

Market Basket Analysis using Apriori Algorithm

- python -m pip install mlxtend
- python -m pip install apyori
- python -m pip install squarify
- python -m pip install wordcloud
- conda install -c <https://conda.anaconda.org/conda-forge> (https://conda.anaconda.org/conda-forge) wordcloud

Import important libraries

In [2]:

```
1 import numpy as np
2 import pandas as pd
3
4 import matplotlib.pyplot as plt
5 import squarify
6 import seaborn as sns
7 from wordcloud import WordCloud
8 import networkx as nx
9
10 from mlxtend.frequent_patterns import apriori
11 from mlxtend.frequent_patterns import association_rules
12 from mlxtend.preprocessing import TransactionEncoder
13
14 import warnings
15 warnings.filterwarnings('ignore')
16 plt.style.use('fivethirtyeight')
17 %matplotlib inline
```

Reading the dataset

```
In [4]: 1 data = pd.read_csv('C:/Users/Eric/Documents/Jupyter Notebook/practical/data/MBA.csv', header = None)
```

```
In [5]: 1 # checking the head of the data
        2
        3 data.head()
```

Out[5]:

[illegible]

```
In [6]: 1 # checking the tail of the data
        2
        3 data.tail()
```

Out[6]:

[illegible]

```
In [7]: 1 # Let's check the shape of the dataset
        2 data.shape
```

Out[7]: (7501, 20)

```
In [8]: 1 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
```

```
In [9]: 1 # let's describe the dataset
        2
        3 data.describe()
```

Out[9]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	1
count	7501	5747	4389	3345	2529	1864	1369	981	654	395	256	154	87	47	25	8	4	
unique	115	117	115	114	110	106	102	98	88	80	66	50	43	28	19	8	3	
top	mineral water	mineral water	mineral water	mineral water	green tea	french fries	green tea	green tea	green tea	green tea	low fat yogurt	green tea	green tea	green tea	magazines	salmon	frozen smoothie	protein bar
freq	577	484	375	201	153	107	96	67	57	31	22	15	8	4	3	1	2	

```
In [10]: 1 data.isnull().sum()
```

```
Out[10]: 0      0
         1    1754
         2    3112
         3    4156
         4    4972
         5    5637
         6    6132
         7    6520
         8    6847
         9    7106
        10    7245
        11    7347
        12    7414
        13    7454
        14    7476
        15    7493
        16    7497
        17    7497
        18    7498
        19    7500
```

```
In [11]: 1 data[0]
```

```
Out[11]: 0          shrimp  
         1          burgers  
         2          chutney  
         3          turkey  
         4    mineral water  
         ...  
        7496          butter  
        7497          burgers  
        7498          chicken  
        7499          escalope  
        7500           eggs  
Name: 0, Length: 7501, dtype: object
```

EDA

Plotting most popular name of items

In [12]:

```
1 plt.rcParams['figure.figsize'] = (15, 15)
2 wordcloud = WordCloud(background_color = 'white', width = 1200, height = 1200, max_words = 121).generate(str(dat
3 plt.imshow(wordcloud)
4 plt.axis('off')
5 plt.title('Most Popular Items', fontsize = 20)
6 plt.show()
```


