

Introduction

The Bread Basket, a bakery situated in Edinburgh, this is the market basket analysis based on the dataset consisting of 20507 records with 4 columns, which represents over 9000 transactions.

Objectives

- Download a DataSet from *.csv files
- Create new and recalculate values of existing columns
- Transform a DataSet of transactions into a market basket DataSet
- Visualize data with seaborn
- Produce Association rules
- Analyze market basket
- Visualize graph of association rules

Requirements

- [Python]
- [Pandas]
- [SeaBorn]
- [mlxtend]
- [pyvis]

```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from mlxtend.frequent_patterns import apriori, association_rules
from mlxtend.preprocessing import TransactionEncoder
from pyvis.network import Network
import datetime as dt
import numpy as np
import warnings
warnings.filterwarnings("ignore")
```

```
df = pd.read_csv("https://cf-courses-data.s3.us.cloud-object-storage.appdomain.cloud/IBM-GPXX0R8UEN/bread%20basket.csv")
df
```

	Transaction	Item	date_time	period_day
weekday_weekend				
0	1	Bread	30-10-2016 09:58	morning
weekend				
1	2	Scandinavian	30-10-2016 10:05	morning
weekend				

2	2	Scandinavian	30-10-2016	10:05	morning
weekend					
3	3	Hot chocolate	30-10-2016	10:07	morning
weekend					
4	3	Jam	30-10-2016	10:07	morning
weekend					
...
...					
20502	9682	Coffee	09-04-2017	14:32	afternoon
weekend					
20503	9682	Tea	09-04-2017	14:32	afternoon
weekend					
20504	9683	Coffee	09-04-2017	14:57	afternoon
weekend					
20505	9683	Pastry	09-04-2017	14:57	afternoon
weekend					
20506	9684	Smoothies	09-04-2017	15:04	afternoon
weekend					

[20507 rows x 5 columns]

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20507 entries, 0 to 20506
Data columns (total 5 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Transaction            20507 non-null  int64
1   Item                   20507 non-null  object
2   date_time              20507 non-null  object
3   period_day             20507 non-null  object
4   weekday_weekend        20507 non-null  object
dtypes: int64(1), object(4)
memory usage: 801.2+ KB
```

1. Transaction: the transaction id which is unique for each order
2. Item: a list of items to be ordered/placed by customer
3. date_time: the date and time of the transaction.
4. period_day: the period of the day when a customer ordered/placed
5. weekday_weekend: is the day is weekend (sat or sun) or a weekday.

Transforming the data type of the date_time column.

```
df['date_time']=pd.to_datetime(df['date_time'])
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20507 entries, 0 to 20506
Data columns (total 5 columns):
#   Column                Non-Null Count  Dtype
---  -
```

```

0 Transaction 20507 non-null int64
1 Item 20507 non-null object
2 date_time 20507 non-null datetime64[ns]
3 period_day 20507 non-null object
4 weekday_weekend 20507 non-null object
dtypes: datetime64[ns](1), int64(1), object(3)
memory usage: 801.2+ KB

df['time']=df['date_time'].dt.time
df['hour']=df['date_time'].dt.hour

df['month'] = df['date_time'].dt.month
df['month name'] = df['month'].replace([1,2,3,4,5,6,7,8,9,10,11,12],
['January', 'February', 'March', 'April', 'May', 'June', 'July', 'August', 'September', 'October', 'November', 'December'])

df['day'] = df['date_time'].dt.day
df['weekday'] = df['date_time'].dt.weekday
df['weekday name'] = df['weekday'].replace([0,1,2,3,4,5,6],
['Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday', 'Saturday', 'Sunday'])

df

Transaction Item date_time period_day \
0 1 Bread 2016-10-30 09:58:00 morning
1 2 Scandinavian 2016-10-30 10:05:00 morning
2 2 Scandinavian 2016-10-30 10:05:00 morning
3 3 Hot chocolate 2016-10-30 10:07:00 morning
4 3 Jam 2016-10-30 10:07:00 morning
... ..
20502 9682 Coffee 2017-09-04 14:32:00 afternoon
20503 9682 Tea 2017-09-04 14:32:00 afternoon
20504 9683 Coffee 2017-09-04 14:57:00 afternoon
20505 9683 Pastry 2017-09-04 14:57:00 afternoon
20506 9684 Smoothies 2017-09-04 15:04:00 afternoon

weekday_weekend time hour month month name day weekday
\
0 weekend 09:58:00 9 10 October 30 6
1 weekend 10:05:00 10 10 October 30 6
2 weekend 10:05:00 10 10 October 30 6
3 weekend 10:07:00 10 10 October 30 6
4 weekend 10:07:00 10 10 October 30 6
... ..

```

20502	weekend	14:32:00	14	9	September	4	0
20503	weekend	14:32:00	14	9	September	4	0
20504	weekend	14:57:00	14	9	September	4	0
20505	weekend	14:57:00	14	9	September	4	0
20506	weekend	15:04:00	15	9	September	4	0

	weekday name
0	Sunday
1	Sunday
2	Sunday
3	Sunday
4	Sunday
...	...
20502	Monday
20503	Monday
20504	Monday
20505	Monday
20506	Monday

[20507 rows x 12 columns]

df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20507 entries, 0 to 20506
Data columns (total 12 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Transaction            20507 non-null  int64
1   Item                   20507 non-null  object
2   date_time              20507 non-null  datetime64[ns]
3   period_day             20507 non-null  object
4   weekday_weekend        20507 non-null  object
5   time                   20507 non-null  object
6   hour                   20507 non-null  int64
7   month                  20507 non-null  int64
8   month name             20507 non-null  object
9   day                    20507 non-null  int64
10  weekday                20507 non-null  int64
11  weekday name           20507 non-null  object
dtypes: datetime64[ns](1), int64(5), object(6)
memory usage: 1.9+ MB
```

11 columns with all necessary information for preliminary visual market basket analysis.

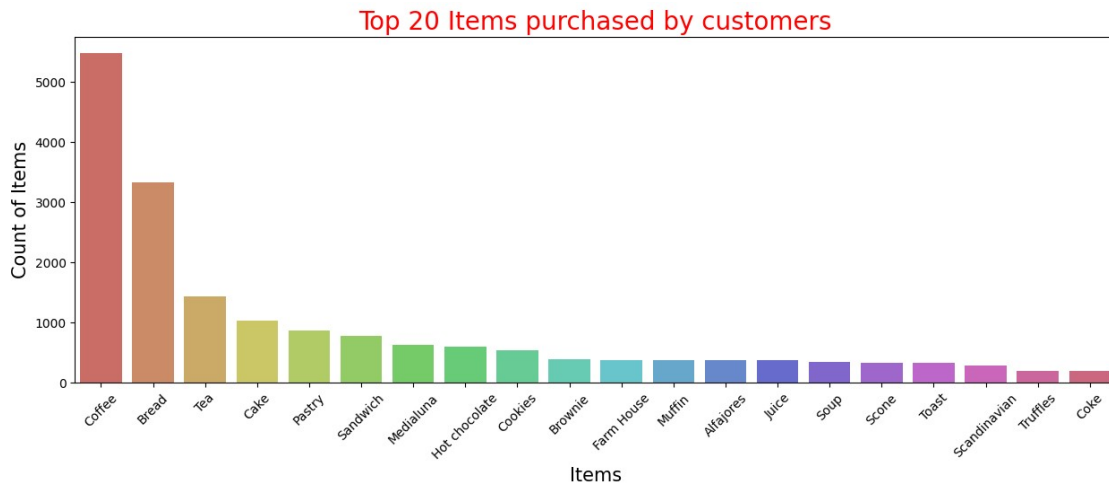
Data Visualizations

Top 20 most popular purchases.

```
popular = df['Item'].value_counts()  
(df['Item'].value_counts(normalize=True)*100).head(20)
```

