DATA MINING 2

Anomaly & Outliers Detection

Riccardo Guidotti

a.a. 2023/2024

Slides edited from Tan, Steinbach, Kumar, Introduction to Data Mining and from Kriegel, Kröger, Zimek Tutorial on Outlier Detection Techniques

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What is an Outlier?

Definition of Hawkins [Hawkins 1980]:

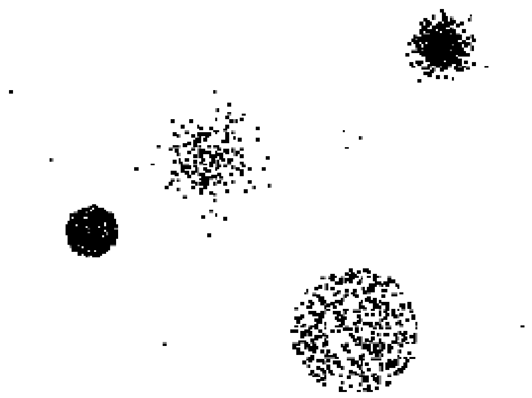
- "An outlier is an observation which deviates so much from the other observations as to arouse suspicions that it was generated by a different mechanism"

Statistics-based intuition

- Normal data objects follow a "generating mechanism", e.g. some given statistical process
- Abnormal objects deviate from this generating mechanism

Anomaly/Outlier Detection

- What are anomalies/outliers?
  - The set of data points that are considerably different than the remainder of the data
- Natural implication is that anomalies are relatively rare
  - One in a thousand occurs often if you have lots of data
  - Context is important, e.g., freezing temps in July
- Can be important or a nuisance
  - 10 foot tall 2 year old
  - Unusually high blood pressure



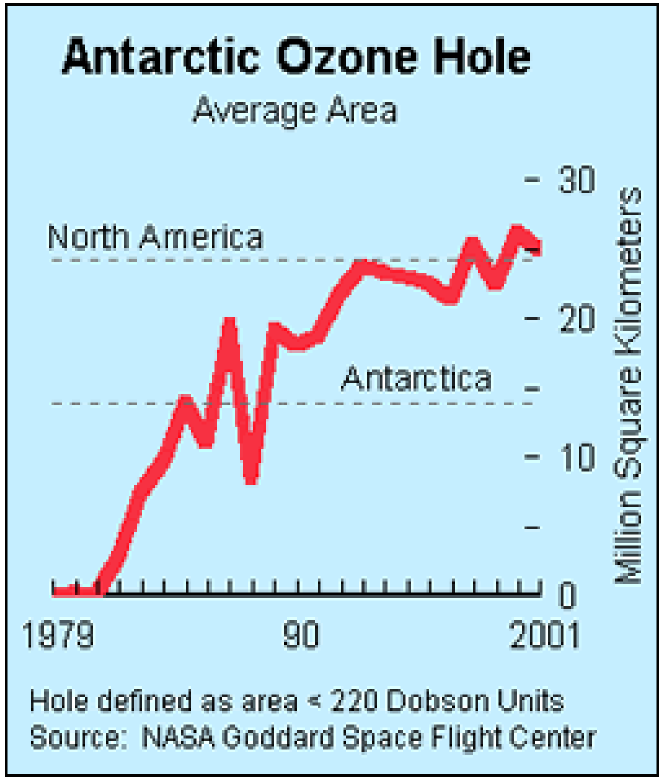
Applications of Outlier Detection

- Fraud detection
  - Purchasing behavior of a credit card owner usually changes when the card is stolen
  - Abnormal buying patterns can characterize credit card abuse
- Medicine
  - Unusual symptoms or test results may indicate potential health problems of a patient
  - Whether a particular test result is abnormal may depend on other characteristics of the patients (e.g. gender, age, …)
- Public health
  - The occurrence of a particular disease, e.g. tetanus, scattered across various hospitals of a city indicate problems with the corresponding vaccination program in that city
  - Whether an occurrence is abnormal depends

Importance of Anomaly Detection

Ozone Depletion History

- In 1985 three researchers (Farman, Gardinar and Shanklin) were puzzled by data gathered by the British Antarctic Survey showing that ozone levels for Antarctica had dropped 10% below normal levels
- Why did the Nimbus 7 satellite, which had instruments aboard for recording ozone levels, not record similarly low ozone concentrations?
- The ozone concentrations recorded by the satellite were so low they were being treated as outliers by a computer program and discarded!



Causes of Anomalies

- Data from different classes
  - Measuring the weights of oranges, but a few grapefruit are mixed in
- Natural variation
  - Unusually tall people
- Data errors
  - 200 pound 2 year old

Distinction Between Noise and Anomalies

- Noise is erroneous, perhaps random, values or contaminating objects
  - Weight recorded incorrectly
  - Grapefruit mixed in with the oranges

- Noise does not necessarily produce unusual values or objects
- Noise is not interesting
- Anomalies may be interesting if they are not a result of noise
- Noise and anomalies are related but distinct concepts

General Issues: Number of Attributes

- Many anomalies are defined in terms of a single attribute
  - Height
  - Shape
  - Color
- Can be hard to find an anomaly using all attributes
  - Noisy or irrelevant attributes
  - Object is only anomalous with respect to some attributes
- However, an object may not be anomalous in any one attribute

General Issues: Anomaly Scoring

- Many anomaly detection techniques provide only a binary categorization
  - An object is an anomaly or it is not
  - This is especially true of classification-based approaches

- Other approaches assign a score to all points
  - This score measures the degree to which an object is an anomaly
  - This allows objects to be ranked

- In the end, you often need a binary decision
  - Should this credit card transaction be flagged?
  - Still useful to have a score
- How many anomalies are there?

Other Issues for Anomaly Detection

- Find all anomalies at once or one at a time
  - Swamping
  - Masking

- Evaluation
  - How do you measure performance?
  - Supervised vs. unsupervised situations

- Efficiency

- Context

Variants of Anomaly Detection Problems

- Given a data set D, find all data points **x** $\in$ D with anomaly scores greater than some threshold *t*

- Given a data set D, find all data points **x** $\in$ D having the top-*n* largest anomaly scores

- Given a data set D, containing mostly normal (but unlabeled) data points, and a test point **x**, compute the anomaly score of **x** with respect to D

Model-Based Anomaly Detection

Build a model for the data and see

- Unsupervised
  - Anomalies are those points that don’t fit well
  - Anomalies are those points that distort the model
  - Examples:
    - Statistical distribution
    - Clusters
    - Regression
    - Geometric
    - Graph
- Supervised
  - Anomalies are regarded as a rare class
  - Need to have training data

Machine Learning for Outlier Detection

- If the ground truth of anomalies is available we can prepare a classification problem to unveil outliers.
- As classifiers we can use all the available machine learning approaches: Ensembles, SVM, DNN.
- The problem is that the dataset would be very unbalanced
- Thus, ad-hoc formulations/implementation should be adopted.

Unsupervised Anomaly Detection Techniques

- **Proximity-based**
  - Anomalies are points far away from other points
  - Can detect this graphically in some cases
- **Density-based**
  - Low density points are outliers
- **Pattern matching**
  - Create profiles or templates of atypical but important events or objects
  - Algorithms to detect these patterns are usually simple and efficient

Outliers Detection Approaches Taxonomy

- **Global vs local** outlier detection
  - Considers the set of reference objects relative to which each point's "outlierness" is judged
- **Labeling vs scoring** outliers
  - Considers the output of an algorithm
- **Modeling properties**
  - Considers the concepts based on which "outlierness" is modeled

Global versus Local Approaches

- Considers the resolution of the reference set w.r.t. which the "outlierness" of a particular data object is determined
- **Global approaches**
  - The reference set contains all other data objects
  - Basic assumption: there is only one normal mechanism
  - Basic problem: other outliers are also in the reference set and may falsify the results
- **Local approaches**
  - The reference contains a (small) subset of data objects
  - No assumption on the number of normal mechanisms
  - Basic problem: how to choose a proper reference set
- Notes
  - Some approaches are somewhat in between
  - The resolution of the reference set is varied e.g. from only a single object (local) to the entire database (global) automatically or by a user-defined input parameter

Labeling versus Scoring

- Considers the output of an outlier detection algorithm
- **Labeling approaches**
  - Binary output
  - Data objects are labeled either as normal or outlier
- **Scoring approaches**
  - Continuous output
  - For each object an outlier score is computed (e.g. the probability for being an outlier)
  - Data objects can be sorted according to their scores
- Notes
  - Many scoring approaches focus on determining the top-n outliers (parameter n is usually given by the user)
  - Scoring approaches can usually also produce binary output if necessary (e.g. by defining a suitable threshold on the scoring values)

Model-based Approaches

Approaches classified by the properties of the underlying modeling

- Intuition
  - Apply a model to represent normal data points
  - Outliers are points that do not fit to that model
- Sample approaches
  - Probabilistic tests based on statistical models
  - Depth-based approaches
  - Deviation-based approaches
  - Some subspace outlier detection approaches

Model-based Approaches

Proximity-based Approaches

- Intuition
  - Examine the spatial proximity of each object in the data space
  - If the proximity of an object considerably deviates from the proximity of other objects it is considered an outlier
- Sample approaches
  - Distance-based approaches
  - Density-based approaches
  - Some subspace outlier detection approaches

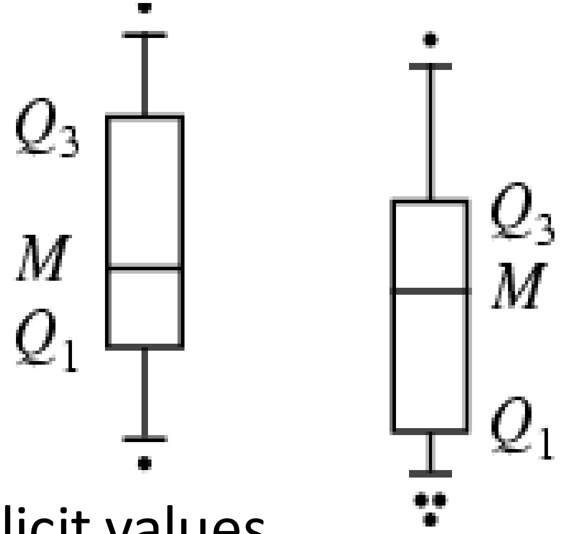
Model-based Approaches

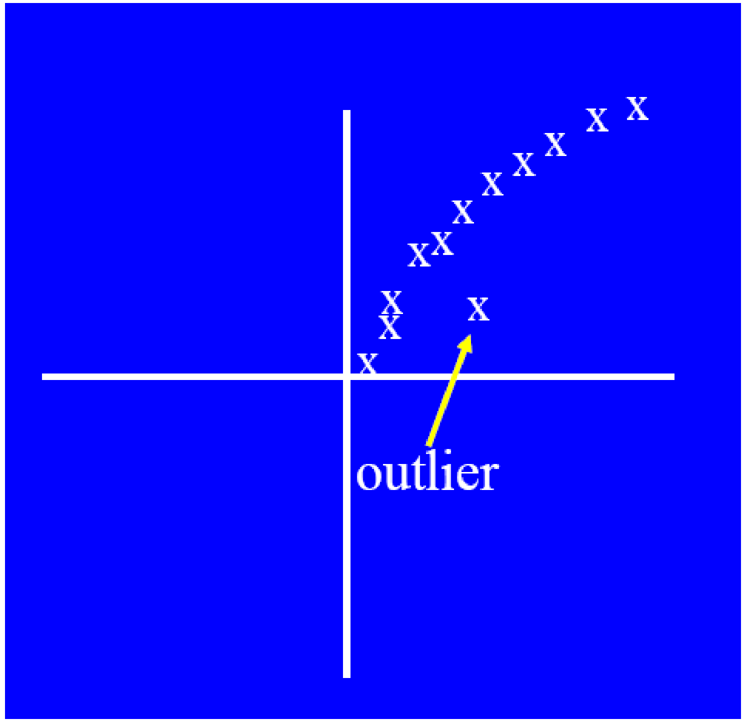
Angle-based approaches

- Intuition
  - Examine the spectrum of pairwise angles between a given point and all other points
  - Outliers are points that have a spectrum featuring high fluctuation

Visual Approaches

- Boxplots
- Scatter plots

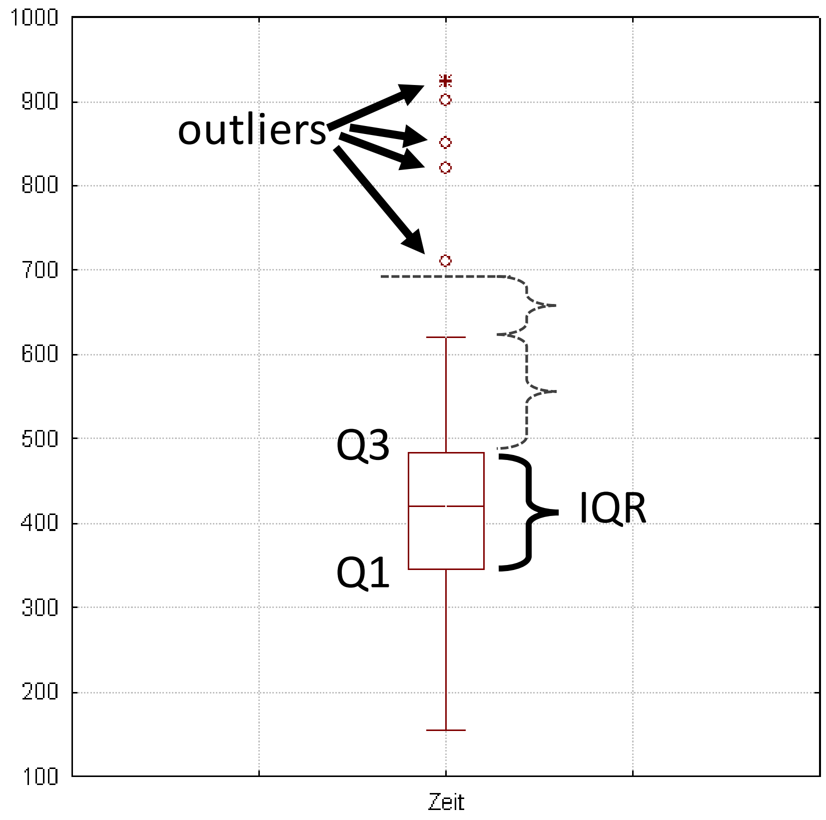




- Limitations
  - They do not return explicit values
  - Subjective

From Visual Box-plot to Automatic Approach

- The IQR of a set of values is calculated as the difference between the upper and lower quartiles, Q3 and Q1. *IQR = Q3 - Q1*
- x is an outlier if $x < Q1 - k\ IQR$ or $x > Q3 + k\ IQR$ (generally k=1.5)
- In a boxplot, the highest and lowest occurring value within this limit are indicated by *whiskers* of the box and any outliers as individual points.



HBOS - Histogram-based Outlier Score

- *It assumes feature independence* and calculates the outlier scores by building histograms.
- Univariate histogram for each single feature
  - Categorical data: Simple counting
  - Numerical data:
    1. Bin width with *k* bins having equal width
    2. Bin width with *N/k* instances per bin (equal frequency)
- Frequency (relative amount) of records in a bin is used as density estimation
- Histograms are normalized to [0,1] for each single feature
- HBOS for each record p is computed as a product of the inverse of the estimated density:

$$HBOS(p) = \sum_{i=0}^{d} log(\frac{1}{hist_i(p)})$$

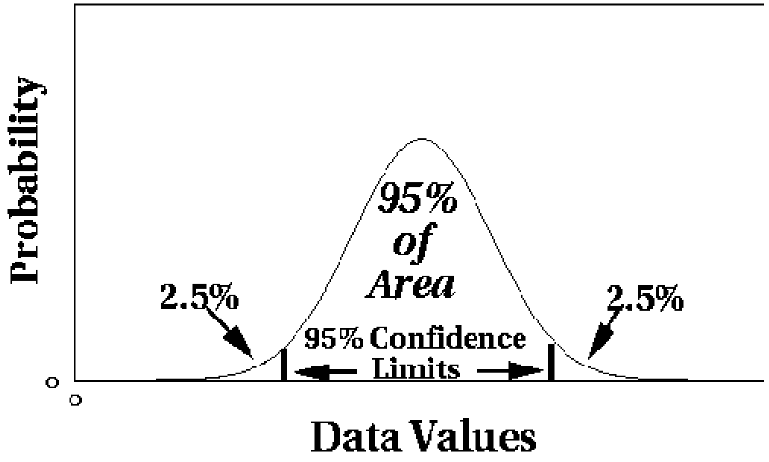
Statistical Approaches

Statistical Approaches

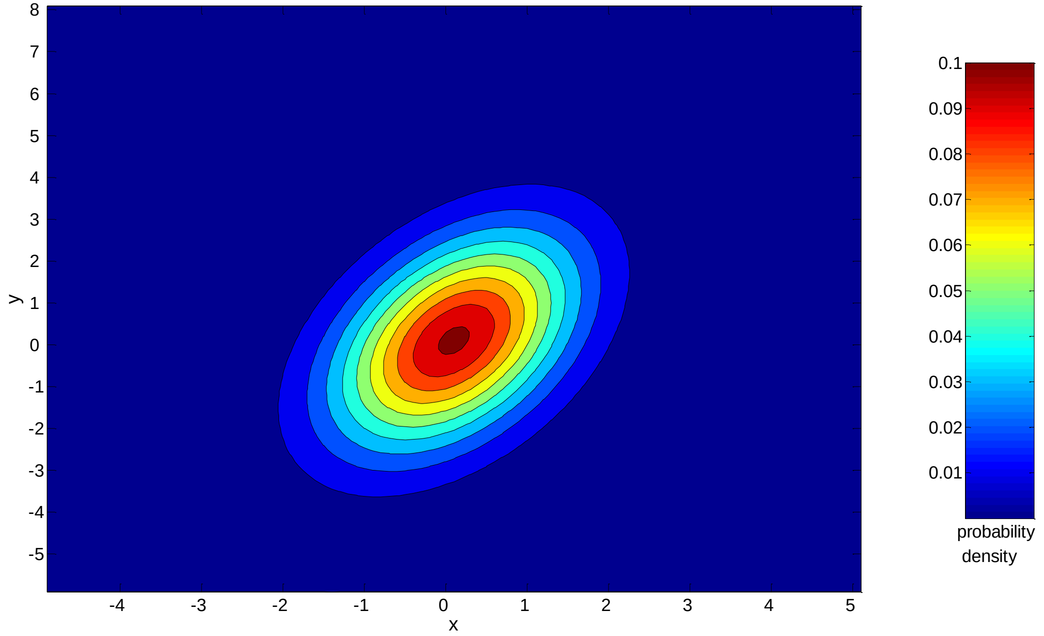
Probabilistic definition of an outlier: An outlier is an object that has a low probability with respect to a probability distribution model of the data.

