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Frequent Pattern Analysis of Moving Objects Using Apriori Algorithm

Heena Rani[1]
M.Tech. (Computer Sc. & Engg.)
Dept. of Computer Sc. & Applications
Kurukshetra University, Kurukshetra
Kurukshetra, India

Dr. (Mrs.) Shuchita Upadhyaya[2]
Professor
Dept. of Computer Sc. & Applications
Kurukshetra University, Kurukshetra
Kurukshetra, India

Vinod Kumar[3]
Assistant Professor
Dept. of Computer Sc. & Applications
Kurukshetra University, Kurukshetra
Kurukshetra, India

Abstract :

Data mining is one of the fastest area of research. But the conventional studies on data mining do not consider both aspects spatial and temporal simultaneously. In this paper, the author discuss a new algorithm and technique to find the temporal patterns found in frequent sequence of moving objects that have spatial and temporal dimensions.

Keywords : Apriori Algorithm, Association Rule, Frequent Patterns, Frequent items, Item set, Pattern mining.

I. INTRODUCTION

A mobile object can be defined as an object that changes its geographical position as time passes. Such objects have spatial and temporal properties. The space-time nature of this kind of data results in the generation of huge amounts of trajectory data and imposes new challenges regarding their efficient management. To store this information, the traditional database technology has been extended into Moving Object Databases (MODs) that handle modelling, indexing and query-processing issues for trajectories [4], [5]. Trajectory data warehouse (TDW) is used to analyzed these objects. With the time passage moving objects changes and this posses a unique pattern. The pattern generated by moving objects can be traced by using the temporal data mining technique [6]. In this paper, the author adopts a methodological approach that is used to generate the frequent pattern of moving objects using apriori algorithm of association rules.

II. MOVING OBJECTS DISCRIPTION

Data mining existing models are too static to properly identify the location of moving objects, which continues to change over time. Many researches followed to trace moving objects in temporal and spatial dimensions [9], [10], [11], [7], [8]. Moving objects location change may occur in a discrete or continuous pattern, and thus, it can be described as a point in time or time periods. Till now, there is no consistent and well-developed definition of the moving objects.

The definition of moving objects can be defined as:

Mpoint = oid,{(T1 , L1), (T2 , L2), ... (Tn , Ln)}

where

oid = a discriminator for the object that possesses unique components

T = effective time

L = location of the sampled object denoted by x, y

Since to draw the continuous change of moving objects is impossible, we draw the moving locations of objects using discrete points. Each point represents the starting and ending points of the time span of the object. By using a plane coordinate system with x- and y-axis spatial attributes of moving objects can be describe.

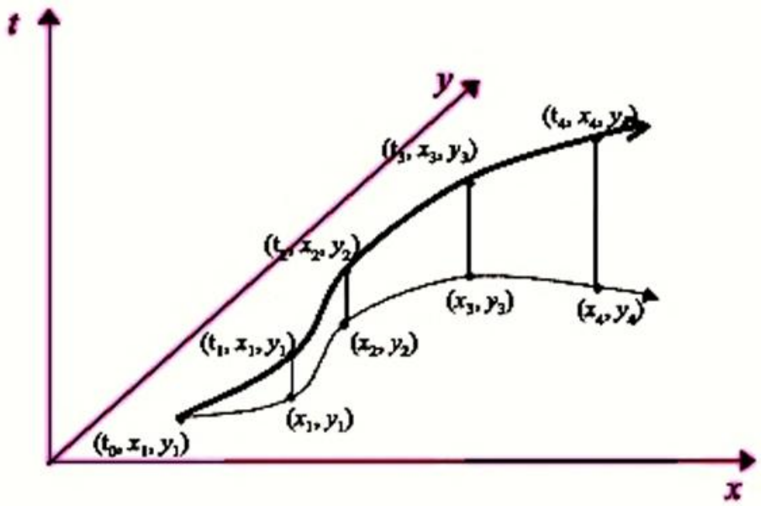

Fig.1 : Moving Object Location Variation

Table 1 shows examples of moving objects in a form of a relational database table

OID	T	X	Y
100	2001/10/10/13/10	3321000	-233100
100	2001/10/10/13/20	3397000	-463600
100	2001/10/10/13/25	3385000	-523600

TABLE I : Example of Moving Objects

III. FREQUENT PATTERN ANALYSIS

Let L={l_1, l_2, ... l_k} denotes a finite set of coordinates that represent the spatial location of moving objects, where l_i = (x_i , y_i), xi and yi are coordinates of two dimensional plane, and let A = {a_1, a_2, ... a_m} represents set of areas that represent spatial location attributes which is obtained by transforming coordinate value into area. Hence, it is called as "generalization of the location". A sequence S = {s_1, s_2, ... s_n} is an ordered list of the areas, where n denotes the length of this sequence, and S_k = (t_k, a_k), where t_k denotes the specific time for which moving objects were sampled, and a_k ϵ A. Apriori algorithm is used for frequent pattern mining , this algorithm uses breadth first search. [1]

