Market Basket Analysis and Recency Frequency Monetary Analysis for Groceries

```
[60]:
      !pip install mlxtend
      !pip install apriori
      import os
      import plotly.express as px
      import numpy as np
      import pandas as pd
      import plotly.graph_objects as go
      import matplotlib.pyplot as plt
      import seaborn as sns
      import operator as op
      from mlxtend.frequent_patterns import apriori
      from mlxtend.frequent patterns import association rules
      for dirname, _, filenames in os.walk('/kaggle/input'):
          for filename in filenames:
              print(os.path.join(dirname, filename))
```

Requirement already satisfied: mlxtend in c:\users\n347u\anaconda3\lib\site-packages (0.23.1)

Dataset Exploration

In [61]: # Loading dataset
 data.head()

Out[61]:

	Member_number	Date	itemDescription
0	1808	21-07-2015	tropical fruit
1	2552	05-01-2015	whole milk
2	2300	19-09-2015	pip fruit
3	1187	12-12-2015	other vegetables
4	3037	01-02-2015	whole milk

As we can see from the first 5 rows of the dataset, we have 3 different columns: Member_number is a number that is unique for each customer. Date represents the date of the transaction, and finally itemDescription represents the corresponding product bought for this date.

```
In [62]: # To check the data types of the columns, I use info() function. According to result below, Member_number and Date columns are no
        #For the following steps, I will change them into correct form.
        data.info()
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 38765 entries, 0 to 38764
         Data columns (total 3 columns):
          # Column
                              Non-Null Count Dtype
          0 Member_number 38765 non-null int64
          1 Date
                              38765 non-null object
             itemDescription 38765 non-null object
         dtypes: int64(1), object(2)
         memory usage: 908.7+ KB
In [63]: # Renaming the columns, because it would be easier to understand what that means.
         data.columns = ['memberID', 'Date', 'itemName']
        data.head()
```

Out[63]:

itemName	Date	memberID	
tropical fruit	21-07-2015	1808	0
whole milk	05-01-2015	2552	1
pip fruit	19-09-2015	2300	2
other vegetables	12-12-2015	1187	3
whole milk	01-02-2015	3037	4

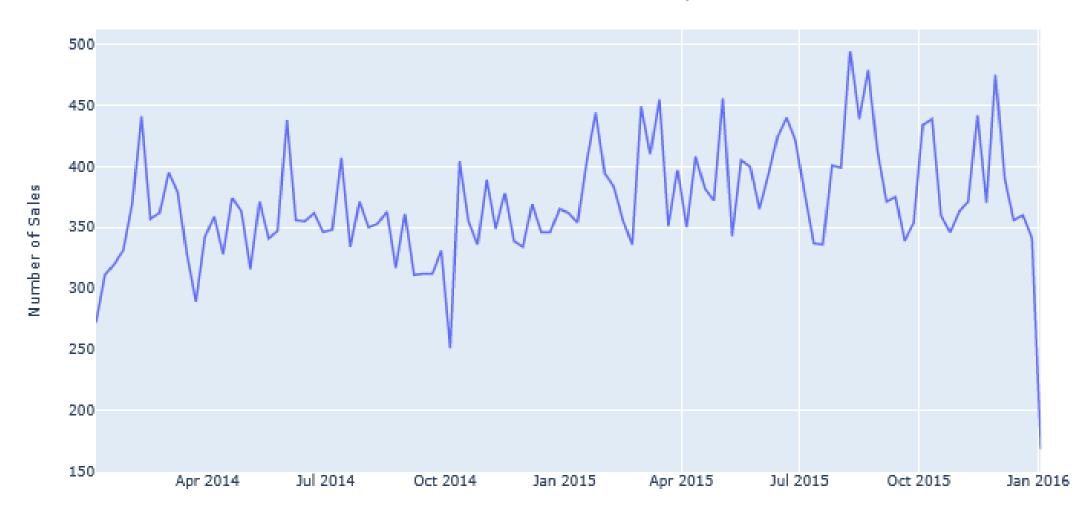
```
In [64]: # Checking for the missing values
         nan_values = data.isna().sum()
         nan values
Out[64]: memberID
                     0
         Date
                     0
         itemName
         dtype: int64
         According to result above, there is no missing values for all columns.
In [65]: # Converting Date column into correct datatype which is datetime
         data.Date = pd.to_datetime(data.Date)
         data.memberID = data['memberID'].astype('str')
         data.info() # They are in correct datatype now
         <class 'pandas.core.frame.DataFrame'>
         RangeIndex: 38765 entries, 0 to 38764
         Data columns (total 3 columns):
              Column
                        Non-Null Count Dtype
              memberID 38765 non-null object
                        38765 non-null datetime64[ns]
              Date
              itemName 38765 non-null object
         dtypes: datetime64[ns](1), object(2)
```

