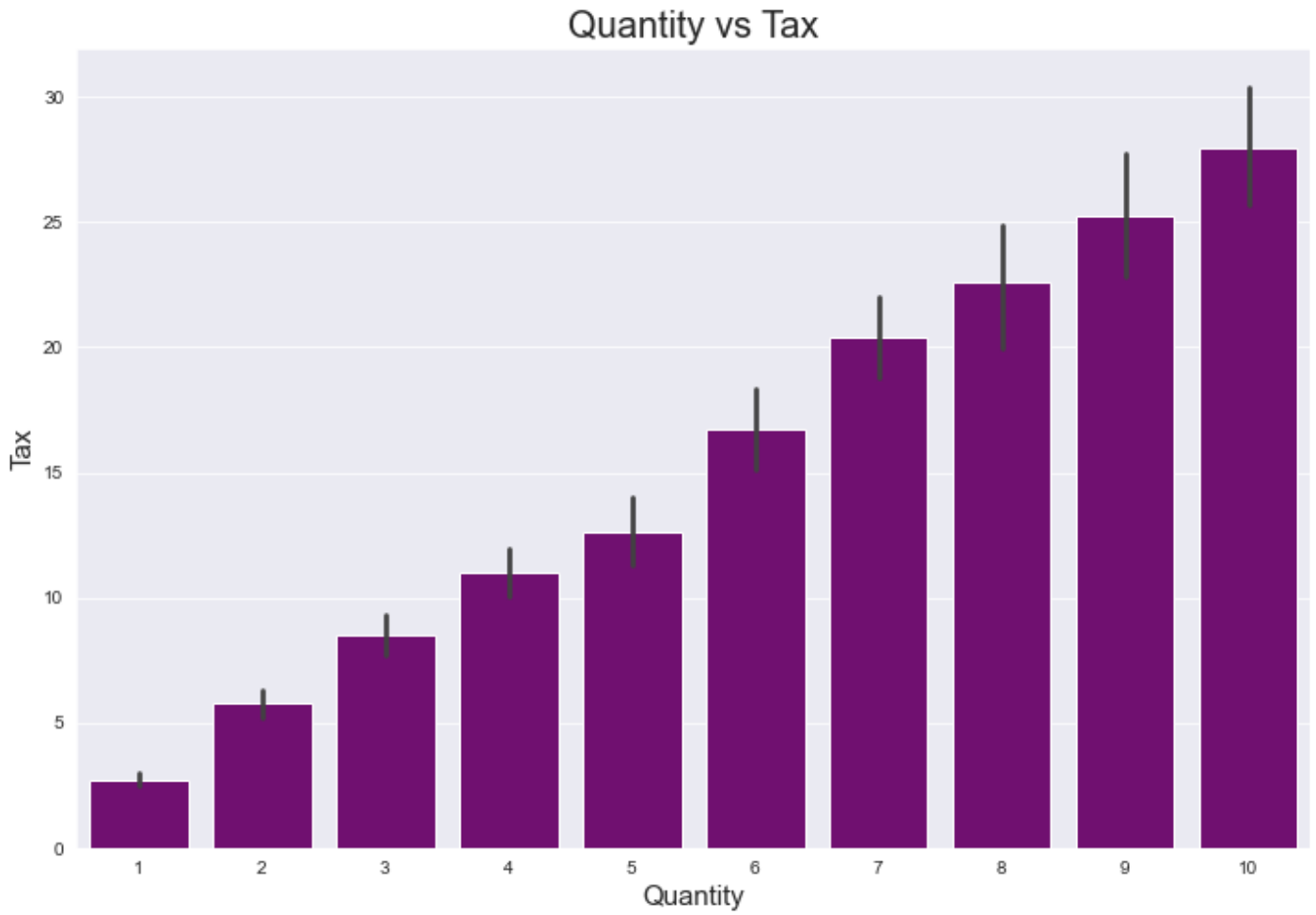
```
(array([142., 160., 146.,  99.,  89.,  68.,  63.,  53.,  43.,  28.,  38.,
         30.,  15.,  17.,   9.]),
 array([ 0.5085,  3.7846,  7.0607, 10.3368, 13.6129, 16.889 , 20.1651,
        23.4412, 26.7173, 29.9934, 33.2695, 36.5456, 39.8217, 43.0978,
        46.3739, 49.65  ]),
 <BarContainer object of 15 artists>)
```



We can clearly see that as the gross income decreases with the decrease in quantities sold.

```
plt.figure(figsize = (12,8))
ax = sns.barplot(x="Quantity", y= "Tax 5%", data = sales_df, color='Purple')
ax.set_title(label = "Quantity vs Tax", fontsize= 20)      #object oriented style
ax.set_xlabel(xlabel = "Quantity", fontsize = 15)
ax.set_ylabel(ylabel = "Tax", fontsize = 15)
```

```
Text(0, 0.5, 'Tax')
```

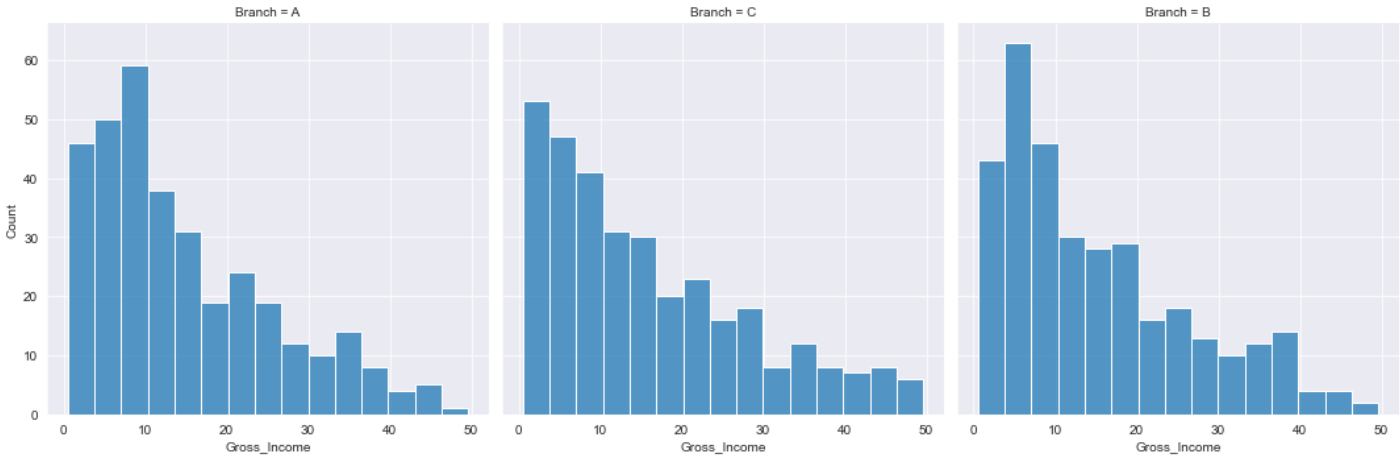


From the above graph,we can conclude that with the increase in sales of item quantity, imposed tax on the items also increases.

```
plt.figure(figsize = (12,8))
sns.displot(sales_df, x="Gross_Income", col="Branch", multiple = "dodge")
```

```
<seaborn.axisgrid.FacetGrid at 0x2212de463d0>
```

```
<Figure size 864x576 with 0 Axes>
```



