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DATA MINING DATA WAREHOUSING: ANALYSIS OF APPLICATIONS MEASURES OF MULTI DIMENSIONAL MOVING DATA OBJECTS THROUGH TRAJECTORY DATA WARE HOUSE

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ABSTRACT

The key goals associated with this research includes to evaluate the assorted perspective of trajectory data warehouse and its related aspects, to perform the implementation based on noveland effective approach on trajectory data warehouse so that the effectual response can be achieved, to implement a novel or integrate the metaheuristic based approach so that the soft computing based optimized results can be achieved and to associate the applications of soft computing and related aspects so that the better results can be achieved. The main objective of this research is to explain the concept of data mining and data warehousing and its application measures of multi dimensional moving data object through trajectory data warehouse, to identify the issues related to the data warehouse, and to suggest ways of resolving them. The main objective of study includes to study the relationship between data mining and data warehousing, to study the design of schema for trajectory data warehouses conceptual modeling, to study different measures of trajectory data warehouse and to study SQL for determination of computed measures. The motivation behind this work done is the realization that with increasing in the advance technologies like location aware devices, traffic control, location based services, fleeting management-commerce these system requires trajectory data warehouse of gliding object. Today's applications have trajectory data warehouses of gliding objects but it has limited measures, None of the present day stand-alone application measures that predict average motion major direction of gliding objects which will help to location aware devices for decision making.

Keywords: Data Mining Data Warehousing, Applications Measures of Multi Dimensional Moving Data Objects, Trajectory Data Ware House

I. TRAJECTORY DATA WAREHOUSE AND CUTTING EDGE TECHNOLOGIES

Cutting edge area mindful gadgets and applications convey colossal amounts of spatiotemporal data concerning moving items, which must be either rapidly techniques for continuous applications, similar to activity control administration, or deliberately dug for complex, information finding undertakings. Regardless of the possibility that such reality and figures generally begin as planned, found perceptions of all around distinguished articles,

IJARSE
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they should regularly be put away in total structure, without recognizable proof of the comparing moving items, either for security reasons, or just for the sheer measure of data which ought to be kept online to perform explanatory operations. Such a total is typically an unpredictable errand, and inclined to the presentation of mistakes which are enhanced by resulting total operations. Consequently, we propose a way to deal with the issue which depends on traditional Data Warehouse (DW) ideas, so we can receive a settled and concentrated on data model, and inaddition the proficient devices and frameworks effectively created for such a model. Our DW is gone for characterizing, as essential components of interest, not the perceptions of the moving articles, yet rather their directions, so we can think about properties, for example, normal velocity, voyaged separation, most extreme increasing speed, and nearness of unmistakable directions. We accept the granularity of the reality table given by a consistent three-dimensional framework on the spatial and fleeting measurements, where the truths are the arrangement of directions which cross every cell of the lattice, and the measures are properties identified with that set. One of the principle issues to face is the productive populace of the Trajectory DW (TDW) from surges of direction perceptions, touching base in an unusual and unbounded route, with various rates. The test is to misuse a constrained measure of support memory to store a couple of approaching past perceptions, with a specific end goal to accurately remake the different directions, and register the required measures for the base cells, lessening however much as could reasonably be expected the approximations. The model of our TDW and the relating stacking issues has been presented. In this study we talk about in point of interest the stacking and calculation of an intricate total measure, the nearness, which can be characterized as the quantity of unmistakable directions lying in a cell. Such a measure postures non paltry computational issues. On one hand, in the stacking stage, just a limited measure of memory can be utilized for breaking down the information streams. This suffices for direction remaking, however at times we may in any case tally an article, with numerous perceptions in the same cell, more than once. Henceforth the measure nearness registered for base cells is as a rule an estimate of the careful quality. A second estimate is presented in the move up stage. Truth be told, following the move up capacity for the measure nearness is, as unmistakable tally, an all encompassing capacity; it can't be figured utilizing a limited number of helper measures beginning from sub-totals. Our proposition depends on a surmised, albeit extremely precise, nearness total capacity, which mathematically consolidates a limited measure of other sub-total measures, put away in the base cells of the network. The study gave an intensive examination of the aforementioned strategy, centering, specifically, on the mistakes presented by the approximations. From our tests, our strategy ended up producing a blunder which is sensibly littler than the one of an as of late proposed calculation [Tao et al. 2004], in view of representations, which are a surely understood probabilistic including technique data bases applications. We additionally understood a model of our TDW, so as to examine its plausibility when utilizing item warehousing apparatuses, similar to the Oracle one. The principal test is the ETL strategy of DW: by abusing a couple of recollections, we need to change a flood of direction perceptionson-the-fly and total them to upgrade the base cells of our spatio-transient 3D shape. Utilizing aJava application, playing out the data change, and a particular stacking technique accessible in theOracle suite, we ready to expand and stack around 7000 perceptions for every second. The othertest is the productive calculation of our rough total capacity, used to move up the nearness measure.By studying all literature mentioned above I inspired to find out one of the measure called asmajor direction this measure average motion angle of different objects in a spatial area.

