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Batch: 09012021

ASSOCIATION RULES

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. 5.) transaction_retail.csv

Importing Libraries

In [1]:

```
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules
```

Importing Data Set

In [2]:

```
transaction = []
with open(r"F:\360\associationrules\transactions_retail1.csv") as f:
    transaction = f.read()
```

splitting the data into separate transactions using separator as "\n"

In [3]:

```
transaction = transaction.split("\n")
```

In [4]:

```
transaction_list = []
for i in transaction:
    transaction_list.append(i.split(","))
```

In [5]:

```
all_transaction_list = [i for item in transaction_list for i in item]
```

In [6]:

```
from collections import Counter
```

In [7]:

```
item_frequencies = Counter(all_transaction_list)
```

after sorting

In [8]:

```
item_frequencies = sorted(item_frequencies.items(), key = lambda x:x[1])
```

Storing frequencies and items in separate variables

In [9]:

```
frequencies = list(reversed([i[1] for i in item_frequencies]))
items = list(reversed([i[0] for i in item_frequencies]))
```

barplot of top 10

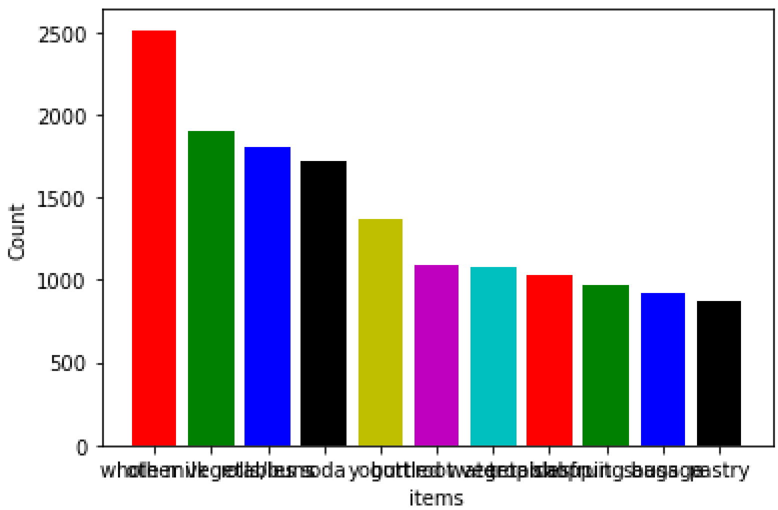
In [10]:

```
import matplotlib.pyplot as plt
```

In [11]:

```
plt.bar(height = frequencies[0:11], x = list(range(0, 11)), color = 'rgbkymc')
plt.xticks(list(range(0, 11), ), items[0:11])
plt.xlabel("items")
plt.ylabel("Count")
plt.show()
```

```
<ipython-input-11-8f013887356d>:1: MatplotlibDeprecationWarning: Using a str
ing of single character colors as a color sequence is deprecated since 3.2 a
nd will be removed two minor releases later. Use an explicit list instead.
  plt.bar(height = frequencies[0:11], x = list(range(0, 11)), color = 'rgbky
mc')
```



Creating Data Frame for the transactions data

In [12]:

```
transaction_series = pd.DataFrame(pd.Series(transaction_list))
transaction_series = transaction_series.iloc[:9835, :]
```

In [13]:

```
transaction_series.columns = ["transactions"]
```

creating a dummy columns for the each item in each transactions ... Using column names as item name

In [14]:

```
X = transaction_series['transactions'].str.join(sep = '*').str.get_dummies(sep = '*')
```

In [15]:

```
frequent_itemsets = apriori(X, min_support = 0.0075, max_len = 4, use_colnames = True)
```