Branch B, has much higher income in compare to Branch C irrespective of the items sold.

```
payment_methods = sales_df.Payment.value_counts()
payment_methods
```

```
Ewallet        345
Cash           344
Credit card    311
Name: Payment, dtype: int64
```

```
jovian.commit()
```

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```

```
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```
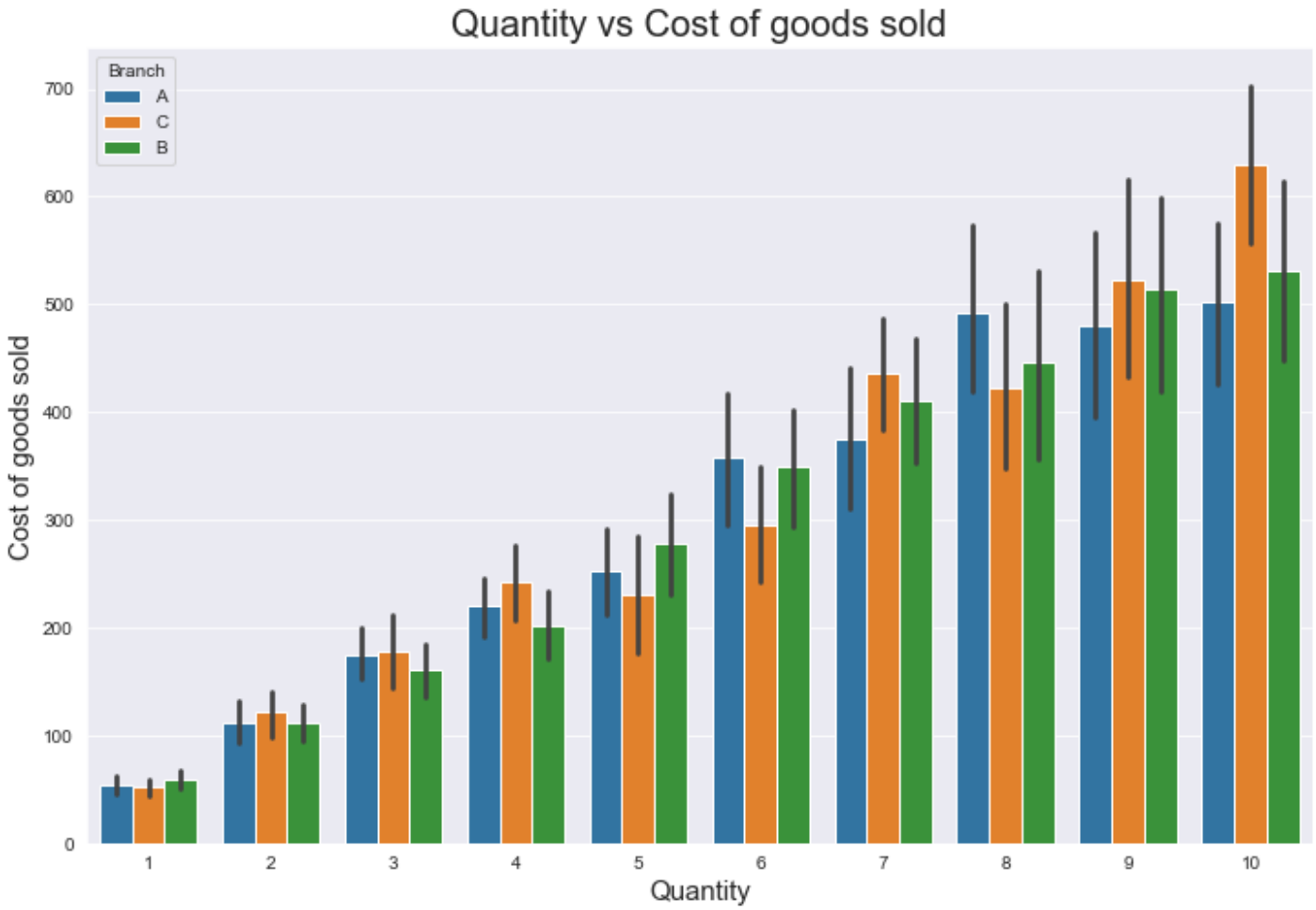

```
plt.figure(figsize = (12, 8))
sns.barplot(x= "Quantity", y = 'cogs', hue = "Branch", data = sales_df)
plt.title("Quantity vs Cost of goods sold", fontsize= 20)
plt.xlabel(xlabel = "Quantity", fontsize = 15)
plt.ylabel(ylabel = "Cost of goods sold", fontsize = 15)
```

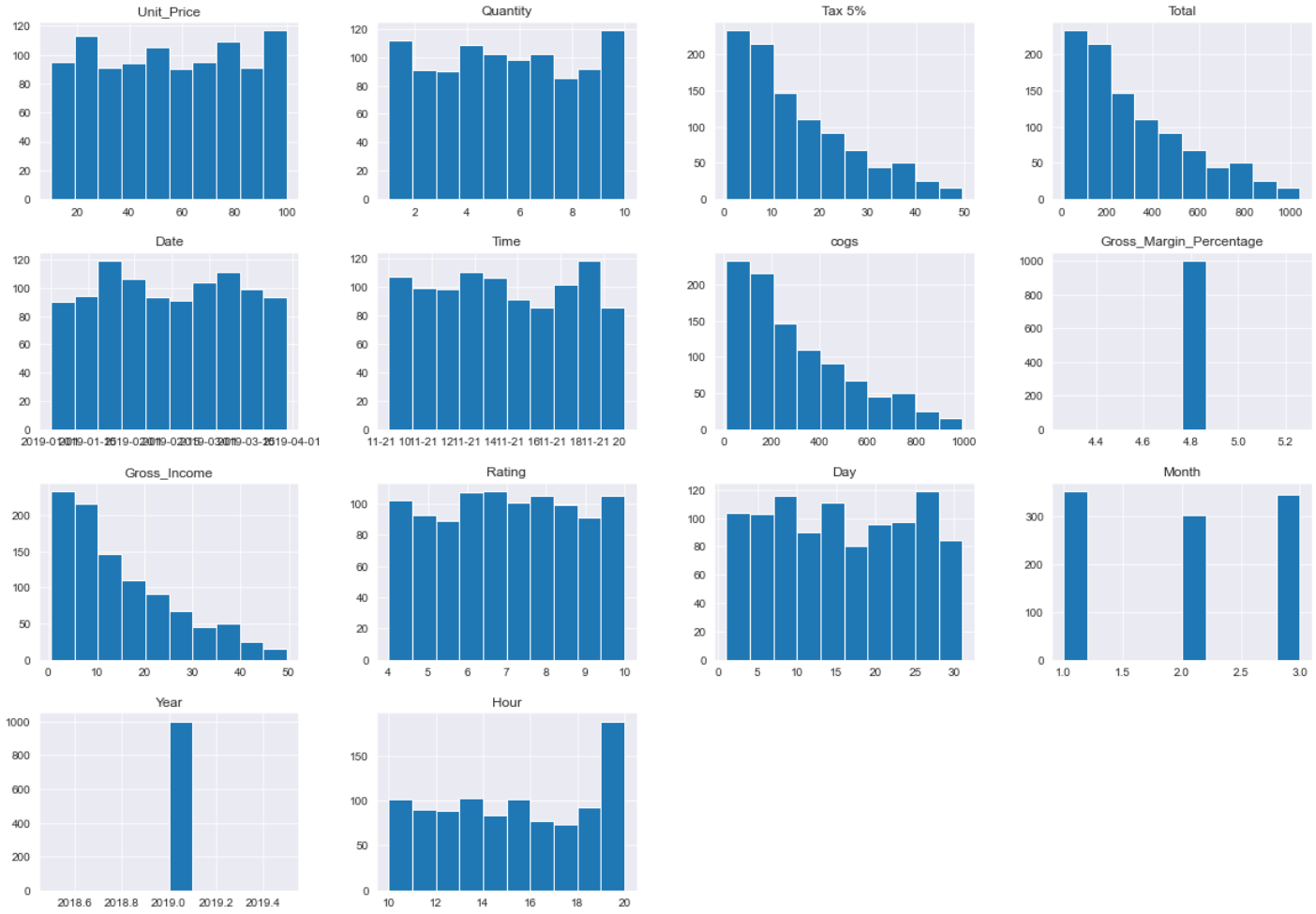
```
Text(0, 0.5, 'Cost of goods sold')
```



As the Quantity is increasing, the cost of good sold also increases.

Lets see the distribution for different columns depending upon their row values.

