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# PTP-Mine: Range Based Mining of Transitional Patterns in Transaction databases

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**GJCST Classification**: H.2.8



PTP-MINE RANGE BASED MINING OF TRANSITIONAL PATTERNS IN TRANSACTION DATABASES

*Strictly as per the compliance and regulations of:*



# PTP-Mine: Range Based Mining of Transitional Patterns in Transaction databases

Shyamala Pogula<sup>α</sup>, Sujatha Dandu<sup>Ω</sup>

**Abstract** - Transaction database is a collection of transactions along with the related time stamps. These transactions are defined using some prototypes. They are called as the Transitional patterns that denote the vibrant nature of the frequent patterns in the database. The considerable high points for the transaction database are the timestamps also called as time durations. They are the points that have the alteration in the recurrence of the prototypes. There is majorly couple of stages in existing TP-Mine algorithm. The initial stage is to find out the frequent patterns and the second stage is to discover Transitional patterns or the styles and the significant milestones. These patterns consist of the two kinds of the styles likely the positive one and the negative one. In the previous time cases the effort that was made on the research was to build up the algorithms by planning the total series of the transitional patterns. In our paper we consider that the alterations made in the consequent period regarding the total concept of database is not noteworthy. So for this reason we have put forward an entirely latest transitional patterns methodology called periodical transitional pattern mining. The experimental outputs are appealing and apparent those were produced by this periodical transitional pattern mining and has high importance that when evaluated utilizing the present patterns.

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## 1. INTRODUCTION

In the recent time the expansively considered field in the data mining is the frequent pattern mining. The advantage of this technique is that it can be widely utilized in several methodologies such as Association rule mining [2] [3] [12], sequential pattern mining [4], structured pattern mining [7], correlation mining [5], and associative classification [9]. Even to determine these frequent patterns that are present in the transaction databases, plenty of procedures were put forward specifically Apriori [3], FP-growth [8], and Eclat [15]. The drawback of these procedures is that they can produce huge amount of the patterns on the condition of low support threshold value. As this drawback being one of the reasons, maximum procedures are not utilized for the data mining job. So, as a case of evading the above mentioned ineffectual and outmoded patterns, the latest patterns such as frequent itemsets [1] [6] [11], and closed frequent itemsets [10] were been established.

One of the common characteristic of these procedures is that they don't determine the time stamps that are related to the actions in the database. This leads to the loss of exposure of the vibrant nature of the patterns. For an illustration let us consider an electronic showroom's database. The amount of retails of refrigerator during the peak summer season is very much more when compared to that of the retails in the winter. But when we determine all the transactions in whole on an average the retails are frequent, while in actual they are frequent only in the peak season. So in order to find out such a vibrant characteristics, latest patterns have been established like Transitional patterns [13] [14]. There are two kinds in them such as the positive patterns and the negative patterns. Positive transitional patterns have the characteristic of incrementing the recurrence of the pattern's time stamp where as the negative patterns decrement the recurrence of the pattern's time stamp.

The periodic positions where the recurrence of the transitional patterns alters often are termed as the significant milestones of the transitional pattern. So to determine these transitional patterns and the respective significant milestones TP-Mine algorithm [13][14] [17] has been projected.

The two most important and chief stages of the TP-Mine[14] algorithm are as follows:

1. In the Initial stage each and every frequent pattern is produced from the present transaction database.
2. The consumer have some of the preferences, In the consequent stage based on those preferences the frequent patterns are utilized for the production of the transitional patterns and significant milestones,

By considering all the above mentioned problems we in our article are introducing an adaption to the present TP-Mine[14] algorithm with a view of decrementing the patterns that were derived in the initial stage. As a result the count of the calculations required for the production of transitional patterns gets decremented. By this there is a feasibility to develop the importance of transitional patterns by keeping in account the periodicity of the mentioned series as the milestones.

The structure of the remaining paper is designed as below: The second part of the paper illustrates the preface and defining of the terms that

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were being utilized in the TP-Mine[14] algorithm. The later part that is the 3<sup>rd</sup> one illustrates the PTP-Mine Algorithm and the 4<sup>th</sup> one represents the tentative outputs of the approach. And as a final part, the 5<sup>th</sup> one terminates the approach.

