Individual Final Project

```
# Import the appropriate libraries

import matplotlib.pyplot as plt
import pandas as pd
import datetime as dt
import matplotlib.pyplot as plt
import seaborn as sns
import os
%matplotlib inline
```

```
!pip install openpyxl
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Requirement already satisfied: openpyxl in /usr/local/lib/python3.10/dist-packages (3.0.10)
Requirement already satisfied: et-xmlfile in /usr/local/lib/python3.10/dist-packages (from openpyxl) (1.1.0)
```

```
# import the dataset from Kaggle website. It was first csv file then I convert it to excel file
df = pd.read_excel('supermarket_sales - 0772934.xlsx', sheet_name='Sheet1')
```

```
# Check the shape
df.shape
```

```
(1000, 16)
```

```
# Use the head function
df.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Invoice Date	Payment	cogs	gross margin percentage	gro inco
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	2019-01-05 13:08:00	Ewallet	522.83	4.761905	26.14
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	2019-03-08 10:29:00	Cash	76.40	4.761905	3.82
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	2019-03-03 13:23:00	Credit card	324.31	4.761905	16.21
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	2019-01-27 20:33:00	Ewallet	465.76	4.761905	23.28

```
#using the info function
df.info()
```

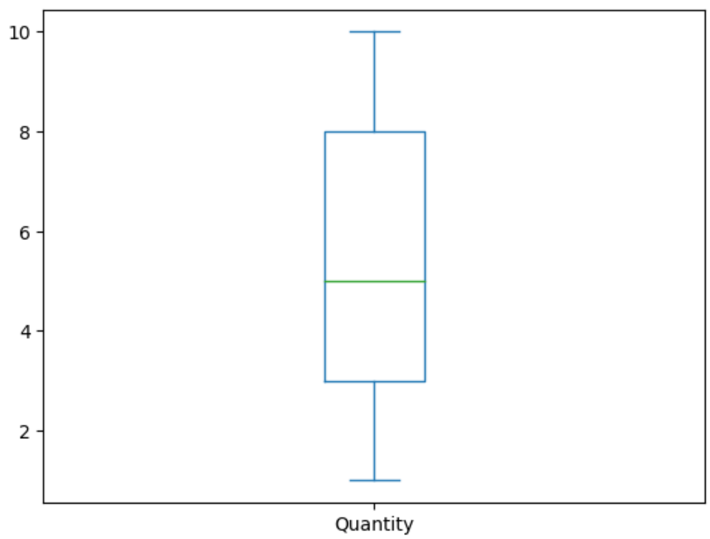
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 16 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Invoice ID               1000 non-null   object
 1   Branch                   1000 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  Invoice Date             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](1), float64(7), int64(1), object(7)
memory usage: 125.1+ KB
```

```
#checking isnull
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
Invoice Date               0
Payment                    0
cogs                       0
gross margin percentage    0
gross income               0
Rating                     0
dtype: int64
```

```
# Create a box plot to identify outliers
ax = df['Quantity'].plot.box()
```

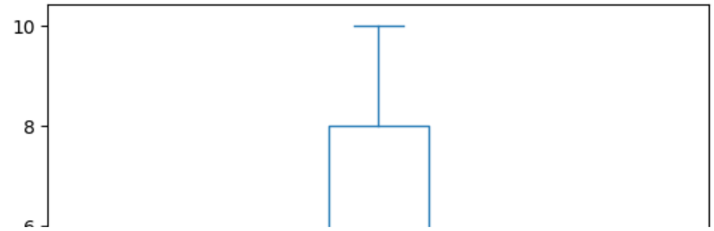



```
# Filter out the negative quantity orders
df = df.loc[df['Quantity']>0]
```

```
# Check the shape again
df.shape
```

```
(1000, 16)
```

```
# Create a Box plot without negative quantity
ax = df['Quantity'].plot.box()
```



Time Series Trends

- Number of customer
- Revenue

```
# resample function resamples the data and converts the data into the desired
# Summarize the data on a monthly basis
m_orders_df = df.set_index('Invoice Date')['Invoice ID'].resample('M').nunique()
```

```
m_orders_df
```

```
Invoice Date
2019-01-31    352
2019-02-28    303
2019-03-31    345
Freq: M, Name: Invoice ID, dtype: int64
```

```
# Create a Line Chart for the data
ax = pd.DataFrame(m_orders_df.values).plot(
    grid=True,
    figsize=(10,7),
    legend=False
)

ax.set_xlabel('Date')
ax.set_ylabel('Number of orders/invoices')
ax.set_title('Total Number of Orders Over Time')

# use x.strftime('%m.%Y'), where x is the Pythondate object, %m is the placeholder for
# the month value, and %Y is the placeholder for the year value. The strftime function
# of the Pythondate object formats the date into the given format.

plt.xticks(
    range(len(m_orders_df.index)),
    [x.strftime('%m.%Y') for x in m_orders_df.index],
    rotation=45
)

plt.show()
```


```
# Get all invoice dates from Jan 1, 2019
invoice_dates = df.loc[
    df['Invoice Date'] >= '2019-01-01',
    'Invoice Date'
]
```

```
# Print Min and Max dates in that series
print('Min date: %s\nMax date: %s' % (invoice_dates.min(), invoice_dates.max()))
```

```
Min date: 2019-01-01 10:39:00
Max date: 2019-03-30 20:37:00
```