Most Popular Items

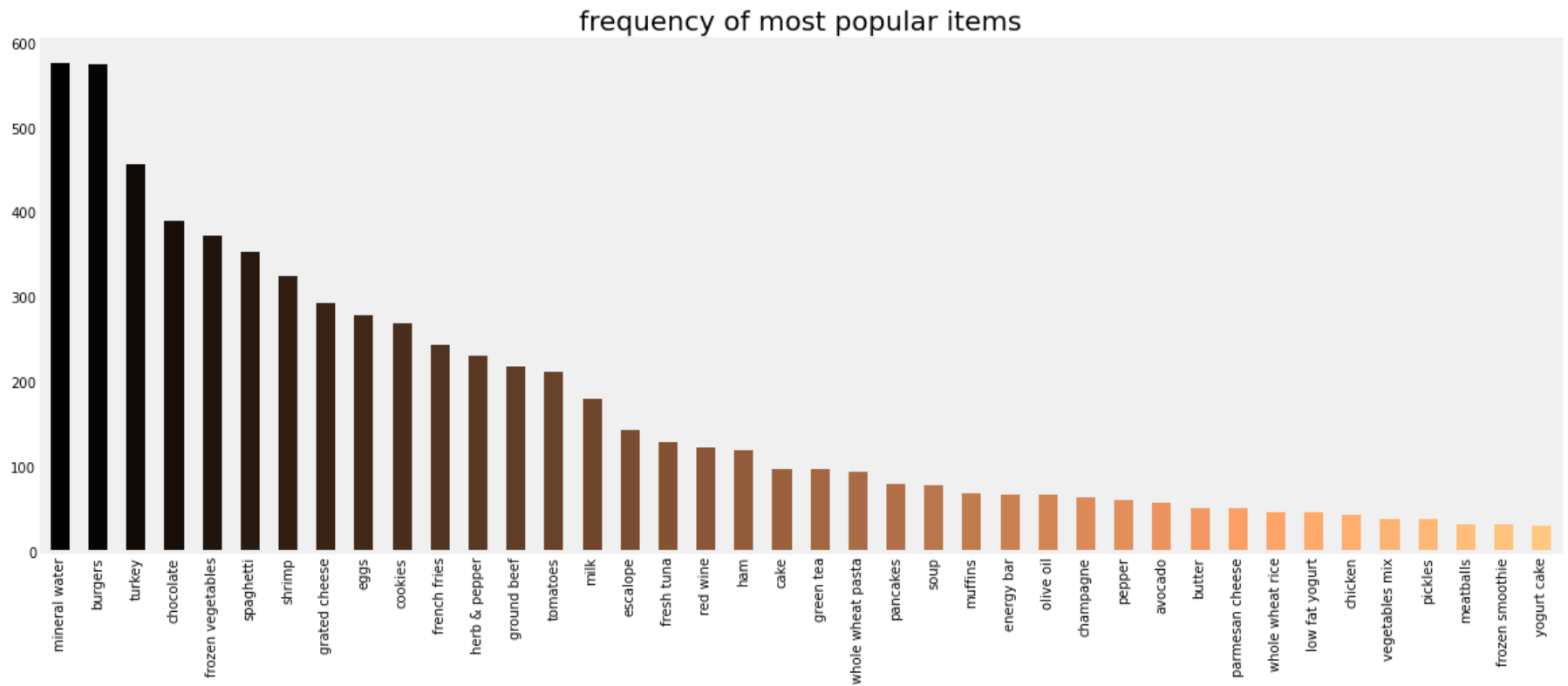
Name shrimp object
mineral
burgers
chicken water
turkey dtype
escalope Length
chitney


```
In [13]: 1 data[0].value_counts()
```

```
Out[13]: mineral water      577  
burgers      576  
turkey      458  
chocolate      391  
frozen vegetables      373  
...  
cauliflower      1  
ketchup      1  
cream      1  
body spray      1  
oatmeal      1  
Name: 0, Length: 115, dtype: int64
```

Looking at the frequency of most popular items

```
In [14]: 1 plt.rcParams['figure.figsize'] = (18, 7)
2 color = plt.cm.copper(np.linspace(0, 1, 40))
3 data[0].value_counts().head(40).plot.bar(color = color)
4 plt.title('frequency of most popular items', fontsize = 20)
5 plt.xticks(rotation = 90 )
6 plt.grid()
7 plt.show()
```



```
In [15]: 1 data[0].value_counts().head(50)
```

```
Out[15]: mineral water      577  
         burgers          576  
         turkey           458  
         chocolate        391  
         frozen vegetables 373  
         spaghetti        354  
         shrimp           325  
         grated cheese    293  
         eggs             279  
         cookies          270  
         french fries     244  
         herb & pepper    232  
         ground beef      218  
         tomatoes        212  
         milk             181  
         escalope         143  
         fresh tuna       129  
         red wine         123  
         ham              120  
         ,                22
```

```
In [16]: 1 y = data[0].value_counts().head(50).to_frame()
          2 y
```

Out[16]:

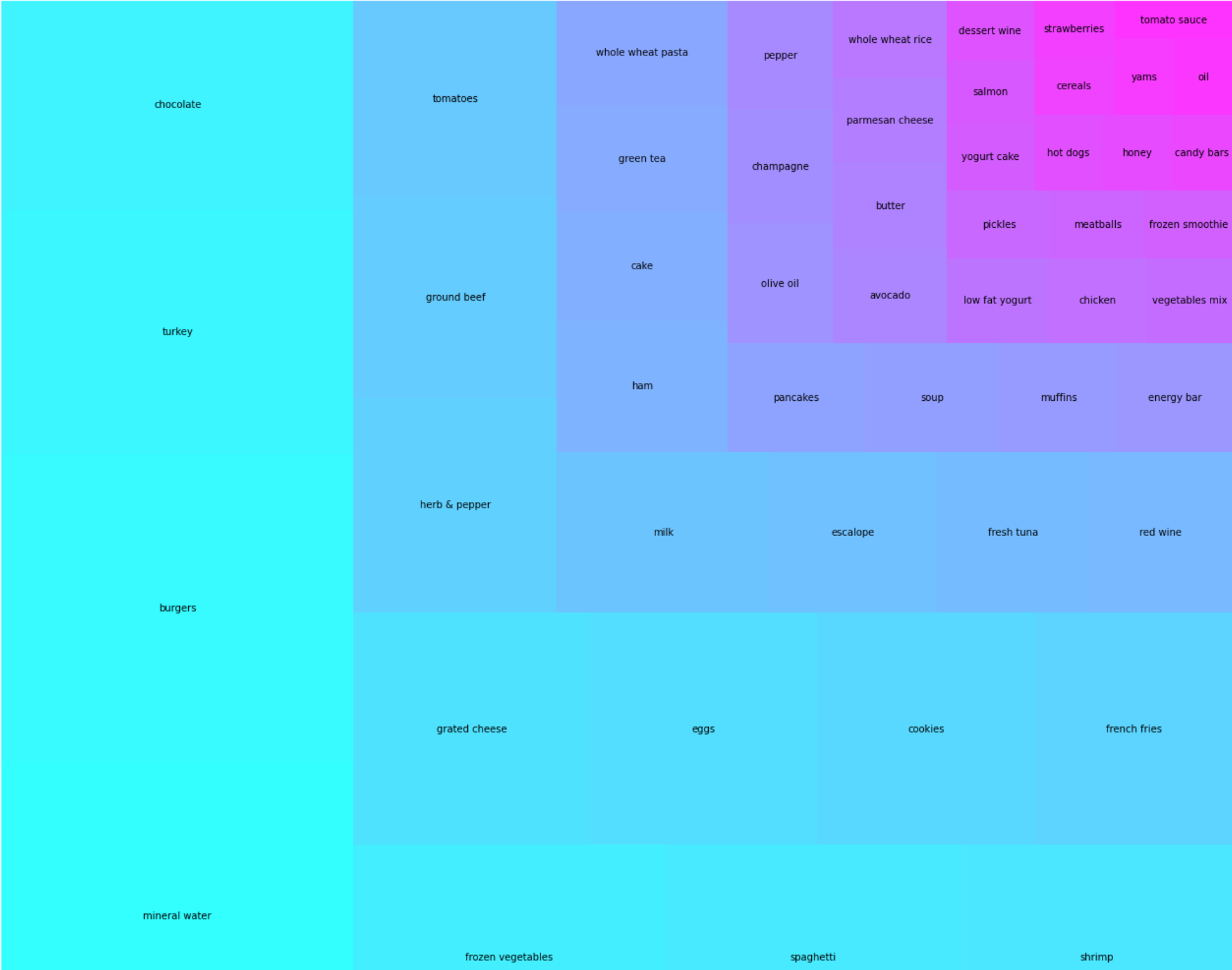
	0
mineral water	577
burgers	576
turkey	458
chocolate	391
frozen vegetables	373
spaghetti	354
shrimp	325
grated cheese	293
eggs	279
cookies	270
french fries	244

Plotting a tree map

In [17]:

```
1 plt.rcParams['figure.figsize'] = (20, 20)
2 color = plt.cm.cool(np.linspace(0, 1, 50))
3 squarify.plot(sizes = y.values, label = y.index, alpha=.8, color = color)
4 plt.title('Tree Map for Popular Items')
5 plt.axis('off')
6 plt.show()
```


Tree Map for Popular Items



Syntax: DataFrame.truncate(before=None, after=None, axis=None, copy=True)

- Parameter :
- before : Truncate all rows before this index value.
- after : Truncate all rows after this index value.
- axis : Axis to truncate. Truncates the index (rows) by default.
- copy : Return a copy of the truncated section.
- Returns : The truncated Series or DataFrame.

```
In [18]: 1 data['food'] = 'Food'
          2 food = data.truncate(before = -1, after = 15)
```

```
In [19]: 1 food
```

Out[19]:

	0	1	2	3	4	5	6	7	8	9	...	11	12	13	14	15	
0	shrimp	almonds	avocado	vegetables mix	green grapes	whole weat flour	yams	cottage cheese	energy drink	tomato juice	...	green tea	honey	salad	mineral water	salmon	antioxyc ju
1	burgers	meatballs	eggs	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	M
2	chutney	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	M
3	turkey	avocado	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	M
4	mineral water	milk	energy bar	whole wheat rice	green tea	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	M
5	low fat yogurt	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	M
6	whole wheat pasta	french fries	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN	M


```
from_pandas_edgelist(df, source='source', target='target',  
edge_attr=None, create_using=None, edge_key=None)
```

Parameters

- `df` : Pandas DataFrame An edge list representation of a graph
- `source` : str or int A valid column name (string or integer) for the source nodes.
- `target` : str or int A valid column name (string or integer) for the target nodes.
- `edge_attr` : str or int, iterable, True, or None A valid column name (str or int) or iterable of column names that are used to retrieve items and add them to the graph as edge attributes. If True, all of the remaining columns will be added. If None, no edge attributes are added to the graph.
- `create_using` : NetworkX graph constructor, optional (default=nx.Graph) Graph type to create. If graph instance, then cleared before populated.
- `edge_key` : str or None, optional (default=None) A valid column name for the edge keys (for a MultiGraph). The values in this column are used for the edge keys when adding edges if `create_using` is a multigraph