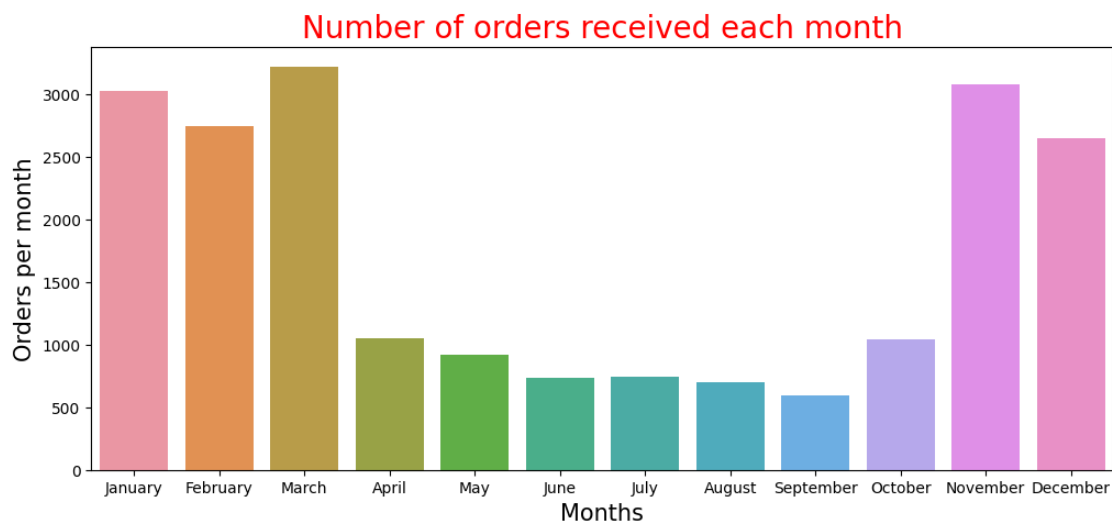
```
Coffee          26.678695  
Bread           16.213976  
Tea             6.997611  
Cake            4.998293  
Pastry          4.174184  
Sandwich        3.759692  
Medialuna       3.003852  
Hot chocolate   2.877066  
Cookies         2.633247  
Brownie         1.848149  
Farm House     1.823767  
Muffin          1.804262  
Alfajores       1.799386  
Juice           1.799386  
Soup           1.667723  
Scone           1.594577  
Toast           1.550690  
Scandinavian    1.350758  
Truffles        0.941142  
Coke            0.902131  
Name: Item, dtype: float64
```

```
plt.figure(figsize=(15,5))  
sns.barplot(x = popular.head(20).index, y = popular.head(20).values,  
palette = 'hls')  
plt.xlabel('Items', size = 15)  
plt.xticks(rotation=45)  
plt.ylabel('Count of Items', size = 15)  
plt.title('Top 20 Items purchased by customers', color = 'red', size =  
20)  
plt.show()
```



The dynamics of monthly purchases.

```
monthTran = df.groupby(['month', 'month name'])
['Transaction'].count().reset_index()
plt.figure(figsize=(12,5))
sns.barplot(data = monthTran[['month name', 'Transaction']], x =
"month name", y = "Transaction")
plt.xlabel('Months', size = 15)
plt.ylabel('Orders per month', size = 15)
plt.title('Number of orders received each month', color = 'red', size
= 20)
plt.show()
```



Monthly purchases for the six most popular products.

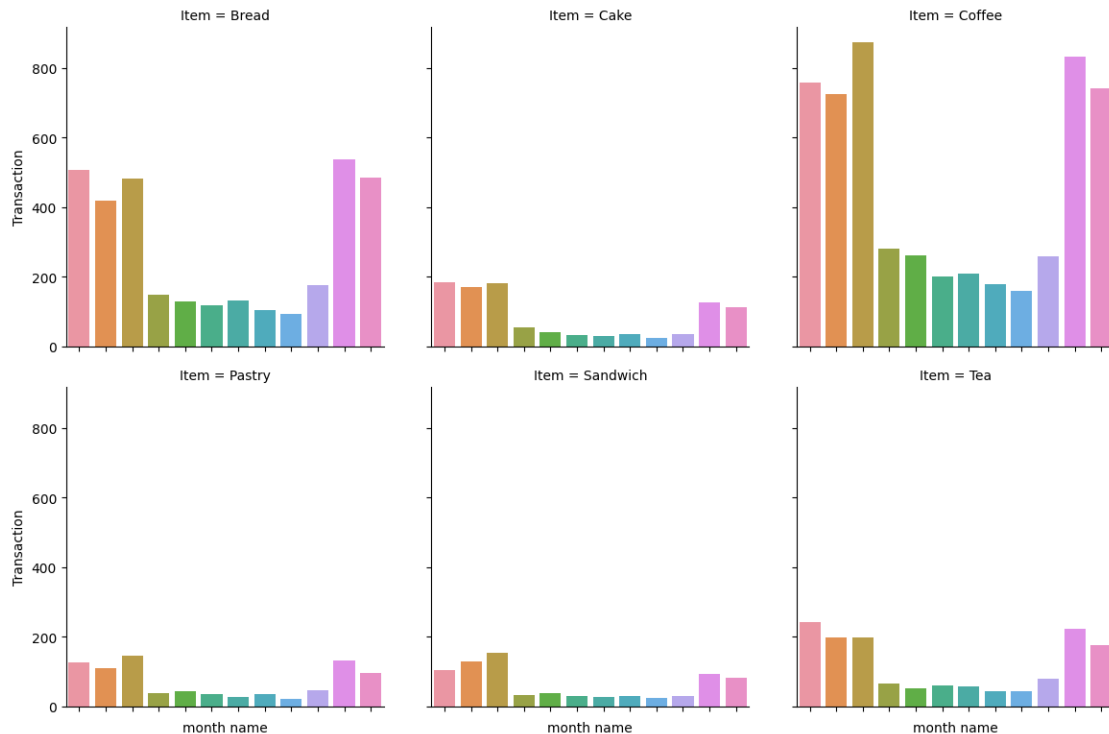
```
monthTranTransaction =
df[df.Item.isin(popular.head(6).index)].groupby(['month', 'month
name', 'Item'])['Transaction'].count().reset_index()
```

```
ax = sns.catplot(x="month name", y="Transaction",
```

```

col="Item",
data=monthTranTransaction, kind="bar",
height=4, col_wrap=3)
ax.set_xticklabels(rotation=45)
<seaborn.axisgrid.FacetGrid at 0x1dd5ec6cee0>