Q. What do you observe?

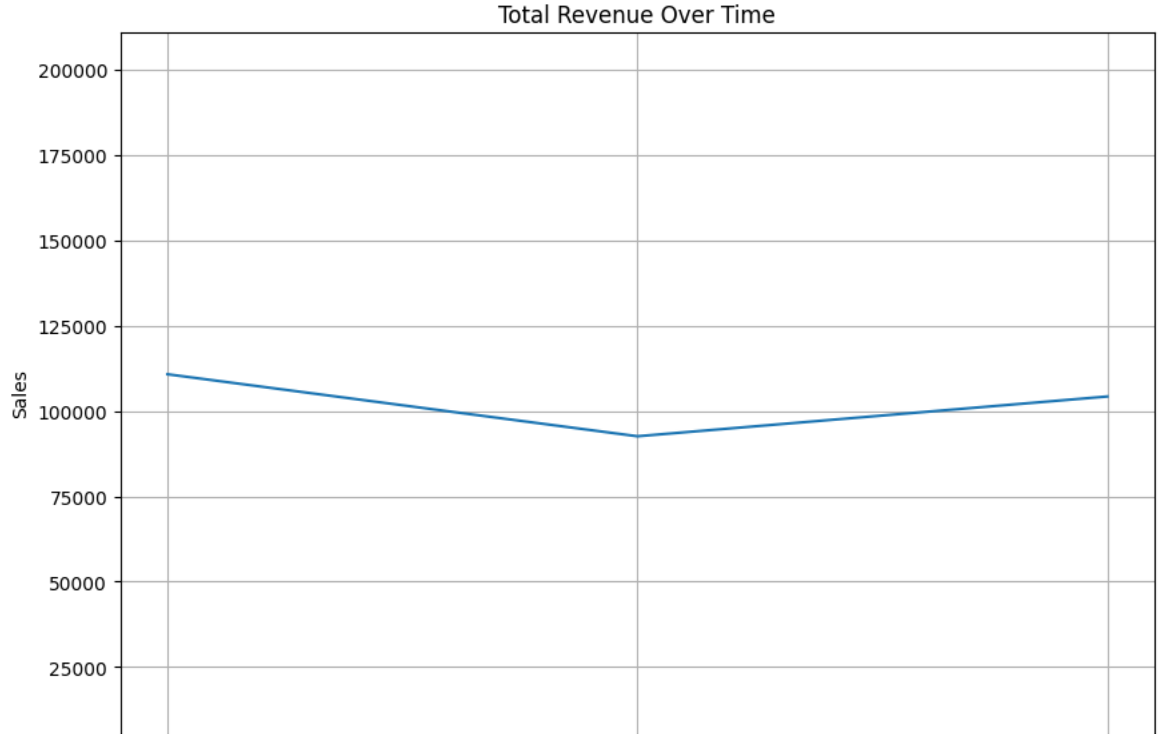
Here, we can see that in the beginning month of Jan the number of order was nearly 360 but, later it fell down by 50 in the next month will, in the month of March it raised to somewhat 330.

```
# Calculate sales
df['Sales'] = df['Quantity'] * df['Unit price']

# Look at monthly revenue data by using sum as an aggregate function
m_revenue_df = df.set_index('Invoice Date')['Sales'].resample('M').sum()
```

```
m_revenue_df
```

```
Invoice Date
2019-01-31    110754.16
2019-02-28     92589.88
2019-03-31    104243.34
Freq: M, Name: Sales, dtype: float64
```

```
# Create a Line Plot for revenue
ax = pd.DataFrame(m_revenue_df.values).plot(
    grid=True,
    figsize=(10,7),
    legend=False
)

ax.set_xlabel('Date')
ax.set_ylabel('Sales')
ax.set_title('Total Revenue Over Time')

ax.set_ylim([0, max(m_revenue_df.values)+100000])

plt.xticks(
    range(len(m_revenue_df.index)),
    [x.strftime('%m.%Y') for x in m_revenue_df.index],
    rotation=45
)
plt.show()
```



Do you see a similar pattern with the order by month line chart? Comment

From the chart we can see that the sales was dropped in Feb 2019 for around 40,000 sales but, later it increased in the next month that is March 2019.

```
# Run the head function on  the original dataframe
df.head()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Invoice Date	Payment	cogs	gross margin percentage	gro inco
0	750-67-8428	A	Yangon	Member	Female	Health and beauty	74.69	7	26.1415	548.9715	2019-01-05 13:08:00	Ewallet	522.83	4.761905	26.14
1	226-31-3081	C	Naypyitaw	Normal	Female	Electronic accessories	15.28	5	3.8200	80.2200	2019-03-08 10:29:00	Cash	76.40	4.761905	3.82
2	631-41-3108	A	Yangon	Normal	Male	Home and lifestyle	46.33	7	16.2155	340.5255	2019-03-03 13:23:00	Credit card	324.31	4.761905	16.21
3	123-19-1176	A	Yangon	Member	Male	Health and beauty	58.22	8	23.2880	489.0480	2019-01-27 20:33:00	Ewallet	465.76	4.761905	23.28
4	373-73-7910	A	Yangon	Normal	Male	Sports and travel	86.31	7	30.2085	634.3785	2019-02-08 10:37:00	Ewallet	604.17	4.761905	30.20

```
# Run the tail function on the original dataframe
df.tail()
```

	Invoice ID	Branch	City	Customer type	Gender	Product line	Unit price	Quantity	Tax 5%	Total	Invoice Date	Payment	cogs	gross margin percentage	i
995	233-67-5758	C	Naypyitaw	Normal	Male	Health and beauty	40.35	1	2.0175	42.3675	2019-01-29 13:46:00	Ewallet	40.35	4.761905	2
996	303-96-2227	B	Mandalay	Normal	Female	Home and lifestyle	97.38	10	48.6900	1022.4900	2019-03-02 17:16:00	Ewallet	973.80	4.761905	48
997	727-02-1313	A	Yangon	Member	Male	Food and beverages	31.84	1	1.5920	33.4320	2019-02-09 13:22:00	Cash	31.84	4.761905	1
	347-56-					Home and					2019-				
	3807					accessories									

Calculate the repeat customers

```
# Aggregate the raw data for each Invoice ID.
invoice_df = df.groupby(
    by=['Invoice ID', 'Invoice Date']
).agg({
    'Sales': sum,
    'Rating': max,
    'City': sum,
}).reset_index()
```

```
invoice_df.head()
```

	Invoice ID	Invoice Date	Sales	Rating	City
0	101-17-6199	2019-03-13 19:44:00	320.53	7.0	Yangon
1	101-81-4070	2019-01-17 12:36:00	125.64	4.9	Naypyitaw
2	102-06-2002	2019-03-20 17:52:00	126.25	6.1	Naypyitaw
3	102-77-2261	2019-03-05 18:02:00	457.17	4.2	Naypyitaw
4	105-10-6182	2019-02-27 12:22:00	42.96	6.6	Yangon

```
# Aggregate by month
#Group by Month and Rating.
# Filter selects customers who have more than one record in the group
# Basically customers with more than one order in a month

m_repeat_customers_df = invoice_df.set_index('Invoice Date').groupby([
    pd.Grouper(freq='M'), 'Rating'
]).filter(lambda x: len(x) > 1).resample('M').nunique()['Rating']
```

```
m_repeat_customers_df
```

```
Invoice Date
2019-01-31    58
2019-02-28    60
2019-03-31    60
Freq: M, Name: Rating, dtype: int64
```

```
# Calculate the unique customers
m_unique_customers_df = df.set_index('Invoice Date')['Rating'].resample('M').nunique()
```

```
m_unique_customers_df
```

```
Invoice Date
2019-01-31    60
2019-02-28    61
2019-03-31    61
Freq: M, Name: Rating, dtype: int64
```