Here Target is 0

```
In [20]: 1 food = nx.from_pandas_edgelist(food, source = 'food', target = 0, edge_attr = True)
```

```
In [21]: 1 pos = nx.spring_layout(food)
```

In [22]:

1 pos

```
Out[22]: {'Food': array([0.00235065, 0.00337298]),
'shrimp': array([ 0.12044205, -0.91478962]),
'burgers': array([0.82326287, 0.38959108]),
'chutney': array([ 1.          , -0.09331728]),
'turkey': array([0.5452815 , 0.75414647]),
'mineral water': array([-0.68300856,  0.58609314]),
'low fat yogurt': array([-0.9785123 ,  0.19404559]),
'whole wheat pasta': array([-0.33402417, -0.84198262]),
'soup': array([0.11757481, 0.90901038]),
'frozen vegetables': array([ 0.60071806, -0.76919842]),
'french fries': array([-0.71956048, -0.17044391]),
'eggs': array([ 0.61072909, -0.3120902 ]),
'cookies': array([-0.33488785,  0.88109727]),
'spaghetti': array([-0.77036567, -0.61553487])}
```

In [23]:

```
1 plt.rcParams['figure.figsize'] = (20, 20)
2 color = plt.cm.Wistia(np.linspace(0, 15, 1))
3 nx.draw_networkx_nodes(food, pos, node_size = 15000, node_color = color)
4 nx.draw_networkx_edges(food, pos, width = 3, alpha = 0.6, edge_color = 'black')
5 nx.draw_networkx_labels(food, pos, font_size = 20, font_family = 'sans-serif')
6 plt.axis('off')
7 plt.grid()
8 plt.title('Top 15 First Choices', fontsize = 40)
9 plt.show()
```


Top 15 First Choices



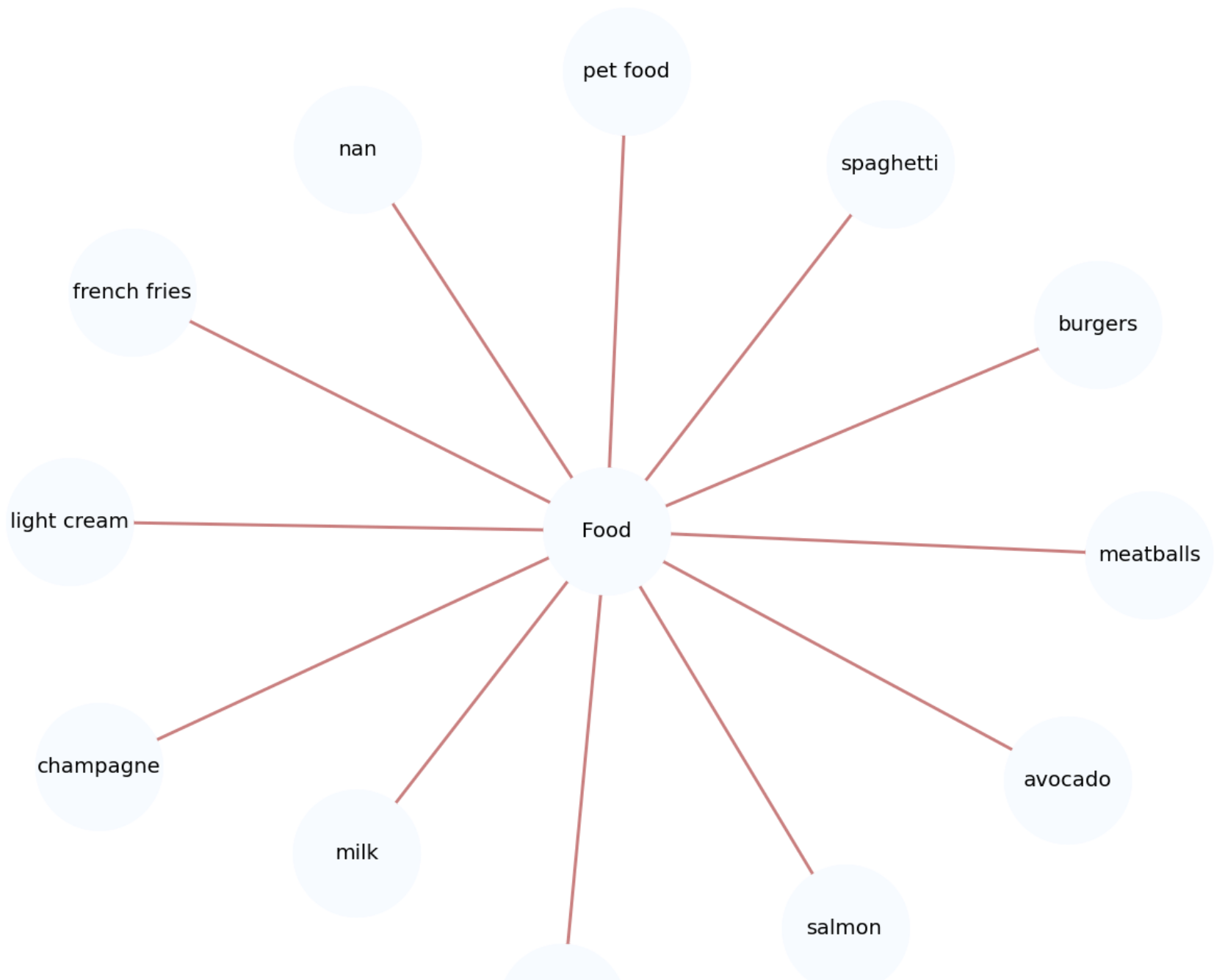

```
In [25]: 1 secondchoice = nx.from_pandas_edgelist(secondchoice, source = 'food', target = 1, edge_attr = True) # Here Target
          2 pos = nx.spring_layout(secondchoice)
          3 pos
```

```
Out[25]: {'Food': array([0.0036716 , 0.00661285]),
          'almonds': array([-0.07372186, -1.          ]),
          'meatballs': array([ 0.94079314, -0.04432206]),
          nan: array([-0.42740855,  0.81300829]),
          'avocado': array([ 0.80002361, -0.51825204]),
          'milk': array([-0.4279372 , -0.67362954]),
          'french fries': array([-0.81565396,  0.51057963]),
          'light cream': array([-0.92437157,  0.02626485]),
          'spaghetti': array([0.49354618, 0.78074858]),
          'pet food': array([0.03797973, 0.97753847]),
          'burgers': array([0.85123077, 0.44367474]),
          'champagne': array([-0.8735947 , -0.49105485]),
          'salmon': array([ 0.41544281, -0.83116893])}
```