memory usage: 908.7+ KB

Data Visualization

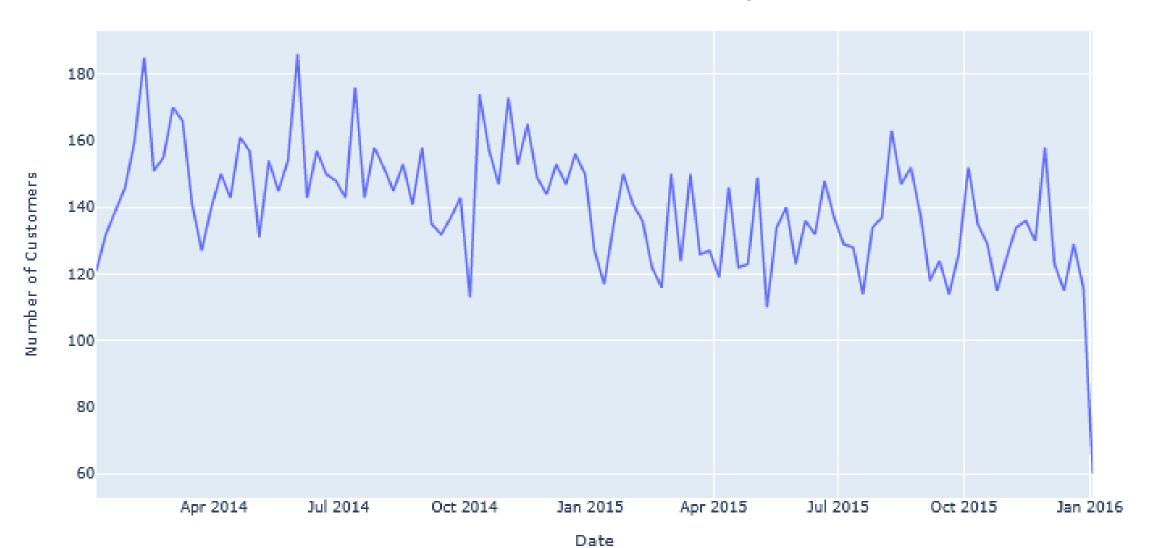
Number of Sales Weekly

Number of Sales Weekly



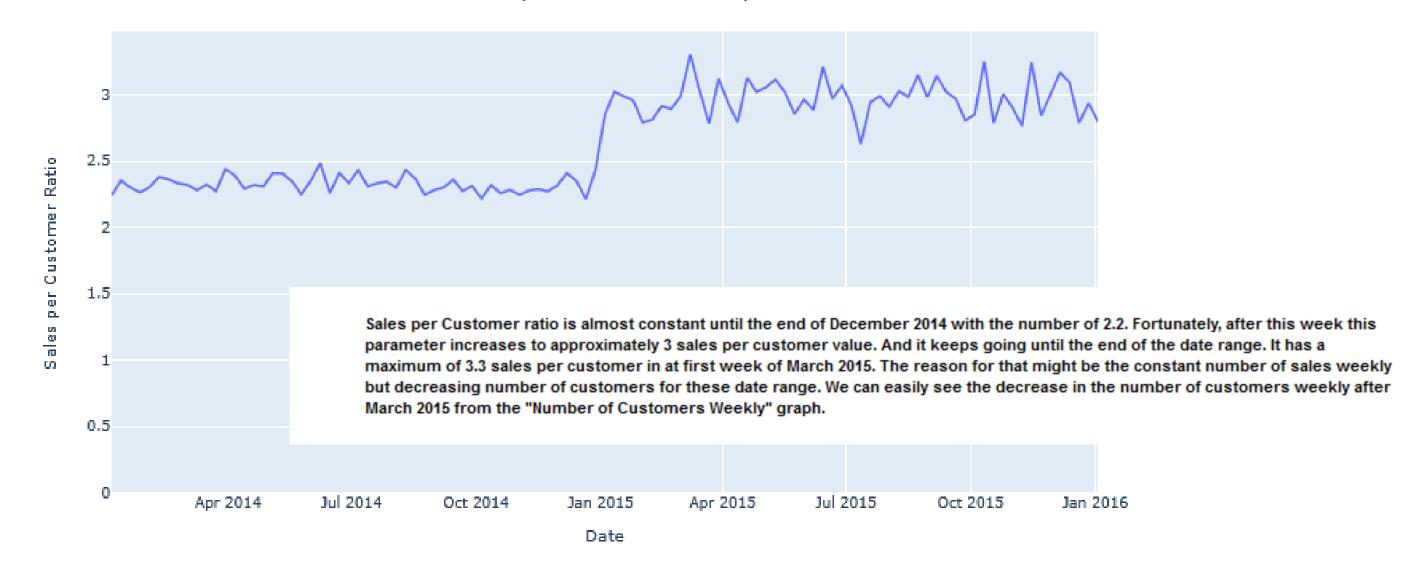
Number of Customers Weekly

Number of Customers Weekly



Sales per Customer Weekly

Sales per Customer Weekly



