Clustering.
DBScan

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Compare results

- K-means:
- http://www.naftaliharris.com/blog/visualizing-k-means-clustering/
- (I'll choose -> Gaussian Mixture, Smiley Face)
- DBScan:
- http://www.naftaliharris.com/blog/visualizing-dbscan-clustering/
- (Gaussian Mixture, Smiley Face)

DBSCAN

Density-based spatial clustering of applications with noise (**DBSCAN**) is a data clustering algorithm proposed by Martin Ester, Hans-Peter Kriegel, Jörg Sander and Xiaowei Xu in 1996. It is a density-based clustering algorithm: given a set of points in some space, it groups together points that are closely packed together (points with many nearby neighbors), marking as outliers points that lie alone in low-density regions (whose nearest neighbors are too far away). DBSCAN is one of the most common clustering algorithms and also most cited in scientific literature.

- In 2014, the algorithm was awarded the test of time award (an award given to algorithms which have received substantial attention in theory and practice) at the leading data mining conference, KDD.

Preliminary

Consider a set of points in some space to be clustered. For the purpose of DBSCAN clustering, the points are classified as *core points*, (*density*-) *reachable points* and *outliers (noise)*, as follows:

- A point p is a core point if at least minPts points are within distance ε of it, and those points are said to be *directly reachable* from p.
-
- A point q is reachable from p if there is a path $p_1, \ldots, p_n$ with $p_1 = p$ and $p_n = q$, where each p_{i+1} is directly reachable from p_i (so all the points on the path must be core points, with the possible exception of q).
- All points not reachable from any other point are outliers.

Preliminary

If *p* is a core point, then it forms a *cluster* together with all points
(core or non-core) that are reachable from it. Each cluster contains at
least one core point; non-core points can be part of a cluster, but they
form its "edge", since they cannot be used to reach more points.

