

```
In [1]: import pandas as pd
import numpy as np
```

Objective:

From the transaction dataset, recommend which items can be sold/recommended together in a combo.

```
In [2]: df=pd.read_csv(r"C:\Users\kanwar\Downloads\Online_Retail.csv")
```

```
In [3]: df.shape
```

```
Out[3]: (541909, 8)
```

```
In [4]: df.head()
```

```
Out[4]:
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	01/12/10 8:26	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	01/12/10 8:26	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	01/12/10 8:26	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	01/12/10 8:26	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	01/12/10 8:26	3.39	17850.0	United Kingdom

```
In [5]: df.info()
```

```

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
#   Column          Non-Null Count  Dtype
---  ---
0   InvoiceNo        541909 non-null object
1   StockCode        541909 non-null object
2   Description      540455 non-null object
3   Quantity         541909 non-null int64
4   InvoiceDate       541909 non-null object
5   UnitPrice        541909 non-null float64
6   CustomerID       406829 non-null float64
7   Country          541909 non-null object
dtypes: float64(2), int64(1), object(5)
memory usage: 33.1+ MB

```

```
In [6]: ## exclude the return products by excluding the negative unitprice
```

```
In [7]: df[df.UnitPrice<0]
```

```
Out[7]:
```

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
299983	A563186	B	Adjust bad debt	1	12/08/11 14:51	-11062.06	NaN	United Kingdom
299984	A563187	B	Adjust bad debt	1	12/08/11 14:52	-11062.06	NaN	United Kingdom

```
In [8]: df=df[df['UnitPrice']>=0]
```

```
In [9]: df.describe()
```

Out[9]:

	Quantity	UnitPrice	CustomerID
count	541907.000000	541907.000000	406829.000000
mean	9.552281	4.651957	15287.690570
std	218.081560	94.395447	1713.600303
min	-80995.000000	0.000000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

In [10]: `df.Country.value_counts()`

```
Out[10]: Country
United Kingdom      495476
Germany             9495
France              8557
EIRE                8196
Spain               2533
Netherlands         2371
Belgium             2069
Switzerland         2002
Portugal            1519
Australia           1259
Norway              1086
Italy               803
Channel Islands     758
Finland             695
Cyprus              622
Sweden              462
Unspecified         446
Austria             401
Denmark             389
Japan               358
Poland              341
Israel              297
USA                 291
Hong Kong           288
Singapore           229
Iceland             182
Canada              151
Greece              146
Malta               127
United Arab Emirates 68
European Community  61
RSA                 58
Lebanon             45
Lithuania           35
Brazil              32
Czech Republic      30
Bahrain             19
Saudi Arabia        10
Name: count, dtype: int64
```

```
In [11]: ## Main data is from UK, Lets keep one country data for analysis
df=df[df.Country=='United Kingdom']
df.Country.value_counts()
```

Out[11]: Country
United Kingdom 495476
Name: count, dtype: int64

```
In [12]: data=df.groupby(['InvoiceNo','Description'])['Quantity'].sum().unstack().fillna(0)
data.head()
```

Out[12]:

Description	4 PURPLE FLOCK DINNER CANDLES	50'S CHRISTMAS GIFT BAG LARGE	DOLLY GIRL BEAKER	I LOVE LONDON MINI BACKPACK	NINE DRAWER OFFICE TIDY	OVAL WALL MIRROR DIAMANTE	RED SPOT GIFT BAG LARGE	SET 2 TEA TOWELS I LOVE LONDON	SPACEBOY BABY GIFT SET	TOADSTOOL BEDSIDE LIGHT	...	wrongly coded 20713
InvoiceNo												
536365	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
536366	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
536367	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
536368	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0
536369	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0

5 rows × 4202 columns