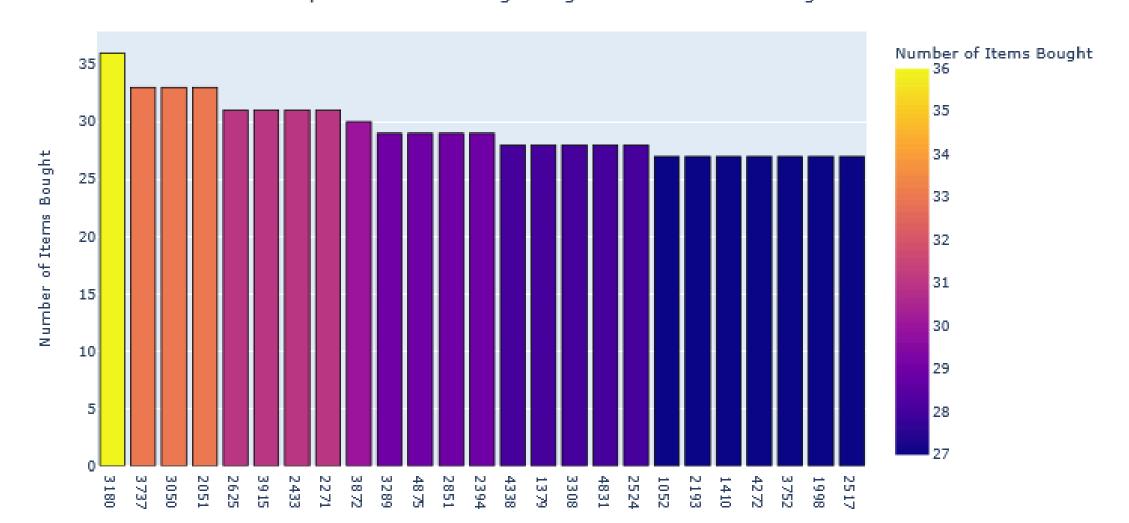
Frequency of the Items Sold

Frequency of the Items Sold



Top Customers regarding Number of Items bought

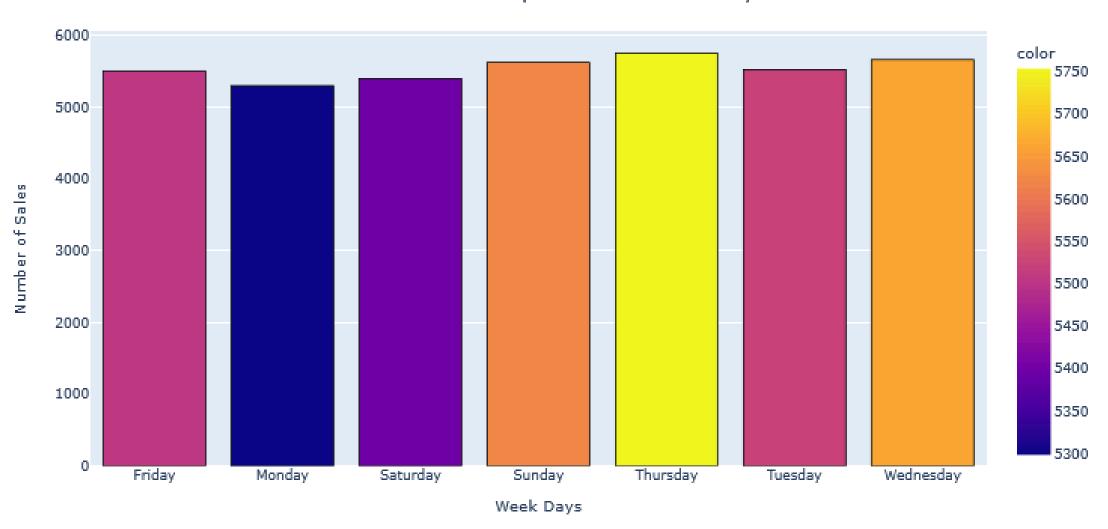
Top 20 Customers regarding Number of Items Bought



Customer 3180 looks like our the best customer:)