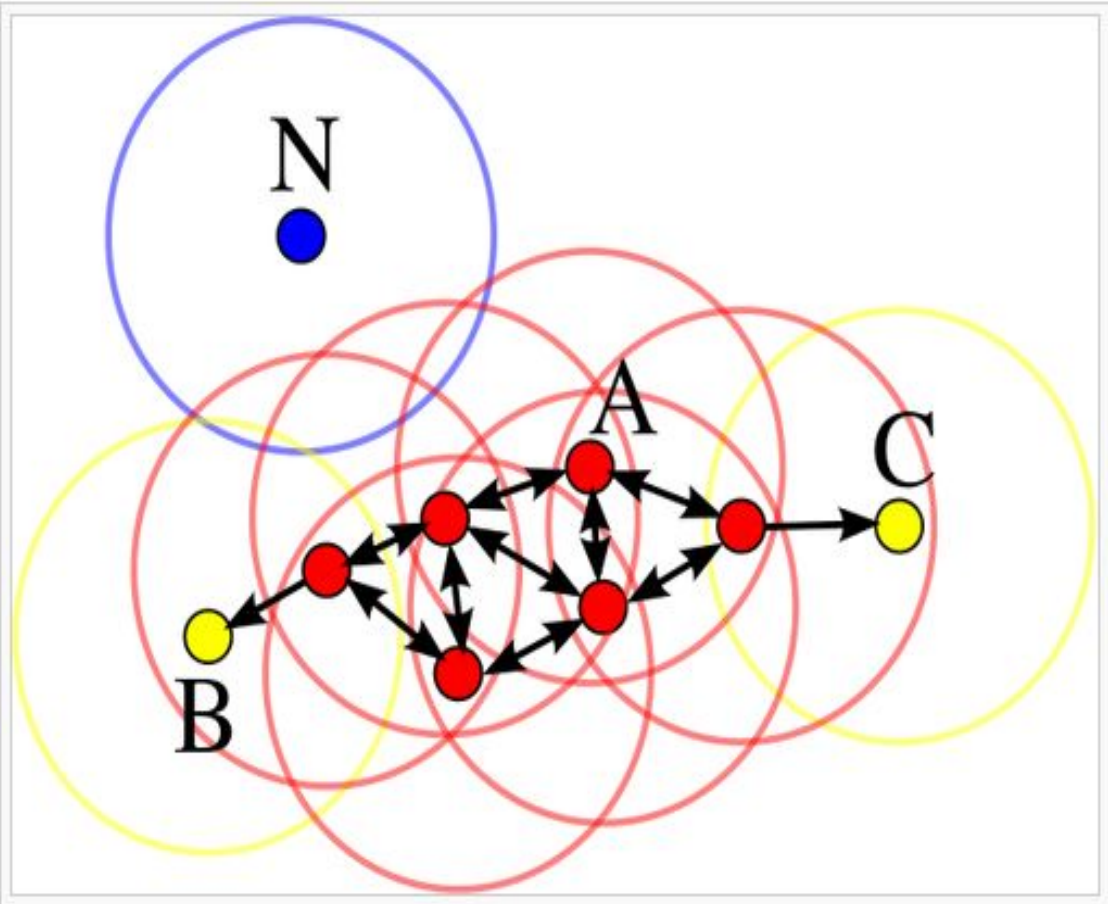
Preliminary

Two points *p* and *q* are density-connected if there is a point *o* such that both *p* and *q* are density-reachable from *o*. Density-connectedness *is* symmetric.

A cluster satisfies two properties:

- All points within the cluster are mutually density-connected.
- If a point is density-reachable from any point of the cluster, it is part of the cluster as well.

Example



In this diagram, minPts = 3. Point A and the other red points are core points, because at least three points surround it in an ε radius. Because they are all reachable from one another, they form a single cluster. Points B and C are not core points, but are reachable from A (via other core points) and thus belong to the cluster as well. Point N is a noise point that is neither a core point nor density-reachable.

Algorithm

DBSCAN requires two parameters: ε (eps) and the minimum number of points required to form a dense region (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.

Algorithm

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. The algorithm can be expressed as follows, in pseudocode following the original published nomenclature.

Main procedure

```
DBSCAN(D, eps, MinPts) {
   C = 0
   for each point P in dataset D {
      if P is visited
         continue next point
      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)
      }
   }
}
```

Procedure expandCluster

```
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
         add P' to cluster C
   }
}
```

Procedure regionQuery

```
regionQuery(P, eps)
    return all points within P's eps-neighborhood (including P)
```

Note

The algorithm can be simplified by merging the per-point "has been visited" and "belongs to cluster C" logic, as well as by inlining the contents of the "expandCluster" subroutine, which is only called from one place. These simplifications have been omitted from the above pseudocode in order to reflect the originally published version. Additionally, the regionQuery function need not return P in the list of points to be visited, as long as it is otherwise still counted in the local density estimate.

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 regionQuery invocations. DBSCAN executes exactly one such query for each point, and if an indexing structure is used that executes a neighborhood query in O(log *n*), an overall average runtime complexity of O(*n* log *n*) is obtained (if parameter ε is chosen in a meaningful way, i.e. such that on average only O(log *n*) points are returned). Without the use of an accelerating index structure, or on degenerated data (e.g. all points within a distance less than ε), the worst case run time complexity remains $O(n^2)$.

Parameter estimation (minPts)

Ideally, *minPts* is the desired minimum cluster size. Otherwise a minimum *minPts* can be derived from the number of dimensions *D* in the data set, as $minPts \geq D + 1$. The low value of $minPts = 1$ does not make sense, as then every point on its own will already be a cluster. With $minPts \leq 2$, the result will be the same as of hierarchical clustering. Therefore, *minPts* must be chosen at least 3. However, larger values are usually better for data sets with noise. The larger the data set, the larger the value of *minPts* should be chosen.

Parameter estimation (ε)

If ε is chosen much too small, a large part of the data will not be clustered; whereas for a too high value of ε, clusters will merge and the majority of objects will be in the same cluster. In general, small values of ε are preferable, and as a rule of thumb only a small fraction of points should be within this distance of each other.

- Distance function: The choice of distance function is tightly coupled to the choice of ε, and has a major impact on the results. In general, it will be necessary to first identify a reasonable measure of similarity for the data set, before the parameter ε can be chosen.

Advantages

- DBSCAN does not require to specify the number of clusters in the data a priori, as opposed to k-means.
- 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.
- DBSCAN can find outliers.
- 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)
- The parameters minPts and ε can be set by an expert, if the data is well understood.

Disadvantages

- DBSCAN is not entirely deterministic: border points that are reachable from more than one cluster can be part of either cluster, depending on the order the data is processed.
- The quality of DBSCAN depends on the distance measure used in the function regionQuery(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 "Curse 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.
- DBSCAN cannot cluster data sets well with large differences in densities, since the minPts-ε combination cannot then be chosen appropriately for all clusters.
- If the data and scale are not well understood, choosing a meaningful distance threshold ε can be difficult.

DBMS and DBMS

Task 5

- Generate 3-4 areas (2D or 3D).
- Create an application and show the areas.
- Realize DBScan algorithm and cluster the areas.
- Show the result of clustering (paint the clusters with different colors).