Multi Density DBSCAN

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Abstract. Clustering algorithms are attractive for the task of class identification in spatial databases. However, the application to large spatial databases rises the following requirements for clustering algorithms: minimal requirements of domain knowledge to determine the input parameters, discovery of clusters with arbitrary shape and good efficiency on large databases.DBSCAN clustering algorithm relying on a density-based notion of clusters which is designed to discover clusters of arbitrary shape. DBSCAN requires only one input parameter and supports the user in determining an appropriate value for it. DBSCAN cannot find clusters based on difference in densities. We extend the DBSCAN algorithm so that it can also detect clusters that differ in densities and without the need to input the value of Eps because our algorithm can find the appropriate value for each cluster individually by replacing Eps by Local cluster density.

Keywords: Clustering, Arbitrary Shape, DBSCAN, variable Densities.

1 Introduction

The density-based clustering approach is a methodology that is capable of finding arbitrarily shaped clusters, where clusters are defined as dense regions separated by low-density regions. A density-based algorithm needs only one scan of the original data set and can handle noise. The number of clusters is not required, since density-based clustering algorithms can automatically detect the clusters, along with the natural number of clusters [1].

Basic density based clustering techniques such as DBSCAN [2] and DENCLUE [3] treat clusters as regions of high densities separated by regions of no or low densities. So they are able to suitably handle clusters of different sizes and shapes besides effectively separating noise (outliers). But they fail to identify clusters with differing densities unless the clusters are separated by sparse regions.

We extend DBSCAN algorithm to discover clusters with different densities even if there is no low-density region separates them. Two adjacent spatial regions are separated into two clusters when the density difference violates a threshold. The proposed algorithm can automatically find Eps value for each cluster.

1.1 Density Based Clustering (DBSCAN)

DBSCAN is based on the concept of dense areas to form data clustering. The distribution of points in the cluster should be denser than that outside of the cluster. It defines a cluster as a maximal set of density-connected points.

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The basic ideas of density-based clustering involve a number of new definition:

- The neighborhood within a radius Eps of a given object is called the ε - *neighborhood* of the object.
- If the ε-neighborhood of an object contains at least a minimum number, *MinPts*, of objects, then the object is called a *core object*.
- Given a set of objects, D, we say that an object p is *directly density-reachable* from object q if p is within the ε-neighborhood of q, and q is a core object.
- An object p is density-reachable from object q with respect to Eps and *MinPts* in a set of objects, D, if there is a chain of objects $p_1, \ldots, p_n$, where $p_1 = q$ and $p_n = p$ such that p_{i+1} is directly density-reachable from p_i with respect to ε and *MinPts*, for $1 \leq i \leq n$, $p_i \in D$.
- An object p is density-connected to object q with respect to Eps and *MinPts* in a set of objects, D, if there is an object $O \in D$ such that both p and q are density-reachable from O with respect to ε and *MinPts*.

Density reachability is the transitive closure of direct density reachability, and this relationship is asymmetric. Only core objects are mutually density reachable [2].

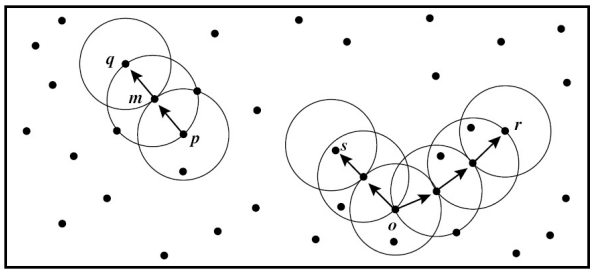


Fig. 1. Density reachability and density connectivity in density-based clustering (Source: Data Mining Concepts and Tecniques, Secnd edition, p419)

DBSCAN searches for clusters by checking the ε-neighborhood of each point in the database. If the ε-neighborhood of a point P contains more than MinPts, a new cluster with P as core point is created. DBSCAN then iteratively collects directly density-reachable points from these core points, which may involve the merge of a few density-reachable clusters.

2 Related Work

Early efforts like GAM [7] and CLARANS [8] detect clusters within huge data sets but demand high CPU effort. Later, BIRCH [9] was able to find clusters in the presence of noise. DBSCAN [2] detect clusters of arbitrary shapes. Recently, CHAMELEON [10] report clusters of different densities when data sets exhibit bridges and high discrepancy in density and noise [6].