Number of Sales per Discrete Week Days

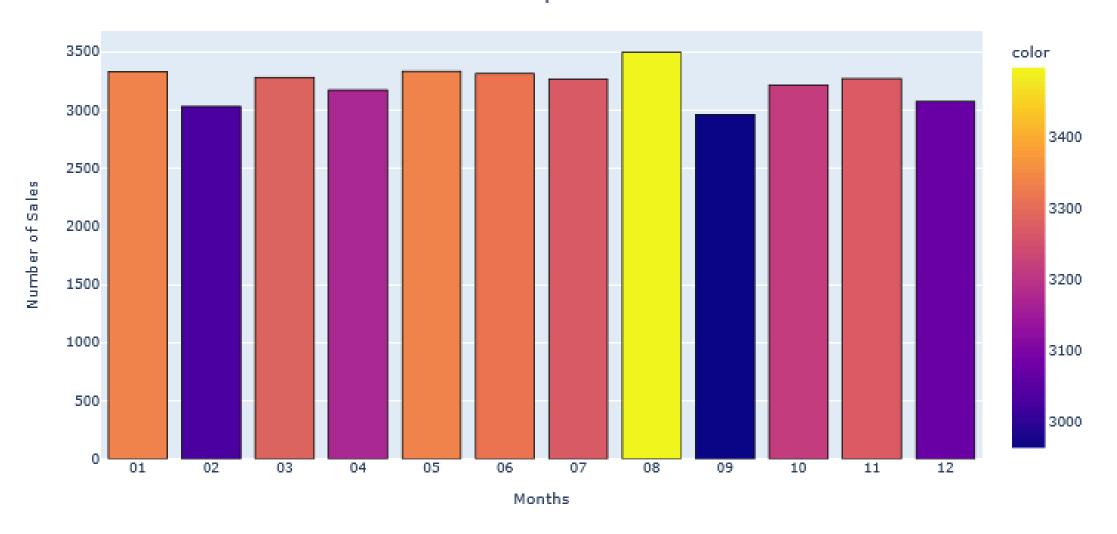
Number of Sales per Discrete Week Days



According to the graph above, there are more sales on Thursdays. Sunday and Wednesday are the following days for the most sales made.

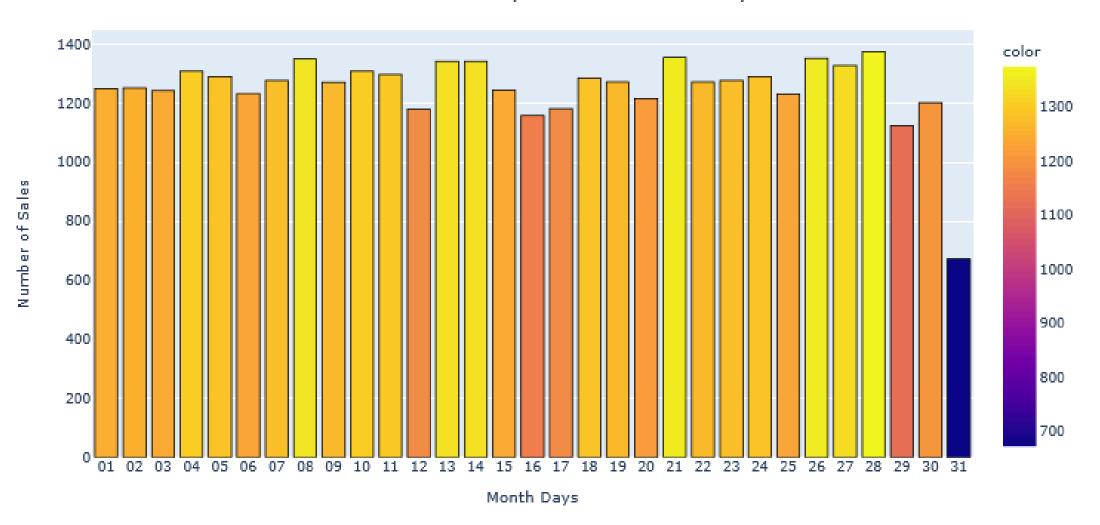
Number of Sales per Discrete Months

Number of Sales per Discrete Months



Number of Sales per Discrete Month Days

Number of Sales per Discrete Month Days



Market Basket Analysis

Market basket analysis is a data mining technique used by retailers to increase sales by better understanding customer purchasing patterns. It involves analyzing large data sets, such as purchase history, to reveal product groupings, as well as products that are likely to be purchased together [1].

Let's Create Baskets

```
In [74]: baskets = data.groupby(['memberID', 'itemName'])['itemName'].count().unstack().fillna(0).reset_index()
baskets.head()
```

Out[74]:

itemName	memberID	Instant food products	UHT- milk	abrasive cleaner	artif. sweetener	baby cosmetics	bags	baking powder	bathroom cleaner	beef	 turkey	vinegar	waffles	whipped/ sour cream	whisky	wl br
0	1000	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	
1	1001	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	 0.0	0.0	0.0	1.0	0.0	
2	1002	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	
3	1003	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	
4	1004	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	 0.0	0.0	0.0	0.0	0.0	

5 rows x 168 columns

According to the query above, we created the customers-items matrix. Each row represents the transactions of each customer, and each column represents the items bought. The numbers corresponding to the matrix represent the number of times that item is bought by the individual user.

```
In [75]: # Let's check the most sold -item which is whole milk- has the same number of sales as we discussed above in the treemap.
baskets['whole milk'].sum()
# Yep it satisfies our results.
```

Out[75]: 2502.0

```
In [76]: # Encoding the items that sold more than 1
def one_hot_encoder(k):
    if k <= 0:
        return 0
    if k >= 1:
        return 1
```

```
In [77]: baskets_final = baskets.iloc[:, 1:baskets.shape[1]].applymap(one_hot_encoder)
baskets_final.head()
```

Out[77]:

it	emName	Instant food products	UHT- milk	abrasive cleaner	artif. sweetener	baby cosmetics	bags	baking powder	bathroom cleaner	beef	berries	 turkey	vinegar	waffles	whipped/ sour cream	whisky	white bread
	0	0	0	0	0	0	0	0	0	0	0	 0	0	0	0	0	(
	1	0	0	0	0	0	0	0	0	1	0	 0	0	0	1	0	1
	2	0	0	0	0	0	0	0	0	0	0	 0	0	0	0	0	C
	3	0	0	0	0	0	0	0	0	0	0	 0	0	0	0	0	C
	4	0	0	0	0	0	0	0	0	0	0	 0	0	0	0	0	(

5 rows x 167 columns

Final form of our customer-item matrix.

