Mining Association Rules From Time Series Data Using Hybrid Approaches

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Abstract:
Due to the frequent appearance of time series data in various fields, it has always been an essential and interesting research field. A time series analysis involves the methods for analyzing time series data, in order to mine meaningful and other relevant characteristics of the data. In most cases, time series data are quantitative values, so to come up with an intellectually appealing data mining algorithm to deal with quantitative type of data presents a biggest challenge to researchers in this field. In this paper, an extended Fuzzy Frequent Pattern (FP) growth approach is proposed and analyzed against the existing approach called Fuzzy Apriori (FA).

Keywords: Conditional Pattern Base, Fuzzy Apriori, Frequent Pattern, Fuzzy Logic, Genetic Algorithm , Neural Network and Frequent Pattern tree.

1. Introduction

Time series is defined as a series of well defined data values of a variable at successive time interval. The applications of time series includes FP analysis, predictions etc. FP analysis in time series data has become one of the most vital parts of data mining tasks and has attracted extreme interest among the researchers.Many approaches are available to examine time series data such as the Genetic Algorithm (GA), statistical methods etc. But the outputs of these approaches are difficult to understand/interpret the quantitative results. Apriori is the classic algorithm of association rules which determine the number of frequent items proposed by Agrawal et. al [6]. But uncertain time series are difficult to be dealt with this approach. So the fuzzy sets are used, in order to handle uncertain time series data. Fuzzy sets are the sets containing degrees of membership. Fuzzy set theory was introduced by L.A.Zadeh et. al [1] and this approach was followed by Hong et. al [2], [3], [4] and proposed several fuzzy algorithms to extract quantitative data and to mine meaningful association rules. The fuzzy mining algorithm integrates the concept of Apriori algorithm as well as fuzzy concepts.

However, in the Apriori algorithm, candidate generation suffers from significant costs such as: it may need to generate a huge number of candidate sets as well as it needs to scan the database repeatedly and to check a large set of candidates using pattern matching. This would be a tedious workload to go over each transaction in the database to determine the support value of candidate item sets. The approach to mine complete set of frequent item sets without candidate generation is one of the important motivations and also to generate efficient and scalable method for mining both long and short frequent patterns. An approach based on FP-Growth to find fuzzy association rules is proposed by Papadimitriou et. al [5]. In this approach each value in the transactions are transferred into two corresponding fuzzy regions. A support value is set and those fuzzy regions in the transaction which doesn’t meet or exceed the predefined support would be removed. Here only the frequent fuzzy 1-itemsets obtained from each transaction are used for extracting. The expression of the fuzzy items with more fuzzy regions is successive. No fuzzy operation is used to combine the regions together. However, this made the rules mined to be difficult to interpret. The proposed extended Fuzzy FP growth approach overcomes this limitation to a certain extend. In this paper, an extended FP growth approach has been proposed and evaluated against the existing approach FA. It is an interesting method used for mining frequent item sets. The remainder of this paper is organized as follow: Section 2 describes the related works. Section 3 presents the hybrid approach using FA technique. Section 4 presents fuzzy FP-growth approach. Section 5 describes the experimental results. Finally, conclusion is discussed in Section 6.

2. Related Works

In this section some related concepts and algorithms are discussed such as: Apriori algorithm, FP-growth algorithm and Fuzzy set theory.

A. Apriori algorithm

The classic algorithm for mining frequent item sets and for learning association rule over the transactional database was proposed as Apriori algorithm by Agrawal et. al [6]. The algorithm involves two steps. Firstly, it find out the frequent item sets which exceeds or satisfies the minimum support. Secondly, the rules are generated which satisfies the minimum confidence value. In this algorithmic method, the database is scanned repeatedly in order to generate all frequent item sets. It would be costly to go over each transaction and to count the support for each candidate item set. Also this approach generates huge number of candidate sets.