```



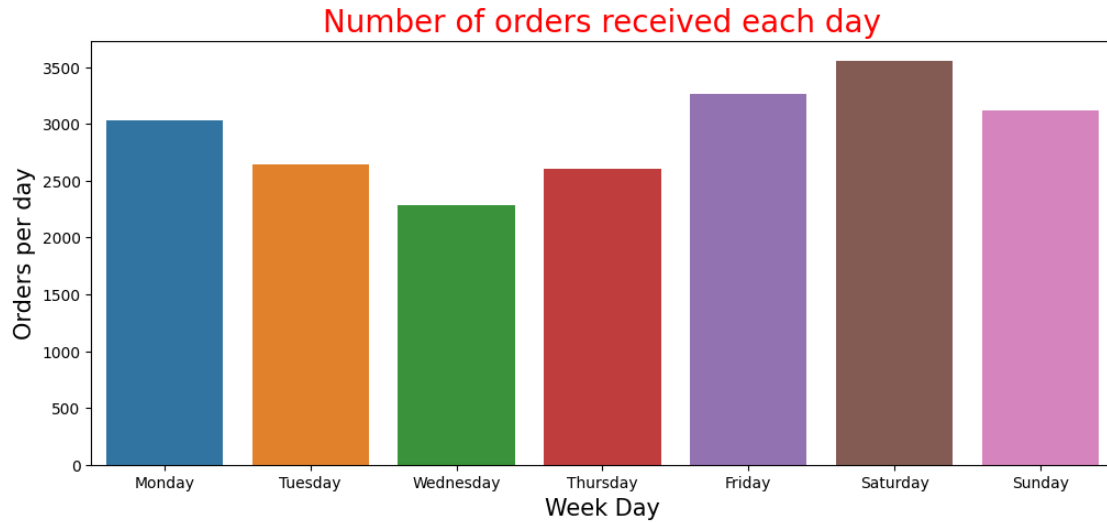
The weekly activity.

```

weekTran = weekTran = df.groupby(['weekday', 'weekday name'])
['Transaction'].count().reset_index()

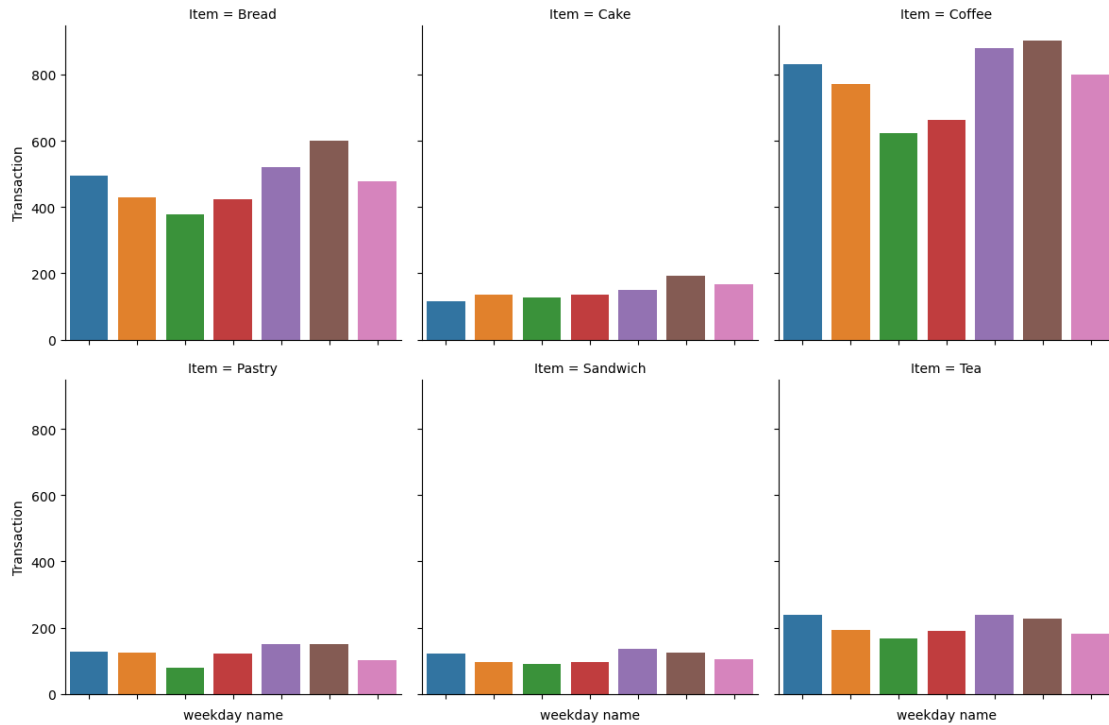
plt.figure(figsize=(12,5))
sns.barplot(data = weekTran[['weekday name', 'Transaction']], x =
"weekday name", y = "Transaction")
plt.xlabel('Week Day', size = 15)
plt.ylabel('Orders per day', size = 15)
plt.title('Number of orders received each day', color = 'red', size =
20)
plt.show()

```



The six most popular products

```
weekTran =  
df[df.Item.isin(popular.head(6).index)].groupby(['weekday', 'weekday  
name', 'Item'])['Transaction'].count().reset_index()  
  
ax = sns.catplot(x="weekday name", y="Transaction",  
                 col="Item",  
                 data=weekTran, kind="bar",  
                 height=4, col_wrap=3)  
ax.set_xticklabels(rotation=45)  
  
<seaborn.axisgrid.FacetGrid at 0x1dd748bcb50>
```

The share of purchases on weekends and weekdays.

```
size = df['weekday_weekend'].value_counts()
```

```
labels = size.index.values
```

```
colors = ["cyan", "lightblue"]
```

```
explode = [0, 0.1]
```

```
plt.figure(figsize=(12,5))
```

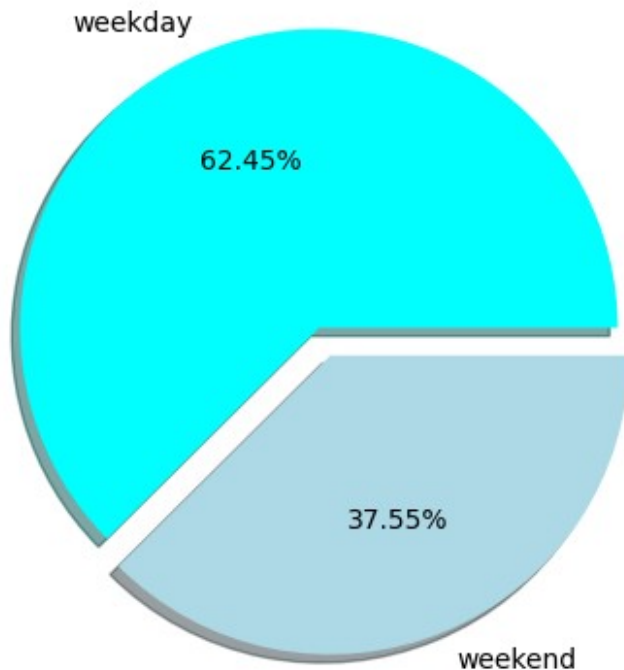
```
plt.pie(size, labels = labels, colors = colors, explode = explode,
```

```
shadow = True, autopct = "%.2f%%")
```

```
plt.title('Transaction by week period')
```

```
plt.show()
```

