A Technical Survey on DBSCAN Clustering Algorithm

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***Abstract*— Data mining refers to the process of retrieving data by discovering novel and relative patterns from large database. Clustering is a distinct phase in data mining that work to provide an established, proven structure from a collection of databases. A good clustering approach should be efficient and detect clusters of arbitrary shapes. Density Based Clustering is a well-known density based clustering algorithm which having advantages for finding out the clusters of different shapes and size from a large amount of data, which containing noise and outliers. In this paper I have discussed integrated Density Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm that is multiphase clustering algorithms which improves scalability and efficiency of clusters. Different DBSCAN algorithms perform different task to make cluster more dynamic and effective. Several DBSCAN clustering methods and their corresponding algorithms are described below which helps to further analysis.**

***Keywords*—** Clustering, Density-based clustering, DBSCAN algorithm.

I. INTRODUCTION

Clustering is a popular data analysis technique. Clustering algorithms can be widely applied in many fields including: pattern recognition, machine learning, image processing, information retrieval and so on. It also plays an important role in data mining. All the existing clustering algorithms have their own characteristics, but also have their own flaws. As a kind of other clustering, density based algorithm is simple and high efficiency algorithm[1].

Density-based clustering algorithms, which are designed to discover clusters of arbitrary shape in databases with noise, a cluster is defined as a high-density region partitioned by low-density regions in data space. Density Based Spatial Clustering of Applications with Noise (DBSCAN) is a typical density-based clustering algorithm. DBSCAN can discover clusters of arbitrary shape. But it is sensitive to the input parameters, especially when the density of data is non-uniform [1].

The DBSCAN clustering algorithms usually can be classified into the following different categories: (a) partitioning based DBSCAN clustering; (b) grid-based DBSCAN clustering; (c) hierarchical DBSCAN clustering; (d) Detection Based DBSCAN clustering, (e) Incremental DBSCAN clustering (f) spatial–temporal DBSCAN clustering.

Partition based DBSCAN clustering method generally result in a set of M clusters, each object belonging to one cluster. Each cluster may be represented by a centroid or a cluster representative; this is some sort of summary description of all the objects contained in a cluster. The precise form of this description will depend on the type of the object which is being clustered. In case where real-valued data is available, the arithmetic mean of the attribute vectors for all objects within a cluster provides an appropriate representative; alternative types of centroid may be required in other cases, e.g., a cluster of documents can be represented by a list of those keywords that occur in some minimum number of documents within a cluster. If the number of the clusters is large, the centroids can be further clustered to produces hierarchy within a dataset [2].

Grid-based DBSCAN clustering technique quantize the data set in to a no of cells and then work with objects belonging to these cells. They do not relocate points but ratter build several hierarchical levels of groups of objects. The merging of grids and consequently clusters, does not depend on a distance measure .It is determined by a predefined parameter [2].

Hierarchical DBSCAN clustering is a method of cluster analysis which seeks to build a hierarchy of clusters. . The basics of hierarchical clustering include Lance-Williams formula, using idea of conceptual clustering. The hierarchical algorithms build clusters gradually (as crystals are grown)Strategies for hierarchical clustering generally fall into two types: In hierarchical clustering the data are not partitioned into a particular cluster in a single step. Instead, a

series of partitions takes place, which may run from a single cluster containing all objects to n clusters each containing a single object. Hierarchical Clustering is subdivided into agglomerative methods, which proceed by series of fusions of the n objects into groups, and divisive methods, which separate n objects successively into finer groupings. Agglomerative techniques are more commonly used. Hierarchical clustering may be represented by a two dimensional diagram known as dendrogram which illustrates the fusions or divisions made at each successive stage of analysis [2].

Detection Based DBSCAN clustering Technique simplified detection problem can be solved efficiently as an upper bound on a discredited likelihood function. This is an efficient algorithm for recovering the maximum likelihood number of sides and orientation only at the locations of the most likely polygons. The first stage of the detection is posed as a discrete Hough-based algorithm. The second stage takes an approximation to the full likelihood function to recover orientation and number of sides [14].

Incremental DBSCN clustering algorithm is used to handle dynamic databases. It has the ability to changing the radius threshold value dynamically. The algorithm restricts the number of the final clusters and reads the original dataset only once. At the same time the frequency information of the attribute values is introduced by this algorithm. It can be used for the categorical data. The algorithm can not only overcome the impact of the inadequate of the memory when clustering the large scale data set, but also accurately reflect the characteristics of the data set [9].

