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Roll No:-03 Batch:T3

Class: TY(CSE-AIML)

Experiment No. 11

Title :- Implement A-priori algorithm in data mining.

Aim: Demonstrate A-priori algorithm in data mining.

Implementation:

```
from itertools import combinations
# Sample transaction dataset
transactions = [
  ['Milk', 'Bread', 'Butter'],
  ['Beer', 'Bread'],
  ['Milk', 'Bread', 'Butter', 'Beer'],
  ['Milk', 'Bread', 'Butter'],
  ['Bread', 'Butter']
1
# Minimum support threshold
min\_support = 2
# Total number of transactions
num transactions = len(transactions)
# Function to generate candidate itemsets of size k
def generate_candidates(frequent_itemsets, k):
  items = set()
  for itemset in frequent_itemsets:
     items.update(itemset)
  items = sorted(items)
  return [frozenset(comb) for comb in combinations(items, k)]
# Function to get itemsets with support >= min_support
def get_frequent_itemsets(transactions, candidates, min_support):
  itemset counts = {}
  for transaction in transactions:
     transaction = set(transaction)
     for candidate in candidates:
       if candidate.issubset(transaction):
          itemset_counts[candidate] = itemset_counts.get(candidate, 0) + 1
  return [(itemset, count) for itemset, count in itemset_counts.items() if count >= min_support]
# Apriori algorithm implementation
def apriori(transactions, min_support):
  items = set(item for transaction in transactions for item in transaction)
  candidates = [frozenset([item]) for item in items]
  frequent_itemsets = []
```

```
k = 1
  while candidates:
     current_frequent_itemsets = get_frequent_itemsets(transactions, candidates, min_support)
     if not current frequent itemsets:
       break
     frequent itemsets.extend(current frequent itemsets)
     print(f"Frequent itemsets of size {k} (Support > {min support}):")
     for itemset, count in current frequent itemsets:
       print(f"{list(itemset)} : {count}")
     print("-" * 40)
     k += 1
     candidates = generate_candidates([itemset for itemset, _ in current_frequent_itemsets], k)
  return frequent itemsets
# Generate Association Rules
def generate association rules(frequent itemsets):
  print("\nAssociation Rules:")
  for itemset, itemset count in frequent itemsets:
     if len(itemset) >= 2:
       subsets = [frozenset(x) for i in range(1, len(itemset)) for x in combinations(itemset, i)]
       for antecedent in subsets:
          consequent = itemset - antecedent
          if consequent:
            antecedent_count = next((count for i, count in frequent_itemsets if i == antecedent), 0)
            if antecedent_count > 0:
               confidence = itemset count / antecedent count
               support = itemset_count / num_transactions
               consequent count = next((count for i, count in frequent itemsets if i == consequent), 0)
               lift = confidence / (consequent_count / num_transactions) if consequent_count else 0
               print(f"Rule: {list(antecedent)} -> {list(consequent)}")
               print(f"Support: {support:.2f}, Confidence: {confidence:.2f}, Lift: {lift:.2f}")
               print("-" * 50)
# Run the Apriori algorithm
frequent itemsets = apriori(transactions, min support)
# Final Result Output
if not frequent_itemsets:
  print("No frequent itemsets found.")
else:
  print("\n \checkmark Final Frequent Itemsets (Support \geq 2):")
  for itemset, count in frequent_itemsets:
     print(f"{list(itemset)} : {count}")
# Generate and print Association Rules
generate association rules(frequent itemsets)
```

Output:

```
[Running] python -u "e:\ADBS\exp11.py"
Frequent itemsets of size 1 (Support ≥ 2):
['Milk']: 3
['Bread'] : 5
['Butter'] : 4
['Beer'] : 2
Frequent itemsets of size 2 (Support ≥ 2):
['Bread', 'Butter'] : 4
['Milk', 'Bread'] : 3
['Milk', 'Butter'] : 3
['Beer', 'Bread'] : 2
Frequent itemsets of size 3 (Support ≥ 2):
['Milk', 'Bread', 'Butter']: 3
Final Frequent Itemsets (Support ≥ 2):
['Milk']: 3
['Bread'] : 5
['Butter'] : 4
['Beer'] : 2
['Bread', 'Butter']: 4
['Milk', 'Bread'] : 3
['Milk', 'Butter'] : 3
['Beer', 'Bread'] : 2
['Milk', 'Bread', 'Butter'] : 3
```

```
Association Rules:
Rule: ['Bread'] -> ['Butter']
Support: 0.80, Confidence: 0.80, Lift: 1.00
Rule: ['Butter'] -> ['Bread']
Support: 0.80, Confidence: 1.00, Lift: 1.00
Rule: ['Milk'] -> ['Bread']
Support: 0.60, Confidence: 1.00, Lift: 1.00
Rule: ['Bread'] -> ['Milk']
Support: 0.60, Confidence: 0.60, Lift: 1.00
Rule: ['Milk'] -> ['Butter']
Support: 0.60, Confidence: 1.00, Lift: 1.25
Rule: ['Butter'] -> ['Milk']
Support: 0.60, Confidence: 0.75, Lift: 1.25
Rule: ['Beer'] -> ['Bread']
Support: 0.40, Confidence: 1.00, Lift: 1.00
Rule: ['Bread'] -> ['Beer']
Support: 0.40, Confidence: 0.40, Lift: 1.00
Rule: ['Milk'] -> ['Bread', 'Butter']
Support: 0.60, Confidence: 1.00, Lift: 1.25
Rule: ['Bread'] -> ['Milk', 'Butter']
Support: 0.60, Confidence: 0.60, Lift: 1.00
Rule: ['Butter'] -> ['Milk', 'Bread']
Support: 0.60, Confidence: 0.75, Lift: 1.25
Rule: ['Milk', 'Bread'] -> ['Butter']
Support: 0.60, Confidence: 1.00, Lift: 1.25
```

Conclusion: Students are able to implement A-priori algorithm for Data mining