- Usually assume a parametric model describing the distribution of the data (e.g., normal distribution)
- Apply a statistical test that depends on
  - Data distribution
  - Parameters of distribution (e.g., mean, variance)
  - Number of expected outliers (confidence limit)
- Issues
  - Identifying the distribution of a data set
    - Heavy tailed distribution
  - Number of attributes
  - Is the data a mixture of distributions?

Normal Distributions



One-dimensional Gaussian



Two-dimensional Gaussian

Statistical-based – Grubbs' Test

- Detect outliers in univariate data
- Assume data comes from normal distribution
- Detects one outlier at a time, remove the outlier, and repeat
  - H_0: There is no outlier in data
  - H_A: There is at least one outlier
- Grubbs' test statistic:

  one-sided test with alpha/N

  two-sided test with alpha/2N

mean

$$G = \frac{\max \left| X - \overline{X} \right|}{s}$$

std dev

- Reject null hypothesis H_0 of no outliers if:

alpha significance

t – Student's distribution

$$G > \frac{(N-1)}{\sqrt{N}} \sqrt{\frac{t^2_{(\alpha/N,\,N-2)}}{N-2+t^2_{(\alpha/N,\,N-2)}}}$$

degrees of freedom

upper critical value of t-distribution

Statistical-based – Likelihood Approach

- Assume the data set D contains samples from a mixture of two probability distributions:
  - M (majority distribution)
  - A (anomalous distribution)
- General Approach:
  - Initially, assume all the data points belong to M
  - Let $L_t(D)$ be the log likelihood of D at time t
  - For each point x_t that belongs to M, move it to A
    - Let $L_{t+1}(D)$ be the new log likelihood.
    - Compute the difference, $\Delta = L_t(D) - L_{t+1}(D)$
    - If $\Delta > c$ (some threshold), then x_t is declared as an anomaly and moved permanently from M to A

Statistical-based – Likelihood Approach

- Data distribution, $D = (1 - \lambda)\, M + \lambda\, A$
- M is a probability distribution estimated from data
  - Can be based on any modeling method (naïve Bayes, maximum entropy, etc.)
- A is initially assumed to be uniform distribution
- Likelihood at time t:

$$L_t(D) = \prod_{i=1}^{N} P_D(x_i) = \left((1-\lambda)^{|M_t|} \prod_{x_i \in M_t} P_{M_t}(x_i) \right) \left(\lambda^{|A_t|} \prod_{x_i \in A_t} P_{A_t}(x_i) \right)$$

$$LL_t(D) = |M_t| \log(1-\lambda) + \sum_{x_i \in M_t} \log P_{M_t}(x_i) + |A_t| \log \lambda + \sum_{x_i \in A_t} \log P_{A_t}(x_i)$$

Strengths/Weaknesses of Statistical Approaches

Pros

- Firm mathematical foundation
- Can be very efficient
- Good results if distribution is known

Cons

- In many cases, data distribution may not be known
- For high dimensional data, it may be difficult to estimate the true distribution
- Anomalies can distort the parameters of the distribution
  - Mean and standard deviation are very sensitive to outliers

Deviation-based Approaches

Deviation-based Approaches

- General idea
  - Given a set of data points (local group or global set)
  - Outliers are points that do not fit to the general characteristics of that set, i.e., the variance of the set is minimized when removing the outliers
- Basic assumption
  - Outliers are the outermost points of the data set

Deviation-based Approaches

Model [Arning et al. 1996]

- Given a smoothing factor SF(I) that computes for each I ⊆ DB how much the variance of DB is decreased when I is removed from DB
- With equal decrease in variance, a smaller exception set E is better
- The outliers are the elements of E ⊆ DB for which the following holds: SF(E) ≥ SF(I) for all I ⊆ DB

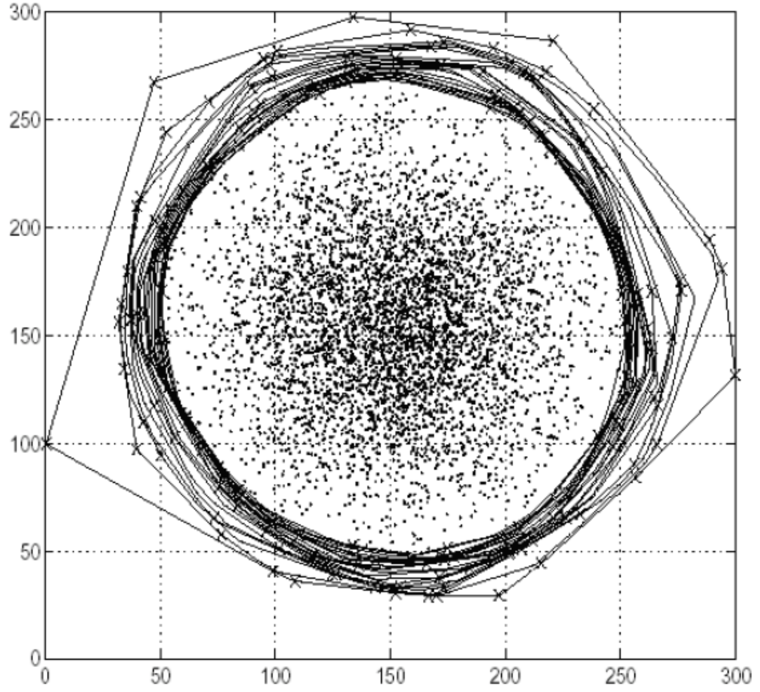
Discussion:

- Similar idea like classical statistical approaches (assuming one distribution) but independent from the chosen kind of distribution
- Naïve solution is in O(2n) for *n* data objects
- Heuristics like random sampling or best first search are applied
- Applicable to any data type (depends on the definition of SF)
- Originally designed as a global method
- Outputs a labeling

Depth-based Approaches

Depth-based Approaches

- General idea
  - Search for outliers at the border of the data space but independent of statistical distributions
  - Organize data objects in convex hull layers
  - Outliers are objects on outer layers

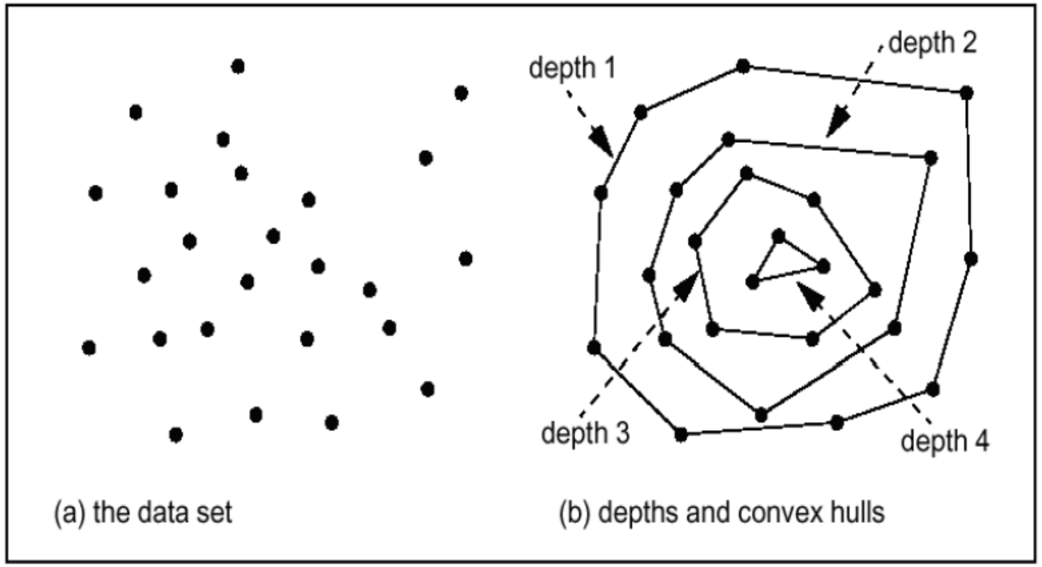


- Basic assumption
  - Outliers are located at the border of the data space
  - Normal objects are in the center of the data space

Depth-based Approaches

Model [Tukey 1977]

- Points on the convex hull of the full data space have depth = 1
- Points on the convex hull of the data set after removing all points with depth = 1 have depth = 2
- – …
- Points having a depth ≤ k are reported as outliers



(a) the data set (b) depths and convex hulls

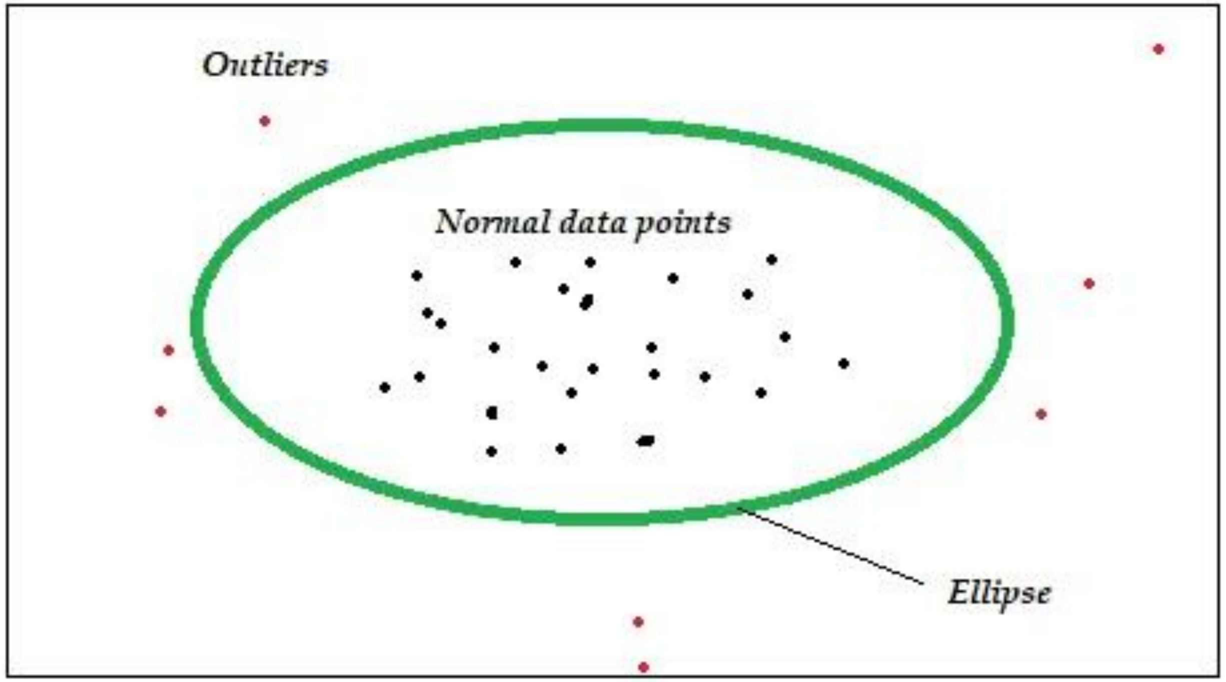
Depth-based Approaches

- Similar idea like classical statistical approaches (k = 1 distributions) but independent from the chosen kind of distribution
- Convex hull computation is usually only efficient in 2D / 3D spaces
- Originally outputs a label but can be extended for scoring easily (take depth as scoring value)
- Uses a global reference set for outlier detection

- Sample algorithms
  - ISODEPTH [Ruts and Rousseeuw 1996]
  - FDC [Johnson et al. 1998]

Elliptic Envelope

- It creates an imaginary elliptical area around a given dataset.
- The elliptic envelope finds the center of the data samples and then draws an ellipsoid around that center.
- Values that fall inside the envelope are considered normal data and anything outside the envelope is returned as outliers.
- The algorithm works best if data has a Gaussian distribution.



Distance-based Approaches

Distance-based Approaches

- 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

Distance-based Approaches

- Several different techniques
- Approach 1: An object is an outlier if a specified fraction of the objects is more than a specified distance away (Knorr, Ng 1998)
  - Some statistical definitions are special cases of this
- Approach 2: The outlier score of an object is the distance to its *k*-th nearest neighbor

Outlier scoring based on kNN distances

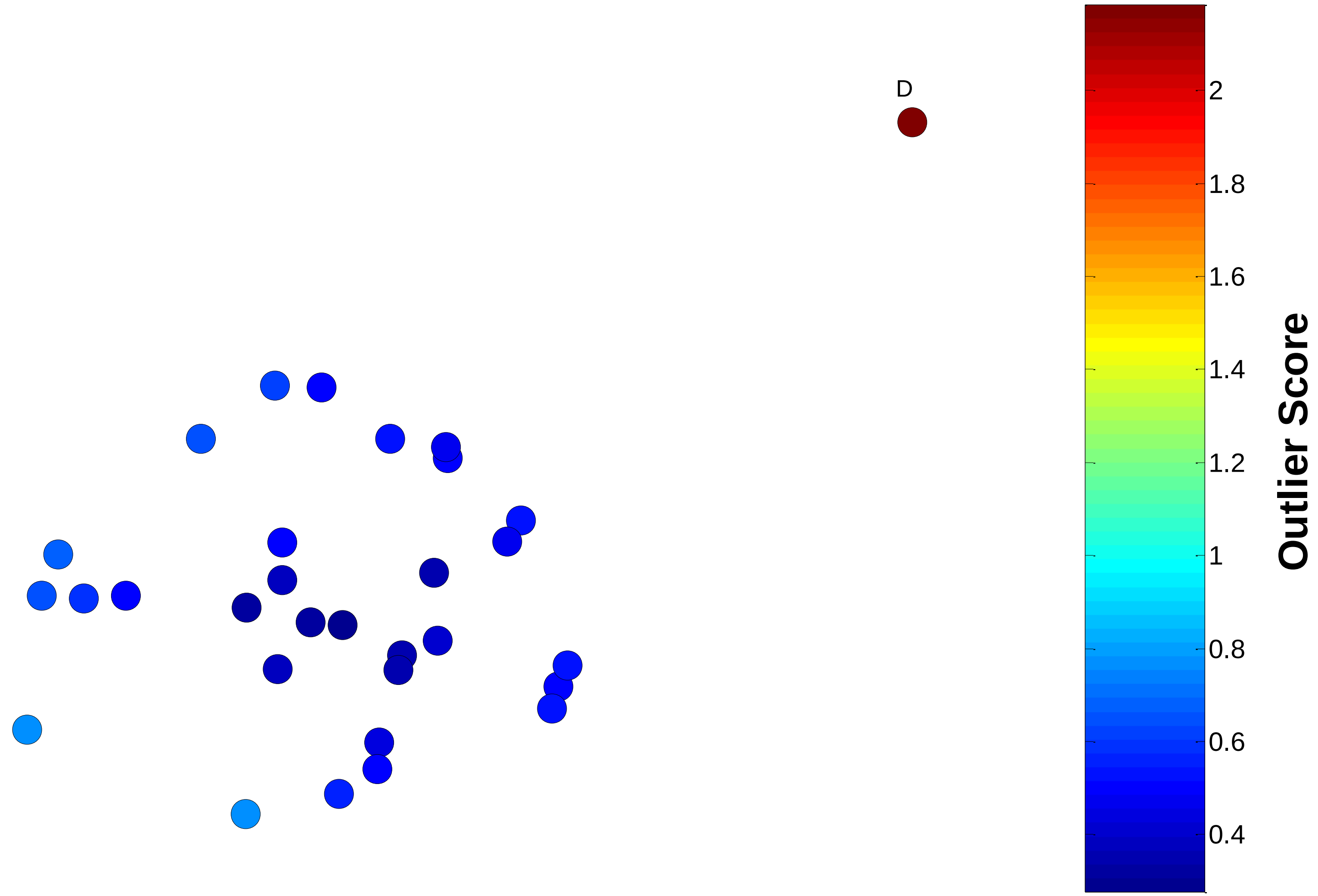
General models

- Take the kNN distance of a point as its outlier score [Ramaswamy et al 2000]
- Aggregate the distances of a point to all its 1NN, 2NN, …, kNN as an outlier score [Angiulli and Pizzuti 2002]