In [78]: # Finding the most frequent items sold together

frequent_itemsets = apriori(baskets_final, min_support=0.025, use_colnames=True, max_len=3).sort_values(by='support')
frequent_itemsets.head(25)

C:\Users\N347u\anaconda3\Lib\site-packages\mlxtend\frequent_patterns\fpcommon.py:109: DeprecationWarning:

DataFrames with non-bool types result in worse computationalperformance and their support might be discontinued in the fut ure.Please use a DataFrame with bool type

Out[78]:

	support	itemsets
161	0.025141	(shopping bags, butter)
69	0.025141	(spread cheese)
405	0.025141	(whole milk, sliced cheese)
412	0.025141	(specialty bar, whole milk)
85	0.025141	(pip fruit, beef)
248	0.025141	(shopping bags, domestic eggs)
467	0.025141	(tropical fruit, whole milk, citrus fruit)
480	0.025141	(yogurt, whole milk, frankfurter)
119	0.025141	(chocolate, bottled water)
239	0.025141	(root vegetables, dessert)
540	0.025141	(yogurt, shopping bags, rolls/buns)
559	0.025141	(shopping bags, tropical fruit, whole milk)
524	0.025141	(whole milk, root vegetables, pastry)
224	0.025398	(root vegetables, cream cheese)
217	0.025398	(sausage, coffee)
204	0.025398	(pork, citrus fruit)
302	0.025398	(tropical fruit, margarine)
167	0.025398	(rolls/buns, butter milk)
473	0.025398	(yogurt, whole milk, curd)
476	0.025654	(yogurt, whole milk, domestic eggs)
462	0.025854	(rolls/buns, soda, citrus fruit)
434	0.025654	(tropical fruit, bottled water, other vegetables)
186	0.025654	(chewing gum, whole milk)
88	0.025654	(sausage, beef)
171	0.025854	(domestic eggs, canned beer)

As we can see from the results above, the most items that appeared together are butter and shopping bags, and spread cheese, and so on.

Out[79]:

	antecedents	consequents	support	confidence	lift
878	(sausage)	(yogurt, rolls/buns)	0.035659	0.173101	1.554717
875	(yogurt, rolls/buns)	(sausage)	0.035659	0.320276	1.554717
456	(root vegetables, whole milk)	(shopping bags)	0.029246	0.258503	1.538048
457	(shopping bags)	(root vegetables, whole milk)	0.029246	0.173780	1.538048
876	(sausage, rolls/buns)	(yogurt)	0.035659	0.433022	1.530298
877	(yogurt)	(sausage, rolls/buns)	0.035659	0.128020	1.530298
946	(sausage)	(yogurt, other vegetables)	0.037199	0.180573	1.500795
943	(yogurt, other vegetables)	(sausage)	0.037199	0.309168	1.500795
631	(shopping bags)	(soda, other vegetables)	0.031042	0.184451	1.485518
630	(soda, other vegetables)	(shopping bags)	0.031042	0.250000	1.485518
1194	(sausage, whole milk)	(yogurt)	0.044895	0.419664	1.483093
1195	(yogurt)	(sausage, whole milk)	0.044895	0.158658	1.483093
323	(canned beer)	(whole milk, root vegetables)	0.027707	0.167702	1.482317
318	(whole milk, root vegetables)	(canned beer)	0.027707	0.244898	1.482317
882	(rolls/buns, soda)	(sausage)	0.035916	0.299788	1.455249
883	(sausage)	(rolls/buns, soda)	0.035916	0.174346	1.455249
199	(whole milk, soda)	(curd)	0.026424	0.174873	1.447248
202	(curd)	(whole milk, soda)	0.028424	0.218884	1.447248
1193	(yogurt, whole milk)	(sausage)	0.044895	0.298126	1.447192
1196	(sausage)	(yogurt, whole milk)	0.044895	0.217933	1.447192
903	(shopping bags)	(whole milk, soda)	0.038685	0.217988	1.442843
902	(whole milk, soda)	(shopping bags)	0.038685	0.242784	1.442643
247	(yogurt)	(whole milk, butter)	0.026937	0.095195	1.438255
246	(whole milk, butter)	(yogurt)	0.026937	0.406977	1.438255
944	(sausage, other vegetables)	(yogurt)	0.037199	0.400552	1.415552

As we can see from the result above:

sausage --> yogurt, rolls/buns

root vegetables, whole milk --> shopping bags

rolls/buns, soda --> sausage

butter, whole milk --> yogurt,

and etc. have strong relationships.