```
In [13]: data=(data>0).astype('int')
```

```
In [14]: data=data.astype('bool')
```

```
In [15]: ### 22038 invoices and 4202 items
```

```
In [16]: ## Apriori algorithm
```

```
In [17]: pip install mlxtend
```

```
Requirement already satisfied: mlxtend in c:\users\kanwar\anaconda3\lib\site-packages (0.23.4)
Requirement already satisfied: scipy>=1.2.1 in c:\users\kanwar\anaconda3\lib\site-packages (from mlxtend) (1.15.3)
Requirement already satisfied: numpy>=1.16.2 in c:\users\kanwar\anaconda3\lib\site-packages (from mlxtend) (2.1.3)
Requirement already satisfied: pandas>=0.24.2 in c:\users\kanwar\anaconda3\lib\site-packages (from mlxtend) (2.2.3)
Requirement already satisfied: scikit-learn>=1.3.1 in c:\users\kanwar\anaconda3\lib\site-packages (from mlxtend) (1.6.1)
Requirement already satisfied: matplotlib>=3.0.0 in c:\users\kanwar\anaconda3\lib\site-packages (from mlxtend) (3.10.0)
Requirement already satisfied: joblib>=0.13.2 in c:\users\kanwar\anaconda3\lib\site-packages (from mlxtend) (1.4.2)
Requirement already satisfied: contourpy>=1.0.1 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (1.3.1)
Requirement already satisfied: cyclor>=0.10 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (0.11.0)
Requirement already satisfied: fonttools>=4.22.0 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (4.55.3)
Requirement already satisfied: kiwisolver>=1.3.1 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (1.4.8)
Requirement already satisfied: packaging>=20.0 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (24.2)
Requirement already satisfied: pillow>=8 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (11.1.0)
Requirement already satisfied: pyparsing>=2.3.1 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (3.2.0)
Requirement already satisfied: python-dateutil>=2.7 in c:\users\kanwar\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in c:\users\kanwar\anaconda3\lib\site-packages (from pandas>=0.24.2->mlxtend) (2024.1)
Requirement already satisfied: tzdata>=2022.7 in c:\users\kanwar\anaconda3\lib\site-packages (from pandas>=0.24.2->mlxtend) (2025.2)
Requirement already satisfied: six>=1.5 in c:\users\kanwar\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.17.0)
Requirement already satisfied: threadpoolctl>=3.1.0 in c:\users\kanwar\anaconda3\lib\site-packages (from scikit-learn>=1.3.1->mlxtend) (3.5.0)
Note: you may need to restart the kernel to use updated packages.
```

```
In [18]: from mlxtend.frequent_patterns import apriori
```

```
In [19]: ## min_support 2.28 % means the item should be present in atleast 3% of the dataset
frequent_itemsets_plus=apriori(data,min_support=0.02,use_colnames=True).sort_values('support',ascending=False).reset_index(drop=True)
```

```
In [20]: frequent_itemsets_plus['len']=frequent_itemsets_plus['itemsets'].apply(lambda x:len(x))
```

```
In [21]: frequent_itemsets_plus
```

```
Out[21]:
```

	support	itemsets	len
0	0.098285	(WHITE HANGING HEART T-LIGHT HOLDER)	1
1	0.087939	(JUMBO BAG RED RETROSPOT)	1
2	0.076459	(REGENCY CAKESTAND 3 TIER)	1
3	0.072330	(PARTY BUNTING)	1
4	0.063164	(LUNCH BAG RED RETROSPOT)	1
...
237	0.020329	(KNITTED UNION FLAG HOT WATER BOTTLE)	1
238	0.020329	(SMALL HEART MEASURING SPOONS)	1
239	0.020192	(CHOCOLATE THIS WAY METAL SIGN)	1
240	0.020147	(LUNCH BAG SUKI DESIGN , LUNCH BAG CARS BLUE)	2
241	0.020011	(PACK OF 60 SPACEBOY CAKE CASES)	1

242 rows × 3 columns

```
In [22]: frequent_itemsets_plus[frequent_itemsets_plus['len']>2]
```

```
Out[22]:
```

	support	itemsets	len
182	0.02237	(GREEN REGENCY TEACUP AND SAUCER, ROSES REGENCY TEACUP AND SAUCER)	3

```
In [30]: ## what two items we can buy together or reccommend  
from mlxtend.frequent_patterns import association_rules
```