Transaction by week period



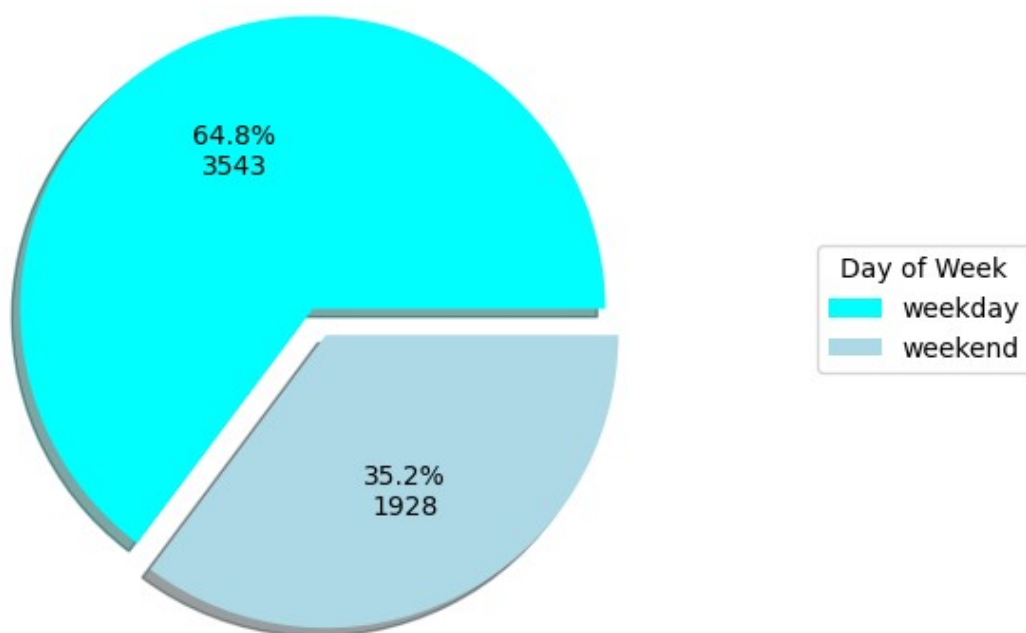
```
def func(pct, allvals):
    absolute = int(np.round(pct/100.*np.sum(allvals)))
    return "{:.1f}%\n{:d}".format(pct, absolute)

size = df[df.Item.isin(popular.head(6).index)]
size = pd.crosstab(size['weekday_weekend'],
                    size['Item'])
# size
labels = size.index.values
colors = ["cyan", "lightblue"]

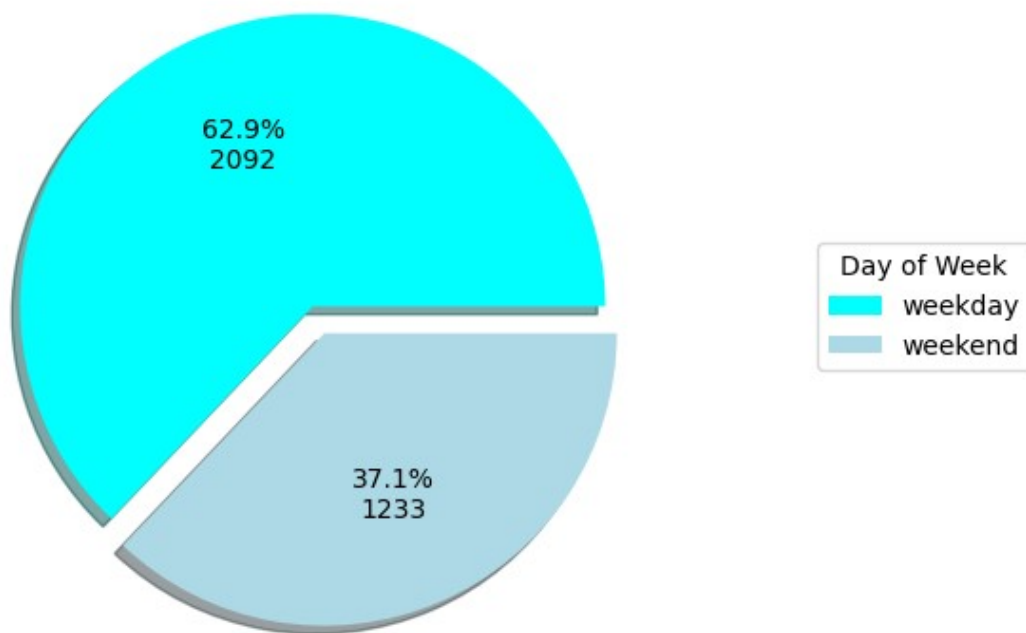
for e in popular.head(3).index:
    plt.figure(figsize=(12,5))
    dt = size[e]
    explode = [0, 0.1]
    plt.pie(dt, colors = colors, explode = explode, shadow = True,
            autopct=lambda pct: func(pct, dt.values))

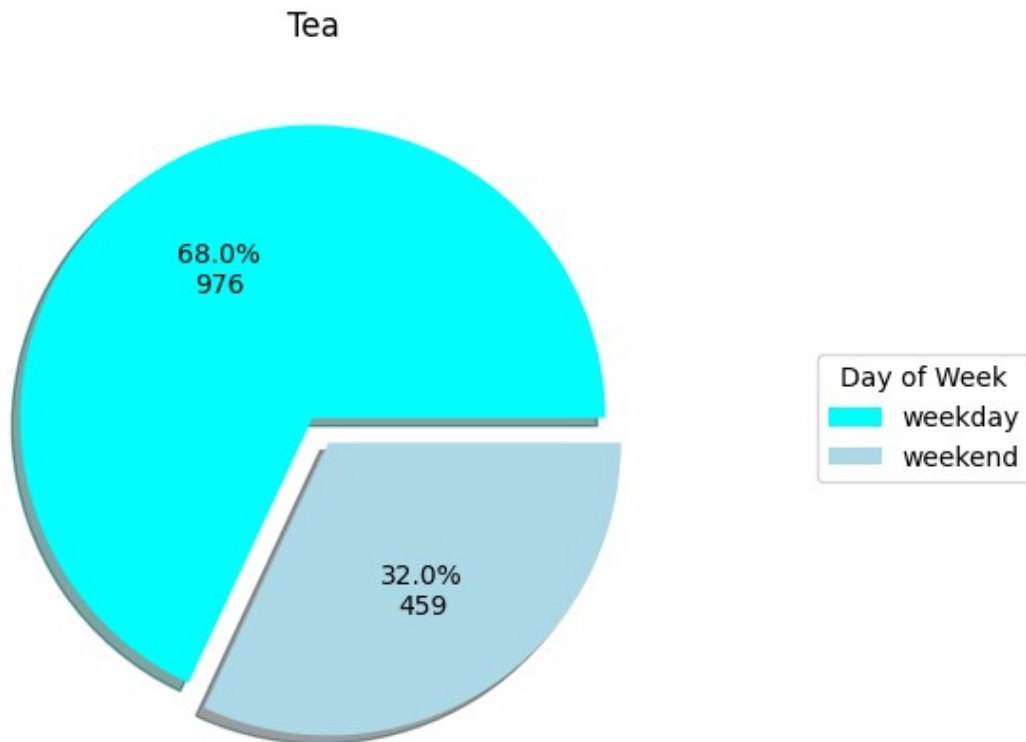
    plt.title(e)
    plt.legend(labels = labels, title="Day of Week",
              loc="center right", bbox_to_anchor=(1, 0, 0.5, 1))
    plt.show()
```

