Problem Statement: -

A retail store in India, has its transaction data, and it would like to know the buying pattern of the consumers in its locality, you have been assigned this task to provide the manager with rules on how the placement of products needs to be there in shelves so that it can improve the buying patterns of consumes and increase customer footfall

Objective :-

use the Association rules concept and improve the buying patterns of consumes and increase customer footfall

In [34]:
```
import numpy as np
import pandas as pd

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

In [35]:
```
dataset = pd.read_csv("D:\\360Digi\\transactions_retail1.csv", sep=";", header= N
```

In [36]:
```
dataset= dataset[0:5000]
dataset
```

Out[36]:

	0
0	'HANGING','HEART','HOLDER','T-LIGHT','WHITE',NA
1	'LANTERN','METAL','WHITE',NA,NA,NA
2	'COAT','CREAM','CUPID','HANGER','HEARTS',NA
3	'BOTTLE','FLAG','HOT','KNITTED','UNION','WATER'
4	'HEART.','HOTTIE','RED','WHITE','WOOLLY',NA
...	...
4995	'KIT','SEWING','TRAVEL',NA,NA,NA
4996	'CAKE','RED','RETROSPOT','ROUND','TINS',NA
4997	'BASKET','PICNIC','SMALL','WICKER',NA,NA
4998	'CAN','CREAM','ENAMEL','WATERING',NA,NA
4999	'BOX','GINGHAM','JEWELLERY','RED','ROSE',NA

5000 rows × 1 columns

In [37]:
```
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 [38]:
```
unique_items_list
```

```
 "'WATERING'",
 "'BUNNY'",
 "'AIR'",
 "'HOSTESS'",
 "'RAKE'",
 "'BRUSH'",
 "'LUDO'",
 "'CLAY'",
 "'MODELLING'",
 "'CARDHOLDER'",
 "'CROQUET'",
 "'BABY'",
 "'DIVA'",
 "'MOTORBIKE'",
 "'PLANTER'",
 "'CONTAINER'",
 "'8'",
 "'NUMBER'",
 "'CHILDREN'",
 "'NAUGHTY'",
```

In [39]:
```
unique_items_list.remove("NA")
unique_items_list
```

```
  PISTACHIO  ,
 "'HONEYCOMB'",
 "'LEVEL'",
 "'SPIRIT'",
 "'PLATTER'",
 "'TEACUP'",
 "'SLICE'",
 "'EIGHT'",

 "'FUN'",
 "'SPORTING'",
 "'ASS'",
 "'COL'",
 "'GECKO'",
 "'P''WEIGHT'",
 "'SAND'",
 "'POSTCARD'",
 "'SPRING'",
 "'CHATEAU'",
 "'SCALES'",
 "'MULTI'"
```

In [40]:
```
df_apriori = pd.DataFrame(columns=unique_items_list)
```

In [ ]:

In [ ]:

In [41]:
```
dataset1 =df_apriori.copy()
```

In [42]:
```
## 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 [43]:
```
dataset1.head()
```

Out[43]:

	'HANGING'	'HEART'	'HOLDER'	'T-LIGHT'	'WHITE'	'LANTERN'	'METAL'	'COAT'	'CREAM'	'CUPI
0	1	1	1	1	1	0	0	0	0	
1	0	0	0	0	1	1	1	0	0	
2	0	0	0	0	0	0	0	1	1	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	1	0	0	0	0	

5 rows × 1435 columns

In [44]:
```
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 [45]:
```
count_df = pd.DataFrame([zero,one], columns=df_apriori.copy().columns)
```

In [46]:
```
count_df.head()
```

Out[46]:

	'HANGING'	'HEART'	'HOLDER'	'T-LIGHT'	'WHITE'	'LANTERN'	'METAL'	'COAT'	'CREAM'	'CUPI
0	4868	4688	4811	4835	4740	4971	4843	4970	4914	498
1	132	312	189	165	260	29	157	30	86	1

2 rows × 1435 columns

In [47]:
```
count_df.index = ['Not_Purchased', 'Purchased']
count_df
```

Out[47]:

	'HANGING'	'HEART'	'HOLDER'	'T-LIGHT'	'WHITE'	'LANTERN'	'METAL'	'COAT'	'CI
Not_Purchased	4868	4688	4811	4835	4740	4971	4843	4970	
Purchased	132	312	189	165	260	29	157	30	

