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Lattice Structure-Based Spatial Co-Location Pattern Mining Using Rect Search Algorithm

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Abstract: It's getting more significant to recognize how to determine spatial knowledge naturally from spatial datasets with the rapid development and broad applications of the spatial dataset. Spatial co-location patterns speak to the rifts of peculiarities whose incidences are oftentimes speckled mutually in geographic space. It "s" hard to revelation co-location design in outlook of the immense compute of information brought by the incidences of spatial peculiarities. The existing system exploit order-clique-based methodology to mine the maximal co-location design which makes exploitation of the tree structure though with an exact end goal to build the ability of the methodology; the lattice structure is employed to mine the maximal co-location rather than the tree structure. The maximal co-location models is mined by the proposed calculation utilizing three noteworthy steps: The spatial neighbor connections lattice structure development and mining of maximal co-location design the implementation of the proposed figuring is assessment with real and synthetic dataset. The execution is calculated by the memory space, running time and the quantity of sequence needed for the proposed and the existing system. The execution study exhibits that the projected system is more efficient than that of the order-clique-based strategy.

Key words: Lattice structure, order-clique-based method, tree structure, maximal co-location, spatial neighbor

INTRODUCTION

Advanced spatial data collecting systems, like NASA Earth's Observing System (EOS) and Global Positioning System (GPS) have been accumulating gradually generous spatial data sets (Huang *et al*., 2006, 2008; Li *et al*., 2010). Spatial data mining is the process of haul outing fascinating information from spatial databases. The spatial databases contain objects that signify space. The spatial data signifies topological and distance information. This spatial object is compiled by spatial indexing structures. Spatial data mining or knowledge discovery in spatial database, alludes to the withdrawal of implicit knowledge, spatial relocations or other patterns not clearly stored in spatial databases (Celik *et al*., 2008; He *et al*., 2013). Spatial data mining methods can be functional to extract interesting and regular knowledge from large spatial databases. This information can be exploited for comprehension spatial and non spatial data and their relationships. This knowledge is very useful in Geographic Information Systems (GIS) image processing, remote sensing and so on (LI Gai *et al*., 2010; Wan *et al*., 2008). Association rule finding is a vital data mining method which assists retailers discovering items frequently, bought jointly to make store arrangements, plan cat logs and promote products together. For conclusion support systems to get improved with information like changes and trends happened in the spatial zones. Particularly, the acuity on the representation of co-location outline and its varying size utilizing semantically upheld components is of more imperative to archeologists, GIS scientists, governments for analyzing the changing trends in the civilization. Numerous spatial datasets comprise of occasions of a collection of Boolean spatial features. Spatial association statistics measures the concentration of an attribute over a space (Dai and Lin, 2011; Wan *et al*., 2008).

Spatial data mining includes different errands and, for one mission, diverse distinctive routines are regularly accessible, whether computational, statistical, visual, or some combination of them. The projected process temporarily present chooses a set of tasks and associated techniques as well as classification (supervised classification), association rule mining, clustering (unsupervised classification) and multivariate geo

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visualization (Venkatesan *et al*., 2011; Xiao *et al*., 2008). Co-location pattern exposure aim to determine the objects whose spatial features/events that are frequently co-located in the same region (Barua and Sander, 2014). It might expose essential phenomena in various applications together with location based services geographic information systems, geo-marketing, remote sensing, image database exploration, medical imaging, navigation, traffic control and environmental studies. With usual association rule mining algorithms it is hard to discover co-location patterns successive to there is no concept of customary "transaction" in vast majority of spatial datasets. The illustrations of a spatial characteristic are getting expressed in a spatial framework, these incidences share complex spatial locality relationships with other spatial instances. Time complexity to produce the table instances of co-location pattern is very high (Huang *et al*., 2004, 2006).

Co-location rule discovery presents challenges because in light of the accompanying reasons (Huang *et al*., 2006, 2004; Yoo *et al*., 2005) as the illustrations of spatial features are roofed in an unrelenting space and share neighbor relationships, it is hard to recognize co-location instances. Along these lines, an extensive piece of the computation time is utilized to discover the co-location cases and as there are no pre-defined transactions in numerous spatial datasets of steadily expanding size and difficulty, it is essential to reuse organization rule mining algorithms for co-location pattern mining. Nonetheless, for spatial datasets, the comparative shift of concept in spatial co-location mining gets to be tremendously unpredictable because of the absence of a transaction idea which is noteworthy in recurrent pattern definition and its mining algorithms. Neighborhood that is, co-location row instance, details is a main challenge and a major piece of any co-location mining algorithm (Yoo *et al*., 2005; Wang *et al*., 2006, 2008, 2009).

Literature review: Event centric modeling approach in co-location pattern analysis from spatial data was provided by Venkatesan *et al*. (2011). They have scrutinized diverse methodologies used to determine the co-location intend from the spatial information. Spatial co-location examples were the subsets of Boolean spatial peculiarities whose incidences were frequently found in close geographic proximity. Association rule-based methodologies can be exploited which were added inaccessible into transaction-based approaches and distance-based approaches. The usual idea of swaps was non-attendant in spatial information sets which were put in persistent geographic space. As a result they have established the similitude's and contrasts between the co-location belief issue and the classic organization rules crisis. An algorithm to locate co-location instances were outlined which generates positive areas and their table cases. A distance–based methodology was shaped to mine co-location proposes from spatial information by utilizing the idea of closeness neighborhood. An interest measure, a participation index was exploited for spatial co-location intends as it possesses an anti-monotone property. At last the co-location tenet was fabricated to identify the example.

Jiang *et al*. (2010) were proposed the Discovering both positive and negative co-location rules from spatial data sets. They have categorized the design of the negative co-location designs. In light of the exploration of the relationship in the middle of negative and positive participation index, strategies for negative participation index count and negative examples pruning systems was specified. In traditional computations for positive co-location mining, some co-locations may be abolished in the event that they include spatial gimmicks which have uncommon spatial cases. In any case perform the projected algorithm, the helpful co-location principles was established as negative guidelines. The strategies make it possible to find both positive and negative colocations efficiently.

