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LOCATION BASED MOBILE SPATIAL TEMPORAL DATABASE FRAMEWORK

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ABSTRACT----The number of users with mobile is increasing and this trend is likely to continue in the future. Applications running on mobile clients download information by periodically connecting to repositories of data. Mobile users carry location–enabled mobile terminals (PDA, mobile phone, etc). By location– enabled it is meant that applications running on the mobile terminal have the ability to get the current, historical, or potentially even future locations of the mobile user. Localization of the mobile terminals can be achieved through a wide variety of positioning technologies, including but not limited to, cellular network based positioning, GPS based positioning, geo–referenced sensor based positioning, or even geo– referenced user entry. In this paper, we present a new framework for mobile database systems which takes mobile environments into consideration. This architecture allows us to address issues of concurrency control, disconnection, replica control in mobile database.

KEYWORDS: Mobility, Spatio-Temporal data, GIS

I. INTRODUCTION

Managing spatio-temporal data requires providing spatio-temporal data types and operations, extensions to the query and data manipulation language, and index support for spatio-temporal data. Such issues arise not only in a spatio-temporal context but also when building spatial only or temporal only systems. Over the recent years we witnessed three base variants of extending system architectures.

1. The layered approach uses an off the shelf database system and extends it by implementing the missing functionality on top of the database system as application programs.
2. In the monolithic approach, the database manufacturer integrates all the necessary application-specific extensions into the database system.
3. The extensible approach provides a database system which allows plugging user-defined extensions into the database system.

The Extensible Architecture

The layered as well as the monolithic architecture do not support an easy adaptation of the DBMS to new requirements of advanced applications. The user, however, should be able to "Taylor" the DBMS flexibly, according to his specific requirements. Extensible database systems provide generic system capable of being extended internally by application specific modules. New data types and functionality required for specialized applications is integrated as close as possible in to the DBMS. Traditional DBMS functionality like indexing, query optimization, and transaction management is supported for user-defined data types and functions in a seamless fashion. In this way, an extensible architecture takes the advantage of the monolithic architecture while avoiding its deficiencies. It thus provides the basis for an easy integration of advanced spatio-temporal data types, operations, and access methods which can be used by the DBMS analogously to its standard data types and access methods.

The first extensible system prototypes have been developed to support especially non-standard DBMS applications like geographical or engineering information systems extensions in to the database system. The extensible approach provides a database system which allows plugging user-defined extensions in to the database system.

Spatio temporal mining details are discussed in section 2. In section 3 spatio market basket analyses are discussed. Issues and challenges are focused in section 4. Section 5 deals with Geographical Information Systems. The work is concluded in the section 6.

II. SPATIO–TEMPORAL MINING

Issues and Techniques are carrying online and position–aware cameras and wrist watches, vehicles with computing and navigation equipment, etc. These developments pave the way to a range of qualitatively new types of Internet–based services. These types of services, which either make little sense or are of limited interest in the context of fixed–location, desktop computing, include: traffic coordination and management, way–finding, location–aware advertising, integrated information services, e.g., tourist services. A single generic scenario may be envisioned for these location–based services. Moving service users disclose their positional information to services, which use this and other information to provide specific functionality. To customize the interactions between the services and users, data mining techniques can be applied to discover interesting knowledge about the behavior of users. For example, groups of users can be identified exhibiting similar behavior. These groups can be characterized based on various attributes of the group members or the requested services.

This paper describes experiences with ST rule mining in the Danish spatial data mining company, Geomatic. The task of finding ST rules is challenging because of the high cardinality of the two added dimensions: space and time. Additionally, straight–forward application of association rule mining methods cannot always extract all the interesting knowledge in ST data. The proposed method can in many cases efficiently eliminate the above mentioned explosion of the search space, and allows for the discovery of both implicit and explicit ST rules.

Third, the projection method is applied to a number of different type of ST data such that traditional association rule mining methods are able to find ST rules which are useful for LBSes. Fourth, as a natural extension to the proposed method, spatio–temporally restricted mining is described, which in some cases allows for further quantitative and qualitative mining improvements. Finally, a number of issues in ST rule mining are identified, which point to possible future research directions. Despite the abundance of ST data, the number of algorithms that mine such data is small.

In the STM (Space, Time & Man) project activities of thousands of individuals are continuously registered through GPS–enabled mobile phones, referred to as mobile terminals. These mobile terminals, integrated with various GIS services, are used to determine close–by services such as shops. Based on this information in certain time intervals the individual is prompted to select from the set of available services, which currently might be using.

Upon this selection, answers to subsequent questions can provide more detailed information about the nature of the used service. Some of the attributes collected include: location and time attributes, demographic user attributes, and attributes about the services used. This data set will be referred to as STM in the following. The second ST data set is a result of a project carried out by the Greater Copenhagen Development Council involves a number of city busses each equipped with a GPS receiver, a laptop, and infrared sensors for counting the passengers getting on and off at each bus stop. While the busses are running, their GPS positions are continuously sampled to obtain detailed location information. In this way an individual payment dependent on the person and the length of the travel can be obtained. The data recorded from the chip cards can provide valuable passenger information. When analyzed, data can reveal general travel patterns that can be used for suggesting new and better bus routes.

The third ST data set is the publicly available INFATI data set, which comes from the intelligent speed adaptation (INtelligent FArtTIlpasning (INFATI)) project conducted by the Traffic Research Group at Aalborg University. This data set records cars moving around in the road network of Aalborg, Denmark over a period of several months. During this period, periodically the location and speeds of the cars are sampled and matched to corresponding speed limits. This data set is interesting, as it captures the movement of private cars on a day–to–day basis, i.e., the daily activity patterns of the drivers. This data set will be referred to as INFATI in the following. Finally, the last example data set comes from the Danish Meteorology Institute (DMI) and records at fixed time intervals atmospheric measurements like temperature, humidity, and pressure for Denmark for 5 km grid cells. This data set is unique in that unlike the other data sets it does not capture ST characteristics of moving objects, but nonetheless is ST. This data set will be referred to as DMI in the following.

A Taxonomy of ST Data, Data mining in the ST domain is yet largely unexplored. There does not even exist any generally accepted taxonomy of ST data. To analyze such data it is important to establish taxonomy. Perhaps the most important criterion for this categorization is whether the measured entities are mobile or immobile. The ST data in the DMI data set is immobile in the sense that the temperature or the amount of sunshine does not move from one location to the other, but rather, as a continuous phenomenon, changes its attribute value over time at a given location. On the other hand, the observed entities in the other four data sets are rather mobile.

Another important criterion for categorization is whether the attribute values of the measured entities are static or dynamic. There are many examples of static attributes values but perhaps one that all entities possess is a unique identifier. Dynamic attributes values change over time. This change can be slow and gradual, like in the case of the age of an observed entity, or swift and abrupt, like in the case of an activity performed by the observed entity, which starts at a particular time and last for a well–specified time interval only.

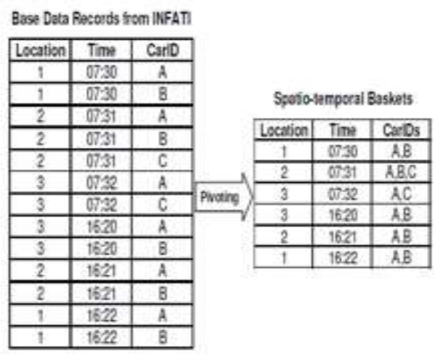
III. SPATIO–TEMPORAL BASKETS

Following the methodology of market basket analysis, to extract ST rules for a given data set, one needs to define ST items and baskets. This task is important, since any possible knowledge that one can extract using association rule mining methods will be about the possible dependencies of the items within the baskets.

Mobile Entities with Static and Dynamic Attributes Consider the STM data; it is mobile in nature and has several static and dynamic attributes. Base data contains the identity and some demographic attributes of the user, and the activity performed by user at a particular location and time. Further attributes of the locations where the activity is performed are also available. By applying association rule mining on this base data one can find possible dependencies between the activities of the users, the demographics of the users, the characteristics of the locations there the activities are performed, and the location and time of the activities.

In the INFATI data set, a record in the base data contains a location, a time, a driver identifier, and the current speed of the car along with the maximum allowed speed at the particular location. The possible knowledge one can discover by applying association rule mining on the base data is where and when drivers or a particular driver occur(s) and/or speed(s) frequently. However, one may in a sense pivot this table of base data records such that each new row represents an ST region and records the car identifiers that happen to be in that region. Applying association rule mining on these ST baskets one may find which cars co–occur frequently in space and time. Such knowledge can be used to aid intelligent rideshare services. It can also be valuable information for constructing traffic flow models and for discovering travel patterns. While the possible knowledge discovered may be valuable for certain applications, the extracted rules are not clearly ST, i.e.: there is no explicit ST component in them. In fact the same set of cars may frequently co–occur at several ST regions which may be scattered in space and time. Nonetheless, it can be argued that since the “co–occurrence” between the items in the ST baskets is actually an ST predicate in itself, the extracted rules are implicitly ST. An alternative to this approach might be to restrict the mining of the ST baskets to larger ST regions. While this may seem useless at first, since the baskets themselves already define more fine–grained ST regions, it has several advantages. First, it allows the attachment of an explicit ST component to each extracted rule. Second, it enhances the quality of the extracted rules. Finally, it significantly speeds up the mining process, as no two itemsets from different regions are combined and tried as a candidate. Figure 3.1 shows the process of pivoting of some example records abstracted from the INFATI data set.

Figure 3.2 shows the process and results of spatio–temporally restricted and unrestricted mining of the ST baskets. In this example the shown frequent itemsets are based on an absolute minimum support of 2 in both cases, however in the restricted case specifying a relative minimum support would yield more meaningful results. Naturally the adjective “relative” refers to the number of baskets in each of the ST regions. The above mentioned qualitative differences in the result obtained from spatio–temporally restricted vs. unrestricted mining. While the frequent co–occurrence of cars A and B, and cars A and C are detected by unrestricted mining, the information that cars A and B are approximately equally likely to co–occur in area A1 in the morning as in the afternoon, and that cars A and C only co–occur in area A1 in the morning is missed. Similar pivoting techniques based on other attributes can also reveal interesting information.



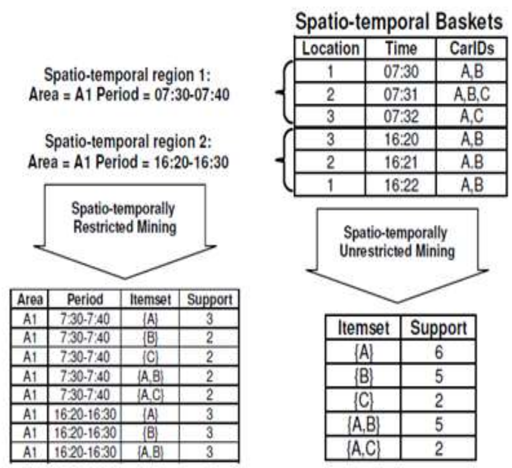
Location	Time	CarID
1	07:30	A
1	07:30	B
2	07:31	A
2	07:31	B
2	07:31	C
3	07:32	A
3	07:32	C
3	16:20	A
3	16:20	B
2	16:21	A
2	16:21	B
1	16:22	A
1	16:22	B

Location	Time	CarIDs
1	07:30	A,B
2	07:31	A,B,C
3	07:32	A,C
3	16:20	A,B
2	16:21	A,B
1	16:22	A,B

Figure 3.1 Process of Pivoting to obtain ST Baskets from INFATI Base Data

This record contains the identifier of the user, the transportation line used, and the location and time of the usage. For simplicity assume that a trip is defined to last at most 2 hours. As a first step of the mining, one can retrieve all the records that fall within the ST region of the origin. Following, one can retrieve all the records within 2 hours of the users that belonged to the first set. By pivoting on the user–identifiers, one can derive ST baskets that contain locations where the user generated a record by making use of a transportation service.

Applying association rule mining to the so–derived ST baskets one may find frequently travelled routes originating from a specific ST region. The pivoting process for obtaining such ST baskets and the results of mining such baskets is illustrated in a simple example in the light bordered box of Figure 3.3. Naturally, the frequent itemset mining is only applied to the ”Unique Locations” column of the ST baskets. As before the minimum support is set to 2. Considering the spatial relation between the locations one might consider altering the bus routes to better meet customer needs. For example, if locations A and C are close by on the road network, but no bus line exists with a suitable schedule between A and C, then in light of the evidence, i.e., support of A,B,C is 2, such a line can be added. Note that while the discovered frequent location sets do not encode any temporal relation between the locations, one can achieve this by simply placing ST regions into the ST baskets as items. The pivoting process and the results of mining are shown in the dark bordered box of Figure 3.3. The discovered ST itemsets can help in adjusting timetables of busses to best meet customer needs.



Location	Time	CarIDs
1	07:30	A,B
2	07:31	A,B,C
3	07:32	A,C
3	16:20	A,B
2	16:21	A,B
1	16:22	A,B

Area	Period	Itemset	Support
A1	7:30-7:40	{A}	3
A1	7:30-7:40	{B}	2
A1	7:30-7:40	{C}	2
A1	7:30-7:40	{A,B}	2
A1	7:30-7:40	{A,C}	2
A1	16:20-16:30	{A}	3
A1	16:20-16:30	{B}	3
A1	16:20-16:30	{A,B}	3

Itemset	Support
{A}	6
{B}	5
{C}	2
{A,B}	5
{A,C}	2

Figure 3.2 Process and Results of Spatio-Temporally Restricted Vs Unrestricted Mining of ST Baskets

The base data can be viewed as transactions in a relational table with a timestamp, a location identifier and some atmospheric measurements like temperature, humidity, and pressure. Considering the geographical locations A, B, C, and D depicted in Figure 3.4, one might be interested in trends like, when the temperature in regions A and B is high and the pressure in regions A and C is low, then at the same time the humidity in region D is medium. By applying something similar to the pivoting techniques above, one can extract such information as follows. For each record concatenate the location identifiers with the atmospheric measurements. Then, for each distinct time interval when measurements are taken, put all concatenated values, each of which is composed of a location identifier and an atmospheric measurement, into a single, long ST basket.

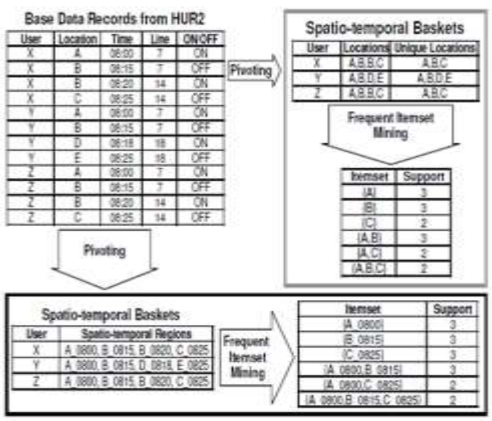
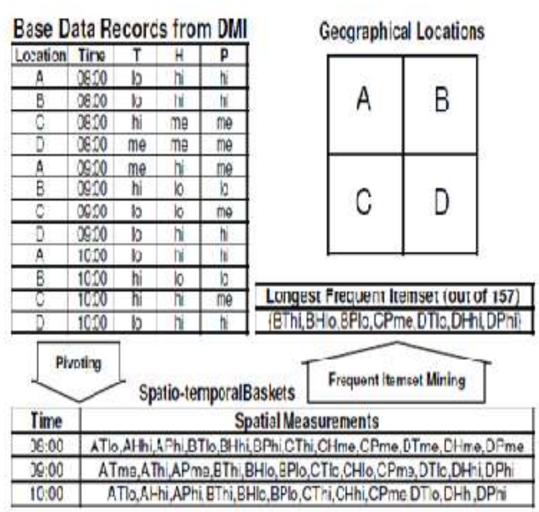


Figure 3.3: ST Baskets and Frequent Itemset Mining for HUR2

By performing association mining on the derived ST baskets one can obtain the desired knowledge. As an illustrative example, depicted in Figure 3.4, consider the four neighboring cells A, B, C, and D and the corresponding measurements of temperature (T), humidity (H), and pressure (P) at three different times. Items in the ST baskets are derived by concatenating a location identifier followed by an attribute symbol and an attribute value. Hence, the item 'ATlo' in the ST basket at time '08:00' encodes the fact that at '08:00' at location 'A' the temperature ('T') was low ('lo'). Notice that the extracted knowledge refers to specific locations. If one is interested in obtaining knowledge about the inter–dependencies of these attributes relative (in space) to one another, for each base data record at each distinct time interval when measurements are taken, an ST basket can be constructed that encodes measurements from neighboring cells only. So, for example considering the immediate 8 neighbors of a cell and assuming three different attributes the number of items in each basket is 3 + 8 × 3 = 27. Considering a five–by–five relative neighborhood centered around a cell the number of items in each basket is 75, and the number of possible itemsets, given three possible attribute values for each of the attributes is 3 75 ≈ 6.1 × 1034.

To reduce complexity, top–down and bottom–up mining can occur at different spatial and temporal granularities. While in the above examples the type of ST data that was analyzed and the type of ST knowledge that was extracted is quite different the underlying problem transformation method—referred to as pivoting—is the same. In general, one is given base records with two sets of attributes A and B, which are selected by a data mining expert and can, contain either spatial, temporal and/or ordinary attributes. Pivoting is then performed by grouping all the base records based on the A–attribute values and assigning the B–attribute values of base records in the same group to a single basket. Bellow, attributes in A are referred to as pivoting attributes or predicates, and attributes in B are referred to as pivoted attributes or items.



pred/item type	s–i	t–i	st–i	ordinary–i
s–predicate	s–b	**st–b**		s–b
t–predicate	**st–b**	t–b		t–b
st–predicate	**st–b**	**st–b**	**st–b**	**st–b**
other–predicate	s–b	t–b	**st–b**	ordinary–b

This restriction is possible due to a side effect of the pivoting technique. When a particular basket is constructed, the basket is assigned the value of the pivoting attribute as an implicit label. When this implicit basket label contains a spatial, temporal, or ST component, restricting the mining to a particular spatial, temporal, or ST sub region becomes a natural possibility. It is clear that not all basket types can be mined using spatial, temporal, or ST restrictions. Table 3.2 shows for each basket type the type of restrictions for mining that are possible. The symbols s, t, st, r, and unr in the table are used to abbreviate the terms 'spatial', 'temporal', 'spatio–temporal', 'restricted', and 'unrestricted' respectively.

Table 3.2: Possible Mining Types of Different Types of Baskets

basket/mining type	s–r	t–r	st–r	unr
s–basket	X			X
t–basket		X		X
st–basket	X	X	X	X
other–basket				X

IV. ISSUES IN SPATIO–TEMPORAL RULE MINING

The proposed pivoting method naturally brings up questions about feasibility and efficiency. In cases where the pivoted attributes include spatial and/or temporal components, the number of items in the baskets is expected to be large. Thus, the number and length of frequent itemsets or rules is expected to grow. Bottom–up, level–wise algorithms are expected to suffer from excessive candidate generation, thus top–down mining methods seem more feasible. Furthermore, due to the presence of very long patterns, the extraction of all frequent patterns has limited use for analysis. In such cases closed or maximal frequent itemsets can be mined. Useful patterns for LBSes are expected to be present only in ST subregions, hence spatio–temporally restricted rule mining will not only make the proposed method computationally more feasible, but will also increase the quality of the result. Finding and merging patterns in close–by ST subregions is also expected to improve efficiency of the proposed method and the quality of results. Placing concatenated location and time attribute values about individual entities as items into an ST basket allows traditional association rule mining methods.

SPATIOTEMPORAL DATABASE: APPLICATIONS

„
There are three Types of Spatiotemporal Applications which are given below.
‰
1. Applications may involve objects with continuous motion, Navigational systems manage moving objects, Objects change position, but not shape.
‰
2. Applications dealing with discrete changes of and among objects, Objects' shape and their positions may change discretely in time.
‰
3. Applications may manage objects integrating continuous motion as well as changes of shape

„
A "storm" is modeled as a "moving" object with changing properties, (e.g., intensity) and shape over time

V. GEOGRAPHICAL INFORMATION SYSTEMS

Geographical information systems (GIS) and applications assist us in commuting, traveling and locating our points of interests. The efficient implementation and support of spatial queries in those systems is of particular interest and importance. Manipulating the spatial component of a single layer of data is useful, but the full potential of GIS lies in its ability to integrate data from a variety of layers. At a basic level this merely involves combining layers on - screen to compare patterns. This might be as simple as taking a raster scan of a map and placing a vector layer over the top. The raster layer provides a spatial context for the features in the vector layer. Another option is to lay one vector layer on top of another, for example to compare the pattern of roads with the location of farms to see which farms lies near the major roads. Field boundaries might be a third layer added to this. This approach goes beyond basic mapping, as querying the underlying attribute database allows a detailed understanding of a multi-faceted study area to be developed. In this way an integrated understanding of the problem can be derived from many (possibly highly disparate) sources. In this section various single and multiple layer operation are mentioned.

Overlay Operations for Vector data In addition to simply combining layers, querying them and comparing them, layers can be combined to produce new layers through geometric intersections. This is called overlay. Any of the three types of vector data can be overlaid with any of the others.

5.1 Overlay Operations

An overlay operation combines not only the spatial data but also the attribute data . This has many potential uses. Overlay is one of the most important function of GIS. These involve combining different feature type (point, line, area) from different layers to produce a new map containing features and attributes of user interest. Thus it of three types:

i. Point-in-polygon Overlay
ii. Line-in-polygon Overlay
iii. Polygon-in-polygon Overlay

5.1.1 Point-in-polygon Overlay

Overlays point coverages on an polygon coverage. It computes contained in relationship and the resulting point coverage contains new attributes (point features assumes the polygon attributes they lie within). For e.g. combining wells (point coverage) and planning districts (polygon coverage) will help in queries like how many wells are there in each district.

5.1.2 Line-in-polygon Overlay

Overlays line coverage onto a polygon coverage. The line features in the output coverage assumes the attribute of the polygon they lie within. The lines are broken at each area object boundary

5.1.3 Polygon-in-polygon Overlay

Polygon overlay is a spatial operation which overlays one polygon coverage onto another to create a new polygon coverage. The spatial locations of each set of polygons and their polygon attributes are joined to derive new data relationships. The output coverage of such overlay operation is a polygon coverage. Polygo-in-polygon overlay is of three types: Union, Intersection, Identity.

Union

The UNION procedure is equivalent to the boolean operator "OR" in which two or more data layers are overlaid to produce a combined coverage. Every polygon in the output coverage carries the attribute information of both the input and union coverage. The input and the union coverages must be a polygon coverage.

Intersect

The INTERSECT procedure is equivalent to the boolean AND operation. When the two coverages are over-layed, only portion of the input coverage that falls inside the intersect coverage will remain in the output coverage. While the intersect coverage must be a polygon, the input coverage can be a line, polygon or point coverage. If the input coverage is a line coverage the output coverage will also be a line coverage.

Identity

The IDENTITY overlay function everything located within the boundaries of the input coverage is collected in the output coverage. The boundary of the output coverage is identical to the input coverage. The identity procedures applies to point, line and polygon coverages . If the input coverage is a point feature the output coverage is also a point coverage.

5.2 Connectivity Analysis

Connectivity analysis is to analyze the connectivity between points, lines and areas in terms of distance, area, travel time, optimum path etc. Connectivity analysis consists of the following analyses.

i. Proximity Analysis
ii. Neighbourhood analysis
iii. Network Analysis

5.2.1 Proximity Analysis

Proximity analysis is measurement of distances from points, lines and boundaries of polygons. One of the most popular proximity analysis is based on "buffering", by which a buffer can be generated around a point, line and area with a given distance. Buffering is easier to generate for raster data than for vector data. Proximity analysis is not always based on distance but also time. For example, proximity analysis based on access time or travel time will give the distribution of time zones indicating the time to reach a certain point.