Coffee



Bread

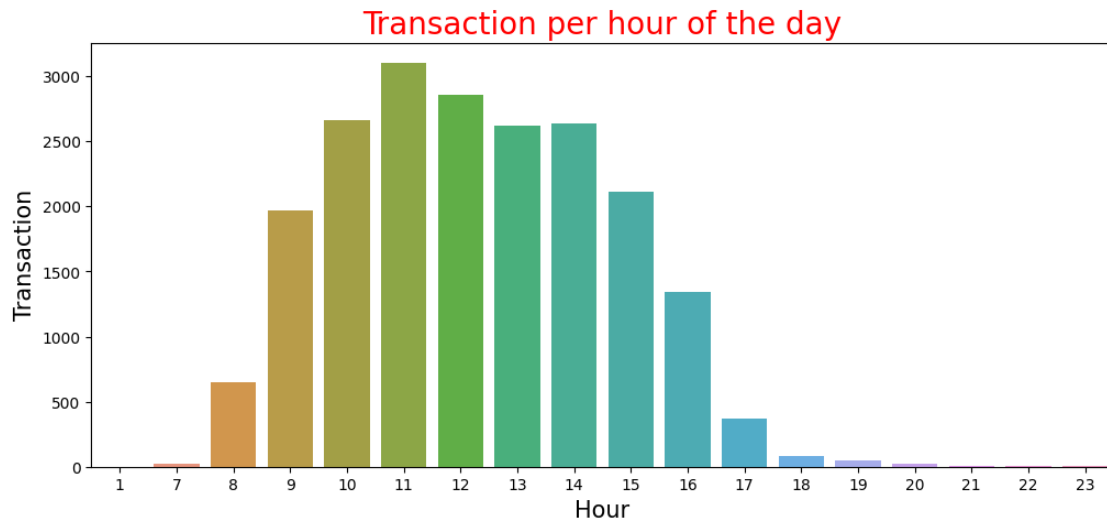




The activity of consumers during the day.

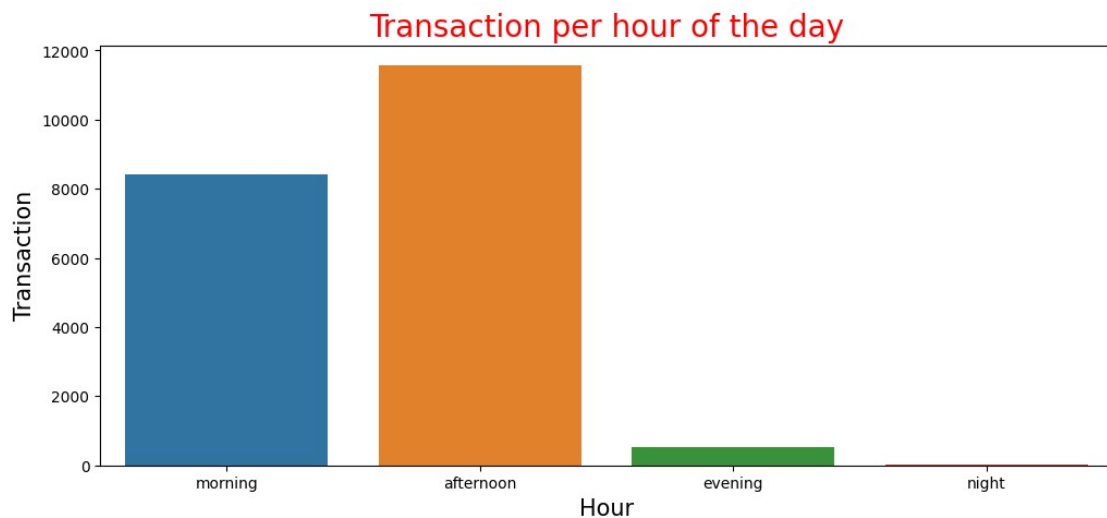
```
coutbyhour=df.groupby('hour')['Transaction'].count().reset_index()  
coutbyhour.sort_values('hour',inplace=True)
```

```
plt.figure(figsize=(12,5))  
sns.barplot(data=coutbyhour, x='hour', y='Transaction')  
plt.xlabel('Hour', size = 15)  
plt.ylabel('Transaction', size = 15)  
plt.title('Transaction per hour of the day', color = 'red', size = 20)  
plt.show()
```



The activity of buyers during parts of the day.

```
coutbyweekday=df.groupby('period_day')
['Transaction'].count().reset_index()
coutbyweekday.loc[:,"dayorder"] = [1, 2, 0, 3]
coutbyweekday.sort_values("dayorder",inplace=True)
plt.figure(figsize=(12,5))
sns.barplot(data=coutbyweekday, x='period_day', y='Transaction')
plt.xlabel('Hour', size = 15)
plt.ylabel('Transaction', size = 15)
plt.title('Transaction per hour of the day', color = 'red', size = 20)
plt.show()
```



Association Rules

To create association rules, it's important to establish the connection between purchases. This can be achieved by converting the transaction dataset into a specific table format where the columns represent the types of purchases and the rows represent the

transactions. The cells of this table should be boolean values (true or false). There are two commonly used methods to accomplish this.

Using Pivot table

```
transactions = df.groupby(['Transaction', 'Item'])
['Item'].count().reset_index(name='Count')
transactions
```

	Transaction	Item	Count
0	1	Bread	1
1	2	Scandinavian	2
2	3	Cookies	1
3	3	Hot chocolate	1
4	3	Jam	1
...
18882	9682	Tacos/Fajita	1
18883	9682	Tea	1
18884	9683	Coffee	1
18885	9683	Pastry	1
18886	9684	Smoothies	1

[18887 rows x 3 columns]

```
basket = transactions.pivot_table(index='Transaction', columns='Item',
values='Count', aggfunc='sum').fillna(0)
basket
```

Item	Adjustment	Afternoon with the baker	Alfajores
Argentina Night \			
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			
...
...			
9680	0.0	0.0	0.0
0.0			
9681	0.0	0.0	0.0
0.0			
9682	0.0	0.0	0.0
0.0			
9683	0.0	0.0	0.0

0.0
9684
0.0

0.0

0.0

0.0

Item Transaction \	Art Tray	Bacon	Baguette	Bakewell	Bare Popcorn	Basket
...						
1	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
...						
3	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
...						
5	0.0	0.0	0.0	0.0	0.0	0.0
...						
...
...						
9680	0.0	0.0	0.0	0.0	0.0	0.0
...						
9681	0.0	0.0	0.0	0.0	0.0	0.0
...						
9682	0.0	0.0	0.0	0.0	0.0	0.0
...						
9683	0.0	0.0	0.0	0.0	0.0	0.0
...						
9684	0.0	0.0	0.0	0.0	0.0	0.0
...						