Efficiently mining dynamic zonal co-location patterns based on maximal co-locations was projected by Dai and Lin (2011). They have taken into evidence the facts of maximal example to group the grateful memory space and to diminish the execution time of mining methodology. Moreover, they auxiliary intensify the process to element zonal Co-location example mining where co-location proposes in the district progressively tagged by the client will be determined. They have outlined an index structure (mclQuad-tree) and algorithm (mZoloc-Miner) for mining element zonal co-location. The proposed index structure was joined with peculiarities of maximal co-locations and the recommend calculation was furthermore made by the record structure to reduce the computing time. The exploratory results demonstrated that the information can mine co-location plans in the tagged zone of investment all the more prolifically.

A Maximal Clique enumeration based on ordered star neighbourhood for co-location patterns was propounded by Cheng *et al*. (2013) and Zhao *et al*. (2008). They regard as the opportunity and useful come near to apply the predictable following item set mining systems on spatial dataset. They have planned a Maximal faction Count decisive around appealed Star Neighborhood (MCEBOSON) calculation to authorize the transactionalization of spatial Boolean information which makes the application of incredible productive techniques on general information mining conceivable. They have demonstrated that the MCEBOSON was a decent decision to appear the exchanges and its blend with Fptree can yield preferred execution over join-based calculation. Utilizing maximal inner circles likewise legalized us to part the club example era from the pervasive example mining methodology. The test results display that the MCEBOSON reckoning effectively produces all maximal inner circles in the engineered dataset and performs better than the join-based computation.

The Discovering co-location pattern from spatial domain using a Delaunay approach was developed by Sundaram and Paneer. They have exhibited co-location excavate calculation for decision spatial co-location designs. They have residential Delaunay graph based co-location mining approach to mine co-location intends from spatial in sequence by utilizing the design of spatial vicinity. They have utilized Delaunay outline to determine neighborhood of objects. Delaunay chart was a structure exclamation to the location of article in concise and unique way. Spatial information mining without unambiguous neighborhood definition returns idiosyncratic results relying upon the customary window size or the range in which dissimilar articles are considered neighbor and strengths a variety of implementation of the digging methodology for miscellaneous estimations of the appropriate parameters. An interest measure and enrolment index was employed for spatial co-location designs as it has a unreceptive to monotone possessions. The co-location computation to mine co-location design from the spatial information was exhibited and dismembered.

A general framework to identify spatio-temporal co-occurring patterns for continuously evolving spatio-temporal events that have polygon-like representations was proposed by Pillai *et al*. (2012). They have similarly proposed a set of measures to differentiate spatio-temporal co-occurring examples and projected an Apriori-based spatio-transient co-occurrence mining algorithm to institute common spatio-temporal co-occurring illustrations for thickened spatial representations that extend over time. They have measured our structure on genuine information to explain the sufficiency of computed and the calculation. The Experimental result has exhibited that highlighting the essentialness of measured in distinguished spatio-temporal co-occurance designs.

Measurements and physics-based analysis of Co-located antenna pattern diversity system was given by Dagefu *et al*. (2013). They have scrutinized about the focal points obtainable by radiation design inconsistent qualities by another physics-based analysis that considers the compound radiation examples of the Transmit (Tx) and Receive (Rx) diversity antennas in coincidence with a precise deterministic, cognizant and schism saving spread model for a composite indoor situation. It proffered a chance to achieve minimal diversity antenna frameworks particularly with the exterior of authorizing reception apparatus scaling down systems. A co-placed receiver radiation pattern diversity system was projected and its implementation was examined performing an exact physics based differences examination strategy. The projected framework was recognized and tried in perplexing indoor situations resolute around which complex correlation coefficients between dissimilar channels and the correlation was catalogued which were then used as an issue of legitimacy for improved channel dependability.

The spatial data mining using cluster analysis was illustrated by Kumar *et al*. (2012). They have exhibited how spatial information mining was talented employing clustering. The primary purpose of the spatial information withdrawal was to find hidden complex learning from spatial and not spatial information in spite of their enormous sum and the comprehensive nature of spatial connections figuring. Notwithstanding, the spatial information mining systems were still an expansion of those performed as a part of ordinary information mining. Spatial information was a very appealing field in light of the fact that tremendous measures of spatial information have been gathered in different applications, running from remote sensing, to topographical data frameworks (GIS), machine cartography, natural appraisal and arranging and so forth. Spatial information mining tasks include: spatial arrangement, spatial affiliation tenet mining, spatial grouping, trademark guidelines, segregate principles, pattern discovery. Group investigation gatherings objects (perceptions, occasions) focused around the data found in the information portraying the articles or their connections. All the parts of the bunch have comparative gimmicks. Parts have a place with distinctive bunches has different peculiarities.

MATERIALS AND METHODS

Spatial co-location pattern mining is a fascinating and important issue in spatial data mining zones which discovers the subset of peculiarities whose occasions are frequently spotted together in geographic space. Geospatial data repositories have a propensity to be considerable, arrive at and dissimilarities of geographic information positions which show particular difficulties.

