Problem Statement: -

```
The Departmental Store, has gathered the data of the products it sells o
n a Daily basis. Using Association Rules concepts, provide the insights
 on the rules and the plots.
```

Objective :-

Using Association Rules concepts, provide the insights on the rules and the plots

In [20]:
```
import numpy as np
import pandas as pd

import matplotlib.pyplot as plt
import seaborn as sns
```

In [12]:
```
dataset = pd.read_csv("D:\\360Digi\\Machine learning\\Association Rule\\groceries
```

In [13]:
```
dataset.head()
```

Out[13]:

	0
0	citrus fruit,semi-finished bread,margarine,rea...
1	tropical fruit,yogurt,coffee
2	whole milk
3	pip fruit,yogurt,cream cheese ,meat spreads
4	other vegetables,whole milk,condensed milk,lon...

In [14]:
```
unique_items_list = []

# for each index it will iter row by row
for index, row in dataset.iterrows():

    # splitting items with , and creating a new list for row & it will going add
    # ...item_series list for each iteration..so item_series will be list of list
    items_series = list(row.str.split(','))


    # agian reading each list elements from item_Series which is big list as ment
    for each_row_list in items_series:

        # iterating each item from each_row_lists
        for item in each_row_list:

            # for first iteration..unique_items_list is empty so first item direc
            #...from next onwards..it will start to check condition 'not in'
            #....& if item not found in unique_items_list list then it will apper
            #......finally we will get one unique item list..
            if item not in unique_items_list:
                unique_items_list.append(item)
```

In [15]:
```
unique_items_list
```

```
 'dog food',
 'prosecco',
 'frozen fish',
 'make up remover',
 'cleaner',
 'female sanitary products',
 'dish cleaner',
 'cookware',
 'meat',
 'tea',
 'mustard',
 'house keeping products',
 'skin care',
 'potato products',
 'liquor',
 'pet care',
 'soups',
 'rum',
 'salad dressing',
 'sauces',
```

In [16]:
```
df_apriori = pd.DataFrame(columns=unique_items_list)
```

In [17]:
```
df_apriori
```

Out[17]:

citrus fruit	semi-finished bread	margarine	ready soups	tropical fruit	yogurt	coffee	whole milk	pip fruit	cream cheese	...	baby food

0 rows × 169 columns

In [18]:
```
dataset1 =df_apriori.copy()
```

In [21]:
```
## If for the item names obesrved w.r.t. each list will be assigned as number 1 &
##...row number iterating will be assigned with nuber 0.

for index, row in dataset.iterrows():
    items = str(row[0]).split(',')
    one_hot_encoding = np.zeros(len(unique_items_list),dtype=int)
    for item_name in items:
        for i,column in enumerate(dataset1.columns):
            if item_name == column:
                one_hot_encoding[i] = 1
    dataset1.at[index] = one_hot_encoding

# Transction encoder is fastest method to do all this.
```

In [22]:
```
dataset1.head()
```

Out[22]:

	citrus fruit	semi-finished bread	margarine	ready soups	tropical fruit	yogurt	coffee	whole milk	pip fruit	cream cheese	...	baby food	pu pc
0	1	1	1	1	0	0	0	0	0	0	...	0	
1	0	0	0	0	1	1	1	0	0	0	...	0	
2	0	0	0	0	0	0	0	1	0	0	...	0	
3	0	0	0	0	0	1	0	0	1	1	...	0	
4	0	0	0	0	0	0	0	1	0	0	...	0	

5 rows × 169 columns

In [23]:
```
zero =[]
one = []
for i in df_apriori.columns:
    zero.append(list(dataset1[i].value_counts())[0])
    one.append(list(dataset1[i].value_counts())[1])
```

In [37]:
```
count_df = pd.DataFrame([zero,one], columns=df_apriori.copy().columns)
```

