Review of Spatial Algorithms in Data Mining

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Abstract: Data mining, is the process or action of taking out the obscure and predictive information from wide range of databases, is proven to be new technology with much potential to help companies focus on the most important information in their respective data wares. Mining techniques can be used frequently on existing software and hardware platforms to increase the value of existing information resources, and can be combined with new products and systems. In this study I discussed many reviews, their pros and cons features. I have proposed future work for a hierarchical based clustering algorithm known as CURE algorithm for spatial and non spatial objects. It is suitable with huge datasets and produces optimum results with minimum errors and handles outlier conditions.

Keywords: CURE, Spatial Clustering algorithm, BANG, Pattern

1. Introduction

This Paper deals with the review of mining the spatial data but the set of techniques that I will discuss applies to many different types of dataset, including time related, spatial and textual databases. I have made further comparative studies of the various clustering algorithms for different size of clusters given by various reviewers.

2. Review of the Related Literature

2.1 Development Work for Spatial Data Mining Primitives & Algorithms

I have taken the related work of Martin ester and Alexander frommelt which reveals study about spatial data mining for conventional database, algorithmic approach and efficient dbms support in following way:-

Spatial data mining algorithms heavily depend on the efficient processing of neighborhood relations since the neighbors of many objects have to be investigated in a single run of a distinctive algorithm. Therefore, it provides general concepts for nearby relations as well as an efficient implementation of these concepts will allow a tight integration of spatial data mining algorithms with a spatial database management system. In this paper, I have taken surrounding graphs and paths and a small set of conventional databases for their manipulations. I showed that distinctive spatial data mining algorithms are well supported by the proposed basic operations.

2.2 Discourse for Efficient Clustering Algorithm

Second work I have added of Mohamed el-zawawy, who has developed in the title of algorithm for spatial clustering with obstacles. In this review, I have undergone for an efficient clustering technique to solve the problem of clustering while obstacles are coming while forming clusters. The proposed algorithm divides the spatial area into rectangular shapes as cells, where each cell contains statistical information that enables us to tag the cell as dense or non-dense. Further I also mark each cell as obstructed (i.e. intersects any obstacle) or non-obstructed cells. Then the algorithm finds the regions (clusters) of connected, dense, non-obstructed cells. Finally, the algorithm finds a center point for each such region and returns results of those as centers of the relatively dense regions (clusters) in the spatial area.

Spatial databases contain spatial-related information such databases include geographical area databases, VLSI chip technology databases, and medical and satellite image databases. It can be used in many applications such as seismology (grouping earthquakes clustered along seismic faults), minefield detection (grouping mines in a minefield), and astronomy (grouping stars in galaxies). Clustering in spatial data mining, is a useful technique for grouping a set of objects into classes or clusters such that objects within a cluster have high similarity among each other, but are dissimilar to objects in other clusters.

In the last few years, many effective and differentiable clustering methods have been developed. These methods can be categorized into partitioning methods [KR90, NH94, BFR98], hierarchical methods [KR90, ZRL96, GRS98, KHK98], density based methods [EKSN96, ABKS99, HK98], grid-based methods [WYM97, SCZ98, AGG98], model-based methods [SD90, Koh82], and constrained-based

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methods [THH01]. Most of these algorithms, however, provide very few solutions for users to specify real life constraints such as physical obstacles. In many applications, physical obstacles like mountains and rivers could substantially affect the result of a clustering algorithm. For example, consider a telephone-company planner who wishes to locate a suitable number of telephone connections in the area shown in Figure 1(a) to serve the customers who are represented by points in the figure. In such a situation, however, natural obstacles exist in the area and they should not be ignored. Ignoring these obstacles will result in clusters like those in Figure 1(b), which are obviously inappropriate and hence not a good practice. For example, a river splits cluster c1, and some customers on one side of the river will have to travel a long way to reach the telephone cabinet at the other side. Thus the ability to handle such real life constraints in a clustering algorithm is very important.

The algorithm has several advantages over existing algorithms. First, it does not use randomized search to determine the center of a cluster, therefore the quality of results is guaranteed. Second the algorithm requires minimum input. Third, outliers are efficiently handled as they are disregarded from the clusters. Extending the algorithm to work for $d$ dimensions, $d > 2$, is an interesting and challenging task.

2.3 Development Work for Mining Large Spatial Databases

Third review I taken of “Xiaowei, xu,hans, peter kriegel, jorg sander ref.in [4]” in the title of A distribution based clustering algorithm for mining in large spatial data bases. In this, I undergone with the new clustering algorithm as Distribution Based Clustering of Large Spatial Databases to discover clusters of this type. Experimental based study reveals that this algorithm, as contrast to partition making algorithms such as algorithm of Clustering using large applications with randomized search, finds arbitrary shape like clusters. In addition, Distribution based algorithm does not require any input parameters, as consider for the clustering algorithm. Distribution based scanning “In [4]” requires two input parameters which may be difficult to be given for large databases. Hence, the productivity of “DBCLASD In ref [4]” on large spatial databases is very impressive when considering its nonparametric nature and its good quality for clusters of arbitrary shape.

In this paper, I consider the task of clustering in spatial databases, regarding the problem of detecting clusters of points which are distributed as belonging to same group also called uniform distribution or random distribution. The problem finds many areas e.g. seismology In [4] (collection of earthquakes clustered containing seismic faults), In 4 minefield detection (grouping mines in a minefield) and astronomy In [4] (grouping stars in galaxies). Content rich spatial database applications requires the following requirements for clustering algorithms:

1. Minimal number of input parameters.
2. Discovery of clusters with arbitrary shapes..
3. Good efficiency on huge databases.

None of the well-known clustering algorithms fulfills the combination of these requirements. In this review, I discussed on the new clustering algorithm DBCLASD In [4](Distribution Based Clustering of Large Spatial Database) which is based on the assumption that the points inside a cluster are uniformly distributed and is quite reasonable for many applications.

Applications of DBCLASD:-
• It works effectively on real databases where the data is not exactly uniformly distributed.
• It dynamically determines the appropriate number and shape of clusters for a database without requiring any input parameters.

Finally, the algorithm will be efficient for large databases.

(a) Customer’s locations and obstacles (b) Clusters formed when ignoring obstacles

Figure 1: Planning the locations of ATMs

In this paper, I have gone with an efficient spatial clustering technique, SCPO, which considers the presence of obstacles. The algorithm finds all the dense, non-obstructed regions that form the clusters by a breadth-first search and determines a center for each region (cluster). The proposed algorithm has the following advantages over the work that has done to solve the problem of clustering in the presence of obstacles [THH01].
1) It handles noise or other outlier conditions. Outliers are spatial objects, which are not covered in any cluster and should be discarded during the data mining process.
2) It does not use any randomized search.
3) Instead of specifying the number of the desired clusters in advance, it finds the natural number of clusters in the spatial area.
4) When the data is updated, we do not need to re-compute all information in the cell grid. Instead, incremental update can be provided later on.

Many studies have been conducted in cluster analysis. Methods related to my work are discussed briefly in this section and I emphasize what I believe are some limitations which are addressed by my approach.

Conclusion in this review, I discussed a new approach to spatial clustering in the presence of obstacles. The algorithm, SCPO, finds clusters in the spatial area along with their centers taking into consideration existing of natural obstacles.

**Figure 1:** Planning the locations of ATMs

In this case, I would like to consider the task of clustering in spatial databases, regarding the problem of detecting clusters of points which are distributed as belonging to same group also called uniform distribution or random distribution. The problem finds many areas e.g. seismology In [4] (collection of earthquakes clustered containing seismic faults), In 4 minefield detection (grouping mines in a minefield) and astronomy In [4] (grouping stars in galaxies). Content rich spatial database applications requires the following requirements for clustering algorithms:

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Applications of DBCLASD:-
• It works effectively on real databases where the data is not exactly uniformly distributed.
• It dynamically determines the appropriate number and shape of clusters for a database without requiring any input parameters.

Finally, the algorithm will be efficient for large databases.
In review, I presented with the new clustering algorithm DBCLASD In[4] which is appropriate to fulfill the combination of above stated requirements where as the most concerned algorithms fails to offer solution to these.

2.4 Development Work for Production of Useful Patterns

Fourth review I added here are the works given by “shashi shekar, pushing zhang, yan huang, ranga, raju vatsavai In[7]” who have developed the research in title of Trends in spatial data mining as follows:-

Spatial data mining is the process of discovering interesting and previously un-known, but potentially useful patterns from large spatial datasets. They stated about how to get useful patterns from spatial datasets which is more difficult than getting the corresponding patterns from traditional, numeric and categorical data due to the complexity of spatial data types, relationships and autocorrelation features.

2.4.1 Description

The incremented growth of spatial data and widespread use of spatial databases focuses on the need for the automated discovery system of spatial knowledge. The inherent complexity of spatial data and their relationships limits the use of typical data mining techniques for getting spatial patterns. For extracting information some effective tools from geo-spatial data are sensitive to organizations which take decisions based on huge spatial datasets, like “In [7]NASA, the United States Department of Transportation (US DOT). The National Imagery and Mapping Agency (NIMA), the National Cancer Institute (NCI).” They consist of many application domains consisting of ecology and environmental management, public safety, transportation, Earth science, epidemiology, and climatology.

Clementine, See5/C5.0, and Enterprise Miner, all these data mining tools were designed to reveal facts for massive commercial databases. To know customer-buying patterns strategies and techniques those tools were mainly designed according to based on market data, in analyzing scientific, engineering data, astronomical data, multi-media data, and web based data. Getting patterns from spatial data sets is more difficult than getting corresponding patterns from traditional numeric and categorical data due to the various complexity issues of spatial data types, spatial relationships, and spatial autocorrelation features.

In this review I focused on the unique features that distinguish spatial data mining from classical data mining in the following four categories: data input, statistical foundation, output patterns, and computational process. Major requirements are presented by me of spatial data mining research, especially consisting of output patterns in the form of predictive models, spatial outliers, spatial correlation rules, and clusters. Finally, I got areas of spatial data mining where further research is needed.

2.4.2 Data Input

The data inputs for spatial data mining are more complicated than the input parameters for classical data mining because they include objects of type such as points, lines, and polygons, circles, ellipses etc. Spatial data mining have two broad categories of attributes: non-spatial and spatial. Non-spatial are used to refer non-spatial features of objects, such as name of any object, population data, and literacy rate for a city which are similar to attributes used in the data inputs of conventional data mining whereas spatial is about spatial locations e.g. longitude, latitude and elevation, arbitrary shapes.

2.4.3 Statistical Foundation

In this study I used statistical models to represent observations in terms of random variables. These models are preferred for spatial data estimation, description, and prediction based on probability theory. Spatial data is a resultant from observations carried on the number of random variables on a variable parameter as time like Z(s): s is an element D, where s is a spatial location and D is possibly a random set in a spatial framework.

Here I discussed some of the spatial statistical problems which can occur: point process, lattice, and geostatistics.

Point process: A structure for the spatial arrangement of points in a pattern set. Natural processes can be modeled as spatial point patterns, e.g., positions of trees in forest areas and locations of bird living areas. Spatial point patterns are grouped into random or non-random processes. For a random pattern, the average distance calculations are to be

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\frac{1}{2\pi}\sqrt{\text{density}}, \text{ where density is the average number of points per unit area. for real processes, the calculative distance lies within certain limits, then I conclude that the pattern is generated by a random process; otherwise it is by non-random process.}
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Lattice: It refers to a gridded structure in a spatial framework, which is a countable set of regular or irregular spatial sites related to each other via a neighborhood relationship.

Geostatistics: Geostatistics reveals the study of spatial continuity and weak stationary objects which is one of the characteristics of spatiotemporal data sets. Geostatistics provides a set of statistics tools, such as kriging [Cressie1993] for the interjection of attributes at unsampled locations

Figure 2: Attribute Values in Space with Independent Identical Distribution and Spatial Autocorrelation

The basic requirement of statistical analysis is that the data samples are independently generated e.g. successive tosses of coin, or the rolling of a die, selection of playing cards at random. But in the analysis of spatial data, this independence is mostly false. In real, spatial data continues to be highly

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self-correlated. The economies of a region tend to be similar. A change in natural resources, wildlife, and temperature varies gradually from space to space. The spatial statistics study states, an area within statistics dedicated to the analysis of spatial data, then the property is called as spatial autocorrelation. For example, Figure 2 shows the value distributions of an attribute in a spatial framework for an independent identical distribution and a distribution with spatial autocorrelation.

In this review I have presented the features of spatial data mining that distinguish it from classical data mining in the following categories: description, input and statistical foundation.

I have also discussed major research accomplishments and techniques in spatial data mining, especially those related to four important output patterns: predictive models, spatial outliers, spatial correlation rules, and spatial clusters. I have also identified research needs and requirements for spatial data mining.

References

[4] Published in Proceedings of 2nd International Conference on Knowledge Discovery and Data Mining (KDD-96): “A Density-Based Algorithm for Discovering Clusters in Large Spatial Databases with Noise” by Martin Ester, Hans-Peter Kriegel, Jörg Sander, Xiaowei Xu

Author Profile

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