

Discovering NULL & Outliers

404 Not Found

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Outline

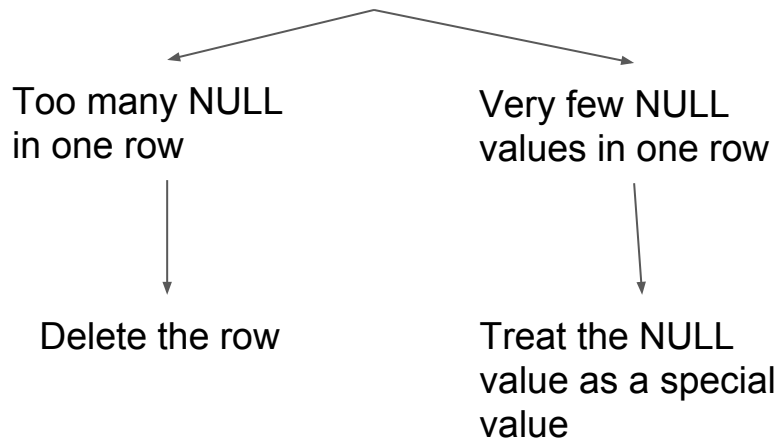
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Normalization

Example column		After nomalization
1	range:(1,4) →	0
2		$(2-1)/3=1/3$
2		$(2-1)/3=1/3$
4		1

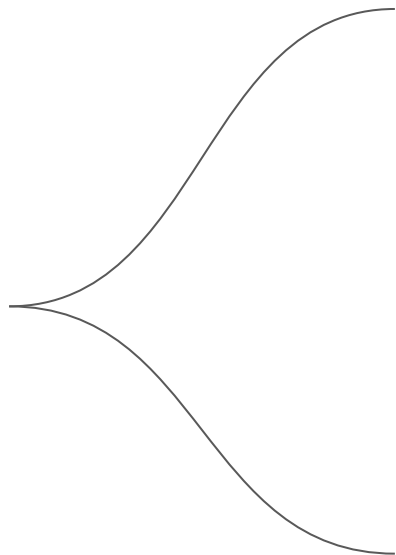
Null detection

Use spark to find the NULL value



Encoding

Fruit
Apple
Orange
Orange
Pear



Origin column	After encoding
Apple	1
Orange	2
Orange	2
Pear	3

Label encoding

Origin column	Apple	Orange	Pear
Apple	1	0	0
Orange	0	1	0
Orange	0	1	0
Pear	0	0	1

One hot encoding

Distance-based Method

- General Idea
 - Judge a point based on the distance(s) to its neighbors
 - Several variants proposed
- Basic Assumption
 - Normal data objects have a dense neighborhood
 - Outliers are far apart from their neighbors, i.e., have a less dense neighborhood

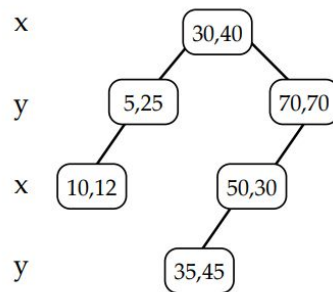
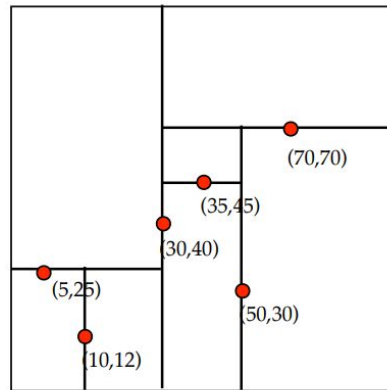
Kth-Neighbor Algorithm

- General models
 - Take the KNN distance of a point as its outlier score [Ramaswamy et al 2000]
 - The larger KNN distance -> Sparser neighborhood -> The point far apart from its neighborhood -> Outlier
- Algorithm:
 - Nest-Loop(Naïve approach):
 - For each object: compute kNNs with a sequential scan
 - Rank the scores: Higher score -> high Outlier Possibility
 - Complexity: $O(kN^2)$