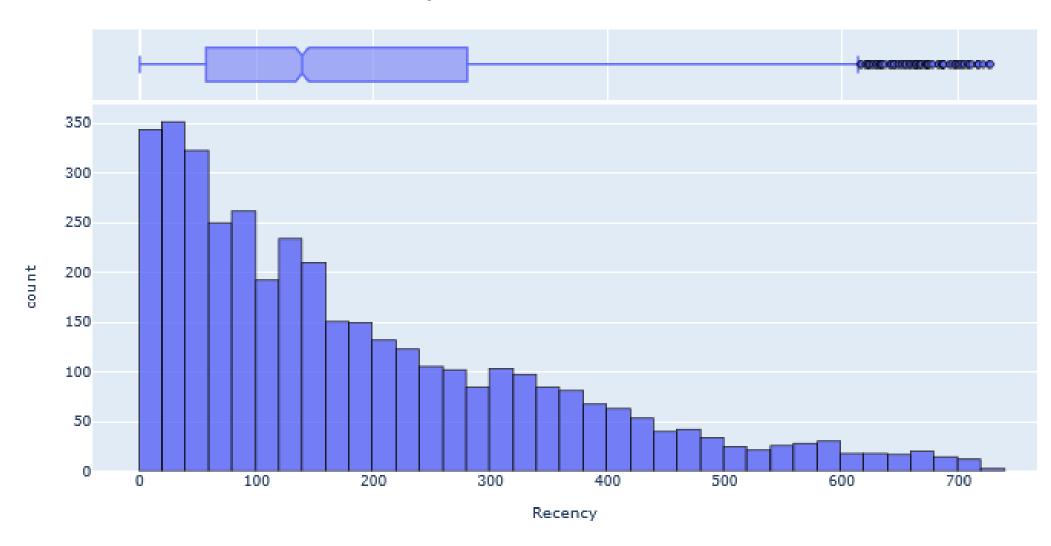
RFM Analysis

Recency

```
In [80]: # Lets Start with the calculate the Recency
         # Finding Last purchase date of each customer
         Recency = data.groupby(by='memberID')['Date'].max().reset_index()
         Recency.columns = ['memberID', 'LastDate']
         Recency.head()
Out[80]:
             memberID LastDate
                 1000 2015-11-25
                 1001 2015-04-14
                 1002 2015-08-30
                 1003 2015-10-02
                 1004 2015-02-12
In [81]: # Finding Last date for our dataset
         last_date_dataset = Recency['LastDate'].max()
         last_date_dataset
Out[81]: Timestamp('2015-12-30 00:00:00')
In [82]: # Calculating Recency by subtracting (last transaction date of dataset) and (last purchase date of each customer)
         Recency['Recency'] = Recency['LastDate'].apply(lambda x: (last_date_dataset - x).days)
         Recency.head()
Out[82]:
             memberID LastDate Recency
                 1000 2015-11-25
                                    35
                 1001 2015-04-14
                                    260
                 1002 2015-08-30
                                    122
                 1003 2015-10-02
                                    89
                 1004 2015-02-12
```

Recency Distribution of the Customers

Recency Distribution of the Customers



According to Recency Historgram of the Customers, we can see that most of the customers are distributed between 57th-280th day of thier last purchase.

Visit Frequency

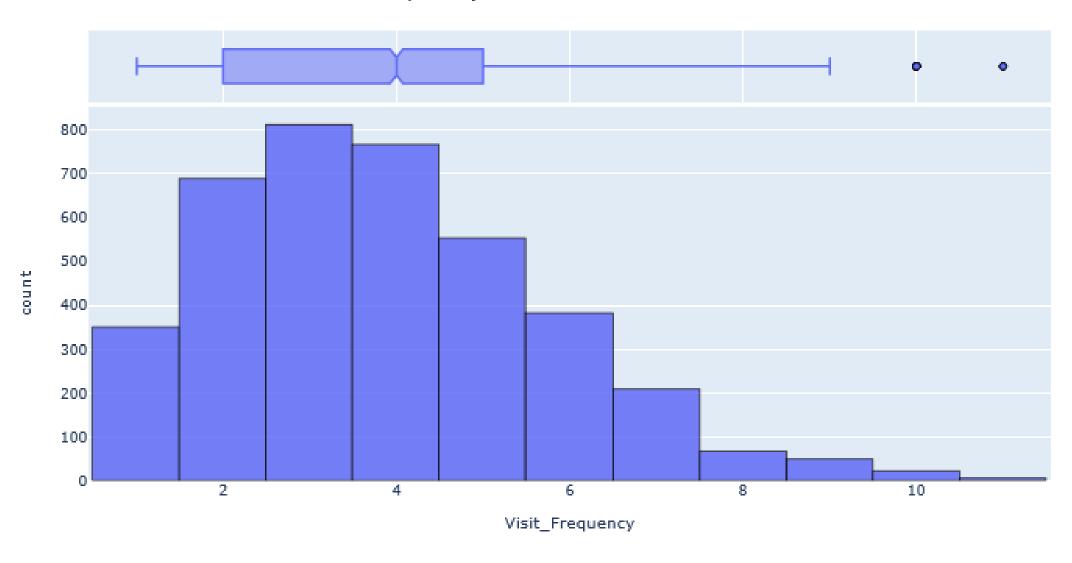
```
In [84]: # Frequency of the customer visits
Frequency = data.drop_duplicates(['Date', 'memberID']).groupby(by=['memberID'])['Date'].count().reset_index()
Frequency.columns = ['memberID', 'Visit_Frequency']
Frequency.head()
```