2 rows × 1435 columns

In [53]:
```
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: 'RED' : 472
minimum purchased item: 'TOMATO' : 4999
```

In [54]:

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

Out[54]:

	Not_Purchased	Purchased
'RED'	4528	472
'SET'	4586	414
'OF'	4644	356
'CHRISTMAS'	4663	337
'RETROSPOT'	4670	330
'HEART'	4688	312
'BOX'	4739	261
'WHITE'	4740	260
'VINTAGE'	4742	258
'BAG'	4748	252
'PINK'	4773	227
'DESIGN'	4796	204
'HOLDER'	4811	189
'BOTTLE'	4817	183
'CAKE'	4822	178
'WATER'	4823	177
'HOT'	4824	176
'WARMER'	4828	172
'HAND'	4833	167
'T-LIGHT'	4835	165

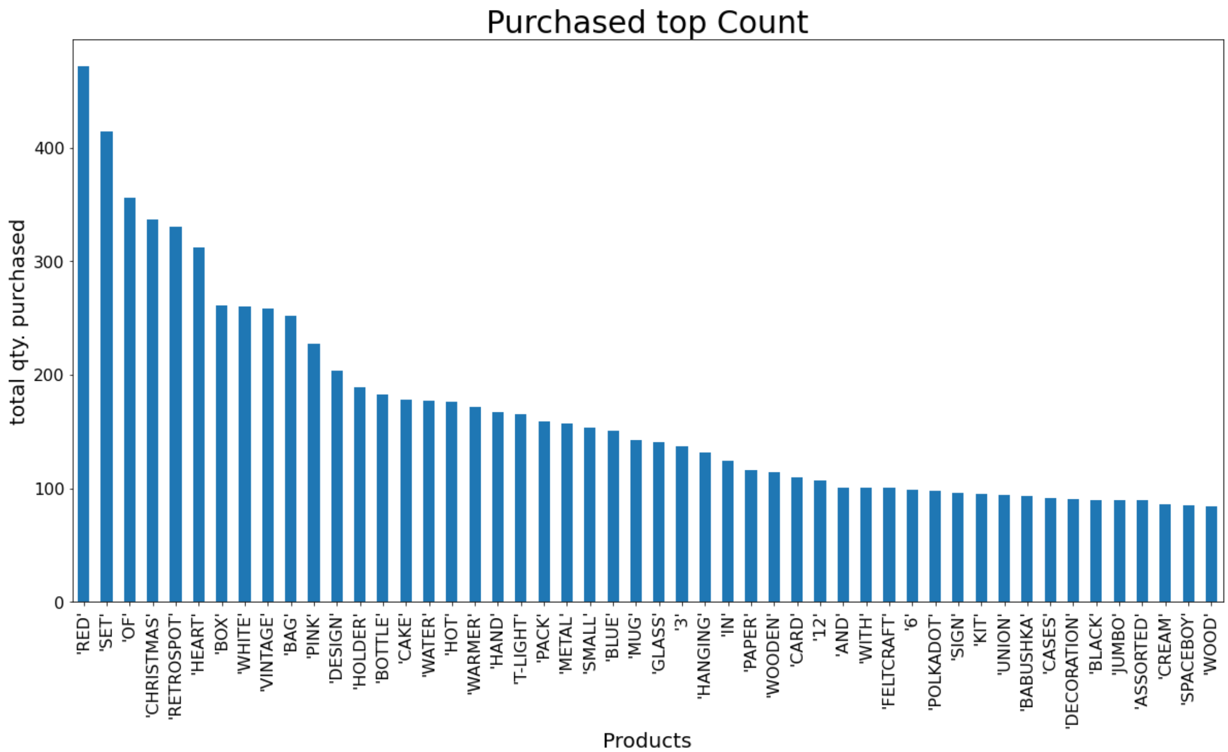
In [55]:

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

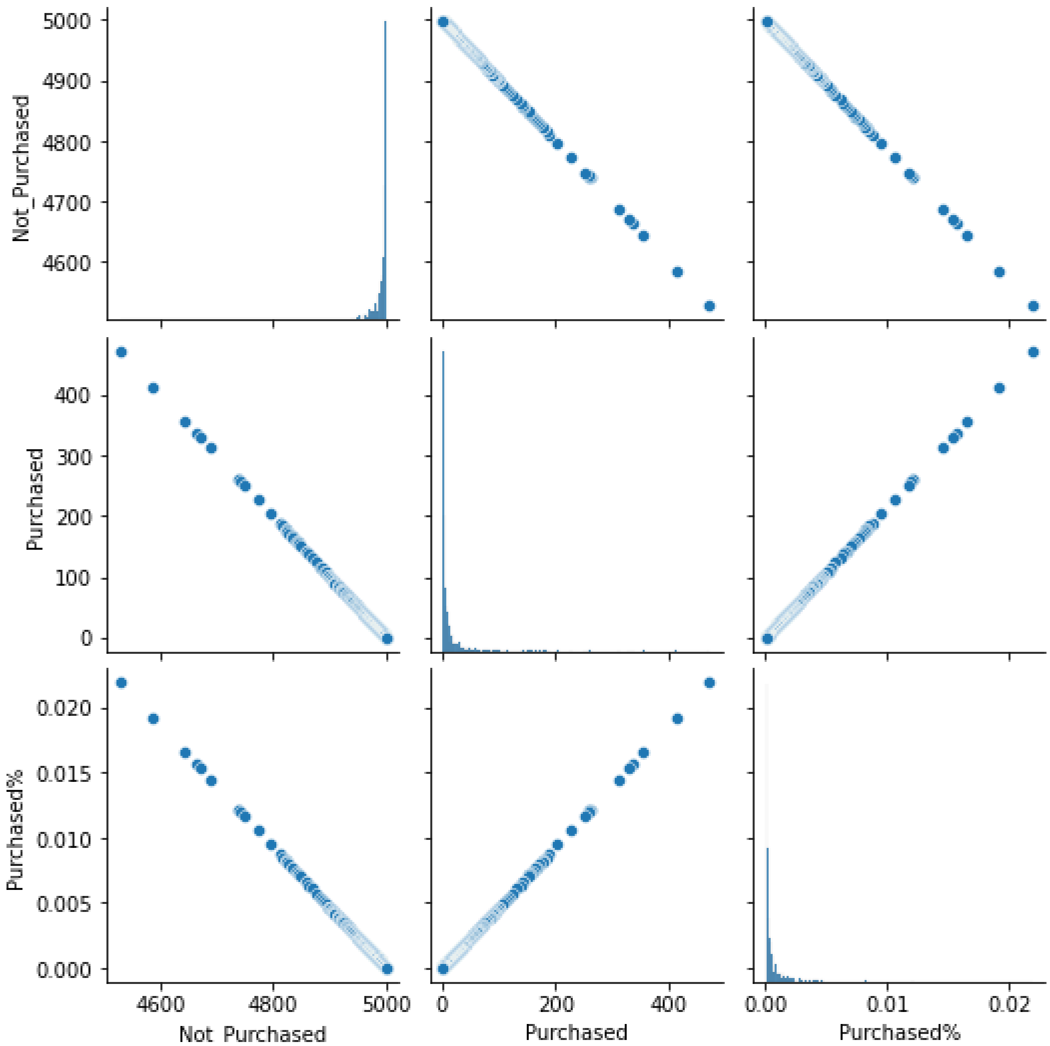
Out[55]:

	Not_Purchased	Purchased	Purchased%
'RED'	4528	472	0.021915
'SET'	4586	414	0.019222
'OF'	4644	356	0.016529
'CHRISTMAS'	4663	337	0.015647
'RETROSPOT'	4670	330	0.015322