Another algorithm [4] has introduced a simple idea to improve the results of DBSCAN algorithm by detecting clusters with large variance in density without

requiring the separation between clusters.This algorithm adds a new point to the cluster depending on its core point density (the most dense point in the cluster) which will cause a problem in nearly similar density neighbor clusters with large internal density variance, which is solved in our algorithm by calculating the average density of the cluster in a slow learning process.

Another method [5], DDSC(A Density Differentiated Spatial Clustering Technique) detects clusters, which are having non-overlapped spatial regions with reasonable homogeneous density variations within them. If there is significant change in densities of adjacent regions then all are separated into different clusters.

2.1 DBSCAN Limitation: Sparse Clusters Adjacent to High-Density Clusters

For the data set in Fig. 2, DBSCAN will fall in a trap since it depends on a single Eps value so it will extract just one cluster from any adjacent clusters.

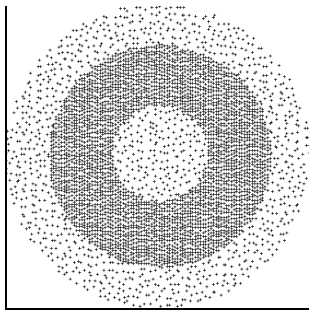


Fig. 2. Three adjacent clusters with different densities for 4700 point dataset

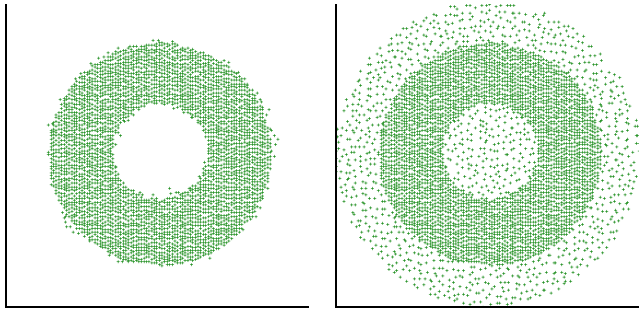


Fig. 3. DBSCAN Result using MinPts=4 and: (a) small Eps value, (b) large Eps value

As we mentioned above DBSCAN depends on single Eps, for small Eps (high density) it will extract only the dense class (Fig.3.a) and supposes that other classes are noise, but for large enough Eps (Fig.3.b) all clusters realize the density conditions and they are connected so it assumes that they are a single cluster.

3 The Proposed Algorithm

As DBSCAN is sensitive to Eps we will use another variable: ***AVGDST*** which will represent the average distances between any point in the cluster and its k[th]-neighbors, that variable will be cluster dependent which means it will be varied from a cluster to another and it will be calculated automatically for each cluster.

In the algorithm we use another concept, since DBSCAN collects the nearest neighbors using the predefined Eps value, here we calculate $\boldsymbol{DST_p}$ value by taking the average distance of the nearest k[th]-neighbors of any point ***p***. The *AVGDST* of the cluster and the DST_p will decide if this point belong to that cluster or not.

The algorithm will follow these steps:

1. Calculate the Euclidean distance between each two points of the dataset.
2. For each point ***p***, find the average distance between it and its k^{th} nearest neighbors.

$$DST_p = \sum_{q \in N_p} \frac{dist(p,q)}{k}$$

Where N_p is the group of k^{th} nearest neighbors of p.

3. Insert all points in the queue list.
4. Starting from the most dense point in the queue which have the smallest *DST* value and do the following:
   (a) Assign the point ***p*** to new cluster (C_i).
   (b) Remove ***p*** from the queue list.
   (c) The initial average distances of the cluster will be:

$$\mathrm{AVGDST_{Ci}} = \mathrm{DST_p}$$

   (d) Call: *gather*(C_i, *p*)
5. *gather* (C_i, *p*): For each point ***q*** in the nearest k^{th}-neighbors of ***p*** do the following:
   (a) if (***q*** in queue list) **and** ($DST_q \leq var * AVGDST_{Ci}$) then:
      (i) Add *q* to C_i members
      (ii) Remove *q* from the queue list.
      (iii) Calculate $AVGDST_{Ci}$ from the equation:

$$AVGDST_i = \frac{AVGDST_i * (N_i - 1) + DST_q}{N_i}$$

      (iv) Call: *gather*(C_i, *q*)
      (v) End if

Where *var* is the distances variance in the class and its value must be ≥ 1, since we start with the most dense point and the new points added to the cluster will be the same *DST* or little larger, this variable will select the density variance in the same cluster, in other words the new added point to a cluster must has *DST* value the same as cluster *AVGDST* value or with some acceptable difference, this acceptable

