

Mining Sequential Patterns using Two-Tail Time Effect

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Abstract

The temporal component of the spatio-temporal databases is the key factor that leads to large accumulation of data. It can be said that continuous collection of spatial data, leads to spatio-temporal databases. An event type sequence is called as a sequential pattern and extracting such sequential patterns from spatio-temporal event data sets paves way to define causal relationships between event types. In this paper, Relative Sequential Patterns (ReSPs) are introduced and an algorithm ReSP-Miner has been proposed to support efficient mining of the same. The interestingness measures proposed includes spatio-temporal features to be suitable for extraction of patterns from spatio-temporal databases. The proposed algorithm is evaluated in comparison with the STS-Miner algorithm for efficiency.

Keywords

Frequent Pattern Mining, Sequential Patterns, Spatio Temporal Databases, Events, Two-tail time effect.

I. Introduction

An event is the real-world object which inherently has spatial and temporal extent. Along with the object, if its location and time of occurrence are also recorded, the database is called as a spatio-temporal database. Hence, a spatio-temporal database contains both spatio-temporal as well as non-spatio-temporal attributes. Spatio-temporal extent of the data provides dynamic view of the underlying phenomenon. Algorithms handling extraction of sequential patterns from spatio-temporal databases has to mainly concentrate on: (1) scalability of algorithms as spatio-temporal databases are inherently large (2) design of efficient data structures to store and retrieve data quickly (3) design of good interestingness measures to prove the importance of sequential patterns.

Consider spatio-temporal database $STDB$, which consists of a set of events of various event types. The term event type is used to represent a type of event and the term event to represent the physical occurrence of an event type in the real-world. In some literature, events and event types are termed as 'data observations' and 'data events' respectively. Each event defines a real-world event that has occurred at a definite location and time. Each event in the database is uniquely identified by its event ID and is described by its event type, location of occurrence, time of occurrence and context-level attributes. Each event belongs to any one of the event types. Let all the event types in the given spatio-temporal database be $E = \{E_1, E_2, \dots, E_n\}$ where n specifies the number of event types. A relative

sequential pattern is an event type sequence of form $E_i \rightarrow E_j \rightarrow \dots \rightarrow E_k$ where $E_i, E_j, \dots, E_k \in E$.

A discrete view of spatio-temporal conceptual model is assumed. Each event is considered to be a point in the space-time plane under observation. In real-world, the location of occurrence of an event can be represented by using latitude, longitude and elevation. Hence, generally location attribute is 3-dimensional. But, in scenarios where events have occurred with elevation near to 0, elevation need not be specified. Hence, in practice, location of occurrence of an event is considered to be 2-dimensional. Time of occurrence of event is 1-dimensional attribute where date and time of occurrence of the event in the real-world is recorded.

The main problem approached in this paper is to extract all significant causal patterns from the given spatio-temporal event database. Two interestingness measures '*relative significance index*' and '*significance index*' are proposed for efficient identification of causal interactions between event types and for measuring the significance of the relative sequential patterns respectively.

Since the idea of sequential pattern mining is proposed in [1], there has been colossal research done in this area. Substantial number of algorithms has been proposed to work with a variety of spatio-temporal databases such as trajectory databases, geographical databases, scientific databases, web traffic databases etc [2].

Work in [3], [4] has concentrated on mining frequent trajectory patterns by extending sequential pattern mining paradigm. [5] have proposed their theories on finding evolution patterns in satellite image time series. The authors have proposed significant work on extracting significant sequential patterns from spatio-temporal event datasets [6]. Roddick et al. [7] presented a brief review on spatial, temporal and spatio-temporal data mining. The authors of [8] have focused on presenting a scientific and systematic of statistical foundations for spatio-temporal data.

