GB - Final project

March 14, 2024

1 Customer Transactions Data Analysis

1.1 Introduction:

This customer transactions data can be used to obtain meaningful product recommendations based on the frequency of items bought by all customers. At the high-level, this type of data can be used by big e-commerce companies to provide or guide them when deciding on sales events, product promotion and powerful product recommendation. This work will explore some basic plots and underlying trends in the data.

Data source: https://www.kaggle.com/datasets/devchauhan1/market-basket-optimisationcsv?select=Market_Basket_Optimisation.csv

[1]:
```
#!pip install mlxtend
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
import warnings #To suppress all warnings
warnings.filterwarnings("ignore")
```

[2]:
```
sns.set(style="darkgrid", color_codes=True)
pd.set_option('display.max_columns', 75)
```

[3]:
```
data = pd.read_csv('Market_Basket_Optimisation.csv', header = None)
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7501 entries, 0 to 7500
Data columns (total 20 columns):
 #   Column  Non-Null Count  Dtype
---  ------  --------------  -----
 0   0       7501 non-null   object
 1   1       5747 non-null   object
 2   2       4389 non-null   object
 3   3       3345 non-null   object
 4   4       2529 non-null   object
```

```
 5   5       1864 non-null   object
 6   6       1369 non-null   object
 7   7       981 non-null    object
 8   8       654 non-null    object
 9   9       395 non-null    object
 10  10      256 non-null    object
 11  11      154 non-null    object
 12  12      87 non-null     object
 13  13      47 non-null     object
 14  14      25 non-null     object
 15  15      8 non-null      object
 16  16      4 non-null      object
 17  17      4 non-null      object
 18  18      3 non-null      object
 19  19      1 non-null      object
dtypes: object(20)
memory usage: 1.1+ MB
```

[4]:
```
data.head()
```

[4]:
```
               0          1           2                 3             4  \
0         shrimp    almonds     avocado    vegetables mix  green grapes
1        burgers  meatballs        eggs               NaN           NaN
2        chutney        NaN         NaN               NaN           NaN
3         turkey    avocado         NaN               NaN           NaN
4  mineral water       milk  energy bar  whole wheat rice     green tea

                 5     6               7             8             9  \
0  whole weat flour  yams  cottage cheese  energy drink  tomato juice
1               NaN   NaN             NaN           NaN           NaN
2               NaN   NaN             NaN           NaN           NaN
3               NaN   NaN             NaN           NaN           NaN
4               NaN   NaN             NaN           NaN           NaN

               10         11     12     13             14      15  \
0  low fat yogurt  green tea  honey  salad  mineral water  salmon
1             NaN        NaN    NaN    NaN            NaN     NaN
2             NaN        NaN    NaN    NaN            NaN     NaN
3             NaN        NaN    NaN    NaN            NaN     NaN
4             NaN        NaN    NaN    NaN            NaN     NaN

                  16               17       18         19
0  antioxydant juice  frozen smoothie  spinach  olive oil
1                NaN              NaN      NaN        NaN
2                NaN              NaN      NaN        NaN
3                NaN              NaN      NaN        NaN
4                NaN              NaN      NaN        NaN
```

[5]:
```
data.describe()
```

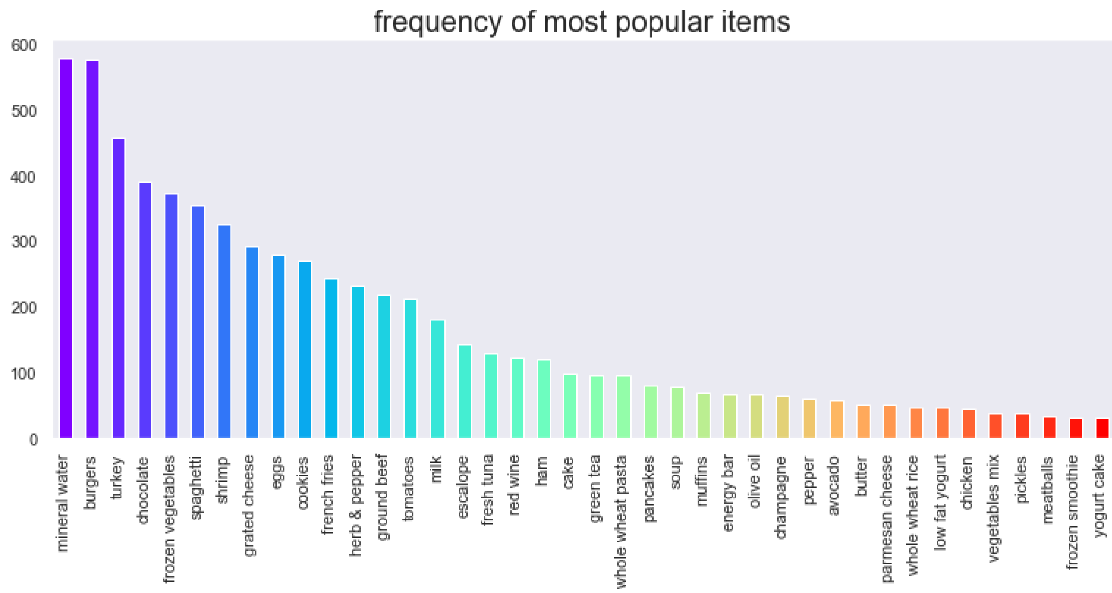
[5]:
```
                    0              1              2              3          4  \
count            7501           5747           4389           3345       2529
unique            115            117            115            114        110
top     mineral water  mineral water  mineral water  mineral water  green tea
freq              577            484            375            201        153

                   5          6          7          8          9  \
count           1864       1369        981        654        395
unique           106        102         98         88         80
top     french fries  green tea  green tea  green tea  green tea
freq             107         96         67         57         31

                    10         11         12         13         14      15  \
count              256        154         87         47         25       8
unique              66         50         43         28         19       8
top     low fat yogurt  green tea  green tea  green tea  magazines  salmon
freq                22         15          8          4          3       1

                     16           17       18         19
count                 4            4        3          1
unique                3            3        3          1
top     frozen smoothie  protein bar  spinach  olive oil
freq                  2            2        1          1
```