B. Frequent Pattern –Growth algorithm

One of the interesting methods to extract frequent item sets is FP-Growth algorithmic method and this is proposed by Han et. al [3]. The proposed algorithm does not require the candidate generations. The extraction of frequent patterns using Apriori is not efficient since it requires the repeated scanning of database and may need to generate large candidate item sets. In order to overcome this, an extended FP-Growth algorithm is used. The Approach involves several steps: First it scans the database to obtain all items with their corresponding support count. The items which exceed or satisfy the predefined minimum support are selected as the frequent 1-itemsets. Next step is to arrange the frequent 1-itemsets according to the decreasing order of their support count. Finally, the database is scanned again to construct the FP tree. All transactions are processed bottom up one by one and after processing all the transactions, a complete FP tree is constructed. Once the tree is constructed, FP-Growth procedure is executed to obtain all frequent item sets. FP growth generates the frequent patterns directly from the FP tree instead of candidate generation (C.W. Lin et.al [8]). For each frequent item, a conditional FP tree would be generated and the corresponding frequent item sets are derived from the same.

C. Fuzzy set theory

The word fuzzy means vagueness. Fuzzy sets have been introduced by Lotif A. Zadeh [1]. It is actually an extension of the classic set theory which defines the set membership as possibility distribution.

The rule for the fuzzy set theory can be expressed as:

$$f : [0, 1]^{X} = [0, 1] \qquad (1)$$

Here "x" number of possibilities may occur.

A logic based on the truth values such as "true" and "false" would be sometimes inadequate while describing the human reasoning. Fuzzy logic uses the entire interval between 0 (false) and 1(true) for describing human reasoning.

3. Fuzzy Apriori Approach

The FA approach integrates the concept of Fuzzy as well as Apriori algorithm. The architecture for the FA approach implemented by C.H.Chen.et al [9] is shown in fig 1.

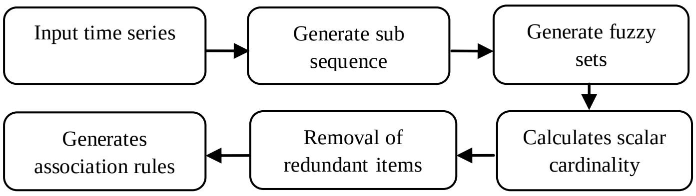

Fig 1: Architectural diagram of FA approach

The architecture describes the procedures for generating rules using FA algorithm. First, the time series data has been taken as input and from the given time series data, the subsequences of any length according to the sliding window size are generated. After the subsequence generation, each data point of the subsequences is transformed into fuzzy set. The total count or scalar cardinality of the corresponding fuzzy set based on the membership function is obtained. Frequent candidate sets are generated based on this support value which exceeds or satisfies the predefined support value. Pruning processes has been applied to filter away irrelevant large candidate sets. Finally the association rules are generated.

4. Fuzzy Frequent Pattern Growth Approach

The proposed approach uses the concept of fuzzy set and FP-growth approach to generate the frequent item sets without any candidate generation. The architecture for the proposed fuzzy FP-growth approach for time series data is shown in fig 2.

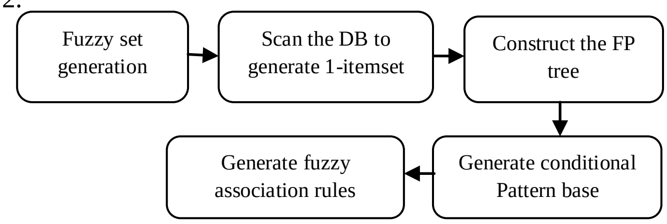

Fig 2: Architectural diagram of Fuzzy FP-growth approach

The approach uses the transformed fuzzy set for generating frequent patterns. It involves different phases. First step is to construct FP-tree from a database and from the resulting FP-tree, frequent patterns are generated. FP tree construction involves several steps such as: Scanning the databases to generate 1-itemset then rescanning to establish FP tree. Next generating conditional pattern base and corresponding conditional FP tree respectively. Finally fuzzy association rules are generated as proposed by C.W. Lin et. al [8].