Out[84]:

	memberID	Visit_Frequency
0	1000	5
1	1001	5
2	1002	4
3	1003	4
4	1004	8

Visit Frequency Distribution of the Customers

Visit Frequency Distribution of the Customers



According to Frequency Historgram of the Customers, we can see that most of the customers are distributed between their 2nd-5th visit to the Groceries Store.

Monetary

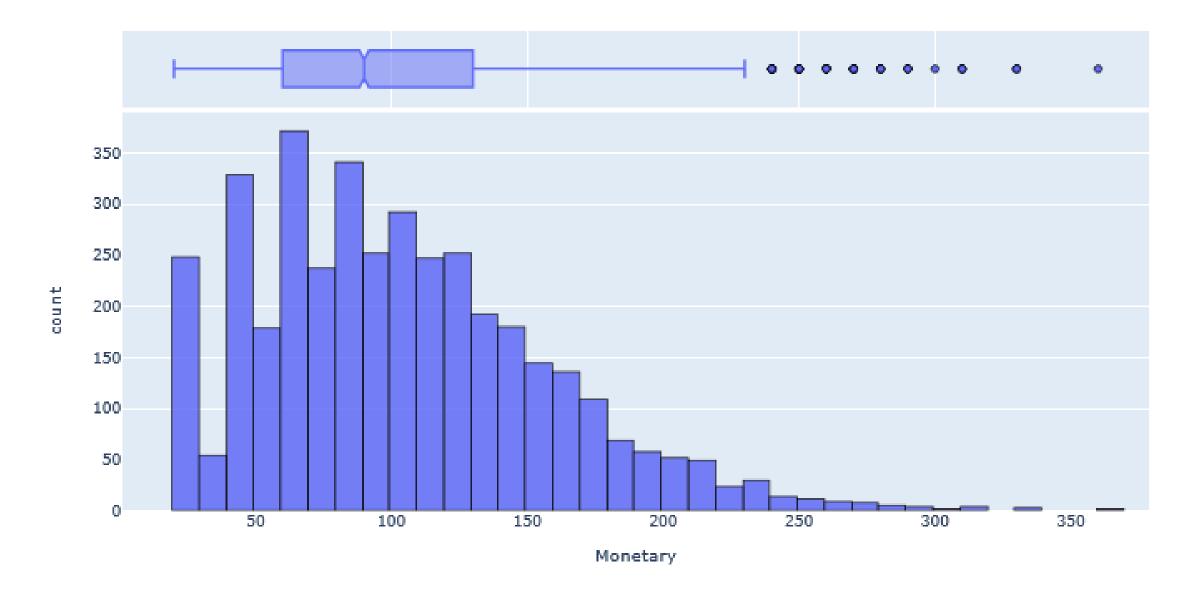
Due to our dataset, we have no data regarding the price of the products. Therefore I will consider the number of item bought per user as the Monetary value.

```
In [86]: Monetary = data.groupby(by="memberID")['itemName'].count().reset_index()
         Monetary.columns = ['memberID', 'Monetary']
         Monetary.head()
Out[86]:
            memberID Monetary
                           13
          0
                1000
         1
                1001
                           12
         2
                1002
                           8
         3
                1003
                           8
                1004
                          21
In [87]: # I assumed each item has equal price and price is 10
         Monetary['Monetary'] = Monetary['Monetary'] * 10
         Monetary.head()
Out[87]:
            memberID Monetary
```

0 1000 130 1 1001 120 2 1002 80 3 1003 80 4 1004 210

Monetary Distribution of the Customers

Monetary Distribution of the Customers



```
In [89]: # Combining all scores into one DataFrame
RFM = pd.concat([Recency['memberID'], Recency['Recency'], Frequency['Visit_Frequency'], Monetary['Monetary']], axis=1)
RFM.head()
```

Out[89]:

	memberID	Recency	Visit_Frequency	Monetary
0	1000	35	5	130
1	1001	260	5	120
2	1002	122	4	80
3	1003	89	4	80
4	1004	321	8	210

RFM Scores

```
In [90]: # 5-5 score = the best customers
RFM['Recency_quartile'] = pd.qcut(RFM['Recency'], 5, [5, 4, 3, 2, 1])
RFM['Frequency_quartile'] = pd.qcut(RFM['Visit_Frequency'], 5, [1, 2, 3, 4, 5])
RFM['RF_Score'] = RFM['Recency_quartile'].astype(str) + RFM['Frequency_quartile'].astype(str)
RFM.head()
```