Spatial Temporal DBSCAN clustering is new clustering algorithm designed for storing and clustering a wide range of spatial–temporal data. Environmental data, from a variety of sources, were integrated as coverages, grids, shapefiles, and tables. Special functions were developed for data integration, data conversion, visualization, analysis and management. User-friendly interfaces were also developed allowing relatively inexperienced users to operate the system [13].

Spatial–temporal data is indexed and retrieved according to spatial and time dimensions. A time period attached to the spatial data expresses when it was valid or stored in the database. A temporal database may support valid time, transaction time or both. Valid time denotes the time period during which a fact is true with respect to the real world. Transaction time is the time period during which a fact is stored in the database. This study focuses on valid time aspect of temporal data [13].

II. Literature on Dbcan Clustering Algorithm

There are number of clustering techniques but this paper mainly focuses on the widely used DBSCAN clustering technique. Significant work is done in the field of Density based clustering. This section represents a brief overview of some work done in Density based clustering including email classification, spam detection etc. Number of application areas and techniques are highlighted in Density-based clustering. One approach developed the incremental clustering for mining large database environment. This approach present the first incremental clustering algorithm based on DBSCAN clustering which is applicable to any database containing data from a metric space. Due to the density based nature of DBSCAN, the insertion or deletion of an object affects the current clustering only in the neighbourhood of this object. Thus, efficient algorithm scan be given for incremental insertions and deletions to an existing clustering. Incremental DBSCAN yields significant speed-up factors over DBSCAN even for large numbers of daily updates in a data warehouse. In this paper, sets of updates are processed one at a time without considering the relationships between the single updates [4].

A innovative technique which is used to compare in between two different clustering algorithms (DBSCAN and SNN) described several implementations of the DBSCAN and SNN algorithms, two density-based clustering algorithms. These implementations can be used to cluster sets of points based on their spatial density. The results obtained through the use of these algorithms show that SNN performs better than DBSCAN since it can detect clusters with different densities while DBSCAN cannot [5].

Many clustering algorithms have been proposed so far, seldom was focused on high dimensional and incremental databases. An incremental approach on Grid Density-Based Clustering Algorithm (GDCA) discovers clusters with arbitrary shape in spatial databases. It first partitions the data space into a number of units, and then deals with units instead of points. Only those units with the density no less than a given minimum density threshold are useful in extending clusters. An incremental clustering algorithm--IGDCA is also presented in this paper, applicable in periodically incremental environment [6].

An innovative approach presents a new density-based clustering algorithm, ST-DBSCAN, which is based on DBSCAN. It proposes three marginal extensions to DBSCAN related with the identification of (i) core objects, (ii) noise objects, and (iii) adjacent clusters. In contrast to the existing density-based clustering algorithms, this algorithm has the ability of discovering clusters according to non-spatial, spatial and temporal values of the objects. In this paper, it also presents a spatial–temporal data warehouse system designed for storing and clustering a wide range of spatial–temporal data [7].

One of the new concepts is presented on clustering technique which provides an effective method for Clustering Incremental Gene Expression data. It is designed based on

density based approach where the efficiency of Gen Clus in detecting quality clusters over gene expression data. This work presents a density based clustering approach which finds useful subgroups of highly coherent genes within a cluster and obtains a hierarchical structure of the dataset where the sub clusters give the finer clustering of the dataset [8].

A famous concept which discovers distributed clustering environment using DBSCAN algorithm. This approach ultimately forms a distributed clustering algorithm. This approach helps to cluster the data locally and independently from each other and transmitted only aggregated information about the local data to a central server [10].

Therefore incremental DBSCAN clustering algorithm requires less space and less time than the actual one [3].

III. Improvements on Dbcan Clustering Algorithm

A. Basic Dbcan Clustering Algorithm

DBSCAN requires two parameters: ε (eps) and the minimum number of points required to form a cluster (minPts). It starts with an arbitrary starting point that has not been visited. This point's ε -neighborhood is retrieved, and if it contains sufficiently many points, a cluster is started. Otherwise, the point is labeled as noise. Note that this point might later be found in a sufficiently sized ε-environment of a different point and hence be made part of a cluster.