Kth-Neighbor Algorithm--Using KD-Tree

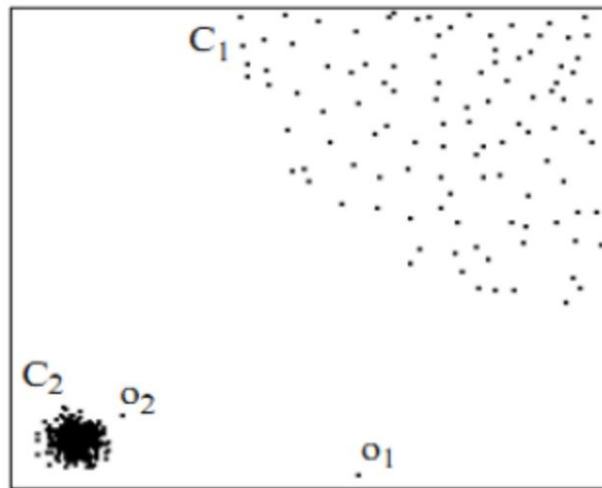
- Algorithm:
 - Use KD-Tree structure for KNN queries
 - Each level has a “cutting dimension”
 - Cycle through the dimensions as you walk down the tree.
 - Complexity: $O(N \log N)$

insert: (30,40), (5,25), (10,12), (70,70), (50,30), (35,45)



Innovation on KNN method– Local Outlier Factor

- Backward of KNN Method:
 - Need decide optimal K
 - Distance-based outlier detection models have problems with different densities
- Local Outlier Factor (LOF) [Breunig et al. 2000]
 - Consider relative density
 - Measuring the local deviation of a given data point with respect to its neighbours.



Local Outlier Factor

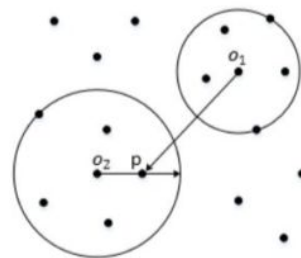
- Model

- **K-Distance**

- **Reachability Distance:**

- Introduces a smoothing factor:

$$reach - distance_k(p, o) = \max\{k - distance(o), d(p, o)\}$$



$$reach - dist_k(p, o_1) = d(p, o_1)$$

$$reach - dist_k(p, o_2) = d_5(o_2)$$

- **Local Reachability Distance (lrd)** of point p:

- Inverse of the average reach-dists of the kNNs of p

$$lrd_k(p) = 1 / \left(\frac{\sum_{o \in N_k(p)} reach - dist_k(p, o)}{|N_k(p)|} \right)$$

Local Outlier Factor

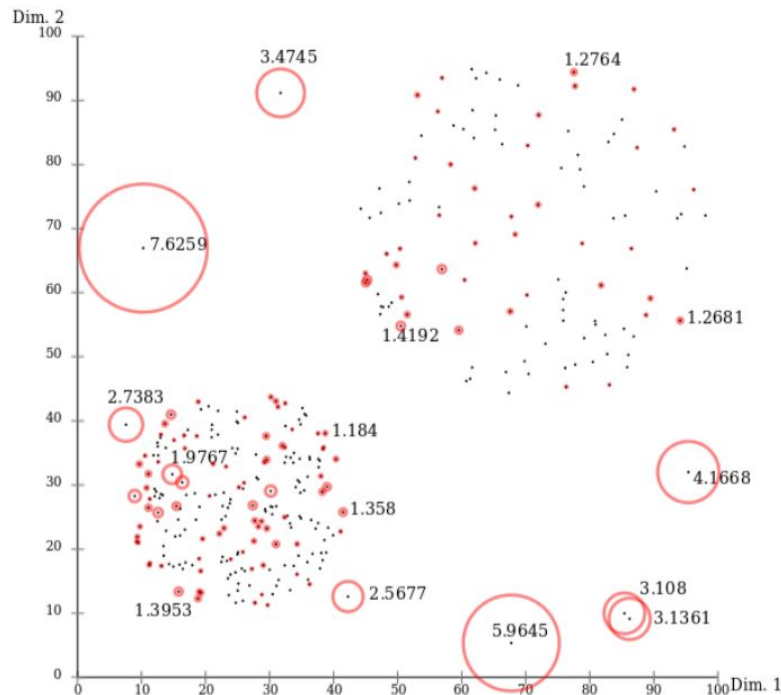
- Model

- **Local outlier factor (LOF)** of point p
 - Average ratio of lrd s of neighbors of p and lrd of p

$$LOF_k(p) = \frac{\sum_{o \in N_k(p)} \frac{lrd_k(o)}{lrd_k(p)}}{|N_k(p)|} = \frac{\sum_{o \in N_k(p)} lrd_k(o)}{|N_k(p)|} / lrd_k(p)$$

