1. Introduction

1.1 Objective

The main of this project is use **Market Basket Analysis** to understand customer purchasing behaviour so as improve customer experience whilst improve sales. With transaction data collected on items purchased we aim to understand which items leads to the purchase of other items in other to provide better product recommedation , better product arrangement in malls and online website to ease the stress of buy hence improving customers satisfaction.

1.2 Business Problem

- Which products are commonly purchased together?

In [40]:
```
#to ignore the Deprecation warning message we might get when running some codes
import warnings
warnings.filterwarnings('ignore',category=DeprecationWarning)
```

In [41]:
```
import os
import numpy as np
import pandas as pd
from itertools import permutations
from mlxtend.preprocessing import TransactionEncoder
from mlxtend.frequent_patterns import apriori, association_rules
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
import plotly.express as px
import plotly.offline as pyo
import igraph as ig
from plotly.graph_objs import *
from plotly.subplots import make_subplots
import plotly.io as pio
```

In [38]:
```
#set noteook mode to work in offline
pyo.init_notebook_mode()
```

In [4]:
```
# Print the current working directory
print("Current working directory: {0}".format(os.getcwd()))
# Change the current working directory
os.chdir('C:\\Users\\Richard\\Downloads\\Data')
# Print the current working directory
print("Current working directory: {0}".format(os.getcwd()))
```

```
Current working directory: C:\Users\Richard
Current working directory: C:\Users\Richard\Downloads\Data
```

2. Prepare & Process

The cleaned dataset was downloaded from kaggle

In [5]:
```python
#reading my Groceries Dataset
df = pd.read_csv("Groceries data.csv")
x  = pd.read_csv("basket.csv")
```

In [6]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 38765 entries, 0 to 38764
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   Member_number    38765 non-null  int64 
 1   Date             38765 non-null  object
 2   itemDescription  38765 non-null  object
 3   year             38765 non-null  int64 
 4   month            38765 non-null  int64 
 5   day              38765 non-null  int64 
 6   day_of_week      38765 non-null  int64 
dtypes: int64(5), object(2)
memory usage: 2.1+ MB
```

In [7]:
```python
#changing the data format for my columns
df["Date"] = pd.to_datetime(df['Date'])
#df[['Member_number','year','month','day','day_of_week']] = df[['Member_number','year','month','day','day_of_week']].astype(str)
```

In [8]:
```python
#checking how many transaction we have in our dataset
len(df)
```

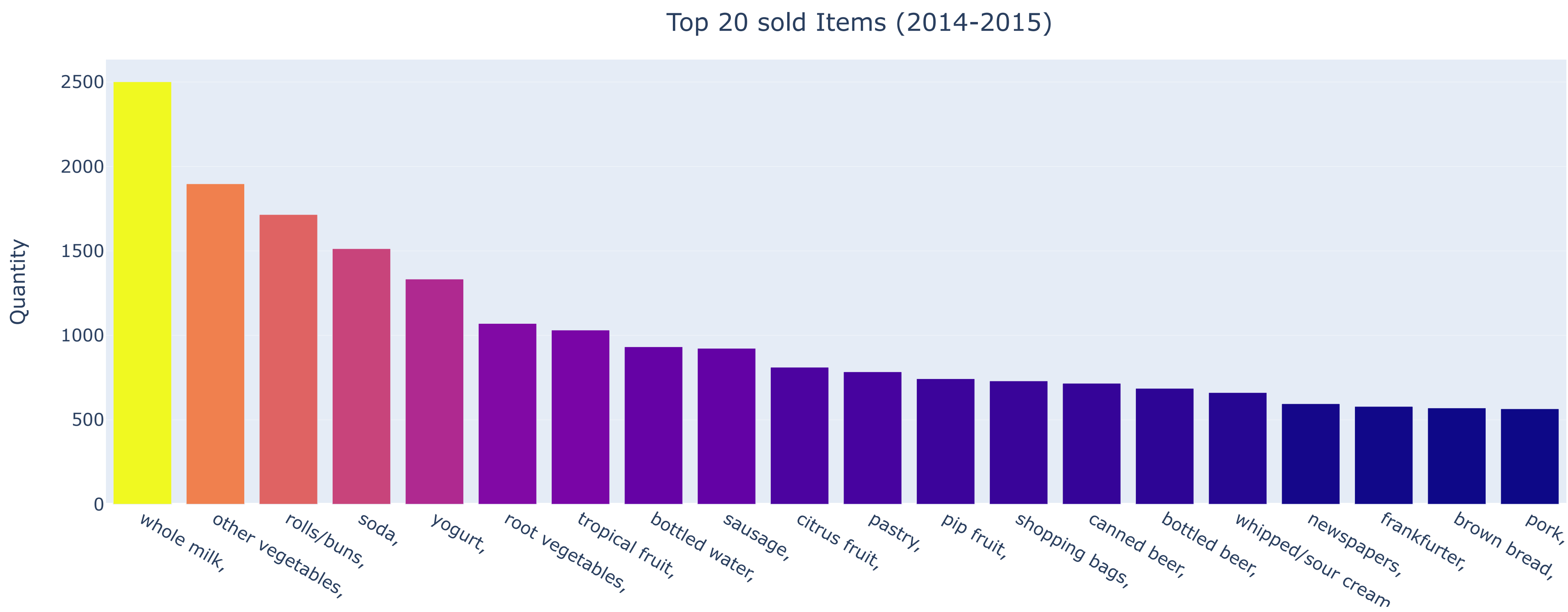
Out[8]:
```
38765
```

3. Analyze

3.1 Exploratory Data Analysis (EDA)

In [42]:
```python
#showing the Top 20 most bought item for the combine year 2014 and 2015
freq_item = df['itemDescription'].value_counts().head(20)