In [25]:
```
count_df.head()
```

Out[25]:

	citrus fruit	semi-finished bread	margarine	ready soups	tropical fruit	yogurt	coffee	whole milk	pip fruit	cream cheese	...	baby food	pu p
0	9021	9661	9259	9817	8803	8463	9264	7322	9091	9445	...	9834	
1	814	174	576	18	1032	1372	571	2513	744	390	...	1	

2 rows × 169 columns

In [26]:
```
count_df.index = ['Not_Purchased', 'Purchased']
count_df
```

Out[26]:

	citrus fruit	semi-finished bread	margarine	ready soups	tropical fruit	yogurt	coffee	whole milk	pip fruit	cream cheese
Not_Purchased	9021	9661	9259	9817	8803	8463	9264	7322	9091	9445
Purchased	814	174	576	18	1032	1372	571	2513	744	390

2 rows × 169 columns

In [27]:
```
print('maximum purchased item:',count_df.idxmax(axis = 1)[1],':',count_df.loc['Pu
print('minimum purchased item:',count_df.idxmax(axis = 1)[0],':',count_df.loc['No
```

```
maximum purchased item: whole milk : 2513
minimum purchased item: baby food : 9834
```

In [28]:

```
sorted_df = pd.DataFrame(count_df.sort_values(by=['Purchased'],axis=1,ascending=F
sorted_df.head(20)
```

Out[28]:

	Not_Purchased	Purchased
whole milk	7322	2513
other vegetables	7932	1903
rolls/buns	8026	1809
soda	8120	1715
yogurt	8463	1372
bottled water	8748	1087
root vegetables	8763	1072
tropical fruit	8803	1032
shopping bags	8866	969
sausage	8911	924
pastry	8960	875
citrus fruit	9021	814
bottled beer	9043	792
newspapers	9050	785
canned beer	9071	764
pip fruit	9091	744
fruit/vegetable juice	9124	711
whipped/sour cream	9130	705
brown bread	9197	638
domestic eggs	9211	624

In [29]:

```
sorted_df['Purchased%']= sorted_df.Purchased/sum(sorted_df.Purchased)
sorted_df.head()
```

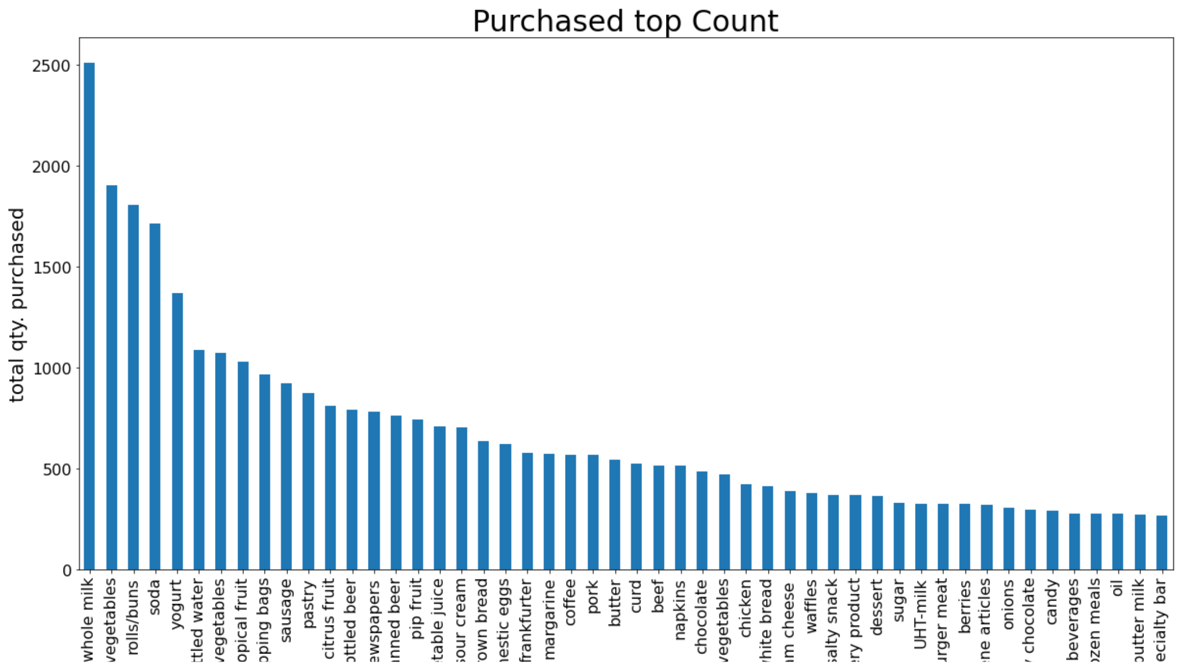
Out[29]:

	Not_Purchased	Purchased	Purchased%
whole milk	7322	2513	0.057947
other vegetables	7932	1903	0.043881
rolls/buns	8026	1809	0.041714
soda	8120	1715	0.039546
yogurt	8463	1372	0.031637

EDA

In [30]:

```python
fig = plt.subplots(figsize=(20,10))
purchased = sorted_df.head(50).xs('Purchased' ,axis = 1)
purchased.plot(kind='bar',fontsize=16)
plt.title('Purchased top Count',fontsize=30)
plt.xlabel('Products', fontsize=20)
plt.ylabel('total qty. purchased', fontsize=20)
plt.show()
```



In [38]:

```python
sns.pairplot(sorted_df)
plt.figure(figsize=(8,8))
plt.show()
```

In [39]:
```
a = sorted_df.corr(method ='pearson')
sns.heatmap(a>0.85,annot=True)
```

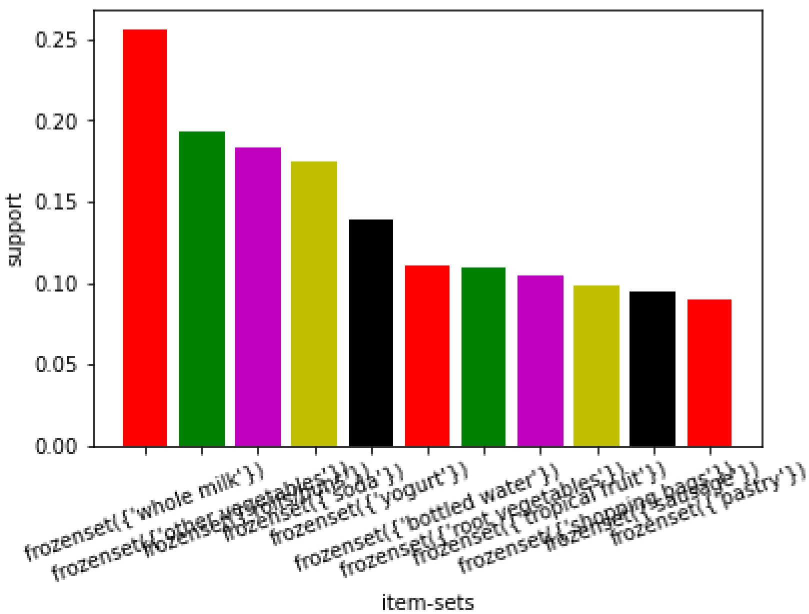
Out[39]: <AxesSubplot:>

In [31]:
```
from mlxtend.frequent_patterns import apriori, association_rules

freq_items = apriori(dataset1, min_support=0.02, use_colnames=True, max_len=5)
```

In [32]:

```python
# Most Frequent item sets based on support
frequent_itemsets.sort_values('support', ascending = False, inplace = True)

plt.bar(x = list(range(0, 11)), height = frequent_itemsets.support[0:11], color =
plt.xticks(list(range(0, 11)), frequent_itemsets.itemsets[0:11], rotation=20)
plt.xlabel('item-sets')
plt.ylabel('support')
plt.show()
```

```
<ipython-input-32-b6a00b440570>:4: MatplotlibDeprecationWarning: Using a string
of single character colors as a color sequence is deprecated since 3.2 and will
be removed two minor releases later. Use an explicit list instead.
  plt.bar(x = list(range(0, 11)), height = frequent_itemsets.support[0:11], col
or ='rgmyk')
```