If a point is found to be a dense part of a cluster, its ε-neighborhood is also part of that cluster. Hence, all points that are found within the ε-neighborhood are added, as is their own ε-neighborhood when they are also dense. This process continues until the density-connected cluster is completely found. Then, a new unvisited point is retrieved and processed, leading to the discovery of a further cluster or noise.

Pseudocode

```
DBSCAN(D, eps, MinPts)
  C = 0
  for each unvisited point P in dataset D
    mark P as visited
    NeighborPts = regionQuery(P, eps)
    if sizeof(NeighborPts) < MinPts
      mark P as NOISE
    else
      C = next cluster
      expandCluster(P, NeighborPts, C, eps, MinPts)

expandCluster(P, NeighborPts, C, eps, MinPts)
  add P to cluster C
  for each point P' in NeighborPts
    if P' is not visited
      mark P' as visited
      NeighborPts' = regionQuery(P', eps)
      if sizeof(NeighborPts') >= MinPts
        NeighborPts = NeighborPts joined with NeighborPts'
    if P' is not yet member of any cluster
```

Complexity

DBSCAN visits each point of the database, possibly multiple times (e.g., as candidates to different clusters). For practical considerations, however, the time complexity is mostly governed by the number of region Query invocations. DBSCAN executes exactly one such query for each point, and if an indexing structure is used that executes such a neighborhood query in $O(\log n)$, an overall runtime complexity of $O(n \cdot \log n)$ is obtained. Without the use of an accelerating index structure, the run time complexity is $O(n^2)$. Often the distance matrix of size $(n^2 - n)/2$ is materialized to avoid distance recomputations. This however also needs $O(n^2)$ memory.

Advantages

1. DBSCAN does not require one to specify the number of clusters in the data a priori, as opposed to k-means.
2. DBSCAN can find arbitrarily shaped clusters. It can even find a cluster completely surrounded by (but not connected to) a different cluster. Due to the MinPts parameter, the so-called single-link effect (different clusters being connected by a thin line of points) is reduced.
3. DBSCAN has a notion of noise.
4. DBSCAN requires just two parameters and is mostly insensitive to the ordering of the points in the database. (However, points sitting on the edge of two different clusters might swap cluster membership if the ordering of the points is changed, and the cluster assignment is unique only up to isomorphism.)

Disadvantage

1. The quality of DBSCAN depends on the distance measure used in the function region Query (P,ε). The most common distance metric used is Euclidean distance. Especially for high dimensional data, this metric can be rendered almost useless due to the so-called "cure of dimensionality", making it difficult to find an appropriate value for ε. This effect, however, is also present in any other algorithm based on Euclidean distance.
2. DBSCAN cannot cluster data sets well with large differences in densities, since the min Pts-ε combination cannot then be chosen appropriately for all clusters.

B. PARTITION BASED DBCAN CLUSTERING ALGORITHM

Because of the memory problem, the researches begin to partition large data set into some small partitions. In 2000 partitioning technique was first used in DBSCAN algorithm. It run DBSCAN algorithm on each partition which is partitioned by special rules.

With PDBSCAN, the R*-tree should be built. DBSCAN requires to specify two global parameters Eps and MinPts. In order to reduce the computational complexity, MinPts is fixed to 4 usually. Then the k-dist graph must be plotted to decide the value of Eps. K-dist graph needs to calculate the distance of an object and its kth nearest neighbors for all the objects. Next, sort all the objects on the basis of the previous distances. Finally, plot the k-dist graph according to all the sorted objects and distances.

Considering that building the R⁄-tree and plotting the k-dist graph have to cost much time especially for a large database, the initial database is partitioned into N partitions to reduce the time cost. Partitioning database can also alleviate the burden of memory and find more precise parameter Eps for every partition.

The steps of PDBSCAN are as follow:
(1) Partitioning the initial database into N partitions.
(2) For each partition, building local R⁄-tree, analyzing and selecting local Eps and MinPts, and then clustering it with DBSCAN.
(3) Merging the partial clusters [11].