Item Transaction \	The BART	The Nomad	Tiffin	Toast	Truffles	Tshirt
1	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
3	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
5	0.0	0.0	0.0	0.0	0.0	0.0
...
9680	0.0	0.0	0.0	0.0	0.0	0.0
9681	0.0	0.0	0.0	0.0	1.0	0.0
9682	0.0	0.0	0.0	0.0	0.0	0.0
9683	0.0	0.0	0.0	0.0	0.0	0.0
9684	0.0	0.0	0.0	0.0	0.0	0.0

Item Sponge Transaction	Valentine's card	Vegan Feast	Vegan mincepie	Victorian
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			
...
...			
9680	0.0	0.0	0.0
0.0			
9681	0.0	0.0	0.0
0.0			
9682	0.0	0.0	0.0
0.0			
9683	0.0	0.0	0.0
0.0			
9684	0.0	0.0	0.0
0.0			

[9465 rows x 94 columns]

```
def encode_units(x):
    if(x==0):
        return False
    if(x>0):
        return True
```

```
basket_sets = basket.applymap(encode_units)
basket_sets
```

Item	Adjustment	Afternoon with the baker	Alfajores
Argentina Night \ Transaction			
1	False	False	False
False			
2	False	False	False
False			
3	False	False	False
False			
4	False	False	False
False			
5	False	False	False
False			
...
...			
9680	False	False	False

False			
9681	False	False	False
False			
9682	False	False	False
False			
9683	False	False	False
False			
9684	False	False	False
False			

Item ... \	Art Tray	Bacon	Baguette	Bakewell	Bare Popcorn	Basket
Transaction						
...						
1	False	False	False	False	False	False
...						
2	False	False	False	False	False	False
...						
3	False	False	False	False	False	False
...						
4	False	False	False	False	False	False
...						
5	False	False	False	False	False	False
...						
...
...						
9680	False	False	False	False	False	False
...						
9681	False	False	False	False	False	False
...						
9682	False	False	False	False	False	False
...						
9683	False	False	False	False	False	False
...						
9684	False	False	False	False	False	False
...						

Item Transaction	The BART	The Nomad	Tiffin	Toast	Truffles	Tshirt \
1	False	False	False	False	False	False
2	False	False	False	False	False	False
3	False	False	False	False	False	False
4	False	False	False	False	False	False
5	False	False	False	False	False	False
...
9680	False	False	False	False	False	False
9681	False	False	False	False	True	False
9682	False	False	False	False	False	False
9683	False	False	False	False	False	False
9684	False	False	False	False	False	False

Item	Valentine's card	Vegan Feast	Vegan mincepie	Victorian
Sponge				
Transaction				
1	False	False	False	
False				
2	False	False	False	
False				
3	False	False	False	
False				
4	False	False	False	
False				
5	False	False	False	
False				
...	
...				
9680	False	False	False	
False				
9681	False	False	False	
False				
9682	False	False	False	
False				
9683	False	False	False	
False				
9684	False	False	False	
False				

[9465 rows x 94 columns]

Using mlxtend framework

```
transactions=[]
for item in df['Transaction'].unique():
    lst=list(set(df[df['Transaction']==item]['Item']))
    transactions.append(lst)
```

transactions[0:10]

```
[['Bread'],
 ['Scandinavian'],
 ['Cookies', 'Jam', 'Hot chocolate'],
 ['Muffin'],
 ['Coffee', 'Pastry', 'Bread'],
 ['Medialuna', 'Pastry', 'Muffin'],
 ['Tea', 'Coffee', 'Medialuna', 'Pastry'],
 ['Bread', 'Pastry'],
 ['Bread', 'Muffin'],
 ['Scandinavian', 'Medialuna']]
```

```
te = TransactionEncoder()
encodedData = te.fit(transactions).transform(transactions)
basket_sets_2 = pd.DataFrame(encodedData, columns=te.columns_)
basket_sets_2
```

	Adjustment	Afternoon with the baker	Alfajores	Argentina	Night
0	False		False	False	False
1	False		False	False	False
2	False		False	False	False
3	False		False	False	False
4	False		False	False	False
...
9460	False		False	False	False
9461	False		False	False	False
9462	False		False	False	False
9463	False		False	False	False
9464	False		False	False	False

Basket	Art Tray	Bacon	Baguette	Bakewell	Bare	Popcorn	
0	False	False	False	False		False	False ...
1	False	False	False	False		False	False ...
2	False	False	False	False		False	False ...
3	False	False	False	False		False	False ...
4	False	False	False	False		False	False ...
...
9460	False	False	False	False		False	False ...
9461	False	False	False	False		False	False ...

9462	False	False	False	False	False	False	...
9463	False	False	False	False	False	False	...
9464	False	False	False	False	False	False	...

	The BART	The Nomad	Tiffin	Toast	Truffles	Tshirt
Valentine's card \						
0	False	False	False	False	False	False
False						
1	False	False	False	False	False	False
False						
2	False	False	False	False	False	False
False						
3	False	False	False	False	False	False
False						
4	False	False	False	False	False	False
False						
...
...						
9460	False	False	False	False	False	False
False						
9461	False	False	False	False	True	False
False						
9462	False	False	False	False	False	False
False						
9463	False	False	False	False	False	False
False						
9464	False	False	False	False	False	False
False						

	Vegan Feast	Vegan mincepie	Victorian Sponge
0	False	False	False
1	False	False	False
2	False	False	False
3	False	False	False
4	False	False	False
...
9460	False	False	False
9461	False	False	False
9462	False	False	False
9463	False	False	False
9464	False	False	False

[9465 rows x 94 columns]

```
frequentItems= apriori(basket_sets, use_colnames=True,
min_support=0.01)
frequentItems.sort_values("support", ascending=False)
```

	support	itemsets
6	0.478394	(Coffee)
2	0.327205	(Bread)
26	0.142631	(Tea)
4	0.103856	(Cake)
34	0.090016	(Bread, Coffee)
11	0.010565	(Hearty & Seasonal)
20	0.010460	(Salad)
30	0.010354	(Bread, Alfajores)
58	0.010037	(Bread, Cake, Coffee)
60	0.010037	(Tea, Coffee, Cake)

[61 rows x 2 columns]

Metrics

```
rules = association_rules(frequentItems, metric="confidence",
min_threshold=0.2)
rules.sort_values('confidence', ascending = False, inplace=True)
rules
```

support	antecedents	consequents	antecedent support	consequent support
24	(Toast)	(Coffee)	0.478394	0.033597
22	(Spanish Brunch)	(Coffee)	0.478394	0.018172
16	(Medialuna)	(Coffee)	0.478394	0.061807
18	(Pastry)	(Coffee)	0.478394	0.086107
1	(Alfajores)	(Coffee)	0.478394	0.036344
15	(Juice)	(Coffee)	0.478394	0.038563
19	(Sandwich)	(Coffee)	0.478394	0.071844
11	(Cake)	(Coffee)	0.478394	0.103856
20	(Scone)	(Coffee)	0.478394	0.034548
13	(Cookies)	(Coffee)	0.478394	0.054411
14	(Hot chocolate)	(Coffee)	0.478394	0.058320
10	(Brownie)	(Coffee)	0.478394	0.040042
17	(Muffin)	(Coffee)	0.478394	0.038457