```
# Compare the repeat and unique customers by month and calculate percentage by month
m_repeat_percentage = m_repeat_customers_df/m_unique_customers_df*100.0
m_repeat_percentage
```

```
Invoice Date
2019-01-31    96.666667
2019-02-28    98.360656
2019-03-31    98.360656
Freq: M, Name: Rating, dtype: float64
```

```
# Visualize thsese two in a dual axis chart

plot1 = pd.DataFrame(m_repeat_customers_df.values).plot(
    figsize=(10,7))

pd.DataFrame(m_unique_customers_df.values).plot(
    ax=plot1,
    grid=True
)

plot2 = pd.DataFrame(m_repeat_percentage.values).plot.bar(
    ax=plot1,
    grid=True,
    secondary_y=True,# for dual axis with different scale
    color='green',
    alpha=0.4
)

plot1.set_xlabel('Date')
plot1.set_ylabel('Cost of sales')
plot1.set_title('Number of All vs. Repeat Customers Over Time')

plot2.set_ylabel('percentage (%)')

plot1.legend(['Repeat Customers', 'All Customers'])
plot2.legend(['Percentage of Repeat'], loc='upper right')

plot1.set_ylim([0, m_unique_customers_df.values.max()+100])
plot2.set_ylim([0, 100])

plt.xticks(
    range(len(m_repeat_customers_df.index)),
    [x.strftime('%m.%Y') for x in m_repeat_customers_df.index],
    rotation=45
)
plt.show()
```

Number of All vs. Repeat Customers Over Time

Q. Comment on the distribution

Total customers and returning customers are almost same throughout the 3 months. This means that new customers are added in his year and new customers are making purchases over several months.

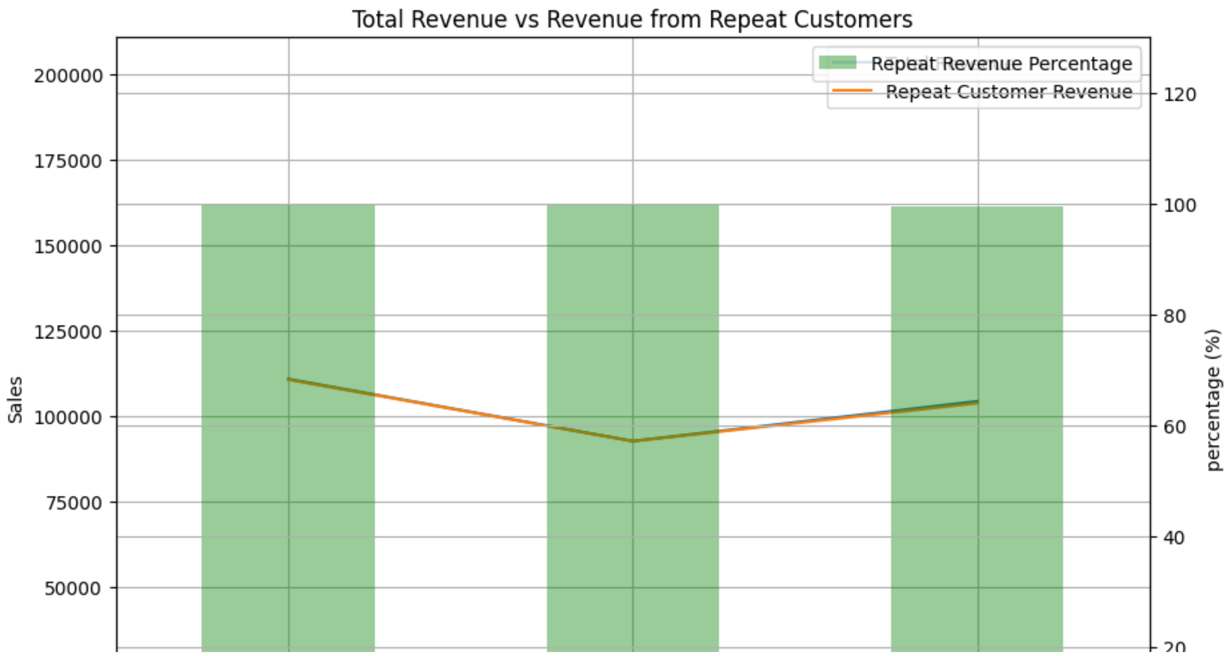
```
# Calculate Monthly revenue of repeat customers
m_rev_repeat_customers_df = invoice_df.set_index('Invoice Date').groupby([
    pd.Grouper(freq='M'), 'Rating'
]).filter(lambda x: len(x) > 1).resample('M').sum()['Sales']


# Calculate and show the % of revenue for repeat and all customers by month
m_rev_perc_repeat_customers_df = m_rev_repeat_customers_df/m_revenue_df * 100.0
```

```
<ipython-input-63-2ac15cc2b5d5>:4: FutureWarning: The default value of numeric_only in DataFrameGroupBy.sum is deprecated. In a future
  ]).filter(lambda x: len(x) > 1).resample('M').sum()['Sales']
```

```
m_rev_repeat_customers_df
```

```
Invoice Date
2019-01-31    110580.05
2019-02-28     92537.53
2019-03-31    103683.00
Freq: M, Name: Sales, dtype: float64
```

```
# Plot the  chart for Revenue and % (Dual axis chart)
plot1 = pd.DataFrame(m_revenue_df.values).plot(
    figsize=(10,7))

pd.DataFrame(m_rev_repeat_customers_df.values).plot(
    ax=plot1,
    grid=True
)

plot2 = pd.DataFrame(m_rev_perc_repeat_customers_df.values).plot.bar(
    ax=plot1,
    grid=True,
    secondary_y=True, # for dual axis with different scale
    color='green',
    alpha=0.4
)
plot1.set_xlabel('Date')
plot1.set_ylabel('Sales')
plot1.set_title('Total Revenue vs Revenue from Repeat Customers')

plot1.legend(['Total Revenue', 'Repeat Customer Revenue'])

plot1.set_ylim([0, max(m_revenue_df.values)+100000])

plot2.set_ylim([0, max(m_rev_perc_repeat_customers_df.values)+30])
plot2.set_ylabel('percentage (%)')
plot2.legend(['Repeat Revenue Percentage'])

plot2.set_xticklabels([
    x.strftime('%m.%Y') for x in m_rev_perc_repeat_customers_df.index
])