5. Experimental Analysis

The Hybrid approach using both fuzzy concept and apriori algorithm is an efficient method for handling time series data to find linguistic association rules proposed by C.H. Chen et. al [9], A.M Palacious et. al [10]. Home price time series data over the years from 1999 to 2012 period has been used for analyzing the performance of the existing FA approach against the proposed Fuzzy FP growth approach [16]. The home price time series used for analyzing these two hybrid approaches are shown in table1.

Table 1: Home price time series data used as input

Years	Home price	Years	Home price
1999	127	2006	124
2000	129	2007	118
2001	132	2008	121
2002	130	2009	120
2003	126	2010	115
2004	132	2011	113
2005	129	2012	119

A. FA Method Analysis

The time series data is first transformed into subsequences according to the predefined window size, which could be of any length. Here in this example, window size is set as 5. So the total subsequence transactions will be 10 (T1, T2….T10) according to the formula (total length of time series – window size + 1). The transactions of subsequences generated are shown in table 2.

Table 2: Transaction of subsequences

TID	Transaction	TID	Transaction
T1	127,129,132,130,126	T6	132,129,124,118,121
T2	129,132,130,126,132	T7	129,124,118,121,120
T3	132,130,126,132,129	T8	124,118,121,120,115
T4	130,126,132,129,124	T9	118,121,120,115,113
T5	126,132,129,124,118	T10	121,120,115,113,119

After transforming the time series data into subsequences, the data points in each subsequence are converted to fuzzy values according to predefined membership function. The membership values used are Low, Middle and High and is used for the transformation of fuzzy sets from the given time series. The representation of membership function is given in fig 3.

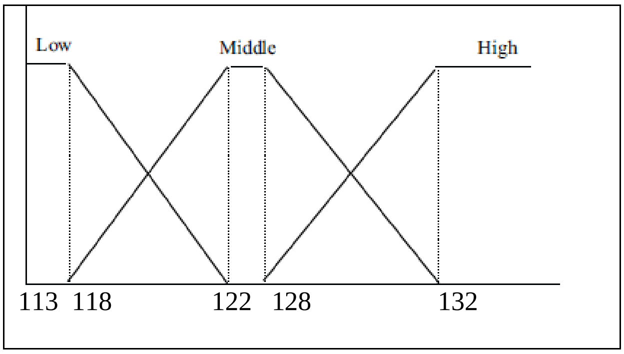

Fig 3: Membership function

The fuzzy values of each subsequence are shown in table 3. Each data point (A1, A2 …An) in the transaction each subsequence will take the value of low (L), middle (M) and high (H).

Table 3: Fuzzy set transformed from time series

T	A1 L	A1 M	A1 H	A2 L	A2 M	A2 H	A3 L	A3 M	A3 H	A4 L	A4 M	A4 H	A5 L	A5 M	A5 H
T1	0	1	0	0	0.67	0.33	0	0	1	0	0	0	0	1	0
T2	0	0.67	0.33	0	0	1	0	0	0	0	1	0	0	0	1
T3	0	0	1	0	0	0	0	1	0	0	0	1	0	0.67	0.33
T4	0	0	0	0	1	0	0	0	1	0	0.67	0.33	0	1	0
T5	0	1	0	0	0	1	0	0.67	0.33	0	1	0	1	0	0
T6	0	0	1	0	0.67	0.33	0	1	0	1	0	0	0.67	0.33	0
T7	0	0.67	0.33	0	1	0	1	0	0	0.67	0.33	0	0.67	0.33	0
T8	0	1	0	1	0	0	0.67	0.33	0	0.67	0.33	0	1	0	0
T9	1	0	0	0.67	0.33	0	0.67	0.33	0	1	0	0	1	0	0
T10	0.67	0.33	0	0.67	0.33	0	1	0	0	1	0	0	0.67	0.33	0
Total	1.67	4.67	2.66	2.34	4	2.66	3.34	3.33	2.33	4.34	3.33	1.33	5.01	3.66	1.33

