# ARM

# **Association Rule Mining**

2019111019 - 2019111026

## **Question 1: FP Growth**

## **Optimization Strategy**

#### Bottom Up technique (with removal of redundant paths)

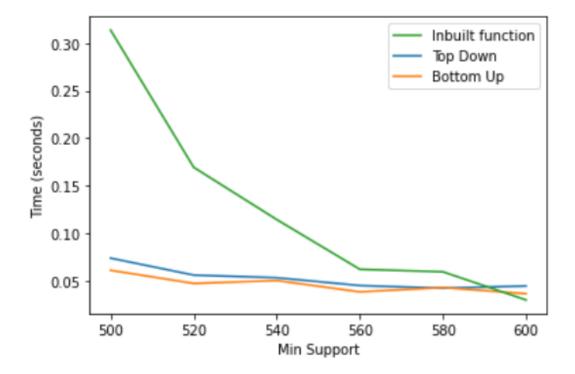
- We traverse through the header linked list of a particular item and then for each node we get its path to the root.
- We have to traverse the itemsets in the opposite order of what the itemsets are ordered.
- We have deleted the part of the path that becomes redundant after the traversal and rather push into the earlier node's conditional pattern base. That is, we have pushed right the branches that have been mined for a particular item to the remaining branch. This is expected to somewhat (minor) speed up the algorithm and the deletion of the redundant path will save up some space.

#### • Top Down technique

- We traverse through the header linked list of a particular item and then for each node apply depth first search for each node to generate the conditional pattern base.
- We have to traverse the itemsets in the same order in which the itemsets were ordered during the building strategy.
- Since only the bottom up approach has been optimized, we expect it to perform better.

#### **OUTPUT AND PLOTS:**

```
/mnt/c/Users/Tushar Choudhary/Desktop/DA/Data-Analytics/Project-2 main *2 !5 ?2 > py 2019111019\ 2019111026\ fpg.py RUNNING FOR TOP DOWN
                TIME: 0.044722557067871094 seconds
MINSUP: 600
MINSUP: 580
                TIME: 0.04230809211730957 seconds
MINSUP: 560
                TIME: 0.04513859748840332 seconds
MINSUP: 540
                TIME: 0.05336594581604004 seconds
MINSUP: 520
                TIME: 0.05614161491394043 seconds
MINSUP: 500
                TIME: 0.07393717765808105 seconds
RUNNING FOR BOTTOM UP
                TIME: 0.03654813766479492 seconds
MINSUP: 600
MINSUP:
        580
                TIME: 0.04297065734863281 seconds
MINSUP:
        560
                TIME: 0.03847551345825195 seconds
MINSUP:
        540
                TIME: 0.05039858818054199 seconds
MINSUP:
        520
                TIME: 0.047370195388793945 seconds
              TIME: 0.06116986274719238 seconds INBUILT LIBRARY
MINSUP:
        500
RUNNING USING
                TIME: 0.029991626739501953 seconds
TIME: 0.05961751937866211 seconds
MINSUP: 600
MINSUP:
        580
MINSUP:
        560
                TIME: 0.06219840049743652 seconds
MINSUP: 540
                TIME: 0.11445021629333496 seconds
MINSUP: 520
                TIME: 0.16938447952270508 seconds
MINSUP: 500
                TIME: 0.31352853775024414 seconds
/mnt/c/Users/Tushar Choudhary/Desktop/DA/Data-Analytics/Project-2 main *2 !5 ?2 >
```



#### **Observations and Inferences**

Bottom Up FP Growth **runs faster** than Top Down strategy for the given dataset. This might be due to the optimization strategy or could be because of implementational differences that such a thing is happening as the run time difference is very small. Top Down FP Growth runs faster than the inbuilt library for the given dataset.

## **Question 2: Apriori**

## **Optimization Strategy**

#### • Hash Mapping

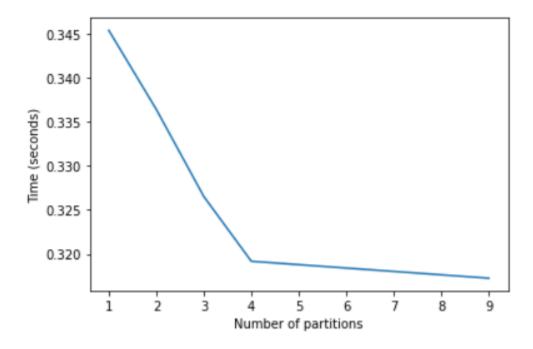
- o Instead of using apriorGen for generating 2-candidate we use a counting procedure and a 2D array.
- We iterate through all the transitions and remove the non frequent 1-itemsets from the transaction . For each transaction we then form all the 2 candidates and increment their count in a 2d map.
- The ones whose bucket has a count >=minSupport is a 2-candidate

#### Partitioning

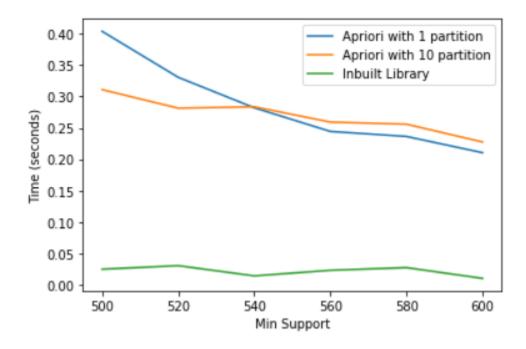
 Here, for calculating the frequent item sets, we have first partitioned the original dataset and checked if a set is frequent in any of the partitions. If an item set is not frequent in any of the partitions, then it can't be frequent in the complete dataset either.
 Hence, such item sets have been scrapped.

#### **OUTPUT AND PLOTS:**

#### Plot for Time vs Number of partitions:



#### Plot for support vs time:



#### **Observations:**

Partitioning technique produces a little improvement and runs faster when the number of frequent itemsets are high (that is, **when minimum support is low**). However, **when the minimum support is high**, the number of frequent itemsets is low, and the algorithms waste time when scanning the partitions individually (as not many item sets are to be found, we can scan the whole dataset at once) and give higher runtime compared to the naive approach.

Also, the hashing technique produces significant improvement compared to the naive approach.

## **Combined Analysis**

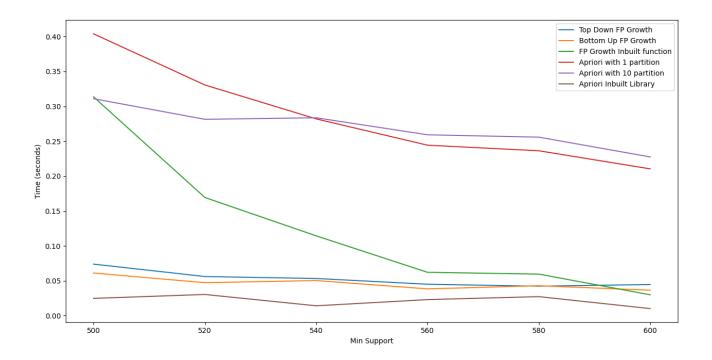
### For the Apriori Algorithm

- Hashing technique **produces improvement**: This is because in the Apriori algorithm the bottleneck happens at the 2-candidate and 2-itemset generation and hashing technique is targeting that very step and trying to optimize that step itself
- Apriori is **most steep** with respect to support. If a lower support leads to huge number of frequent itemsets then apriori tends to become very slow which tells us that it is not a very good algorithm for frequent itemset mining
- If the number of unique elements are large then the 2-itemset 2-candidate generation becomes very slow since it is O(n^2) with respect to the number of unique elements

### For the FP growth Algorithm

• It looks like that Bottom Up FP growth **is producing results better** than the Top Down FP growth. This might be due to the optimization strategy or could be because of implementational differences that such a thing is happening as the run time difference is very small.

## Plots for FP Growth and Apriori:



From here we can see that FP growth with bottom up strategy is giving the best run time and apriori without partitioning is giving the highest runtime among all the algorithms. Also, do notice that apriori algorithms are most steep with respect to the minimum support.

Dataset source: https://www.philippe-fournier-viger.com/spmf/datasets/SIGN.txt