A Survey on Temporal Databases and Data mining

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Abstract

Temporal database is a database which captures and maintains past, present and future data. Conventional databases are not suitable for handling such time varying data. In this context temporal database has gained a significant importance in the field of databases and data mining. The major objective of this research is to perform a detailed survey on temporal databases and the various temporal data mining techniques and explore the various research issues in temporal data mining. We also throw light on the temporal association rules and temporal clustering works carried in literature.

Categories and Subject Descriptors

F.4.1 [**Mathematical Logic**]: Temporal logic; D.2.11 [**Software Architectures**]: Patterns; H.2.8 [**Database Applications**]: Data mining

General Terms

Novel Approach, Survey, Methodology

Keywords

Temporal Database, Conventional Database, Outliers

1 INTRODUCTION

Traditionally Databases are designed to maintain organization data and to handle its activities. Databases were primarily responsible for maintaining data consistency and correctness so that necessary information may be extracted from the underlying data which is suitable or required for various applications. In other words, the Conventional databases were originally designed with the only aim of capturing the recent data and not the time varying data. We call the recent data as present data or current data. The most common operations which are performed on databases include insert, update, delete, and modify to name a few. It is common for a database to undergo changes as the changes to the databases are inevitable unless the changes are strictly restricted. With the availability of new data values through various update operations, the past values are removed from the databases. Because of this reason, the traditional databases only capture a snapshot of reality. This is where the conventional databases fall prey.

The main problem with the conventional databases coins out when there is an essential need to store the past, present and future data values. This is because the conventional databases are not suitable for storing such type of historical information. In essence, what we require is the database which is capable of capturing past, present and the future data. Such a database should support the historical storage and also facilitate for querying the time varying information. In a broader sense, any database which supports past, present and future data may be defined as a temporal database. The attribute which differentiates between conventional and temporal databases is the time attribute. The attribute time may be viewed in two different views. It may be continuous or discrete. In both the cases, time attribute follows linear ordering. Practically speaking time is continuous in nature. Formally, Continuous time may be mapped isomorphically to real valued numbers while discrete time may be a subset of real numbers or may also be isomorphic to natural numbers. For any two time unequal instants, say t_1 and t_2 either t_1 must occur before t_2 or t_2 must occur before t_1. This simple principle makes the time attribute satisfy the linear ordering property. Of the two views of time, the temporal database researchers practiced the use of discrete notion of time. This is mainly because of the simplicity of discrete notion of time followed by the ease of implementation. A discrete time is a set of ordered time points which are equally spaced usually denoted by T and represented as a set, T = 0, 1, 2, 3 now... n.

Temporal database was originally coined by Richard Snordgrass [1, 2] in 1992. Tansel, 2004 defines the term temporal database as "The database applications are stored in to the database with the aspect of time". Section-2 of this paper introduces the importance of temporal databases and how it coined in the literature. Section-3 includes detailed literature survey performed on various temporal data mining tasks and techniques. Section 4 concentrates on the temporal data mining tasks and challenges involved. Section 5 discusses various research issues in temporal data mining. Finally, Section-6 concludes the paper.

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2 TAXANOMY

In the last 40 years, a significant contribution from researchers of database community is towards studying the temporal databases and various aspects of temporal information systems. In the year 1986, summaries of temporal database research which were discussed in various symposiums and workshops followed by universities and work carried out at various research labs was first published in ACM SIGMOD Record. The importance of the area has come in to the existence with the IEEE Data Engineering devoting a complete issue for temporal databases in 1988. Consequently in the year 1990 and 1992, two research papers contributing to survey in temporal databases were published. In this paper, we restrict our survey to the research contributions towards temporal frequent items, association rules and temporal association patterns for the discussions.

3 TEMPORAL ASSOCIATION PATTERNS AND RULES

In this section, we discuss the various significant research works published in the literature in specific to finding frequent items in temporal databases, temporal association rules and discovering temporal association patterns.

In [16] the authors consider handling the time series problem by the use of time expressions to find the temporal association rules. Finally the authors propose a incremental approach to find the temporal association rules, given a transaction database. Most of the existing algorithms in the literature considered only the events existing at a single instance of time They do not consider the time interval based events. Given an interval based data, the authors Edi Winarko, Roddick in [17], propose ARMADA, an efficient method for discovering relatively richer temporal association rules. In [18] the authors define a fuzzy calendar algebra which allows the user to input the temporal requirements. The authors propose a border based algorithm which can efficiently find the hidden fuzzy temporal association rules.

Most of the existing algorithms address the problem of mining association rules in non-temporal sense. The support value considered usually is not a function of utility value, temporal varying feature. In [20], the authors address the problem of mining the utility oriented temporal association rules by using the support which is a function of time interval or time period and utility value. The problem of mining temporal association rules in temporal documents collection is handled in [24]. The problem of handling calendar based temporal association rules is discussed in [21, 23]. The transaction databases in reality, inherently exhibit the time varying behavior and temporal characteristic which makes temporal data mining active area for research. In [25], the authors use the concept of p-tree and t-tree to discover the association rules from the underlying time dependent data. For a given time interval, the algorithm designed by the authors yields a smaller dataset and hence reduces the overall processing time.

In [19], an approach for discovering the temporal association rules on evolving attributes is discussed. The importance of this work includes considering an extra attribute called density in addition to support and strength which are used in the traditional association rule mining algorithms. The traditional association rule finding algorithms are not suitable to find the temporal association rules from publication databases. In publication database each item consists its own exhibition period. The problem of discovering temporal association rules from the publication databases is discussed by the authors in [22] which over comes the limitation of conventional temporal association rule mining algorithms. Some of the significant research contributions in discovering temporal association rules include [26, 27-32] but are not exhaustive.

4 TEMPORAL DATA MINING - TASKS

4.1 Temporal Clustering

Conventional Clustering technique is basically a unsupervised learning process which aims to group the underlying data in to a finite set of strongly cohesive groups with least coupling and strong cohesion. In short, it is a data mining technique which is used to place sets of similar data in to one single group. Classical Clustering process is widely studied in the literature. [2,39, 40-42] Temporal clustering may be defined as a temporal data mining task which aims at placing subsets of similar temporal data in to one group and dissimilar temporal data into a separate group. Temporal Clustering has its own challenges and limitations.

1. Choosing an appropriate temporal distance measure or dissimilarity measure, which may be used to cluster the temporally varying data or dataset.
2. Finding temporal frequent patterns in a temporal database requires handling itemsets whose support values are numeric sequences.
3. Temporal Clustering requires forming the new clusters as the data is added periodically.
4. Temporal Clustering and Classification requires choice of appropriate distance measure.
5. Conventional frequent pattern mining algorithms which are used to find the frequent items and association rules do not require distance measure; however finding temporal association patterns requires the use of a suitable distance measure.
6. The conventional pattern search algorithms are not applicable to find the required pattern of interest in the temporal databases, time series databases.
7. The choice of suitable clustering algorithm is also one of the few challenges in the temporal context.
8. In context of text clustering, temporal clustering of documents has its own challenges as it requires computation of frequent patterns dynamically from the time varying document collection.

4.2 Temporal Classification

Another task in temporal data mining is the temporal classification. Temporal classification is a supervised learning process which is used to classify the temporal data to one

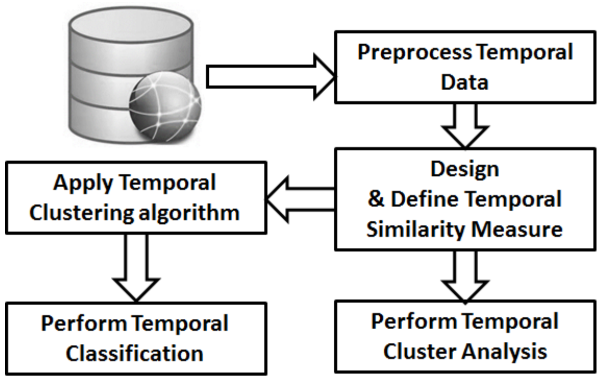

Figure 1. Outline of typical Temporal Clustering process

of the known labeled classes. Temporal Classification also requires the choice of a proper distance measure which can efficiently and accurately serve the need. Temporal Classification may also be carried out by the choice of the temporal association rules by properly adopting them to classify the underlying temporal data.

The problem of temporal classification is not applied and dealt extensively w.r.t text processing. Most of the earlier researches include sentimental analysis, email classification, Question & Answering systems , temporal ordering of events, text based temporal reasoning, topic classification to name a few. A temporal approach for text classification using predicted writing time and document creation time is discussed in [52]. Another significant work in temporal classification includes [53] in which the authors propose an unsupervised learning approach for extraction of periodicity information from the underlying text data. The authors make use of natural language property where the word frequency count exhibits both the periodic and non-periodic behavior if the data is analyzed as a time series. An approach for temporal classification using the concept of linear classifiers is discussed in [54]. However the temporal classification using non-linear classifiers is not applied extensively in the literature and has a good scope for active research. Most of the real world data is not static and varies temporally. Also expressing the real world datasets in terms of features statically is not efficient and some times not feasible. We may have to represent the features in a temporal sense. An approach for temporal classification w.r.t multivariate time series is discussed in [55]. The figure 1 shows the outline of temporal clustering and classification process.

4.3 Temporal Frequent Items and Patterns

The algorithms used to find the frequent items in a static database are not applicable for finding the frequent temporal itemsets in the temporal databases. Conventional frequent item set finding algorithms use the concept of support and confidence to find the frequent itemsets and the corresponding association rules. This is not true w.r.t temporal databases. This is because in temporal databases, we must also consider the time at which the transaction occurs. Due to this reason, the itemsets which are frequent earlier may not be frequent later. We need to consider the periodicity property when discovering the temporal frequent itemsets.

An approach for finding local frequent sets, periodical frequent sets and periodical association rules is handled in [56]. Another significant research recently is the approach for finding the temporal maximum utility itemsets from the data streams [57]. The salient features of their work include single pass database scan, efficient and easy to maintain tree called TMUI tree applied to data streams. Also finding the temporal association patterns w.r.t a given reference sequence requires the use of a distance measure to find the similarity between the generated patterns. Given a reference sequence, the problem of finding temporal frequent patterns or itemsets from the temporal databases requires using a suitable distance measure to compute the degree of similarity between the temporal itemsets and the reference sequence.

This coins the need for coming up with various methods and approaches to find the temporal association patterns. There is a scope for research towards defining the suitable temporal distance measures to discover the temporal association patterns. These temporal patterns which are discovered using a similarity measure are called the similarity profiled temporal association patterns [51].

4.4 Temporal Pattern Discovery

Temporal pattern discovery is concerned with the discovery of temporal patterns of interest and depends essentially on the underlying application and domain. The diverse nature of such applications, has given scope for coming up with various temporal pattern discovery frameworks. The most popular temporal pattern discovery frameworks are sequence mining, frequent episode discovery, temporal association rule discovery. The problem of temporal association pattern mining is an extension of temporal pattern mining which is useful in mining the behavioral aspects of underlying temporal data.

4.5 Handling Temporal Sequences

One of the important subfield of data mining is the sequence pattern mining. Temporal sequence pattern mining is one of the research topics which is gaining a lot of practical importance presently. Given a time interval based data, the problem is to find the temporal patterns in the work of the authors [37]. For this the authors define two representations called end point and end time. Given a temporal sequence, the problem is to find the temporal associations among the sequences or within a sequence . In [33], the authors propose a method to discover patterns in temporal sequences which uses the interval properties for mining the temporal patterns of user interest. Other contribution on temporal sequences include [35, 36, 58, and 59].

4.6 Temporal Outlier Detection

The problem of outlier detection in time series has been widely studied in statistics [43]. With the rapid advances in software and hardware technologies, from a computational perspective there is scope for research in discovering temporal outliers. The most recent survey by the popular authors Han, Guo and Gupta contributes a detailed survey in temporal outlier detection [43, 44].

5 RESEARCH ISSUES IN TEMPORAL DATA MINING

5.1 Choice of Temporal Similarity Measure

The first challenge before the temporal data mining researchers is the choice of temporal similarity measure which may be used for clustering temporal data. The distance measures such as Euclidean, Cosine, Jaccard, Manhattan used for finding distance and also for clustering non-temporal data are not much effective when handling temporal data. For example, the distance value computed using the popular Euclidean distance measure has lower bound but does not consist the upper bound. The lower bound value is a minimum value equal to zero but the upper bound value is not finite (i.e infinite). Though several researchers have been proposing solutions towards finding similar temporal patterns, but no effort is made to design a new similarity measure suitable for temporal data. Very few researchers contributed to the design of new temporal similarity measures which are countable [11,12, 13, 14]. With a comparatively less research effort put in this direction, hence there is a scope and also the need for coming up with effective and efficient temporal distance measures for handling the temporal data. We call this distance measure also as a temporal similarity measure.

5.2 Deciding on Temporal Clusters

The second challenge for the temporal data mining researchers is coming up with the decision on the number of clusters to be obtained from the underlying temporal data which is provided as the input for temporal clustering algorithms. This problem becomes more complex when we do not know in advance or practically if the number of clusters cannot be estimated in advance.

5.3 Choice of Temporal Clustering Algorithm

It is the time to revisit the conventional clustering algorithms designed for handling the non-temporal data available in the literature and to come out with the design of new clustering approaches for handling the temporal data. The trivial clustering algorithms such as k-means may not be effective for clustering temporal data as that of non-temporal data.

5.4 Temporal Classification

Another task in temporal data mining is the temporal classification. Temporal classification is a supervised learning process which is used to classify the temporal data to one of the known labeled classes. Temporal Classification also requires the choice of a proper distance measure which can efficiently and accurately serve the need. Temporal Classification may also be carried out by the choice of the temporal association rules and properly adopting them to classify the underlying temporal data.

5.5 Temporal Frequent Patterns

Finding temporal frequent patterns or temporal similar patterns of interest requires the use of suitable distance measure which may be applied even for temporal data. This is because the items or itemsets are usually represented in the form of numeric sequences. The traditional frequent item finding algorithms such as apriori, fp-tree, incremental frequent item set to name a few do not require the use of distance measures. Due to this reason, the algorithms and methods used to find the frequent patterns are not suitable for finding temporal frequent patterns from the temporal database.

6 CONCLUSION

Temporal data mining is the process of discovering the unknown and hidden knowledge from the huge temporal data. In this research, our main intention is to come up with a detailed survey which essentially introduces the importance of temporal databases, temporal data mining and discuss the various techniques involved in handling temporal data. This is followed by discussing some of the research challenges when handling temporal data. We hope this survey shall help the researchers in temporal data mining community to understand the need of temporal databases and the research issues in handling temporal data.

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