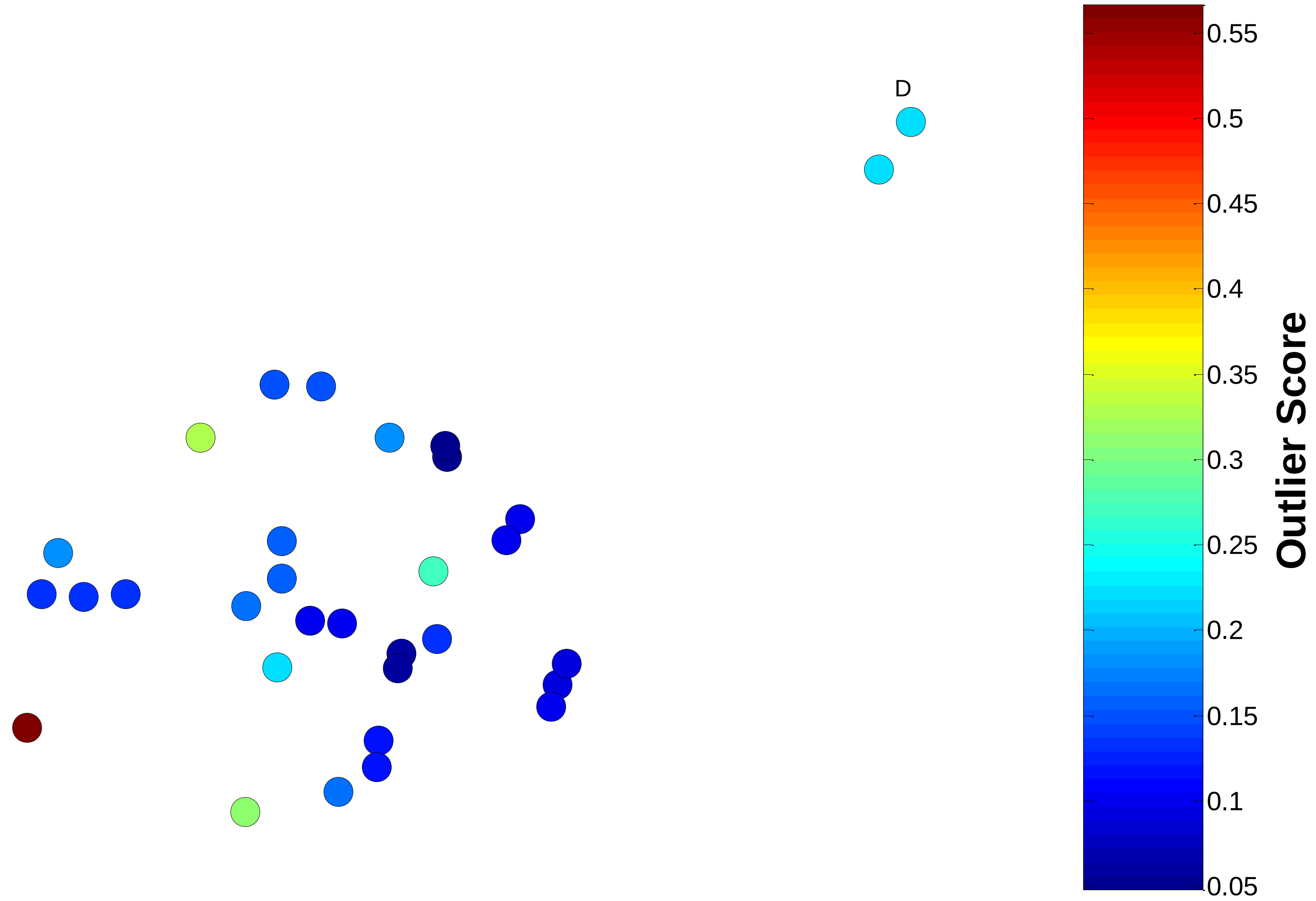
Algorithms - General approaches

- Nested-Loop
  - Naïve approach: For each object: compute kNNs with a sequential scan
  - Enhancement: use index structures for kNN queries
- Partition-based
  - Partition data into micro clusters
  - Aggregate information for each partition (e.g. minimum bounding rectangles)
  - Allows to prune micro clusters that cannot qualify when searching for the kNNs of a particular point

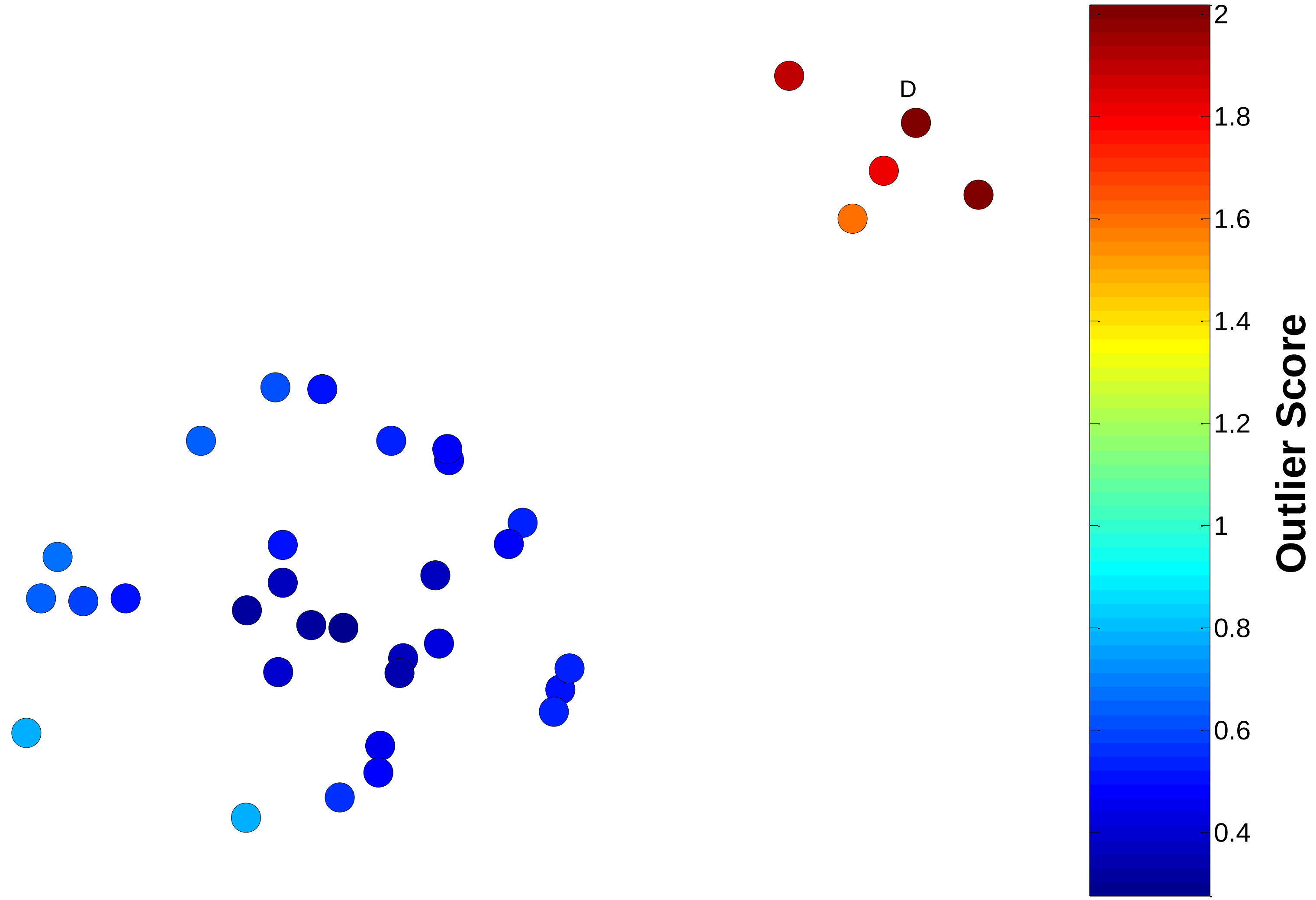
One Nearest Neighbor - One Outlier



One Nearest Neighbor - Two Outliers



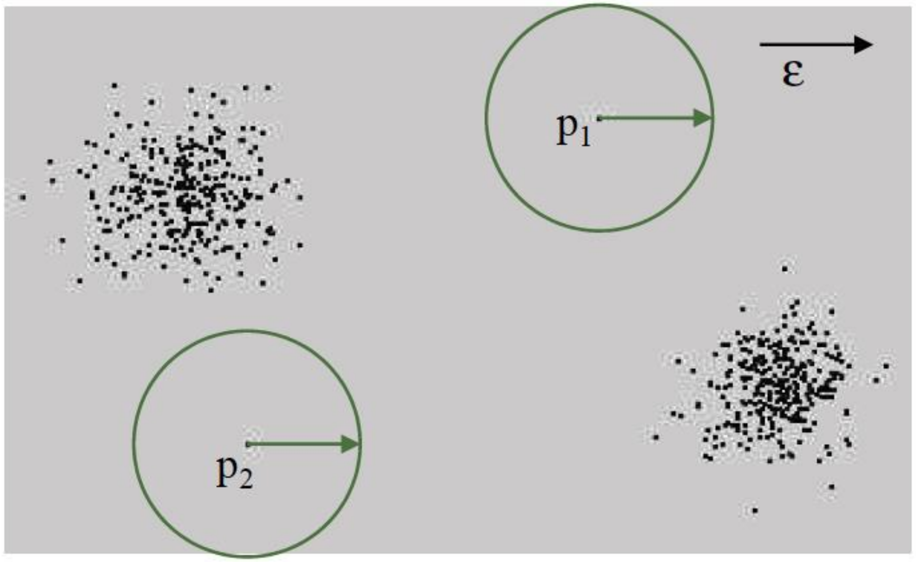
Six Nearest Neighbors - Small Cluster



Distance-based Approaches

DB(ε,π)-Outliers

- Basic model [Knorr and Ng 1997]
- Given a radius ε and a percentage π
- A point p is considered an outlier if at most π percent of all other points have a distance to p less than ε, *i.e., it is close to few points*



$$OutlierSet(\varepsilon,\pi) = \{p \mid \frac{Card(\boxed{\{q \in DB \mid dist(p,q) < \varepsilon\}})}{Card(DB)} \leq \pi\}$$

range-query with radius ε

Outlier Detection using In-degree Number

- Idea: Construct the kNN graph for a data set
  - Vertices: data points
  - Edge: if $q \in kNN(p)$ then there is a directed edge from *p* to *q*
  - A vertex that has an indegree less than equal to *T* (user threshold) is an outlier
- Discussion
  - The indegree of a vertex in the kNN graph equals to the number of reverse kNNs (RkNN) of the corresponding point
  - The RkNNs of a point *p* are those data objects having *p* among their kNNs
  - Intuition of the model: outliers are
    - points that are among the kNNs of less than *T* other points
    - have less than *T* RkNNs
  - Outputs an outlier label
  - Is a local approach (depending on user defined parameter *k*)

Strengths/Weaknesses of Distance-Based Approaches

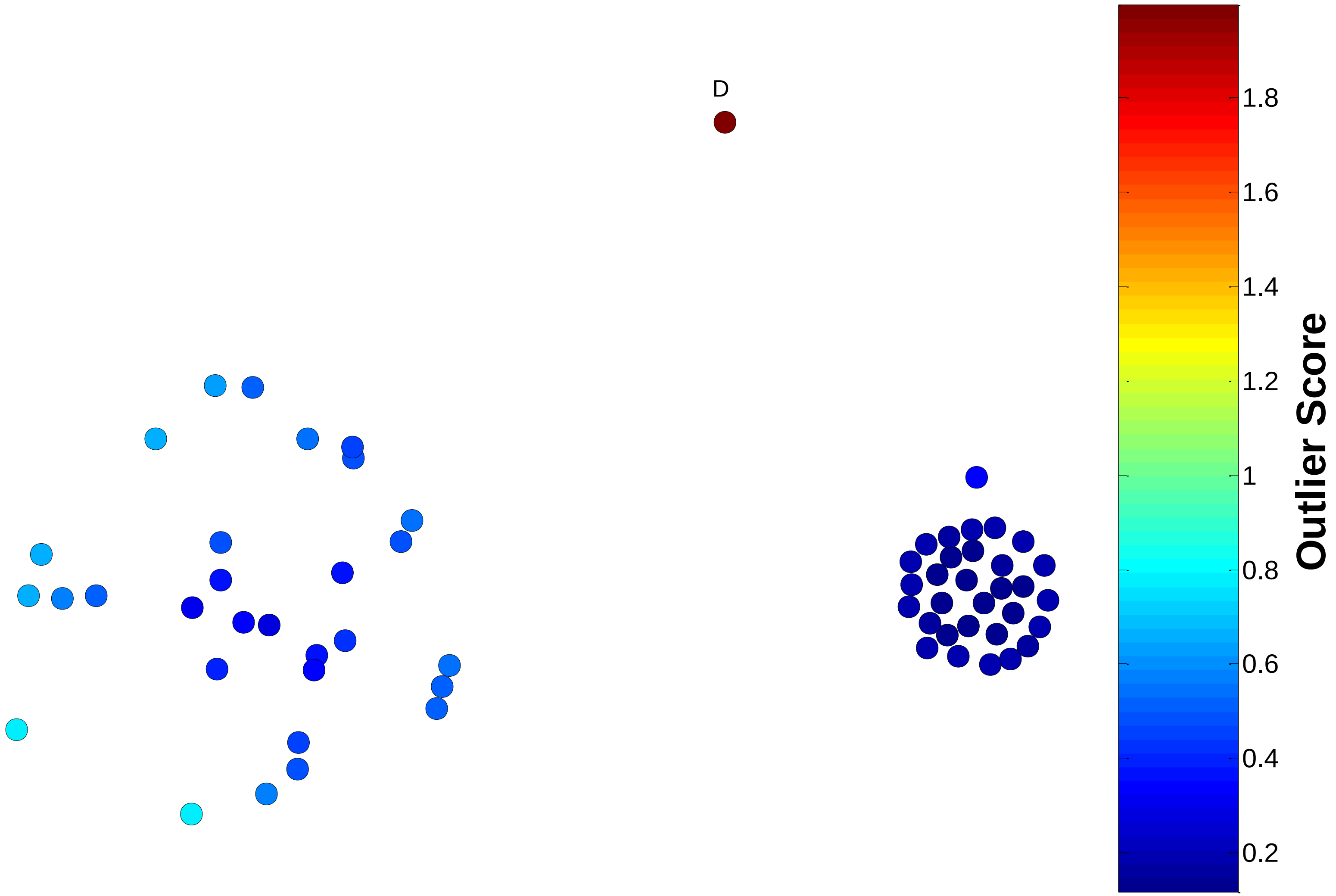
Pros

- Simple

Cons

- Expensive – $O(n^2)$
- Sensitive to parameters
- Sensitive to variations in density
- Distance becomes less meaningful in high-dimensional space

Five Nearest Neighbors - Differing Density



Density-based Approaches

Density-based Approaches

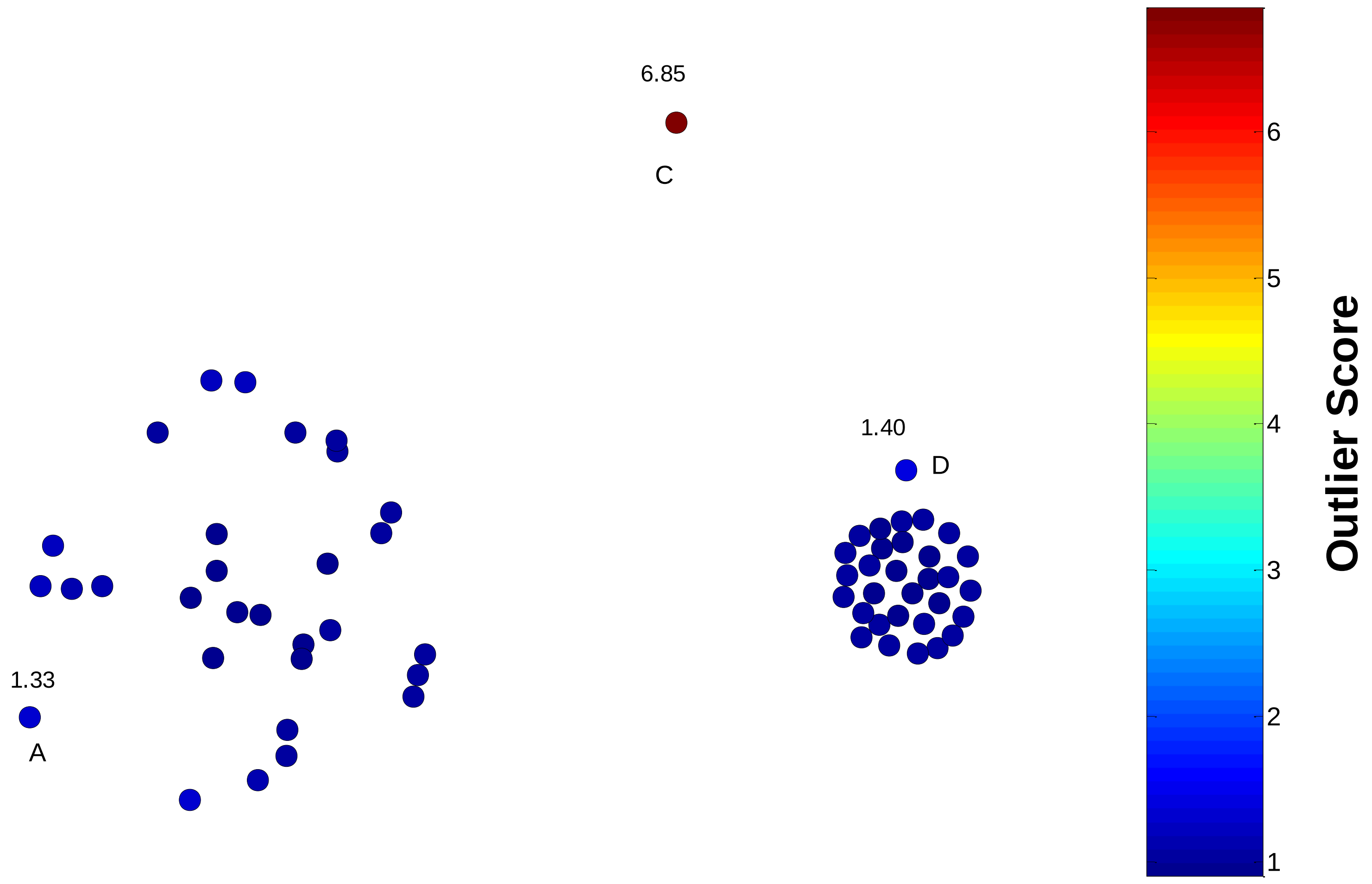
- General idea
  - Compare the density around a point with the density around its local neighbors
  - The relative density of a point compared to its neighbors is computed as an outlier score
  - Approaches differ in how to estimate density
- Basic assumption
  - The density around a normal data object is similar to the density around its neighbors
  - The density around an outlier is considerably different to the density around its neighbors

Density-based Approaches

- **Density-based Outlier:** The outlier score of an object is the inverse of the density around the object.
  - Can be defined in terms of the *k* nearest neighbors
  - One definition: Inverse of distance to *k*th neighbor (a.k.a. SimpleLOF)
  - Another definition: Inverse of the average distance to *k* neighbors
  - DBSCAN definition

- If there are regions of different density, this approach can have problems

Relative Density Outlier Scores



Relative Density

- Consider the density of a point relative to that of its k nearest neighbors

$$average\ relative\ density(\mathbf{x}, k) = \frac{density(\mathbf{x}, k)}{\sum_{\mathbf{y} \in N(\mathbf{x},k)} density(\mathbf{y}, k)/|N(\mathbf{x}, k)|}. \quad (10.7)$$

Algorithm 10.2 Relative density outlier score algorithm.