The total count or scalar cardinality has been calculated from the fuzzy set generated and is calculated as its count value. After the calculation, fuzzy items generated are collected as the 1-itemset [13], [14], [15]. The total count is then checked against the support value, which is predefined. Here in this example, support value is set as 30%. The item set whose values are greater than or equal to 30% has been taken and are the following: A1.Middle, A2.Middle, A3.Low, A3.Middle, A4.Low, A4.Middle, A5.Low, and A5.Middle. The 1-itemsets are represented in table 4:

Table 4: The 1-itemset generated with total count

1-Itemset	Total	1-Itemset	Total	1-Itemset	Total
A1.Middle	0.467	A2.Middle	0.4	A3.Low	0.334
A3.Middle	0.333	A4.Low	0.434	A4.Middle	0.333
A5.Low	0.501	A5.Middle	0.366	-	-

After the generation of 1-itemsets, corresponding 2-itemsets are obtained. The fuzzy items with the same attribute Ai are not put in to 2-itemset collection. The resulting 2-itemsets generated are shown in the table 5.

Table 5: The resulting 2-itemset satisfy the support

2-itemset	Total
A1.Middle ∩ A5.Low	3
A3.Low ∩ A4.Low	3.01
A4.Low ∩ A5.Low	3.68

The association rules thus generated from the 2-itemsets with corresponding confidence values are shown in table 6:

Table 6: The Association rules with confidence values

Final Rule	Confidence
A1.Middle,A5.Low	0.64
A3.Low, A4.Low	0.9
A4.Low, A5.Low	0.84

The confidence value of the above association rules are calculated using the formula given below:

$$Confidence = \frac{\text{Support(item.a U item.b)}}{\text{Support (item.a)}} \qquad (2)$$

The confidence value of rule is then compared with the predefined confidence threshold. The rule obtained here means that "if the value of a data point is low at the third time units then the value of a data point after fourth time units will also be low with a high probability". Though the rule generated is useful to understand the corresponding time series data, the amount of effort required to generate the rules are more as candidate generation is more costly in time. In order to avoid the limitations of FA, the Fuzzy FP-Growth approach has been implemented and evaluated against FA approach.

B. FP-Growth Method Analysis

The Fuzzy FP–Growth approach is analyzed using the same home price time series data. The case study results of fuzzy FP growth approach are explained in table 7:

Table 7: Transactions and corresponding items

TID	Items
T1	(A1:127)(A2:129)(A3:132)(A4:130)(A5:126)
T2	(A1:129)(A2:132)(A3:130)(A4:126)(A5:132)
T3	(A1:132)(A2:130)(A3:126)(A4:132)(A5:129)
T4	(A1:130)(A2:126)(A3:132)(A4:129)(A5:124)
T5	(A1:126)(A2:132)(A3:129)(A4:124)(A5:118)
T6	(A1:132)(A2:129)(A3:124)(A4:118)(A5:121)
T7	(A1:129)(A2:124)(A3:118)(A4:121)(A5:120)
T8	(A1:124)(A2:118)(A3:121)(A4:120)(A5:115)
T9	(A1:118)(A2:121)(A3:120)(A4:115)(A5:113)
T10	(A1:121)(A2:120)(A3:115)(A4:113)(A5:119)

Each value of the transaction items are transformed in to fuzzy sets using this membership function. The fuzzy set transformed from the data is represented in table 8:

Table 8: Fuzzy sets generated from home price time series data

Tid	Items
T1	(1/A1Middle)(0.67/A2Middle+0.33/A2High)(1/A3High)(1/A5Middle)
T2	(0.67/A1Middle+0.33/A1High)(1/A2High) (1/A4Middle)(1/A5High)
T3	(1/A1High)(1/A3Middle)(1/A4High) (0.67/A5Middle+0.33/A5High)
T4	(1/A2Middle)(1/A3High)(0.67/A4Middle+0.33/A4High) (1/A5Middle)
T5	(1/A1Middle)(1/A2High)(0.67/A3Middle+0.33/A3High)(1/A4Middle)(1/A5Low)
T6	(1/A1High)(0.67/A2Middle+0.33/A2High) (1/A3Middle)(1/A4Low) (0.67/A5Low +0.33/A5Middle)
T7	(0.67/A1Middle+0.33/A1High)(1/A2Middle)(1/A3Low)(0.67/A4Low+0.33/A4Middle) (0.67/A5Low+ 0.33/A5Middle)
T8	(1/A1Middle)(1/A2Low)(0.67/A3Low+0.33/A3Middle)(0.67/A4Low+0.33/A4Middle) (1/A5Low)
T9	(1/A1Low)(0.67/A2Low+0.33/A2Middle)(0.67/A3Low+0.33/A3Middle)(1/A4Low) (1/A5Low)
T10	(0.67/A1Low+0.33/A1Middle)(0.67/A2Low+0.33/A2Middle)(1/A3Low)(1/A4Low) (0.67/A5Low+0.33/A5Middle)

The counts of all fuzzy regions are calculated. For example, in the case of A1.Low the total count will be 1+0.67=1.67. Likewise the steps are repeated for other regions. The corresponding results are shown in table 9.

Table 9: The scalar cardinality of each fuzzy region

Item	Count	Item	Count
A1.Low	1.67	A3.High	2.33
A1.Middle	4.67	A4.Low	4.34
A1.High	2.66	A4.Middle	3.33
A2.Low	2.34	A4.High	1.33
A2.Middle	2.66	A5.Low	5.01
A2.High	4	A5.Middle	3.66
A3.Low	3.34	A5.High	1.33
A3.Middle	3.33	-	-

The fuzzy region with the maximum count among the three possible regions for each item is selected. Take A1 as an example. Its count is 1.67 for low, 4.67 for middle and 2.66 for high. Since the count for middle is the maximum among three counts, the region middle is thus used to represent item A1 in the later mining process. This step would be repeated for the other items. The count of any region selected is checked against with the predefined minimum support value. Here support value assumed as 30%. That means (10*30%=3.0). The table 10 shows the set of frequent fuzzy region. Here every region satisfies the support 30%.

Table10: Frequent Fuzzy regions and count

Frequent fuzzy regions	Count
A1. Middle	4.67
A2.Middle	4
A3.Low	3.34
A4.Low	4.34
A5.Low	5.01

After finding the regions with higher counts, the header table is arranged based on the decreasing order of the support count. It is shown in table 11:

Table 11: The header table of the regions

Frequent fuzzy regions	Count
A5.Low	5.01
A1.Middle	4.67
A4.Low	4.34
A2.Middle	4
A3.Low	3.34

The fuzzy regions which are not in the header table are removed from each transaction [11]. The remaining fuzzy regions in each transaction are then sorted according to the membership values in a descending order. This is shown in table 12.

Table 12: The transactions transformed with the fuzzy regions

Tid	Frequent fuzzy region
T1	(1/A1Middle)(0.67/A2Middle)
T2	(0.67/A1Middle)
T3	0
T4	(1/A2Middle)
T5	(1/A1Middle)(1/A5Low)
T6	(0.67/A2Middle)(1/A4Low)(0.67/A5Low)
T7	(0.67/A1Middle)(1/A2Middle)(0.67/A4Low)(0.67/A5Low)
T8	(1/A1Middle)(0.67/A4Low)(1/A5Low)
T9	(0.33/A2Middle)(1/A4Low)(1/A5Low)
T10	(0.33/A1Middle)(0.33/A2Middle)(1/A4Low)(0.67/A5Low)

After this step, the transactions with only the sorted frequent fuzzy regions selected which are shown in table 13:

Table 13: The transactions with sorted the fuzzy regions

TID	Frequent fuzzy region
T1	(1/A1Middle)(0.67/A2Middle)
T2	(0.67/A1Middle)
T3	0
T4	(1/A2Middle)
T5	(1/A1Middle)(1/A5Low)
T6	(1/A4Low)(0.67/A2Middle)(0.67/A5Low)
T7	(1/A2Middle)(1/A3Low)(0.67/A1Middle)(0.67/A4Low)(0.67/A5Low)
T8	(1/A1Middle)(1/A5Low)(0.67/A3Low)(0.67/A4Low)
T9	(1/A4Low)(1/A5Low)(0.33/A2Middle)(0.67/A3Low)
T10	(1/A4Low)(1/A3Low)(0.67/A5Low)(0.33/A1Middle)(0.33/A2Middle)

All transactions up to 10 are inserted in the fuzzy FP tree [12]. In the FP tree representation, header table is shown in the left side and it contains the frequent Fuzzy Regions (FR) and their supporting count. The final fuzzy FP tree is shown in figure 4.