#plot the top 20 most frequent item
fig = px.bar(data_frame=freq_item, title = 'Top 20 sold Items (2014-2015)', color = freq_item,
            labels = {'index':'Item',
                      'value':'Quantity'})
```

```
fig.update_layout(title_x=0.5, title_y=0.87)
pyo.iplot(fig)
```



The above bar chart shows the products with the most sales, with ***whole milk, other vegetables, rolls/buns, soda and yougurt*** being their **top 5 selling products**.

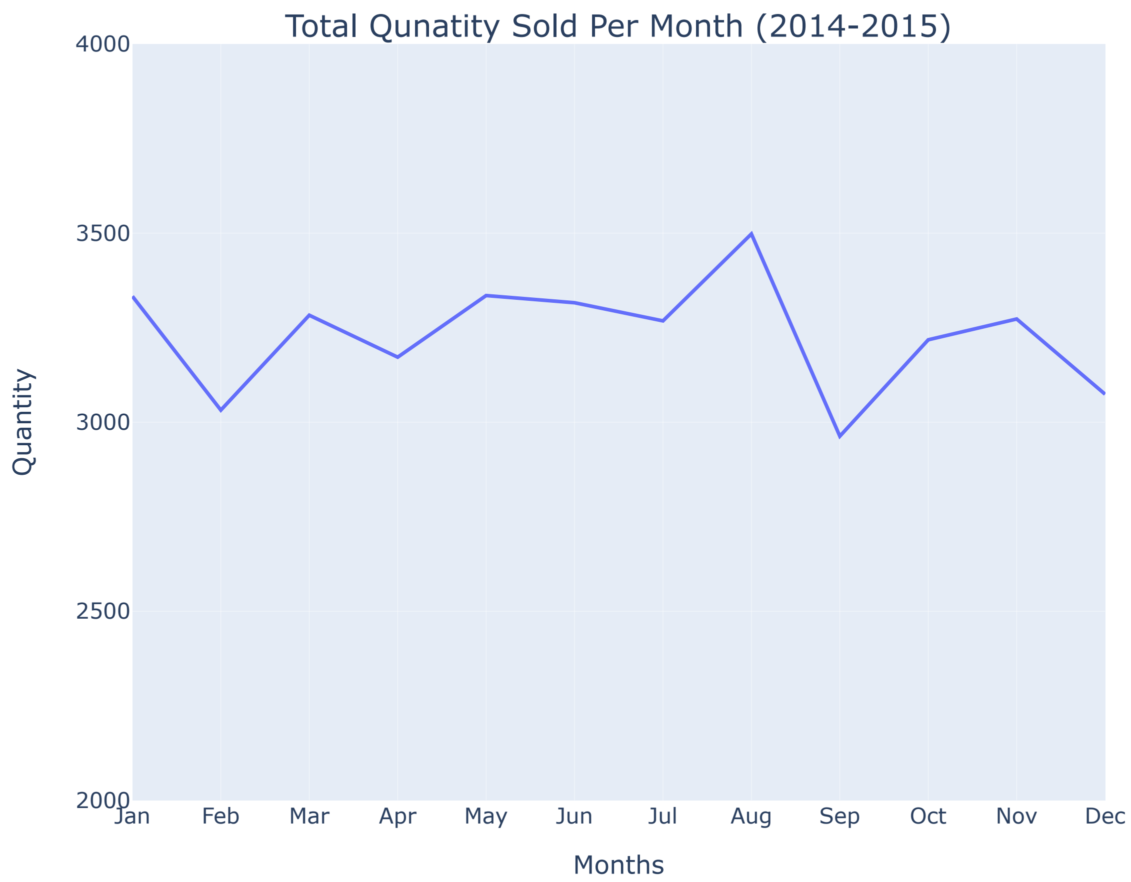
In [10]:
```
df.head()
```

Out[10]:

	Member_number	Date	itemDescription	year	month	day	day_of_week
0	1808	2015-07-21	tropical fruit	2015	7	21	1
1	2552	2015-05-01	whole milk	2015	5	1	4
2	2300	2015-09-19	pip fruit	2015	9	19	5
3	1187	2015-12-12	other vegetables	2015	12	12	5
4	3037	2015-01-02	whole milk	2015	1	2	4

In [11]:
```
# creating a new dataframe by filtering out by years
df14 = df[df['year'] == 2014]
df15 = df[df['year'] == 2015]
```

In [43]:
```
#finding the total number of quantity sold per month and arranging the data according to the index
total_items = df['month'].value_counts().sort_index()