The digital geographic data transformation is making new sorts of information configurations past the customary “vector” and “raster” positions. The essential plan of the study is to outline and create a strategy for spatial co-location pattern mining that discovers the intriguing and helpful data for investigation. Literature shows a few procedures for spatial co-location pattern mining from spatial datasets by adjusting candidate generation-based algorithm or tree structure dependant algorithm. One of the significant works is displayed in (Manikandan and Sisrinivasa, 2013) that mines maximal spatial collocation example performing frequency pattern growth. At the point when examine the work, the execution of the mining calculation can be better by employing the lattice structure rather than tree structure and it is stiff to fit the frequency pattern growth inside the memory and it is very time consuming. In tree arrangement, the child nodes have only one parent whereas in a lattice structure, the child nodes have more parents. Instead of the tree structure, here, we have get a feel forced the lattice structure that adapts the spatial data into the transactional data format which is more efficient to find the co-located pattern effectively. The max-min mining algorithm is planned to mine the spatial co-location patterns from the converted format of data which devour less memory then that of frequent pattern growth. In order to diminish the calculation time and memory space, the projected method makes use of lattice structure that is spatial data structure to mine the spatial co-location patterns.

Contribution: The following contributions are made by the lattice structure-based algorithm for maximal spatial co-location patterns:

Rectangular search algorithm: Proposed to find the neighbour relationship, here, the data’s are selected randomly by using rectangle. Density threshold will be set to a constant value. The width and the height of rectangle is increased if its value is lower than that of the given density threshold. If it satisfies the conditions, then form the next rectangle and it is continued until all the data’s are inserted within the rectangles.

Lattice structure: In order to enhance the mining calculation, lattice structure is used in the proposed method. Lattice structure consists of the entire object from the database in the form of a lattice. The set which consist of the maximum data will be the root node A, followed by its child nodes B and C. B is the parent node of D and E. If there is no child node for D then check the sibling node of D which is E. The lattice child can have more than one parent. In this case, D has two parents(B and C) where as F has only one (C) The example of the lattice structure, is given in Fig.1.

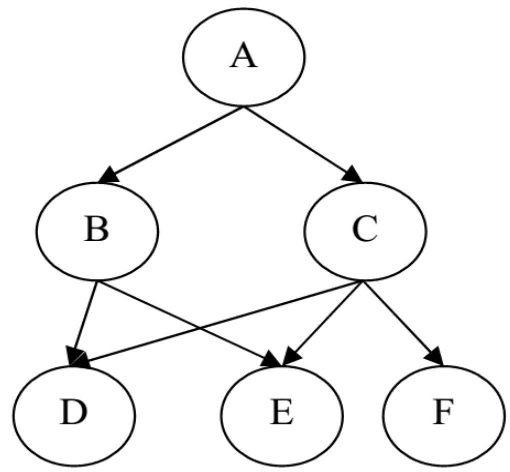

Fig. 1: Example of lattice structure

Maximum to minimum search: To mine the maximal co-locations pattern for the proposed method. Constant threshold values are set and then the frequency of the top length pattern is found. Check whether that frequency satisfies the threshold condition, if it did satisfies the condition, then halt and go to the next highest pattern.

Definition (rectangular search algorithm): The data’s are selected in the form of rectangles. Density threshold is set to a constant value. The height and width of the rectangles are increased or decreased based on the given threshold value. If the shape of the rectangle satisfy the given threshold value, all data within the particular rectangle is considered as a unique set.

Definition (maximum to minimum search): The searching process will start from the maximum dataset to the minimum dataset. The threshold will be set to a constant value, if the given condition is satisfied, then the searching algorithm will be stopped.

Lattice structure-based spatial co-location pattern mining using rect search algorithm: The maximal co-location patterns is mined by the proposed algorithm utilizing three significant steps, the spatial neighbor relationships, lattice structure construction and mining of maximal positive and negative pattern. Initially, from the spatial database, the neighbors are generated. By comparing the data, spatial neighbor relationship is discovered and afterwards, lattice structure will be constructed based on the neighbor relationship and the input spatial database. Once the lattice structure of the data is constructed, the maximal co-location patterns will be mined utilizing the proposed mining algorithm. The block diagram of the Lattice structure-based algorithm for maximal spatial co-location Patterns is shown in Fig. 2.

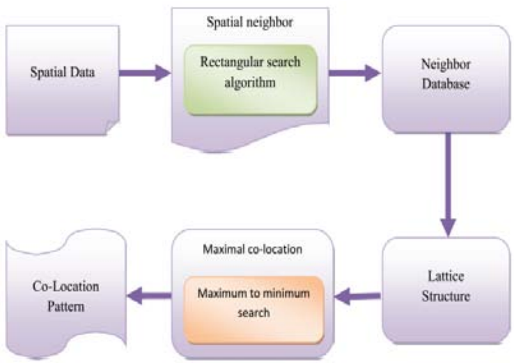

Fig. 2: Lattice structure-based algorithm for maximal spatial co-location patterns

Table 1: Spatial database positions

Object	X-position	Y-position
Q_1	1.7	0.8
Q_{21}	1.72	0.5
Q_3	2.3	0.9
Q_4	1.4	0.94

Table 2: Neighbor database

Rectangles	objects
R_1	Q_1, Q_3
R_2	Q_1, Q_2, Q_3
R_3	Q_1, Q_2, Q_3, Q_4,
R_4	Q_3, Q_4
R_5	Q_1, Q_3, Q_4
R_6	Q_1, Q_2

Table 3: Object combinations and their frequency

Object combination	Frequency
$C_1 = \{Q_1, Q_2, Q_3, Q_4\}$	1
$C_2 = \{Q_1, Q_3, Q_4\}$	2
$C_3 = \{Q_1, Q_2, Q_3\}$	2
$C_4 = \{Q_1, Q_2, Q_4\}$	1
$C_5 = \{Q_2, Q_3, Q_4\}$	1
$C_6 = \{Q_1, Q_2\}$	3
$C_7 = \{Q_1, Q_3\}$	4
$C_8 = \{Q_1, Q_4\}$	1
$C_9 = \{Q_2, Q_3\}$	2
$C_{10} = \{Q_2, Q_4\}$	1
$C_{11} = \{Q_3, Q_4\}$	3
$C_{12} = \{Q_1\}$	5
$C_{13} = \{Q_2\}$	3
$C_{14} = \{Q_3\}$	5
$C_{15} = \{Q_4\}$	3