In [33]:

```
rules = association_rules(frequent_itemsets, metric = "lift", min_threshold = 1)
rules.head(20)
rules.sort_values('lift', ascending = False).head(10)
```

Out[33]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverag
1153	(yogurt, other vegetables)	(tropical fruit, whole milk)	0.043416	0.042298	0.007626	0.175644	4.152546	0.0057ɛ
1152	(tropical fruit, whole milk)	(yogurt, other vegetables)	0.042298	0.043416	0.007626	0.180288	4.152546	0.0057ɛ
1060	(yogurt, root vegetables)	(other vegetables, whole milk)	0.025826	0.074835	0.007829	0.303150	4.050919	0.0058ᵍ
1061	(other vegetables, whole milk)	(yogurt, root vegetables)	0.074835	0.025826	0.007829	0.104620	4.050919	0.0058ᵍ
772	(berries)	(whipped/sour cream)	0.033249	0.071683	0.009049	0.272171	3.796886	0.0066ɛ
773	(whipped/sour cream)	(berries)	0.071683	0.033249	0.009049	0.126241	3.796886	0.0066ɛ
1154	(yogurt, whole milk)	(tropical fruit, other vegetables)	0.056024	0.035892	0.007626	0.136116	3.792358	0.0056ʻ
1151	(tropical fruit, other vegetables)	(yogurt, whole milk)	0.035892	0.056024	0.007626	0.212465	3.792358	0.0056ʻ
1028	(other vegetables, beef)	(root vegetables)	0.019725	0.108998	0.007931	0.402062	3.688692	0.0057ɛ
1033	(root vegetables)	(other vegetables, beef)	0.108998	0.019725	0.007931	0.072761	3.688692	0.0057ɛ

In [34]:
```
###########################extra ##################### Redudancy is defined as the
def to_list(i):
    return (sorted(list(i)))

ma_X = rules.antecedents.apply(to_list) + rules.consequents.apply(to_list)

ma_X = ma_X.apply(sorted)

rules_sets = list(ma_X)

unique_rules_sets = [list(m) for m in set(tuple(i) for i in rules_sets)]

index_rules = []

for i in unique_rules_sets:
    index_rules.append(rules_sets.index(i))

# getting rules without any redudancy
rules_no_redudancy = rules.iloc[index_rules, :]

# Sorting them with respect to list and getting top 10 rules
rules_no_redudancy.sort_values('lift', ascending = False).head(10)
```

Out[34]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	lev
772	(berries)	(whipped/sour cream)	0.033249	0.071683	0.009049	0.272171	3.796886	0.0(
1028	(other vegetables, beef)	(root vegetables)	0.019725	0.108998	0.007931	0.402062	3.688692	0.0(
690	(tropical fruit, other vegetables)	(pip fruit)	0.035892	0.075648	0.009456	0.263456	3.482649	0.0(
1016	(whole milk, beef)	(root vegetables)	0.021251	0.108998	0.008033	0.377990	3.467851	0.0(
534	(other vegetables, citrus fruit)	(root vegetables)	0.028876	0.108998	0.010371	0.359155	3.295045	0.0(
558	(other vegetables, yogurt)	(whipped/sour cream)	0.043416	0.071683	0.010168	0.234192	3.267062	0.0(
1054	(yogurt, other vegetables, whole milk)	(root vegetables)	0.022267	0.108998	0.007829	0.351598	3.225716	0.0(
360	(tropical fruit, other vegetables)	(root vegetables)	0.035892	0.108998	0.012303	0.342776	3.144780	0.0(
782	(tropical fruit, other vegetables)	(citrus fruit)	0.035892	0.082766	0.009049	0.252125	3.046248	0.0(