1: {k is the number of nearest neighbors}
2: **for all** objects $\mathbf{x}$ **do**
3: Determine $N(\mathbf{x}, k)$, the k-nearest neighbors of $\mathbf{x}$.
4: Determine $density(\mathbf{x}, k)$, the density of $\mathbf{x}$, using its nearest neighbors, i.e., the objects in $N(\mathbf{x}, k)$.
5: **end for**
6: **for all** objects $\mathbf{x}$ **do**
7: Set the *outlier score*$(\mathbf{x}, k)$ = *average relative density*$(\mathbf{x}, k)$ from Equation 10.7.
8: **end for**

Local Outlier Factor (LOF) [Breunig et al. 1999], [Breunig et al. 2000]

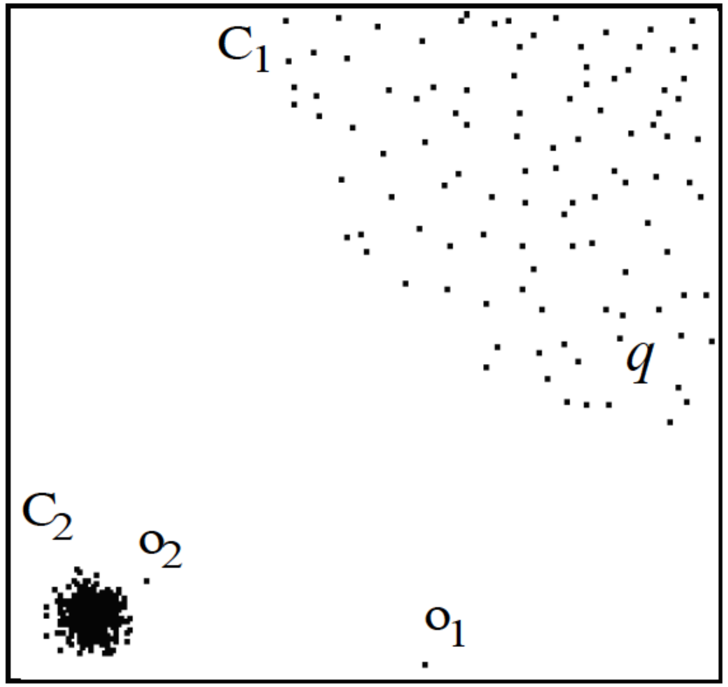
Motivation:

- Distance-based outlier detection models have problems with different densities
- How to compare the neighborhood of points from areas of different densities?

Example

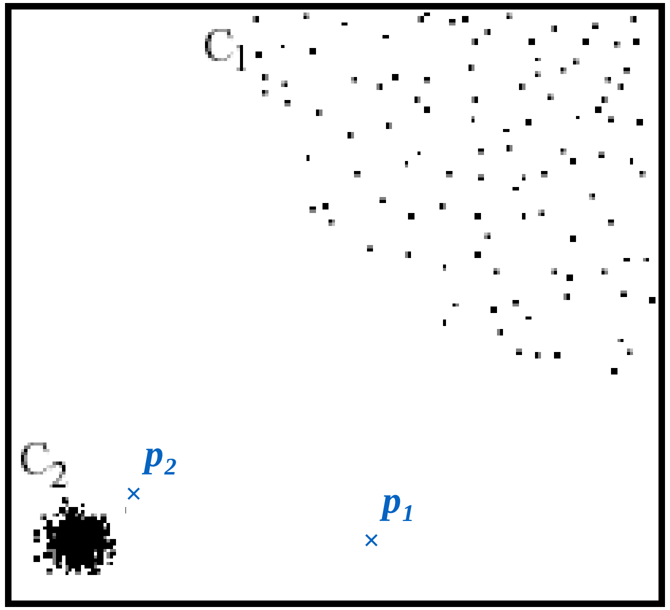
- DB(ε,π)-outlier model
  - Parameters ε and π cannot be chosen so that o_2 is an outlier but none of the points in cluster C_1 (e.g. q) is an outlier
- Outliers based on kNN-distance
  - kNN-distances of objects in C_1 (e.g. q) are larger than the kNN-distance of o_2

Solution: consider relative density



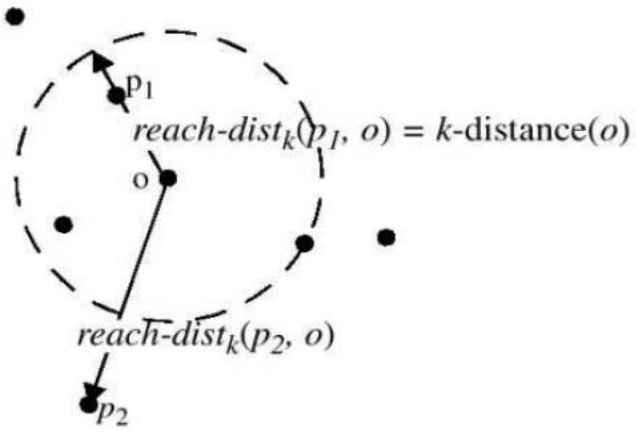
Local Outlier Factor (LOF)

- For each point, compute the density of its local neighborhood
- Compute local outlier factor (LOF) of a sample *p* as the average of the ratios of the density of sample *p* and the density of its nearest neighbors
- Outliers are points with largest LOF value



In the NN approach, p_2 is not considered as outlier, while LOF approach find both p_1 and p_2 as outliers

Local Outlier Factor (LOF)



- Reachability distance
  - Introduces a smoothing factor

$$reach-dist_k(p,o) = \max\{k-\text{distance}(o), dist(p,o)\}$$

- Local reachability distance (*lrd*) of point *p*
  - Inverse of the average reach-dists of the kNNs of *p*

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

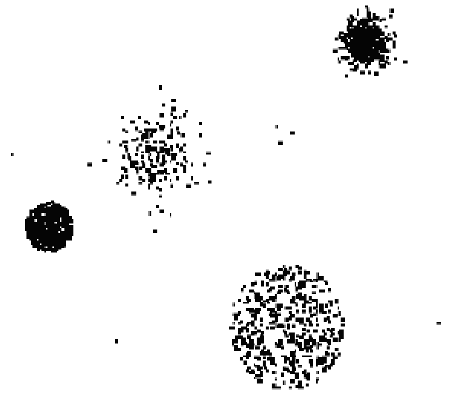
- Local outlier factor (LOF) of point *p*
  - Average ratio of *lrds* of neighbors of *p* and *lrd* of *p*

$$LOF_k(p) = \frac{\sum_{o \in kNN(p)} \frac{lrd_k(o)}{lrd_k(p)}}{Card(kNN(p))}$$

Local Outlier Factor (LOF)

Properties

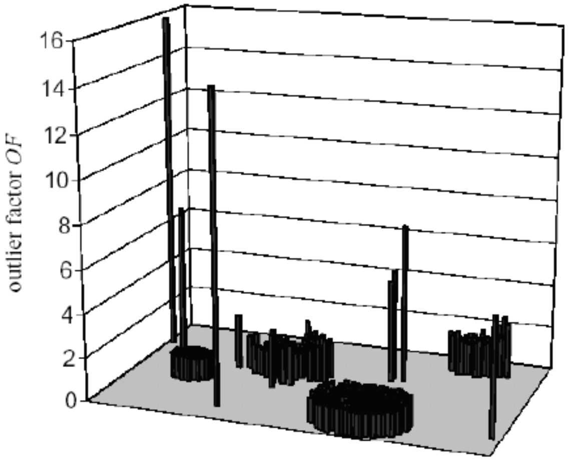
- LOF ≈ 1: point is in a cluster (region with homogeneous density around the point and its neighbors)
- LOF >> 1: point is an outlier



Data set

Discussion

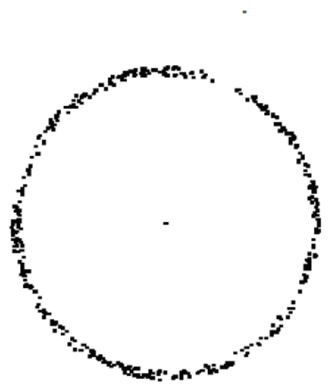
- Choice of *k* (MinPts in the original paper) specifies the reference set
- Originally implements a *local* approach (resolution depends on the user's choice for *k*)
- Outputs a scoring (assigns an LOF value to each point)



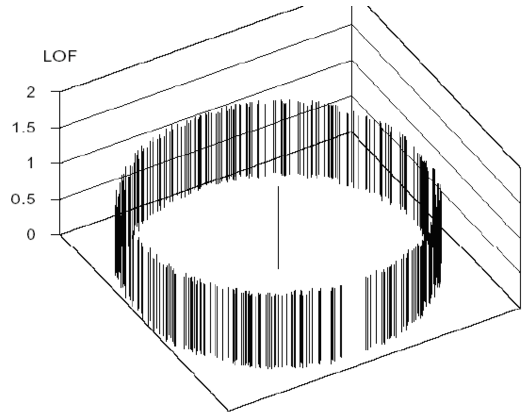
LOFs (*MinPts* = 40)

Connectivity-based outlier factor (COF) [Tang et al. 2002]

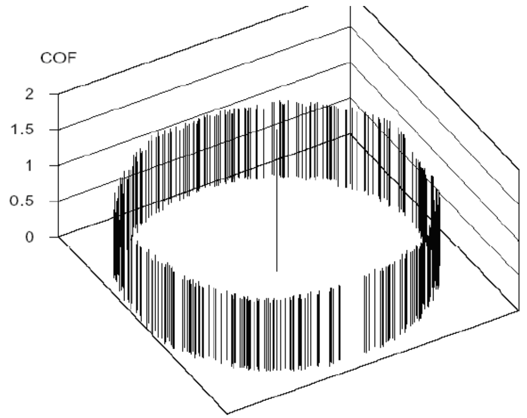
- Motivation
  - In regions of low density, it may be hard to detect outliers
  - Choose a low value for *k* is often not appropriate
- Solution
  - Treat “low density” and “isolation” differently
- Example



Data set



LOF



COF

COF

- Introduced because although a high-density set can represent a pattern, not all patterns need to be high-density.
- COF differs from LOF as it uses the chaining distance to calculate the kNN.
- The average chaining distance in contrast to the local reachability distance of does not use the distance between the point to the points in its neighborhood.
- Idea: the chaining distance for a point can be seen as the minimum of the total sum of the distances linking all neighbors. Practically is calculated using a graph-like structure, i.e., a minimum spanning tree.
- COF is then calculated as the ratio between the average chaining distance of the record and the mean average chaining distance of the records in the kNN.

$$COF_k(p) = \frac{|N_k(p)| ac - dist_{N_{k(p)}}(p)}{\sum_{o \in N_k(p)} ac - dist_{N_{k(o)}}(o)}$$

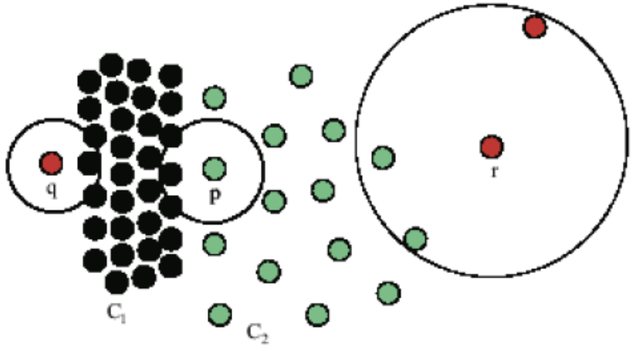
$$ac - dist_{N_{k(p_1)}}(p_1) = \sum_{i=1}^{r} \frac{2(r-1+1)}{r(r+1)} CDS_i \qquad r = |N_k(p_1)|$$

CDS_i cost description sequenc of removing the i-th neighbor

Influenced Outlierness (INFLO) [Jin et al. 2006]

Motivation

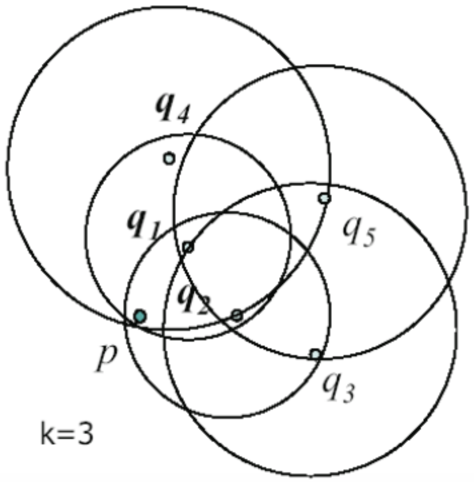
- If clusters of different densities are not clearly separated, LOF will have problems



Point *p* will have a higher LOF than points *q* or *r* which is counter intuitive

Idea

- Take symmetric neighborhood relationship into account
- Influence space *kIS(p)* of a point *p* includes its kNNs *(kNN(p))* and its reverse kNNs *(RkNN(p))*



$kIS(p) = kNN(p) \cup RkNN(p))$

$= \{q_1, q_2, q_4\}$

Influenced Outlierness (INFLO) [Jin et al. 2006]

Model

- Density is simply measured by the inverse of the kNN distance, i.e.,
  - *den(p) = 1/k-distance(p)*
- Influenced outlierness of a point *p*

$$INFLO_k(p) = \frac{\sum_{o \in kIS(p)} den(o) \Big/ Card(kIS(p))}{den(p)}$$

- INFLO takes the ratio of the average density of objects in the neighborhood of a point *p* (i.e., in *kNN(p)* $\cup$ *RkNN(p)*) to *p*'s density

Influenced Outlierness (INFLO) [Jin et al. 2006]

Properties

- Similar to LOF
- INFLO ≈ 1: point is in a cluster
- INFLO >> 1: point is an outlier

Discussion

- Outputs an outlier score
- Originally proposed as a *local* approach (resolution of the reference set *kIS* can be adjusted by the user setting parameter *k*)

Strengths/Weaknesses of Density-Based Approaches

Pros

- Simple

Cons

- Expensive – $O(n^2)$
- Sensitive to parameters
- Density becomes less meaningful in high-dimensional space