C. GRID BASED DBCAN CLUSTERING ALGORITHM

As we all known, during the algorithm of clustering, especially for large data, the exist of border ofdata and noise may discard the cluster's border, degrade the precision of cluster, what's more, the value of Eps may effect the final answer of cluster at some extent. So, it is necessary to improve the useful of the algorithm according to choosing parameters automatically in dynamic testing data. As grid-based clustering algorithm is mainly for massive data, building a unified grid size to divide data space, and then storing its internal data statistics in each grid, all the clustering operations are targeted to the grid cell to cluster in the integral structure of grid, the clustering answer is nothing to do with the order of data inputted, it is beneficial to achieve the algorithm's Incremental processing; For the density-based clustering algorithm (DBSCAN), the cluster's each data object, whose Eps-Neighbor' objects must smaller than a Minpts . The algorithm defines these data objects as core objects, defines the maximum density of a collection of objects connected as cluster. DBSCAN looks for the object density arriving that start with P about Eps and Minpts from the core object P which never visited form data set D, generate a cluster that contains p and its objects density arriving. The algorithm ends with unvisited objects in the data set D. If it can deal with the parameters Eps, User can make use of the two goodness proposed ahead to achieve the "data mutation", therefore, giving some definitions in order to design the algorithm [12]

Grid-based DBSCAN Algorithm with Referential Parameters in order to deal with massive data "mutation" and noise. The algorithm can find clusters of arbitrary shape and remove noise, and then carry out the parameters of DBSCAN automatically, which shield the algorithm' sensitivity of parameters ,finally, the algorithm makes answer more precise. Experimental results show that the improved algorithm is robust. Its operating efficiency is also greatly improved. Therefore, the data mining algorithm has a very broad application prospects [12].

D. HIERARCHICAL DBCAN CLUSTERING ALGORITHM

First divide the spatial area into rectangle cells (e.g., using latitude and longitude) and employ a hierarchical structure. Let the root of the hierarchy be at level 1; its children at level 2, etc. A cell in level *i* corresponds to the union of the areas of its children at level *i* + 1. In this paper each cell (except the leaves) has 4 children and each child corresponds to one quadrant of the parent cell. The root cell at level 1 corresponds to the whole spatial area (which assume as rectangular for simplicity). The size of the leaf level cells is dependent on the density of objects. As a rule of thumb, choose a size such that the average number of objects in each cell is in the range from several dozens to several thousands. In addition, a desirable number of layers could be obtained by changing the number of cells that form a higher level cell. This algorithm will use 4 as the default value unless otherwise specified. This algorithm assume space is of two dimensions although it is very easy to generalize this hierarchy structure to higher dimensional models.

For each cell, algorithm have attribute-dependent and attribute-independent parameters. The attribute independent parameter is:

· *n* --- number of objects (points) in this cell As for the attribute-dependent parameters, assume that for each object, its attributes have numerical values. For ***each*** numerical attribute, algorithm have the following five parameters for each cell:

· *m* --- mean of all values in this cell
· *s* --- standard deviation of all values of the attribute in this cell
· *min* --- the minimum value of the attribute in this cell
· *max* --- the maximum value of the attribute in this cell
· *distribution* --- the type of distribution that the attribute value in this cell follows

The parameter *distribution* is of enumeration type. Potential distribution types are: normal, uniform, exponential, and so on. The value NONE is assigned if the distribution type is

unknown. The distribution type will determine a "kernel" calculation in the generic algorithm as will be discussed in detail shortly.

E. DETECTION BASED DBCAN CLUSTERING ALGORITHM

FINDING SHAPES

In perceptual grouping, image elements are grouped according to some perceptual criteria. Several authors have investigated iterative relaxation style operators for grouping edges. This algorithm examine what shapes may be contributed to by each pair of edges. At a high level this can be composed as recovering a graph of relational arrangement. A common approach is spectral graph theory. Probabilistic approaches in this area include Byes nets and combining evidence from raw edge attributes. More recent approaches have used EM. One of the basic algorithmic approaches here is examining pair wise relations. For examining edge pixels, the complexity is at least OðN2Þ, where N is the number of edge elements.

Alternatively, this may fit functions to image data to find particular shapes. In the Hough transform edge 'vote' to the parameter space of the shape to be detected. Circular Hough [20] detects circle centre points and radii. Each pixel votes for each feature that it could contribute to. This approach is inherently robust, as gaps, noise, and partial occlusion are ignored, but decrease the support for the feature. These methods have been generalised to detect arbitrary shapes, where the detection space has one dimension for each parameter of the shape. In high dimensional spaces this becomes computationally intensive, and in practice, the Hough transform is seldom used in more than three dimensions. The distributed Hough transform is between perceptual grouping and Hough algorithms, by performing a Hough transform over possible combinations of edges. Castano and Hutchinson examined probabilistic perceptual grouping for straight-lines and bilateral symmetries with a Gaussian over the distance of points from the line [14].