plt.show()
```



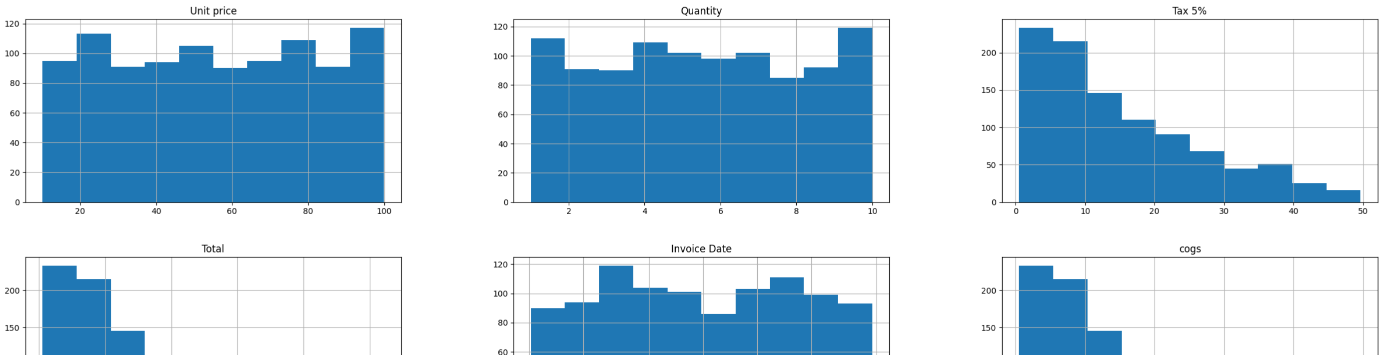
Q. Comment on the distribution

There is a direct relationship between total sales and repeat customer sales. Here, the repeat customers went down in Feb month by almost 20% but later it increased to around 65% in march month.

Exploratory Data Analysis (EDA)

Histogram

```
df.hist(figsize=(30,20))
plt.show()
```



Heatmap

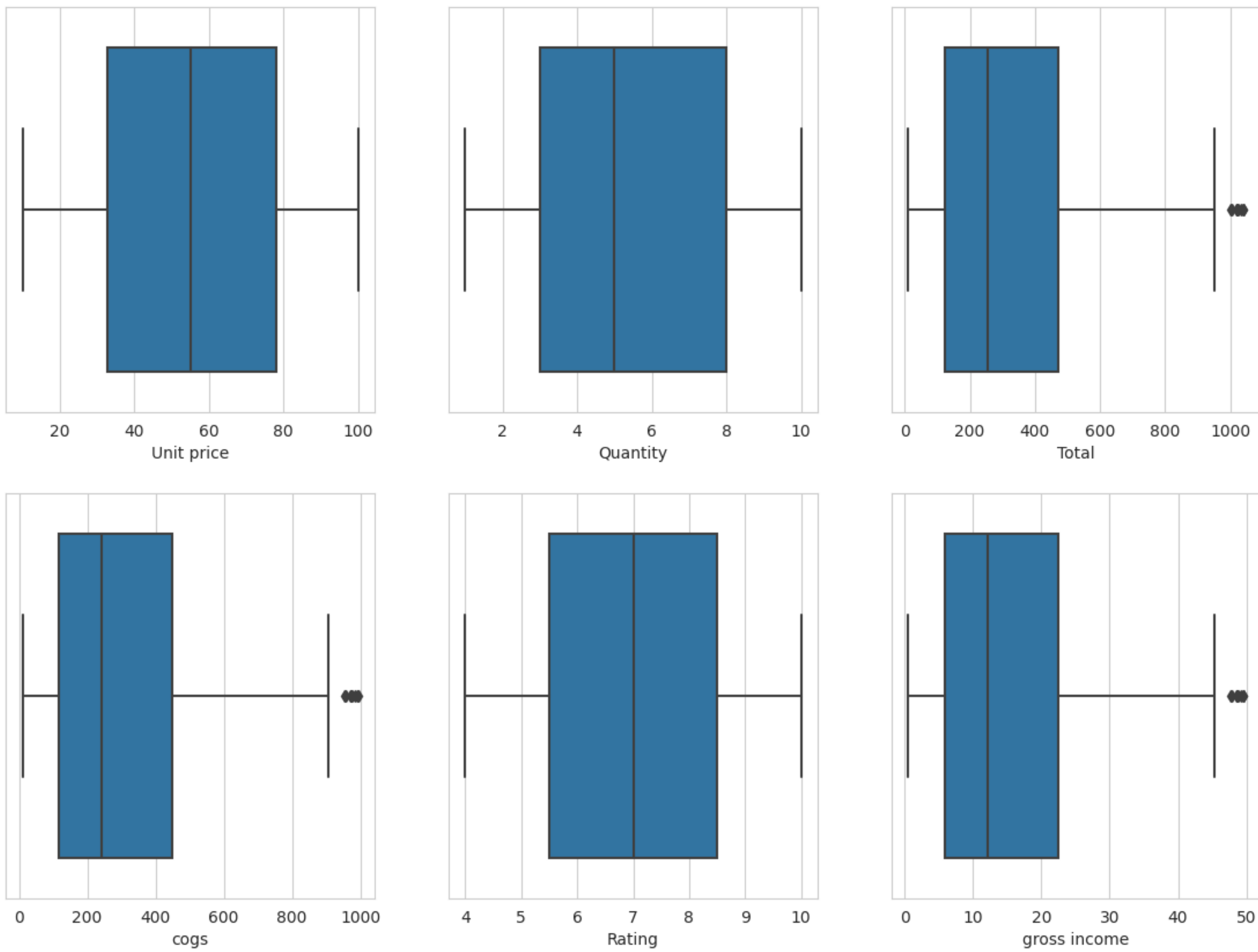
```
#Heatmap of all the columns
plt.figure(figsize = (12,10))

sns.heatmap(df.corr(), annot =True)
```

```
<ipython-input-67-fdef6aaaf4a8>:4: FutureWarning: The default value of numeric_only in DataFrame.corr is deprecated. In a future vers:
  sns.heatmap(df.corr(), annot =True)
```

Boxplot