## II. PREFACE AND DEFINITIONS

The following are the definitions taken from [14]. Apart from these, new definition defined in definition 3.2. The major elementary function of data mining approaches in digging out the valuable patterns that are present in the databases is excavation of the frequent patterns. Assuming a group of items is  $I = \{i_1, i_2 \dots i_n\}$  with a group of database transactions  $D$  that consists of individual transaction  $T$ .  $T$  is termed as the group of items and the count of the transactions in  $D$  is derived by  $\|D\|$ .

The specified equation

$X = \{i_j \dots i_k\} \subseteq I (j \leq k \text{ and } 1 \leq j, k \leq n)$  is termed as a pattern. The pattern's  $X$  in an action  $D$  has a support value, which is termed as the count of the transactions in the  $D$  that consists of the respective pattern  $X$ . This  $X$  is defined as recurrent or simply frequent if and only if the corresponding support value is greater to the consumer mentioned the least support threshold value.

**Definition 2.1:** The representation of the cover for the individual itemset  $X$  in  $D$ . This is represented using  $\text{cov}(X, D)$ . This is the count of the transactions that consists of the item  $X$ .

**Definition 2.2:** The individual itemset  $X$  for the transaction database  $D$  consists of a support value. The representation of it is  $\text{sup}(X, D)$ . This is termed as the proportionate value involving the  $\text{cov}(X, D)$  and the count of transactions in  $D$  which is represented by  $\|D\|$ .

$$\text{sup}(X, D) = \frac{\text{cov}(X, D)}{\|D\|}$$

**Definition 2.3:** Let us consider that the all the transactions in the transaction database  $D$  are arranged according to the respective time-stamps then the position of the transaction  $T$  in  $D$  which is represented using  $\rho(T)$ , is defined as the count transactions for which the time-stamp is lower or equivalent to the time stamp value of  $T$ . Hence  $1 \leq \rho(T) \leq \|D\|$ .

**Definition 2.4:** For a pattern  $X$  in  $D$ , the  $i^{\text{th}}$  transaction which is represented by  $T^i(X)$  is defined as the  $i^{\text{th}}$  transaction for the cover of  $X$  i.e.,  $\text{cov}(X)$  that has the transactions arranged based on their positions. Here  $1 \leq i \leq \text{cov}(X, D)$ .

**Definition 2.5:** For a pattern  $X$  in  $D$ , the  $i^{\text{th}}$  milestone which is represented by  $\xi^i(X)$ , is termed as

$$\xi^i(X) = \frac{\rho(T^i(X))}{\|D\|} \times 100\%, \text{ where } 1 \leq i \leq \text{cov}(X)$$

**Definition 2.6:** For a pattern  $X$  in  $D$ , the support value preceding its  $i^{\text{th}}$  milestone in  $D$  which is represented by  $\text{sup}^i_-(X)$  is termed as follows:

$$\text{sup}^i_-(X) = \frac{i}{\rho(T^i(X))}, \text{ where } 1 \leq i \leq \text{cov}(X)$$

**Definition 2.7** For a pattern  $X$  in  $D$ , the support value following its  $i^{\text{th}}$  milestone in  $D$  which is represented by  $\text{sup}^i_+(X)$  is termed as follows:

$$\text{sup}^i_+(X) = \frac{\text{cov}(X) - i}{\|D\| - \rho(T^i(X))}, \text{ where } 1 \leq i \leq \text{cov}(X)$$

**Definition 2.8:** For a pattern  $X$  in  $D$  at the  $i^{\text{th}}$  milestone the Transitional ratio is termed as follows:

$$\text{tran}^i(X) = \frac{\text{sup}^i_+(X) - \text{sup}^i_-(X)}{\text{Max}(\text{sup}^i_+(X), \text{sup}^i_-(X))},$$

where  $1 \leq i \leq \text{cov}(X)$

**Definition 2.9:** For a pattern  $X$  in  $D$  is considered as transitional pattern (TP) in  $D$  if on minimum, single milestone of  $X$ ,  $\xi^k(X) \in T_\xi$  must be present, so that:

$$\text{sup}^k_-(X) \geq t_s \text{ and } \text{sup}^k_+(X) \geq t_s \text{ and } |\text{tran}^i(X)| \geq t_t$$

here  $T_\xi$  is the series of  $\xi^i(X)$  ( $1 \leq i \leq \text{cov}(X)$ )  $t_s$  and  $t_t$  are named correspondingly as pattern support threshold and transitional pattern threshold. Here  $X$  is defined as a Positive Transitional Pattern (PTP) only on condition that  $\text{trans}^k(X) > 0$ ; and  $X$  is defined as a Negative Transitional Pattern (PTP) only on condition that  $\text{tran}^k(X) < 0$ .

**Definition 2.10:** The significant frequency-incrementing milestone for the derived positive transitional pattern  $X$  by considering the time period  $T_\xi$  is termed in form of a tuple,  $(\xi^M(X), \text{tran}^M(X))$ , where  $\xi^M(X) \in T_\xi$  is considered as the  $M^{\text{th}}$  milestone for a pattern  $X$  such that

$$\text{sup}^M_-(X) \geq t_s \text{ and } \forall \xi^i(X) \in T_\xi, \text{tran}^M(X) \geq \text{tran}^i(X)$$

**Definition 2.11:** The significant frequency-

decrementing milestone for the derived negative transitional pattern  $X$  by considering the time period  $T_\xi$  is termed in form of a tuple,  $(\xi^N(X), tran^N(X))$ , where  $\xi^N(X) \in T_\xi$  is considered as the  $N^{th}$  milestone for a pattern  $X$  such that  $su_{-i}^N(X) \geq t_s$  and  $\forall \xi^i(X) \in T_\xi, tran^N(X) \leq tran^i(X)$

### III. TP-MINE[14] ALGORITHM

Let us assume the below transaction database as represented in Table 1.

Table 1 : Illustration Database

TID	List of Item IDs	Time stamp
001	P1,P2,P3,P5	Nov, 2005
002	P1,P2	Dec, 2005
003	P1,P2,P3,P8	Jan, 2006
004	P1,P2,P5	Feb, 2006
005	P1,P2,P4	Mar, 2006
006	P1,P2,P4,P5,P6	Apr, 2006
007	P1,P2,P3,P4,P6	May, 2006
008	P1,P4,P6	Jun, 2006
009	P4,P5,P6	Jul, 2006
010	P1,P2,P3,P4,P5,P6	Aug, 2006
011	P1,P3,P4,P6	Sep, 2006
012	P1,P3,P5	Oct, 2006
013	P1,P2,P3,P6,P7	Nov, 2006
014	P1,P3,P4,P5	Dec, 2006
015	P1,P3,P4	Jan, 2007
016	P1,P2,P3,P5	Feb, 2007

The group of positive and negative transitional patterns including their significant milestones is produced using TP-Mine algorithm [14].

**Input:** A transaction database (D), milestone range ( $T_\xi$ ), pattern support threshold ( $t_s$ ), and transitional pattern threshold ( $t_t$ ).

D is assumed as a group of transactions scheduled in Table 1,  $T_\xi = \{25\%, 75\%\}$ ,  $t_s = 0.05$ ,  $t_t = 0.5$ . As mentioned above the algorithm consists of a couple of important stages. Coming to the initial stage the production of every recurrent itemsets including the support values is done utilizing Apriori [3] or FP-growth [8] considering  $t_s$  as minimum support threshold. This stage involves the generation of n count of frequent patterns by the algorithm for which support  $\geq t_s$  in the transaction database D. The consequential frequent patterns (n=87) have been represented in Table 2.

