A Recent Survey on Knowledge Discovery in Spatial Data Mining

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Abstract

Spatial data mining is the process of discovering, motivating and previously unknown, but potentially helpful patterns from large spatial datasets. Extracting interesting and useful patterns from spatial datasets is more tricky than extracting the parallel patterns from established numeric and definite data due to the complexity of spatial data types, spatial relationships, and spatial autocorrelation. This paper focuses on the sole features that distinguish spatial data mining from traditional data mining. Major activities and research needs in spatial data mining research are discussed. And it gives the Applications and Techniques, Issues and challenges on spatial data mining. It shows that spatial data mining is a promising field with rich research results and many challenging issues.

Keywords: *Spatial data mining, Knowledge discovery in databases, surveys.*

1. Introduction

Owing to the advances in technical and scientific data collection and data automation we are faced with a huge and endlessly rising amount of data or information which makes it impossible to interpret all this data yourself. Therefore, the growth of innovative applications, techniques and tools that support the human in transforming data into useful facts has been the focus of the comparatively new and interdisciplinary research area “knowledge discovery in databases”. The explosive growth of spatial data and extensive use of spatial databases emphasize the need for the computerized discovery of spatial knowledge. Spatial data mining [Roddick & Spiliopoulou1999, Shekhar & Chawla2003] is the process of discovering motivating and previously unknown, but potentially useful patterns from spatial databases. The difficulty of spatial data and essential spatial relationships restricts the convenience of conventional data mining techniques for extracting spatial patterns. Spatial analysis can possibly be measured to have arisen with in the early hours attempts at cartography and surveying but many fields have contributed and helped to its climb in current appearance.

And the spatial analysis starts with early cartography, surveying and geography at the beginning of history, although the techniques of spatial analysis were not formalized until the later part of the twentieth century. Recently the spatial analysis focuses on computer based techniques because of the huge amount of data, the authority of modern statistical and geographic information science (GIS) software, and the complication of the computational modeling. Some of the contributors of the spatial analysis includes (i) Biology contributed through botanical studies of global and local plant distributions and locations, ethological studies of animal association, landscape environmental studies of plants blocks, ecological studies of spatial population changes, and the study of biogeography. (ii) Epidemiology contributed with early work on disease mapping, notably John Snow's work mapping an outbreak of cholera, with research on mapping the spread of disease and with locational studies for health care delivery. (iii) Statistics has contributed greatly through work in spatial statistics. (iv) Economics has contributed notably through spatial econometrics. (v) Remote sensing has contributed extensively in morphometric and clustering analysis. (vi)Computer science has contributed extensively through the study of algorithms and applications, especially in computational geometry. (vii) Geographic information system is currently a major contributor due to the importance of geographic software in the modern analytic toolbox. Scientific modeling provides a useful framework for new approaches.

2. The Foundation Of Spatial Data Mining

2.1 The Systematic Structure of Spatial Data Mining

The spatial data mining can be used to understand spatial data, discover the relation between space and the non-space data, set up the spatial knowledge base, excel the query, reorganize spatial database and obtain concise total characteristic etc.. The system structure of the spatial data mining can be divided into three layer structures mostly, such as the Figure 1 show .The customer interface layer is mainly used for input and output, the miner layer is mainly used to manage data, select algorithm and storage the mined knowledge, the data source layer, which mainly includes the spatial database (camalig) and other related data and knowledge bases, is original data of the spatial data mining.

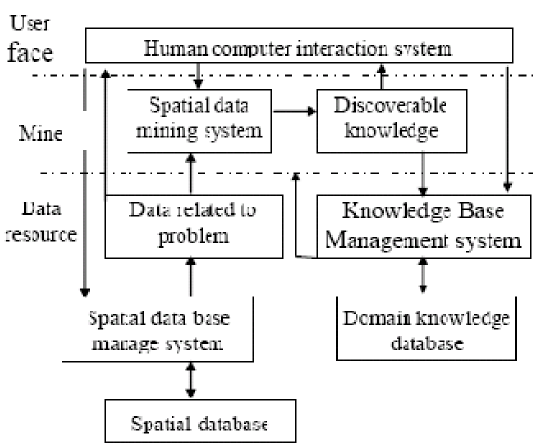

Fig.1 The systematic structure of spatial data mining

2.2 The Method of Spatial Data Mining

The spatial data mining is newly arisen edge course when computer technique, database applied technique and management decision support technique etc. develop the certain stage. The spatial data mining gathered productions that come from machine learning, pattern recognition, database, statistics, artificial intelligence and management information system etc. According to different theories, put forward the different methods of spatial data mining, such as methods in statistics, proof theories, rule inductive, association rules, cluster analysis, spatial analysis, fuzzy sets, cloud theories, rough sets, neural network, decision tree and spatial data mining technique based on information entropy etc..