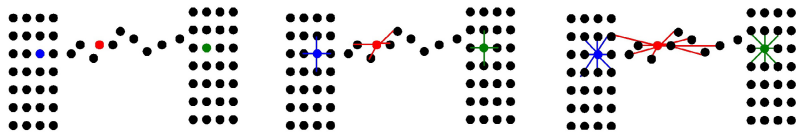
difference defined by the variable *var*. $(N_i - 1)$ represent the number of C_i members before adding the new point $\boldsymbol{q}$.

6. Eliminate very small clusters (noise).
7. Finish.

3.1 K-Value Problems

Since the algorithm depends on k value to calculate the *DST* for each point, selecting this value must avoid two problems depending on the dataset we use.

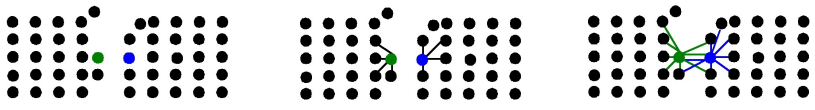
Bridges between two clusters
With huge dataset, some noise points may create bridges between clusters, Fig.4.a, these bridges lead our algorithm to merge bridged clusters if we use small k value (4 or 5 points), Fig. 4.b, but when increasing the value of k, Fig.4.c, the effect of the bridge will be eliminated since increasing the k value will increase the Eps value of the noise faster than the normal points and then the noise will be recognized. In the other side increasing the value of k leads to high processing time and complexity and will cause another problem, which is discussed in Fig.5.



(a) (b) (c)

Fig. 4. (a) shows two clusters connected by a noise bridge, (b) using k=4, the noise point Eps value similar to the core points Eps, (c) increasing the value of k, will increase the Eps value of the noise

Cracks within a cluster
With huge non uniform datasets, cracks within clusters are a normal result, so fixing the k value to 4 or 5 will cause large clusters with cracks to be separated into two or more clusters, Fig.5.b, so as the dataset becomes huge the value of k must be increased to avoid the cracks problem, but a large value of k may cause to merge a well separated clusters. So the value of k must be large enough to eliminate noise bridges and connects cluster parts but not too large to merge well separated clusters.

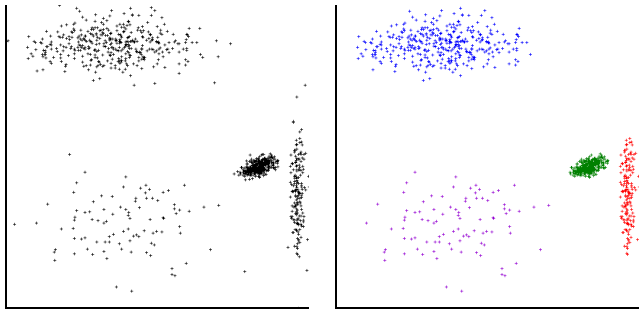


(a) (b) (c)

Fig. 5. (a) cracked cluster, (b) choosing k=4 will separate this cluster into two clusters, (c) increasing the value of k will merge cluster's parts

4 Experimental Results

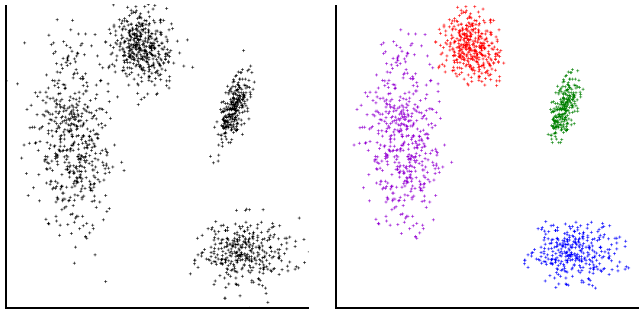
Here we evaluate the performance of the proposed algorithm. We implemented this algorithm in C#. We have used two dimensional datasets to test the algorithm.