Subsequently in the second stage the support count ( $c_k$ ) for each and every frequent patterns in the group of transactions starting from the initial action to latest one with the time stamp  $T_\xi$  is derived by the algorithm. Later the milestones of  $P_k (1 \leq k \leq n)$  in the series  $T_\xi$  are also derived. It checks whether the

derived milestones are legal or not and for the legal ones  $\xi^{c_k}(P_k)$  it determines the value for the support  $P_k$  preceding  $\xi^{c_k}(P_k)$  i.e.,  $sup_{-}^{c_k}(P_k)$  and support value  $P_k$  following  $\xi^{c_k}(P_k)$  i.e.,  $sup_{+}^{c_k}(P_k)$ . Then it compares whether the values are higher to that of  $t_s$ , and if they are higher, then algorithm verifies the transitional ratio  $P_k$ . It again compares whether the ratio value is more than that of the  $t_t$ . If more, then  $P_k$  is considered as the positive transitional pattern. This comparison is continued with the current maximal transitional ratio of  $P_k$ , if proved to be more, then that group of significant frequency incrementing milestones of  $P_k$  is made to consist the  $\{\xi^{c_k}(P_k), tran^{c_k}(P_k)\}$  as its only component. If proved to be less, then  $\{\xi^{c_k}(P_k), tran^{c_k}(P_k)\}$  is summed up with the significant frequency incrementing milestone of  $P_k$ . This format is repeated for the determination of negative transitional patterns and their significant milestones in the condition that  $tran^{c_k}(P_k) \leq -t_t$ .

Table 2 : A group of frequent patterns

FP	Sup
P1	15
P3,P5	5
P1,P6,P7	1
P1,P2,P5,P6	2
P2	10
P3,P6	4
P2,P3,P4	2
P1,P2,P6,P7	1
P3	10
P3,P7	1
P2,P3,P5	3
P1,P3,P4,P5	2
P4	9
P3,P8	1
P2,P3,P6	3
P1,P3,P4,P6	3
P5	8
P4,P5	4
P2,P3,P7	1
P1,P3,P5,P6	1
P6	7
P4,P6	6
P2,P3,P8	1
P1,P3,P6,P7	1
P7	1
P5,P6	3
P2,P4,P5	2
P1,P4,P5,P6	2
P8	1
P6,P7	1

P2,P4,P6	3
P2,P3,P4,P5	1
P1,P2	10
P1,P2,P3	6
P2,P5,P6	2
P2,P3,P4,P6	2
P1,P3	10
P1,P2,P4	4
P2,P6,P7	1
P2,P3,P5,P6	1
P1,P4	8
P1,P2,P5	5
P3,P4,P5	2
P2,P3,P6,P7	1
P1,P5	7
P1,P2,P6	4
P3,P4,P6	3
P2,P4,P5,P6	2
P1,P6	6
P1,P2,P7	1
P3,P5,P6	1
P3,P4,P5,P6	1
P1,P7	1
P1,P2,P8	1
P3,P6,P7	1
P1,P2,P3,P4,P5	1
P1,P8	1
P1,P3,P4	5
P4,P5,P6	3
P1,P2,P3,P4,P6	2
P2,P3	6
P1,P3,P5	5
P1,P2,P3,P4	2
P1,P2,P3,P5,P6	1
P2,P4	4
P1,P3,P6	4
P1,P2,P3,P5	3
P1,P2,P3,P6,P7	1
P2,P5	5
P1,P3,P7	1
P1,P2,P3,P6	3
P1,P2,P4,P5,P6	2
P2,P6	4
P1,P3,P8	1
P1,P2,P3,P7	1
P1,P3,P4,P5,P6	1
P2,P7	1
P1,P4,P5	3
P1,P2,P3,P8	1
P2,P3,P4,P5,P6	1
P2,P8	1
P1,P4,P6	5
P1,P2,P4,P5	2
P1,P2,P3,P4,P5,P6	1
P3,P4	5
P1,P5,P6	2
P1,P2,P4,P6	3

*Table 3* : A group of Positive transitional patterns and the corresponding incrementing milestones.

Pattern	Incrementing Milestone	Transitional Ratio
P3	Aug2006(62.5%)	60.0%
P4	Mar2006(31.25%)	72.50%
P6	Apr2006(37.5%)	72.0%
P1, P3	Aug2006(62.5%)	60.0%
P1, P4	Mar2006(31.25%)	68.57%
P1, P6	Apr2006(37.5%)	66.66%
P3, P4	May2006(43.75%)	67.85%
P3, P5	Aug2006(62.5%)	60%
P3, P6	May2006(43.75%)	57.14%
P4, P6	Apr2006(37.5%)	66.66%
P1,P3, P4	May2006(43.75%)	67.85%
P1,P3, P5	Aug2006(62.5%)	60%
P1,P3, P6	May2006(43.75%)	57.14%
P1,P4, P6	Apr2006(37.5%)	58.33%

*Table 4* : A group of Negative transitional patterns and the corresponding decrementing milestones.