5.2.2 Neighbourhood Analysis

Some kind of spatial associations are made in case of neighbourhood analysis. It evaluates the characteristics of an area surrounding a specified location. Neighbourhood functions include the calculation of a value representing a weighted average, maximum value, minimum value, measure of diversity or rate of change of a part of the statistical surface represented by the overlay in an area around the point, and so on. The various methods of identification of neighbours includes: Contiguity based neighbours and Distance based neighbours.

5.2.3 Network Analysis

Network analysis includes determination of optimum paths using specified decision rules. The decision rules are likely based on minimum time or minimum distance, maximum correlation occurrence or capacity, shortest path and so on.

5.3 Spatial Analysis of Raster Data

There are four basic functions of raster data according to which analysis of raster data is done. These are:

Local functions: that work on ever single cell, Focal functions: that process the data of each cell based on the information of a specified neighborhood, Zonal functions: that provide operations that work on each group of cells of identical values Gobal functions: that work on a cell based on the data of the entire grid.

5.3.1 Overlay Operation in Raster Data

Overlay can also be performed on raster datasets providing they use the same pixel sizes. This is sometimes referred to as map algebra as two or more input layers are used to create an output layer whose cell values are calculated based on a mathematical operation between the input layers. Cell values on the two input layers are added to calculate values on the output layer. Other mathematical operations such as subtraction and multiplication can also be used.

Map algebra with raster data In raster overlay the values of cells in the output layer is calculated from the results of a mathematical operation on the input layers. In this example the two input layers have been added. Other operations such as multiplication and subtraction can also be used. When two layers are combined using an overlay operation, the resulting layer will be at best as accurate as the less accurate layer. Raster based overlay operation tools are:

i. Arithmetic functions (+, -, * , /)
ii. Relational functions (< , > , =)
iii. Logical operations (and , or , xor , not)
iv.Conditional functions (if , then , else)

5.4 Classification

Based on the number of classes before and after the classification, three types of classifications can be differentiated:
a) one to one (1:1): The number of classes before is thesame as the number of classes after the classification process: there are no changes in the geometry of the spatial objects, they have been re-assigned.

b) many to one (M:1): The number of classes after the classification is smaller than the number of classes before the process: generalization, aggregation, merging

c) one to many (1:M): The number of classes after the classification process is more than the those before the classification: in vector format spatial objects are split in different objects; in raster format e.g. unique ID's are assigned to each
pixel in the output map

5.5 Reclassification:

Reclassification involves the selection and presentation of a selected layer of data based on the classes or values of a specific attribute. It involves looking at an attribute, or a series of attributes, for a single data layer and classifying the data layer based on the range of values of the attribute. For examples: Reclassify a soil map into a PH map, classify an elevation map into classes with intervals of 50 m.

5.6 Spatio-Temporal Operators

‰Location-temporal Operator ST_SP(A, T)„
Returns the spatial representations
of object A valid at time T
‰
Orientation-temporal Operators
„ Return a boolean value indicating whether there exists specific relationship between two objects (A and B) ST_NORTH(A,B) or ST_EAST(A,B), etc
‰
Metric-temporal Operators
„ The metric of object A at a time value T, ST_AREA(A, T) Distance between two spatial components A and B at time T: ST_DISTANCE(A,B,T)
‰
Topologic-temporal Operators
„ Return a Boolean value indicating the topologic relationship between A and B during the time T: ST_DISJOINT (A, B, T)
Mobile users access LBSes through their mobile terminals. An LBS is a service that has one or more of the following characteristics. An LBS is either explicitly or implicitly requested by the users via the mobile terminal. An LBS delivers its service selectively based on the context of the mobile user.

There are many aspects of user–contexts are considered: the current, historical and future locations of the user, any possible user–patterns in the user location data, and common patterns in the location data of a group of users.

VI. CONCLUSION

This paper focuses the following implications and consequences. First, all subsets of frequent and long itemsets are also frequent, but not necessarily long and of interest. Second, due to the low support requirement a traditional association rule mining algorithm, disregarding the length requirement, would explore an excessive number of itemsets, which are frequent but can never be part of a long and frequent itemset. Hence, simply filtering out "short" itemsets after the mining process is inefficient and infeasible. New mining methods are needed that efficiently use the length criterion during the mining process.

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