### **Department of Computer Science and Engineering (Data Science)**

### **Machine Learning – IV**

### **Experiment 6**

Name: Umang Kirit Lodaya SAP ID: 60009200032

Batch: D11

#### Aim:

To implement and comprehend the Apriori algorithm, a fundamental technique for mining frequent itemsets in large datasets.

### Theory:

### **Introduction to Apriori Algorithm:**

- Developed by Agrawal and Srikant, Apriori is a classical algorithm for association rule mining.
- It identifies frequent itemsets by iteratively generating candidates and pruning infrequent ones.

#### **Algorithm Overview:**

#### • Step 1: Candidate Generation

- Generate candidate itemsets of length k from frequent itemsets of length k-1.
- The algorithm starts with frequent individual items and incrementally builds longer itemsets.

#### • Step 2: Pruning

 Eliminate candidates that contain infrequent subsets, as any superset containing an infrequent subset would also be infrequent.

#### Step 3: Counting Support

- Scan the dataset to count the support of each candidate itemset.
- o Discard itemsets below a specified minimum support threshold.

## **Step-by-Step Implementation:**

### • Step 1: Frequent Itemset Generation

- o Implement a function to find frequent itemsets of length 1.
- o Iteratively generate longer itemsets until no more can be formed.

### • Step 2: Candidate Generation

 Write a function to generate candidate itemsets of length k from frequent itemsets of length k-1.

### • Step 3: Pruning

 Implement a pruning mechanism to eliminate candidates with infrequent subsets.

### • Step 4: Support Counting

- Scan the dataset and count the support for each candidate itemset.
- o Discard itemsets below the minimum support threshold.

## • Step 5: Association Rule Generation (Optional)

 If desired, implement a step to generate association rules from the frequent itemsets.

# **Implementation Tips:**

- Efficiently store and index datasets for faster itemset counting.
- Experiment with different minimum support thresholds to observe their impact.

## Lab Experiments to be Performed in This Session:

Execute the Apriori algorithm on a dataset to gain insights into its functionality and operation.

NAME: UMANG KIRIT LODAYA

**SAP ID: 60009200032** 

BATCH: D11

# **APRIORI ALGORITHM**

```
In [1]: import pandas as pd
from itertools import combinations

In [2]: data = {
    "T1": "COKE,FRIES,NUGGETS",
    "T2": "BURGER,COKE,FRIES",
    "T3": "COKE,FRIES,NUGGETS",
    "T4": "BURGER,FRIES,NUGGETS",
    "T5": "BURGER,COKE,FRIES,NUGGETS",
}

data = pd.DataFrame(data.items(), columns = ["TRANSACTIONS",
"ITEMS BOUGHT"])
data["ITEMS BOUGHT"] = data["ITEMS BOUGHT"].apply(lambda x: x.
upper().split(","))
data
```