Pattern	Decrementing Milestone	Transitional Ratio
P2	May2006(43.75%)	-66.66%
P6	Sep2006(68.75%)	-63.33%
P1, P2	May2006(43.75%)	-66.66%
P1, P6	Sep2006(68.75%)	-56.0%
P2, P4	May2006(43.75%)	-74.07%
P2, P5	apr2006(37.5%)	-60.0%
P4, P6	aug2006(62.5%)	-66.66%
P1,P2, P4	may2006(43.75%)	-74.07%
P1,P2, P5	apr2006(37.5%)	-60.0%
P1,P4, P6	aug2006(62.5%)	-58.33%
P2,P4, P6	may2006(43.75%)	-61.11%
P1,P2,P4, P6	may2006(43.75%)	-61.11%

There is a clear understanding from the outcome in the tables that the count for the transitional patterns that were produced in the transaction data group of magnitude 16 that come in the lower region of support and threshold value is just 26. And it is also found out that those transactions that were produced from the standard data groups that has more than ten transactions directs towards the large value complication and maximum patterns are also not significant patterns. Due to this reason the patterns must be produced in the periodical series which will help us to determine the large significant patterns. In order to reduce the complication an algorithm called Bide [16] algorithm is preferred for determining the frequent patterns and decrementing the count of the pattern.



**Definition 3.1:** A pattern can be sniped out if it is a resident of other patterns and their support values are equal.

Assuming that  $A$  and  $B$  are a couple of patterns such that

$$\text{sup}(A) \text{ is } \omega$$

$$\text{sup}(B) \text{ is } \omega'$$

$$\text{and } \omega \cong \omega'$$

if  $A \subseteq B$  then  $A$  has a chance to be sniped out from the group of patterns.

**Definition 3.2:** The development in the impact of the transitional patterns is done by checking  $T_\xi$  for the specified timely intervals of transactions rather than checking the particular time threshold value.

Assuming that  $TD = \{td_1, td_2, \dots, td_n\}$  is a group of dates on which the transitions are occurred,

$$TDR = \{tdr_1, tdr_2, \dots, tdr_s\}$$

here

$$tdr_1 = \{td_1, td_2, \dots, td_m\}$$

$$tdr_2 = \{td_{m+1}, td_{m+2}, \dots, td_{m+i}\}$$

$$tdr_3 = \{td_{m+i+1}, td_{m+i+2}, \dots, td_{m+i+x}\}$$

.....

$$td_n = \{td_{m+i+x} \dots td_n\}$$

$TD$  denotes the group of transitional dates

$TDR$  denotes the group of transition interval and every interval consists of the group of transition dates.

At this instant the transition patterns threshold  $T_\xi$  checked among the interval Transition range  $tdr_i$ .

As a result there is an apparent development in the count of the transition patterns that are based on  $tdr_i$  when compared to that of transition patterns based on  $td_i$

$$TP(tdr_i) = TP(td_{i_1}) \cup TP(td_{i_2}) \cup TP(td_{i_3}) \dots \cup TP(td_{i_s})$$

### Periodic Transitional Patterns

*Input:*

A transaction database ( $D$ ), an appropriate milestone range that the user is interested ( $T_\xi$ ), pattern support threshold ( $t_s$ ), and transitional pattern threshold ( $t_t$ ), transition range ( $tdr_i$ )

*Output:*

The group of transitional patterns (positive( $S_{PTP}$ ) and negative( $S_{NTP}$ )) including their significant milestones.

