## Problem Statement:

You work in XYZ Company as a Python. The company officials want you to write code for Association Rule Mining. Dataset: retail\_dataset.csv

## Tasks To Be Performed:

```
1. Using pandas import the dataset as DataFrame
```

2. Install the mixtend library to use Apriori and association rule mining

3. Using the Apriori algorithm generate a list of items frequently bought together 4. Generate the association rules for the given items from the Apriori algorithm

```
In [1]: import pandas as pd
        from sklearn.preprocessing import MultiLabelBinarizer
        from mlxtend.frequent_patterns import apriori
```

```
from mlxtend.frequent_patterns import association_rules
In [2]: retail_shopping = {'ID': [1,2,3,4,5,6,7,8,9,10], 'Basket': [['Pencils', 'Markers', 'Highlighters', 'Papers'],
```

```
['Markers', 'Erasers'],
['Staplerpins', 'Papers', 'Erasers', 'Cardholders', 'Highlighters'],
['Papers', 'Erasers', 'Cardholders'],
['Markers', 'Postit', 'Erasers'],
['Envelop'],
['Markers', 'Erasers'],
['Pencils', 'Markers', 'Staplerpins', 'Postit', 'Highlighters', 'Papers', 'Erasers'],
['Staplerpins', 'Postit', 'Markers', 'Erasers'],
['Envelop']
```

df = pd.DataFrame(retail\_shopping)

Basket	ID	t[2]:
[Pencils, Markers, Highlighters, Papers]	1	-
[Markers, Erasers]	2	
[Staplerpins, Papers, Erasers, Cardholders, Hi	3	
[Papers, Erasers, Cardholders]	4	
[Markers, Postit, Erasers]	5	
[Envelop]	6	
[Markers, Erasers]	7	
[Pencils, Markers, Staplerpins, Postit, Highli	8	
[Staplerpins, Postit, Markers, Erasers]	9	

In [3]: pip install mlxtend

9 10

Requirement already satisfied: mlxtend in c:\users\roy\anaconda3\lib\site-packages (0.22.0)  $Requirement already satisfied: matplotlib >= 3.0.0 in c: \users \land oy \land an a conda 3 \land lib \land site-packages (from mlxtend) (3.7.0)$ Requirement already satisfied: numpy>=1.16.2 in c:\users\roy\anaconda3\lib\site-packages (from mlxtend) (1.23.5) Requirement already satisfied: setuptools in c:\users\roy\anaconda3\lib\site-packages (from mlxtend) (65.6.3) Requirement already satisfied: pandas>=0.24.2 in c:\users\roy\anaconda3\lib\site-packages (from mlxtend) (1.5.3) Requirement already satisfied: scipy>=1.2.1 in c:\users\roy\anaconda3\lib\site-packages (from mlxtend) (1.10.0) Requirement already satisfied: scikit-learn>=1.0.2 in c:\users\roy\anaconda3\lib\site-packages (from mlxtend) (1.2.1) Requirement already satisfied: joblib>=0.13.2 in c:\users\roy\anaconda3\lib\site-packages (from mlxtend) (1.1.1) Requirement already satisfied: contourpy>=1.0.1 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (1.0.5) Requirement already satisfied: packaging>=20.0 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (22.0) Requirement already satisfied: pillow>=6.2.0 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (9.4.0) Requirement already satisfied: kiwisolver>=1.0.1 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (1.4.4) Requirement already satisfied: pyparsing>=2.3.1 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (3.0.9) Requirement already satisfied: fonttools>=4.22.0 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (4.25.0) Requirement already satisfied: python-dateutil>=2.7 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (2.8.2) Requirement already satisfied: cycler>=0.10 in c:\users\roy\anaconda3\lib\site-packages (from matplotlib>=3.0.0->mlxtend) (0.11.0) Requirement already satisfied: pytz>=2020.1 in c:\users\roy\anaconda3\lib\site-packages (from pandas>=0.24.2->mlxtend) (2022.7) Requirement already satisfied: threadpoolctl>=2.0.0 in c:\users\roy\anaconda3\lib\site-packages (from scikit-learn>=1.0.2->mlxtend) (2.2.0) Requirement already satisfied: six>=1.5 in c:\users\roy\anaconda3\lib\site-packages (from python-dateutil>=2.7->matplotlib>=3.0.0->mlxtend) (1.16.0)

C:\Users\Roy\anaconda3\lib\site-packages\mlxtend\frequent\_patterns\fpcommon.py:110: DeprecationWarning: DataFrame with non-bool types result in worse computationalperformance and their support might be discontinued in the future.Please use a DataFrame with bool type

In [4]: mlb = MultiLabelBinarizer() encoded\_basket = mlb.fit\_transform(df['Basket'])

encoded\_df = pd.DataFrame(encoded\_basket, columns=mlb.classes\_) encoded\_df

Note: you may need to restart the kernel to use updated packages.