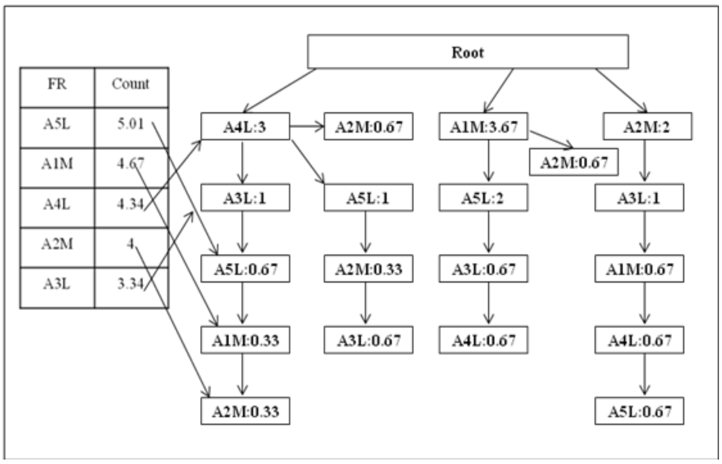

Fig 4: The Complete FP tree

While processing the items from bottom of the header table, first item would be **A3L**: the traversal from which **A3L** exist are:

1) (A4L:3)(A3L:1)
2) (A4L:3)(A5L:1)(A2M:0.33)(A3L:0.67)
3) (A1M:3.67)(A5L:2)(A3L:0.67)
4) (A2M:2)(A3L:1)

Table 14: The frequent item sets with A3L

1-Item	2-Item	3-Item
A5L:5.01	A4L, A3L:1.67	A1M, A5L, A3L:0.67
A1M:4.67	A5L, A3L:1.34	A4L, A5L, A3L:0.67
A4L:4.34	A2M, A3L:1.33	A5L, A2M, A3L:0.33
A2M:4	A1M, A3L:0.67	-
A3L:3.34	-	-

Here in this example taking the intersection (minimum) of items to obtain 2-itemset and 3-itemsets. For eg: A4L:3 and A3L:1 means1 (taking the smaller value or minimum operator) and then if the same transaction occurs again, it would be incremented with the corresponding value. Likewise all regions in the header table should be processed and frequent item sets are generated. On processing the items bottom up from the header table, corresponding item sets are obtained. Same item sets from all transactions are taken together and their count is evaluated using the intersection (minimum operator). From the corresponding item sets of all transactions, those exceed or meet the support count are chosen as the rules. The rules obtained are shown in table 15 and are similar to the rules generated by FA approach.

Table 15: The final rules generated

Final Rules	Count
A1.Middle,A5.Low	3
A3.Low, A4.Low	3
A4.Low, A5.Low	3.01

The two hybrid approaches are implemented in VB.NET at a personal computer with Intel Core i3, 2.10 GHZ and 4GB RAM. The data set used is the home price time series data over the period of 1999 to 2012. The sliding window size is predefined as 5. The experimental result shows the FA approach require more number of scans for each transaction compared to the proposed approach. In the case of FA approach, for 20 support value it requires 1001 total number of scans. Likewise for 25 support value, it requires a total scan of 539 and for 30, it requires 275 total scans. Whereas FP approach requires only 11 times total number of scans for each transaction. This is one of the major advantages of the proposed approach over FA approach. The graphical representation of number of scans required for both the approaches shown in the fig 5.

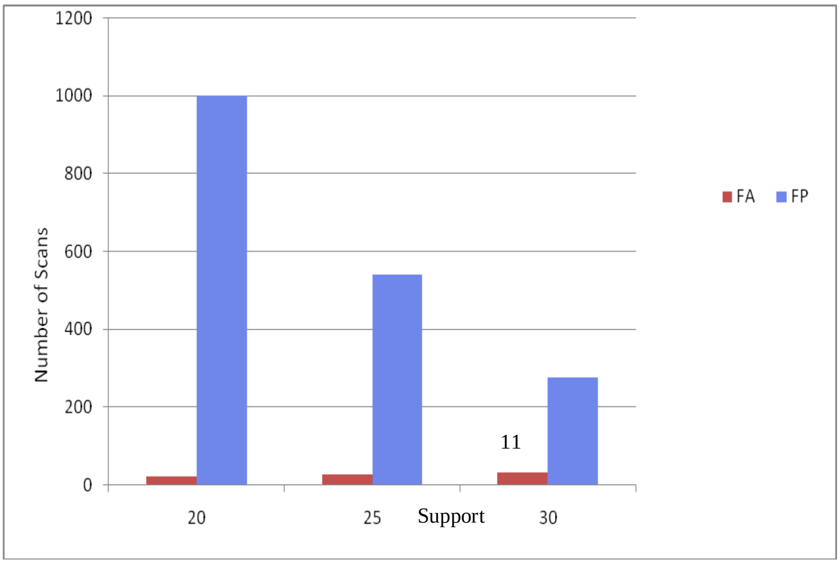

Fig 5: The graphical representation of number of scans

The execution time required for the proposed approach is less than FA approach. This is another benefit. The graph showing the execution time required for both the approaches are shown in fig 6.

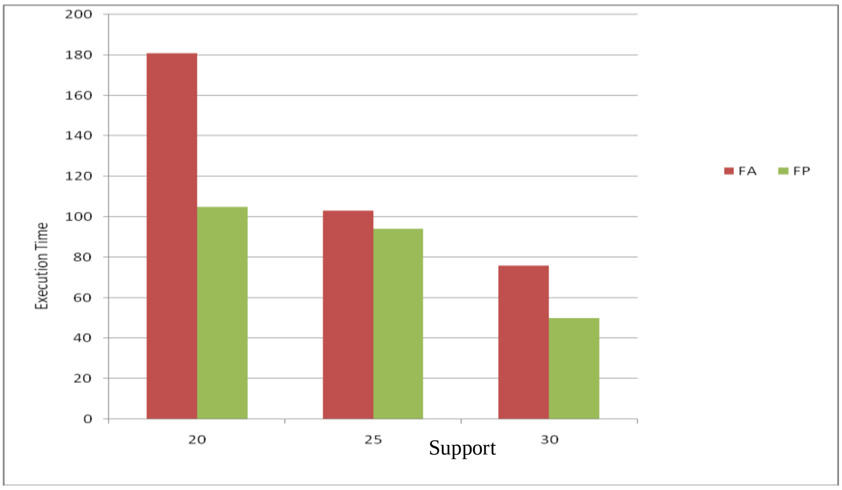

Fig 6: The graphical representation showing execution time

6. Conclusion

The paper discusses about two different hybrid approaches. The main aim of this analysis is to explore highly efficient method for generating non redundant and relevant rules. This technical report provides association rule mining on the existing hybrid approach and the proposed one. In this work, an efficient FP-Growth approach has been used to mine the complete set of frequent item sets without candidate generation. This approach helps to overcome the problems of FA, which requires a need to repeated scanning of the database and checking large set of candidates by pattern matching. The analytical study of this framework shows that it is efficient and scalable for extracting both small and long frequent patterns. The Fuzzy FP-Growth approach transforms the problem of finding long frequent patterns to search for shorter ones recursively and then concatenate the corresponding suffix. It uses the least frequent items as a suffix and there by offering good selectivity. The approach reduces the search costs to a great extend. FP growth approach provides less execution time compared to FA approach.

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