Most Frequent item sets based on support

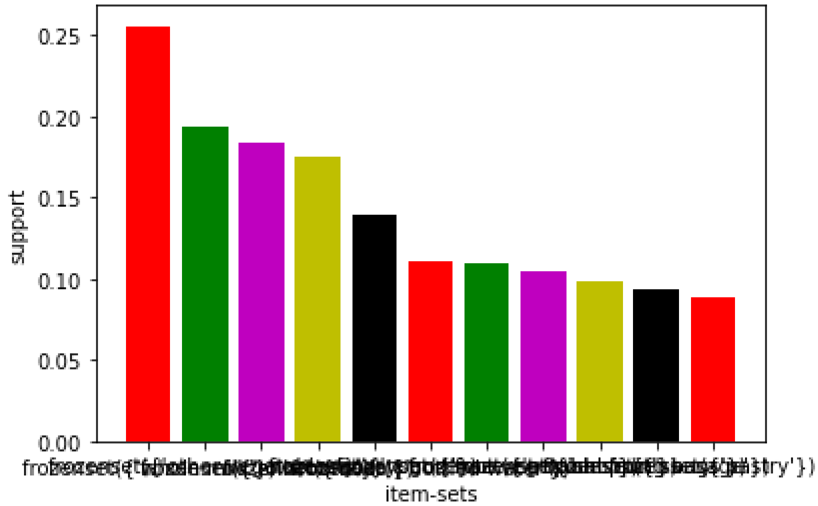
In [16]:

```
frequent_itemsets.sort_values('support', ascending = False, inplace = True)
```

In [17]:

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

```
<ipython-input-17-3f6c91c30844>:1: MatplotlibDeprecationWarning: Using a str
ing of single character colors as a color sequence is deprecated since 3.2 a
nd 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],
color ='rgmyk')
```



In [18]:

```
rules = association_rules(frequent_itemsets, metric = "lift", min_threshold = 1)
rules.head(20)
```

Out[18]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	levera
0	(other vegetables)	(whole milk)	0.193493	0.255516	0.074835	0.386758	1.513634	0.0253
1	(whole milk)	(other vegetables)	0.255516	0.193493	0.074835	0.292877	1.513634	0.0253
2	(whole milk)	(rolls/buns)	0.255516	0.183935	0.056634	0.221647	1.205032	0.0096
3	(rolls/buns)	(whole milk)	0.183935	0.255516	0.056634	0.307905	1.205032	0.0096
4	(whole milk)	(yogurt)	0.255516	0.139502	0.056024	0.219260	1.571735	0.0203
5	(yogurt)	(whole milk)	0.139502	0.255516	0.056024	0.401603	1.571735	0.0203
6	(whole milk)	(root vegetables)	0.255516	0.108998	0.048907	0.191405	1.756031	0.0210
7	(root vegetables)	(whole milk)	0.108998	0.255516	0.048907	0.448694	1.756031	0.0210
8	(other vegetables)	(root vegetables)	0.193493	0.108998	0.047382	0.244877	2.246605	0.0262
9	(root vegetables)	(other vegetables)	0.108998	0.193493	0.047382	0.434701	2.246605	0.0262
10	(other vegetables)	(yogurt)	0.193493	0.139502	0.043416	0.224383	1.608457	0.0164
11	(yogurt)	(other vegetables)	0.139502	0.193493	0.043416	0.311224	1.608457	0.0164
12	(other vegetables)	(rolls/buns)	0.193493	0.183935	0.042603	0.220179	1.197047	0.0070
13	(rolls/buns)	(other vegetables)	0.183935	0.193493	0.042603	0.231620	1.197047	0.0070
14	(whole milk)	(tropical fruit)	0.255516	0.104931	0.042298	0.165539	1.577595	0.0154
15	(tropical fruit)	(whole milk)	0.104931	0.255516	0.042298	0.403101	1.577595	0.0154
16	(soda)	(rolls/buns)	0.174377	0.183935	0.038332	0.219825	1.195124	0.0062
17	(rolls/buns)	(soda)	0.183935	0.174377	0.038332	0.208402	1.195124	0.0062
18	(other vegetables)	(tropical fruit)	0.193493	0.104931	0.035892	0.185497	1.767790	0.0155
19	(tropical fruit)	(other vegetables)	0.104931	0.193493	0.035892	0.342054	1.767790	0.0155

In [19]:

```
rules.sort_values('lift', ascending = False).head(10)
```

Out[19]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	lev
1172	(other vegetables, yogurt)	(whole milk, tropical fruit)	0.043416	0.042298	0.007626	0.175644	4.152546	0.0
1173	(whole milk, tropical fruit)	(other vegetables, yogurt)	0.042298	0.043416	0.007626	0.180288	4.152546	0.0
1093	(yogurt, root vegetables)	(other vegetables, whole milk)	0.025826	0.074835	0.007829	0.303150	4.050919	0.0
1088	(other vegetables, whole milk)	(yogurt, root vegetables)	0.074835	0.025826	0.007829	0.104620	4.050919	0.0
792	(berries)	(whipped/sour cream)	0.033249	0.071683	0.009049	0.272171	3.796886	0.0
793	(whipped/sour cream)	(berries)	0.071683	0.033249	0.009049	0.126241	3.796886	0.0
1174	(whole milk, yogurt)	(other vegetables, tropical fruit)	0.056024	0.035892	0.007626	0.136116	3.792358	0.0
1171	(other vegetables, tropical fruit)	(whole milk, yogurt)	0.035892	0.056024	0.007626	0.212465	3.792358	0.0
1053	(root vegetables)	(other vegetables, beef)	0.108998	0.019725	0.007931	0.072761	3.688692	0.0
1048	(other vegetables, beef)	(root vegetables)	0.019725	0.108998	0.007931	0.402062	3.688692	0.0

To eliminate retundancy

In [20]:

```
def to_list(i):
    return (sorted(list(i)))
```

In [21]:

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

In [22]:

```
ma_X = ma_X.apply(sorted)
```

In [23]:

```
rules_sets = list(ma_X)
```

In [24]:

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

In [25]:

```
index_rules = []
```

In [26]:

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

getting rules without any redudancy

In [27]:

```
rules_no_redudancy = rules.iloc[index_rules, :]
```

Sorting them with respect to list and getting top 10 rules

In [28]:

```
rules_no_redudancy.sort_values('lift', ascending = False).head(10)
```

Out[28]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leve
792	(berries)	(whipped/sour cream)	0.033249	0.071683	0.009049	0.272171	3.796886	0.00
1048	(other vegetables, beef)	(root vegetables)	0.019725	0.108998	0.007931	0.402062	3.688692	0.00
1004	(whole milk, beef)	(root vegetables)	0.021251	0.108998	0.008033	0.377990	3.467851	0.00
678	(pip fruit, other vegetables)	(tropical fruit)	0.026131	0.104931	0.009456	0.361868	3.448613	0.00
534	(other vegetables, citrus fruit)	(root vegetables)	0.028876	0.108998	0.010371	0.359155	3.295045	0.00
1084	(other vegetables, whole milk, yogurt)	(root vegetables)	0.022267	0.108998	0.007829	0.351598	3.225716	0.00
1166	(other vegetables, whole milk, tropical fruit)	(yogurt)	0.017082	0.139502	0.007626	0.446429	3.200164	0.00
360	(other vegetables, tropical fruit)	(root vegetables)	0.035892	0.108998	0.012303	0.342776	3.144780	0.00
172	(beef)	(root vegetables)	0.052466	0.108998	0.017387	0.331395	3.040367	0.01
776	(other vegetables, citrus fruit)	(tropical fruit)	0.028876	0.104931	0.009049	0.313380	2.986526	0.00

Perform algorithm for different support, connfidence value and max length

In [29]:

```
frequent_itemsets1 = apriori(X, min_support = 0.007, max_len = 4, use_colnames = True)
```

Most Frequent item sets based on support

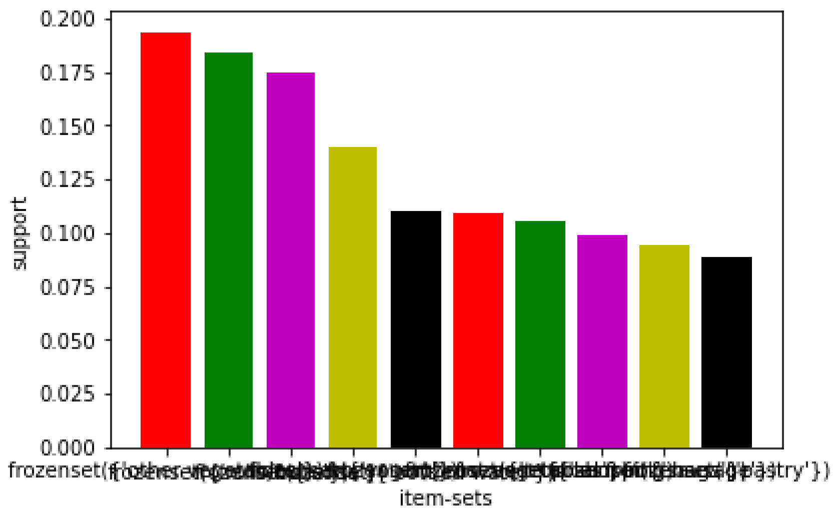
In [30]:

```
frequent_itemsets1.sort_values('support',ascending = False,inplace=True)
plt.bar(x = list(range(1,11)),height = frequent_itemsets1.support[1:11],color='rgmyk')
plt.xticks(list(range(1,11)),frequent_itemsets1.itemsets[1:11])
plt.xlabel('item-sets')
plt.ylabel('support')
```

```
<ipython-input-30-53e7063e2dae>:2: MatplotlibDeprecationWarning: Using a str
ing of single character colors as a color sequence is deprecated since 3.2 a
nd will be removed two minor releases later. Use an explicit list instead.
  plt.bar(x = list(range(1,11)),height = frequent_itemsets1.support[1:11],co
lor='rgmyk')
```

Out[30]:

```
Text(0, 0.5, 'support')
```



In [31]:

```
rules1 = association_rules(frequent_itemsets1, metric="lift", min_threshold=1)
rules1.head(20)
rules1.sort_values('lift',ascending = False,inplace=True)
```

In [32]:

```
frequent_itemsets2 = apriori(X, min_support=0.009, max_len=5,use_colnames = True)
```

Most Frequent item sets based on support

In [33]:

```
frequent_itemsets2.sort_values('support',ascending = False,inplace=True)
```

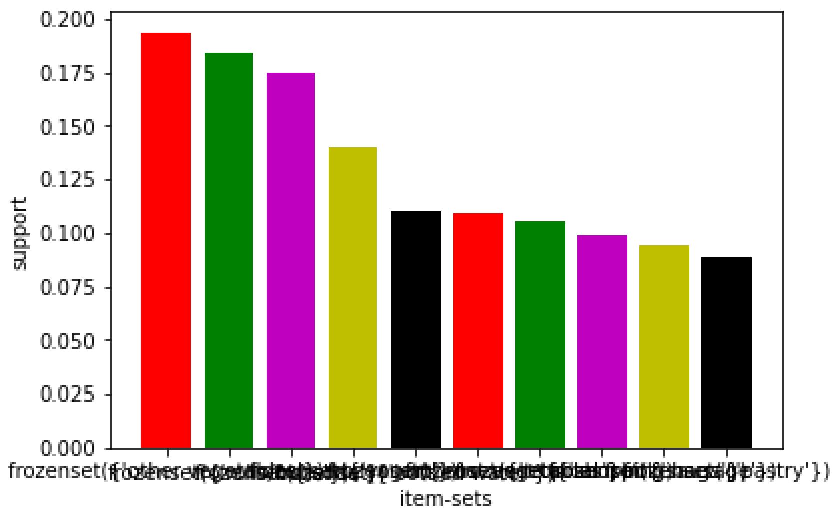
In [34]:

```
plt.bar(x = list(range(1,11)),height = frequent_itemsets2.support[1:11],color='rgmyk')
plt.xticks(list(range(1,11)),frequent_itemsets2.itemsets[1:11])
plt.xlabel('item-sets')
plt.ylabel('support')
```

```
<ipython-input-34-8b16ecdf46e9>:1: MatplotlibDeprecationWarning: Using a str
ing of single character colors as a color sequence is deprecated since 3.2 a
nd will be removed two minor releases later. Use an explicit list instead.
  plt.bar(x = list(range(1,11)),height = frequent_itemsets2.support[1:11],co
lor='rgmyk')
```

Out[34]:

```
Text(0, 0.5, 'support')
```



In [35]:

```
rules2 = association_rules(frequent_itemsets2, metric="lift", min_threshold=1)
rules2.head(20)
rules2.sort_values('lift',ascending = False,inplace=True)
```

As min lenth value is changing the rules is changing.

#rules =1198 #rules1=1390 #rules2=796