*Algorithm:*

1. Determine frequent patterns
  - a. In order to preserve the individual patterns, snip out the patterns that are as subset for the superset frequent patterns and has the equal support values (definition 3.1). As a result the count of the patterns gets reduced.
2. Utilizing the Periodic Transitional Pattern –Mining methodology.
  - a. Check the positive and negative transition for every pattern in a group of transitional dates  $tdr_i$  (definition 3.2).
3. In order to evaluate the supports  $S_{ptp}$  for a pattern aroused preceding  $tdr_i$  and supports  $S_{ntp}$  for the same pattern aroused following  $tdr_i$ , examine the transaction data group.
4.  $S_{PTP} = \emptyset, S_{NTP} = \emptyset$
5. for all  $k = 1$  to  $n$  do
6.  $\text{MaxTran}(P_k) = 0, \text{MinTran}(P_k) = 0$
7.  $S_{FAM}(P_k) = \emptyset, S_{FDM}(P_k) = \emptyset$
8. end for
9. for all transactions  $T_i$  whose position satisfying  $T_\xi$  do
10. for  $k = 1$  to  $n$  do
11. if  $T_i \supseteq P_k$  then
12.  $C_k = C_k + 1$
13. if  $\text{sup}_+^{T_i}(P_k) \geq t_s$  and  $\text{sup}_-^{T_i}(P_k) \geq t_s$  then
14. if  $\text{tran}^{T_i}(P_k) \geq t_t$  then
15. if  $P_k \notin S_{PTP}$  then
16. Add  $P_k$  to  $S_{PTP}$
17. end if
18. if  $\text{tran}^{T_i}(P_k) > \text{MaxTran}(P_k)$  then
19.  $S_{FAM}(P_k) = \{t^{T_i}(P_k), \text{tran}^{T_i}(P_k)\}$
20.  $\text{MaxTran}(P_k) = \text{tran}^{T_i}(P_k)$
21. else if  $\text{tran}^{T_i}(P_k) = \text{MaxTran}(P_k)$  then
22. Add  $\{t^{T_i}(P_k), \text{tran}^{T_i}(P_k)\}$  to  $S_{FAM}(P_k)$
23. end if
24. else if  $\text{tran}^{T_i}(P_k) \leq -t_t$  then
25. if  $P_k \notin S_{NTP}$  then
26. Add  $P_k$  to  $S_{NTP}$
27. end if
28. If  $\text{tran}^{T_i}(P_k) < \text{MinTran}(P_k)$  then
29.  $S_{FDM}(P_k) = \{t^{T_i}(P_k), \text{tran}^{T_i}(P_k)\}$
30.  $\text{MinTran}(P_k) = \text{tran}^{T_i}(P_k)$
31. else if  $\text{tran}^{T_i}(P_k) = \text{MinTran}(P_k)$  then
32. Add  $\{t^{T_i}(P_k), \text{tran}^{T_i}(P_k)\}$  to  $S_{FDM}(P_k)$

33.       end if  
 34.       end if  
 35.       end if  
 36.       end if  
 37.       end for  
 38.       end for  
 39.       return  $S_{PTP}$  and  $S_{FAM}$ ,  $(P_k)$  for each  $P_k \in S_{PTP}$   
 40.       return  $S_{NTP}$  and  $S_{FDM}$ ,  $(P_k)$  for each  $P_k \in S_{NTP}$

#### IV. TENTATIVE OUTPUTS

**Input:** A transaction database (D), milestone range ( $T_\xi$ ), pattern support threshold ( $t_s$ ), and transitional pattern threshold ( $t_t$ ).

D is assumed as a group of transactions

scheduled in Table 1,  $T_\xi = 25\%$ ,  $t_s = 0.05$ ,  $t_t = 0.1$ ,  $tdr_i = 3$  months.

**Table 5:** A group of frequent patterns which are generated by PTP-Mine algorithm.

FP	SUP	FP	SUP
P1	15	P1, P3, P6	4
P1, P2	10	P1, P2, P3, P5	3
P1, P3	10	P1, P4, P5	3
P4	9	P4, P6	6
P1, P4	8	P1, P2, P3, P6	3
P1, P2, P3	6	P1, P4, P6	5
P5	8	P1, P3, P4, P5	2
P1, P5	7	P1, P2, P4, P6	3
P1, P2, P4	4	P1, P3, P4, P6	3
P1, P6	6	P1, P2, P3, P8	1
P6	7	P1, P2, P3, P4, P6	2
P1, P3, P4	5	P4, P5, P6	3
P1, P2, P5	5	P1, P2, P4, P5, P6	2
P1, P3, P5	5	P1, P2, P3, P6, P7	1
P1, P2, P6	4	P1, P2, P3, P4, P5,	1
P4, P5	4		