Alatrasta-Salas et al. [9] proposed two algorithms, an apriori based approach and pattern-growth based approach for extracting patterns from spatio-temporal datasets. The algorithms have been evaluated on two data sets – water pollution data of rivers in France, dengue epidemics data of New Caledonia. The approach of assigning priorities to elements of patterns allows extraction of patterns focused with regard to event types, time periods, length of patterns

etc. The research work presented in [10] is the first in its content applying weighted pattern mining approach to extract sequential patterns from spatio-temporal databases.

II. Motivation

Extracting significant sequential patterns from the spatio-temporal event data set as proposed by Huang et al. [7] has been analyzed and the following limitation is observed. The STS-Miner algorithm proposed considers the density of events in the spatio-temporal neighborhood of each event to clarify the significance of the sequential patterns. Consider an event e that has occurred at t , where t is time of occurrence of e . The temporal neighborhood of e is defined as the time period $\in [t, t+\mathcal{T}]$ where \mathcal{T} defines the extent of temporal neighborhood. The temporal neighborhood according to the definition is considered through forward in time (after the occurrence of e). This definition considers only one-tail time effect and is not efficient in identifying causal patterns. Consider Fig 1 which shows space-time representation of the spatio-temporal data. Here, for the purpose of simplicity in explanation, space is considered to be 1-dimensional.

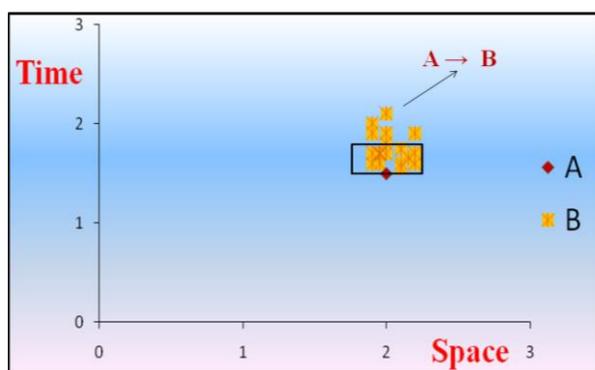


Fig 1. Pattern discovered based on one-tail time effect

Let there be two event types A and B . Let there be an event e of type A that has occurred at (l, t) where l and t determine the location of occurrence and time of occurrence of e . There are number of event occurrences of type B in the spatio-temporal neighborhood of e . The temporal neighborhood here is considered forward in time i.e., after the occurrence of e . Analyzing this scenario, STS-Miner algorithm concludes that this is a causal pattern $A \rightarrow B$.

Consider Fig 2. By visual inspection, it can be said that the density of B type events is higher before the occurrence of event e than after the occurrence of e . Hence, it can be determined that the occurrence of event e has actually reduced the density of B type events. Hence, it can be concluded that an occurrence of event of type A blocks (or reduces) the occurrence of events of type B . Hence, it is a blocking pattern which can be represented as $A \rightarrow \neg B$. STS-Miner algorithm has falsely concluded this pattern as causal pattern and this problem has aroused because of considering the temporal neighborhood only forward in

time. Hence, efficient differentiation between causal patterns and blocking patterns is necessary.

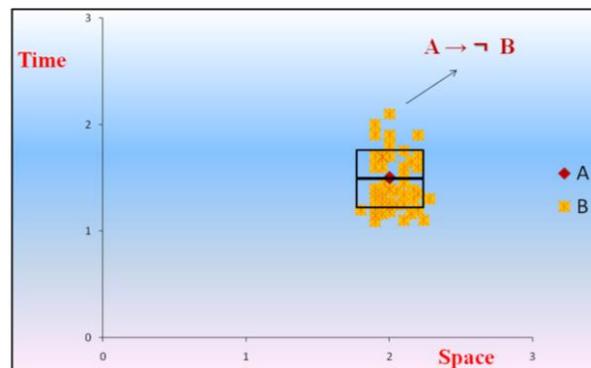


Fig 2. Pattern discovered based on two-tail time effect

In this regard, the work in this paper proposes an interestingness measure to efficiently differentiate causal patterns from blocking patterns. The purpose is achieved by considering two-tail time effect i.e., considering temporal neighborhood both forward and backward in time.