A. Apriori Algorithm

C_K – K item set candidates, L_k – frequent k item set, that is candidate with support count>= min support count

Steps

- Step 1
  scan all transaction to count the number of occurrence of each transaction
  C_1

Item set	Support count

{The support of sequence s can be defined as a proportion of entire (including s) moving sequence i.e., SUP(S) = {Si | S ⊆ Si } / m where m is the length of the sequence. Minimum support threshold is the lowest value that each frequent sequence satisfies. It is called as min_sup. If a sequence s has sup (s) ≥ min_sup, then it can be referred as frequent sequence. Each item set will be counted only once although it appears more than once in the sequence.}

- Step 2
  Determine L1 – set of frequent 1 item set [2]
- Step 3
  Generate C2 – 2 item set candidates and scan D for support count
- Step 4
  Determine L2 – set of frequent 2 item set
- Step 5
  Generate C3 – 3 item set candidates

*prune {apriori property – all subsets of a frequent itemset must be frequent} [2]

- Step 6
  Find the support count of C3
- Step 7
  Determine L3 – set of frequent 3 item set
- Step 8

Generation of candidate set remain continues until sup_count>= min sup_count and return the frequent item set [3]

1) Example of Frequent Pattern Analysis:

Data set D (say)

CK – K item set candidates, Lk – frequent k item set, that is candidate with support count>= min support count

Let min support count=2

Transaction	Item
1	I1,I2,I5
2	I2,I4
3	I2,I3
4	I1,I2,I4
5	I1,I3
6	I2,I3

7	I1,I3
8	I1,I2,I3,I5
9	I1,I2,I3

TABLE II : Dataset of moving objects

- Step 1
  Scan all transaction to count the number of occurrence of each transaction

Item set	Support count
{I1}	6
{I2}	7
{I3}	6
{I4}	2
{I5}	2

TABLE III : Candidate set of size one

- Step 2
  Determine L1 – set of frequent 1 item set

Item set	Support count
{I1}	6
{I2}	7
{I3}	6
{I4}	2
{I5}	2

TABLE IV : Frequent set of size one

- Step 3
  Determine C2 – set of candidate 2 item set
  {
  Candidate 2 item set means take set of 2 items together and then calculate the support count with the all possible subsets of these item set.
  }

Item set	Support count
{I1 , I2}	4
{I1 , I3}	4
{I1 , I4}	1
{I1 , I5}	2
{I2 , I3}	4
{I2 , I4}	2
{I2 , I5}	2
{I3 , I4}	0
{I3 , I5}	1
{I4 , I5}	0

TABLE V : Candidate set of size two

- Step 4
  Determine L2 – set of frequent 2 item set

Item set	Support count
{I1 , I2}	4
{I1 , I3}	4
{I1 , I5}	2
{I2 , I3}	4
{I2 , I4}	2
{I2 , I5}	2

TABLE VI : Frequent set of size two

- Step 5
  Determine C3 – set of candidate 3 item set
  *prune {apriori property – all subsets of a frequent itemset must be frequent}

Item set	Subsets	Support count
{I1,I2,I3}	{I1 ,I2} {I1 ,I3} {I2 ,I3}	2
{I1,I2,I5}	{I1 ,I2} {I1 ,I5} {I2 ,I5}	2
{I1,I3,I5}	{I1 ,I3} {I1 ,I5} {I3 ,I5}	Not valid
{I2,I3,I4}	{I2 ,I3} {I2 ,I4} {I3 ,I4}	Not valid
{I2,I3,I5}	{I2 ,I3} {I2 ,I5} {I3 ,I5}	Not valid
{I2,I4,I5}	{I2 ,I4} {I2 ,I5} {I4,I5}	Not valid

TABLE VII : Candidate set of size three

Some values in the support field is invalid due to *prune property of Apriori algorithm because subset of these item set does not exist in above frequent set table.

- Step 6
  Determine L3 – set of frequent 3 item set

Item set	Support count
{I1,I2,I3}	2
{I1,I2,I5}	2

TABLE VIII : Frequent set of size three

- Step 7
  Determine C4 – set of candidate 4 item set

Item set	Subsets	Support count
{I1,I2,I3 ,I5}	{I1 ,I2,I3} {I1 ,I2,I5} {I2 ,I3,I5}	Not valid

TABLE IX : Candidate set of size four

- Final frequent sequence

Item set	Support count
{I1,I2,I3}	2
{I1,I2,I5}	2

TABLE X : Final frequent set of size three

IV. CONCLUSION

In this paper, the author concluded an idea about data mining of moving objects that has spatial and temporal coordinates by using candidate item sets and frequent item sets. Frequent pattern mining will provide idea about the locations that are most frequently accessed by moving objects. This technique can be helpful for Location Based Services (LSB).

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