21	(Soup)	(Coffee)	0.034443
0.478394			
26	(Bread, Cake)	(Coffee)	0.023349
0.478394			
30	(Tea, Cake)	(Coffee)	0.023772
0.478394			
27	(Bread, Pastry)	(Coffee)	0.029160
0.478394			
23	(Tea)	(Coffee)	0.142631
0.478394			
8	(Pastry)	(Bread)	0.086107
0.327205			
0	(Alfajores)	(Bread)	0.036344
0.327205			
4	(Bread)	(Coffee)	0.327205
0.478394			
7	(Medialuna)	(Bread)	0.061807
0.327205			
2	(Brownie)	(Bread)	0.040042
0.327205			
5	(Cookies)	(Bread)	0.054411
0.327205			
9	(Sandwich)	(Bread)	0.071844
0.327205			
28	(Coffee, Pastry)	(Bread)	0.047544
0.327205			
6	(Hot chocolate)	(Bread)	0.058320
0.327205			
12	(Cake)	(Tea)	0.103856
0.142631			
3	(Cake)	(Bread)	0.103856
0.327205			
29	(Tea, Coffee)	(Cake)	0.049868
0.103856			
25	(Sandwich)	(Tea)	0.071844
0.142631			

	support	confidence	lift	leverage	conviction
24	0.023666	0.704403	1.472431	0.007593	1.764582
22	0.010882	0.598837	1.251766	0.002189	1.300235
16	0.035182	0.569231	1.189878	0.005614	1.210871
18	0.047544	0.552147	1.154168	0.006351	1.164682
1	0.019651	0.540698	1.130235	0.002264	1.135648
15	0.020602	0.534247	1.116750	0.002154	1.119919
19	0.038246	0.532353	1.112792	0.003877	1.115384
11	0.054728	0.526958	1.101515	0.005044	1.102664
20	0.018067	0.522936	1.093107	0.001539	1.093366
13	0.028209	0.518447	1.083723	0.002179	1.083174
14	0.029583	0.507246	1.060311	0.001683	1.058553
10	0.019651	0.490765	1.025860	0.000495	1.024293

17	0.018806	0.489011	1.022193	0.000408	1.020777
21	0.015848	0.460123	0.961807	-0.000629	0.966156
26	0.010037	0.429864	0.898557	-0.001133	0.914880
30	0.010037	0.422222	0.882582	-0.001335	0.902779
27	0.011199	0.384058	0.802807	-0.002751	0.846843
23	0.049868	0.349630	0.730840	-0.018366	0.802014
8	0.029160	0.338650	1.034977	0.000985	1.017305
0	0.010354	0.284884	0.870657	-0.001538	0.940818
4	0.090016	0.275105	0.575059	-0.066517	0.719561
7	0.016904	0.273504	0.835879	-0.003319	0.926082
2	0.010777	0.269129	0.822508	-0.002326	0.920538
5	0.014474	0.266019	0.813004	-0.003329	0.916638
9	0.017010	0.236765	0.723596	-0.006498	0.881503
28	0.011199	0.235556	0.719901	-0.004357	0.880109
6	0.013418	0.230072	0.703144	-0.005665	0.873841
12	0.023772	0.228891	1.604781	0.008959	1.111865
3	0.023349	0.224822	0.687097	-0.010633	0.867923
29	0.010037	0.201271	1.937977	0.004858	1.121962
25	0.014369	0.200000	1.402222	0.004122	1.071712

This data set contains all possible causal relationships.

All rules that have lift>1:

```
rules[rules["lift"]>1].sort_values("support",ascending = False)
```

support	antecedents	consequents	antecedent support	consequent
11	(Cake)	(Coffee)	0.103856	
0.478394				
18	(Pastry)	(Coffee)	0.086107	
0.478394				
19	(Sandwich)	(Coffee)	0.071844	
0.478394				
16	(Medialuna)	(Coffee)	0.061807	
0.478394				
14	(Hot chocolate)	(Coffee)	0.058320	
0.478394				
8	(Pastry)	(Bread)	0.086107	
0.327205				
13	(Cookies)	(Coffee)	0.054411	
0.478394				
12	(Cake)	(Tea)	0.103856	
0.142631				
24	(Toast)	(Coffee)	0.033597	
0.478394				
15	(Juice)	(Coffee)	0.038563	
0.478394				
1	(Alfajores)	(Coffee)	0.036344	
0.478394				
10	(Brownie)	(Coffee)	0.040042	

0.478394			
17	(Muffin)	(Coffee)	0.038457
0.478394			
20	(Scone)	(Coffee)	0.034548
0.478394			
25	(Sandwich)	(Tea)	0.071844
0.142631			
22	(Spanish Brunch)	(Coffee)	0.018172
0.478394			
29	(Tea, Coffee)	(Cake)	0.049868
0.103856			

	support	confidence	lift	leverage	conviction
11	0.054728	0.526958	1.101515	0.005044	1.102664
18	0.047544	0.552147	1.154168	0.006351	1.164682
19	0.038246	0.532353	1.112792	0.003877	1.115384
16	0.035182	0.569231	1.189878	0.005614	1.210871
14	0.029583	0.507246	1.060311	0.001683	1.058553
8	0.029160	0.338650	1.034977	0.000985	1.017305
13	0.028209	0.518447	1.083723	0.002179	1.083174
12	0.023772	0.228891	1.604781	0.008959	1.111865
24	0.023666	0.704403	1.472431	0.007593	1.764582
15	0.020602	0.534247	1.116750	0.002154	1.119919
1	0.019651	0.540698	1.130235	0.002264	1.135648
10	0.019651	0.490765	1.025860	0.000495	1.024293
17	0.018806	0.489011	1.022193	0.000408	1.020777
20	0.018067	0.522936	1.093107	0.001539	1.093366
25	0.014369	0.200000	1.402222	0.004122	1.071712
22	0.010882	0.598837	1.251766	0.002189	1.300235
29	0.010037	0.201271	1.937977	0.004858	1.121962

A situation where a customer buys a Cake. Let's predict what else they can buy:

```
rules[rules['antecedents'] == frozenset({'Cake'})]
```

	antecedents	consequents	antecedent support	consequent support
11	(Cake)	(Coffee)	0.103856	0.478394
12	(Cake)	(Tea)	0.103856	0.142631
3	(Cake)	(Bread)	0.103856	0.327205

	confidence	lift	leverage	conviction
11	0.526958	1.101515	0.005044	1.102664
12	0.228891	1.604781	0.008959	1.111865
3	0.224822	0.687097	-0.010633	0.867923

1. Coffee - 47%
2. Tea - 14%

3. Bread - 3%

This can be a recommendation of which product should be placed closer to or farther from the cake on the shelves. Depending on the strategy of the supermarket.