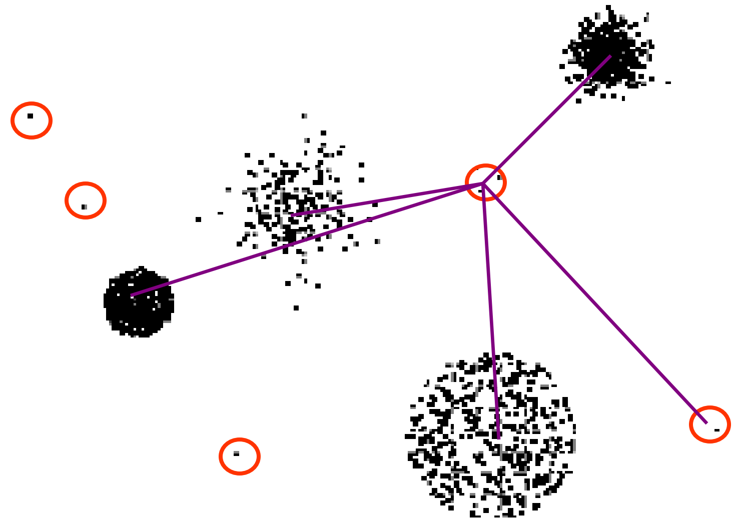
Clustering-based Approaches

Clustering and Anomaly Detection

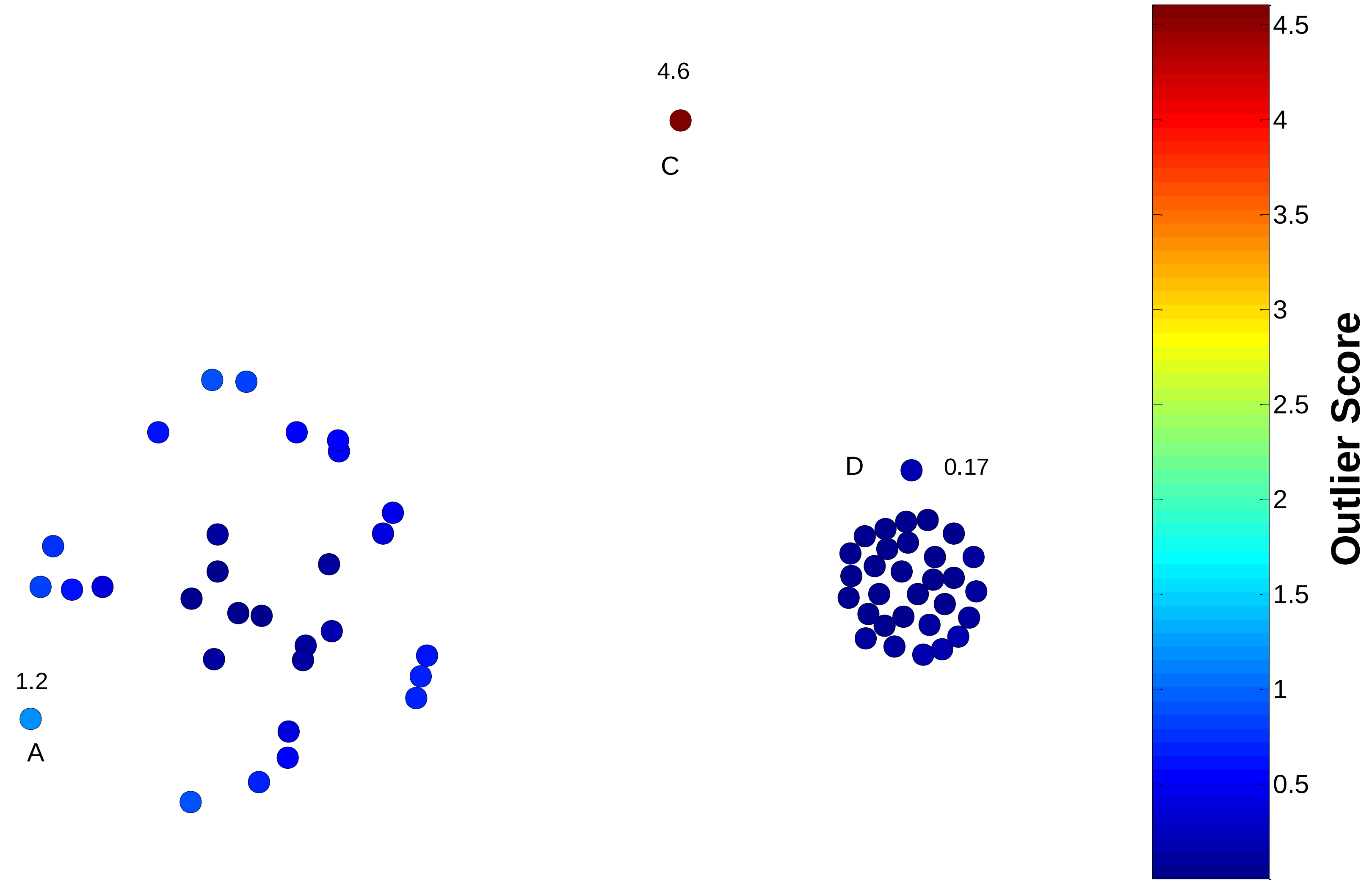
- Are outliers just a side product of some clustering algorithms?
  - Many clustering algorithms do not assign all points to clusters but account for noise objects (e.g. DBSCAN, OPTICS)
  - Look for outliers by applying one algorithm and retrieve the noise set
- Problem:
  - Clustering algorithms are optimized to find clusters rather than outliers
  - Accuracy of outlier detection depends on how good the clustering algorithm captures the structure of clusters
  - A set of many abnormal data objects that are similar to each other would be recognized as a cluster rather than as noise/outliers

Clustering-Based Approaches

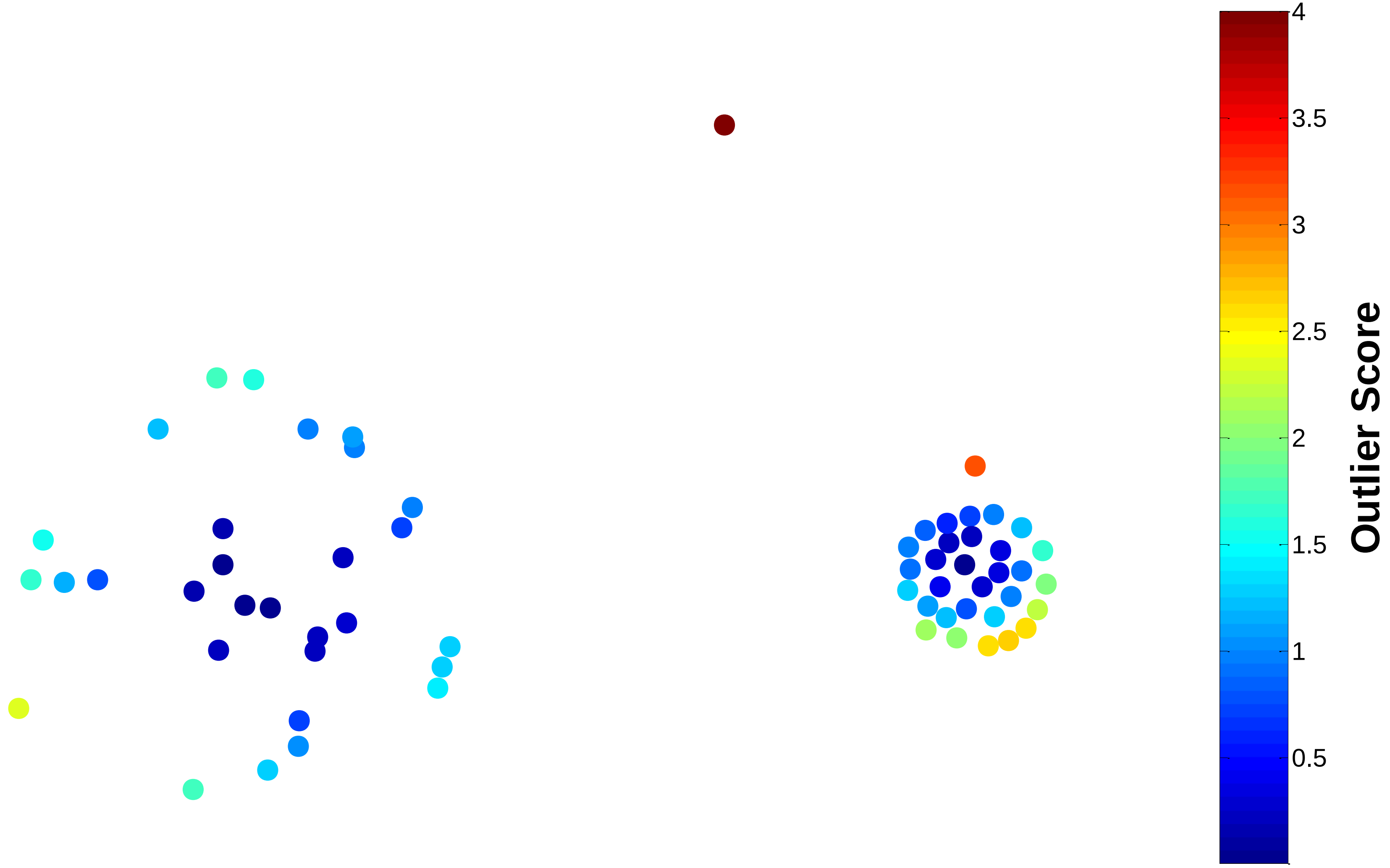
- **Clustering-based Outlier:** An object is a cluster-based outlier if it does not strongly belong to any cluster
  - For prototype-based clusters, an object is an outlier if it is not close enough to a cluster center
  - For density-based clusters, an object is an outlier if its density is too low (noise points)
  - For graph-based clusters, an object is an outlier if it is not well connected (community discovery)
- Other issues include the impact of outliers on the clusters and the number of clusters



Distance of Points from Closest Centroids

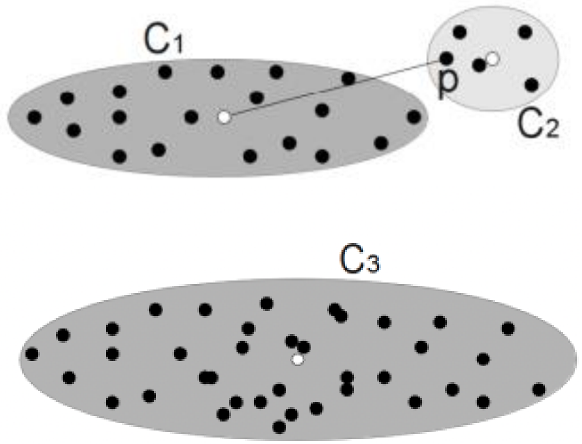


Relative Distance of Points from Closest Centroid



CBLOF - Cluster-Based Local Outlier Factor

- First, perform clustering on the dataset.
- Then, it classifies the clusters into small clusters (SC) and large clusters (LG) using parameters alpha and beta.
- The anomaly score is calculated w.r.t. the size of the cluster the point belongs to as well as the distance to the nearest large cluster.
- If the record lies in a SC, CBLOF is measured as a product of the size of the cluster the record belongs to and the distance to the center of the closest LC.
- If the record belongs to a LC, CBLOF is measured as a product of the size of the cluster that the record belongs to and the distance between the record and the center of the cluster it belongs to.



$$CBLOF(p) = \begin{cases} |C_i| \cdot \min(d(p, C_j)) \text{ if } C_i \in SC \text{ where } p \in C_i \text{ and } C_j \in LC \\ |C_i| \cdot d(p, C_i) \text{ if } C_i \in LC \text{ where } p \in C_i \end{cases}$$

Strengths/Weaknesses of Clustering-Based Approaches

Pros

- Simple
- Many clustering techniques can be used

Cons

- Can be difficult to decide on a clustering technique
- Can be difficult to decide on number of clusters and on clustering parameters
- Outliers can distort the clusters

High-dimensional Approaches

Challenges

Curse of dimensionality

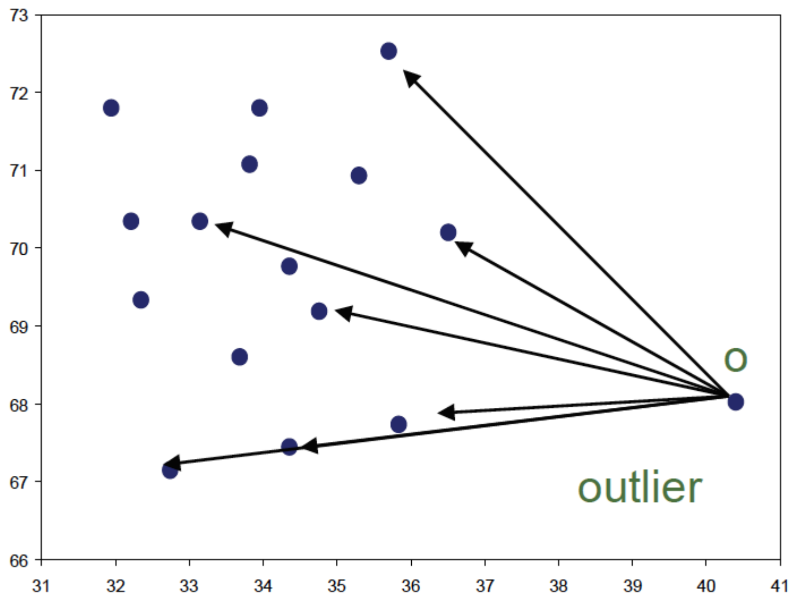
- Relative contrast between distances decreases with increasing dimensionality
- Data is very sparse, almost all points are outliers
- Concept of neighborhood becomes meaningless

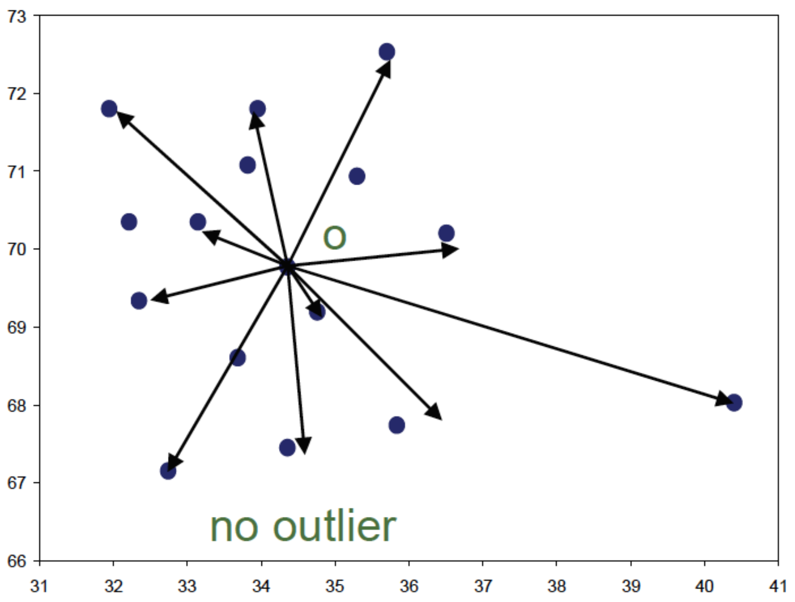
Solutions

- Use more robust distance functions and find full-dimensional outliers
- Find outliers in projections (subspaces) of the original feature space

ABOD – Angle-based Outlier Degree [Kriegel et al. 2008]

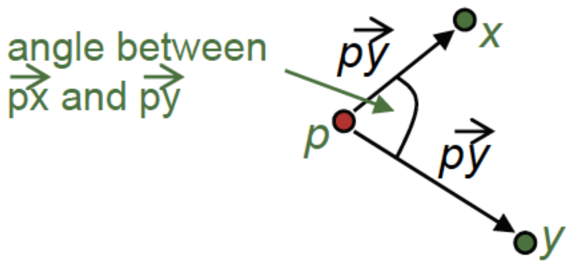
- Angles are more stable than distances in high dimensional spaces (e.g. the popularity of cosine-based similarity measures for text data)
- Object *o* is an outlier if most other objects are located in similar directions
- Object *o* is no outlier if many other objects are located in varying directions



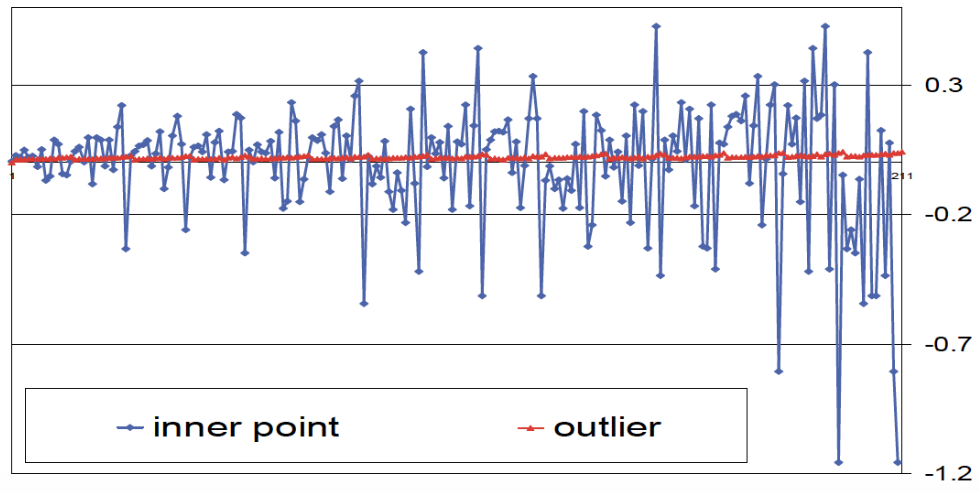


ABOD – Angle-based Outlier Degree [Kriegel et al. 2008]

- Basic assumption
  - Outliers are at the border of the data distribution
  - Normal points are in the center of the data distribution



- Model
  - Consider for a given point *p* the angle between any two instances *x* and *y*
  - Consider the spectrum of all these angles
  - The broadness of this spectrum is a score for the outlierness of a point, i.e., a low variance (small spectrum) highlights an outlier



ABOD – Angle-based Outlier Degree [Kriegel et al. 2008]

- Model
  - Measure the variance of the angle spectrum
  - Weighted by the corresponding distances (for lower dimensional data sets where angles are less reliable)

$$ABOD(p) = \underset{x,y \in DB}{VAR}\left(\frac{\left\langle \vec{xp}, \vec{yp} \right\rangle}{\left\| \vec{xp} \right\|^2 \cdot \left\| \vec{yp} \right\|^2} \right)$$