III. Mining Relative Sequential Patterns

This section provides the definitions of proposed interestingness measures. Table 1 shows the notations used further in this paper.

Table 1 Notations used

Symbol	Description
$STDB$	Spatio-Temporal Event Database
E, E_1, E_2, \dots	Event types
$A, B, C \dots$	Event types
e_1, e_2, \dots	Events
$E.\varepsilon$	Event set of event type E
$f.\varepsilon$	Event set of some event type E where $f.\varepsilon \subseteq E.\varepsilon$
S	Spatial-Neighborhood
\mathcal{T}	Temporal-Neighborhood
(l, t)	Location & Time of occurrence of an event

Definition 1. Spatio-Temporal Neighborhoods $N(e)$ and $N'(e)$:

$N(e)$ - Let e be the event occurred at (l, t) . The spatio-temporal neighborhood $N(e)$ of event e is defined as the spatio-temporal volume covering geographical space from $[l - S, l + S]$ and time period $[t, t + \mathcal{T}]$.

$N'(e)$ - Let e be the event occurred at (l, t) . The spatio-temporal neighborhood $N'(e)$ of event e is defined as the spatio-temporal volume covering geographical space from $[l - S, l + S]$ and time period $[t - \mathcal{T}, t]$.

Definition 2. Follow(\rightarrow): Follow predicate is defined for events as well as for event types.

Consider any 2 events e_1 and e_2 . Event e_2 is said to follow event e_1 , denoted as $e_1 \rightarrow e_2$, if and only if e_2 has occurred in the spatio-temporal neighborhood of e_1 i.e., e_2 is inside $N(e_1)$ also represented as

$$(e_2.l - e_1.l) \in [-S, +S] \text{ and } (e_2.t - e_1.t) \in [0, \mathcal{T}]$$

Consider any 2 event types E_1 and E_2 . E_2 is said to follow E_1 , denoted as $E_1 \rightarrow E_2$, if and only if there is high density of events of type E_2 in the spatio-temporal neighborhood of events of type E_1 .

Definition 3. Event Sequence: An event sequence is a sequence of events of form $e_1 \rightarrow e_2 \rightarrow \dots \rightarrow e_n$.

Definition 4. Extending an event sequence: Consider an event sequence $e_1 \rightarrow e_2 \rightarrow \dots \rightarrow e_n$ of length n . This event sequence can be extended by appending an event e to form an event sequence $e_1 \rightarrow e_2 \rightarrow \dots \rightarrow e_n \rightarrow e$ of length $n+1$ if and only if $e_n \rightarrow e$.

Definition 5. k-Sequence: A k -sequence is an event type sequence of length k of form $E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_k$. An event sequence $e_1 \rightarrow e_2 \rightarrow \dots \rightarrow e_n$ is said to be an event sequence of an event type sequence $E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_n$ if and only if

- i) $e_i \in E_i$ for all $i \in 1, 2, \dots, n$ and
- ii) $e_i \rightarrow e_{i+1}$ for all $i \in 1, 2, \dots, n-1$

Definition 6. Tail Event Set of a k-sequence: Consider an event type sequence $E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_n$ of length n . The set of events of type E_n that have participated in one of the event sequences of $E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_n$ forms its tail event set denoted as $TES(E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_n)$.

Definition 7. Extending an k-sequence: Consider a k -sequence $E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_k$. This k -sequence can be extended by appending an event type f to form a $(k+1)$ -sequence $E_1 \rightarrow E_2 \rightarrow \dots \rightarrow E_k \rightarrow f$.

Definition 8. Density: Density of E type events in a given spatio-temporal volume V is defined as the number of E type events in V .

$$\text{density}(E, V) = \frac{|\{e | e \in E, \varepsilon \wedge e \text{ inside } V\}|}{|V|}$$

where $|V|$ represents the spatio-temporal volume $4 \times S \times \mathcal{T}$.