Spatial database: Spatial dataset (D) is given as the input with the size of (M×N) where, M = 1, 2,...m and N = 1,2,...n. A spatial database is a database that is enhanced to store and inquiry data that represents objects (Q_i) characterized in a geometric space, thus $D_{MN} = \{ Q_i | I = 1, 2, ...a\}$. Most spatial databases permit representing simple geometric objects such as points, lines and polygons. The X and Y position is taken for the object, based on this the spatial database is formed. Consider four datasets which is shown in Eq. 1 and their X and Y positions are given in Table 1.

$$D_{MN} = \{Q_1, Q_2, Q_3, Q_4\} \tag{1}$$

Spatial neighbor using rectangular search algorithm: The data's are selected haphazardly from the database in the form of rectangle (R_i). The threshold (t_1) of density of the rectangle is set to a consistent value. By using the density, rectangle is framed from a random position. On the off chance that the data chose as rectangle (R_i) does not fulfill the threshold value (t_i) which was initialized, then increase the height (l_{si}) and the width (W_{si}) of the rectangle. The size is continued to expand until the estimation of limit is met which is shown in Eq. 2 where α is set to a constant value. Thusly construct numerous bounding rectangles as much as required to cover the whole information:

$$R_i = \begin{cases} l_{si} = l_{si} + \alpha \ \&\& \ w_{si} = w_{si} + \alpha & R_i < t_1 \\ R_i = (l_{si}, w_{si}) & \text{else} \end{cases} \tag{2}$$

Neighbor database: From the rectangle design, neighborhood of the objects is classified; the database consists of more number of rectangles R_i where, i = 1, 2, ... f. Each rectangle R_i consist of objects ≤to g, where, g is the maximum length object. For the given database T, six rectangles are formed which is shown in Eq. 3 within each rectangle, objects are arranged in a random manner. Here 'g' is equal to four, thus each rectangle consist of objects less than or equal to four. Objects R_i is shown in Eq. 4. R_3 Consist of four objects whereas R_4 consist of two objects only. Similarly the number of objects may vary for each rectangle. The Table 2 shows all the rectangles formed and their objects:

$$T = \{R_1, R_2, R_3, R_4, R_5, R_6\} \tag{3}$$

$$R_i = \{Q_1, Q_2 .... Q_g\} \tag{4}$$

Lattice structure formation: The spatial neighbor database T is given as the input to form the lattice structure. In order to form the lattice structure, data set are selected from the neighbor database T. All the combination of the object are taken and arranged in database, there are totally fifteen combinations. By comparing the neighbor database and the entire combination, the frequency is computed. The frequency of the combinations (C_j) is found by the Eq. 5 where 'e' = Number of combination. From Table 3 let's consider the set $A = \{Q_1, Q_2, Q_3, Q_4\}$ and $B = \{Q_1, Q_2, Q_3\}$. Check how often the entire objects in sets fits in with the neighbor database. Set A can be seen only in R_3, therefore the frequency is one. In the same way, set B fits in R_1 and R_2, thus the frequency is equal to two. Similarly the frequency

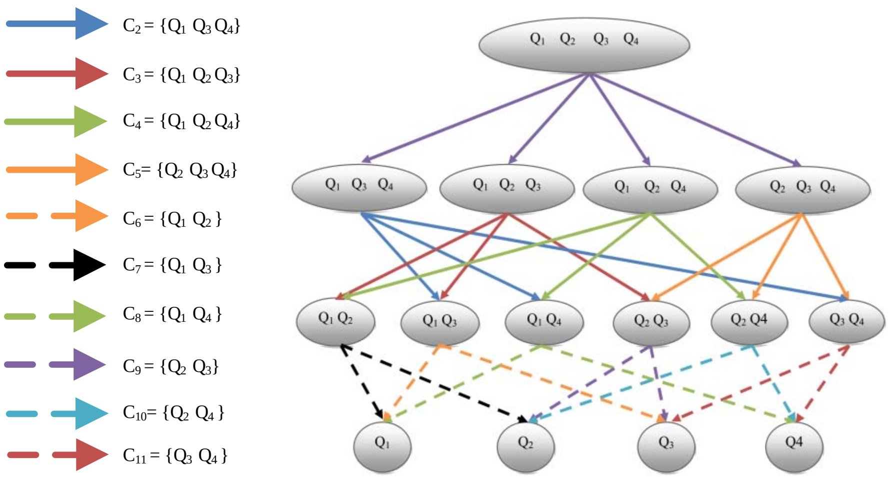

Fig. 3: lattice structure for the given example

is selected for all the combinations. All the conceivable combination of the given dataset and their frequency is shown in Table 3:

$$C_j = \sum_{R_i=1}^{e} \alpha_i \quad (5)$$

The maximum length object will form the root node in this case the root node is C_1 which consist of four objects and C_1 is the set which consist of maximum number of objects. Then the set which consist of maximum number of object will be inserted in as next branch, in this example set C_2, C_3, C_4 and C_5 consist of three combination objects which is the next highest combinations than C_1 thus the lattice structure is formed. The child node of C_2 is C_7, C_8 and C_{11} each child node consist of more than one parent node, here, the child node, C_7 consist of parent C_2 and C_3. The lattice structure for the given example is shown in Fig. 3.

Mining maximal co-location pattern: At first the frequency of the maximum length pattern is determined and the threshold is set to a constant value, If the frequency satisfies the given threshold, then there is no need to progress but if the threshold value is not met then it will kept on continuing until the desire results are obtained.

