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# GSTSM PACKAGE: FINDING FREQUENT SEQUENCES IN CONSTRAINED SPACE AND TIME

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## ABSTRACT

Spatial time-stamped sequences have information about time and space where events occur. Mining such sequences can bring important insights. However, not all sequences are frequent over an entire dataset. Some are only common in subsets of time and space. This article explains the first tool for mining these sequences in constrained space and time: the *GSTSM* R package. It allows users to search for spatio-temporal patterns that are not frequent in the entire database, but are dense in restricted time-space intervals. Thus, making it possible to find non-trivial patterns that would not be found using common data mining tools.

**Keywords** Data Mining · Spatial-Temporal · Time Series · Sequential Mining

## 1 Introduction

Data mining tools have been used to find interesting patterns in different areas of knowledge in various problems [1]. The sequence mining knowledge area is a specialization of data mining, focused on finding sequences or series of events in datasets [12, 15]. Such sequences may form patterns, a set of frequent attributes that appear persistently among the dataset. It means that its frequency exceeds a user-defined minimum threshold [3].

Several types of events involve both temporal and spatial data, such as financial to understand sales patterns over time and space [1], and hydrological data for river water quality monitoring in different points over time [1, 2]. They correspond to Time-stamped Sequence (TS) events distributed in space [11]. Mining sequences related to space and time enables to find knowledge related to phenomena that involve both spatial and temporal components, trying to find all sequences of significant, useful, interesting, and non-trivial events [3, 13, 1].

However, spatio-temporal sequential patterns may have low support if considered the entire dataset, but they can be frequent if considered only a period and region [8]. The Generalized Spatial-Time Sequence Miner (*GSTSM*) package can find these patterns, being able to efficiently discover the region and period where they occur. This way, *GSTSM* would be the right tool to find time-localized patterns.

This work describes the process, structure, and usage of the *GSTSM* package using a synthetic (but still complete) example. However, we also provide a glimpse of applicability in a real-world dataset. *GSTSM* was able to found sequential patterns in seismic data. They correspond to seismic horizons, which are important elements in the application domain.

## 2 Related Work

There are different methods for spatio-temporal data mining. Some use only data mining, searching for frequent patterns, considering only time [10]. Others combine techniques by seeking in time and then grouping in space [7]. Furthermore, there is a diversity in how constraints are handled. Some use global support, a value that is valid for the entire dataset [2]. Others consider local support, using predefined windows of time and space [9].

This work differs by seeking frequent sequences in time that occur in spatial groups. Instead of using predefined constraints for time and space, three density parameters are established: a minimum frequency to be achieved within the period, a maximum distance that a position can be from any other in the group, and a lower limit of distinct positions in the group. Thus, the formalization presented in this work can find different sizes of sequences, time intervals, and spatial regions where a sequence is frequent, based on the concepts of RG, KRG, and SRG introduced in [5].

As far as the conducted research has reached, the only work with a similar approach found in the literature is proposed by [4], which considers one-dimensional space. The present work is a generalization that presents a formalization considering space in its three-dimensional form.

## 3 Demonstration overview

*GSTSM* is a package which provides polymorphic functions that let the user extend its functionalities, as it is based on R [14] language S3 classes. The source code can be found at GitHub [6]. The package has a main class named *GSTSM*, that needs the parameters  $D$ ,  $P$ ,  $\gamma$ ,  $\beta$ , and  $\sigma$  to instantiate an object, explained as follows:

- $D$  and  $P$  represents the TS dataset with their respective positions. Each TS must be associated with one position. It means that the number of timestamped sequences (columns) in  $D$  must be equal to the number of positions (rows) in  $P$ .
- for the user defined thresholds values in the range  $]0, 1]$  for  $\gamma$ , values starting from 2 for  $\beta$ , and integer values starting from 1 for  $\sigma$ .

A *GSTSM* object is an instance of S3 Class built as a list with all this information. Furthermore, it generates an adjacency matrix that informs each position which other positions are at a maximum distance of  $\sigma$ .

The *GSTSM* package has the *mine()* method that implements the entire process of finding frequent sequences. It receives as input a *GSTSM* object and provides as output a list of the SRGs of all sizes found. The user does not need to call any other method to get the results. This method calls and passes all the necessary parameters to make the entire process transparent to the user.

The other methods used in each process step are polymorphic and can be extended by the user. It gives the user the ability to try its implementation. These are described as follows:

- *find()* has two input parameters: a *GSTSM* object and a set of candidate sequences of size  $k$ . It provides as output the KRGs for each candidate.
- *merge()* has also two input parameters: a *GSTSM* object and a set of candidate sequences of size  $k$  containing information about the KRG of each one. The method returns the SRGs with the candidate sequences of size  $k$ .
- *generate\_candidates()* has two input parameters: a *GSTSM* object and a set of SRGs of size  $k$ . There are no SRGs to pass to generate candidates of size one, a NULL value can be used. The method provides the candidate sequences of size  $k + 1$ .

An illustrative example shows the use of the *GSTSM* package functions. To start, the first action is installing and loading *GSTSM* package and then setting all the inputs for the package:  $D$ ,  $P$ ,  $\gamma$ ,  $\beta$ , and  $\sigma$ . For  $D$ , we use a simple dataset. For  $P$ , positions in a row are used, with one unit distance. Each position is associated with a time series, such as  $p_1$  to  $t_1$  and  $p_2$  to  $t_2$ . The values for the user-defined thresholds are:  $\gamma = 0.8$ ,  $\beta = 2$ , and  $\sigma = 1$ . After setting the input parameters, we can instantiate the *GSTSM* object and execute the *mine()* method. Listing 1 shows the code using the R command line.

Listing 1: R example of the use of *GSTSM*

```
# loading the GSTSM package
> library("gstsm")
```

```

# loading Spatial Timestamped Sequence
> path <-
" https://eic.cefet-rj.br/~dal/wp-content/uploads/2023/05/"
> load(url(paste(path, "dataset.rdata"))) # dataset D
> load(url(paste(path, "positions.rdata"))) # positions P
# mining dataset
> gtsm_object <- gtsm(D, P, gamma=0.8, beta=2, sigma=1)
> result <- mine(gtsm_object)

```

## 4 Conclusion

*GSTSM* is the first tool for mining sequences in spatial time-stamped sequences datasets able to discover constrained patterns in time and space with all three dimensions. The package discovers patterns that may not be frequent over an entire dataset but are grouped in space and frequent in a time interval. It would not be easy to find these patterns without this tool. The results can differ from conventional data mining tools and give different insights about data behavior. The patterns are groups of positions and periods where the sequences are frequent according to the input parameters. The package is also extensible, enabling users to incorporate heuristics and optimizations to drive the discovery of patterns.

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