#### Out[2]:

ITEMS BOUGHT	TRANSACTIONS IT	
[COKE, FRIES, NUGGETS]	T1	0
[BURGER, COKE, FRIES]	T2	1
[COKE, FRIES, NUGGETS]	Т3	2
[BURGER, FRIES, NUGGETS]	T4	3
[BURGER, COKE, FRIES, NUGGETS]	Т5	4

```
In [3]: SUPPORT_THRESHOLD = 2
CONFIDENCE_THRESHOLD = 0.6
```

```
In [4]: | COUNT = {}
        for items in data["ITEMS BOUGHT"]:
            for item in items:
                COUNT[item] = COUNT.get(item, 0) + 1
        pd.DataFrame(COUNT.items(), columns = ["ITEMS", "SUPPORT"])
Out[4]:
              ITEMS SUPPORT
         0
              COKE
                          4
              FRIES
                          5
         1
         2 NUGGETS
                          4
           BURGER
                          3
In [5]: UNIQUE_ITEMS = list(COUNT.keys())
        UNIQUE_ITEMS
Out[5]: ['COKE', 'FRIES', 'NUGGETS', 'BURGER']
In [6]: FREQUENT_ITEMS = []
        for item in UNIQUE_ITEMS:
            if COUNT[item] ≥ SUPPORT_THRESHOLD:
                FREQUENT_ITEMS.append(item)
        FREQUENT_ITEMS.sort()
        FREQUENT_ITEMS
Out[6]: ['BURGER', 'COKE', 'FRIES', 'NUGGETS']
In [7]: | MAX_PICK = len(max(data["ITEMS BOUGHT"], key = lambda x: len
        (x)))
        pick = 2
        while pick ≤ MAX_PICK:
            temp = set()
            possibleItemSets = list(combinations(FREQUENT_ITEMS, pic
        k))
            for itemset in possibleItemSets:
                COUNT[" ".join(itemset)] = 0
                A = set(itemset)
                for items in data["ITEMS BOUGHT"]:
                    B = set(items)
                    if A.intersection(B) == A:
                        COUNT[" ".join(itemset)] += 1
                if COUNT[" ".join(itemset)] ≥ SUPPORT_THRESHOLD:
                    for item in A:
                        temp.add(item)
            FREQUENT_ITEMS = list(temp)
            pick += 1
```

```
In [8]: FINAL_ITEMSET = {}
for k, v in COUNT.items():
    if v \geq SUPPORT_THRESHOLD:
        FINAL_ITEMSET[k] = v

pd.DataFrame(FINAL_ITEMSET.items(), columns = ["ITEMS", "SUPPORT"])
Out[8]:
Out[8]:
```

	HEMS	SUPPORT
0	COKE	4
1	FRIES	5
2	NUGGETS	4
3	BURGER	3
4	BURGER COKE	2
5	BURGER FRIES	3
6	BURGER NUGGETS	2
7	COKE FRIES	4
8	COKE NUGGETS	3
9	FRIES NUGGETS	4
10	COKE NUGGETS FRIES	3
11	COKE BURGER FRIES	2
12	NUGGETS BURGER FRIES	2

```
In [9]: last = -1
FINAL = []
for items in list(FINAL_ITEMSET.keys())[::-1]:
    if last == -1:
        last = len(items)

if len(items) == last:
    FINAL.append(items.split())
FINAL
```

Out[9]: [['NUGGETS', 'BURGER', 'FRIES']]

In [10]: last

Out[10]: 20

```
In [11]: RULES = {}
          for items in FINAL:
              supportItems = COUNT[" ".join(items)]
              for i in range(len(items)):
                  A = list(items[:i] + items[i + 1 :])
                  B = items[i]
                  try:
                       supportA = COUNT[" ".join(A)]
                   except:
                       supportA = COUNT[" ".join(A[::-1])]
                   A = ", ".join(A)
                   RULES[A + " \rightarrow " + B] = round(supportItems / supportA,
          2)
                   supportA = COUNT[B]
                   RULES[B + " \rightarrow " + A] = round(supportItems / supportA,
          2)
In [12]: | pd.DataFrame(RULES.items(), columns = ["RULES", "CONFIDENCE"
Out[12]:
                              RULES CONFIDENCE
          0 BURGER, FRIES -> NUGGETS
                                            0.67
           1 NUGGETS -> BURGER, FRIES
                                            0.50
           2 NUGGETS, FRIES -> BURGER
                                            0.50
          3 BURGER -> NUGGETS, FRIES
                                            0.67
          4 NUGGETS, BURGER -> FRIES
                                            1.00
          5 FRIES -> NUGGETS, BURGER
                                            0.40
In [13]: INTERESTING = []
          for k, v in RULES.items():
              if v ≥ CONFIDENCE_THRESHOLD:
                  INTERESTING.append(k)
          for rule in INTERESTING:
              print(rule)
```

BURGER, FRIES  $\rightarrow$  NUGGETS BURGER  $\rightarrow$  NUGGETS, FRIES NUGGETS, BURGER  $\rightarrow$  FRIES