Rules: There are several kinds of rules can be discovered from databases in general. For example, association rules, or deviation and evolution rules, characteristic rules, discriminant rules can be mined. A spatial association rule is a rule which describes the implication of one or a set of features by another set of features in spatial databases. For example, a rule associating the price range of the houses with nearby spatial features, like beaches, is a spatial association rule. A spatial discriminant rule is a general description of the features discriminating or contrasting a class of spatial data from other class(es) like the comparison of price ranges of houses in different geographical regions. A spatial characteristics rules are a general description of spatial data. For example, a rule describing the general price range of houses in various geographic regions in a city is a spatial characteristic rule.

Thematic Maps: Thematic Map is a map primarily designed to show a theme, a single spatial distribution or a pattern, using a specific map type[2]. These maps show the distribution of a features over a limited geographic areas. Each map defines a partitioning of the area into a set of closed and disjoint regions, each includes all the points with the same feature value. Thematic maps present the spatial distribution of a single or a few attributes. This differs from general or reference maps where the main objective is to present the position of objective is to present the position of objects in relation to other spatial objects. Spatial classification is one of the techniques that analyzes spatial and non-spatial attributes of the data objects to partition the data into a set of classes. These classes generates a map representing groups of related data objects. To illustrate, data objects can be houses each with spatial geocoordinate and non-spatial zip code values (ie.,features) would generates an approximate thematic map of the zip code areas. Maps have been widely used as the main references in the playing field of geography. They are the most common tools for features such as population are maintained for large areas. The values of these features has no meaning use when defined for a specific location. For example, zip codes and MSA codes are two different features and different values of each feature corresponds to different class labels. There are two ways to represent thematic maps: raster and vector. In the raster image form thematic maps have pixels associated with the attribute values. For example, a map may have the altitude of the spatial objects coded as the intensity of the pixel (or the color). In the vector representation , a spatial object is represented by its geometry, most commonly being the boundary representation along with the thematic attributes. For example, a park may be represented by the boundary points and corresponding elevation values.

Image Databases: Image databases are special kind of spatial databases where data almost entirely consists of images or pictures. Image databases are used in remote sensing, medical imaging, etc. They are usually stored in the form of grid arrays representing the image intensity in one or more spectral ranges. For example, k is the automatic discovery. Furthermore, to our knowledge there are no solutions "k-automatic discovery" that have been tested in image data sets. Therefore, we limit our presentation to one of the least tested approaches of the state of the art. The approach discovers k automatically in the context of spatial data mining (Raymond & Jiawei, 1985). Our domain of approach is the content-based indexing of large image databases; however, the domain of application of the state of the art approach is spatial data mining. This difference means that there are different objectives, different data item descriptors, and different confidence measures. We particularly emphasize the confidence measure. The proposed solution that considers confidence measures that are more accurate for content-based indexing of large image databases than the approach proposed for spatial data mining. The solution is inspired, partly, by metrics discussed in Milligan and Cooper(1985) for hierarchical clustering, extended and tested for image databases.

2.3 Spatial Data Structures, Computations, and Queries

Algorithms for spatial data mining involve the use of spatial operations like spatial joins, intersections, aggregates, union, minimum distance, map overlays, buffering geometry, ConvexHull, nearest neighbor queries and others. Therefore, efficient *spatial access methods* (SAM) and data structures for such computation is also a concern in spatial data mining [22]. We will briefly introduce some of the prominent spatial data structures and spatial computations.

Spatial Data Structures: Spatial Data Structure consists of points, line, rectangles, polygons, etc. These are all involving the thematic map coverage. Much discussion has been expended in two decades on the appropriate data structures to handle map data-specifically the relationships between polygons, arcs and nodes on a thematic map coverage. The layman may be exempt for (1) being confused by the plethora of protagonists of various schemes and (2) wondering if they are all that different anyhow. In order to build indices for these data, multidimensional trees have been proposed. The discussion can be carried on at least two levels. At the implementation level anxiety may be over word extent, record types and file structures. At the data concept or abstraction level we wonder, for example, whether we should create node records showing or informing us that a particular position forms the connection of three edges (arcs) and three polygons, or if preserving the polygon numbers on each side of an arc will serve just as well. And it also include quad trees [46], k-d trees, R-trees, R*-trees, etc. One of the prominent SAMs which was much discussed in the literature recently is R-tree [23] and its modification R*-tree [6]. Objects stroed in R-trees are approximated by Minimum Bounding Rectangles (MBR). R-tree in every node stores a set of rectangles. At the leaves there are stored pointers to representation of polygon's boundaries and polygon's MBRs. At the internal nodes each rectangle is associated with a pointer to a child and represents minimum bounding rectangle of all rectangles stored in the child.

Spatial Computations: Spatial Computation (SC), which is based on the transaction of high-level language programs directly into hardware structures. SC program implementations are completely spread, with no federal control. SC circuits are optimized for wires at the outlay of multiplication units. Spatial join is one of the most expensive spatial operations. In order to make spatial queries efficient spatial join has to be efficient as well. The author Brinkhoff et al. proposed an efficient multilevel processing of spatial joins using R*-Trees and various approximation of spatial objects [8]. The first step – filter- finds possible of interesting objects using first their MBRs and later other approximations. In second step – refinement – detailed geometric procedure is performed to check for intersection. Another important in Geographic Information Systems.

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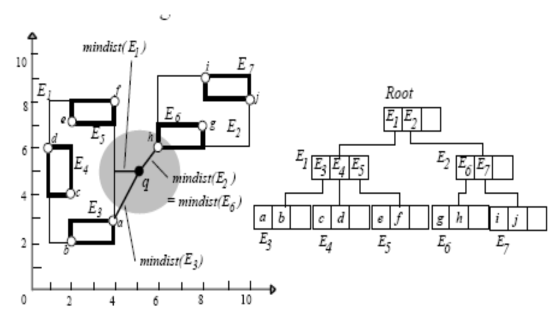

Fig.2 An R-Tree Example

Spatial Query Processing: R-Tree [G84, SRF87, BKSS90] are the most popular indexing for Euclidean query processing due to their simplicity and efficiency. The R-Tree can be viewed as a multi-dimensional extension of the B-tree. Figure2 shows an exemplary R-tree for a set of points {a,b,…,j} assuming a capacity of three entries per node. Points that are close in space (for example a,b) are clustered in the same leaf node (E3) represented as a minimum bounding rectangle (MBR). Nodes are then recursively grouped together following the same principle until the top level, which consists of a single root

3. Algorithms For Knowledge Discovery In Spatial Databases

Spatial data consist of spatial objects and non-spatial description of these objects. Non spatial attributes are used to characterize non-spatial features of objects, such as name, population, and unemployment rate for a city. They are the same as the attributes used in the data inputs f classical data mining. Spatial attributes are used to define the spatial location and extent of spatial objects [7]. The spatial attributes of a spatial object most often include information related to spatial location, e.g., longitude, latitude and elevation, as well as shape.

Table 1. Relationships among Non-spatial data and spatial data

Non-Spatial Relationship (Explicit)	**Spatial Relationship (Often Implicit)**
Arithmetic	Set-oriented: union, intersection, membership,…
Ordering	Topological: meet, within, overlap,…
Is_instance_of	Directional: North, NE, left, above, behind,…
Subclass_of	Metric: e.g., distance,area, perimeter,..
Part_of	Dynamic: update, create, destroy,…
Membership_of	Shape-based and visibility

The algorithms for spatial data mining include generalization-based methods for mining spatial characteristics and discriminant rules [16, 17, 25], two-step spatial computation technique for mining spatial association rules [34], aggregate proximity technique for finding characteristics of spatial clusters [33], etc. In the following sections, we categorize and describe a number of these algorithms.