```
plt.figure(figsize=(14,10))
sns.set_style(style='whitegrid')
plt.subplot(2,3,1)
sns.boxplot(x='Unit price',data=df)
plt.subplot(2,3,2)
sns.boxplot(x='Quantity',data=df)
plt.subplot(2,3,3)
sns.boxplot(x='Total',data=df)
plt.subplot(2,3,4)
sns.boxplot(x='cogs',data=df)
plt.subplot(2,3,5)
sns.boxplot(x='Rating',data=df)
plt.subplot(2,3,6)
sns.boxplot(x='gross income',data=df)
```

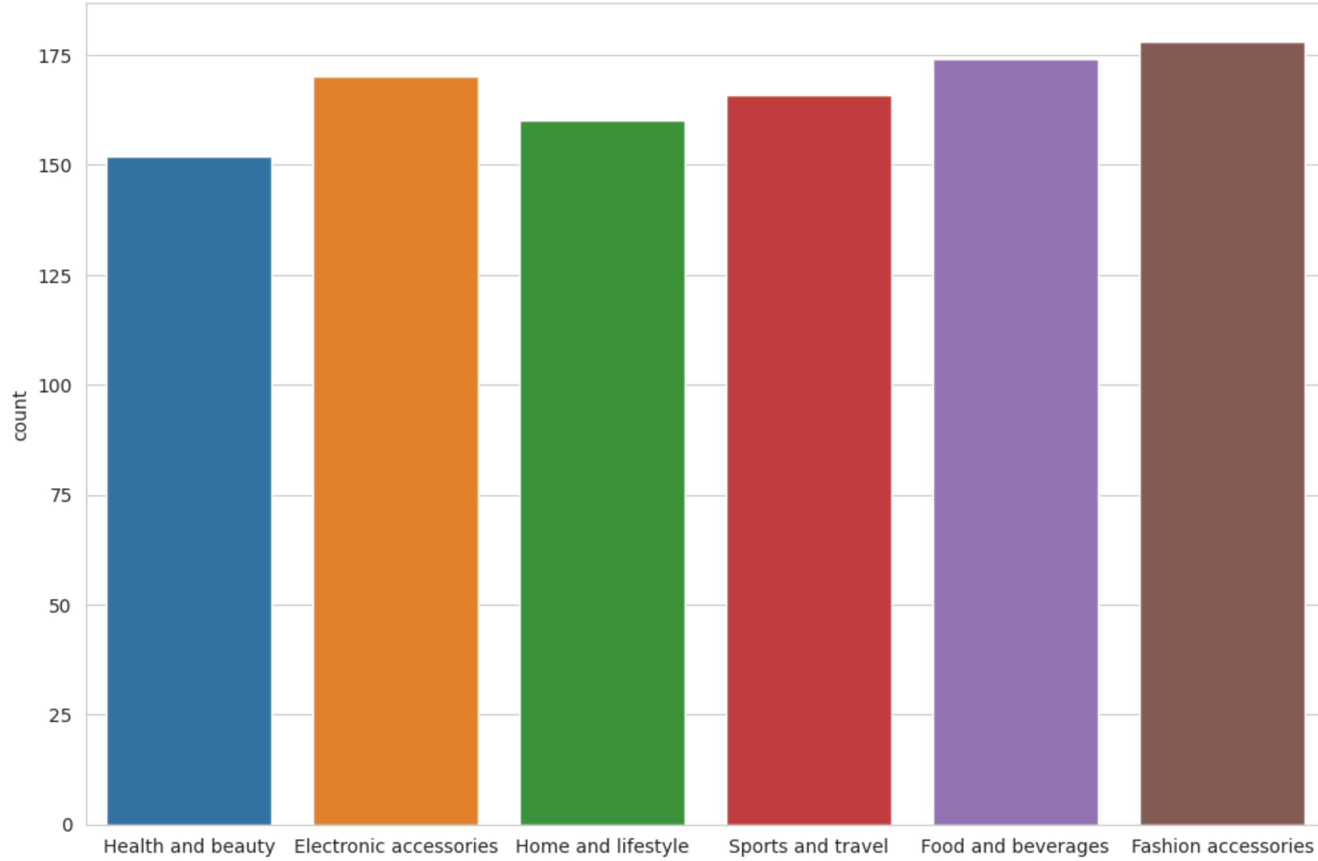
```
<Axes: xlabel='gross income'>
```



Barplot

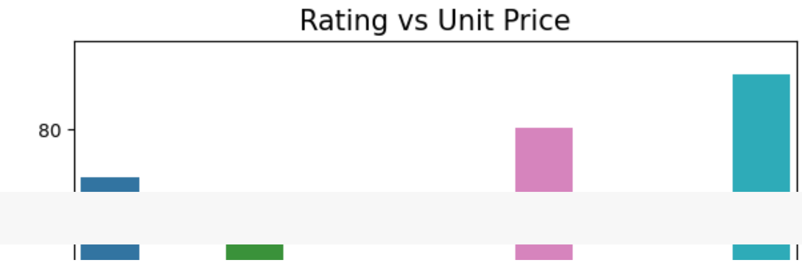
```
# Countplot
plt.figure(figsize=(12,8))
sns.countplot(x='Product line',data=df)
```

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



So, here Fashion accessories was most sale by the customers compare to Home & lifestyle and Sports & travel while, Electronic accessories as well as Food and beverages was almost same whereas, Health & beauty was least opted by the customers.

```
plt.style.use("default")
plt.figure(figsize=(7,7))
sns.barplot(x="Rating", y="Unit price", data=df[170:180])
plt.title("Rating vs Unit Price",fontsize=15)
plt.xlabel("Rating")
plt.ylabel("Unit Price")
plt.show()
```



Let's find the number of unique values in columns with object datatype

```
categorical_columns = [cname for cname in df.columns if df[cname].dtype == "object"]
```

```
categorical_columns
```

```
['Invoice ID',
 'Branch',
 'City',
 'Customer type',
 'Gender',
 'Product line',
 'Payment']
```

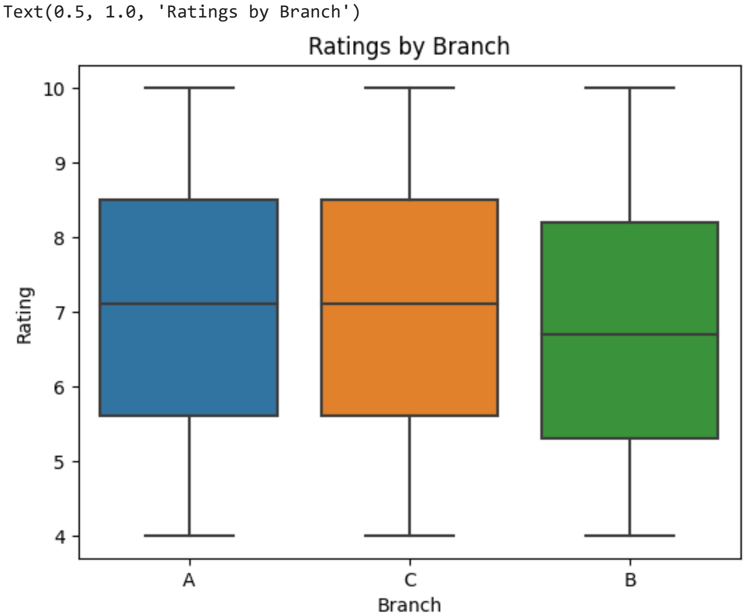
```
print("# unique values in Branch: {0}".format(len(df['Branch'].unique().tolist())))
print("# unique values in City: {0}".format(len(df['City'].unique().tolist())))
print("# unique values in Customer Type: {0}".format(len(df['Customer type'].unique().tolist())))
print("# unique values in Gender: {0}".format(len(df['Gender'].unique().tolist())))
print("# unique values in Product Line: {0}".format(len(df['Product line'].unique().tolist())))
print("# unique values in Payment: {0}".format(len(df['Payment'].unique().tolist())))
```