```
In [31]: data.shape
```

```
Out[31]: (22038, 4202)
```

```
In [32]: ass_rules=association_rules(frequent_itemsets_plus,metric='lift',min_threshold=1,num_itemsets=22038).sort_values('lift',ascend
```

```
In [33]: ass_rules
```


Out[33]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_me
0	(PINK REGENCY TEACUP AND SAUCER)	(GREEN REGENCY TEACUP AND SAUCER, ROSES REGENC...	0.031899	0.031809	0.022370	0.701280	22.046810	1.0	0.021356	3.241136	0.986
1	(GREEN REGENCY TEACUP AND SAUCER, ROSES REGENC...	(PINK REGENCY TEACUP AND SAUCER)	0.031809	0.031899	0.022370	0.703281	22.046810	1.0	0.021356	3.262685	0.986
2	(GREEN REGENCY TEACUP AND SAUCER)	(ROSES REGENCY TEACUP AND SAUCER , PINK REGENC...	0.042381	0.024775	0.022370	0.527837	21.304904	1.0	0.021320	2.065442	0.995
3	(ROSES REGENCY TEACUP AND SAUCER , PINK REGENC...	(GREEN REGENCY TEACUP AND SAUCER)	0.024775	0.042381	0.022370	0.902930	21.304904	1.0	0.021320	9.865279	0.975
4	(ROSES REGENCY TEACUP AND SAUCER)	(GREEN REGENCY TEACUP AND SAUCER,	0.043425	0.026182	0.022370	0.515152	19.675752	1.0	0.021233	2.008500	0.995

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_m
		PINK REGENCY...									
...	
83	(ROSES REGENCY TEACUP AND SAUCER)	(REGENCY CAKESTAND 3 TIER)	0.043425	0.076459	0.020601	0.474399	6.204634	1.0	0.017281	1.757115	0.876
84	(PARTY BUNTING)	(SPOTTY BUNTING)	0.072330	0.047237	0.020510	0.283563	6.003045	1.0	0.017093	1.329864	0.898
85	(SPOTTY BUNTING)	(PARTY BUNTING)	0.047237	0.072330	0.020510	0.434198	6.003045	1.0	0.017093	1.639567	0.874
86	(JUMBO BAG RED RETROSPOT)	(LUNCH BAG RED RETROSPOT)	0.087939	0.063164	0.024095	0.273994	4.337842	1.0	0.018540	1.290397	0.843
87	(LUNCH BAG RED RETROSPOT)	(JUMBO BAG RED RETROSPOT)	0.063164	0.087939	0.024095	0.381466	4.337842	1.0	0.018540	1.474552	0.821

88 rows × 14 columns

```
In [36]: ass_rules.iloc[7]
```

```
Out[36]: antecedents      (PINK REGENCY TEACUP AND SAUCER)
consequents    (GREEN REGENCY TEACUP AND SAUCER)
antecedent support      0.031899
consequent support      0.042381
support            0.026182
confidence         0.820768
lift              19.366261
representativity      1.0
leverage           0.02483
conviction          5.342904
zhangs_metric       0.979613
jaccard            0.54434
certainty           0.812836
kulczynski          0.719271
Name: 7, dtype: object
```

```
In [43]: ass_rules[ass_rules['antecedents']=='PINK REGENCY TEACUP AND SAUCER']]
```

Out[43]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	representativity	leverage	conviction	zhangs_me
0	(PINK REGENCY TEACUP AND SAUCER)	(GREEN REGENCY TEACUP AND SAUCER, ROSES REGENC...	0.031899	0.031809	0.022370	0.701280	22.046810	1.0	0.021356	3.241136	0.9860
7	(PINK REGENCY TEACUP AND SAUCER)	(GREEN REGENCY TEACUP AND SAUCER)	0.031899	0.042381	0.026182	0.820768	19.366261	1.0	0.024830	5.342904	0.9796
8	(PINK REGENCY TEACUP AND SAUCER)	(ROSES REGENCY TEACUP AND SAUCER)	0.031899	0.043425	0.024775	0.776671	17.885355	1.0	0.023390	4.283263	0.9757

In []: