Data mining, a major advance in the area of computing, has been applied in almost all possible fields in science, engineering, and business. The objective of data mining is to discover useful information and knowledge from a large collection of data, in particular, relational databases. One important class of regularities that exist in data is association rules. An example of an association rule is as follows:

\[ \text{cheese} \rightarrow \text{beer} \ [\text{sup} = 10\%, \ \text{conf} = 80\%] \]

This rule says that 10% of customers buy cheese and beer together, and those who buy cheese also buy beer 80% of the time. Although association rule mining was first designed for relational database/transactional systems, it has proven to be a general data mining technique. It can be and has been applied to almost every possible application domains including new applications which involve temporal and spatial data.

Temporal databases capture time-related attributes whose values change with time, for example, stock exchange data. Temporal data mining is an important extension of data mining as it can be used to mine the activity rather than just states, and thus, infer relationships of contextual and temporal proximity, some of which may also indicate a cause-effect association.
Two types of temporal data are dominant in the development of temporal data mining. They are time-series data and sequence data. Time-series data is a sequence of real numbers that vary with time, for example, stock prices, exchange rates, biomedical measurements data, and so forth. Sequence data is a list of transactions, and a transaction time is associated with each transaction, for example, Web page traversal sequences.

Mining patterns from temporal databases is complex due to the existence of time. Time implies an ordering, and this ordering affects the statistical properties of the data and the semantics of the rules being extracted from them. In particular, the incorporation of time into mining techniques provides an ordering on the temporal events and thus, an ability to suggest cause and effect that are overlooked when the temporal component is ignored. Moreover, temporal data mining has the ability to mine the behavioral aspects of objects as opposed to simply mining rules that describes their states at a point in time, that is there is the promise of understanding why rather than what.

Recent advances in positioning technology and location-based services have led to a rapid accumulation of spatial-temporal data. Spatio-temporal databases have become a very active area of research. New techniques have been developed for modeling, indexing, and querying of moving objects (Cai & Ng, 2004; Güting, Böhlen, & Erwig, 2000; Saltenis, Jensen, & Leutenegger, 2000; Sun, Papadias, & Tao, 2004; Tao, Papadias, & Shen, 2002; Tao, Taloutsos, & Papadias, 2004). Even as database technologies play a central role in the development and deployment of spatio-temporal applications, data mining capabilities will become increasingly important to discover and extract information from spatio-temporal databases.

Spatio-temporal data mining can be regarded as a generalization of temporal data mining or spatial data mining in the three-dimensional space. While mining techniques for temporal data and spatial data can be adapted for spatio-temporal data, however, spatio-temporal data contains complex relationships that cannot be discovered simply by looking at the spatial dimension or the temporal dimension independently.

Compared to temporal data mining and spatial data mining, spatio-temporal data mining is more complicated and presents a number of challenges due to the complexity of geographical domains, the mapping of data in spatial and temporal frameworks, and spatial and temporal autocorrelation (Miller & Han, 2001). In spatio-temporal databases, each object is related to other objects in complex interactions which are captured in the form of past, present, and future states in the modeled environment.