In [56]:
```
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 [69]:
```
sns.pairplot(sorted_df)
plt.figure(figsize=(8,8))
plt.show()
```



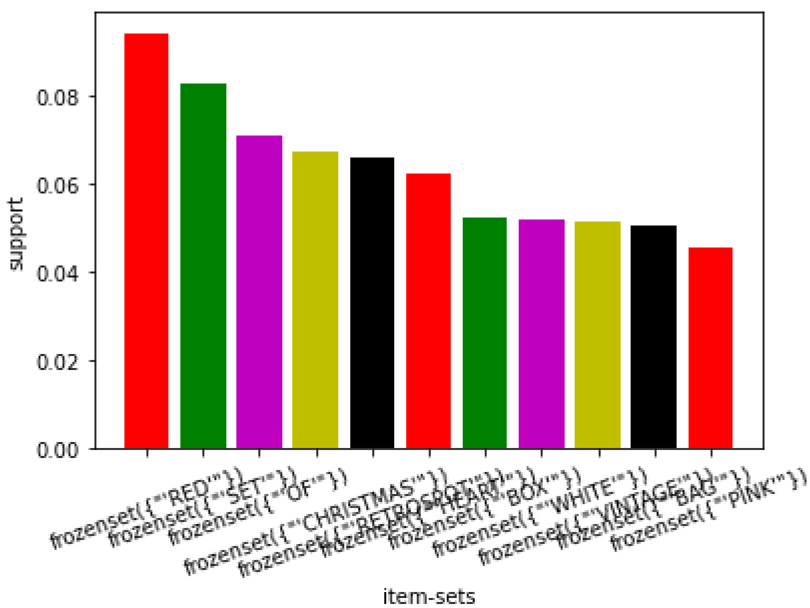
```
<Figure size 576x576 with 0 Axes>
```

In [ ]:

In [70]:
```
from mlxtend.frequent_patterns import apriori, association_rules

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

In [76]:
```

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

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

```
<ipython-input-76-07a3e6c49dca>: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 = freq_items.support[0:11], color ='rg
myk')
```



In [73]:
```
rules = association_rules(frequent_itemsets, metric = "lift", min_threshold = 1)
rules.head(20)
rules.sort_values('lift', ascending = False).head(10)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-73-c1980606c762> in <module>
----> 1 rules = association_rules(frequent_itemsets, metric = "lift", min_thres
hold = 1)
      2 rules.head(20)
      3 rules.sort_values('lift', ascending = False).head(10)

NameError: name 'frequent_itemsets' is not defined
```

In [60]:
```
#Building Association rules using confidence metrics
```

In [64]:
```
# 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 [65]:
```
confidence_association.head(10)
```

Out[65]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	levera
0	('HOLDER')	('T-LIGHT')	0.0378	0.0330	0.0262	0.693122	21.003688	0.0249
1	('T-LIGHT')	('HOLDER')	0.0330	0.0378	0.0262	0.793939	21.003688	0.0249
2	('HOT')	('BOTTLE')	0.0352	0.0366	0.0346	0.982955	26.856682	0.0333
3	('BOTTLE')	('HOT')	0.0366	0.0352	0.0346	0.945355	26.856682	0.0333
4	('BOTTLE')	('WATER')	0.0366	0.0354	0.0324	0.885246	25.006946	0.0311
5	('WATER')	('BOTTLE')	0.0354	0.0366	0.0324	0.915254	25.006946	0.0311
6	('HOT')	('WATER')	0.0352	0.0354	0.0324	0.920455	26.001541	0.0311
7	('WATER')	('HOT')	0.0354	0.0352	0.0324	0.915254	26.001541	0.0311
8	('RETROSPOT')	('RED')	0.0660	0.0944	0.0384	0.581818	6.163328	0.0321
9	('RED')	('RETROSPOT')	0.0944	0.0660	0.0384	0.406780	6.163328	0.0321

In [74]:

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

Out[74]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage
19	('HOT')	('BOTTLE', 'WATER')	0.0352	0.0324	0.0324	0.920455	28.409091	0.031260
18	('BOTTLE', 'WATER')	('HOT')	0.0324	0.0352	0.0324	1.000000	28.409091	0.031260
12	('WARMER')	('HAND')	0.0344	0.0334	0.0320	0.930233	27.851274	0.030851
13	('HAND')	('WARMER')	0.0334	0.0344	0.0320	0.958084	27.851274	0.030851
20	('BOTTLE')	('HOT', 'WATER')	0.0366	0.0324	0.0324	0.885246	27.322404	0.031214
17	('HOT', 'WATER')	('BOTTLE')	0.0324	0.0366	0.0324	1.000000	27.322404	0.031214
2	('HOT')	('BOTTLE')	0.0352	0.0366	0.0346	0.982955	26.856682	0.033312
3	('BOTTLE')	('HOT')	0.0366	0.0352	0.0346	0.945355	26.856682	0.033312
21	('WATER')	('HOT', 'BOTTLE')	0.0354	0.0346	0.0324	0.915254	26.452435	0.031175
16	('HOT', 'BOTTLE')	('WATER')	0.0346	0.0354	0.0324	0.936416	26.452435	0.031175

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 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 [ ]:

```
```