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Title:	Implementation of association mining algorithms like FP
	Growth using languages like JAVA/ python.
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Aim :-To implement the FP-Growth algorithm using Python.

Objective: Understand the working principles of the FP-Growth algorithm and implement it in Python.

Theory

FP-Growth (Frequent Pattern Growth) is an algorithm for frequent item set mining and association rule learning over transactional databases. It efficiently discovers frequent patterns by constructing a compact data structure called the FP-Tree and mining it to extract frequent item sets.

Key Concepts:

- 1. FP-Tree: A data structure that represents the transaction database compressed by linking frequent items in a tree structure, along with their support counts.
- 2. Header Table: A compact structure that stores pointers to the first occurrences of items in the FP-Tree and their support counts.
- 3. Frequent Item Set Mining:
 - Conditional Pattern Base: For each frequent item, construct a conditional pattern base consisting of the prefix paths in the FP-Tree.
 - Conditional FP-Tree: Construct a conditional FP-Tree from the conditional pattern base and recursively mine frequent item sets.

Steps in FP-Growth Algorithm:

- 1. Build FP-Tree: Construct the FP-Tree by inserting transactions and counting support for each item.
- 2. Create Header Table: Build a header table with links to the first occurrences of items in the FP-Tree.
- 3. Mine FP-Tree:
 - Identify frequent single items by their support.
 - o Construct conditional pattern bases and conditional FP-Trees recursively.
 - Combine frequent item sets from conditional FP-Trees to find all frequent item sets.

Example

Given a transactional database:

• Implement the FP-Growth algorithm to find all frequent itemsets with a specified minimum support threshold.

Code

from collections import defaultdict, namedtuple

import itertools

FP-tree node structure

class TreeNode:



```
__init__(self, item, count, parent):
    self.item = item
    self.count = count
    self.parent = parent
    self.children = {}
    self.link = None
  def increment(self, count):
    self.count += count
class FPTree:
  def __init__(self):
    self.root = TreeNode(None, 1, None) # Create the root node
    self.header_table = defaultdict(list) # Header table
  def add_transaction(self, transaction, count):
    current_node = self.root
    for item in transaction:
       if item in current_node.children:
         current_node.children[item].increment(count)
       else:
         new_node = TreeNode(item, count, current_node)
         current_node.children[item] = new_node
         self.header_table[item].append(new_node)
       current_node = current_node.children[item]
```

def conditional_tree(self, base_pattern):



```
conditional_tree = FPTree()
     item_counts = defaultdict(int)
     for node in self.header_table[base_pattern]:
       count = node.count
       path = []
       parent = node.parent
       while parent and parent.item:
          path.append(parent.item)
          parent = parent.parent
       for i in range(count):
          conditional_tree.add_transaction(reversed(path), 1)
          item_counts.update({item: 1 for item in path})
     return conditional_tree, item_counts
def build_fp_tree(transactions, min_support):
  item_count = defaultdict(int)
  for transaction in transactions:
     for item in transaction:
       item_count[item] += 1
  # Remove items that don't meet the min_support threshold
  item_count = {k: v for k, v in item_count.items() if v >= min_support}
```

 $sorted_items = sorted(item_count.items(), key=lambda x: (-x[1], x[0]))$

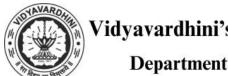


```
def sort_transaction(transaction):
    transaction = [item for item in transaction if item in item_count]
    transaction.sort(key=lambda x: (-item_count[x], x))
    return transaction
  tree = FPTree()
  for transaction in transactions:
    sorted_transaction = sort_transaction(transaction)
    tree.add transaction(sorted transaction, 1)
  return tree, sorted_items
def mine_fp_tree(tree, min_support, prefix):
  patterns = \{\}
  for item, nodes in tree.header_table.items():
    support = sum(node.count for node in nodes)
    if support >= min_support:
       new_pattern = prefix + [item]
       patterns[tuple(new_pattern)] = support
       conditional_tree( item)
       if conditional tree.root.children:
         conditional_patterns = mine_fp_tree(conditional_tree, min_support,
new_pattern)
         patterns.update(conditional_patterns)
```



return patterns

```
def fpgrowth(transactions, min_support):
  fp_tree, sorted_items = build_fp_tree(transactions, min_support)
  return mine_fp_tree(fp_tree, min_support, [])
# Sample usage
if name == " main ":
  transactions = [
     ['milk', 'bread', 'butter'],
     ['beer', 'bread'],
     ['milk', 'bread', 'butter', 'beer'],
     ['bread', 'butter'],
     ['milk', 'bread', 'butter', 'beer'],
  ]
  min_support = 2
  patterns = fpgrowth(transactions, min_support)
  for pattern, support in patterns.items():
     print(f"Pattern: {pattern}, Support: {support}")
Output:
   Pattern: ('bread',), Support: 5
Pattern: ('butter',), Support: 4
Pattern: ('butter', 'bread'), Support: 4
Pattern: ('milk',), Support: 3
Pattern: ('milk', 'bread'), Support: 3
Pattern: ('milk', 'butter'), Support: 3
Pattern: ('milk', 'butter', 'bread'), Support: 3
Pattern: ('milk', 'beer'), Support: 2
Pattern: ('milk', 'beer', 'bread'), Support: 2
```



Pattern: ('milk', 'beer', 'butter'), Support: 2

Pattern: ('milk', 'beer', 'butter', 'bread'), Support: 2

Pattern: ('beer',), Support: 3

Pattern: ('beer', 'bread'), Support: 3 Pattern: ('beer', 'butter'), Support: 2

Pattern: ('beer', 'butter', 'bread'), Support: 2



Conclusion

Explain how FP-Growth manages and mines item sets of varying lengths in transactional databases.

FP-Growth manages and mines itemsets of varying lengths by first building an FP-tree, a compact representation of the transaction database, where frequent items are stored in sorted order and common prefixes are shared. It handles varying-length itemsets by representing each transaction as a path of nodes, with longer itemsets extending deeper in the tree. During mining, the algorithm recursively extracts frequent patterns by constructing conditional FP-trees for each item, progressively building itemsets without generating all possible candidates, ensuring efficiency. This divide-and-conquer approach allows it to mine patterns of different lengths seamlessly.