Out[90]:

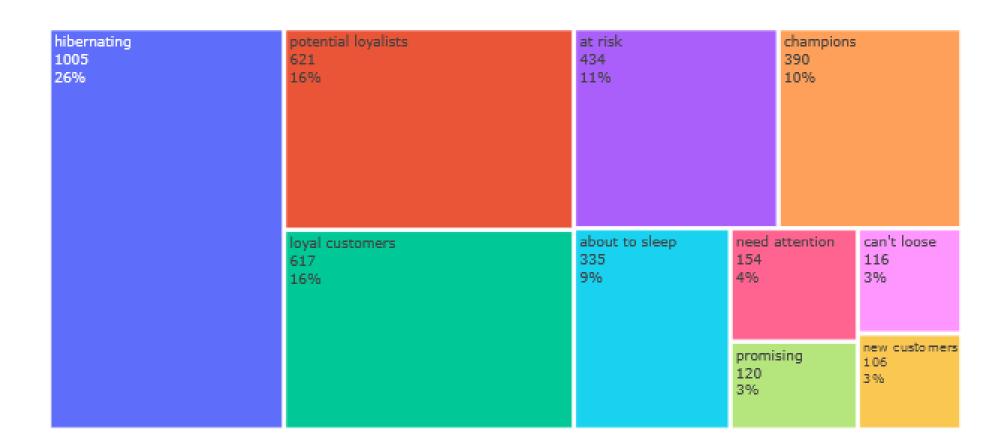
	memberID	Recency	Visit_Frequency	Monetary	Recency_quartile	Frequency_quartile	RF_Score
0	1000	35	5	130	5	4	54
1	1001	260	5	120	2	4	24
2	1002	122	4	80	3	3	33
3	1003	89	4	80	4	3	43
4	1004	321	8	210	2	5	25

Out[91]:

	memberID	Recency	Visit_Frequency	Monetary	Recency_quartile	Frequency_quartile	RF_Score	RF_Segment
0	1000	35	5	130	5	4	54	champions
1	1001	260	5	120	2	4	24	at risk
2	1002	122	4	80	3	3	33	need attention
3	1003	89	4	80	4	3	43	potential loyalists
4	1004	321	8	210	2	5	25	can't loose

Distribution of the RFM Segments

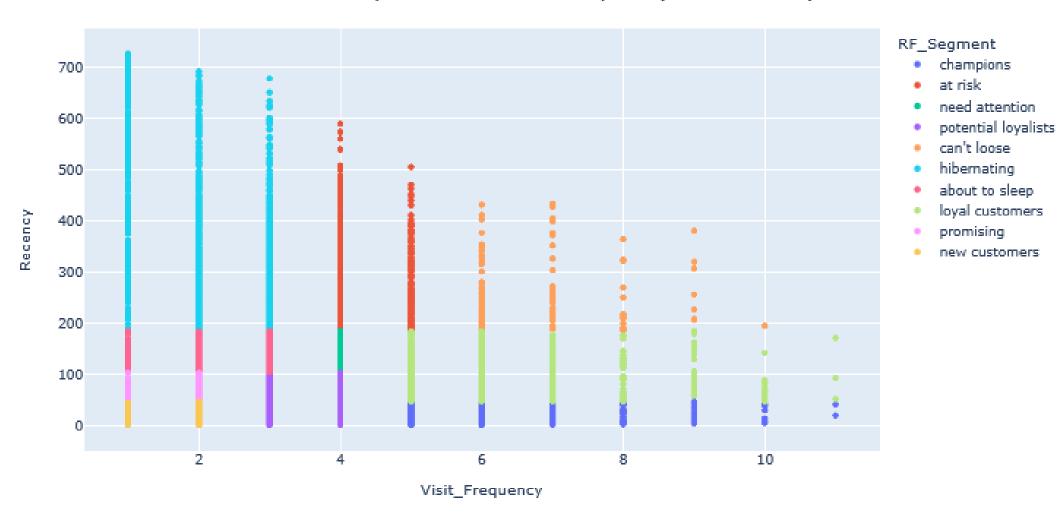
Distribution of the RFM Segments



According to our RFM analysis, most of the customers are segmented into hibernating group which is they are not visiting our store often and it passed pretty much time after their last visit. We can find detailed information about these segments in the references part of this notebook.

Relationship between Visit_Frequency and Recency

Relationship between Visit_Frequency and Recency



As we can see the graph above, when the visit frequency is low and the recency is high, customers are most likely to segmented into hibernating segment. In contrast, when they are visiting our store frequently, and their recency is low, they are most likely to segmented into champions segment which is the best segment for all of the customer segments.

Sources:

- https://www.datacamp.com/community/tutorials/introduction-customer-segmentation-python
- https://guillaume-martin.github.io/rfm-segmentation-with-python.html
- https://towardsdatascience.com/association-rules-2-aa9a77241654

Thank You