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	lev
1082	(tropical fruit, other vegetables)	(whipped/sour cream)	0.035892	0.071683	0.007829	0.218130	3.042995	0.0(

In [ ]:
```
#Building Association rules using confidence metrics
```

In [35]:
```
# for this we need support value dataframe..that is fre_items from measure1.

confidence_association = association_rules(freq_items, metric='confidence', min_t

# min_threshold is nothing but setting min % crieteria. In this case i have choos
#...confidence should be minimum 20%.
```

In [36]:
```
confidence_association.head(10)
```

Out[36]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	(
0	(citrus fruit)	(yogurt)	0.082766	0.139502	0.021657	0.261671	1.875752	0.010111	
1	(citrus fruit)	(whole milk)	0.082766	0.255516	0.030503	0.368550	1.442377	0.009355	
2	(citrus fruit)	(other vegetables)	0.082766	0.193493	0.028876	0.348894	1.803140	0.012862	
3	(margarine)	(whole milk)	0.058566	0.255516	0.024199	0.413194	1.617098	0.009235	
4	(tropical fruit)	(yogurt)	0.104931	0.139502	0.029283	0.279070	2.000475	0.014645	
5	(yogurt)	(tropical fruit)	0.139502	0.104931	0.029283	0.209913	2.000475	0.014645	
6	(tropical fruit)	(whole milk)	0.104931	0.255516	0.042298	0.403101	1.577595	0.015486	
7	(pip fruit)	(tropical fruit)	0.075648	0.104931	0.020437	0.270161	2.574648	0.012499	
8	(tropical fruit)	(other vegetables)	0.104931	0.193493	0.035892	0.342054	1.767790	0.015589	
9	(tropical fruit)	(rolls/buns)	0.104931	0.183935	0.024606	0.234496	1.274886	0.005305	

1 . Antecedent and Consequent
The IF component of an association rule is known as the antecedent. The THEN component is known as the consequent. The antecedent and the consequent are disjoint; they have no items in common.

2. antecedent support
It is antecedent support with all transction numbers.

3. consequent support
It is consequent support with all transction numbers.

4. Support:

```
Here support is considered for antecedent+consequent combination.

5. confidence
Confidence is related to 'consequent item' or 'consequent item combination'
w.r.t. antecedent item or item set.

6. lift
Lift measures how many times more often X and Y occur together than expected
if they where statistically independent. Lift is not down-ward closed and does
not suffer from the rare item problem.

In short firm possibilities of buying consequent whenever Antecedent item is
purchaed by customer

7. Leverage
Leverage measures the difference of X and Y appearing together in the data set
and what would be expected if X and Y where statistically dependent. The
rational in a sales setting is to find out how many more units (items X and Y
together) are sold than expected from the independent sells.

leverage also can suffer from the rare item problem.

leverage(X -> Y) = P(X and Y) - (P(X)P(Y))

8. conviction
conviction(X -> Y) = P(X)P(not Y)/P(X and not Y)=(1-sup(Y))/(1-conf(X -> Y))

Conviction compares the probability that X appears without Y if they were
dependent with the actual frequency of the appearance of X without Y. In that
respect it is similar to lift (see section about lift on this page), however,
it contrast to lift it is a directed measure. Furthermore, conviction is
monotone in confidence and lift.

9. Coverage
coverage(X) = P(X) = sup(X)

A simple measure of how often a item set appears in the data set.
```

Summary:

1- Above the 10 unique Rule that we get by Apply Apriori Algo.

2- Antecedent support variable tells us probability of antecedent product alone.

3- The Support Value is the value of the two Product(Antecedents and Consequents)

4- Confidence is an indication of how often the rule has been found to be True.

5-The ratio of the observed support to that expected if X and Y were independent.

In [ ]:

```

```