```
sales_df.hist(figsize=(20,14))
plt.show()
```

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```

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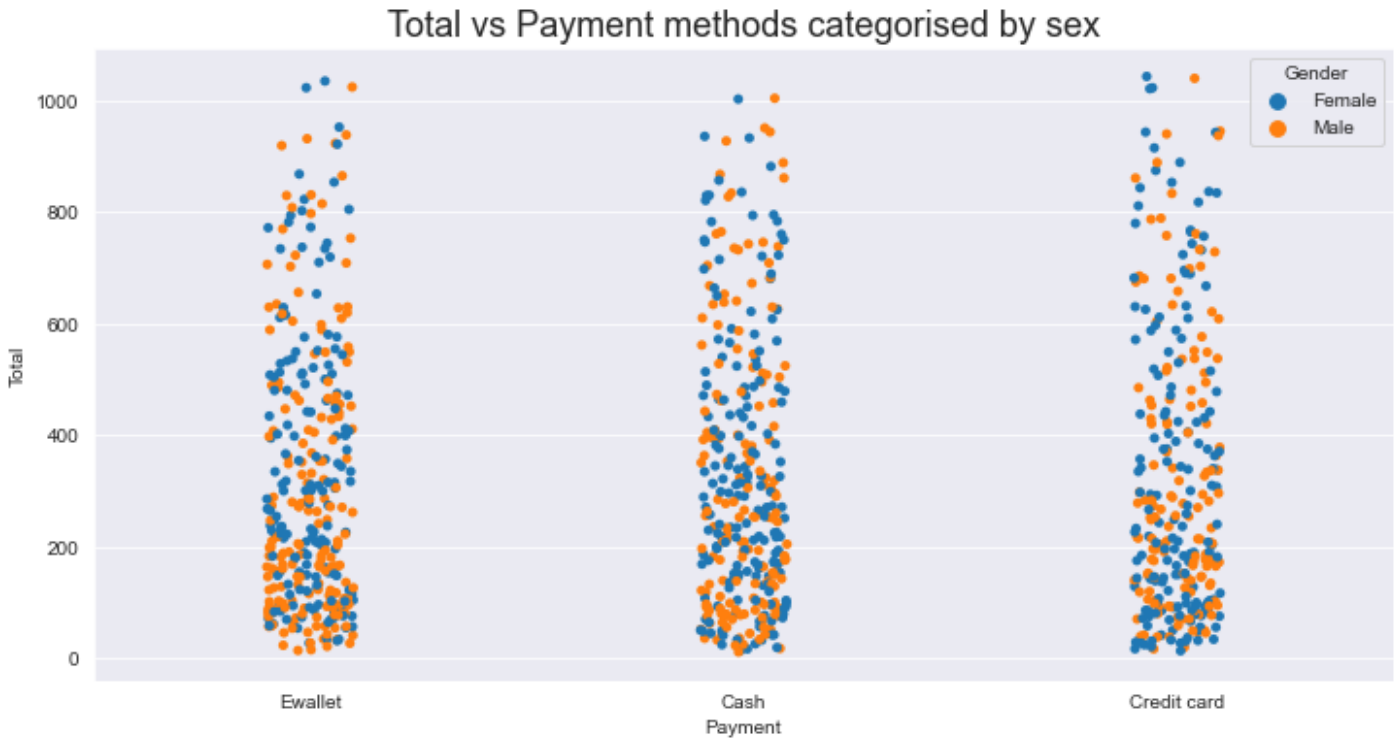
```
plt.figure(figsize = (12,6))
sns.stripplot(y='Total',x='Payment',hue='Gender',data=sales_df)
plt.title("Total vs Payment methods categorised by sex", fontsize = 18)
```

```
Text(0.5, 1.0, 'Total vs Payment methods categorised by sex')
```



Customers and Branches

In a store, it is most important to find the type of customers, in terms of their interest, so that one can introduce more exclusive offers to increase the sales and find the highly demanded product category and the lowest among the customers.

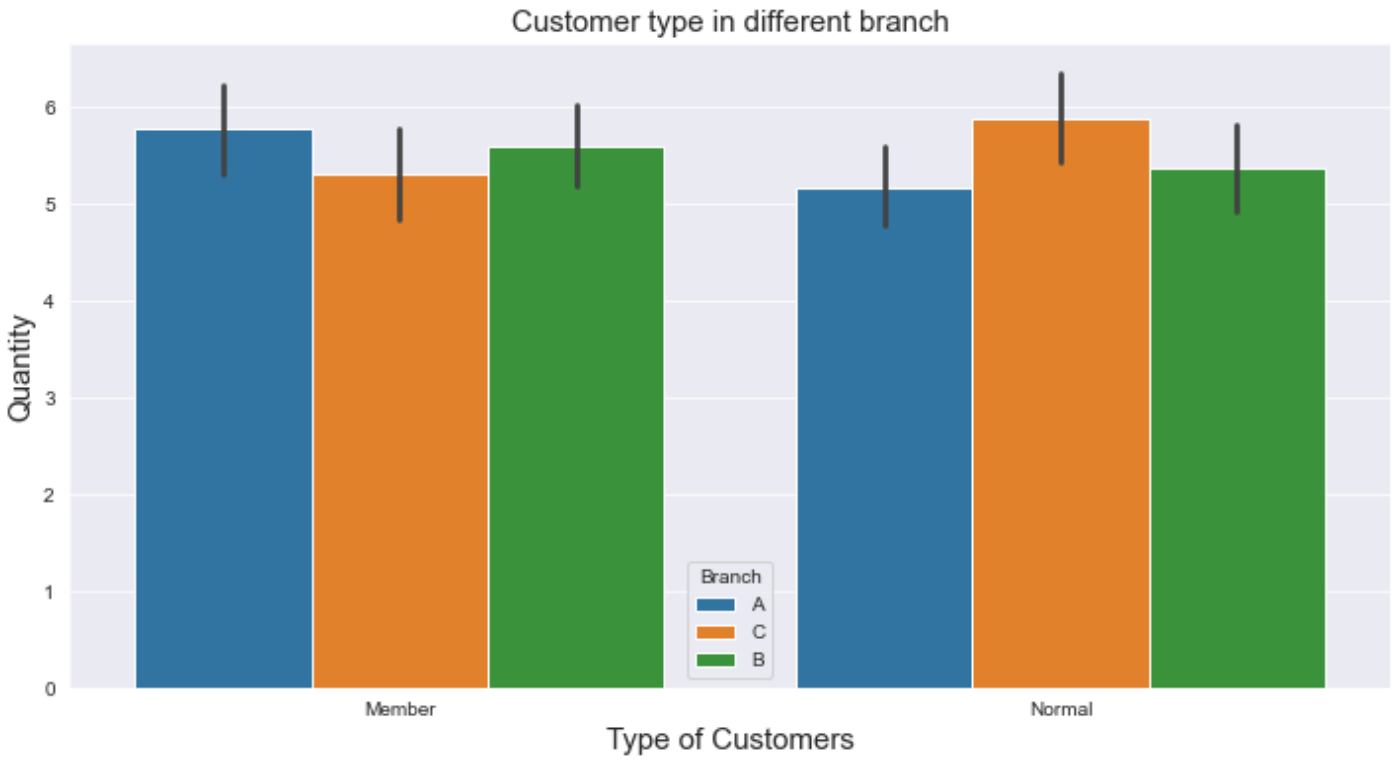
```
sales_df.groupby(['Customer type']).agg({'Total':'sum'})
```

Customer type	Total
Member	164223.444
Normal	158743.305

Customers in different branches