#converting the total_items into a dataframe
total_items_months = pd.DataFrame(total_items)

#creating a month list arranged in monthly order
months = ('Jan','Feb','Mar','Apr','May','Jun','Jul','Aug','Sep','Oct','Nov','Dec')

#adding the months list into the dataframe
total_items_months['months'] = months

#renaming the columns name
total_items_months.rename(columns={'month':'quantity'})

total_items_months

#Plotting the line graph to show the quantity of items sold per month
fig = px.line(data_frame = total_items_months,x='months',y='month', title = "Total Qunatity Sold Per Month (2014-2015)",
       labels = {'month':'Quantity',
                'months':'Months'}).update_layout(height=600, width= 700,title_x=0.50,title_y=0.86).update_yaxes(range=[2000,4000])
pyo.iplot(fig)
```



Looking at the total trend of total quantities of item sold per month(2014-2015).The major trend shows a **increase in sales** from **Feburary to August**.

A deeper look in to the trend line to discover any insights by breaking it down into previous years

In [13]:
```
#finding the total number of quantity sold per month and arranging the data according to the index
total_items14 = df14['month'].value_counts().sort_index()

#converting the total_items into a dataframe
total_items_months14 = pd.DataFrame(total_items14)

#creating a month list arranged in monthly order
months14 = ('jan','feb','mar','apr','may','jun','jul','aug','sep','oct','nov','dec')

#adding the months list into the dataframe
total_items_months14['months'] = months
```

```
#renaming the columns name
total_items_months14.rename(columns={'month':'quantity'})

total_items_months14
```

Out[13]:

	month	months
1	1504	Jan
2	1547	Feb
3	1491	Mar
4	1506	Apr
5	1625	May
6	1525	Jun
7	1623	Jul
8	1535	Aug
9	1350	Sep
10	1555	Oct
11	1496	Nov
12	1520	Dec

The above table shows the total quantity of products sold per month for the year 2014

In [14]:

```
#finding the total number of quantity sold per month and arranging the data according to the index
total_items15 = df15['month'].value_counts().sort_index()

#converting the total_items into a dataframe
total_items_months15 = pd.DataFrame(total_items15)

#creating a month list arranged in monthly order
months15 = ('jan','feb','mar','apr','may','jun','jul','aug','sep','oct','nov','dec')

#adding the months list into the dataframe
total_items_months15['months'] = months

#renaming the columns name
total_items_months15.rename(columns={'month':'quantity'})