In [26]:

```
1 plt.rcParams['figure.figsize'] = (20, 20)
2 color = plt.cm.Blues(np.linspace(0, 15, 1))
3 nx.draw_networkx_nodes(secondchoice, pos, node_size = 15000, node_color = color)
4 nx.draw_networkx_edges(secondchoice, pos, width = 3, alpha = 0.6, edge_color = 'brown')
5 nx.draw_networkx_labels(secondchoice, pos, font_size = 20, font_family = 'sans-serif')
6 plt.axis('off')
7 plt.grid()
8 plt.title('Top 15 Second Choices', fontsize = 40)
9 plt.show()
```


Top 15 Second Choices



In [27]:

```
1 data['thirdchoice'] = 'Third Choice'
2 thirdchoice = data.truncate(before = -1, after = 10)
3 thirdchoice
```

Out[27]:

	0	1	2	3	4	5	6	7	8	9	...	13	14	15	16	17
0	shrimp	almonds	avocado	vegetables mix	green grapes	whole weat flour	yams	cottage cheese	energy drink	tomato juice	...	salad	mineral water	salmon	antioxydant juice	frozen smoothie
1	burgers	meatballs	eggs	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
2	chutney	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
3	turkey	avocado	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
4	mineral water	milk	energy bar	whole wheat rice	green tea	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
5	low fat yogurt	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	...	NaN	NaN	NaN	NaN	NaN
	whole															

In [28]:

```
1 thirdchoice = nx.from_pandas_edgelist(thirdchoice, source = 'food', target = 2, edge_attr = True) # Here Target i
2 pos = nx.spring_layout(thirdchoice)
3 pos
```