**Table 6:** some set of Positive Periodic Transitional pattern and the corresponding incrementing milestones.

Pattern	Incrementing Milestone	Transitional Ratio
P4,P5	Apr2006(37.5%)	44.44%
P1,P5	Aug2006(62.5%)	19.99%
P1,P6	Apr2006(37.5%)	66.66%
P1,P3,P4,P5	Aug2006(62.5%)	40.0%
P3,P1	Aug2006(62.5%)	60.0%
P4,P2,P1,P6	Apr2006(37.5%)	16.66%
P4,P1	Mar2006(31.25%)	68.57%

P3,P2,P1,P6	May2006(43.75%)	35.71%
P4,P3,P1,P6	May2006(43.75%)	35.71%
P4,P6	Apr2006(37.5%)	66.66%
P4	Mar2006(31.25%)	72.5%
P4,P1,P6	Apr2006(37.5%)	58.33%
P1	Aug2006(62.5%)	10.00%
P4,P6,P5	Apr2006(37.5%)	16.66%
P6	Apr2006(37.5%)	72.26
P5	July2006(56.25%)	22.22
P4,P2,P1	Mar2006(31.25%)	26.66
P4,P3,P1	May2006(43.75%)	67.85
P3,P1,P5	Aug2006(62.5%)	60.0%
P2,P1,P6	Apr2006(37.5%)	44.44%
P3,P1,P6	May2006(43.75%)	57.64%
P4,P1,P5	Apr2006(37.5%)	16.66%

**Table 7:** some set of Negative Periodic Transitional Patterns and the corresponding Decrementing Milestones.

Pattern	Decrementing Milestone	Transitional ratio
P4,P2,P1,P6	May2006(43.75%)	-61.11%
P3,P2,P1,P6	Aug2006(62.5%)	-16.66%
P4,P3,P1,P6	Aug2006(62.5%)	-16.66%
P3,P2,P1,P5	Aug2006(62.5%)	-16.66%
P4,P1,P6	Aug2006(62.5%)	-58.33%
P4,P6,P5	July2006(56.25%)	-35.71%
P3,P2,P1	May2006(43.75%)	-22.22%
P4,P2,P1	May2006(43.75%)	-74.07%
P2,P1,P5	Apr2006(37.5%)	-60.0%
P2,P1,P6	Aug2006(62.5%)	-44.44%
P4,P1,P5	Aug2006(62.5%)	-16.66%
P3,P1,P6	Sep2006(68.75%)	-26.66%
P4,P5	Aug2006(62.5%)	-44.44%
P1,P5	Apr2006(37.5%)	-19.99%
P1,P6	Sep2006(68.75%)	-56.0%
P4,P1	Sep2006(68.75%)	-26.66%
P2,P1	May2006(43.75%)	-66.66%
P4,P6	Aug2006(62.5%)	-66.66%
P4	Sep2006(68.75%)	-37.14%
P1	June2006(50.0%)	-12.50%
P4,P2,P1,P6,P5	Apr2006(37.5%)	-40.00%
P4,P3,P2,P1,P6	May2006(43.75%)	22.22%
P6	Sep2006(68.75%)	-63.33%

Many tests have been organized on artificial data groups having 8 values and with transactions greater than 200. JAVA 1.6\_20th build was utilized for execution of the PTP-Mine including TP-Mine[14] for examination. A computer unit prepared with core2duo processor, 2GB RAM and Windows XP loaded was utilized for inquiring the algorithms.