(a) (b)

Fig. 6. (a) 1028 points dataset with four clusters, (b) the result using 2.5 variance, k=15

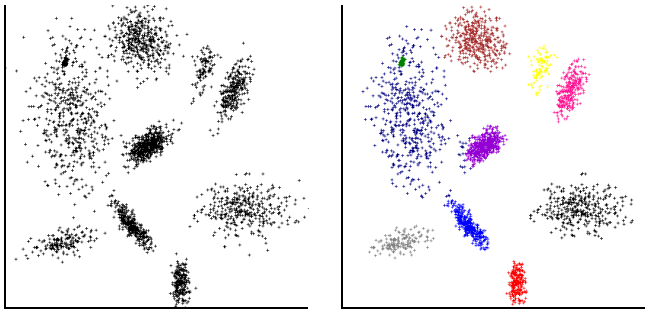
Fig.6.a shows four clusters of different size, shape, and density. The algorithm starts from the most dense point (lies in the green cluster) and collects the similar points around it until there is no more similar density around, then it starts from the most dense point in the remaining points (lies in the red cluster) and starts over again. Note that choosing a large enough k value protects from separating the red cluster by its south crack. The variance value 2.5 chosen by experiments outputs best results.



(a) (b)

Fig. 7. (a) 1572 points, with 4 clusters and (b) the result using 2.5 variance, k=15

In Fig.7.b we see a slightly different density clusters (red and violet) attached each other but since the algorithm has no unique Eps value so it separates them easily depending on the density of each cluster. This result may appear using DBSCAN but we need to select a critical value of Eps to ensure that neighbor clusters (Red and Violet) will not merge together.

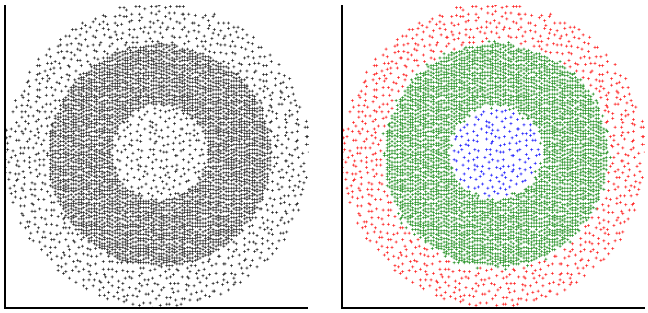


(a) (b)

Fig. 8. (a) 2972 points, with 10 clusters and (b) the result using 2.5 variance, k=15

In Fig.8.a, we have an artificial data set with 10 clusters differ in shape, size and density. While there is no Eps value that can help the DBSCAN to find the clusters due to the variety in densities, our proposed algorithm finds all the clusters successfully as shown in Fig.8.b

In Fig.9 we have three clusters inside each other. DBSCAN will not be able to separate the clusters successfully due the variety in density. If DBSCAN finds the middle cluster, it will assume that the inner and outer clusters are noise. If we modify Eps in an attempt to allow DBSCAN to detect the inner and outer clusters successfully, then DBSCAN will merge all the clusters into one big cluster. Thus there is no value for Eps that allows DBSCAN to solve this data set. While the correct result will not appear in any Eps value using DBSCAN, the proposed algorithm can find the three clusters easily as shown in Fig. 9.b. These results illuminate the purpose of this algorithm, where the DBSCAN failed to find the correct clusters.



(a) (b)

Fig. 9. (a) 4600 points with three clusters and (b) the result using 1.5 variance, k=15

5 Conclusion

In this paper, we have introduced an idea to improve DBSCAN algorithm to solve two main problems in it, the derivation of Eps value and the problem of connected

clusters with different densities since DBSCAN depends on single Eps (threshold) value to all clusters.

Our algorithm starts from the most dense point as the core of a cluster, that cluster will grow by gathering similar density neighbor points, when it finishes that cluster it starts from the most remaining dense point as the core of another cluster an so on. The algorithm proves itself in many different densities, shapes, sizes, and clusters datasets with a very good result. In this paper, we show the problems of selecting small value of k in the large dataset, the noise bridge and the cracked clusters. We show that these problems can be solved by increasing the value of k.

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