```
# unique values in Branch: 3
# unique values in City: 3
# unique values in Customer Type: 2
# unique values in Gender: 2
# unique values in Product Line: 6
# unique values in Payment: 3
```

Branch Type Analysis

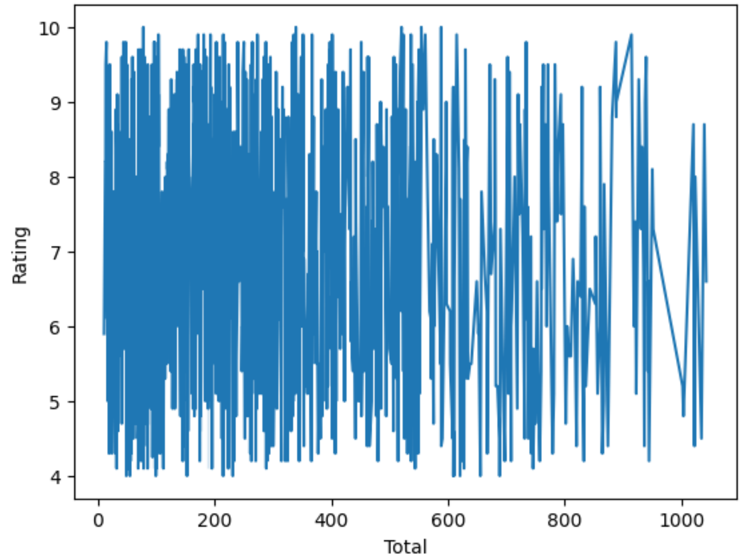
```
sns.boxplot(x="Branch", y = "Rating" ,data =df).set_title("Ratings by Branch")
```

```
Text(0.5, 1.0, 'Ratings by Branch')
```



Here, we can see that Branch B has the lowest rating among all the branches.

```
ageDisSpend = sns.lineplot(x="Total", y = "Rating", data = df)
```



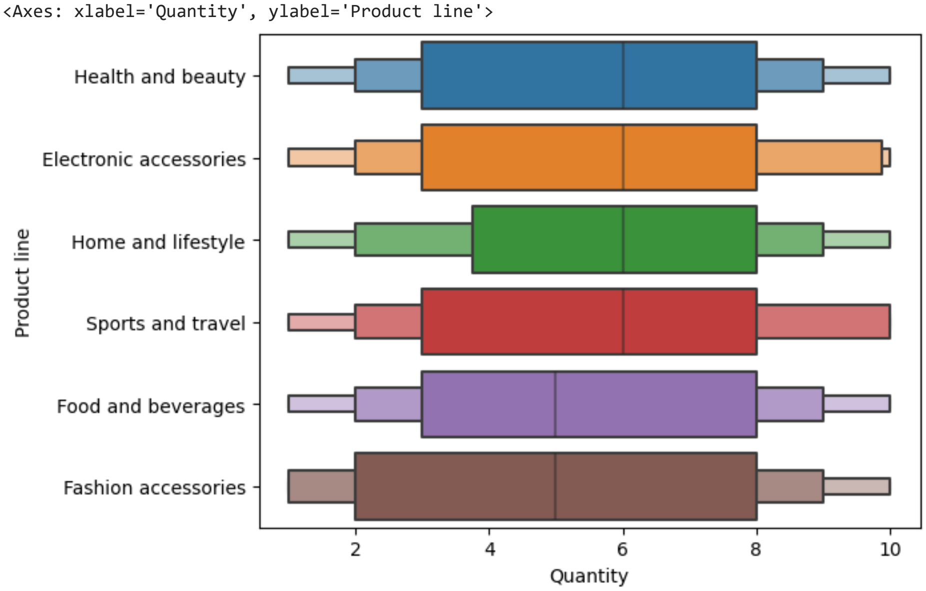
Here, is the graph of total vs rating which shows that how much rating has been given by the customers.

Product Analysis

Let's look at the various products' performance.

```
sns.boxenplot(x = 'Quantity', y = 'Product line', data=df )
```

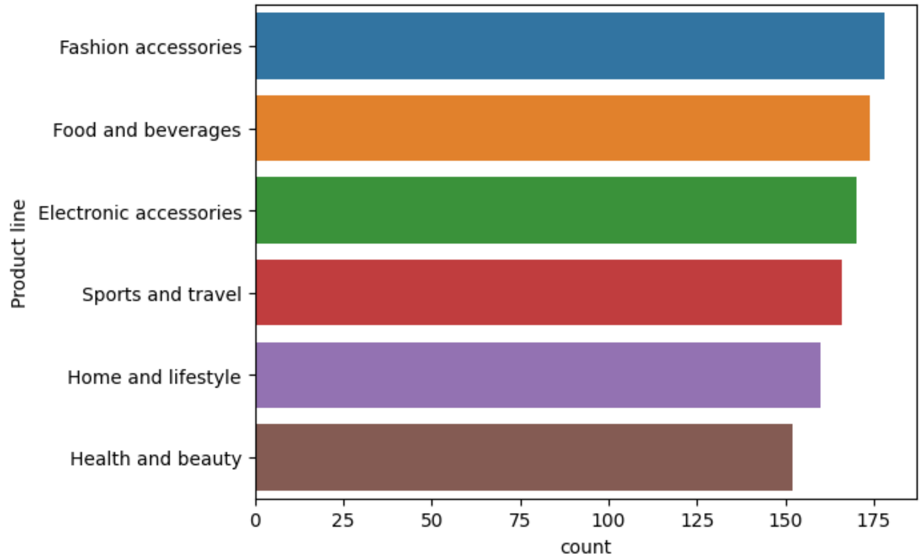
```
<Axes: xlabel='Quantity', ylabel='Product line'>
```



Of the visuals above, Health & Beauty, Electronic Accessories, Home & Lifestyle, and Sports & Travel have higher average sales than Food & Beverage and Fashion Accessories.