Step 1: Set the threshold to a desire constant value and here the threshold is set to three. From Table 3, take the maximum combinations, that is, $C = \{Q_1, Q_2, Q_3, Q_4\}$ check

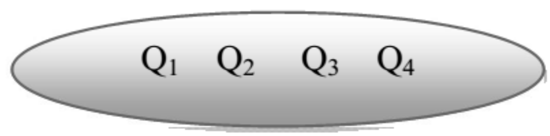

Fig. 4: Step 1 of mining

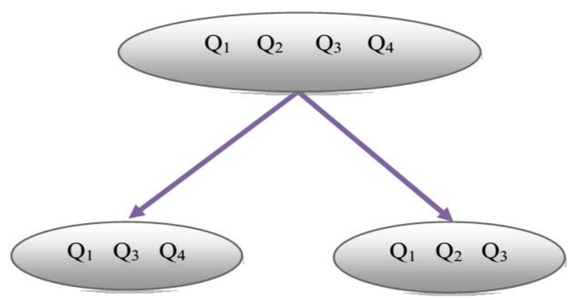

Fig. 5: Branching of A-C

whether the frequency is equivalent to the threshold value three. If it is equal then there is no compelling reason to proceed yet for this situation, the recurrence for 'C_1' is equivalent to one, thus get to the following limbs and check. Step 1 of the lattice structure is given in Fig. 4.

Step 2: There are four three object combinations and they are $C_2 = \{Q_1, Q_3, Q_4,\}$, $C_2 = \{Q_1, Q_2, Q_3,\}$, $C_4 = \{Q_1, Q_2, Q_4\}$ and $C_5 = \{Q_2, Q_3, Q_4\}$. Take the branch which consists of the highest frequency, in this case, C_2 and C_3 consist of the biggest frequency. It is shown in Fig. 5. Then check whether the frequency is above or below the given threshold.

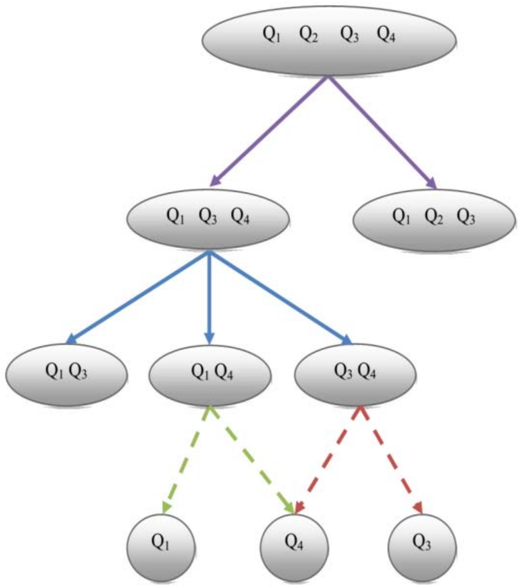

Fig. 6: Branching of B

Step: 3: Here, the condition is not satisfied the given threshold, the frequency of C_2 = {Q_1, Q_3, Q_4} and C_3 = {Q_1, Q_2, Q_3} is below three, select C_2 and C_3 randomly, let's considers C_2. The two combination branch of C_2 is, C_7 = {Q_1,Q_3}, C_8 = {Q_1, Q_4} and C_{11} = {Q_{31}, Q_4}, C_7 is equal to four have the highest frequency among the given branches (C_7, C_8 and C_{11}) since the value C $_7$of is greater than the given threshold, the branching is halted. In the view of the fact that it has satisfied the condition, go to the root, 'C_2'-'C_7', C_{11} has the highest frequency. The two combination branches of C_{11} are C_{14} and C_{15}. The branching process of C_2 is shown in Fig. 6.

Step 4: Between C_{14} and C_{15} has the highest frequency, so consider and the frequency is greater than the threshold value, thus the branching is halted. Then go to the root, the next branch also satisfies the condition thus the branching is halted for. The branching process of and are shown in Fig. 6 and 7. Then go to the root of which is. Similarly, the threshold is checked for all the branches. The maximal co-location pattern of the Lattice structure for the given example is shown in Fig. 8.

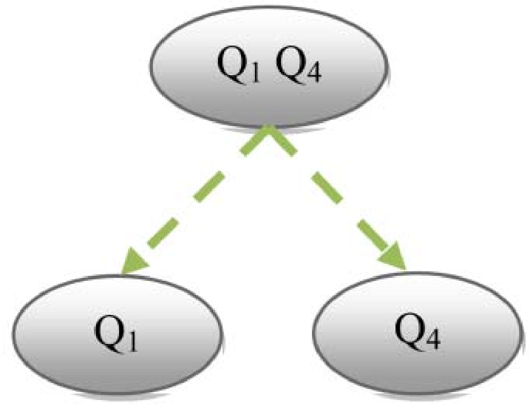

Fig.7: Branches of K = {Q_1 Q_4}

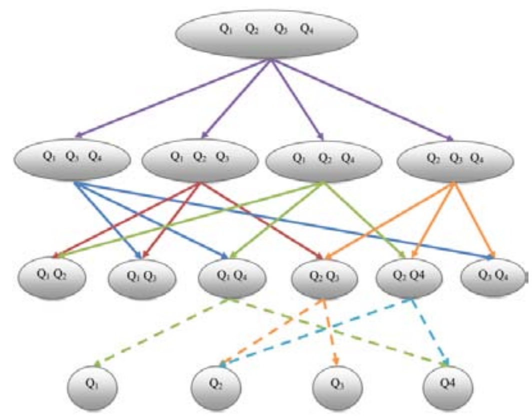

Fig. 8: Maximal co-location pattern of the lattice structure for the given example

