

T.R. GEBZE TECHNICAL UNIVERSITY FACULTY of ENGINEERING DEPARTMENT of COMPUTER ENGINEERING

FPGROWTH ALGORITHM IMPLEMENTATION

CSE 454 DATA MINING ASSIGNMENT 3 REPORT

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1.DESCRIPTION

1.1.Requirements:

- Read FPGrowth: A Frequent Pattern-Growth approach from the book.
- Implement the approach.

You must use the algorithm mentioned in the book.

You can use any programming language.

Find a dataset to present the results.

You can not use any code from anywhere from internet.

You may use a library for the tree implementation.

You have to implement the assignment by yourself.

1.2.Deadline:

- ***** 03.01.2020 23:55
- You must upload your assignment to moodle.

1.3.Demo:

- ❖ Before 15.01.2021 (Please ask an appointment from me to attend the demo)
- You must present your code in the demo section. If you do not attend the demo section, you will get zero from the assignment, even if you upload your assignment.

2.FPGROWTH ALGORITHM IMPLEMENTATION

What is FPGrowth Approach?

6.2.4 A Pattern-Growth Approach for Mining Frequent Itemsets

As we have seen, in many cases the Apriori candidate generate-and-test method significantly reduces the size of candidate sets, leading to good performance gain. However, it can suffer from two nontrivial costs:

- It may still need to generate a huge number of candidate sets. For example, if there are 104 frequent 1-itemsets, the Apriori algorithm will need to generate more than 107 candidate 2-itemsets.
- It may need to repeatedly scan the whole database and check a large set of candidates by pattern matching. It is costly to go over each transaction in the database to determine the support of the candidate itemsets.

"Can we design a method that mines the complete set of frequent itemsets without such a costly candidate generation process?" An interesting method in this attempt is called frequent pattern growth, or simply FP-growth, which adopts a divide-and-conquer strategy as follows. First, it compresses the database representing frequent items into a frequent pattern tree, or FP-tree, which retains the itemset association information. It then divides the compressed database into a set of conditional databases (a special kind of projected database), each associated with one frequent item or "pattern fragment," and mines each database separately. For each "pattern fragment," only its associated data sets need to be examined. Therefore, this approach may substantially reduce the size of the data sets to be searched, along with the "growth" of patterns being examined. You will see how it works in Example 6.5.

Example 6.5 FP-growth (finding frequent itemsets without candidate generation). We reexamine the mining of transaction database, D, of Table 6.1 in Example 6.3 using the frequent pattern growth approach.

What is the algorithm of the FPGrowth mentioned our book?

Algorithm: FP_growth. Mine frequent itemsets using an FP-tree by pattern fragment growth. Input:

- D. a transaction database:
- min_sup, the minimum support count threshold.

Output: The complete set of frequent patterns.

- 1. The FP-tree is constructed in the following steps:
 - (a) Scan the transaction database D once. Collect F, the set of frequent items, and their support counts. Sort F in support count descending order as \hat{L} , the list of frequent items.
 - (b) Create the root of an FP-tree, and label it as "null." For each transaction Trans in D do the following.

Select and sort the frequent items in Trans according to the order of L. Let the sorted frequent item list in Trans be [p|P], where p is the first element and P is the remaining list. Call insert_tree([p|P], T), which is performed as follows. If T has a child N such that N.item-name = p.item-name, then increment N's count by 1; else create a new node N, and let its count be 1, its parent link be linked to T, and its node-link to the nodes with the same item-name via the node-link structure. If P is nonempty, call insert_tree(P, N)recursively.

2. The FP-tree is mined by calling FP_growth(FP_tree, null), which is implemented as follows. procedure FP_growth(Tree, α)

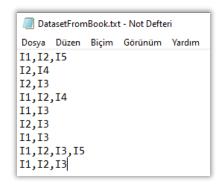
- if Tree contains a single path P then (1)
- for each combination (denoted as β) of the nodes in the path P
- generate pattern $\beta \cup \alpha$ with $support_count = minimum$ support count of nodes in β ;
- (4)else for each ai in the header of Tree {
- (5)
- generate pattern $\beta = a_i \cup \alpha$ with support_count = a_i .support_count; construct β 's conditional pattern base and then β 's conditional FP_tree $Tree_B$; (6)
- (7) if $Tree_{\beta} \neq \emptyset$ then
- call FP_growth($Tree_{\beta}, \beta$); }

Figure 6.9 FP-growth algorithm for discovering frequent itemsets without candidate generation.

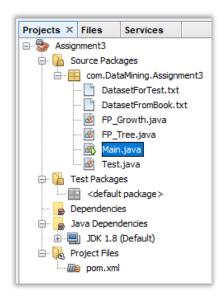
❖ What is the dataset in our book at the Table 6.1?

Table 6.1	Transactional Data for an AllElectronics Branch	
	TID	List of item JDs
	T100	I1, I2, I5
	T200	I2, I4
	T300	12, 13
	T400	I1, I2, I4
	T500	I1, I3
	T600	12, 13
	T700	I1, I3
	T800	11, 12, 13, 15
	T900	11, 12, 13

I used this dataset in my file :



❖ I used Netbeans, and I implemented code in Java programming language :



* My main class:

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Important detail for test :

You should give your own true path when you are testing algorithm.

❖ Test inputs :

D: dataset (Give string filename)

min_sup: minimum support count number (Give integer number)

❖ Test 1.1 Outputs:

Input: Dataset From Book and Minimum Support Number 2

```
TEST 1.1 : Dataset From Book (Table 6.1) with Minimum Support 2
Dataset [D] Items [I]
I1 I2 I5
I2 I4
I2 I3
I1 I2 I4
I1 I3
I2 I3
I1 I3
I1 I2 I3 I5
I1 I2 I3
Items [F] and Frequencies [Count]
I1 : 6
I2 : 7
I3 : 6
I4 : 2
I5 : 2
Sorted List [descending order as L]
I2 : 7
I1 : 6
I3 : 6
I4 : 2
I5 : 2
Removed Items [Count >= Minimum Support Count]
I2 : 7
I1 : 6
I3 : 6
I4 : 2
Mined Frequent Patterns
{ I2 I1 : 4 }
{ I3 I1 : 4 }
{ I3 I2 : 4 }
{ I1 I3 I2 : 2 }
{ I4 I2 : 2 }
{ I5 I1 : 2 }
{ I5 I2 : 2 }
{ I1 I5 I2 : 2 }
```

❖ Test 1.2 Outputs :

Input: Dataset From Book and Minimum Support Number 3

```
TEST 1.2 : Dataset From Book (Table 6.1) with Minimum Support 3
Dataset [D] Items [I]
I1 I2 I5
I2 I4
I2 I3
I1 I2 I4
I1 I3
I2 I3
I1 I3
I1 I2 I3 I5
I1 I2 I3
Items [F] and Frequencies [Count]
I2 : 7
I3 : 6
I4 : 2
Sorted List [descending order as L]
I2 : 7
I1 : 6
I3 : 6
I4 : 2
I5 : 2
Removed Items [Count >= Minimum Support Count]
I2: 7
I1 : 6
I3 : 6
Mined Frequent Patterns
{ I2 I1 : 4 }
{ I3 I1 : 4 }
{ I3 I2 : 4 }
```

❖ Test 2.1 Outputs :

Input: Dataset For Test and Minimum Support Number 2

```
TEST 2.1 : Dataset For Test with Minimum Support 2
Dataset [D] Items [I]
I1 I2 I3
12 13 14
I4 I5
I1 I2 I4
I1 I2 I3 I5
I1 I2 I3 I4
______
Items [F] and Frequencies [Count]
I1: 4
I2 : 5
I3 : 4
I4 : 4
I5 : 2
Sorted List [descending order as L]
12 : 5
I3 : 4
I4 : 4
I5 : 2
Removed Items [Count >= Minimum Support Count]
I1 : 4
I3 : 4
I4 : 4
Mined Frequent Patterns
{ I2 I1 : 4 }
{ I3 I2 : 4 }
{ I3 I1 : 3 }
{ I1 I3 I2 : 3 }
{ I4 I2 : 3 }
{ I4 I1 : 2 }
{ I4 I3 : 2 }
{ I2 I4 I3 : 2 }
{ I1 I4 I2 : 2 }
```

* Test 2.2 Outputs:

Input: Dataset For Test and Minimum Support Number 3

```
TEST 2.2 : Dataset For Test with Minimum Support 3
Dataset [D] Items [I]
I1 I2 I3
I2 I3 I4
I4 I5
I1 I2 I4
I1 I2 I3 I5
I1 I2 I3 I4
Items [F] and Frequencies [Count]
I1:4
I2 : 5
I3 : 4
I4 : 4
I5 : 2
Sorted List [descending order as L]
I2 : 5
I1:4
I3 : 4
I4 : 4
I5 : 2
Removed Items [Count >= Minimum Support Count]
I2 : 5
I1 : 4
I3 : 4
I4 : 4
Mined Frequent Patterns
{ I2 I1 : 4 }
{ I3 I2 : 4 }
{ I3 I1 : 3 }
{ I1 I3 I2 : 3 }
{ I4 I2 : 3 }
```

END OF THE REPORT

UPDATED: 03.01.2021 23:30

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