NAAN MUDHALVAN – IBM SKILL
ARTIFICIAL INTELLIGENCE
GROUP PROJECT

Project Title: Market Basket Insight
Phase 3 Submission

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MARKET BASKET ANALYSIS USING PYTHON

Market basket analysis is a data mining technique used by retailers to increase sales by better understanding customer purchasing patterns. It involves analyzing large data sets, such as purchase history, to reveal product groupings, as well as products that are likely to be purchased together [1].

E.g. the rule **{cucumbers, tomatoes} -> {sunflower oil}** found in the sales data of a supermarket would indicate that if a customer buys cucumbers and tomatoes together, they are likely to also buy sunflower oil.

1. Import Libraries

For market basket analysis I'm going to use mlxtend. For other purposes (reading data, working with data, visualizing data) I'll use all well-known libraries like numpy, pandas etc.

In [1]:

```
import numpy as np
import pandas as pd
import squarify
import matplotlib.pyplot as plt

# for market basket analysis
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules
from mlxtend.preprocessing import TransactionEncoder
```

2. Read data

In [2]:

```
df = pd.read_xlsx(' C:\marketbasket\Assignment1_Data.xlsx ', header = None)
```

In [3]:

```
df.head(5) # looking for the first 5 rows in dataset
```

Out[3]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
0	shrimp	almonds	avocado	vegetables mix	green grap	whole wea	yams	cottage chee	energy drink	tomato jui	low fat yogu	green te	honey	salad	mineral water	salmon	antioxydant juice	frozen smoothie	spinach	olive oil

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
					es	t flour		se		ce	rt	a								
1	burgers	meatballs	eggs	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2	chutney	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
3	turkey	avocado	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
4	mineral water	milk	energy bar	whole wheat rice	green tea	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

3. Visualize data

Here I decided to count all unique values through all columns and build some visualitions. E.g. if we have 5 'almonds' in first column, 3 'almonds' in second column etc, so, will have 8 'almonds' in total.

In [4]:

```
df_res = pd.DataFrame()
for i in range(len(df.columns)):
    df_res = df_res.append(df[i].value_counts())
```

In [5]:

```
df_res.head(3)
```

Out[5]:

	almonds	antioxydant juice	asparagus	avocado	babies food	bacon	barbecue sauce	black tea	blueberries	body spray	...	whole weat flour	whole wheat pasta	whole wheat rice	yams	yogurt cake	tea	water spray	zucchini	napkins	asparagus
0	11.0	18.0	3.0	57.0	5.0	6.0	3.0	9.0	4.0	1.0	...	8.0	95.0	47.0	24.0	31.0	NaN	NaN	NaN	NaN	NaN
1	29.0	10.0	2.0	64.0	5.0	8.0	9.0	31.0	8.0	13.0	...	5.0	68.0	92.0	25.0	38.0	5.0	1.0	10.0	NaN	NaN
2	35.0	12.0	5.0	46.0	4.0	12.0	18.0	15.0	13.0	14.0	...	8.0	33.0	69.0	24.0	32.0	4.0	1.0	2.0	NaN	NaN

3 rows × 120 columns

In [6]:

```
df_sum = df_res.sum()
df_sum = df_sum.sort_values(ascending=False)
```

In [7]:

```
df_sum
```

Out[7]:

```
mineral water    1788.0
eggs             1348.0
spaghetti        1306.0
french fries     1282.0
chocolate        1230.0
                  ...
```