- Properties
  - Small ABOD => outlier
  - High ABOD => no outlier

$\vec{xp}$ denotes the difference vector x-p
$\langle \vec{xp}, \vec{yp} \rangle$ denotes the scalar product
scalar product $\langle a,b \rangle = \sum a_i b_i$

ABOD – Angle-based Outlier Degree [Kriegel et al. 2008]

Algorithms

- Naïve algorithm is in $O(n^3)$
- Approximate algorithm based on random sampling for mining top-n outliers
    - Do not consider all pairs of other points *x, y* in the database to compute the angles
    - Compute ABOD based on samples => lower bound of the real ABOD
    - Filter out points that have a high lower bound
    - Refine (compute the exact ABOD value) only for a small number of points

Discussion

- Global approach to outlier detection
- Outputs an outlier score

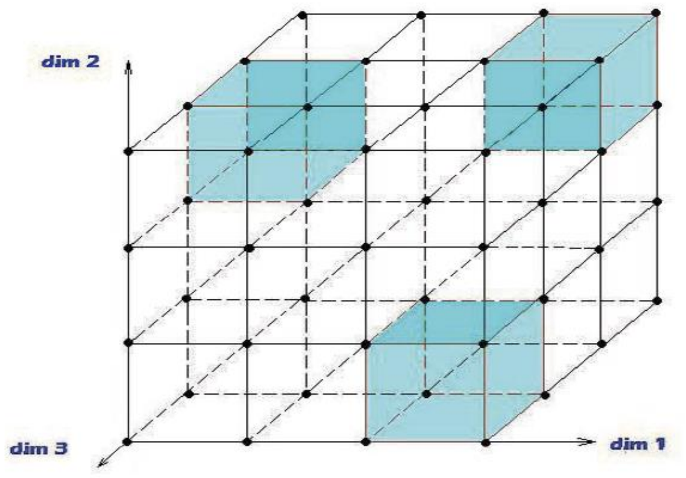
Grid-based Subspace Outlier Detection [Aggarwal and Yu 2000]

Model

- Partition data space by an equi-depth grid (*Φ* = number of cells in each dimension)
- Sparsity coefficient *S(C)* for a *k*-dimensional grid cell *C*

$$S(C) = \frac{count(C) - n \cdot (1/\Phi)^k}{\sqrt{n \cdot (1/\Phi)^k \cdot (1 - (1/\Phi)^k)}}$$

- where count(C) is the number of data objects in C
- *S(C) < 0 => count(C)* is lower than expected
- Outliers are those objects that are located in lower-dimensional cells with negative sparsity coefficient



k = nbr dimensions (e.g. 3)
ϕ = nbr of equi-depth ranges (e.g 3)

Grid-based Subspace Outlier Detection [Aggarwal and Yu 2000]

- Algorithm
  - Find the *m* grid cells (projections) with the lowest sparsity coefficients
  - Brute-force algorithm is *in* $O(\Phi d)$

- Discussion
  - Results need not be the points from the optimal cells
  - Very coarse model (all objects that are in cell with less points than to be expected)
  - Quality depends on grid resolution and grid position
  - Outputs a labeling
  - Implements a global approach (key criterion: globally expected number of points within a cell)

Ensemble-based Approaches

FeaBag - Feature Bagging

- FeaBag exploits a set of OD methods, each of them applied on a random set of features selected from the original feature space.
- Each OD method identifies different outliers and assigns to all instances outlier scores that correspond to their probability of being outliers.
- The combination of such scores is returned as the final output.

LODA - Lightweight On-line Detector of Anomalies

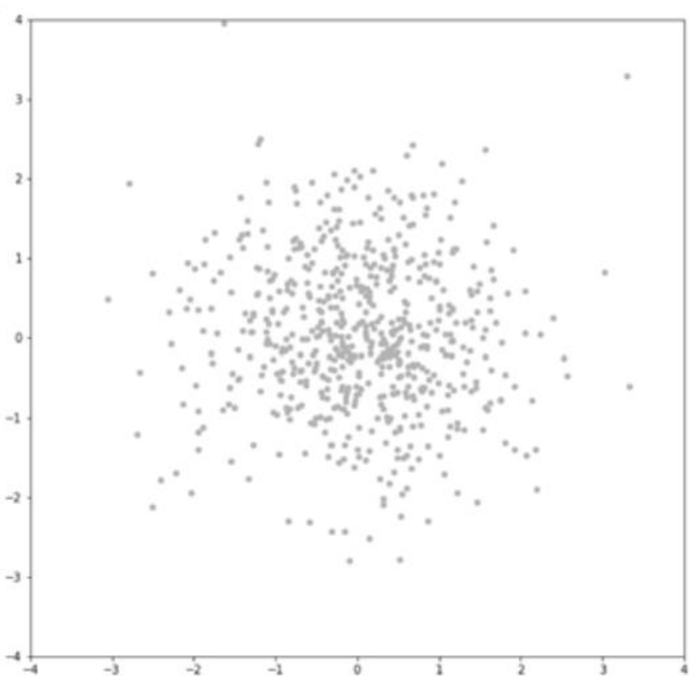
- An extension of HBOS is LODA.
- LODA is an ensemble OD method particularly useful in real-time scenarios domains where many records need to be processed.
- LODA approximates the joint probability using a collection of one-dimensional histograms, where every one-dimensional histogram is efficiently constructed on an input space projected onto a randomly generated vector.
- Even though one-dimensional histograms are weak OD methods, their collection yields a strong OD approach.

Model-based Approaches

Slides revisited from Isolation Forest for Anomaly Detection, Sahand Hariri

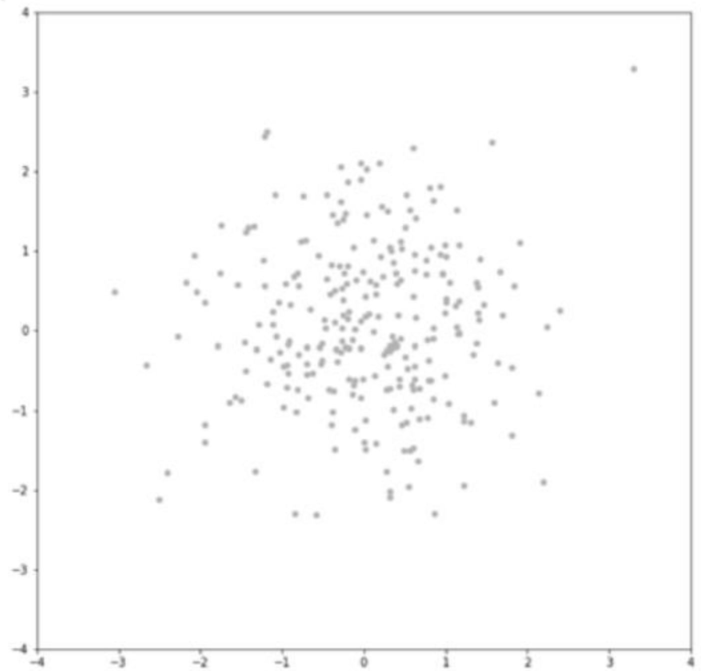
Isolation Forest

- Idea: Few and different instances can be isolated quicker
- Given the dataset build a forest of trees.



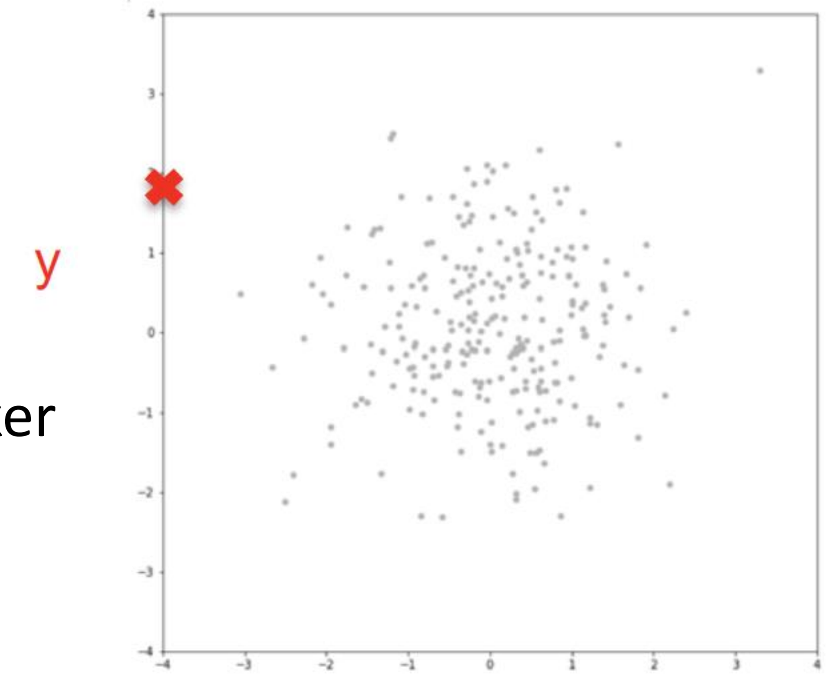
https://scikit-learn.org/stable/auto_examples/miscellaneous/plot_anomaly_comparison.html#sphx-glr-auto-examples-miscellaneous-plot-anomaly-comparison-py
https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.IsolationForest.html#sklearn.ensemble.IsolationForest
https://scikit-learn.org/stable/auto_examples/ensemble/plot_isolation_forest.html

Isolation Forest



- Idea: Few and different instances can be isolated quicker
- Given the dataset build a forest of trees.
- For each tree:
    - Get a sample of the data

Isolation Forest



- Idea: Few and different instances can be isolated quicker
- Given the dataset build a forest of trees.
- For each tree:
  - Get a sample of the data
  - Randomly select a dimension
  - Randomly pick a value in that dimension

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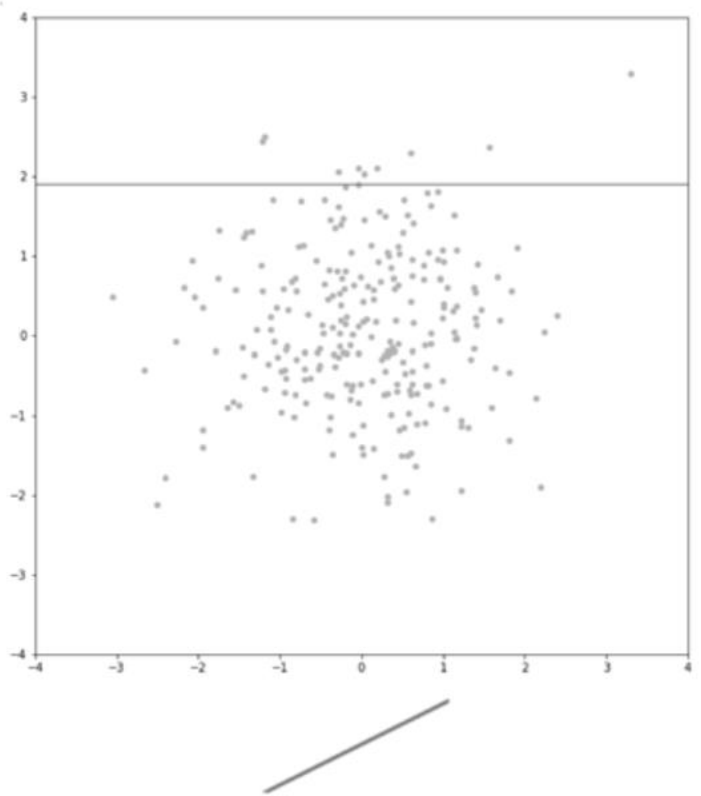

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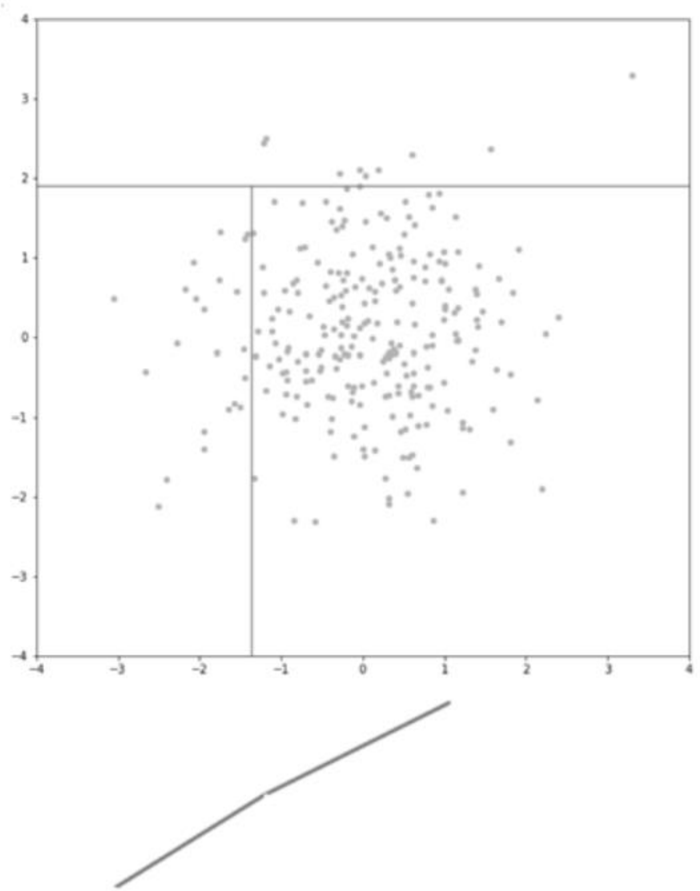

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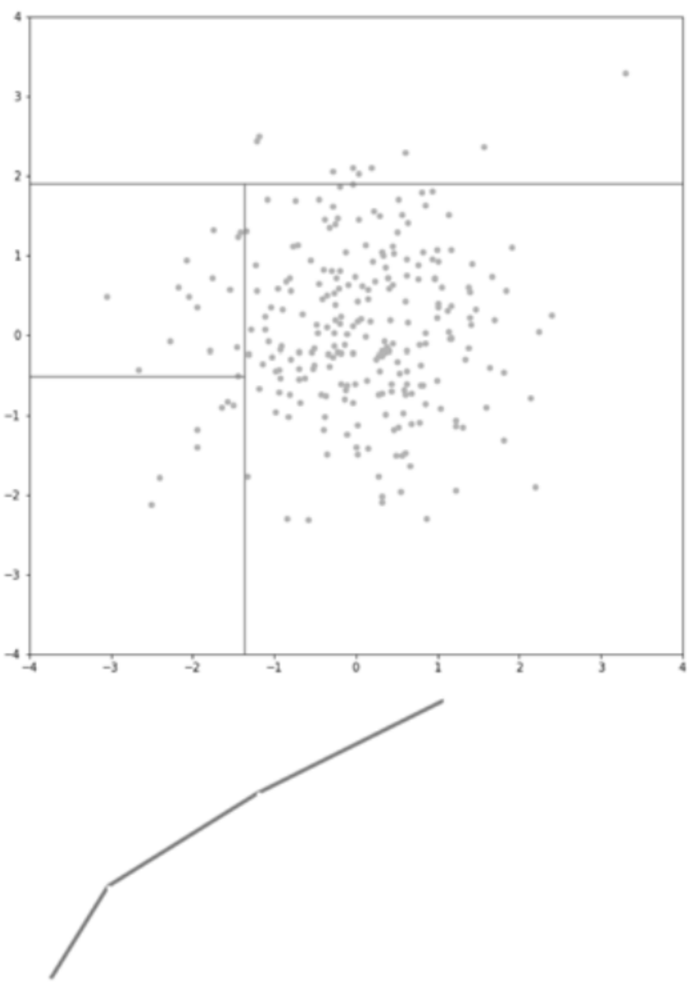
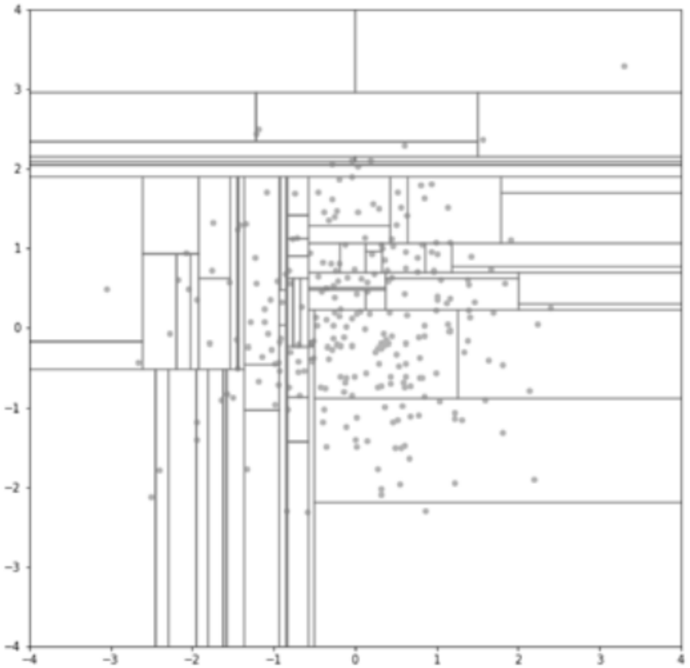


Isolation Forest



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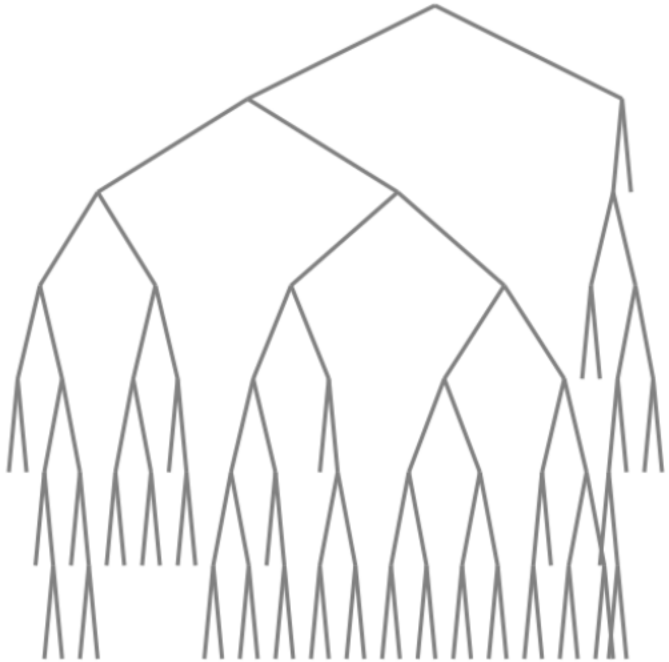

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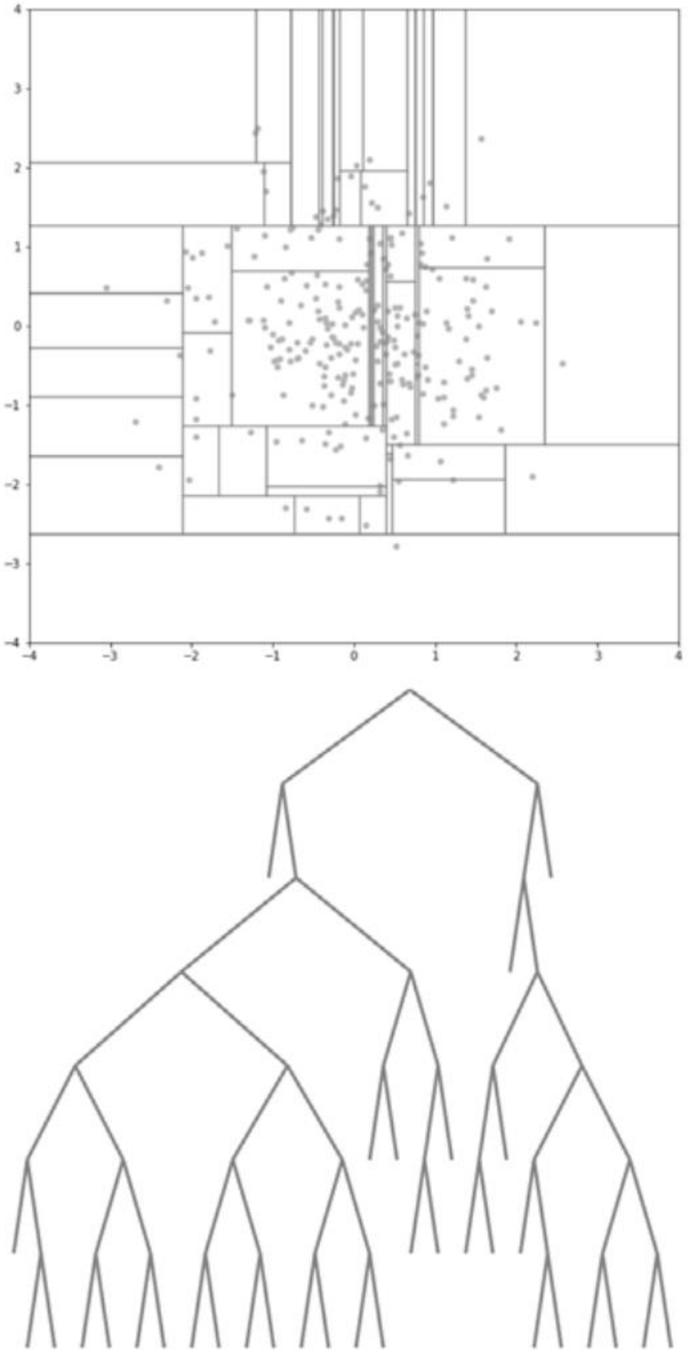
  - Repeat until tree is complete
- Generate multiple trees -> forest



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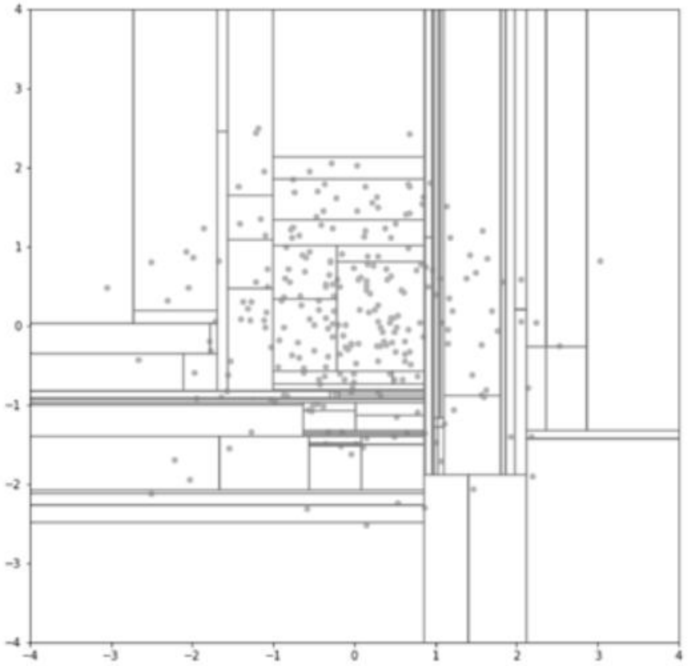

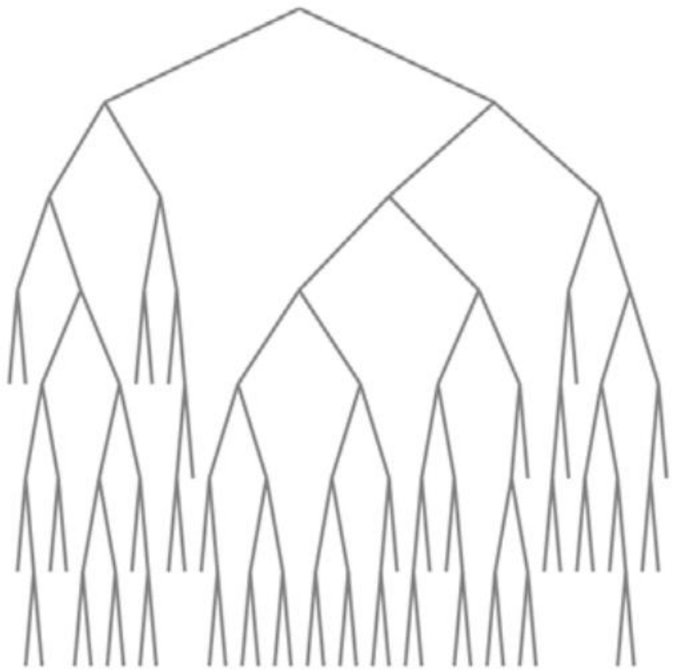

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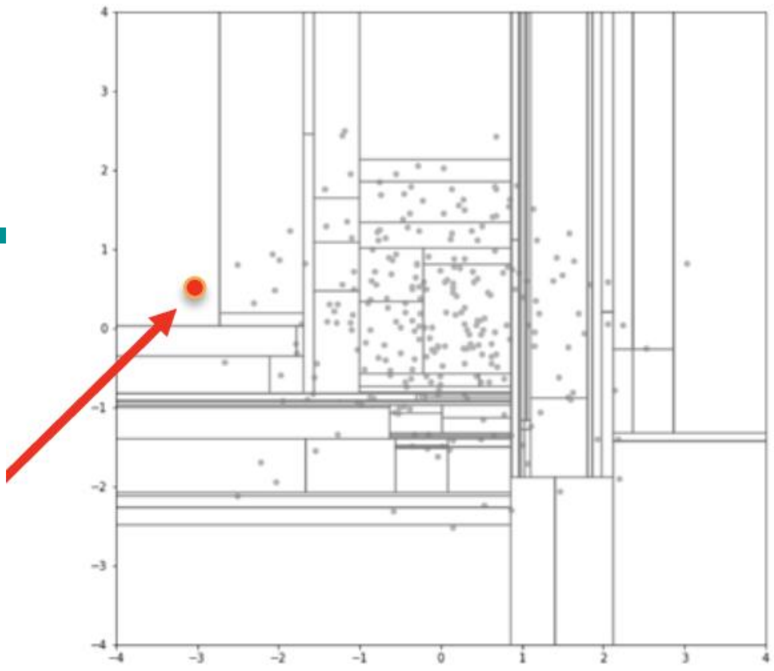
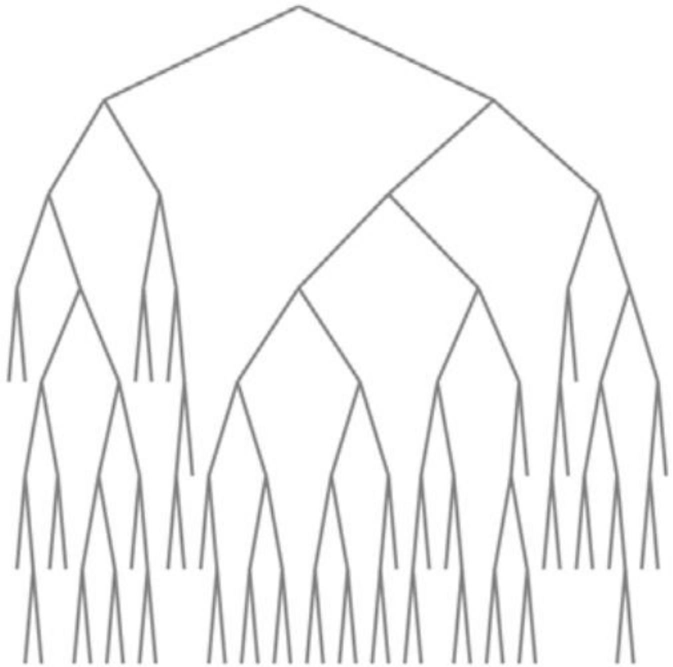
- Generate multiple trees -> forest
- Anomalies will be isolated in only few steps





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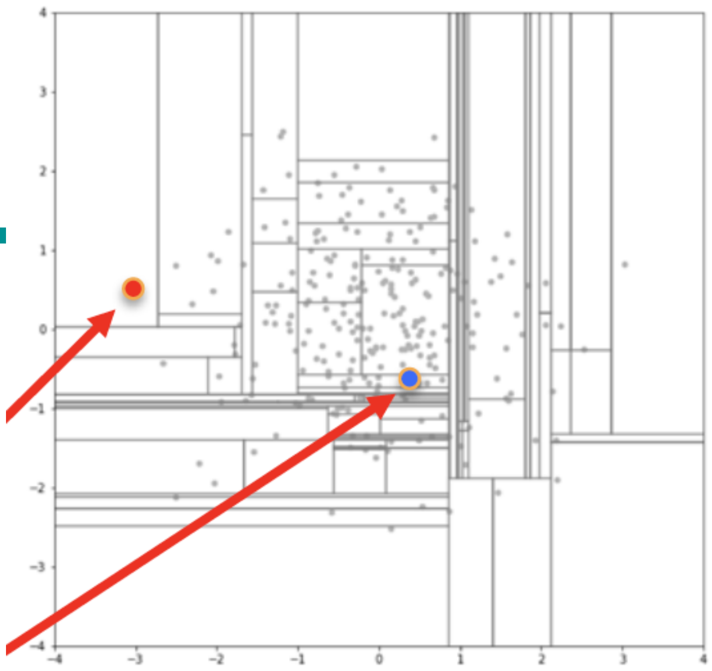
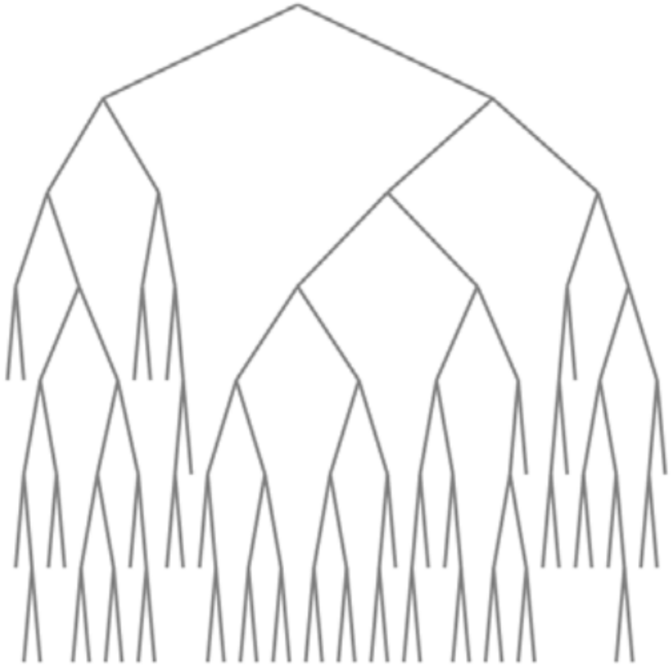
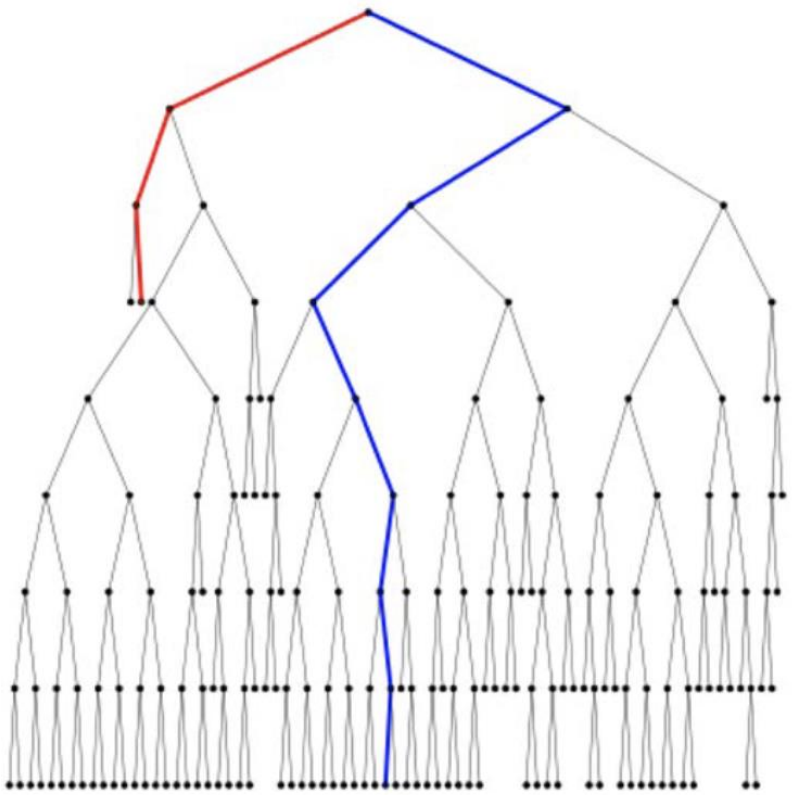
- Generate multiple trees -> forest
- Anomalies will be isolated in only few steps
- Nominal points in more