Definition 9. Density Ratio: Density ratio of E' type events given an event set $f.\varepsilon$ is defined as the ratio of average number of E' type events in the spatio-temporal neighborhood of events of $f.\varepsilon$ to the density of E' type events in the total space and time under observation.

$$\begin{aligned} \text{densityRatio}(f.\varepsilon, E') &= \frac{\text{average}_{e \in f.\varepsilon}(\text{density}(E', N(e)))}{\text{density}(E', STV)} \end{aligned}$$

where STV is the total spatio-temporal volume under observation.

For a 2-sequence, say $E_1 \rightarrow E_2$

$$\text{densityRatio}(E_1 \rightarrow E_2) = \text{densityRatio}(E_1.\varepsilon, E_2)$$

For a k -sequence, $E_1 \rightarrow \dots \rightarrow E_k$ where $k \geq 3$

$$\begin{aligned} \text{densityRatio}(E_1 \rightarrow \dots \rightarrow E_k) &= \text{densityRatio}(TES(E_1 \rightarrow \dots \rightarrow E_{k-1}), E_k) \end{aligned}$$

Definition 10. Relative Density Ratio: Relative density ratio of E' type events given an event set $f.\varepsilon$ is defined as the ratio of average number of E' type events in the spatio-temporal neighborhood $N(e)$ of events of $f.\varepsilon$ to the average number of E' type events in the spatio-temporal neighborhood $N'(e)$ of events of $f.\varepsilon$

$$\begin{aligned} r\text{DensityRatio}(f.\varepsilon, E') &= \frac{\text{average}_{e \in f.\varepsilon}(\text{density}(E', N(e)))}{\text{average}_{e \in f.\varepsilon}(\text{density}(E', N'(e)))} \end{aligned}$$

For a 2-sequence, say $E_1 \rightarrow E_2$

$$r\text{DensityRatio}(E_1 \rightarrow E_2) = r\text{DensityRatio}(E_1.\varepsilon, E_2)$$

For a k -sequence, $E_1 \rightarrow \dots \rightarrow E_k$ where $k \geq 3$

$$\begin{aligned} r\text{DensityRatio}(E_1 \rightarrow \dots \rightarrow E_k) &= r\text{DensityRatio}(TES(E_1 \rightarrow \dots \rightarrow E_{k-1}), E_k) \end{aligned}$$

Definition 11. Relative Significance Index: Relative significance index of a k -sequence $E_1 \rightarrow \dots \rightarrow E_k$ is defined as

$$RelSI(E_1 \rightarrow \dots \rightarrow E_k) = r\text{DensityRatio}(E_1 \rightarrow \dots \rightarrow E_k)$$

Definition 12. Significance Index: Significance index of a k -sequence $E_1 \rightarrow \dots \rightarrow E_k$ is defined as follows.

For a 2-sequence, say $E_1 \rightarrow E_2$

$$SI(E_1 \rightarrow E_2) = \text{densityRatio}(E_1 \rightarrow E_2)$$

For a k -sequence, $E_1 \rightarrow \dots \rightarrow E_k$ where $k \geq 3$

$$\begin{aligned} SI(E_1 \rightarrow \dots \rightarrow E_k) &= \text{MIN}(SI(E_1 \rightarrow \dots \rightarrow E_{k-1}), \text{densityRatio}(E_1 \rightarrow \dots \rightarrow E_k)) \end{aligned}$$

Definition 13. Relative Sequential Pattern(ReSP): A k -sequence $E_1 \rightarrow \dots \rightarrow E_k$ is said to be a relative sequential Pattern if and only if

- a) $RelSI(E_1 \rightarrow \dots \rightarrow E_k) \geq \text{Min_RelSI}$ and
- b) $SI(E_1 \rightarrow \dots \rightarrow E_k) \geq \text{Min_SI}$

where Min_RelSI and Min_SI are user defined thresholds. The Relative Sequential pattern $E_1 \rightarrow E_2$ signifies that if an event e of event type E_1 occurs, then there will be high number of occurrences of events of event type E_2 in the spatio-temporal neighborhood (in nearby space and time) of e .