[6]:
```
color = plt.cm.rainbow(np.linspace(0, 1, 40))
data[0].value_counts().head(40).plot.bar(color = color, figsize=(13,5))
plt.title('frequency of most popular items', fontsize = 20)
plt.xticks(rotation = 90 )
plt.grid()
plt.show()
```



[7]:
```
import networkx as nx
data['food'] = 'Food'
food = data.truncate(before = -1, after = 15)
food = nx.from_pandas_edgelist(food, source = 'food', target = 0, edge_attr =␣
↪True)
```

[8]:
```
import warnings
warnings.filterwarnings('ignore')

plt.rcParams['figure.figsize'] = (13, 13)
pos = nx.spring_layout(food)
color = plt.cm.Set1(np.linspace(0, 15, 1))
nx.draw_networkx_nodes(food, pos, node_size = 15000, node_color = color)
nx.draw_networkx_edges(food, pos, width = 3, alpha = 0.6, edge_color = 'black')
nx.draw_networkx_labels(food, pos, font_size = 20, font_family = 'sans-serif')
plt.axis('off')
plt.grid()
plt.title('Top 15 First Choices', fontsize = 20)
plt.show()
```

[9]:
```python
# Getting the list of transactions from the dataset
transactions = []
for i in range(0, len(data)):
    transactions.append([str(data.values[i,j]) for j in range(0, len(data.
 ↪columns))])

transactions[:1]
```

[9]:
```
[['shrimp',
  'almonds',
  'avocado',
  'vegetables mix',
  'green grapes',
```

```
 'whole weat flour',
 'yams',
 'cottage cheese',
 'energy drink',
 'tomato juice',
 'low fat yogurt',
 'green tea',
 'honey',
 'salad',
 'mineral water',
 'salmon',
 'antioxydant juice',
 'frozen smoothie',
 'spinach',
 'olive oil',
 'Food']]
```

[10]:

```
from apyori import apriori

transactions_list=[]
for i in range(1,7501):
    transactions_list.append([str(data.values[i,j]) for j in range(0,20)])


#applying apriori algorithm
association_rules = apriori(transactions_list, min_support=0.003,␣
 ↪min_confidence=0.2, min_lift=3, min_length=2, max_length=2)
results = list(association_rules)
```

[11]:

```
for i in range(0, len(results)):
    print(results[i][0])
```

```
frozenset({'chicken', 'light cream'})
frozenset({'mushroom cream sauce', 'escalope'})
frozenset({'pasta', 'escalope'})
frozenset({'fromage blanc', 'honey'})
frozenset({'herb & pepper', 'ground beef'})
frozenset({'tomato sauce', 'ground beef'})
frozenset({'light cream', 'olive oil'})
frozenset({'whole wheat pasta', 'olive oil'})
frozenset({'shrimp', 'pasta'})
```

[12]:

```
#VISUALIZING RESULTS
# Display first results from rules
# results = list(rules)
# results
```

```
#Putting results well organised in a Pandas Dataframe
def inspect(results):
    lhs         = [tuple(result[2][0][0])[0] for result in results]
    rhs         = [tuple(result[2][0][1])[0] for result in results]
    supports    = [result[1] for result in results]
    confidences = [result[2][0][2] for result in results]
    lifts       = [result[2][0][3] for result in results]
    return list(zip(lhs, rhs, supports, confidences, lifts))
resultsinDataFrame = pd.DataFrame(inspect(results),
                                  columns = ['Left Hand Side', 'Right Hand␣
 ↪Side', 'Support', 'Confidence', 'Lift'])

# Display results in Data frame sorted by lift column
resultsinDataFrame.nlargest(n = 10, columns='Lift')
```

[12]:

	Left Hand Side	Right Hand Side	Support	Confidence	Lift
3	fromage blanc	honey	0.003333	0.245098	5.178128
0	light cream	chicken	0.004533	0.290598	4.843305
2	pasta	escalope	0.005867	0.372881	4.700185
8	pasta	shrimp	0.005067	0.322034	4.514494
7	whole wheat pasta	olive oil	0.008000	0.271493	4.130221
5	tomato sauce	ground beef	0.005333	0.377358	3.840147
1	mushroom cream sauce	escalope	0.005733	0.300699	3.790327
4	herb & pepper	ground beef	0.016000	0.323450	3.291555
6	light cream	olive oil	0.003200	0.205128	3.120612

1.2 CONCLUSION:

Customers who bought fromage blanc also bought honey with 25% chance and 5 unit of lift strength (strength of association). This rule appeared 0.0033 of transactions approximately 24 transactions. Similar rule and association is also seen for light cream and chicken.

1.3 Lift = The most important metric to measure the strength of rule.