total_items_months15
```

Out[14]:

	month	months
1	1829	Jan
2	1485	Feb
3	1792	Mar
4	1666	Apr
5	1710	May
6	1791	Jun
7	1645	Jul
8	1963	Aug
9	1613	Sep
10	1663	Oct
11	1777	Nov
12	1554	Dec

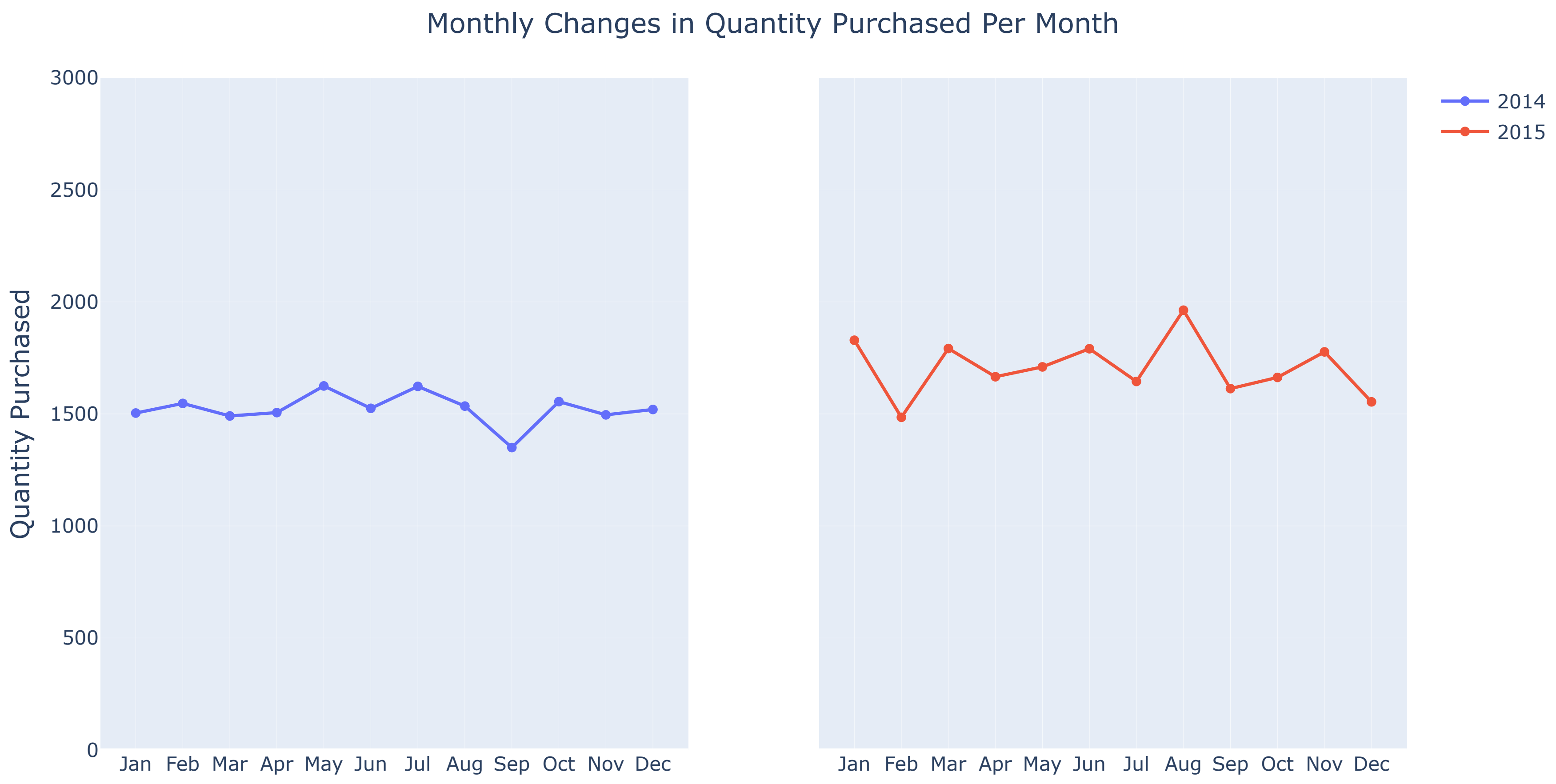
The above table shows the total quantity of products sold per month for the year 2015

In [15]:

```
#plotting our two graphs for the year 2014 and 2015
a=go.Scatter(x = total_items_months14['months'], y = total_items_months14['month'], name = "2014")
b=go.Scatter(x = total_items_months15['months'], y = total_items_months15['month'], name = "2015")
```

In [44]:

```
#Creating a fig with subplots so a align the multiple chart side y side
fig = make_subplots(rows=1,cols=2,shared_xaxes='all',shared_yaxes='all',y_title='Quantity Purchased')

#adding the first chart to the location in the fig
fig.add_trace(a,row=1,col=1)

#adding the second chart to the location in the fig
fig.add_trace(b,row=1,col=2)

#changing the size  editing of chart
fig.update_layout(height=600, width=1000, title='Monthly Changes in Quantity Purchased Per Month',title_x=0.5,title_y=0.90)

#changing the axis ticks
#fig.update_xaxes(range = np.arange())
fig.update_yaxes(range = [0,3000])
pyo.iplot(fig)
```



The insight derived from the breakdown of items purchsed per month aligned with the combined years as there appears to be increase in **sales** from **March to August**.

In [17]:
```
#getting the most sold items from the dataframe
freq_item = [df['itemDescription'].value_counts().head(20)]
```

In [18]:
```
freq_item
```

Out[18]:
```
[whole milk          2502
 other vegetables    1898
 rolls/buns          1716
 soda                1514
 yogurt              1334
 root vegetables     1071
 tropical fruit      1032
 bottled water        933
 sausage              924
 citrus fruit         812
 pastry               785
 pip fruit            744
 shopping bags        731
 canned beer          717
 bottled beer         687
 whipped/sour cream   662
 newspapers           596
 frankfurter          580
 brown bread          571
 pork                 566
 Name: itemDescription, dtype: int64]
```

The Top 5 most sold items from the retail stores are:

- Whole Milk
- Other Vegetables
- Rolls/Buns
- Soda
- Yogurt

Since these are the most purchased items from the retails understanding the consequent items of this sold produts will improve sales and customer statisfaction.

Lets take a dive inside the data using Market Basket Analysis to understand customers purchasing behaviour

3.2 Creating a list of list

From the df dataframe we create a bsk daframe which shows the list of item purchased in a single transcation i.e The list on items an individual bought in a single transaction

In [19]:
```
#duplicating my dataframe
bsk = df

