Importing Libraries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.axes as ax
import seaborn as sns

sns.set()
```

Loading Data

In [3]:

```
data = pd.read_csv(r'C:\Users\vamsi\Desktop\M.Tech\ML\Apriori Algorithm\Mall_
data.head(10)
```

Out[3]:

	Date	Time	Transaction	Item
0	2016-10-30	09:58:11	1	Bread
1	2016-10-30	10:05:34	2	Scandinavian
2	2016-10-30	10:05:34	2	Scandinavian
3	2016-10-30	10:07:57	3	Hot chocolate
4	2016-10-30	10:07:57	3	Jam
5	2016-10-30	10:07:57	3	Cookies
6	2016-10-30	10:08:41	4	Muffin
7	2016-10-30	10:13:03	5	Coffee
8	2016-10-30	10:13:03	5	Pastry
9	2016-10-30	10:13:03	5	Bread

In [4]:

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 21293 entries, 0 to 21292
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Date         21293 non-null  object
 1   Time         21293 non-null  object
 2   Transaction  21293 non-null  int64 
 3   Item         21293 non-null  object
dtypes: int64(1), object(3)
memory usage: 665.5+ KB
```

Preprocessing

In [6]:
```
data['Item'] = data['Item'].str.lower()
```

In [7]:
```
data.head(10)
```

Out[7]:

	Date	Time	Transaction	Item
0	2016-10-30	09:58:11	1	bread
1	2016-10-30	10:05:34	2	scandinavian
2	2016-10-30	10:05:34	2	scandinavian
3	2016-10-30	10:07:57	3	hot chocolate
4	2016-10-30	10:07:57	3	jam
5	2016-10-30	10:07:57	3	cookies
6	2016-10-30	10:08:41	4	muffin
7	2016-10-30	10:13:03	5	coffee
8	2016-10-30	10:13:03	5	pastry
9	2016-10-30	10:13:03	5	bread

In [9]:
```
(data['Item'] == 'none').value_counts()
```

Out[9]:
```
False    20507
True       786
Name: Item, dtype: int64
```

In [11]:
```
data = data.drop(data[data.Item == 'none'].index)
```

In [12]:
```
(data['Item'] == 'none').value_counts()
```

Out[12]:
```
False    20507
Name: Item, dtype: int64
```

In [13]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 20507 entries, 0 to 21292
Data columns (total 4 columns):
 #   Column       Non-Null Count  Dtype 
---  ------       --------------  ----- 
 0   Date         20507 non-null  object
 1   Time         20507 non-null  object
 2   Transaction  20507 non-null  int64 
 3   Item         20507 non-null  object
dtypes: int64(1), object(3)
memory usage: 801.1+ KB
```

Item Exploration

In [14]:

```
data['Item'].nunique()
```

Out[14]:

```
94
```

In [24]:

```
data['Item'].unique()
```

Out[24]:

```
array(['bread', 'scandinavian', 'hot chocolate', 'jam', 'cookies',
       'muffin', 'coffee', 'pastry', 'medialuna', 'tea', 'tartine',
       'basket', 'mineral water', 'farm house', 'fudge', 'juice',
       "ella's kitchen pouches", 'victorian sponge', 'frittata',
       'hearty & seasonal', 'soup', 'pick and mix bowls', 'smoothies',
       'cake', 'mighty protein', 'chicken sand', 'coke',
       'my-5 fruit shoot', 'focaccia', 'sandwich', 'alfajores', 'eggs',
       'brownie', 'dulce de leche', 'honey', 'the bart', 'granola',
       'fairy doors', 'empanadas', 'keeping it local', 'art tray',
       'bowl nic pitt', 'bread pudding', 'adjustment', 'truffles',
       'chimichurri oil', 'bacon', 'spread', 'kids biscuit', 'siblings',
       'caramel bites', 'jammie dodgers', 'tiffin', 'olum & polenta',
       'polenta', 'the nomad', 'hack the stack', 'bakewell',
       'lemon and coconut', 'toast', 'scone', 'crepes', 'vegan mincepie',
       'bare popcorn', 'muesli', 'crisps', 'pintxos', 'gingerbread syrup',
       'panatone', 'brioche and salami', 'afternoon with the baker',
       'salad', 'chicken stew', 'spanish brunch',
       'raspberry shortbread sandwich', 'extra salami or feta',
       'duck egg', 'baguette', "valentine's card", 'tshirt',
       'vegan feast', 'postcard', 'nomad bag', 'chocolates',
       'coffee granules ', 'drinking chocolate spoons ',
       'christmas common', 'argentina night', 'half slice monster ',
       'gift voucher', 'cherry me dried fruit', 'mortimer', 'raw bars',
       'tacos/fajita'], dtype=object)
```

In [33]:

```
items = data['Item'].value_counts()
items = pd.DataFrame(items)
items.head()
```

Out[33]:

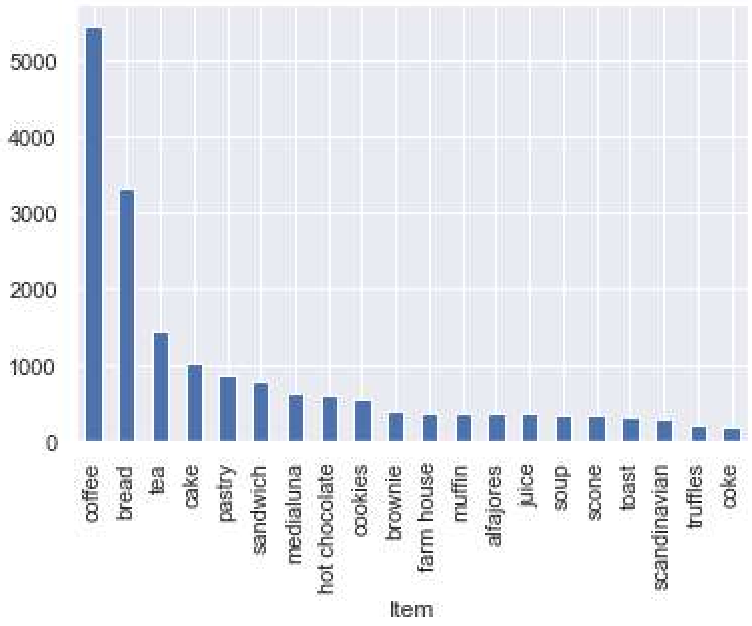
	Item
coffee	5471
bread	3325
tea	1435
cake	1025
pastry	856

```
In [40]:  data.groupby('Item').size().sort_values(ascending=False).head(10)
```

```
Out[40]: Item
         coffee           5471
         bread            3325
         tea              1435
         cake             1025
         pastry            856
         sandwich          771
         medialuna         616
         hot chocolate     590
         cookies           540
         brownie           379
         dtype: int64
```

```
In [47]:  data.groupby('Item').size().sort_values(ascending=False).head(20).plot(kind='
```

```
Out[47]: <AxesSubplot:xlabel='Item'>
```



Understanding how data is working

In [60]:
```
combined_data = pd.DataFrame({'items' : data.groupby('Transaction')['Item'].u
                              'items_count' : data.groupby('Transaction')['It
combined_data.reset_index(inplace=True)
combined_data.head(10)
```

Out[60]:

	Transaction	items	items_count
0	1	[bread]	1
1	2	[scandinavian]	1
2	3	[hot chocolate, jam, cookies]	3
3	4	[muffin]	1
4	5	[coffee, pastry, bread]	3
5	6	[medialuna, pastry, muffin]	3
6	7	[medialuna, pastry, coffee, tea]	4
7	8	[pastry, bread]	2
8	9	[bread, muffin]	2
9	10	[scandinavian, medialuna]	2

Data Exploration

In [57]:
```
data['Date'].min()
```

Out[57]:
```
'2016-10-30'
```

In [58]:
```
data['Date'].max()
```

Out[58]:
```
'2017-04-09'
```

In [59]:
```
data['Date'].nunique()
```

Out[59]:
```
159
```

Apriori Algorithm

In [66]:
```
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
```

Transforming data

Making items as columns and each transaction as a row and count same items bought in one transaction

In [85]:

```
dt = data.groupby(['Transaction','Item']).count().unstack().reset_index().set
dt.head(20)
```

Out[85]:

	Date								
Item	**adjustment**	**afternoon with the baker**	**alfajores**	**argentina night**	**art tray**	**bacon**	**baguette**	**bakewell**	**bare pop**
Transaction									
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
10	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
13	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
14	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
15	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
17	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
18	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
19	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	

20 rows × 188 columns

In [86]:

```
def encode_units(x):
    if x<=0:
        return 0
    if x>=1:
        return 1
dt = dt.applymap(encode_units)
```

In [89]:

```
dt.head(20)
```

Out[89]:

	Date								
Item	adjustment	afternoon with the baker	alfajores	argentina night	art tray	bacon	baguette	bakewell	bare pop
Transaction									
1	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	
5	0	0	0	0	0	0	0	0	
6	0	0	0	0	0	0	0	0	
7	0	0	0	0	0	0	0	0	
8	0	0	0	0	0	0	0	0	
9	0	0	0	0	0	0	0	0	
10	0	0	0	0	0	0	0	0	
11	0	0	0	0	0	0	0	0	
12	0	0	0	0	0	0	0	0	
13	0	0	0	0	0	0	0	0	
14	0	0	0	0	0	0	0	0	
15	0	0	0	0	0	0	0	0	
16	0	0	0	0	0	0	0	0	
17	0	0	0	0	0	0	0	0	
18	0	0	0	0	0	0	0	0	
19	0	0	0	0	0	0	0	0	
20	0	0	0	0	0	0	0	0	

20 rows × 188 columns

In [92]:

```
frequent_items = apriori(dt,min_support=0.01,use_colnames=True)
```

In [93]:

```
frequent_items
```

Out[93]:

	support	itemsets
0	0.036344	((Date, alfajores))
1	0.016059	((Date, baguette))
2	0.327205	((Date, bread))
3	0.040042	((Date, brownie))
4	0.103856	((Date, cake))
...	...	...
418	0.011199	((Date, pastry), (Time, bread), (Time, coffee)...
419	0.010037	((Time, tea), (Date, tea), (Time, coffee), (Da...
420	0.010037	((Date, bread), (Time, bread), (Time, coffee),...
421	0.011199	((Date, pastry), (Date, bread), (Time, bread),...
422	0.010037	((Time, tea), (Date, tea), (Time, coffee), (Da...

423 rows × 2 columns

Metrics Involved

- support
- confidence
- lift
- leverage
- conviction

we are using "Lift" metric

In [94]:

```
rules = association_rules(frequent_items,metric="lift",min_threshold=1)
rules.head()
```

Out[94]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	lever
0	((Date, coffee))	((Date, alfajores))	0.478394	0.036344	0.019651	0.041078	1.130235	0.002
1	((Date, alfajores))	((Date, coffee))	0.036344	0.478394	0.019651	0.540698	1.130235	0.002
2	((Time, alfajores))	((Date, alfajores))	0.036344	0.036344	0.036344	1.000000	27.514535	0.035
3	((Date, alfajores))	((Time, alfajores))	0.036344	0.036344	0.036344	1.000000	27.514535	0.035
4	((Time, coffee))	((Date, alfajores))	0.478394	0.036344	0.019651	0.041078	1.130235	0.002

In [102]:

```
rules[(rules['lift']>=1) & (rules['confidence']>=0.5)]
```

Out[102]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	le
1	((Date, alfajores))	((Date, coffee))	0.036344	0.478394	0.019651	0.540698	1.130235	0.
2	((Time, alfajores))	((Date, alfajores))	0.036344	0.036344	0.036344	1.000000	27.514535	0.
3	((Date, alfajores))	((Time, alfajores))	0.036344	0.036344	0.036344	1.000000	27.514535	0.
5	((Date, alfajores))	((Time, coffee))	0.036344	0.478394	0.019651	0.540698	1.130235	0.
6	((Date, baguette))	((Time, baguette))	0.016059	0.016059	0.016059	1.000000	62.269737	0.
...	...	...	...	...	...	...	...	
2222	((Time, tea), (Date, coffee), (Date, cake))	((Time, coffee), (Date, tea), (Time, cake))	0.010037	0.010037	0.010037	1.000000	99.631579	0.
2225	((Time, coffee), (Date, tea), (Time, cake))	((Time, tea), (Date, coffee), (Date, cake))	0.010037	0.010037	0.010037	1.000000	99.631579	0.
2226	((Time, coffee), (Date, tea), (Date, cake))	((Time, tea), (Date, coffee), (Time, cake))	0.010037	0.010037	0.010037	1.000000	99.631579	0.
2227	((Date, coffee), (Date, tea), (Time, cake))	((Time, tea), (Time, coffee), (Date, cake))	0.010037	0.010037	0.010037	1.000000	99.631579	0.
2228	((Date, coffee), (Date, tea), (Date, cake))	((Time, tea), (Time, coffee), (Time, cake))	0.010037	0.010037	0.010037	1.000000	99.631579	0.

967 rows × 9 columns