3.1 Generalization-Based Knowledge Discovery

Data and items in a database often contain complete information at a ancient idea level. Generalization based mining is the concept of data from more than a few evidences from a concept level to its higher concept level and performing knowledge withdrawal on the widespread data (Mitchell, 1982).It assumes the survival of background knowledge in the form of concept hierarchies, which is either data-driven or assigned clearly by expert-knowledge. The data can be articulated in the form of a generalized relation or data-cube on which many other operations can be performed to change generalized data into different forms of knowledge. A few of the multivariate statistical or arithmetic techniques such as principal components analysis, discriminant analysis, characteristic analysis, correlation analysis, factor analysis and cluster analysis are used for generalization based knowledge discovery (Shaw and Wheeler,1994).The generalization-based knowledge discovery requires the existence of background knowledge in the form of concept hierarchies. Issues on generalization-based data mining in object-oriented databases are investigated in three aspects: (1) generalization of complex objects, (2) class-based generalization, and (3) extraction of different kinds of rules. An object cube model is proposed for class-based generalization, on-Line analytical processing, and Data Mining.

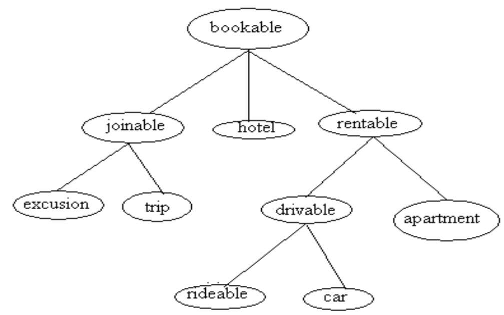

Fig.3 Example of Tourism use concept hierarchy

In the case of spatial database, there can be two kinds of concept hierarchies, non-spatial and spatial. Concept hierarchies can be explicitly given by the experts, or data analysis [26]. An example of a concept hierarchy for tourism is shown in Figure 3.As we ascend the concept tree, information becomes more and more general, but still remains consistent with the lower concept levels. For example, in Figure 3 both ridable and car can be generalized to concept driveable which in turn can be generalized to concept rentable, which also includes apartment. A similar hierarchy may exist for spatial data. For example, in generalization process, regions representing countries can be merged to provinces and provinces can be merged to larger regions. Attribute-oriented induction is performed by climbing the generalization hierarchies and summarizing the general relationships between spatial and non-spatial data by (a) climbing the concept hierarchy when attribute values in a tuple are changed to the generalized values, (b) removing attributes when further generalization is impossible and (c) merging identical tuples. Lu et al. [35] presented two generalization based algorithm, *spatial-data-dominant* and *non-spatial-data-dominant generalizations*. Both algorithms assume that the rules to be mined are general data characteristics and that the discovery pricess is initiated by the user who provides a learning request (query) explicitly, in a syntax similar to SQL. We will briefly describe both algorithms as follows:

Spatial-Data-Dominant Generalization: In the first step all the data described in the query are collected. Given the spatial data hierarchy, generalization can be performed first on the spatial data by merging the concept hierarchy. Generalization of the spatial objects continues until the spatial generalization threshold is reached. The spatial generalization threshold is reached when the number of regions is no greater than the threshold value. After the spatial-oriented induction process, non-spatial data are retrieved and analyzed -for each of the spatial objects using the attribute-oriented induction technique as described.

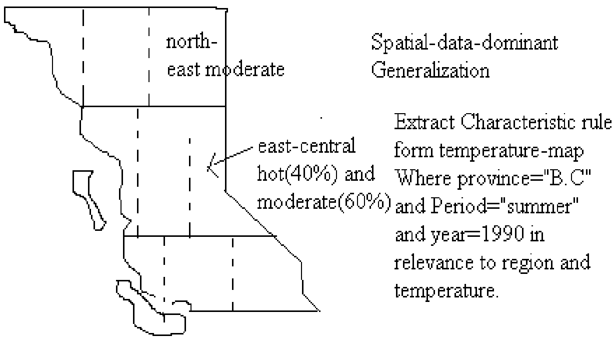

Fig.4 Example of a query and the result of the execution of the spatial-data-dominant generalization

An example of a query and the result of the execution of the spatial-data-dominant generalization algorithm is showed in the Figure 4. In this example, temperature in the range [20, 27) is generalized to moderate, and temperature in the range [27, ∞) to hot. The answer to query is the description of all regions using a disjunction of a few predicates which characterize each of the generalized regions. Temperature measured in the east-central region of British Columbia is in the range [22, 30].The computational complexity of the algorithm is *O(NlogN)*, where N is the number of spatial objects.