```
plt.figure(figsize=(12,6))
sns.barplot(x = "Customer type", y="Quantity", hue = "Branch", data = sales_df)
plt.title("Customer type in different branch", fontsize = 15)
plt.xlabel( "Type of Customers", fontsize = 15)
plt.ylabel("Quantity", fontsize = 15)
```

```
Text(0, 0.5, 'Quantity')
```

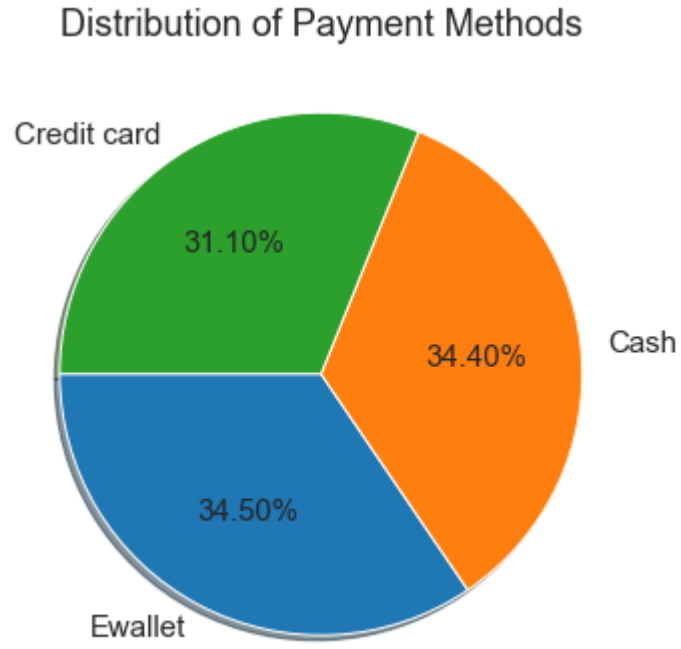


At branch A, members do more purchases and normal customers at branch C. At branch B, approximately equal purchases are done by members and normal customers.

Payment methods at different branches

```
plt.figure(figsize=(15, 6))
#explode = [0.03,0,0.1,0,0]
plt.title("Distribution of Payment Methods", fontsize = 18)
plt.pie(payment_methods, labels=payment_methods.index,

            autopct='%0.2f%%', pctdistance=0.6, shadow=True, radius = 1.0, startangle=
```

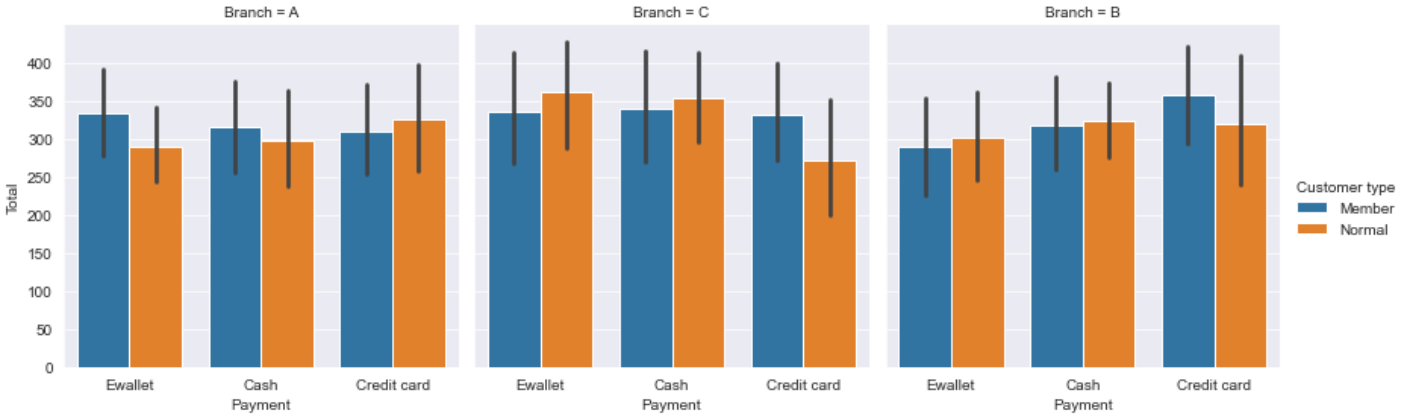


With this pie chart, when we look across all the branches and cities, we can see that there is not much difference in paying with cash or eWallet rather than credit card.

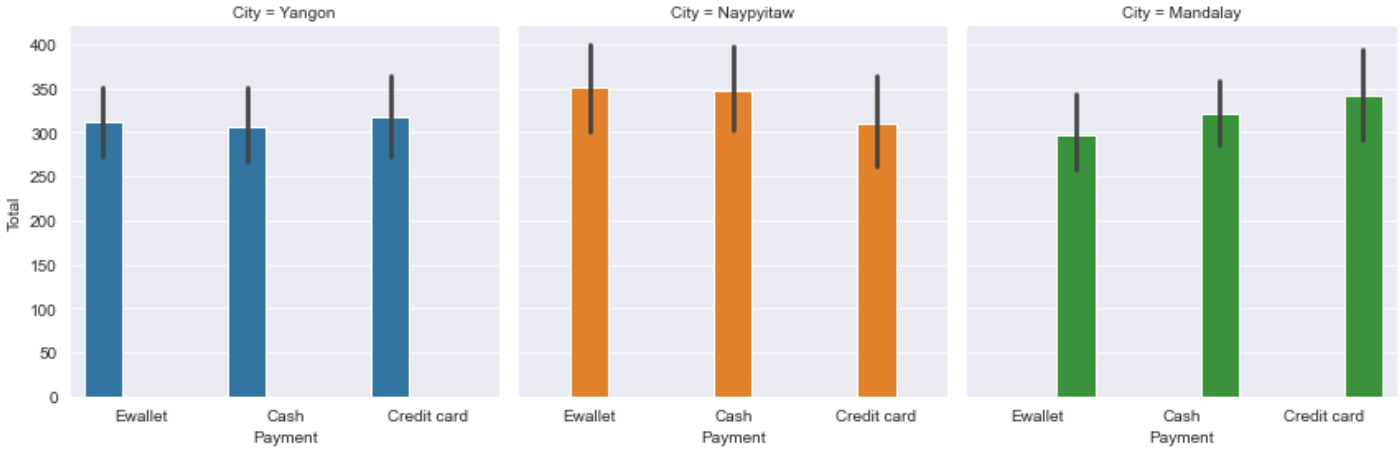
But, with the below categorical plot, we can conclude:

- At Branch A,members are using Ewallet more than normal customers, however there is not much difference in paying Cash or with Credit card.
- At Branch B, members and normal customers are nearly equally using the Ewallet and cash, but the members are using more credit card comparatively.
- At Branch C, things are pretty changed, Ewallets are being used slightly more by normal customers and there is a gap of about 10% in using credit card by members.