#adding coma to the end value in my itemdescription: so when coming the item based on an individual on a single transaction they are separated by coma
bsk['itemDescription'] = bsk['itemDescription'].apply(lambda x : x+',')
bsk
```

Out[19]:

	Member_number	Date	itemDescription	year	month	day	day_of_week
0	1808	2015-07-21	tropical fruit,	2015	7	21	1
1	2552	2015-05-01	whole milk,	2015	5	1	4
2	2300	2015-09-19	pip fruit,	2015	9	19	5
3	1187	2015-12-12	other vegetables,	2015	12	12	5
4	3037	2015-01-02	whole milk,	2015	1	2	4
...	...	...	...	...	...	...	...
38760	4471	2014-08-10	sliced cheese,	2014	8	10	6
38761	2022	2014-02-23	candy,	2014	2	23	6
38762	1097	2014-04-16	cake bar,	2014	4	16	2
38763	1510	2014-03-12	fruit/vegetable juice,	2014	3	12	2
38764	1521	2014-12-26	cat food,	2014	12	26	4

38765 rows × 7 columns

In [20]:

```
#grouping my dataframe by MemberId and Transactioon date.. and suming the itemdescription to concatenate the item together while setting index as false so as
bsk=bsk.groupby(["Member_number","Date"], as_index = False)['itemDescription'].sum()
```

In [21]:

```
pd.DataFrame(bsk)
```

Out[21]:

	Member_number	Date	itemDescription
0	1000	2014-06-24	whole milk,pastry,salty snack,
1	1000	2015-03-15	sausage,whole milk,semi-finished bread,yogurt,
2	1000	2015-05-27	soda,pickled vegetables,
3	1000	2015-07-24	canned beer,misc. beverages,
4	1000	2015-11-25	sausage,hygiene articles,
...	...	...	...
14958	4999	2015-05-16	butter milk,whipped/sour cream,
14959	4999	2015-12-26	bottled water,herbs,
14960	5000	2014-09-03	fruit/vegetable juice,onions,
14961	5000	2014-11-16	bottled beer,other vegetables,
14962	5000	2015-10-02	soda,root vegetables,semi-finished bread,

14963 rows × 3 columns

In [22]:
```
#Creating a list of a list, which is the list of items bought in a single transcation
itemlist = []
for i in range(len(bsk)):
    #appending each list in the itemDescription into the itemlist variable without the last value which is the coma
    itemlist.append(str(bsk.values[i,2][:-1]))
```

In [23]:
```
#checking the first list of item purchased in the basket dataframe
bsk.values[0,2]
```

Out[23]:
```
'whole milk,pastry,salty snack,'
```

In [24]:
```
#cross-checking the item on the list with the item in the item list
itemlist[0]
```

Out[24]:
```
'whole milk,pastry,salty snack'
```

The (Basket) bsk list of all item purchased in a single transaction

In [25]:
```
pd.DataFrame(itemlist)
```

Out[25]:

	0
0	whole milk,pastry,salty snack
1	sausage,whole milk,semi-finished bread,yogurt
2	soda,pickled vegetables
3	canned beer,misc. beverages
4	sausage,hygiene articles
...	...
14958	butter milk,whipped/sour cream
14959	bottled water,herbs
14960	fruit/vegetable juice,onions
14961	bottled beer,other vegetables
14962	soda,root vegetables,semi-finished bread

14963 rows × 1 columns

We can see the itemlist created is a pd.Series with list of items.

We split each of the item in the itemlist into different columns the create a dataframe

In [26]:
```
#we split each of the item in the itemlist into different columns the create a dataframe
f = pd.Series(itemlist)
```

```
itemlist = f.apply(lambda x : pd.Series(str(x).split(',')))
itemlist
```

Out[26]:

	0	1	2	3	4	5	6	7	8	9	10
0	whole milk	pastry	salty snack	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
1	sausage	whole milk	semi-finished bread	yogurt	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	soda	pickled vegetables	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	canned beer	misc. beverages	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	sausage	hygiene articles	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
...	...	...	...	...	...	...	...	...	...	...	...
14958	butter milk	whipped/sour cream	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14959	bottled water	herbs	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14960	fruit/vegetable juice	onions	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14961	bottled beer	other vegetables	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
14962	soda	root vegetables	semi-finished bread	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

14963 rows × 11 columns

In [27]:
```
#replacing the None value with Na
itemlist.fillna('Na',inplace=True)