IJARSE
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II. TRAJECTORY SEGMENT

It is line segment represented as a pair of triplets((xs, ys, ts), (xE, yE, tE))

Where ((xS, yS, tS), (xE, yE, tE)) represent the start and end positions for the segment at times tS, tE respectively.

III. TRAJECTORY OF MOVING OBJECT

It is defined as a finite sequence of trajectory segments (s1, s2, s3…. sn) such that

1. A moving object trajectory is continuous.

2. For every pair of consecutive segments si, si+1 the end points of si is the start point si+1 Trajectory of moving object can be represented by a finite set of observations, that is. a finite subset of points taken from the actual continuous trajectory. This finite set is called a sampling.

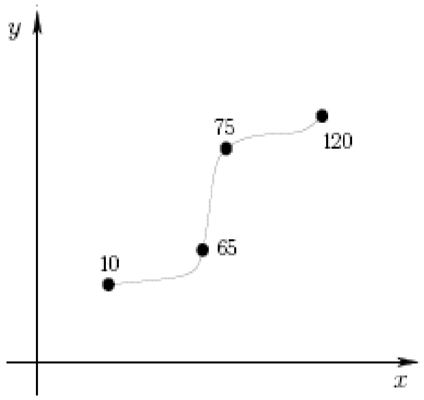

Figure 2.3. Trajectory with sampling

In The above Figure a trajectory of a moving object in a two dimensional space. Each point of the trajectory is given by a tuple (id, x, y, t) corresponding to an object id in a position (x, y) at time t.There may be situations where we have to reconstruct the trajectory of the moving object from its sampling, e. g., when one is interested in computing the continuous increase in number of trajectories in a given area. To solve this problem there is use of linear local interpolation for this assume the movement of the objects between the observed points having constant speed, in a straight way. A Trajectory Data Warehouse (TDW) is to capable to store a stream of samplings, process the data volume, compute and store the measures in order to provide an environment to analyze the information about the objects.

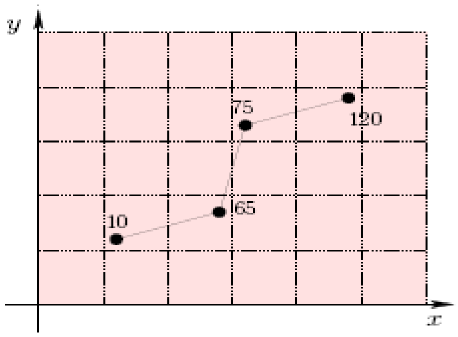

Figure 2.4. Linear interpolation

IJARSE
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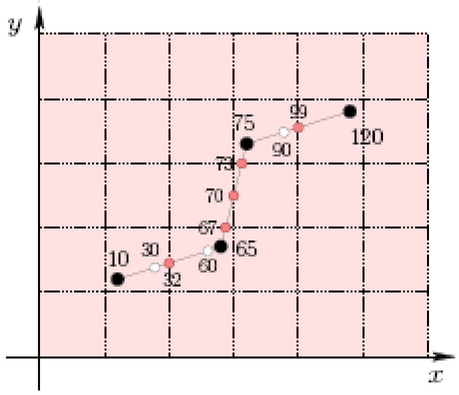

Figure 2.5. Interpolated Trajectory with spatial and temporal points

Object_Id	Timestamp	Type	Lat	Lng
0	0	newpoint	18.355946	77.28329
1	0	newpoint	18.35313	76.645806
2	0	newpoint	18.161188	76.017025
3	0	newpoint	18.124529	77.183317
4	0	newpoint	18.342242	77.284678
5	0	newpoint	18.140906	77.252816
6	0	newpoint	17.996596	76.882355
7	0	newpoint	17.958391	77.053568
8	0	newpoint	18.133967	77.181368
9	0	newpoint	18.159583	77.250413
10	0	newpoint	18.6611	77.264
11	0	newpoint	18.307469	77.254906
12	0	newpoint	18.041483	77.151528
13	0	newpoint	18.417941	76.541608
14	0	newpoint	17.972195	77.082547
15	0	newpoint	18.438634	77.267645
16	0	newpoint	18.3135	77.224315
17	0	newpoint	17.982534	77.20939
18	0	newpoint	18.654593	76.240977
19	0	newpoint	18.636313	76.36676
20	0	newpoint	18.145	76.3885
21	0	newpoint	18.174959	77.142716
22	0	newpoint	18.013993	77.019201
23	0	newpoint	18.115671	76.981009
24	0	newpoint	18.4042	77.1031
25	0	newpoint	18.211721	75.988654
26	0	newpoint	18.112431	77.187118
27	0	newpoint	18.073882	77.287017
28	0	newpoint	18.232452	77.180921
29	0	newpoint	18.176395	77.205728
30	0	newpoint	18.040842	77.157634
31	0	newpoint	18.303228	75.929119
32	0	newpoint	18.182426	76.736672
33	0	newpoint	17.957458	77.291462
34	0	newpoint	18.000684	77.04561
35	0	newpoint	18.334759	76.640372
36	0	newpoint	18.236489	77.069184
37	0	newpoint	18.000684	77.04561
38	0	newpoint	18.253255	76.03048
39	0	newpoint	17.972195	77.082547
40	0	newpoint	18.667471	76.368565
41	0	newpoint	18.318831	76.571678
42	0	newpoint	17.982045	77.042811
43	0	newpoint	18.118924	76.373889
44	0	newpoint	18.002025	77.047195
45	0	newpoint	18.572937	76.027364
46	0	newpoint	18.670052	76.481977
47	0	newpoint	18.643635	76.169612
48	0	newpoint	18.377119	77.250728
49	0	newpoint	18.017615	77.061831
50	0	newpoint	18.180315	76.022144

Figure 4. Dataset of 2000 objects

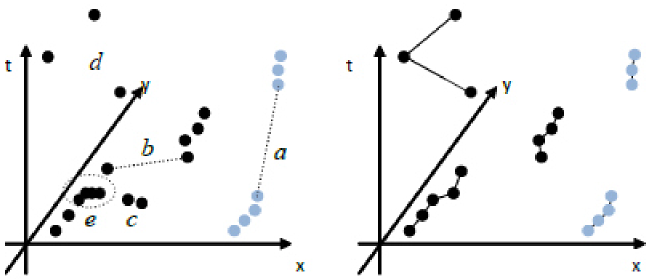

Figure 5. Reconstructed trajectories.

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```
Algorithm Cell-Oriented-ETL(D MODTrajectoryTable)
// For each pair <Region, Interval> forming a s-t cell Cj
FOR EACH cell Cj DO
// Find the set of sub-trajectories inside the cell
S = intersects(D, Cj);
// decompose S to subsets according to object profile
FOR EACH subset S' of S DO
// Compute the various measures
Compute_Measures(S');
END-FOR
END-FOR
```

IV. CONCLUSION

The main objective of this research is to explain the concept of data mining and data warehousing and its application measures of multi dimensional moving data object through trajectory data warehouse, to identify the issues related to the data warehouse, and to suggest ways of resolving them. The main objective of study includes to study the relationship between data mining and data warehousing, to study the design of schema for trajectory data warehouses conceptual modeling, to study different measures of trajectory data warehouse and to study SQL for determination of computed measures. The motivation behind this work done is the realization that with increasing in the advance technologies like location aware devices, traffic control, location based services, fleeting management-commerce these system requires trajectory data warehouse of gliding object. Today's applications have trajectory data warehouses of gliding objects but it has limited measures, None of the present day stand-alone application measures that predict average motion major direction of gliding objects which will help to location aware devices for decision making.

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