```
sns.catplot(x="Payment", y="Total",  hue="Customer type", col="Branch",
                data=sales_df, kind="bar",height=4)
plt.show()
```




```
sns.catplot(x="Payment", y="Total",  hue="City", col="City",
                data=sales_df, kind="bar",height=4)
plt.show()
```



If we talk about cities, in Yangon, all of the payment methods are equally used, in Naypyitaw, eWallets and cash payments are mostly done and in Mandalay, credit cards are mostly preferred.

```
payment_pct = sales_df.Payment.value_counts() * 100 / sales_df.Payment.count()
payment_pct
```

```
Female     50.1
```

```
Male      49.9
Name: Gender, dtype: float64
```

It means, 50.1% shopping is done by Females and 49.9% purchases are done by Males across the branches.

```
jovian.commit()
```

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```
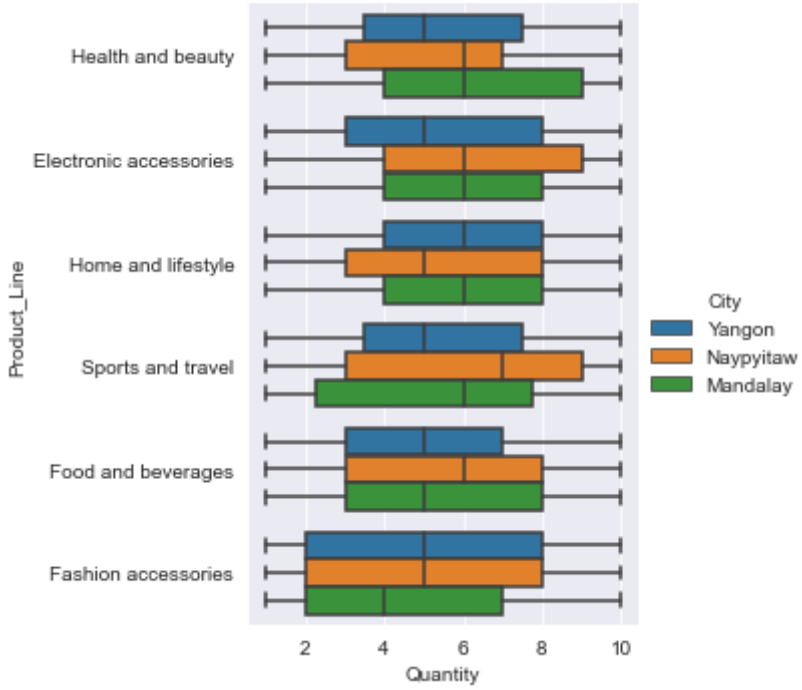

```
'https://jovian.ai/deepak-gupta15336/supermarket-sales'
```

```
plt.figure(figsize=(12,6))
sns.catplot(data=sales_df, x="Quantity", y="Product_Line", hue="City", kind="box")
```

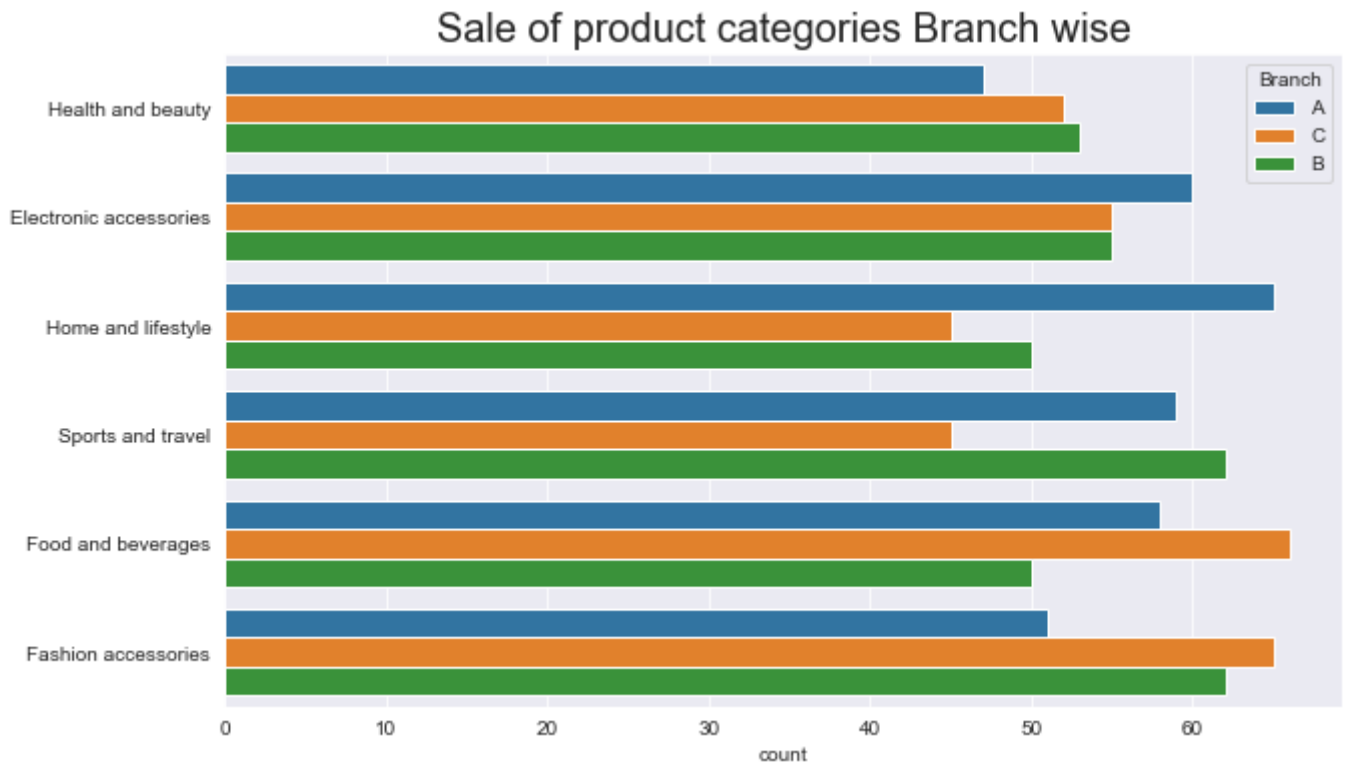
```
<seaborn.axisgrid.FacetGrid at 0x22126e261f0>
<Figure size 864x432 with 0 Axes>
```



Health and beauty products are sold more in Mandalay, while in Naypyitaw, Electronic accessories are highly sold. Home & Lifesyle items are sold equally in all the 3 cities. Naypyitaw seems to be the top seller of Sports & travel items. In Yangon, Food & Beverages seems to be sold comparatively less than other 2 cities, while in Mandalay, Fashion accesories are sold less.

Product Categories across different Branches

```
plt.figure(figsize = (10, 6))
sns.countplot( y=sales_df.Product_Line, hue = "Branch", data = sales_df, dodge = True)

plt.title("Sale of product categories Branch wise", fontsize = 20)
plt.ylabel(None);
```



At branch A, Home and Lifestyle products are sold higher than other items, while at branch B, Soprts & travel and Fashion Accesories are the most sellable items. At branch C, Food & Beverages and Fashion Accesories items are more likely to be sold coparatively to other categories.