Definition 14. *k-Relative Sequential Pattern:* A k -Relative Sequential Pattern is a ReSP with k event types in the pattern.

Definition 15. *Relative Sequential Pattern Mining:* Given a spatio-temporal event database $STDB$, spatial neighborhood \mathcal{S} , temporal neighborhood \mathcal{T} , maximum length of ReSPs to be mined $maxLen$, minimum relative significance index threshold Min_RelSI and minimum significance index threshold Min_SI , the relative sequential pattern mining is defined as the process of extracting all ReSPs of length up to $maxLen$.

Fig 3 shows ReSP-Miner algorithm designed to mine ReSPs from the given spatio-temporal event database. The ReSP-Miner algorithm uses depth-first strategy to mine ReSPs. It takes as input ρ (the L -sequence to be expanded), L (the length of the sequence to be expanded), tes (the tail event set of ρ), SI (the significance index of ρ).

For each event type f in the $STDB$, ρ is extended by adding f to the end of ρ to form a new $(L+1)$ -sequence $newSeq$ (Line 3). The density ratio of $newSeq$ is calculated (Line 4) and the significance index of $newSeq$ is found (Lines 5-9). The relative density ratio of $newSeq$ is calculated and hence the relative significance index of $newSeq$ (Line 10). Then, it is determined whether the $newSeq$ is a ReSP (Line 11). If it is so, $newSeq$ is added to the resultant pattern set (Line 12) and $newSeq$ is considered as a potential candidate pattern to extend it greater length (Lines 14-15). This process is continued recursively until all the ReSPs of length up to $maxLen$ are discovered.

Relative significance index measure is designed to efficiently identify blocking patterns and causal patterns. If the $RelSI(E_1 \rightarrow \dots \rightarrow E_k)$ of a pattern $E_1 \rightarrow \dots \rightarrow E_k$ is found to be between 0 and 1, then $E_1 \rightarrow \dots \rightarrow E_k$ is a blocking pattern and if $RelSI(E_1 \rightarrow \dots \rightarrow E_k)$ is greater than 1, then $E_1 \rightarrow \dots \rightarrow E_k$ is a causal pattern. Hence, the Min_RelSI value should be set to greater than 1 to identify causal patterns and avoid false inclusion of blocking patterns into the resultant pattern set.

Algorithm ReSP-Miner

Input:

ρ – Sequential pattern to be expanded
 L – Length of ρ
 tes – Tail Event Set of ρ
 SI – Significance Index of ρ

Output :

R_{SEQ} - Set of Relative Sequential Patterns

Variables :

$maxLen$ - Maximum length of sequences to be generated
 $newSeq$ – New sequence generated
 $newtes$ – Tail event set of $newSeq$
 DR – Density Ratio of $newSeq$
 $newSI$ - Significance Index of $newSeq$
 $RelSI$ - Relative Significance Index of $newSeq$
 Min_RelSI – Minimum Relative Significance Index Threshold
 Min_SI – Minimum Significance Index Threshold