```
sns.countplot(y = 'Product line', data=df, order = df['Product line'].value_counts().index )
```

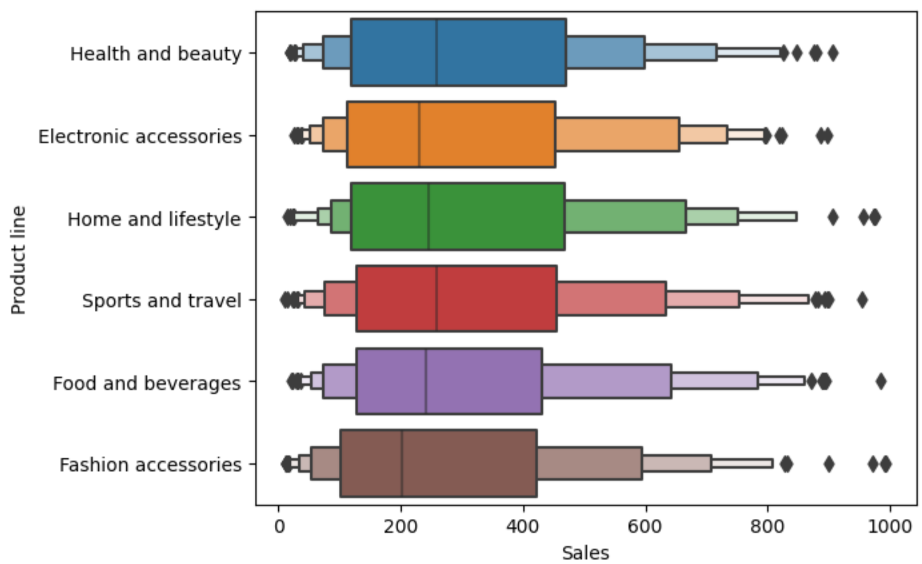
```
<Axes: xlabel='count', ylabel='Product line'>
```



The image above shows the top product types sold for a given data set. Fashion accessories are the best, health and beauty are the worst

```
sns.boxenplot(y = 'Product line', x = 'Sales', data=df )
```

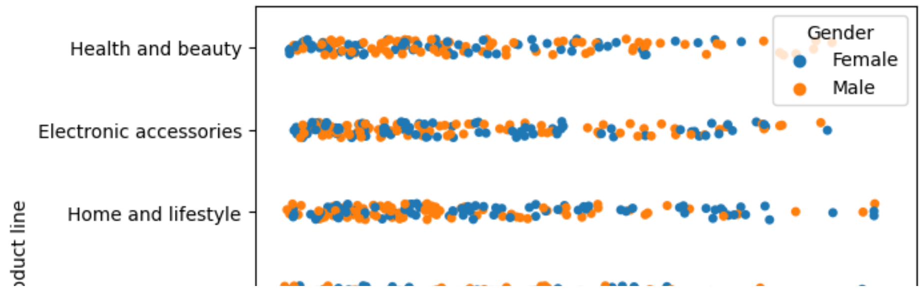
```
<Axes: xlabel='Sales', ylabel='Product line'>
```



Food and Drink has the highest average rating, while Sports and Travel have the lowest average rating.

```
sns.stripplot(y = 'Product line', x = 'Total', hue = 'Gender', data=df )
```

```
<Axes: xlabel='Total', ylabel='Product line'>
```



Here, we can see that the males were more in starting total of sales in product line compare to females.

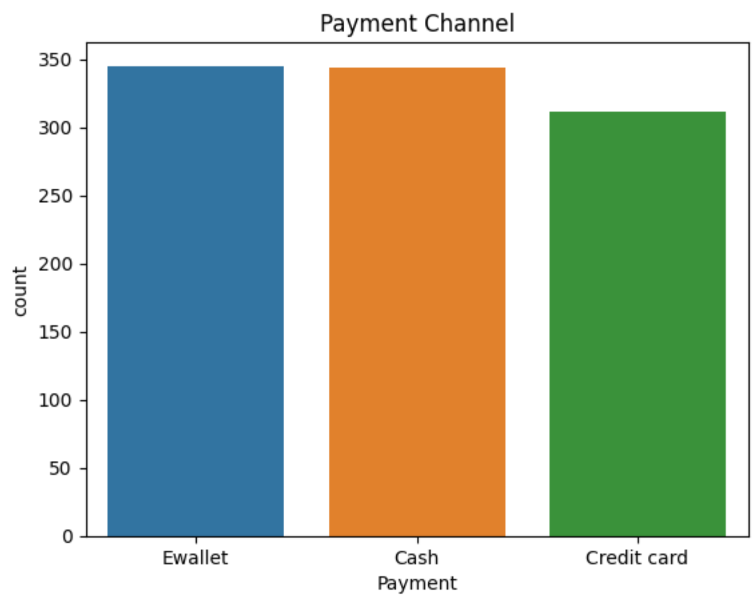
Payment Channel

Total

Let see how customers make payment in this business

```
sns.countplot(x="Payment", data =df).set_title("Payment Channel")
```

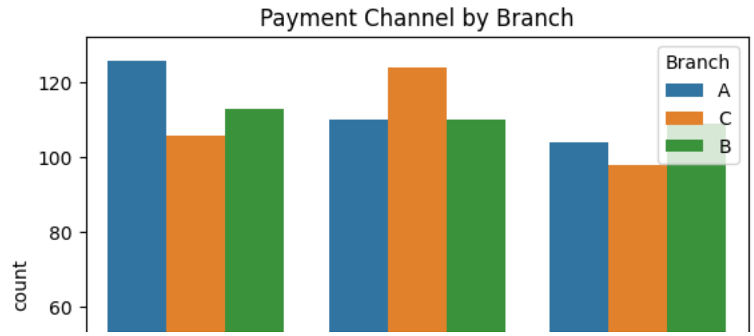
```
Text(0.5, 1.0, 'Payment Channel')
```



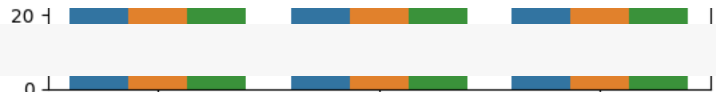
Most customers pay with E-wallet and cash, but less than 40% pay with credit cards. We also want to see the distribution of this payment type across all branches

```
sns.countplot(x="Payment", hue = "Branch", data =df).set_title("Payment Channel by Branch")
```