```
jovian.commit()
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```

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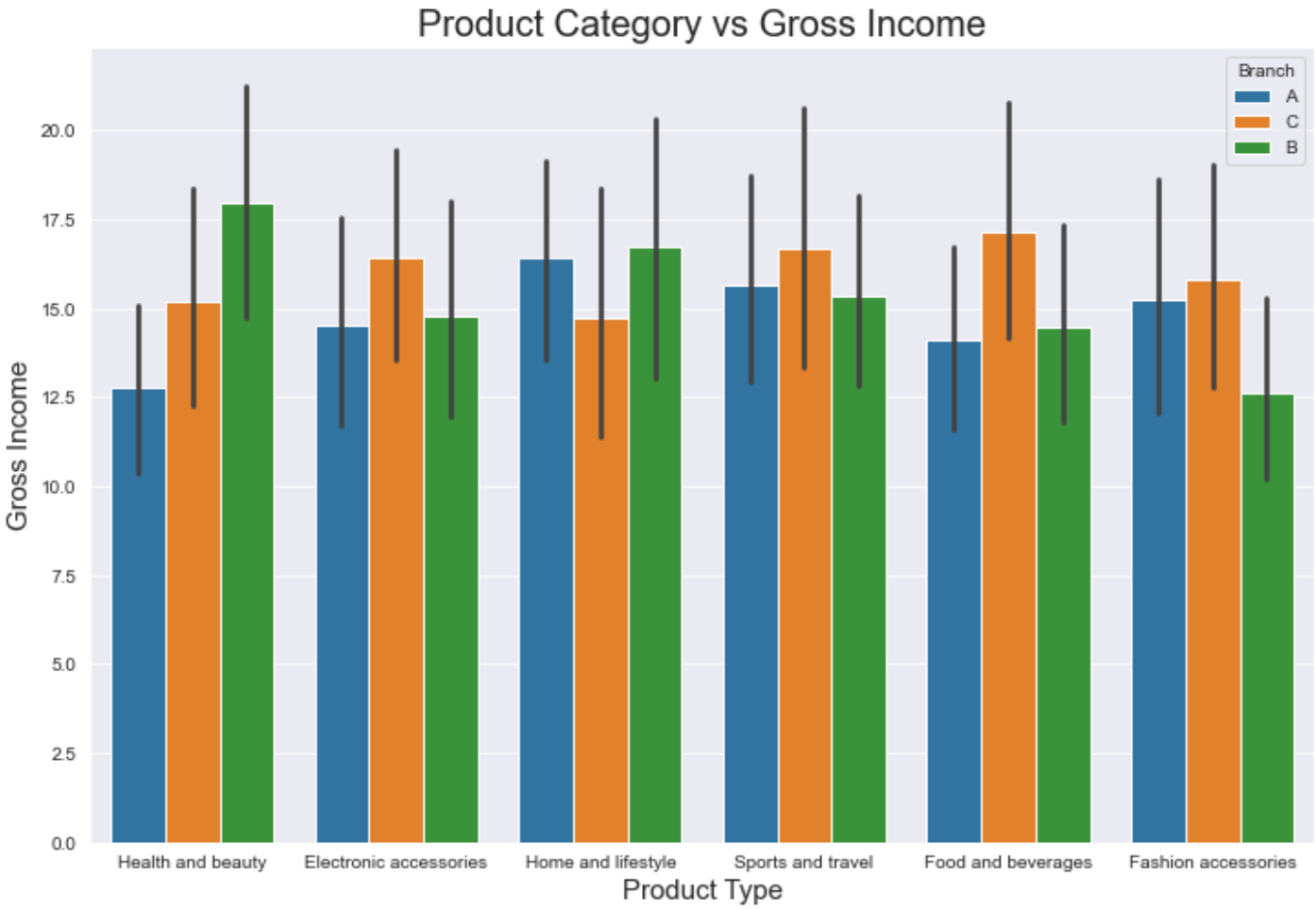
```

```
plt.figure(figsize=(12,8))
sns.barplot(x='Product_Line',y='Gross_Income',hue='Branch',data=sales_df)
plt.title('Product Category vs Gross Income',fontsize= 20)
plt.xlabel('Product Type',fontsize=15)
plt.ylabel('Gross Income',fontsize=15)
plt.show()
```



The highest gross income is recorded in Branch B for health and beauty. Branch A generates less income for health and beauty items and branch B in Fashion accessories. The gross income in Branch C is similar for all product category.

```
jovian.commit()
```

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[jovian] Committed successfully! https://jovian.ai/deepak-gupta15336/supermarket-sales
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```

```
'https://jovian.ai/deepak-gupta15336/supermarket-sales'
```

Asking and Answering Questions

We've already gained several insights about the sales, product categories sold, income etc across different branches and the cities by exploring individual columns of the dataset. Let's ask some specific questions and try to answer them using data frame operations and visualizations.

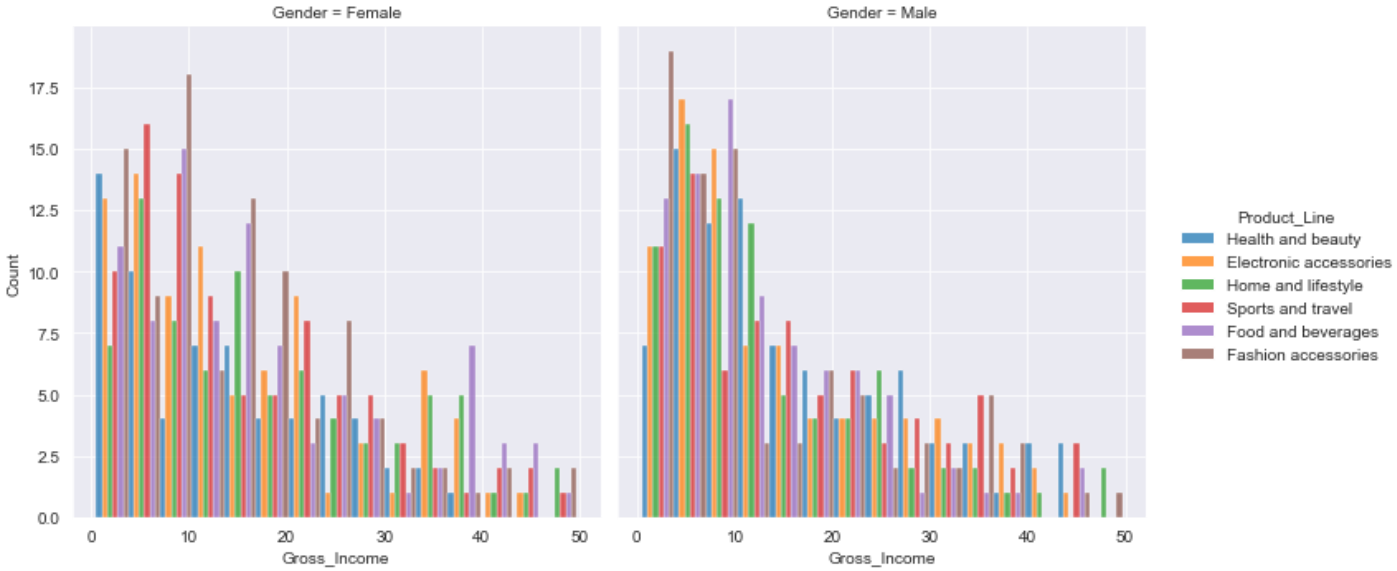
Q: Which product category generates more revenue by different genders?

It'd be interesting to know the types of products males and females prefers across a wide range of available items. For this we can use displot from the seaborn library so that females and males preferences can be shown uniquely.

```
plt.figure(figsize=(15,8))
sns.displot(sales_df, x="Gross_Income", hue="Product_Line", multiple="dodge", col = 'Ge
```

```
<seaborn.axisgrid.FacetGrid at 0x221398a1d00>
```

```
<Figure size 1080x576 with 0 Axes>
```



Sale of fashion accesories contributes the most in the income of the stores whether it is for male or female across all the cities or branches.

Q: Which branch has the highest sales?

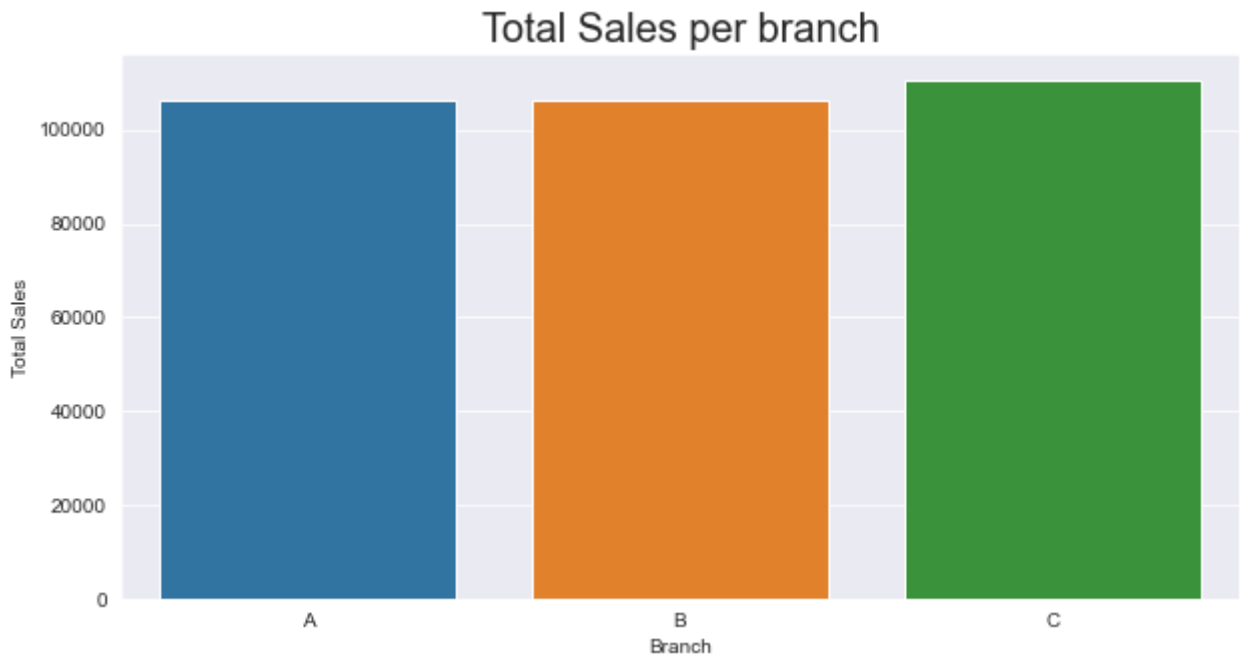
To keep the competition alive and the business running, we need to compete among the branches. We can check the level of competency among the branches using the groupby method and as visualized below.

```
SalesPerBranch=sales_df.groupby('Branch')['Total'].sum()
SalesPerBranch
```

```
Branch
A    106200.3705
B    106197.6720
C    110568.7065
Name: Total, dtype: float64
```

```
plt.figure(figsize =(10, 5) )
sns.barplot(x=SalesPerBranch.index , y=SalesPerBranch.values)
plt.ylabel('Total Sales')
plt.title('Total Sales per branch', fontsize = 20)
```

```
Text(0.5, 1.0, 'Total Sales per branch')
```



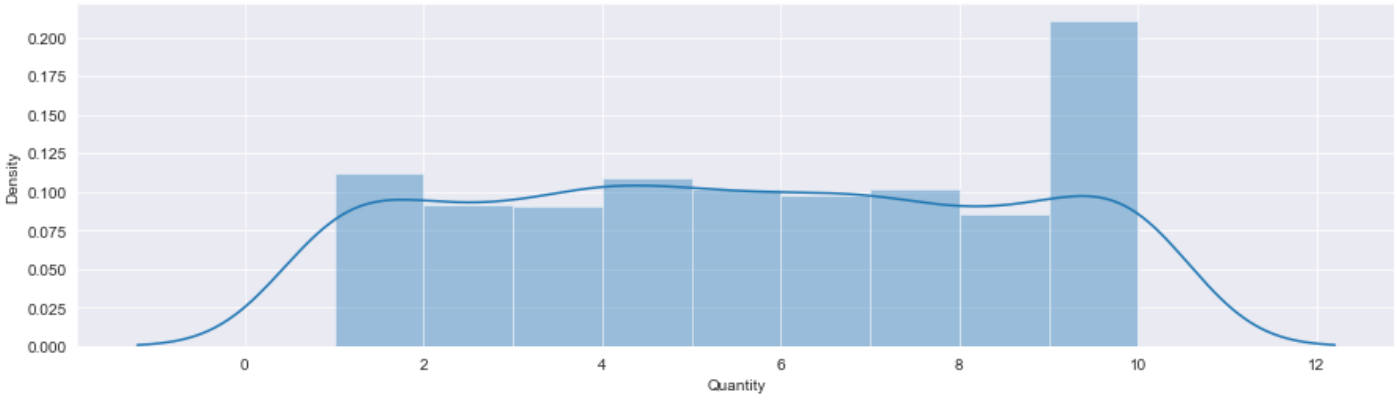
We can say that almost all branches have same performance, just Branch C has little more sales.

Q: How many products are bought by an individual customer in a single order?

```
plt.figure(figsize = (15,4))
sns.distplot(sales_df['Quantity'])
```

```
C:\Users\deepa\anaconda3\lib\site-packages\seaborn\distributions.py:2619:
FutureWarning: `distplot` is a deprecated function and will be removed in a future
version. Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

```
<AxesSubplot:xlabel='Quantity', ylabel='Density'>
```



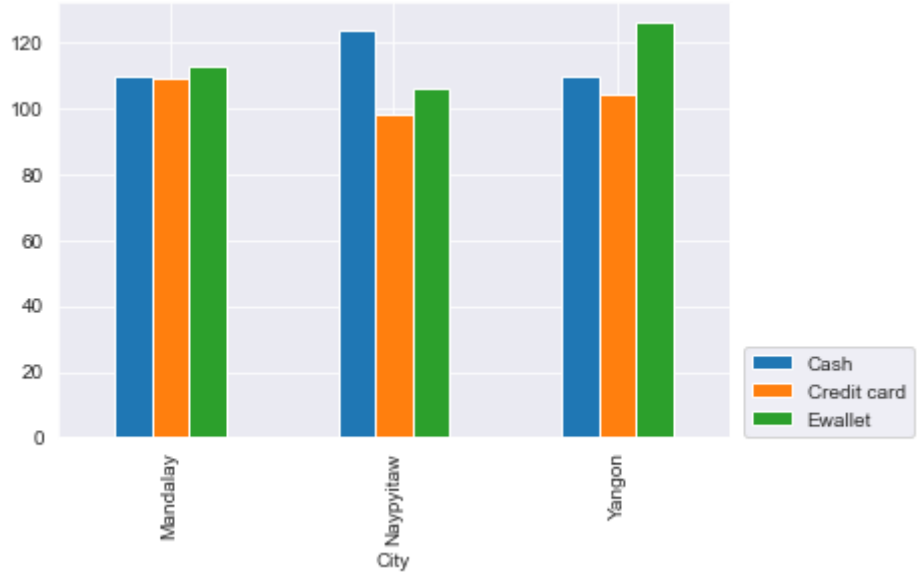
In a single order, an individual bought 10 items altogether.

Q: Which City use more cash comparing to other payment methods?

```
plt.figure(figsize = (15,4))
pd.crosstab(sales_df['City'],sales_df['Payment']).plot.bar()
plt.legend(loc = (1.02, 0))
```

```
<matplotlib.legend.Legend at 0x2213edae5e0>
```

```
<Figure size 1080x288 with 0 Axes>
```



We can conclude that in Naypyitaw, cash is the most prefrred payment method while in Yangon, Ewallet is the most preferred. In Mandalay, all of the payment methods arge equivalently used.

Q: Find highest sale on a day in all months across all branches.

Decoding month columns with their names.

```
sales_df["Month"]=sales_df["Month"].replace({1:"January"})
sales_df["Month"]=sales_df["Month"].replace({2:"February"})
sales_df["Month"]=sales_df["Month"].replace({3:"March"})
sales_df.head(2)
```

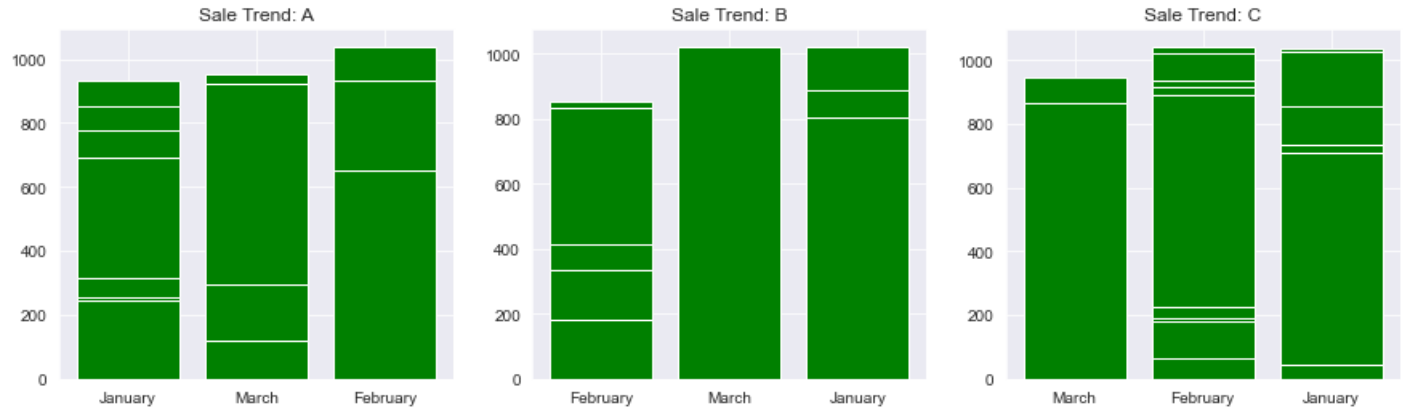
Invoice ID	Branch	City	Customer type	Gender	Product_Line	Unit_Price	Quantity	Tax 5%	Total	Date	Ti
750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	2019-01-05	2022- 13:08:
226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	2019-03-08	2022- 10:29:

```
a=sales_df[sales_df["Branch"] =="A"]
plt.figure(figsize = (15,4))
plt.subplot(1,3,1)
plt.bar(a["Month"],a["Total"],color = 'green')
plt.title("Sale Trend: A")

b=sales_df[sales_df["Branch"] =="B"]
plt.subplot(1,3,2)
plt.bar(b["Month"],b["Total"],color = 'green')
plt.title("Sale Trend: B")

c=sales_df[sales_df["Branch"] =="C"]
plt.subplot(1,3,3)
```

```
plt.bar(c["Month"],c["Total"],color = 'green')
plt.title("Sale Trend: C")
plt.show()
```



At branch A

- Highest sale : February
- Lowest sale : January

At branch B

- Highest sale : March
- Lowest sale : February

At branch C

- Highest sale : February
- Lowest sale : March

Conclusions

- Sale of items varies in different timings of the day but, conclusively, it is uneven when considered daywise across the month.
- Branch B, has much higher income in compare to Branch C irrespective of the items sold.
- Cost of goods sold is directly proportional to the quantities sold.
- Across all the branches and cities, there is not much difference in paying with cash or eWallet.
- Member customers prefers eWallet as payment method, may be because of faster method of payment method than credit card.
- Product categories also play a vital role in generating income at a store.

Insights

- The highest correlation is 0.71 between Quantity and Tax, Quantity and Total Sales, Quantity and Cogs, Quantity and Gross Income.
- The sales is highest at 2pm. Good volume of sales is recorded around 5pm and 7pm and the sales is recorded to be the lowest around 12pm, 3pm and 6pm.

- Each of the 3 cities Yangon, Naypyitaw, Mandalay has got 1 branch each A, B and C with similar Gross Income.
- The most sales is recorded in Home and lifestyle segment made by females.
- In Branch A 'member customers' make more purchases and in Branch C purchases are made more by 'normal customers'.
- Mostly Ewallet and Credit card is used for payments in all 3 branches.
- Sale of fashion accesories contributes the most in the income of the stores whether it is for male or female across all the cities or branches.
- Each branch has their own demand of the product categories.
- Branch B leads in sales of Health and beauty and lowest sales of Fashion Accessories. Branch C leads in Electronic Accessories and Sports and travel.

Proposed Solutions

- Proposed SolutionsBreakfast items should be promoted to increase sales at opening time, the sales between 4pm and 8 pm can be boosted through membership discounts and promotion of products for teen agers and senior citizens.
- Different Membership discounts should be introduced for teenagers, families, senior citizens.
- Male products should be added more in Home and Lifestyle segments. The supermarket needs to concentrate on specific timings of each category of products sold.
- The supermarket should focus on masses and promote products of low and medium prices. Seasonal discounts should be held to increase sales.

References and Future Work

Check out the following resources to learn more about the dataset and tools used in this notebook:

- SuperMarket sales: https://www.kaggle.com/datasets/aungpyaeap/supermarket-sales
- Pandas user guide: https://pandas.pydata.org/docs/user_guide/index.html
- Matplotlib user guide: https://matplotlib.org/3.3.1/users/index.html
- Seaborn user guide & tutorial: https://seaborn.pydata.org/tutorial.html
- opendatasets Python library: https://github.com/JovianML/opendatasets

```
import jovian
jovian.commit()
```

```
```