##### a) Dataset Characteristics

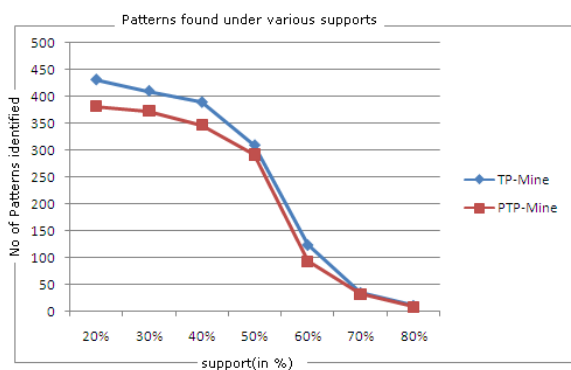
The dataset prepared is a very opaque dataset, which assists in excavating enormous quantity of recurring clogged series with a profitably high threshold

somewhere close to 90%. It also has a distinct element of being enclosed with more than 200 transactional series and 8 divergent objects. Reviewing of serviceable legacy's consistency has been made use of by this dataset.

Comparative study: In assessment with TP-Mine has made its mark as a most preferable, superior and sealed example of transitional pattern mining

**Table 8 :** contrast account of patterns derived below diverse supports by PTP-Mine and TP-Mine[14]

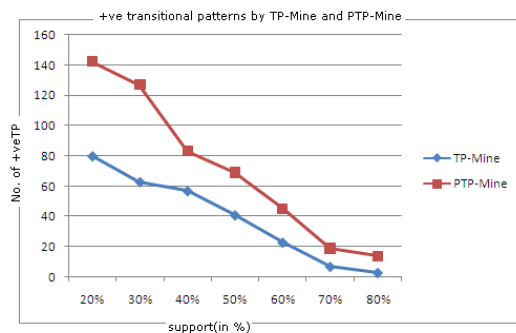
Support	TP-Mine[14]	PTP-Mine
20%	432	382
30%	411	374
40%	390	347
50%	310	292
60%	124	93
70%	35	32
80%	11	9



**Fig1 :** Count of the patterns derived by TP-Mine[14] and PTP-Mine

**Table 9 :** Contrast account of +ve Transitional Patterns derived below diverse supports by PTP-Mine and TP-Mine[14]

Support	TP-Mine[14]	PTP-Mine
20%	80	142
30%	63	127
40%	57	83
50%	41	69
60%	23	45
70%	7	19
80%	3	14

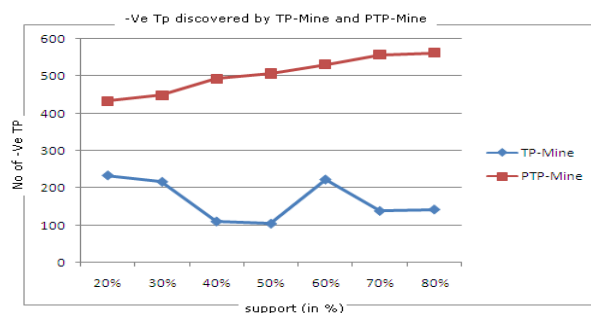


**Fig 2 :** Positive Transition patterns derived by TP-Mine[14] and PTP-Mine.

**Table 10 :** Contrast account of -ve Transitional Patterns derived below diverse supports by PTP-Mine and TP-Mine[14]

support	TP-Mine[14]	PTP-Mine
20%	234	434
30%	217	449
40%	111	493
50%	105	507
60%	223	531
70%	139	557
80%	143	562

The fig-1 represents the count of the patterns that were reduced on contrasting the PTP-Mine with the TP-Mine[14] and equally we can distinguish that the functioning of PTP-Mine in determining the +ve and -ve transitional patterns is sound. This serves as the proof for defining that the PTP-Mine subsequently works better on contrasting with the TP-Mine[14]. The PTP-Mine decreases the count of patterns in order to decrement the calculation complications and generates a large amount of transitional patterns to progress the construction of constraint dependent resolutions impact (fig 2 and fig 3).



**Fig 3 :** Whole count of the -Ve transitional patterns derived by TP-Mine[14] and PTP-Mine



## V. CONCLUSION

We observe that Compare to TPMine[14], PTP-Mine produces less no. of frequent patterns. TP-Mine[14] algorithm produces less number of positive and negative transitional patterns because of transitional pattern threshold that is assumed to be 0.5, in which case only the patterns which change dramatically are displayed. In PTP-Mine the transition pattern threshold is considered as 0.1 so that, even the positive and negative patterns which have less change are also exhibited. The tentative outcome delivered by our methodological algorithm that was put forward is decidedly resourceful and proficient.

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