Pseudo code:

```
Input: Spatial database D = {Q_1, Q_2, ..., Q_n}
Output: Maximal co-locatef patterns

Begin
fetch D ={Q_1, Q_2, ..., Q_n};
R_i = rand(I_si, W_si), i>1;
Sett_1;
For each R_i do
{
   For(i = 1:n);
   {
        if(R_i≥t_1)
        {
                    R++;
        }
        Else
        If(R_i<t_i)
        {
                    l_si = l_si+1;
                    W_si = W_si+1;
                    R_i = (l_si, w_si);
        }
   }
   End;
}End;
//create a database by combing the recatangles
T = {R_1, R_2, ..., R_f};
R_i = {Q_1, Q_2, ..., Q_g};
C = gen (combination from T);
C = C_j|j = 1: S;
While j≤S do
```

```
{
Begin
   U = find(Cj(i) = T);
   fr = count (U);
   Hlr = max(lenght(Cj));
   Ssk = sort(Hlr, descend);
}End;

//costruct latttice L

Set = ϕ;
While Ssk≤S do
{
Begin
  If (K = 1);
  {
   Assign r = k;
  }
  Else
  If (K>1)
  {
   For(K = 2; k≤S; k++)
   {
       If⊆r
       {
       If (Cj == 0)   //Check whetrher any child Cl is exist;
       {
      Set Cl = Pn;
     Set K = Cl;
     }
     Else
         Insert k as new Cl;
     }
    }
    End;
  }
}End;
//Co-located patterns Mining

set τ:
For each node in L do
{
Begin
   If fr (r)<r
   {
     Obtain the co-located pattern:
     Break
   }
   Else
   If fr (r)<r
   {
         Find Cl with higest fr (Hfr);

   if fr (Cl<τ);
   {
   Go ti its child node (Cl);
   }
   Else
   if fr (Cl≥τ);
   }
         Back to parentv node (Pn) or root(r);
         Find next Hf;
         Do the same;
   }
   }
  Obtain the co-located pattern;
}

End;
```

RESULTS AND DISCUSSION

The experimental results of the proposed rectangular search algorithm and the maximum to minimum search algorithm to mine the maximal co-location pattern which is compared with that of the existing method by using the real and synthetic dataset are described in this study.

Experimental design: The proposed approach for efficient mining of co-location patterns is programmed using Java. The experimentation has been carried out using the synthetic datasets as well as the real datasets with facilitate of i5 processor in windows 7 with 4 GB RAM.

Dataset 1: (synthetic data): The synthetic data that comprise of event types and 1000 event id with space and time values is generated for the proposed method.

Dataset 2: (Real world data): For the proposed method real world data is taken, Localization Data for Person Activity Data Set', from the UCI machine learning repository (Celik *et al*., 2008). This dataset comprise of 6 activities (event type), such as 'walking', 'falling', 'lying down', lying', 'sitting down', 'sitting', 'standing up from lying', 'on all fours', 'sitting on the ground', 'standing up from sitting', 'standing up from sitting on the ground' and 1000 event id.

Evaluation metrics: The performance of the proposed lattice structure-based algorithm for maximal spatial co-location patterns is evaluated by three evaluations metric. They are:

- Number of sequence
- Running time
- Memory

Number of sequence: The greatest number of arrangements created based upon the given least threshold and the bounding rectangle.

Running time: The time taken to execute the algorithm (threshold value, minimum bounding rectangle).

Memory usage: The memory utilized by the algorithm to finish the mining procedure.

Evaluation: The result is evaluated by using three performances metric, number of sequence, running time and memory usage. By using the real and synthetic dataset, the proposed "Lattice structure-based spatial co-location pattern mining using rect search

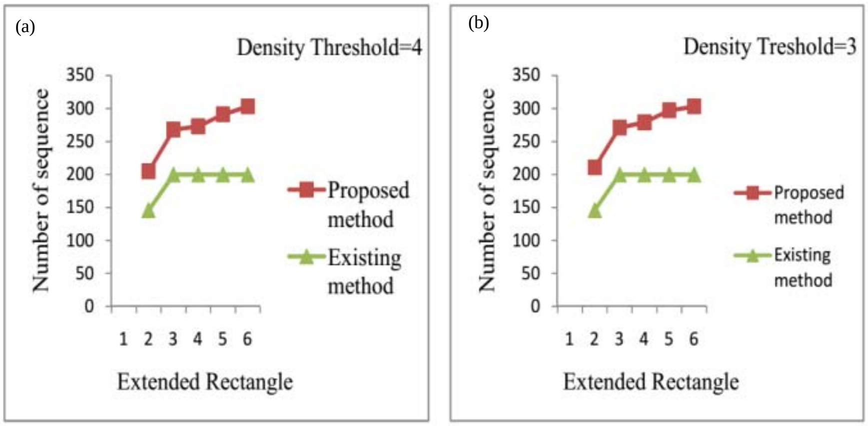

Fig. 9: Distribution of sequences with different threshold values for real dataset: a) Density threshold = 4 and b) Density threshold = 3

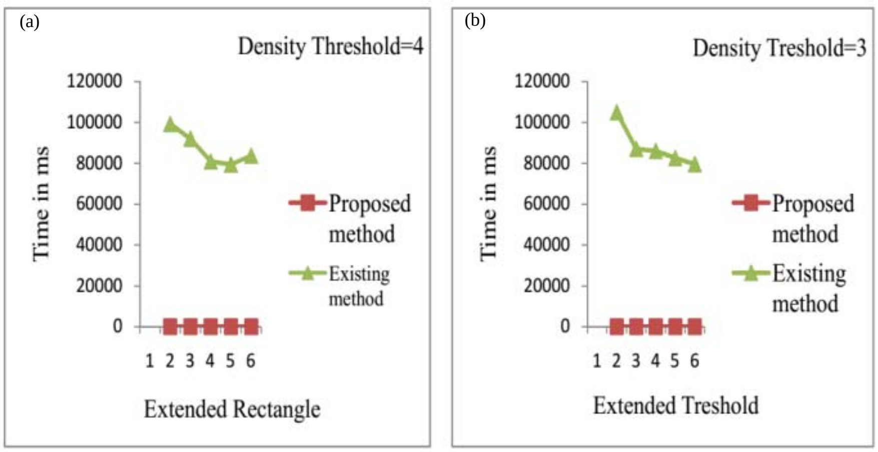

Fig. 10: Run time performance with different threshold values for real dataset: a) Density Threshold = 4 and b) Density Threshold = 4

algorithm" and the existing "an efficient algorithm for mining spatially co-located moving objects" (Manikandan and Srisinasa, 2013) methods are evaluated.