```
Text(0.5, 1.0, 'Payment Channel by Branch')
```



Here, Branch C has used more Cash payments ,whereas Branch A has used E-wallet and Branch B has used Credit card for the payments.



Customer Analysis

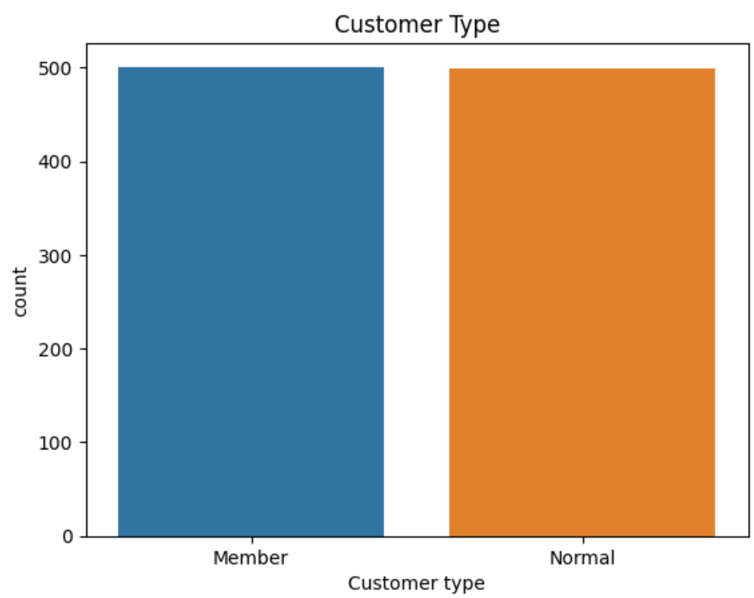
From inspection, there are two types of customers. Members and Normal. Let's see how many they are and where they are

```
df['Customer type'].nunique()
```

```
2
```

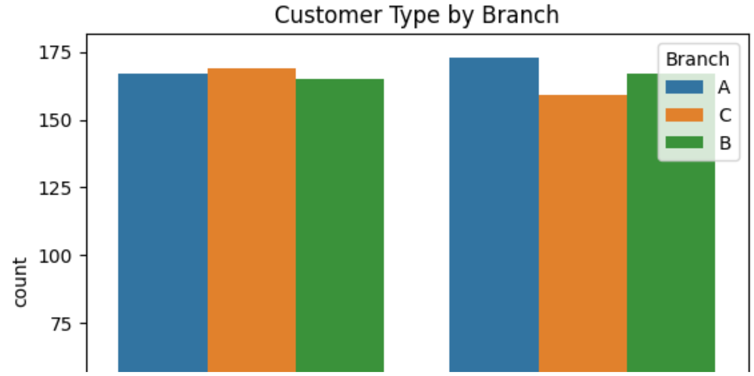
```
sns.countplot(x="Customer type", data =df).set_title("Customer Type")
```

```
Text(0.5, 1.0, 'Customer Type')
```




```
sns.countplot(x="Customer type", hue = "Branch", data =df).set_title("Customer Type by Branch")
```

```
Text(0.5, 1.0, 'Customer Type by Branch')
```

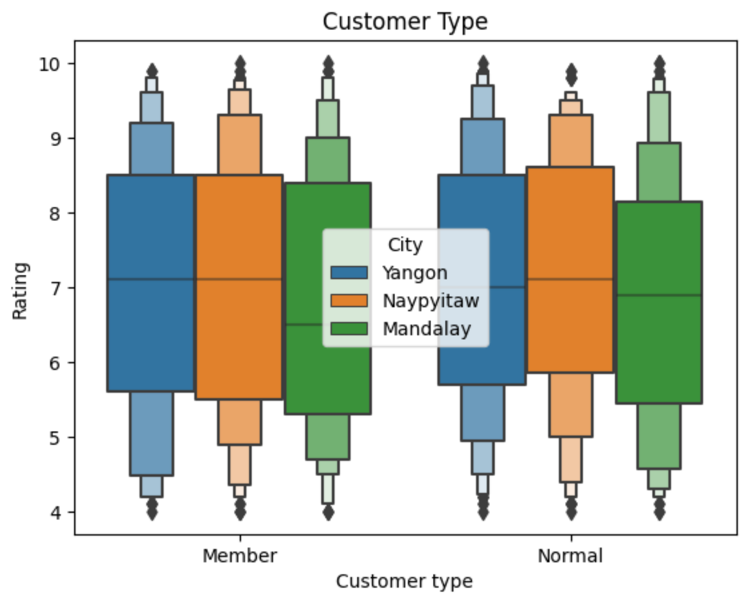


Here, we can see that Branch A was highest in Normal Customer Type While Branch B stands second and Branch C comes last. However, in Member Customer Type all the three branch were almost same.

Do the customer type influence customer rating? Let's find out

```
sns.boxenplot(x="Customer type",  y = "Rating",  hue = "City", data =df).set_title("Customer Type")
```

```
Text(0.5, 1.0, 'Customer Type')
```

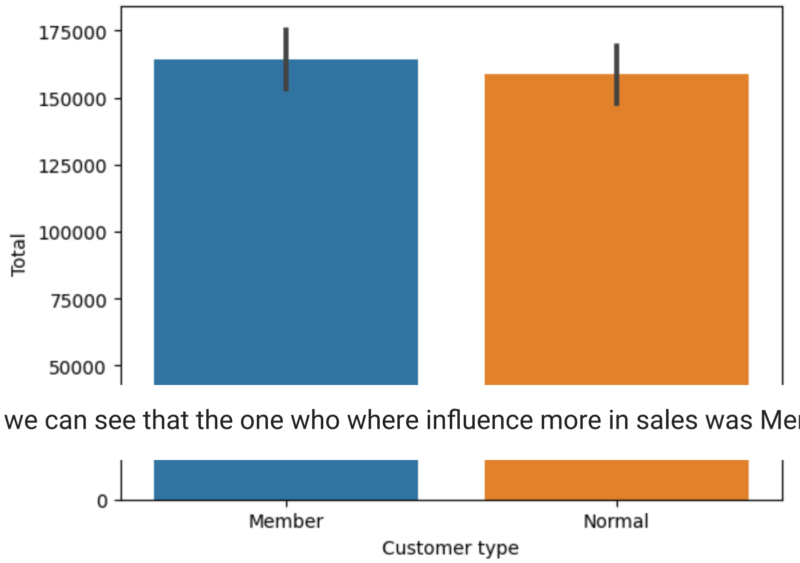


Here, Yangon & Naypyidaw city customers where average in Member type compare to Mandalay city whereas, Naypyidaw city was more than Yangon city & Mandalay city was least in Normal type for customer ratings.

Does customer type influences the sales

```
sns.barplot(x="Customer type", y="Total", estimator = sum, data=df)
```

```
<Axes: xlabel='Customer type', ylabel='Total'>
```



Yes, we can see that the one who where influence more in sales was Member Type compare to Normal Type.