SIGN DETECTION

Road sign recognition research has been around since the mid 1980s. Good results may be achieved for classification by approaches such as normalised cross correlation. Approaches such as a nearest feature transform and coarse to fine matching have been used to ease the heavy computational burden, with limited success. Frequently systems apply a low computational cost detection stage: aiming to detect most signs with a limited number of false positives, massively reducing the input stream. A sign must be reliably detected over the period it is visible, rather than every frame. Colour-based methods are sometimes based on the assumption that only the intensity of lighting changes in outdoor environments; often with statements such as that HSV or HSI spaces are invariant to lighting conditions. However, these methods break down under variation in lighting chrominance. Road scenes are generally well-structured, so some approaches search only part of the image by combining assumptions about structure with colour segmentation. Such assumptions often break down on hills and sharp corners. remove large uniform regions corresponding to road and sky. However, this will fail with overhead branches and road shadows (e.g., Fig. 1). Ref. [19] shows a recent reliable system using two stage detection, firstly colour, followed by shaped-based detection using distance from bounding box as a feature. The second stage of detection and the subsequent classification are performed using an SVM. Such a system demonstrates the utility of shape- based detection followed by classification [14].

F. INCREMENTAL DBCAN CLUSTERING ALGORITHM

The term incremental means "% of δ change in the original database" i.e. insertion of some new data items into the already existing clusters. Such as,

% δ change in DB = (new data – old data)/old data *100[4]

Sometimes DBSCAN may be applied on dynamic database which is frequently updated by insertion or deletion of data. After insertions and deletions to the database, the clustering discovered by DBSCAN has to be updated. Incremental clustering could improve the chances of finding the global optimum. In this approach, first it will form clusters based on the initial objects and a given radius(eps) and minimum number of points(Minpts).Thus algorithm finally get some clusters fulfilling the conditions and some outliers. Now, when new data are inserting into the existing database, have to update our clusters using DBSCAN. At first algorithm compute the means between every core object of clusters and the new coming data and insert the new data into a particular cluster based on the minimum mean distance. The new data which are not inserted into any clusters, they are treated as noise or outliers. Sometimes which fulfil the Minpts & eps criteria,combinly can form clusters using DBSCAN [3].

PROPOSED ALGORITHM

Input:
D: A dataset containing n objects.{*X1,X2, X3 …, Xn*}
n: number of data items.
Minpts: Minimum number of data objects
eps: radius of cluster.
Output:
K1: A Set of clusters.
Algorithm:
Let, Ci (where i=1, 2, 3 …) is the new data item.
1. Run the actual DBSCAN algorithm and clustered the new data item Ci properly based on the radius(eps) and the Minpts criteria. Repeat till all data items are clustered. Actual DBSCAN ⟶ (Processing Time).

Incremental DBSCAN Pseudo-code:
Start:
2. a> Let, K represents the already existing clusters.
b>When new data is coming into the database, the new data will be directly clustered by calculating the minimum mean(M) between that data and the core objects of existing clusters.
for i = 1 to n do
find some mean M in some cluster Kp in
K such that dis (*C*i, *M*) is the smallest;
If (dis (*Ci, M*) is minimum) && (Ci<=eps) && (size(Kp)>=Minpts) then
Kp = Kp U Ci ;
Else
If dis (Ci != min) || (Ci>eps) ||(size(Kp)<Minpts) then
Ci ⟶ Outlier(Oi) .
Else
If Count(Oi) ⟶ Minpts then Oi Form new cluster(Mi).
C > Repeat step b till all the data samples are clustered.
Incremental DBSCAN ⟶ T2. (Processing Time).
End ;
3. Compare (T1, T2)
Result: (T2< T1) ⟵ Upto some certain Threshold value in the database.
4. Compute the actual threshold value.
Finds the incremental clustering as a better time efficient approach [3].

A$_{DVANTAGES}$

The actual DBSCAN approach is not suitable for a large multidimensional database which is frequently updated. In that case, the incremental clustering approach is much better. The system with incremental concept saves lot of time and effort efficiently whereas the existing system has already suffering with some drawbacks and these problems are mainly faced in dynamic large databases by the existing system. When some records are added to existing data, then it deals with this problem of scanning the whole database again. The time complexity is very high due to rescanning the whole database. It requires more effort as well. The Existing system is not efficient with respect to time and effort. That's why new system with incremental clustering approach is more suitable to use in a large multidimensional dynamic database [3].