#converting each row in the itemlist dataframe into a list
itemlist = itemlist.values.tolist()
```

In [28]:
```
#assigning the variable lenght with the number of roles in the dataframe
length = len(itemlist)
length
```

Out[28]: 14963

In [29]:
```
#excluding the Na Value from the list of item
for i in range (length):
    itemlist[i] = [x for x in itemlist[i] if x != 'Na']
itemlist[0]
```

Out[29]: ['whole milk', 'pastry', 'salty snack']

In [30]:
```
#Creating an item matrix
TE = TransactionEncoder()
TE.fit(itemlist)
item_transformed = TE.transform(itemlist)
itemlist_matrix = pd.DataFrame(item_transformed,columns=TE.columns_)
itemlist_matrix
```

Out[30]:

	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	white wine	whole milk	yogurt	zwi
0	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	False	
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	True	True	
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	
3	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	
4	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
14958	False	False	False	False	False	False	False	False	False	False	...	False	False	False	True	False	False	False	False	False	
14959	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	
14960	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	
14961	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	
14962	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	

14963 rows × 167 columns

3.3 Implementation of Market Basket Analysis Algorithm

3.3.1 Apriori Algorithm

In [31]:

```
## Apriori Algorithm to get the support value
bsk_freq_items = apriori(itemlist_matrix, min_support=0.01,use_colnames=True,max_len=None)

#arranging the dataframe based on the support value
bsk_freq_items.sort_values(by='support',ascending=False)
```

Out[31]:

	support	itemsets
62	0.157923	(whole milk)
40	0.122101	(other vegetables)
46	0.110005	(rolls/buns)
52	0.097106	(soda)
63	0.085879	(yogurt)
...	...	...
64	0.010559	(other vegetables, rolls/buns)
29	0.010559	(herbs)
45	0.010493	(red/blush wine)
44	0.010158	(processed cheese)
53	0.010025	(soft cheese)

69 rows × 2 columns

Support Value measures how frequent an association rule happens in a dataset

3.4 Association Rule

In [32]:

```
#Creating a dataframe with product support , confidence and Lift
mba = association_rules(bsk_freq_items, metric='confidence',min_threshold = 0)
mba
```

Out[32]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	(other vegetables)	(rolls/buns)	0.122101	0.110005	0.010559	0.086481	0.786154	-0.002872	0.974249	-0.236553
1	(rolls/buns)	(other vegetables)	0.110005	0.122101	0.010559	0.095990	0.786154	-0.002872	0.971117	-0.234091
2	(other vegetables)	(whole milk)	0.122101	0.157923	0.014837	0.121511	0.769430	-0.004446	0.958551	-0.254477
3	(whole milk)	(other vegetables)	0.157923	0.122101	0.014837	0.093948	0.769430	-0.004446	0.968928	-0.262461
4	(rolls/buns)	(whole milk)	0.110005	0.157923	0.013968	0.126974	0.804028	-0.003404	0.964550	-0.214986
5	(whole milk)	(rolls/buns)	0.157923	0.110005	0.013968	0.088447	0.804028	-0.003404	0.976350	-0.224474
6	(whole milk)	(soda)	0.157923	0.097106	0.011629	0.073635	0.758296	-0.003707	0.974663	-0.274587
7	(soda)	(whole milk)	0.097106	0.157923	0.011629	0.119752	0.758296	-0.003707	0.956636	-0.260917
8	(yogurt)	(whole milk)	0.085879	0.157923	0.011161	0.129961	0.822940	-0.002401	0.967861	-0.190525
9	(whole milk)	(yogurt)	0.157923	0.085879	0.011161	0.070673	0.822940	-0.002401	0.983638	-0.203508

Since we not getting a lift ratio greater than one i.e (Lift>1), which means a strong association between items. This might be due to the fact Association rules needs to appear in hundreds of transactions to be statistically significant.

Due to this problem, based on this data we try to still understand the data

In [33]:
```
#re-arranging the mba dataframe based on the support
mba.sort_values(by='support', ascending =False)
```

Out[33]:

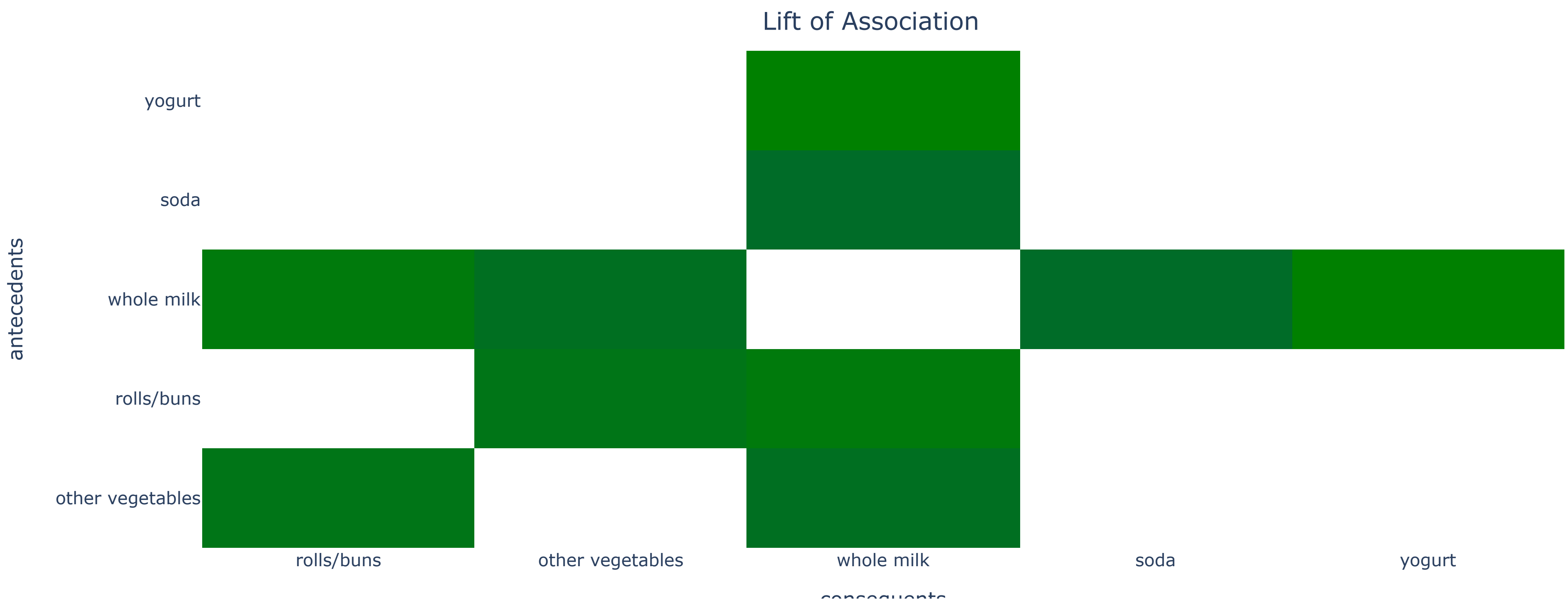
	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
2	(other vegetables)	(whole milk)	0.122101	0.157923	0.014837	0.121511	0.769430	-0.004446	0.958551	-0.254477
3	(whole milk)	(other vegetables)	0.157923	0.122101	0.014837	0.093948	0.769430	-0.004446	0.968928	-0.262461
4	(rolls/buns)	(whole milk)	0.110005	0.157923	0.013968	0.126974	0.804028	-0.003404	0.964550	-0.214986
5	(whole milk)	(rolls/buns)	0.157923	0.110005	0.013968	0.088447	0.804028	-0.003404	0.976350	-0.224474
6	(whole milk)	(soda)	0.157923	0.097106	0.011629	0.073635	0.758296	-0.003707	0.974663	-0.274587
7	(soda)	(whole milk)	0.097106	0.157923	0.011629	0.119752	0.758296	-0.003707	0.956636	-0.260917
8	(yogurt)	(whole milk)	0.085879	0.157923	0.011161	0.129961	0.822940	-0.002401	0.967861	-0.190525
9	(whole milk)	(yogurt)	0.157923	0.085879	0.011161	0.070673	0.822940	-0.002401	0.983638	-0.203508
0	(other vegetables)	(rolls/buns)	0.122101	0.110005	0.010559	0.086481	0.786154	-0.002872	0.974249	-0.236553
1	(rolls/buns)	(other vegetables)	0.110005	0.122101	0.010559	0.095990	0.786154	-0.002872	0.971117	-0.234091

In [34]:
```
# remove the parentheses in the antecedents and consequents columns
mba['antecedents'] = mba['antecedents'].apply(lambda a: ', '.join(list(a)))
mba['consequents'] = mba['consequents'].apply(lambda a: ', '.join(list(a)))
mba.head()
```

Out[34]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
0	other vegetables	rolls/buns	0.122101	0.110005	0.010559	0.086481	0.786154	-0.002872	0.974249	-0.236553
1	rolls/buns	other vegetables	0.110005	0.122101	0.010559	0.095990	0.786154	-0.002872	0.971117	-0.234091
2	other vegetables	whole milk	0.122101	0.157923	0.014837	0.121511	0.769430	-0.004446	0.958551	-0.254477
3	whole milk	other vegetables	0.157923	0.122101	0.014837	0.093948	0.769430	-0.004446	0.968928	-0.262461
4	rolls/buns	whole milk	0.110005	0.157923	0.013968	0.126974	0.804028	-0.003404	0.964550	-0.214986

In [45]:
```
fig = px.density_heatmap(data_frame=mba,x='consequents',y='antecedents',z='lift',title='Lift of Association',color_continuous_scale =['white', 'blue', 'gree
pyo.iplot(fig)
```



The green tiles shows a strong association rule between the antecedents and the consequents

In [48]:
```
#creating a dataframe for the association and support
# concatinating the antecedents column with consequents column with + sign
d =  pd.DataFrame(mba['antecedents']+' '+'->'+' '+mba['consequents']).rename(columns ={0:'association'})