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1: for each event type  $f$  in  $STDB$  do
2:    $L \leftarrow L + 1$ 
3:    $newSeq \leftarrow (\rho \rightarrow f)$ 
4:    $DR \leftarrow findDR(tes, f)$ 
5:   if  $L = 2$  then
6:      $newSI \leftarrow DR$ 
7:   else
8:      $newSI \leftarrow MIN(SI, DR)$ 
9:   end if
10:   $RelSI \leftarrow findRDR(tes, f)$ 
11:  if  $RelSI \geq Min\_RelSI$  and  $newSI \geq Min\_SI$  then
12:     $R_{SEQ}.add(newSeq)$ 
13:    if  $L < maxLen$  then
14:       $newtes \leftarrow findTES(tes, f)$ 
15:       $ReSP-Miner ( newSeq, L, newtes, newSI )$ 
16:    end if
17:  end if
18: end for

```

Fig 3 ReSP-Miner Algorithm

Significance index is used to evaluate the interestingness of a sequential pattern. If the $SI(E_1 \rightarrow \dots \rightarrow E_k)$ of a pattern $E_1 \rightarrow \dots \rightarrow E_k$ is found to be nearer to 0, that the event types have negative correlation, value nearer to 1 shows independence between event types and value greater than 1

indicates a positive correlation between the event types. Hence, the *Min_SI* value should be set to greater than 1 to identify significant patterns.

The ReSP-Miner algorithm mines **Relative Sequential Patterns (ReSPs)** to extract singleton event type interactions. It uses interestingness measures ‘Relative Significance Index’ and ‘Significance Index’ to efficiently differentiate blocking patterns from causal patterns.

Interestingness measures are density-based measures, not frequency-based. It defines spatio-temporal neighborhood using follow predicate. It is based on event-centric model. A ReSP is represented as

Ex: *Earthquake* → *Aftershocks*

If an *Earthquake* occurs at (1, t), then high number of *Aftershocks* will follow in the spatio-temporal neighborhood of (1, t)

IV. Experimental Evaluation

Experiments have been performed on a system with 3Ghz processor and a 3GB memory. ReSP-Miner is compared with STS-Miner by experimenting on synthetic datasets. The space-time framework used to generate synthetic dataset is 120 x 100 x 100. The spatial neighborhood *S* is set to 10 x 10 and temporal neighborhood *T* to 10. Three synthetic datasets syn1, syn2, syn3 are generated using the process as mentioned in [7]. The specifications of syn1 dataset are as shown in Table 2. Let the maximal ReSP *M* be an ReSP whose proper prefixes are all significant and none of its super-sequences having *M* as one of its prefixes are significant.