[Envelop]

Out[4]:		Cardholders	Envelop	Erasers	Highlighters	Markers	Papers	Pencils	Postit	Staplerpins
	0	0	0	0	1	1	1	1	0	0
	1	0	0	1	0	1	0	0	0	0
	2	1	0	1	1	0	1	0	0	1
	3	1	0	1	0	0	1	0	0	0
	4	0	0	1	0	1	0	0	1	0
	5	0	1	0	0	0	0	0	0	0
	6	0	0	1	0	1	0	0	0	0
	7	0	0	1	1	1	1	1	1	1
	8	0	0	1	0	1	0	0	1	1
	9	0	1	0	0	0	0	0	0	0

In [5]: # Apply Apriori algorithm to find frequent itemsets frequent\_itemsets = apriori(encoded\_df, min\_support=0.2, use\_colnames=True)

frequent\_itemsets

warnings.warn( Out[5]: support itemsets 0 0.2 (Cardholders)

1 0.2 (Envelop) 2 0.7 **3** 0.3 (Highlighters) 4 0.6 (Markers) 5 0.4 (Papers) 6 0.2 (Pencils) 0.3 8 (Staplerpins) 9 0.2 (Cardholders, Erasers) 10 0.2 (Cardholders, Papers) 11 0.2 (Highlighters, Erasers) 12 0.5 (Markers, Erasers) **13** 0.3 (Erasers, Papers) 0.3 14 (Postit, Erasers) **15** 0.3 (Staplerpins, Erasers) 0.2 16 (Markers, Highlighters) **17** 0.3 (Highlighters, Papers) 0.2 18 (Pencils, Highlighters) 19 0.2 (Staplerpins, Highlighters) 0.2 20 (Markers, Papers) 0.2 21 (Markers, Pencils) 0.3 22 (Markers, Postit) 0.2 23 (Markers, Staplerpins) 0.2 24 (Pencils, Papers) 0.2 (Staplerpins, Papers) 25 0.2 26 (Staplerpins, Postit)

(Highlighters, Erasers, Papers) 28 0.2 0.2 29 (Staplerpins, Highlighters, Erasers) 0.3 30 (Markers, Postit, Erasers) **31** 0.2 (Markers, Staplerpins, Erasers) (Staplerpins, Erasers, Papers) 32 0.2

(Cardholders, Erasers, Papers)

27

0.2

**33** 0.2 (Staplerpins, Postit, Erasers) 0.2 (Markers, Highlighters, Papers) 34 0.2 35 (Pencils, Markers, Highlighters) 36 0.2 (Pencils, Highlighters, Papers)

37 0.2 (Staplerpins, Highlighters, Papers) 0.2 38 (Markers, Pencils, Papers) 0.2 39 (Markers, Staplerpins, Postit)

0.2 (Staplerpins, Highlighters, Erasers, Papers) 0.2 (Markers, Staplerpins, Postit, Erasers)

0.2 (Pencils, Markers, Highlighters, Papers) 42

## In [6]: association\_rules\_df = association\_rules(frequent\_itemsets, metric="lift", min\_threshold=1.0)

	asso	ciation_rules_df									
Out[6]:		antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction	zhangs_metric
	0	(Cardholders)	(Erasers)	0.2	0.7	0.2	1.000000	1.428571	0.06	inf	0.375
	1	(Erasers)	(Cardholders)	0.7	0.2	0.2	0.285714	1.428571	0.06	1.12	1.000
	2	(Cardholders)	(Papers)	0.2	0.4	0.2	1.000000	2.500000	0.12	inf	0.750
	3	(Papers)	(Cardholders)	0.4	0.2	0.2	0.500000	2.500000	0.12	1.60	1.000
	4	(Markers)	(Erasers)	0.6	0.7	0.5	0.833333	1.190476	0.08	1.80	0.400
	145	(Highlighters, Papers)	(Markers, Pencils)	0.3	0.2	0.2	0.666667	3.333333	0.14	2.40	1.000
	146	(Pencils)	(Markers, Highlighters, Papers)	0.2	0.2	0.2	1.000000	5.000000	0.16	inf	1.000
	147	(Markers)	(Pencils, Highlighters, Papers)	0.6	0.2	0.2	0.333333	1.666667	0.08	1.20	1.000
	148	(Highlighters)	(Markers, Pencils, Papers)	0.3	0.2	0.2	0.666667	3.333333	0.14	2.40	1.000
	149	(Papers)	(Markers, Pencils, Highlighters)	0.4	0.2	0.2	0.500000	2.500000	0.12	1.60	1.000

150 rows × 10 columns