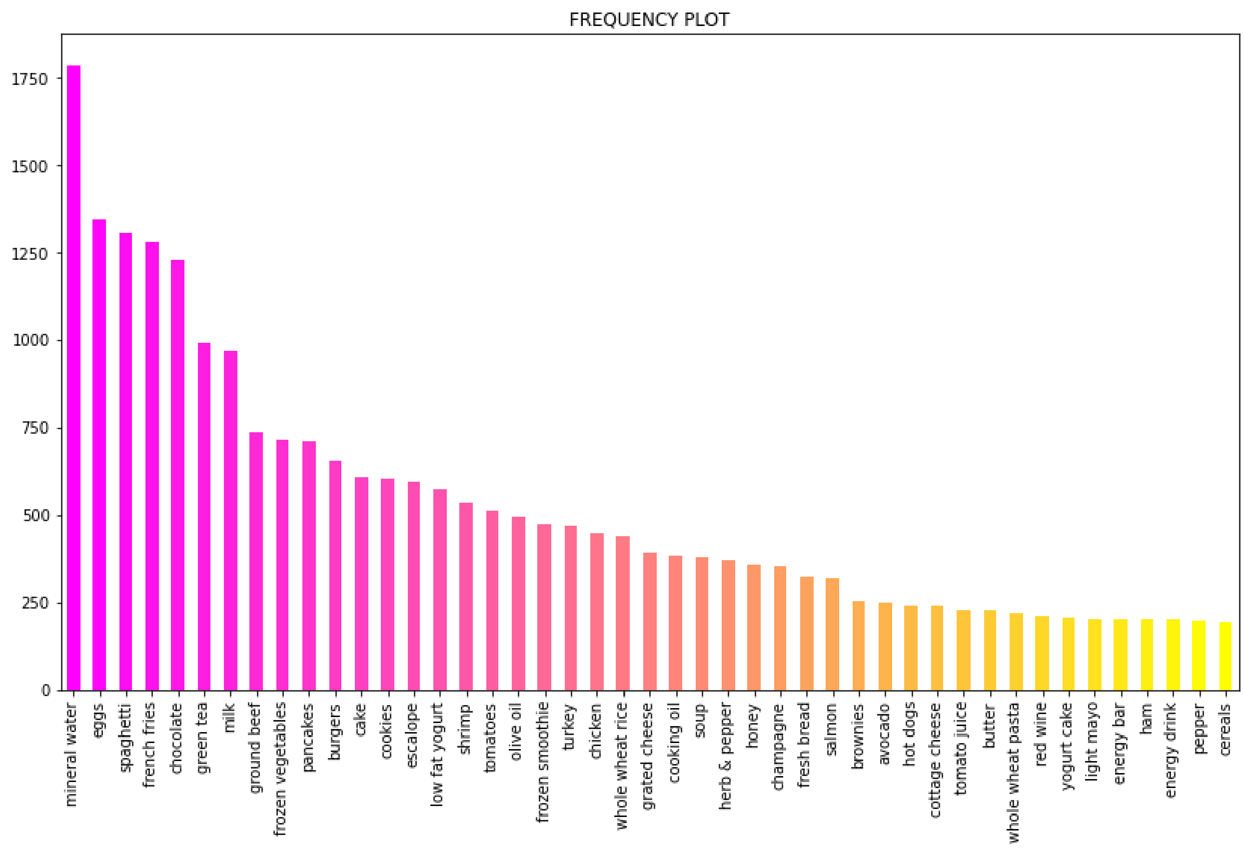
```
bramble            14.0
cream               7.0
napkins             5.0
water spray         3.0
 asparagus          1.0
Length: 120, dtype: float64
```

After counting all values through all columns, we can build a **frequency plot**.

In [8]:

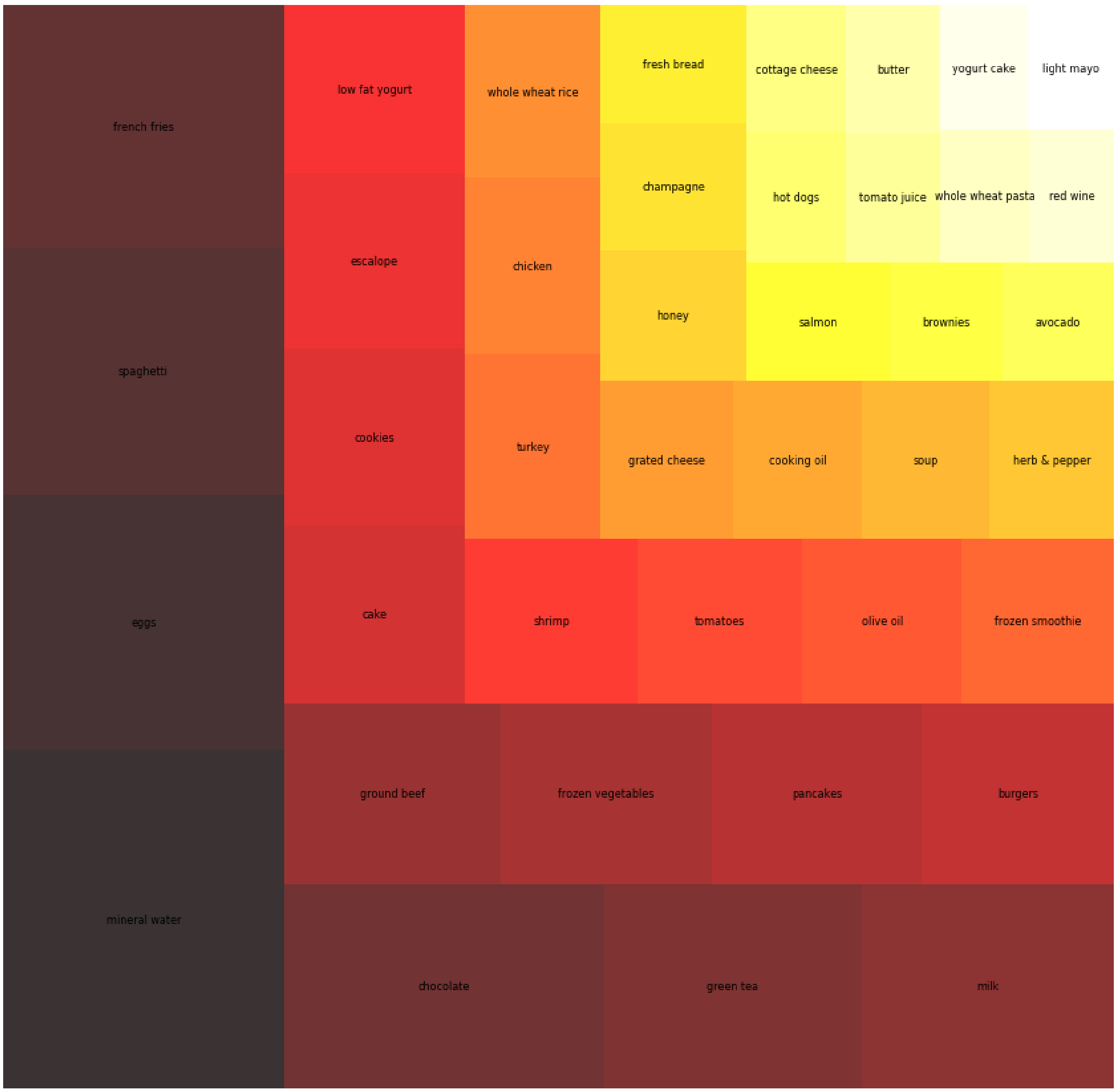
linkcode

```
plt.figure(figsize=(14,8))
plt.title("FREQUENCY PLOT")
cnt = 45 # plot only first 'cnt' values
color = plt.cm.spring(np.linspace(0, 1, cnt))
df_sum.head(cnt).plot.bar(color = color)
plt.xticks(rotation = 'vertical')
plt.grid(False)
plt.axis('on')
plt.show()
```



Also we can frequency plot, but in the form of **heat map**:

```
In [9]:
plt.figure(figsize=(15,15))
cnt = 40 # plot only first 'cnt' values
color = plt.cm.hot(np.linspace(0, 1, cnt))
df_part = df_sum.head(cnt)
squarify.plot(sizes = df_part.values, label = df_part.index, alpha=.8, color = color,
text_kwargs={'fontsize':8})
plt.axis('off')
plt.show()
```



4. Transform data

Before converting dataset to transaction view, we should convert pandas-data to list-data and then list-data to numpy-data.

In [10]:

```
# making each customers shopping items an identical list
arr = []
for i in range(df.shape[0]):
    arr.append([str(df.values[i,j]) for j in range(df.shape[1])])

arr = np.array(arr)
print(arr.shape)
```

```
(7501, 20)
```

And now we can convert our dataset to **transaction view**.

In [11]:

```
te = TransactionEncoder()
data = te.fit_transform(arr)
data = pd.DataFrame(data, columns = te.columns_)
print(data.shape)
```

```
(7501, 121)
```

And then we can check the results:

In [12]:

```
data.head(3)
```

Out[12]:

	asparagus	almonds	antioxydant juice	asparagus	avocado	babies food	bacon	barbecue sauce	black tea	blueberries	...	turkey	vegetables mix	water spray	white wine	whole weat flour	whole wheat pasta	whole wheat rice	yams	yogurt cake	zucchini
0	False	True	True	False	True	False	False	False	False	False	...	False	True	False	False	True	False	False	True	False	False

	asparagus	almonds	antioxydant juice	asparagus	avocado	babies food	bacon	barbecue sauce	black tea	blueberries	...	turkey	vegetables mix	water spray	white wine	whole weat flour	whole wheat pasta	whole wheat rice	yams	yogurt cake	zucchini
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False

3 rows × 121 columns

As we can see, we have **'nan' column**, so we should drop it, because these are just 'not a number' values, which were only empty cells in the original dataset.

In [13]:

```
data = data.drop(columns=['nan'])
data.head(3)
```

Out[13]:

	asparagus	almonds	antioxydant juice	asparagus	avocado	babies food	bacon	barbecue sauce	black tea	blueberries	...	turkey	vegetables mix	water spray	white wine	whole weat flour	whole wheat pasta	whole wheat rice	yams	yogurt cake	zucchini
0	False	True	True	False	True	False	False	False	False	False	...	False	True	False	False	True	False	False	True	False	False
1	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False
2	False	False	False	False	False	False	False	False	False	False	...	False	False	False	False	False	False	False	False	False	False

3 rows × 120 columns

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5. Analyze data with apriori rule

Apriori algorithm assumes that any subset of a frequent itemset must be frequent. Its the algorithm behind Market Basket Analysis. Say, a transaction containing {Grapes, Apple, Mango} also contains {Grapes, Mango}. So, according to the principle of Apriori, if {Grapes, Apple, Mango} is frequent, then {Grapes, Mango} must also be frequent .

Support: Its the default popularity of an item. In mathematical terms, the support of item A is nothing but the ratio of transactions involving A to the total number of transactions. *Support(Grapes) = (Transactions involving Grapes)/(Total transaction)* .

Confidence: Likelihood that customer who bought both A and B. Its divides the number of transactions involving both A and B by the number of transactions involving B. *Confidence(A => B) = (Transactions involving both A and B)/(Transactions involving only A)* .

$$Rule\ X \Longrightarrow Y$$

$$Support = \frac{Frequency\ (X,Y)}{N}$$

$$Confidence = \frac{Frequency\ (X,Y)}{Frequency(X)}$$

$$Lift = \frac{Support}{Support(X)*Support(Y)}$$

So, now we are going to use **apriori rule** to find some dependencies. [Here](#) you can read more about it.

In [14]:

```
freq_rules = apriori(data, min_support = 0.01, use_colnames = True)
freq_rules
```

Out[14]:

	support	itemsets
0	0.020397	(almonds)
1	0.033329	(avocado)
2	0.010799	(barbecue sauce)
3	0.014265	(black tea)
4	0.011465	(body spray)

	support	itemsets
...	...	...
252	0.011065	(ground beef, milk, mineral water)
253	0.017064	(spaghetti, ground beef, mineral water)
254	0.015731	(spaghetti, milk, mineral water)
255	0.010265	(spaghetti, olive oil, mineral water)
256	0.011465	(pancakes, spaghetti, mineral water)

257 rows × 2 columns

So, here we can see all rules, that have minimun support 0.01. If you need **rules with certain length**, we can filter the results:

In [15]:

```
freq_rules['length'] = freq_rules['itemsets'].apply(lambda x: len(x)) # adding
'length' column
freq_rules
```

Out[15]:

	support	itemsets	length
0	0.020397	(almonds)	1
1	0.033329	(avocado)	1

	support	itemsets	length
2	0.010799	(barbecue sauce)	1
3	0.014265	(black tea)	1
4	0.011465	(body spray)	1
...	...	...	...
252	0.011065	(ground beef, milk, mineral water)	3
253	0.017064	(spaghetti, ground beef, mineral water)	3
254	0.015731	(spaghetti, milk, mineral water)	3
255	0.010265	(spaghetti, olive oil, mineral water)	3
256	0.011465	(pancakes, spaghetti, mineral water)	3

257 rows × 3 columns

In [16]:

```
mask = freq_rules['length'] > 1 # creating mask for filtering with certain condition
filtered_freq_rules = freq_rules.loc[mask] # applying mask
filtered_freq_rules # printing the filtering result
```

Out[16]:

	support	itemsets	length
75	0.011598	(avocado, mineral water)	2
76	0.011465	(burgers, cake)	2
77	0.017064	(burgers, chocolate)	2
78	0.028796	(burgers, eggs)	2
79	0.021997	(burgers, french fries)	2
...	...	...	...
252	0.011065	(ground beef, milk, mineral water)	3
253	0.017064	(spaghetti, ground beef, mineral water)	3
254	0.015731	(spaghetti, milk, mineral water)	3
255	0.010265	(spaghetti, olive oil, mineral water)	3
256	0.011465	(pancakes, spaghetti, mineral water)	3

182 rows × 3 columns

So, in the end we can see all rules, which have certain length and which have certain minimum support.

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6. Conclusion

More and more organizations are discovering ways of using market basket analysis to gain useful insights into associations and hidden relationships. As industry leaders continue to explore the technique's value, a predictive version of market basket analysis is making in-roads across many sectors in an effort to identify sequential purchases.

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