G. SPATIAL TEMPORAL DBCAN CLUSTERING ALGORITHM

ST-DBSCAN requires four parameters Eps1, Eps2, MinPts, and D_ because of the extensions described in Section 3. Eps1 is the distance parameter for spatial attributes (latitude and longitude). Eps2 is the distance parameter for non-spatial attributes. A distance metric such as Euclidean, Manhattan or Minkowski Distance Metric can be used for Eps1 and Eps2. MinPts is the minimum number of points within Eps1 and Eps2 distance of a point. If a region is dense, then it should contain more points than MinPts value. Simple heuristic is presented which is effective in many cases to determine the parameters Eps and MinPts. The heuristic suggests MinPts _ ln(n) where n is the size of the database and Eps must be picked depending on the value ofMinPts. The first step of the heuristic method is to determine the distances to the k-nearest neighbors for each object, where k is equal to MinPts. Then thesek-distance values should be sorted in descending order. Then algorithm should determine the threshold point which is the first ''valley'' of the sorted graph. User should select Eps to less than the distance defined by the first valley.

The last parameter D_ is used to prevent the discovering of combined clusters because of the little differences in non-spatial values of the neighboring locations. The algorithm starts with the first point p in database D and retrieves all points density-reachable from p with respect to Eps1 and Eps2. If p is a core object, a cluster is formed. If p is a border object, no points are density-reachable from p and the algorithm visits the next point of the database.

The process is repeated until all of the points have been processed. The algorithm starts with the first point in database D. After processing this point, it selects the next point in D. If the selected object does not belong to any cluster, Retrieve_Neighbors function is called. A call of Retrieve_Neighbors(object,Eps1, Eps2) returns the objects that have a distance less than Eps1 and Eps2 parameters to the selected object. In other words, Retrieve_Neighbors function retrieves all objects density-reachable from the selected object with respect to Eps1, Eps2, and MinPts.

The result set forms the Eps-Neighborhood of the selected object. Retrieve_Neighbours (object,Eps1, Eps2) equals to the intersection of Retrieve_Neighbours(object,Eps1) and Retrieve_Neighbours(object,Eps2). If the total number of returned points in Eps-Neighborhood is smaller than MinPtsinput, the object is assigned as noise. This means that the selected point has not enough neighbors to be clustered. The points which have been marked to be noise may be changed later, if they are not directly density-reachable but they are density-reachable from some other point of the database. This happens for border points of a cluster. If the selected point has enough neighbors within Eps1 and Eps2 distances—if it is a core object—then a new cluster is constructed. Then all directly density-reachable neighbors of this core object are also marked as new cluster label. Then the algorithm iteratively collects density-reachable objects from this core object by using a stack. The stack is necessary to find density-reachable objects from directly density-reachable objects. If the object is not marked as noise or it is not in a cluster, and the difference between the average value of the cluster and the new coming value is smaller than D_, it is placed into the current cluster. After processing the selected point, the algorithm selects the next point in D and algorithm continues iteratively until all of the points have been processed. When the algorithm searches the neighbors of any object by using Retrieve_Neighbors function, it takes into

consideration both spatial and temporal neighborhoods. The non-spatial value of an object such as a temperature value is compared with the non-spatial values of spatial neighbors and also with the values of temporal neighbors (previous day in the same year, next day in the same year, and the same day in other years). By this way, non-spatial, spatial and temporal characteristics of data are used in clustering when the algorithm is applied on the table which contains temporal values, beside spatial and non-spatial values.

If two clusters C1 and C2 are very close to each other, a point p may belong to both, C1 and C2. In this case, the point p must be a border point in both C1 and C2. The algorithm assigns point p to the cluster discovered first [13].

IV. Conclusions

This paper gives an idea about basic Density Based Spatial Clustering of Applications with Noise (DBSCAN) clustering algorithm and a detailed survey of six density based clustering algorithm like partitioning based DBSCAN clustering, grid-based DBSCAN clustering, hierarchical DBSCAN clustering, Detection Based DBSCAN clustering, Incremental DBSCAN clustering, Spatial Temporal DBCAN clustering based on the essential requirements required for any clustering algorithm in spatial data. Each algorithm is unique with its own features.

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