- Properties

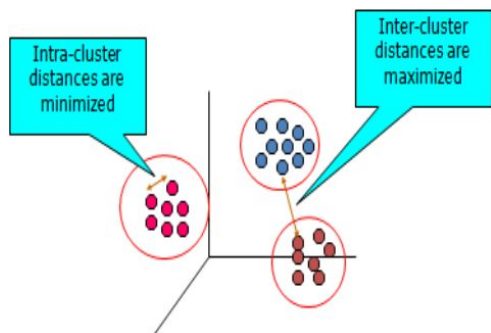
- $LOF \approx 1$: point is in a cluster
(region with homogeneous density around the point and its neighbors)
- $LOF \gg 1$: point is an outlier



Cluster-based Method

- General Idea

- Cluster analysis or clustering is the task of assigning a set of object into groups called clusters so that the objects in the same cluster are more similar in some sense to each other than to those in other clusters.

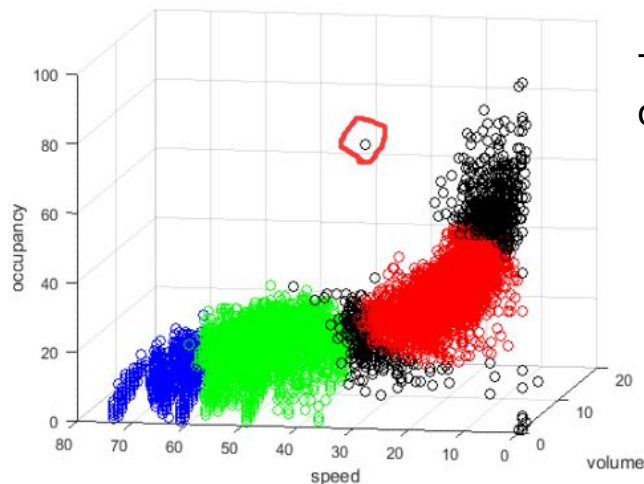


- Implement Distance-based algorithm and Density-based algorithm

- Distance-based: K-Means
- Density-based: DBSCAN

K-Means

- Algorithm
 - K-Means clustering aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean.
 - After clustering, an outlier is the point which has a larger distance to the centers of clusters.
- Process of clustering



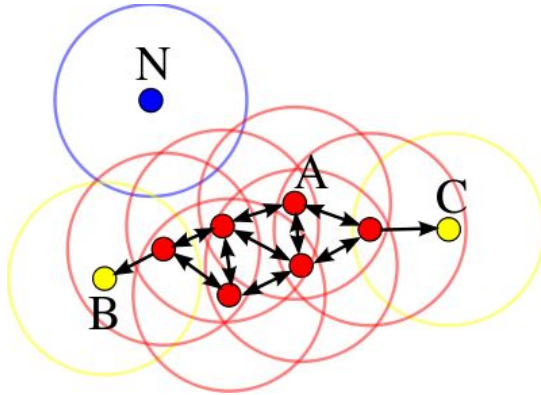
The points that are far from all the centers of clusters are outliers

DBSCAN

- Principle of Density-based spatial clustering of applications with noise
 - Density-based clustering algorithm
 - Based on a set a neighbors of core points to describe tightness.
 - A pair of parameters (ϵ , MinPts)

DBSCAN

- Algorithm
 - Using $(\epsilon, \text{MinPts})$ to determine the core points: If at least MinPts points are within distance ϵ .
 - Determine whether a point is reachable or not.
 - All points not reachable from any other points are outliers.
- Process of clustering

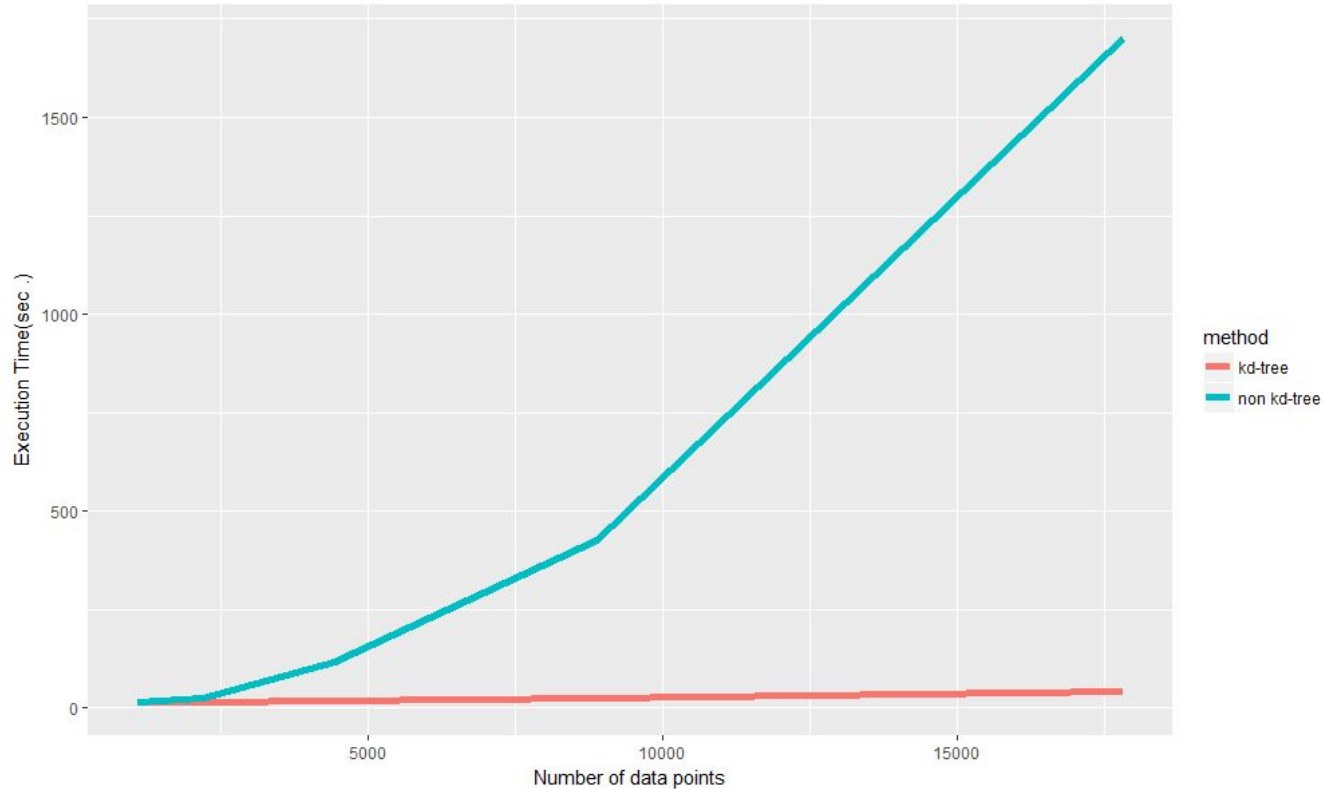


- ❑ We set $\text{MinPts} = 4$. All the red point are core points.
- ❑ Points B and C are not core points
- ❑ Point N is an outlier.