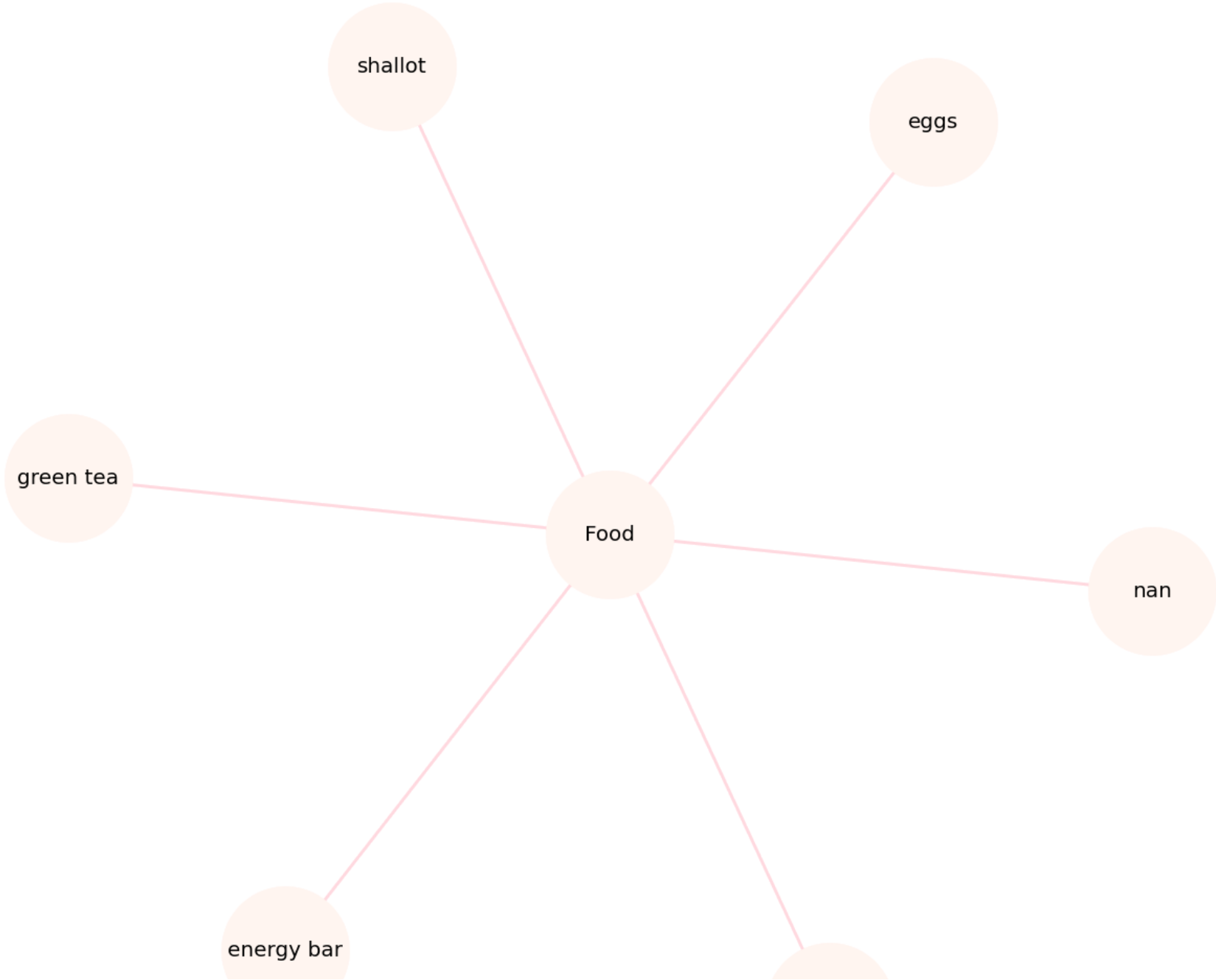
Out[28]:

```
{'Food': array([-0.00038113,  0.00248743]),
 'avocado': array([ 0.40475569, -0.92399341]),
 'eggs': array([0.59651032, 0.81056829]),
 nan: array([ 1.          , -0.10904994]),
 'energy bar': array([-0.59883628, -0.81272252]),
 'shallot': array([-0.40249825,  0.92006306]),
 'green tea': array([-0.99955034,  0.11264709])}
```

In [29]:

```
1 plt.rcParams['figure.figsize'] = (20, 20)
2 color = plt.cm.Reds(np.linspace(0, 15, 1))
3 nx.draw_networkx_nodes(thirdchoice, pos, node_size = 15000, node_color = color)
4 nx.draw_networkx_edges(thirdchoice, pos, width = 3, alpha = 0.6, edge_color = 'pink')
5 nx.draw_networkx_labels(thirdchoice, pos, font_size = 20, font_family = 'sans-serif')
6 plt.axis('off')
7 plt.grid()
8 plt.title('Top 10 Third Choices', fontsize = 40)
9 plt.show()
```


Top 10 Third Choices



Data Preprocessing

- The dataset contains the items bought by a customer i.e. each row represents one customer.
- Converting the dataframe into a list of lists, as required by the apriori algorithm.

In [30]:

```
1 # making each customers shopping items an identical list
2 transactions = []
3 for i in range(0, 7501):
4     transactions.append([str(data.values[i,j]) for j in range(0, 20)])
5
6 print(transactions)
```

```
[['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', 'antio  
xydant juice', 'frozen smoothie', 'spinach', 'olive oil'], ['burgers', 'meatballs', 'eggs', 'nan', 'nan', 'nan',  
'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan'], ['chutney', 'na  
n', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'na  
n', 'nan', 'nan'], ['turkey', 'avocado', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'na  
n', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan'], ['mineral water', 'milk', 'energy bar', 'whole wheat rice',  
'green tea', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'na  
n'], ['low fat yogurt', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan',  
'nan', 'nan', 'nan', 'nan', 'nan', 'nan'], ['whole wheat pasta', 'french fries', 'nan', 'nan', 'nan', 'nan', 'na  
n', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan'], ['soup', 'light cr  
eam', 'shallot', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan',  
'nan', 'nan', 'nan'], ['frozen vegetables', 'spaghetti', 'green tea', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'n  
an', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan'], ['french fries', 'nan', 'nan', 'nan',  
'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan'],  
['eggs', 'pet food', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'n  
an', 'nan', 'nan', 'nan', 'nan'], ['cookies', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'na  
n', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan'], ['turkey', 'burgers', 'mineral water', 'eggs',  
'cooking oil', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan',  
'nan'], ['spaghetti', 'champagne', 'cookies', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'nan', 'na
```

```
In [31]: 1 print("First Transaction:\n")
          2 print(transactions[:1])
          3 print("\nSecond Transaction:\n")
          4 print(transactions[1:2])
```

First Transaction:

```
[[ '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' ]]
```

Second Transaction:

[illegible]

```
In [32]: 1 # converting it into a numpy array
          2 transactions = np.array(transactions)
          3
          4 # checking the shape of the array
          5 print(transactions.shape)
```

(7501, 20)

```
In [33]: 1 transactions
```

```
Out[33]: array([[ 'shrimp', 'almonds', 'avocado', ..., 'frozen smoothie',
    'spinach', 'olive oil'],
    ['burgers', 'meatballs', 'eggs', ..., 'nan', 'nan', 'nan'],
    ['chutney', 'nan', 'nan', ..., 'nan', 'nan', 'nan'],
    ...,
    ['chicken', 'nan', 'nan', ..., 'nan', 'nan', 'nan'],
    ['escalope', 'green tea', 'nan', ..., 'nan', 'nan', 'nan'],
    ['eggs', 'frozen smoothie', 'yogurt cake', ..., 'nan', 'nan',
    'nan']], dtype='<U20')
```



```
In [34]: 1 # create an encoder for apriori algorithm
2 encoder = TransactionEncoder()
3
4 # fit and Tranform encoder to transactions which will create a one-hot encoded(True, Flase) occurence matrix
5 data = encoder.fit_transform(transactions)
6
7 # convert array to pandas dataframe
8 data = pd.DataFrame(data, columns = encoder.columns_)
9
10 data.head(10)
```

Out[34]:

	asparagus	almonds	antioxydant juice	asparagus	avocado	babies food	bacon	barbecue sauce	black tea	blueberries	...	turkey	vegetables mix	water spray	white wine
0	False	True	True	False	True	False	False	False	False	False	...	False	True	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
3	False	False	False	False	True	False	False	False	False	False	...	True	False	False	False
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
5	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
6	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
7	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False
8	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False

```
In [35]: 1 data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7501 entries, 0 to 7500
Columns: 121 entries, asparagus to zucchini
dtypes: bool(121)
memory usage: 886.5 KB
```

```
In [36]: 1 # getting the shape of the data
         2 data.shape
```

Out[36]: (7501, 121)

```
In [37]: 1 # getting correlations for 121 items would be messy
         2 # so let's reduce the items from 121 to 40
         3
         4 data = data.loc[:, ['mineral water', 'burgers', 'turkey', 'chocolate', 'frozen vegetables', 'spaghetti',
         5                     'shrimp', 'grated cheese', 'eggs', 'cookies', 'french fries', 'herb & pepper', 'ground beef',
         6                     'tomatoes', 'milk', 'escalope', 'fresh tuna', 'red wine', 'ham', 'cake', 'green tea',
         7                     'whole wheat pasta', 'pancakes', 'soup', 'muffins', 'energy bar', 'olive oil', 'champagne',
         8                     'avocado', 'pepper', 'butter', 'parmesan cheese', 'whole wheat rice', 'low fat yogurt',
         9                     'chicken', 'vegetables mix', 'pickles', 'meatballs', 'frozen smoothie', 'yogurt cake']]
        10
```

In [38]:

```
1 data
```

Out[38]:

	mineral water	burgers	turkey	chocolate	frozen vegetables	spaghetti	shrimp	grated cheese	eggs	cookies	...	butter	parmesan cheese	whole wheat rice	low fat yogurt	chicken
0	True	False	False	False	False	False	True	False	False	False	...	False	False	False	True	False
1	False	True	False	False	False	False	False	False	True	False	...	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False
3	False	False	True	False	False	False	False	False	False	False	...	False	False	False	False	False
4	True	False	False	False	False	False	False	False	False	False	...	False	False	True	False	False
...
7496	False	False	False	False	False	False	False	False	False	False	...	True	False	False	False	False
7497	False	True	False	False	True	False	False	False	True	False	...	False	False	False	False	False
7498	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	True
7499	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False
7500	False	False	False	False	False	False	False	False	True	False	...	False	False	False	True	False

7501 rows × 40 columns



In [39]:

```
1 # checking the shape
2 data.shape
```

Out[39]: (7501, 40)

Model Training

In [40]:

```
1 #Now, let us return the items and itemsets with at least 3% support:
2 apriori(data, min_support = 0.03, use_colnames = True)
```

Out[40]:

	support	itemsets
0	0.238368	(mineral water)
1	0.087188	(burgers)
2	0.062525	(turkey)
3	0.163845	(chocolate)
4	0.095321	(frozen vegetables)
5	0.174110	(spaghetti)
6	0.071457	(shrimp)
7	0.052393	(grated cheese)
8	0.179709	(eggs)
9	0.080389	(cookies)
10	0.170911	(french fries)

In [41]:

```
1 #Now, let us return the items and itemsets with at least 5% support:  
2 apriori(data, min_support = 0.05, use_colnames = True)
```

Out[41]:

	support	itemsets
0	0.238368	(mineral water)
1	0.087188	(burgers)
2	0.062525	(turkey)
3	0.163845	(chocolate)
4	0.095321	(frozen vegetables)
5	0.174110	(spaghetti)
6	0.071457	(shrimp)
7	0.052393	(grated cheese)
8	0.179709	(eggs)
9	0.080389	(cookies)
10	0.170911	(french fries)

```
In [42]: 1 frequent_itemsets = apriori(data, min_support = 0.05, use_colnames=True)
2 frequent_itemsets['length'] = frequent_itemsets['itemsets'].apply(lambda x: len(x))
3 frequent_itemsets
```

Out[42]:

	support	itemsets	length
0	0.238368	(mineral water)	1
1	0.087188	(burgers)	1
2	0.062525	(turkey)	1
3	0.163845	(chocolate)	1
4	0.095321	(frozen vegetables)	1
5	0.174110	(spaghetti)	1
6	0.071457	(shrimp)	1
7	0.052393	(grated cheese)	1
8	0.179709	(eggs)	1
9	0.080389	(cookies)	1
10	0.170911	(french fries)	1

```
In [43]: 1 frequent_itemsets.sort_values('support', ascending = False)
```

Out[43]:

	support	itemsets	length
0	0.238368	(mineral water)	1
8	0.179709	(eggs)	1
5	0.174110	(spaghetti)	1
10	0.170911	(french fries)	1
3	0.163845	(chocolate)	1
16	0.132116	(green tea)	1
13	0.129583	(milk)	1
11	0.098254	(ground beef)	1
4	0.095321	(frozen vegetables)	1
17	0.095054	(pancakes)	1
1	0.087188	(burgers)	1

```
In [44]: 1 Asso_Rules = association_rules(frequent_itemsets, metric = "lift", min_threshold = 1)
2 Asso_Rules.sort_values('lift',ascending = False)
```

Out[44]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
2	(spaghetti)	(mineral water)	0.174110	0.238368	0.059725	0.343032	1.439085	0.018223	1.159314
3	(mineral water)	(spaghetti)	0.238368	0.174110	0.059725	0.250559	1.439085	0.018223	1.102008
1	(chocolate)	(mineral water)	0.163845	0.238368	0.052660	0.321400	1.348332	0.013604	1.122357
0	(mineral water)	(chocolate)	0.238368	0.163845	0.052660	0.220917	1.348332	0.013604	1.073256
4	(mineral water)	(eggs)	0.238368	0.179709	0.050927	0.213647	1.188845	0.008090	1.043158
5	(eggs)	(mineral water)	0.179709	0.238368	0.050927	0.283383	1.188845	0.008090	1.062815

```
In [45]: 1 # getting the item sets with length = 2 and support more than 1%
2
3 frequent_itemsets[ (frequent_itemsets['length'] == 2) &
4                   (frequent_itemsets['support'] >= 0.01) ]
```

Out[45]:

	support	itemsets	length
24	0.052660	(mineral water, chocolate)	2
25	0.059725	(spaghetti, mineral water)	2
26	0.050927	(mineral water, eggs)	2

```
In [46]: 1 # getting the item sets with length = 1 and support more than 10%
2
3 frequent_itemsets[ (frequent_itemsets['length'] == 1) &
4                   (frequent_itemsets['support'] >= 0.1) ]
```

Out[46]:

	support	itemsets	length
0	0.238368	(mineral water)	1
3	0.163845	(chocolate)	1
5	0.174110	(spaghetti)	1
8	0.179709	(eggs)	1
10	0.170911	(french fries)	1
13	0.129583	(milk)	1
16	0.132116	(green tea)	1

```
In [47]: 1 frequent_itemsets[ frequent_itemsets['itemsets'] == {'eggs', 'mineral water'} ]
```

Out[47]:

	support	itemsets	length
26	0.050927	(mineral water, eggs)	2


```
In [48]: 1 frequent_itemsets[ frequent_itemsets['itemsets'] == {'chocolate'} ]
```

Out[48]:

	support	itemsets	length
3	0.163845	(chocolate)	1

```
In [ ]:
```

```
1
```