Evaluation for Real dataset: To assess the execution of the proposed strategy with that of the current system, the density threshold is settled at three and four; the quantity of sequence, memory and time for the broadened rectangle is figured. Figure 9a demonstrates the circulation of grouping with distinctive edge values for genuine dataset with the density threshold of four and Fig. 9b shows arrangement for the density threshold of three. For the current system, the quantity of arrangement does not change for distinctive density threshold, however for the proposed strategy; there is slight variation in the values. From the graph, it can be comprehended, that the quantity of sequence is more for the proposed system than that of the current strategy. Figure 10a demonstrates the run time execution for the density threshold of four and b demonstrates the run time for density threshold of three. The running time is more for the current system and it is low for the proposed strategy. The running time is in relative to that of the thickness edge, thus the running time increment with that of thickness limit. Along these lines, the memory space and time is low for the proposed system, while, the quantity of sequence is more. Figure 11a and b, demonstrates the memory space needed for extended rectangle.

Figure 12a shows the graph for the bounding threshold and its corresponding sequence. Now the expansion is reduced to two, with density threshold of four, the number of sequence is more for the proposed method than that of the existing method. The sequence reduces slowly proposed method for the same extension. Figure 12b shows the running time required for bounding

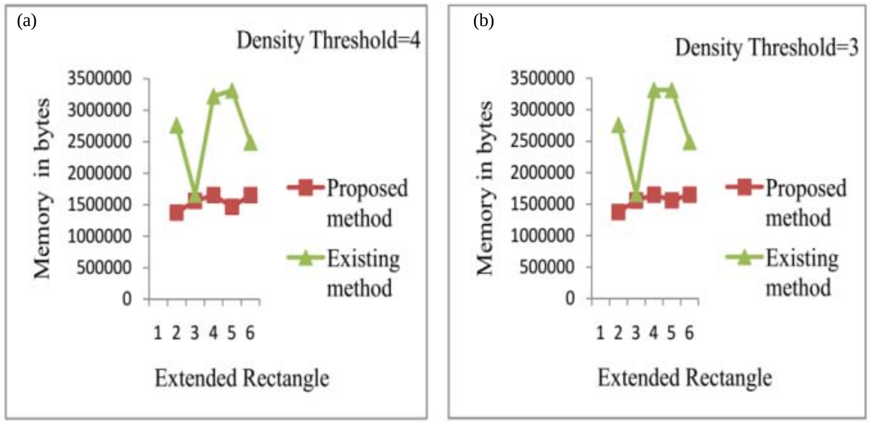

Fig. 11: Memory usage with different threshold values of real dataset: a) Density Threshold = 4 and b) Density Threshold = 4

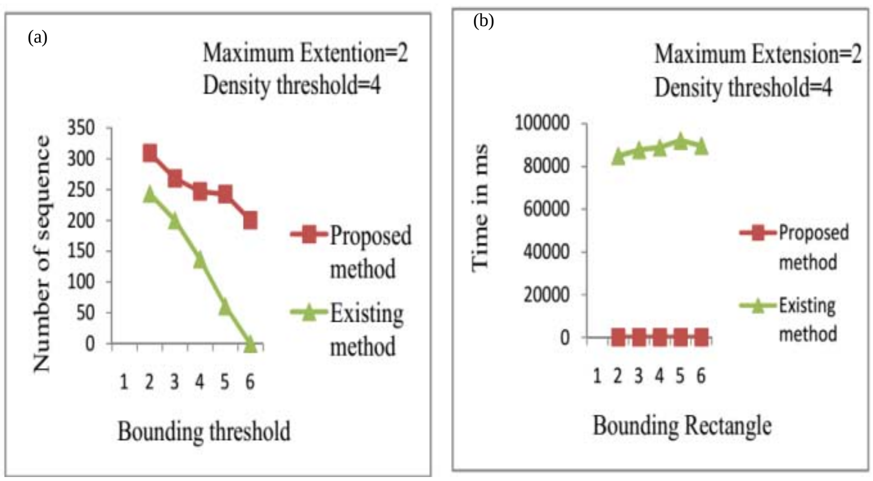

Fig. 12: a) sequence for bounding rectangle of the real dataset and b) running time for bounding rectangle of real dataset

rectangle with a maximum extension of two and density threshold of four. From the graph it is very clear that the running time required for the proposed method is very low.

Evaluation for synthetic dataset: The execution of sequence, memory and running time for the proposed technique on synthetic information is evaluated. In the Fig. 13ab dispersion of the sequence with distinctive threshold values for the synthetic dataset is given. Figure 13a demonstrates the diagram for density threshold of seven and Fig.13b demonstrates the density threshold of five. Everything is Similar to that of the genuine dataset. The sequence is more for the proposed framework than that of the current framework. Figure 14ab demonstrates the variety in the running time for the proposed and existing technique for the threshold of seven and five. From the Fig. 15ab, the memory space needed for the rectangle to expand its size is indicated. From the diagram it is clear that the memory necessity and running time for the proposed strategy is lower to that of the current technique. Fig. 16a demonstrates the diagram for the bounding threshold and its comparing arrangement for the synthetic dataset. The expansion is decreased to two, with density threshold of four and the sequence of grouping is more for the proposed technique than that of the current strategy. The succession decreases gradually for the proposed strategy for the same augmentation. Figure 16b demonstrates the running time needed for bouncing rectangle with a greatest expansion of two and density threshold of four. From the chart it is clear that the running time needed for the proposed system is low.