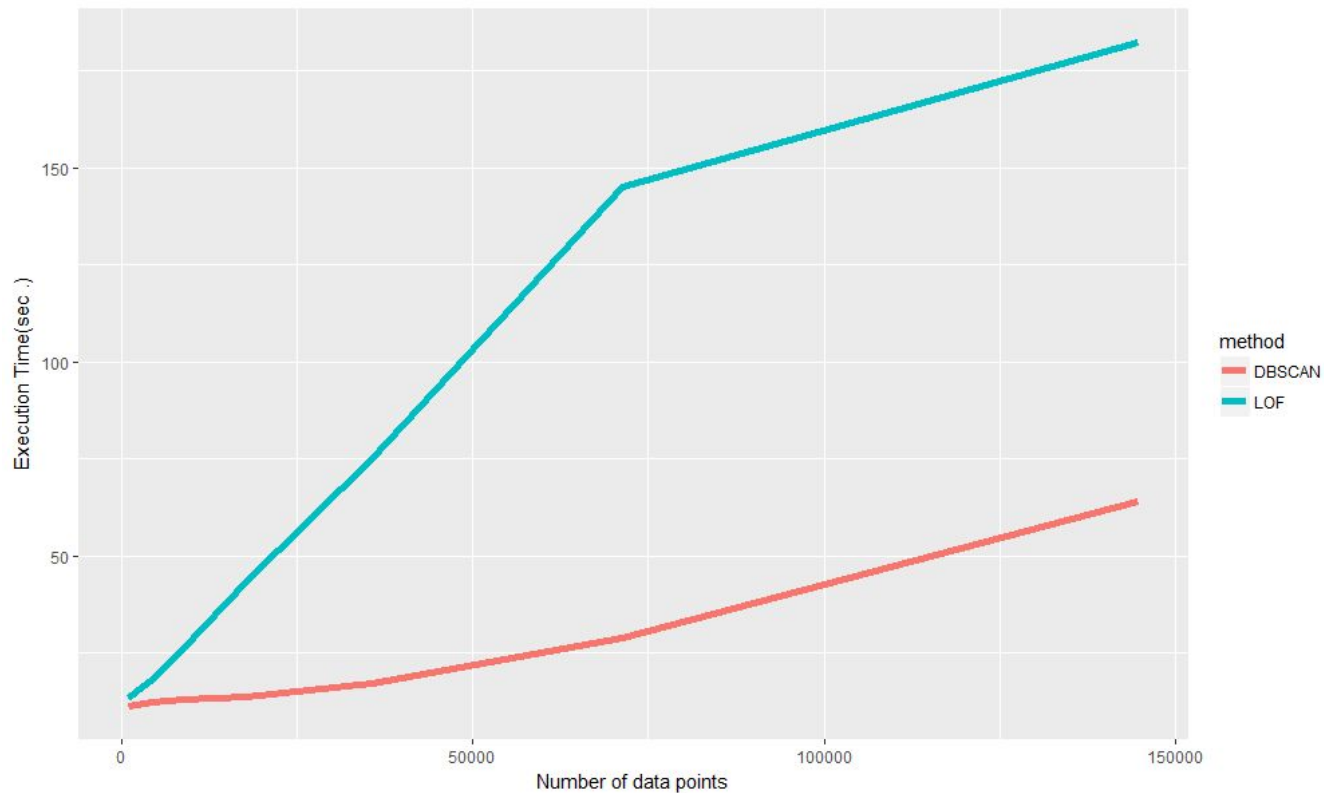
Comparison between K-Means and DBSCAN

- Principle
 - K-Means: Distance-based
 - DBSCAN: Density-based
- Parameters
 - K-Means: Need to define how many clusters in advance.
 - DBSCAN: The number of clusters is determined by the parameter pair: (ϵ , MinPts).

Performance Result Of Kd-tree & Naïve method



Performance Result Of LOF & DBSCAN



Reference & Code Repo

- [BL94] V. Barnett and T. Lewis. Outliers in Statistical Data. John Wiley and Sons, New York, 1994.
- [KN98] Edwin Knorr and Raymond Ng. Algorithms for mining distance-based outliers in large datasets. In Proc. of the VLDB Conference, pages 392-403, New York, USA, September 1998.
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(DBSCAN)<https://en.wikipedia.org/wiki/DBSCAN>
- [BKNS00] Breunig, M. M.; Kriegel, H.-P.; Ng, R. T.; Sander, J. (2000). LOF: Identifying Density-based Local Outliers (PDF). Proceedings of the 2000 ACM SIGMOD International Conference on Management of Data. SIGMOD.

Find us on GitHub:

<https://github.com/PrinceNathaniel/NYUBigDataProject>