

Ex.no : 4

ASSOCIATION MINING

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AIM

To implements programs on forming strong association rules using Apriori andFP Growth algorithms.

1. To Form Association Rules based on Apriori Algorithm**Code :**

```
import pandas as pd
from mlxtend.frequent_patterns import apriori, association_rules transactions=[
'I1':[1,0,0,1,1,0,1,1,1],
'I2':[1,1,1,1,0,1,0,1,1],
'I3':[0,0,1,0,1,1,1,1,1],
'I4':[0,1,0,1,0,0,0,0,0],
'I5':[1,0,0,0,0,0,0,1,0]
]
df=pd.DataFrame(transactions) print(df)

# to generate frequent_item sets
frequent_itemsets=apriori(df,min_support=0.2,use_colnames=True) print(frequent_itemsets)
# to form association rules from the obtained frequent itemset
rules=association_rules(frequent_itemsets,metric="confidence",min_threshold=0.2)
print(rules.iloc[:,6])
```

Output :

| | support | itemsets |
|----|----------|--------------|
| 0 | 0.666667 | (I1) |
| 1 | 0.777778 | (I2) |
| 2 | 0.666667 | (I3) |
| 3 | 0.222222 | (I4) |
| 4 | 0.222222 | (I5) |
| 5 | 0.444444 | (I2, I1) |
| 6 | 0.444444 | (I3, I1) |
| 7 | 0.222222 | (I5, I1) |
| 8 | 0.444444 | (I2, I3) |
| 9 | 0.222222 | (I2, I4) |
| 10 | 0.222222 | (I5, I2) |
| 11 | 0.222222 | (I2, I3, I1) |
| 12 | 0.222222 | (I5, I2, I1) |

2. To Apply Apriori Algorithms on dataset contains list of lists

Code :

```
from mlxtend.preprocessing import TransactionEncoder data = [
['milk', 'bread', 'eggs'],
['milk', 'bread'],
['milk', 'diapers', 'beer', 'bread'], ['bread', 'butter'],
['milk', 'diapers', 'bread', 'butter'],
['bread', 'butter', 'beer'],
['milk', 'bread', 'butter']
]
te=TransactionEncoder() te_ary=te.fit(data).transform(data) # creates an num array
transactions=pd.DataFrame(te_ary,columns=te.columns_) #converts it into an dataframe
print(transactions)
```

```
# to generate frequent_item sets
frequent_itemsets=apriori(transactions,min_support=0.3,use_colnames=True)
print(frequent_itemsets)
# to form association rules from the obtained frequent itemset
rules=association_rules(frequent_itemsets,metric="confidence",min_threshold=0.4)
print(rules.iloc[:,6])
```

Output :

| | antecedents | consequents | antecedent support | consequent support | support |
|---|-------------|-------------|--------------------|--------------------|----------|
| 0 | (butter) | (bread) | 0.571429 | 1.000000 | 0.571429 |
| 1 | (bread) | (butter) | 1.000000 | 0.571429 | 0.571429 |
| 2 | (bread) | (milk) | 1.000000 | 0.714286 | 0.714286 |
| 3 | (milk) | (bread) | 0.714286 | 1.000000 | 0.714286 |

| | confidence |
|---|------------|
| 0 | 1.000000 |
| 1 | 0.571429 |
| 2 | 0.714286 |
| 3 | 1.000000 |

3. To Apply FP growth Algorithms on find Association rules

Code :

```
from mlxtend.frequent_patterns
import fpgrowth,association_rules
frequent_itemsets1=fpgrowth(df,min_support=0.2,use_colnames=True)
print(frequent_itemsets1)
rules=association_rules(frequent_itemsets1,metric="confidence",min_threshold=0. 2)
print(rules.iloc[:,6])
```

Output :

| | support | itemsets |
|----|----------|--------------|
| 0 | 0.777778 | (I2) |
| 1 | 0.666667 | (I1) |
| 2 | 0.222222 | (I5) |
| 3 | 0.222222 | (I4) |
| 4 | 0.666667 | (I3) |
| 5 | 0.444444 | (I2, I1) |
| 6 | 0.444444 | (I3, I1) |
| 7 | 0.222222 | (I2, I3, I1) |
| 8 | 0.222222 | (I5, I1) |
| 9 | 0.222222 | (I5, I2) |
| 10 | 0.222222 | (I5, I2, I1) |
| 11 | 0.222222 | (I2, I4) |
| 12 | 0.444444 | (I2, I3) |

4. To include only Disease Category Items In The Consequent in the Association rule

Code :

```

data1 = [
['fever', 'cough', 'sore throat', 'flu'],
['headache', 'nausea', 'migraine'],
['fever', 'rash', 'measles'],
['fever', 'cough', 'sore throat', 'headache', 'flu'], ['nausea', 'vomiting', 'food poisoning'], ['fever', 'rash', 'headache', 'measles'],
['cough', 'sneezing', 'runny nose', 'cold'],
['fever', 'muscle pain', 'fatigue', 'dengue'], ['headache', 'dizziness', 'blurred vision', 'migraine'],
['nausea', 'diarrhea', 'abdominal pain', 'food poisoning']
]
te=TransactionEncoder() te_ary=te.fit(data1).transform(data1) # creates an num array
transactions_d=pd.DataFrame(te_ary,columns=te.columns_) #converts it into an dataframe
print(transactions_d)

frequent_itemsets_d=apriori(transactions_d,min_support=0.2,use_colnames=True)
print(frequent_itemsets_d)
# to extract association rules that contains only disease in the consequent part
rules = association_rules(frequent_itemsets_d, metric="confidence", min_threshold=0.5)
diseases = ['flu', 'migraine', 'measles', 'food poisoning', 'cold', 'dengue'] # Filter rules to only include those with diseases in the consequent
disease_rules = rules[rules['consequents'].apply(lambda x: all(item in diseases for item in x))]
print(disease_rules.iloc[:,6])

```

Output :

| | antecedents | consequents |
|----|----------------|------------------|
| 1 | (cough) | (flu) |
| 10 | (sore throat) | (flu) |
| 12 | (nausea) | (food poisoning) |
| 15 | (headache) | (migraine) |
| 17 | (rash) | (measles) |
| 19 | (cough, fever) | (flu) |

Result :

Thus, the above association mining algorithms has been applied and successfully produced the strong association rules.