#adding the support column from the mba dataframe to the d dataframe
d['support'] = mba['support']
d
```

Out[48]:

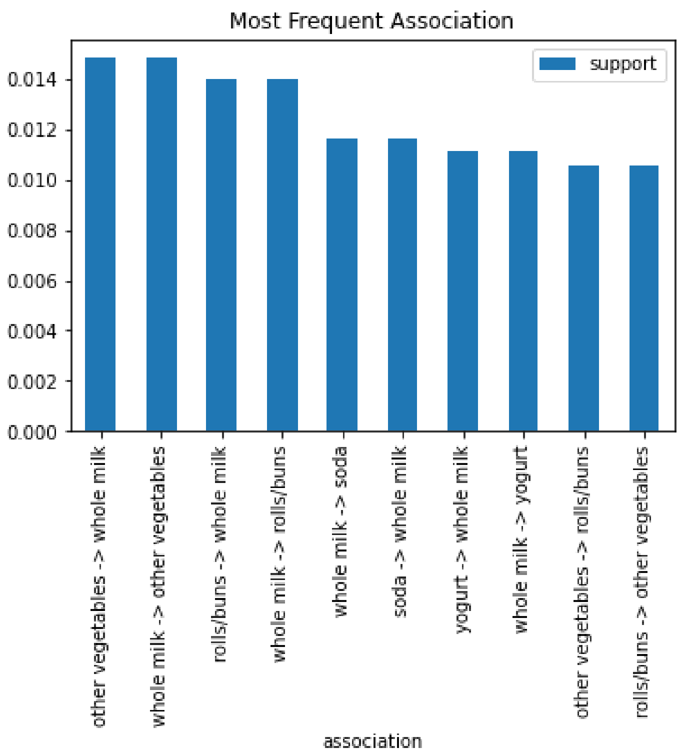
	association	support
0	other vegetables -> rolls/buns	0.010559
1	rolls/buns -> other vegetables	0.010559
2	other vegetables -> whole milk	0.014837
3	whole milk -> other vegetables	0.014837
4	rolls/buns -> whole milk	0.013968
5	whole milk -> rolls/buns	0.013968
6	whole milk -> soda	0.011629
7	soda -> whole milk	0.011629
8	yogurt -> whole milk	0.011161
9	whole milk -> yogurt	0.011161

In [37]:

```
d.sort_values(by='support',ascending=False).plot(kind='bar',y='support',x='association',title='Most Frequent Association')
```

Out[37]:

```
<AxesSubplot:title={'center':'Most Frequent Association'}, xlabel='association'>
```



The above plot shows the most frequent association of goods. This are the most common products sold togther

4. Insights

1. The Top 5 most sold items from the retail stores are:

1. Whole Milk
2. Other Vegetables
3. Rolls/Buns
4. Soda
5. Yogurt

2. Top 5 products sold together are:

1. Other Vegetables and Whole Milk
2. Whole Milk and Other Vegetables
3. Rolls/Buns and Whole Milk
4. Whole Milk and Soda
5. Whole Milk and Yogurt

3.There is a strong connection between Whole Milk and other products i.e Individuals who buy Whole Milk tends to buy the following products:

- Other Vegetables
- Rolls/Buns
- Soda
- Yogurt

4. The Retails Store see a strongs increase in demand for products from March to August

4.1 Recommendation

- The Strong association products(i.e correlated goods) should be placed near each other to increase sales and improve customer experience & Satisfaction.
- Discounted price on consequent products to Whole Milk.
- Increase in stock of the top 5 most sold products between the month March and August.
- To improve analysis data collected on customer features like gender,age,occupation,address might improve the analysis of understanding the customer. so a create a more functional recommodation system

4.2 Problems encountered

- Due to Data ethnics getting real world transaction data available to the public seams impossible. Hence the data used for analysis is a fake real world dataset download from kaggle.
- Market Basket analysis requires a large amount of data for the result to become significant. Hence the analyis result was based on the data available to us.

```
In [ ]:
```