Table 2 Syn1 dataset details

Syn1	
Number of event types	40
Number of events	160K
Average number of event sequences	200
Number of maximal ReSPs	40
Mean length of maximal ReSPs	10

Syn2 and syn3 datasets are generated by inducing 25% and 50% blocking patterns respectively at 2-sequence level into syn1 dataset. Fig 4 shows comparison of ReSP-Miner with STS-Miner. As syn1 dataset contains all causal patterns, hence ReSP-Miner takes more time to discover all the patterns since ReSP-Miner has to check temporal neighborhood of events both backward and forward in time.

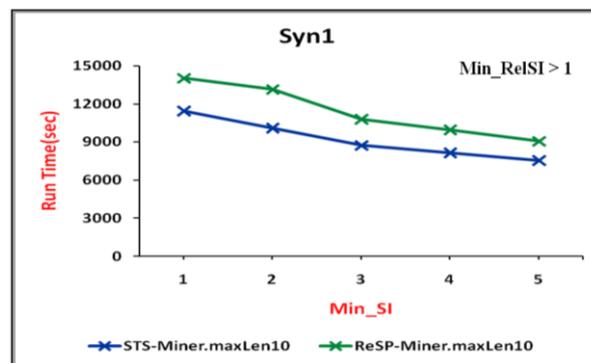


Fig 4 Time complexity of STS-Miner vs ReSP-Miner

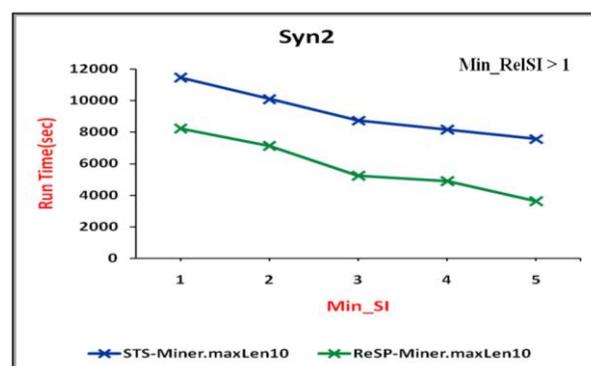


Fig 5 Time complexity of STS-Miner vs ReSP-Miner

Fig 5 and Fig 6 shows the performance of ReSP-Miner when evaluated on syn2 and syn3 datasets respectively. As these two datasets contain a mix of blocking patterns and causal patterns, the time taken by ReSP-Miner to discover the patterns is reduced. Also, it can be seen that as *Min_SI* value increases the run time decreases because the number of patterns satisfying *Min_SI* reduces.

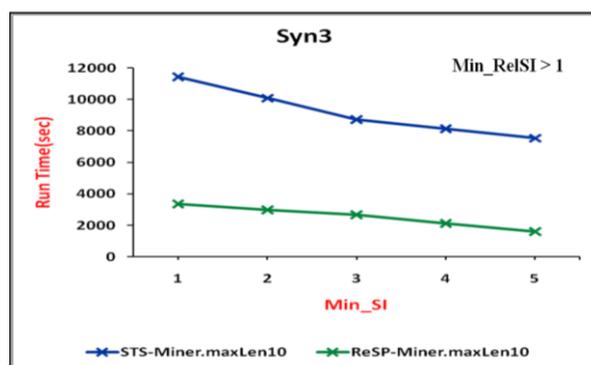


Fig 6 Time complexity of STS-Miner vs ReSP-Miner

Fig 7 shows the number of patterns mined by STS-Miner and ReSP-Miner when experimented using syn3 dataset. STS-Miner algorithm was unable to differentiate between

causal patterns and blocking patterns. Fig 8 shows that ReSP-Miner provides better scalability than STS-Miner with respect to the number of events.

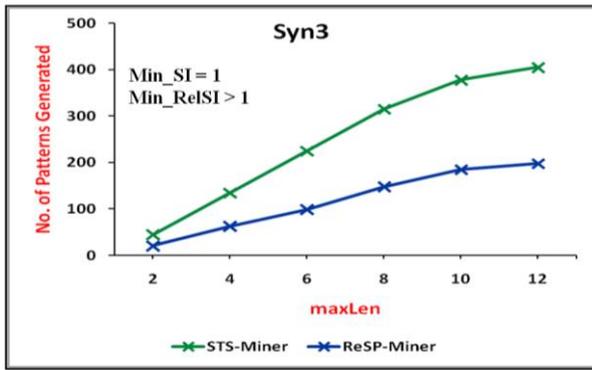


Fig 7 Identification of blocking patterns and causal patterns

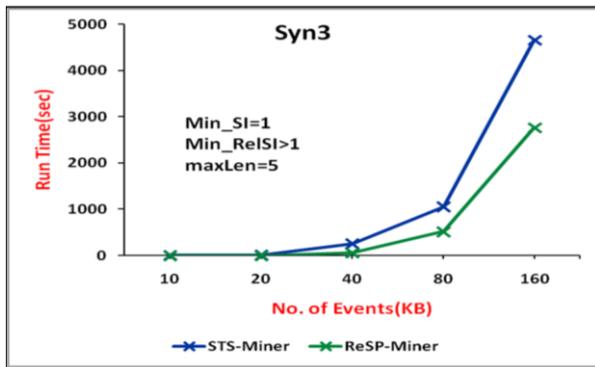


Fig 8 Scalability of STS-Miner vs ReSP-Miner

V. Conclusion

An algorithm ReSP-Miner has been proposed to extract relative sequential patterns from spatio-temporal event datasets. Interestingness measures ‘relative significance index’ and ‘significance index’ have been proposed to efficiently discover significant causal sequential patterns. The experimental results have shown that when there is high number of blocking patterns in the spatio-temporal dataset, ReSP-Miner has reduced time complexity and that ReSP-Miner outperforms STS-Miner by an order of magnitude in time.

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