Products which are bought together the most frequently.

```
frequentItems["antecedent_len"] =  
frequentItems["itemsets"].apply(lambda x: len(x))  
frequentItems[frequentItems["antecedent_len"]>1].sort_values(by=["ante  
cedent_len", "support"], ascending=False)
```

	support	itemsets	antecedent_len
59	0.011199	(Bread, Pastry, Coffee)	3
58	0.010037	(Bread, Cake, Coffee)	3
60	0.010037	(Tea, Coffee, Cake)	3
34	0.090016	(Bread, Coffee)	2
42	0.054728	(Coffee, Cake)	2
55	0.049868	(Tea, Coffee)	2
50	0.047544	(Coffee, Pastry)	2
51	0.038246	(Coffee, Sandwich)	2
48	0.035182	(Coffee, Medialuna)	2
46	0.029583	(Coffee, Hot chocolate)	2
38	0.029160	(Bread, Pastry)	2
45	0.028209	(Cookies, Coffee)	2
40	0.028104	(Tea, Bread)	2
44	0.023772	(Tea, Cake)	2
56	0.023666	(Coffee, Toast)	2
33	0.023349	(Bread, Cake)	2
47	0.020602	(Coffee, Juice)	2
31	0.019651	(Coffee, Alfajores)	2
41	0.019651	(Coffee, Brownie)	2
49	0.018806	(Coffee, Muffin)	2
52	0.018067	(Coffee, Scone)	2
39	0.017010	(Bread, Sandwich)	2
37	0.016904	(Bread, Medialuna)	2
53	0.015848	(Coffee, Soup)	2
35	0.014474	(Cookies, Bread)	2
57	0.014369	(Tea, Sandwich)	2
36	0.013418	(Bread, Hot chocolate)	2
43	0.011410	(Cake, Hot chocolate)	2
54	0.010882	(Coffee, Spanish Brunch)	2
32	0.010777	(Bread, Brownie)	2
30	0.010354	(Bread, Alfajores)	2

```
index_names = rules['consequents'] == frozenset({'Coffee'})  
refinedRules = rules[~index_names].sort_values('lift',  
ascending=False)  
refinedRules.drop(['leverage', 'conviction'], axis=1, inplace=True)  
refinedRules = refinedRules.reset_index()  
refinedRules
```

	index	antecedents	consequents	antecedent support \
0	29	(Tea, Coffee)	(Cake)	0.049868
1	12	(Cake)	(Tea)	0.103856
2	25	(Sandwich)	(Tea)	0.071844
3	8	(Pastry)	(Bread)	0.086107
4	0	(Alfajores)	(Bread)	0.036344
5	7	(Medialuna)	(Bread)	0.061807
6	2	(Brownie)	(Bread)	0.040042
7	5	(Cookies)	(Bread)	0.054411
8	9	(Sandwich)	(Bread)	0.071844
9	28	(Coffee, Pastry)	(Bread)	0.047544
10	6	(Hot chocolate)	(Bread)	0.058320
11	3	(Cake)	(Bread)	0.103856

	consequent support	support	confidence	lift
0	0.103856	0.010037	0.201271	1.937977
1	0.142631	0.023772	0.228891	1.604781
2	0.142631	0.014369	0.200000	1.402222
3	0.327205	0.029160	0.338650	1.034977
4	0.327205	0.010354	0.284884	0.870657
5	0.327205	0.016904	0.273504	0.835879
6	0.327205	0.010777	0.269129	0.822508
7	0.327205	0.014474	0.266019	0.813004
8	0.327205	0.017010	0.236765	0.723596
9	0.327205	0.011199	0.235556	0.719901
10	0.327205	0.013418	0.230072	0.703144
11	0.327205	0.023349	0.224822	0.687097

Visualization of Association Rules

```
Basket_Network = Network(height="1000px", width="1000px",
directed=True, notebook=True)
```

Warning: When `cdn_resources` is 'local' jupyter notebook has issues displaying graphics on chrome/safari. Use `cdn_resources='in_line'` or `cdn_resources='remote'` if you have issues viewing graphics in a notebook.

```
Basket_Network.force_atlas_2based()
Basket_Network.barnes_hut()
Basket_Network.hrepulsion()
Basket_Network.repulsion()
```

```
Basket_Network_Data_zip=zip(rules["antecedents"],
                             rules["consequents"],
                             rules["antecedent support"],
                             rules["consequent support"],
                             rules["confidence"])
```

```
for i in Basket_Network_Data_zip:
```

```
FromItem=str(i[0]).replace("frozenset({'", "" ).replace("'", " ").replace(
e("'", " ", " ", " ")
```

```
ToItem=str(i[1]).replace("frozenset({'", "" ).replace("'", " ").replace(
" ", " ", " ", " ")
```

```
    FromWeight=i[2]
```

```
    ToWeight=i[3]
```

```
    EdgeWeight=i[4]
```

```
    Basket_Network.add_node(n_id=FromItem, shape="dot",
value=FromWeight,
```

```
                        title=FromItem + "<br>Support: " +
```

```
str(FromWeight))
```

```
    Basket_Network.add_node(n_id=ToItem, shape="dot", value=ToWeight,
```

```
                        title=ToItem + "<br>Support: " +
```

```
str(ToWeight))
```

```
    Basket_Network.add_edge(source=FromItem, to=ToItem,
value=EdgeWeight, arrowStrikethrough=False,
```

```
                        title=FromItem + " --> " + ToItem +
```

```
"<br>Confidence:" + str(EdgeWeight))
```

```
Basket_Network.set_edge_smooth(smooth_type="continuous")
```

```
Basket_Network.toggle_hide_edges_on_drag(True)
```

```
Basket_Network.save_graph("Basket_Network1.html")
```

```
Basket_Network.show("Basket_Network1.html")
```

```
Basket_Network1.html
```

```
<IPython.lib.display.IFrame at 0x1dd76abf940>
```

```
Basket_Network2 = Network(height="1000px", width="1000px",
directed=True, notebook=True)
```

```
Basket_Network2.repulsion()
```

```
Basket_Network_Data2_zip=zip(refinedRules["antecedents"],
```

```
                        refinedRules["consequents"],
```

```
                        refinedRules["antecedent support"],
```

```
                        refinedRules["consequent support"],
```

```
                        refinedRules["confidence"])
```

```
for i in Basket_Network_Data2_zip:
```

```
FromItem=str(i[0]).replace("frozenset({'", "" ).replace("'", " ").replace(
e("'", " ", " ", " ")
```

```
ToItem=str(i[1]).replace("frozenset({'", "" ).replace("'", " ").replace(
" ", " ", " ", " ")
```

```
    FromWeight=i[2]
```

```
    ToWeight=i[3]
```

```
    EdgeWeight=i[4]
```

```

    Basket_Network2.add_node(n_id=FromItem, shape="dot",
value=FromWeight,
                                title=FromItem + "<br>Support: " +
str(FromWeight))
    Basket_Network2.add_node(n_id=ToItem, shape="dot", value=ToWeight,
                                title=ToItem + "<br>Support: " +
str(ToWeight))
    Basket_Network2.add_edge(source=FromItem, to=ToItem,
value=EdgeWeight, arrowStrikethrough=False,
                                title=FromItem + " --> " + ToItem +
"<br>Confidence:" + str(EdgeWeight))

Basket_Network2.set_edge_smooth(smooth_type="continuous")
Basket_Network2.toggle_hide_edges_on_drag(True)
Basket_Network2.save_graph("Basket_Network2.html")
Basket_Network2.show("Basket_Network2.html")

```

Warning: When `cdn_resources` is 'local' jupyter notebook has issues displaying graphics on chrome/safari. Use `cdn_resources='in_line'` or `cdn_resources='remote'` if you have issues viewing graphics in a notebook.

Basket_Network2.html

<IPython.lib.display.IFrame at 0x1dd74c4bd00>