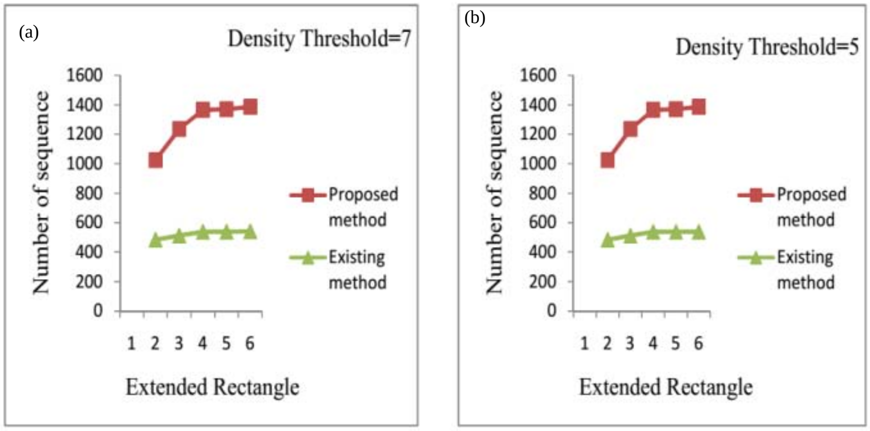

Fig. 13: Distribution of sequences with different threshold values for synthetic dataset: a) Density threshold = 5 and b) Density threshold = 7

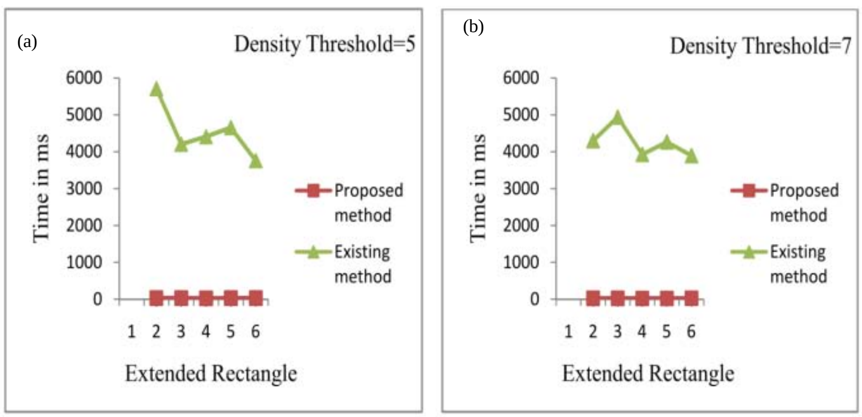

Fig. 14: Run time performance with different threshold values for synthetic dataset: a) Density Threshold = 5 and b) Density Threshold = 7

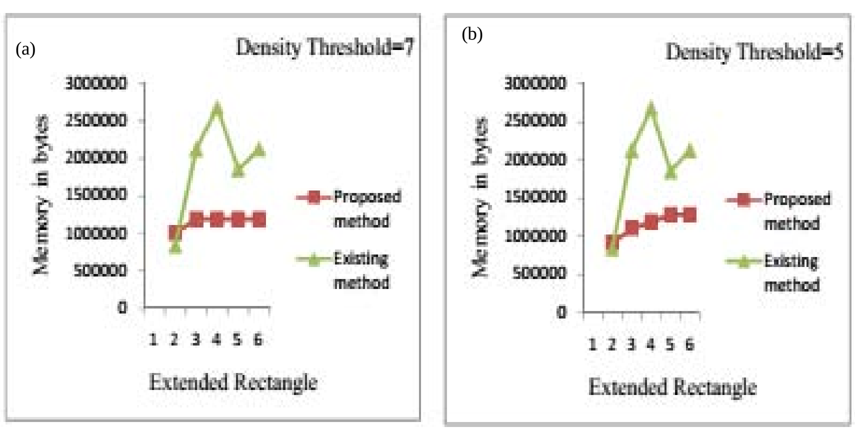

Fig.15: Memory usage with different threshold values of synthetic dataset: a) Density Threshold = 5and b) Density Threshold = 7

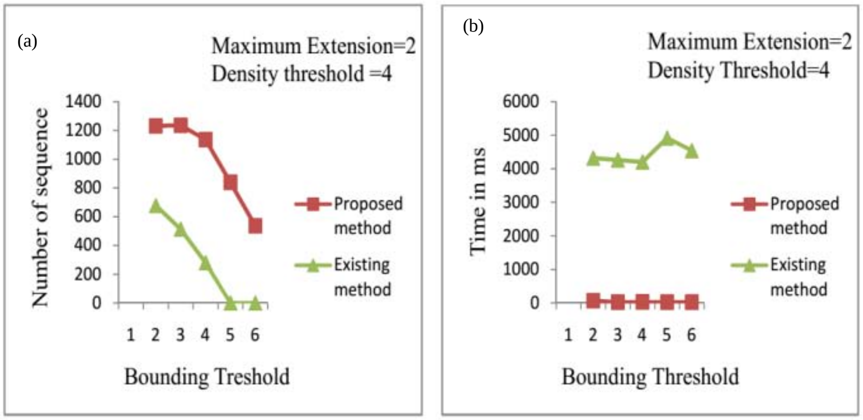

Fig. 16: a) sequence for bounding rectangle of the synthetic dataset and b) running time for bounding rectangle of real dataset

CONCLUSION

In this study, lattice structure-based algorithm for mining maximal co-location is proposed which can rapidly mine maximal co-locations by adopting rectangular search algorithm and maximum to minimum search. Rectangular search is utilized to discover the neighbor of the item and the maximum to minimum search is utilized to mine the maximal co-location. As long last, the performance of the algorithm is analyzed with real and synthetic data. The performance of the algorithm will be compared with the existing algorithm in terms of computation time, memory space, number of sequence and patterns mined. The experimental assessment demonstrates that the lattice structure-based method outperforms the existing methods in the real datasets as well as synthetic dataset.

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