Non-Spatial-Data-Dominant Generalization: In the second step the algorithm performs attribute-oriented induction on the non-spatial attributes, generalizing them to a higher (more general) concept level. For example, the precipitation value in the range (10 in, 15in) can be generalized to the concept wet. The generalization threshold is used to determine whether to continue or stop the generalization process. The third and the last step of the algorithm, neighboring areas with the same generalized attributes are merged together based on the spatial function *adjacent_to*. For example, if in one area the precipitation value was 17 in., and in neighboring area it was 18 in. Both precipitation values are generalized to the concept very wet and both areas are merged.

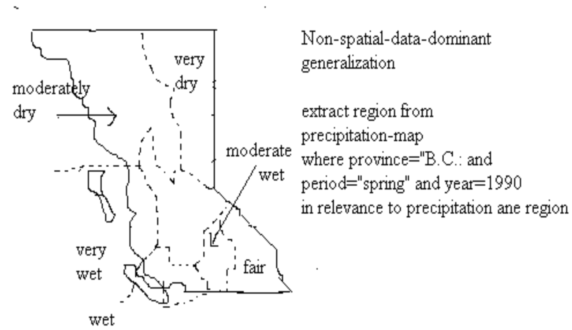

Fig.5 Example of a query and the result of the execution of the non-spatial-data-dominant generalization

The result of the query may be presented in the form of a map with a small number of regions with high level descriptions as it is shown in Figure 5. The computational complexity of this algorithm is also *O(NlogN),* where N is the number of spatial objects.

4. Results And Discussion

As we mentioned earlier, data mining is a young field going back no more than the late 1980s. Spatial data mining is even younger since data mining researchers first concentrated on data mining in relational databases. Many spatial data mining methods we analyzed actually assume the presence of extended relational model for spatial databases. But it is widely believed that spatial data are not handled well by relational databases. As advanced database systems, like Object-Oriented (OO). Deductive, and active databases are being developed, methods for spatial data mining should be studied in these paradigms.

Mining Under Uncertainty: Uncertainty is the inherent property of spatial data and one of significant factors upsetting the course of spatial data mining [41]. There are variety forms for the essentiality and feature of uncertainty in the spatial objects of geographic information system. Essentiality of uncertainty may consist of the mechanism of randomicity, fuzzy, chaos, etc [42]. And finally the characteristic of uncertainty, may include error uncertainty, location uncertainty, attribute uncertainty, topology uncertainty, inconsonance uncertainty, immaturity uncertainty and so on.

Alternative Clustering Techniques: Another interesting future direction is the clusterings of possibly overlapping objects like polygons as opposed to the clustering points. Clustering can be maintained additional information about each object they contain, which can be the degree of membership. In this way, fuzzy clustering can be used to accommodate objects having the same distance from the medoid.

Using Multiple Thematic Maps: We discussed generalization-based methods which used a single thematic map during generalization. Various applications demand spatial data mining to be conducted using multiple thematic maps. This would involve not only clustering but also spatial computations like map overlay, spatial joins, etc. For example, to extract general weather patterns, it may be better to use temperature and precipitation thematic maps and to carry out generalization in both.

Spatial Data Mining Query Language: Design of the user interface can be one of the key issues in the popularization of knowledge discovery techniques. One can create a query language which may be used by non-database specialists in their work. Such a query interface can be supported by Graphical User Interface (GUI) which can make the process of query creation much easier. The user interface can be extended by using pointing devices for the results of a query may give feedback for refinement of the queries and show the direction of further investigation. The language should be powerful enough to cover the number of algorithms and large variety of data types stored in spatial databases.

5. Current Status

We have shown that spatial data mining is a promising field of research with wide applications in GIS, medical imaging, remote sensing, robot motion planning, and so on. Although, the spatial data miming ground is pretty young, a number of algorithms and techniques have been planned and proposed to discover various kinds of knowledge from spatial data. We surveyed existing methods for spatial data mining and mentioned their strengths and weaknesses. This led as to future directions and suggestions for the spatial data mining field in general. We believe that some of the suggestions that we mentioned have already been thought about by researchers and work may have already started on them. But what we hope to achieve is to give the reader a general perspective of the field.

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