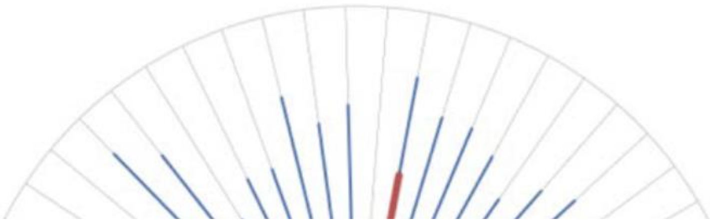


Isolation Forest

Single Tree scores for anomaly and nominal points



Forest plotted radially. Scores for anomaly and nominal shown as lines



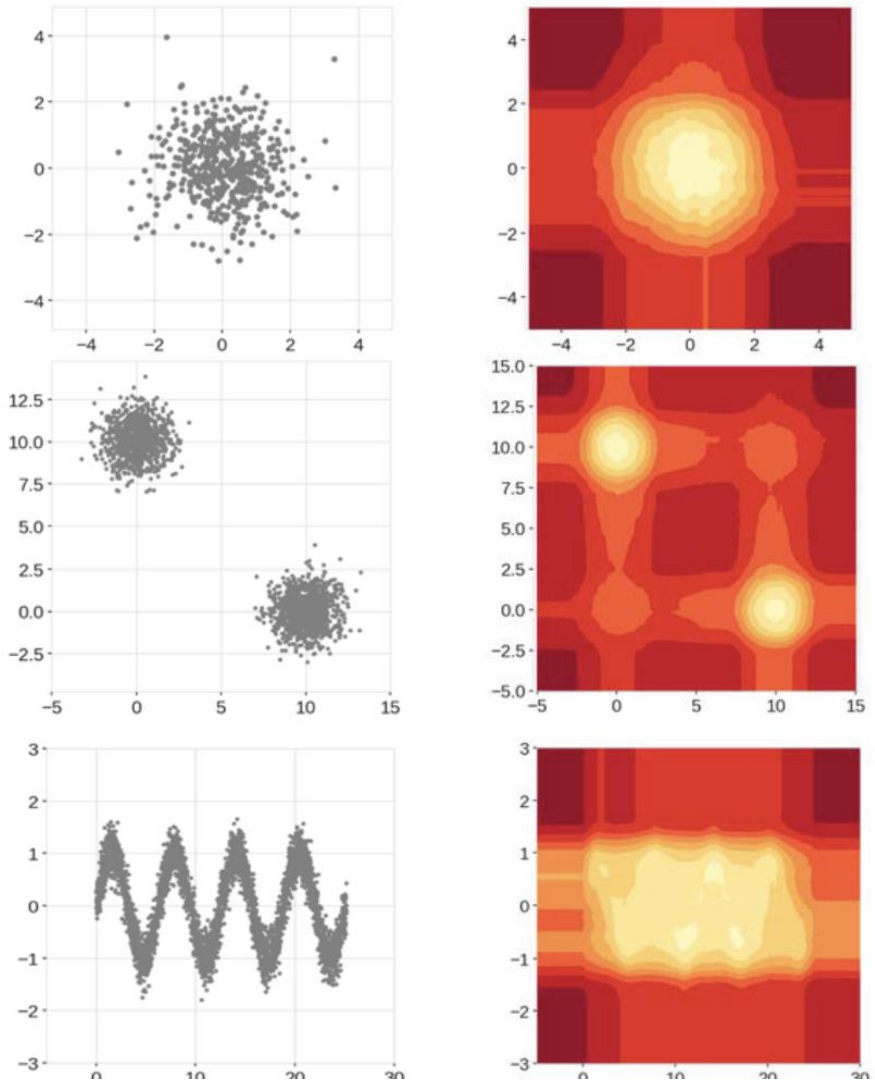
h(x) = path length as number of edges from the root to a leaf
E(h(x)) = average path length (E stands for expectation)
c(m) = average h(x) given m used to normalize h(x)
H = harmonic number estimated as H(i) = ln(i) + ɣ with ɣ = 0.57
m = size of samples

if s is close to 1 then x is very likely to be an anomaly
if s is smaller than 0.5 then x is likely to be a normal value

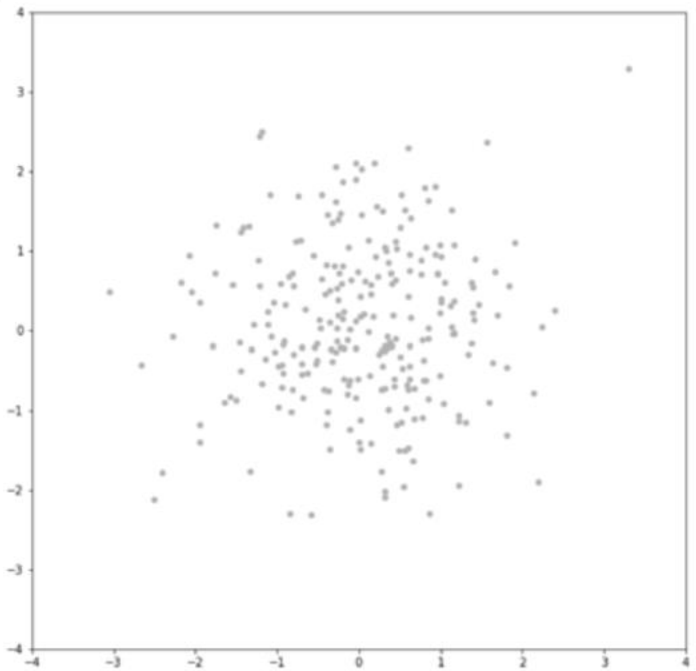
$$s(x,m) = 2^{\frac{-E(h(x))}{c(m)}} \qquad c(m) = \begin{cases} 2H(m-1) - \frac{2(m-1)}{n} & \text{for } m > 2 \\ 1 & \text{for } m = 2 \\ 0 & \text{otherwise} \end{cases}$$

Anomaly Detection with Isolation Forest

- Isolation Forest
  - Computationally Efficient
  - Parallelizable
  - Handle high dimensional data
  - Inconsistent scoring can be observed

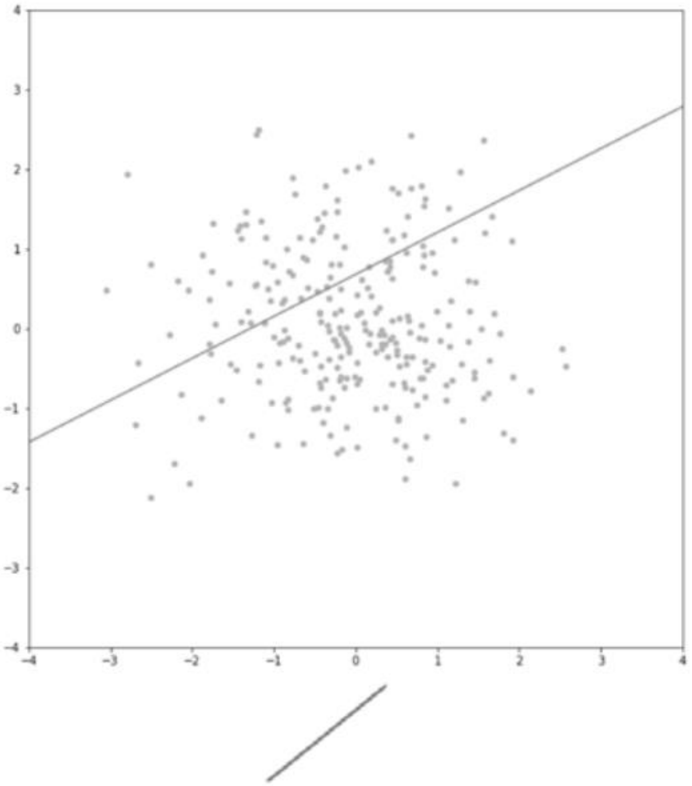


Extended Isolation Forest



- Idea: Few and different instances can be isolated quicker
- Given the dataset build a forest of trees.
- For each tree:
  - Get a sample of the data
  - Randomly select a normal vector
  - Randomly select an intercept

Extended Isolation Forest



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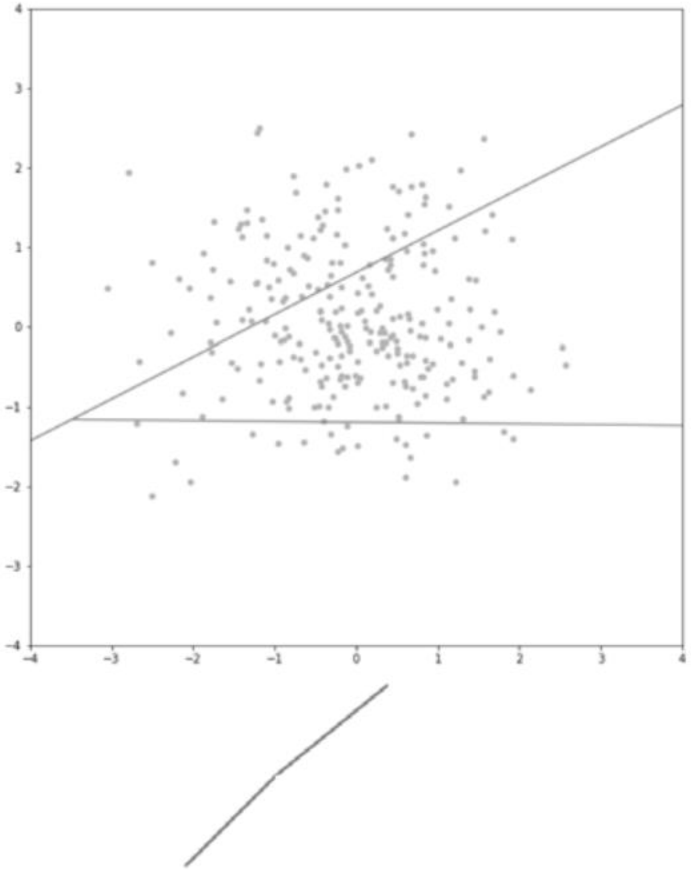

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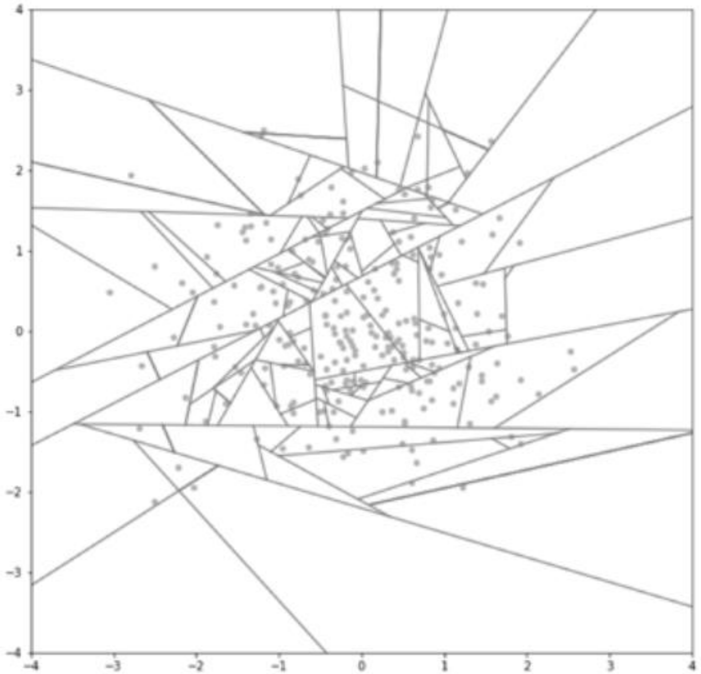
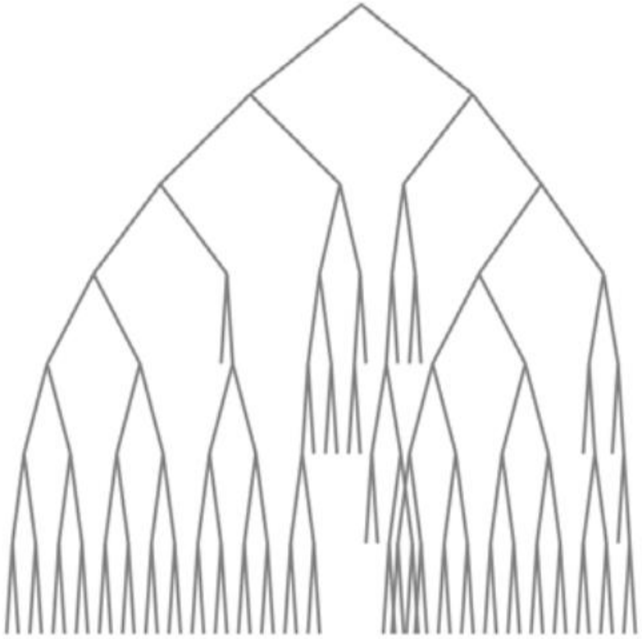
- Given the dataset build a forest of trees.
- For each tree:
    - Get a sample of the data
    - Randomly select a normal vector
    - Randomly select an intercept
    - Draw a straight line through the data at that value and split data
    - Repeat until the tree is complete

Extended Isolation Forest

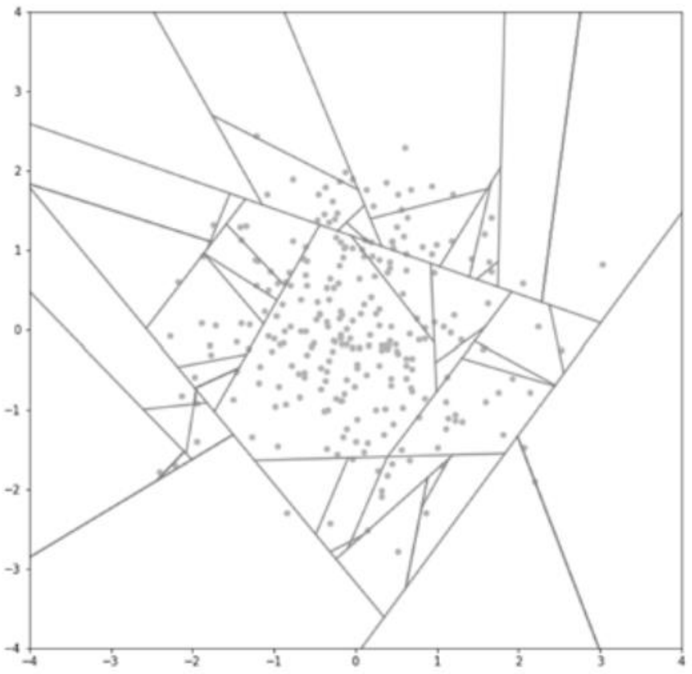
- Idea: Few and different instances can be isolated quicker
- Given the dataset build a forest of trees.
- For each tree:
    - Get a sample of the data
    - Randomly select a normal vector
    - Randomly select an intercept
    - Draw a straight line through the data at that value and split data
    - Repeat until the tree is complete





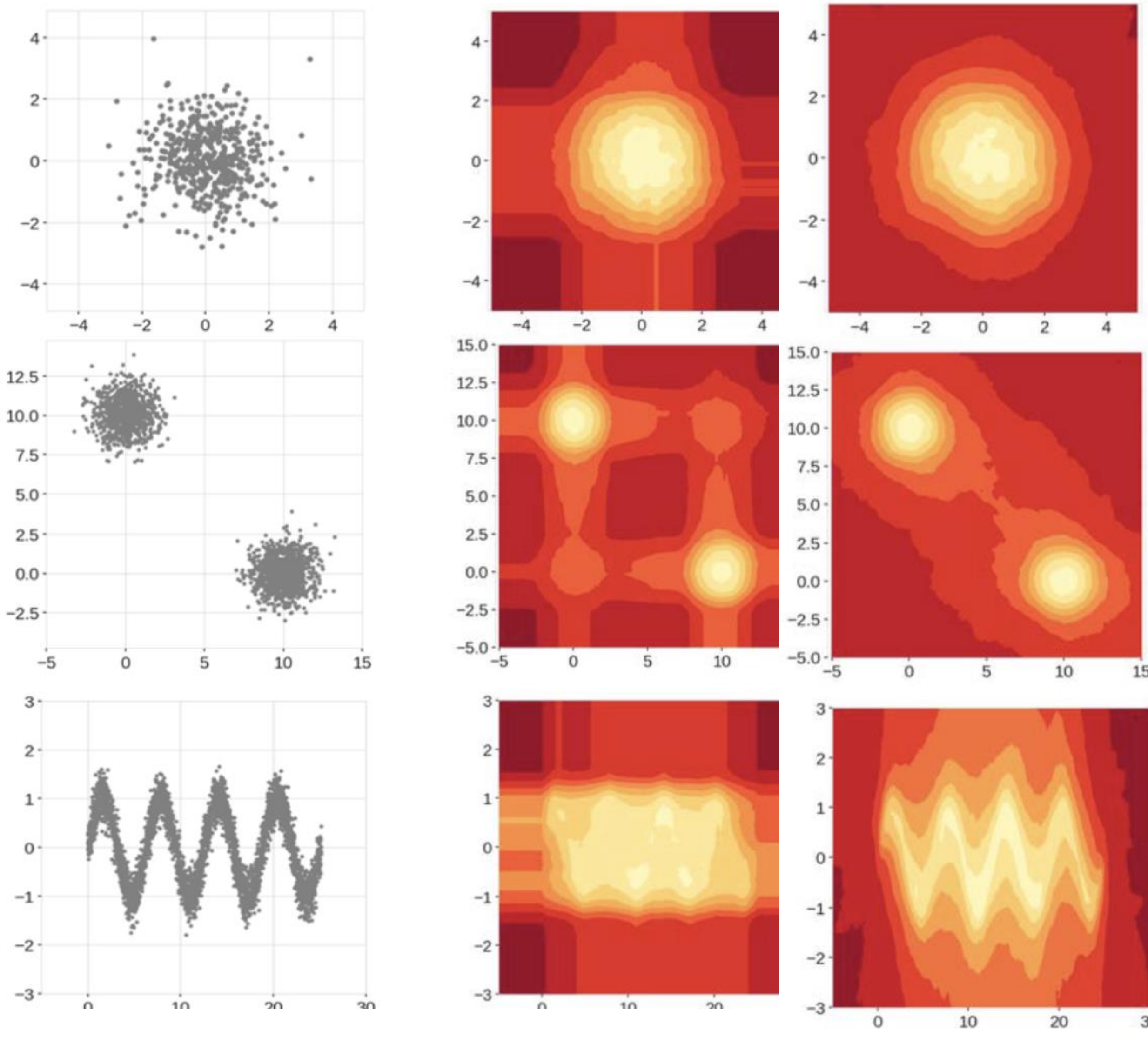
Extended Isolation Forest

- Idea: Few and different instances can be isolated quicker
- Given the dataset build a forest of trees.
- For each tree:
  - Get a sample of the data
  - Randomly select a normal vector
  - Randomly select an intercept
  - Draw a straight line through the data at that value and split data
  - Repeat until the tree is complete
- Generate multiple trees –> forest



Anomaly Detection with Isolation Forest

- Isolation Forest
  - Computationally Efficient
  - Parallelizable
  - Handle high dimensional data
  - Inconsistent scoring can be observed
- Extended Isolation Forest
  - Computationally Efficient
  - Parallelizable
  - Handle high dimensional data
  - Consistent scoring

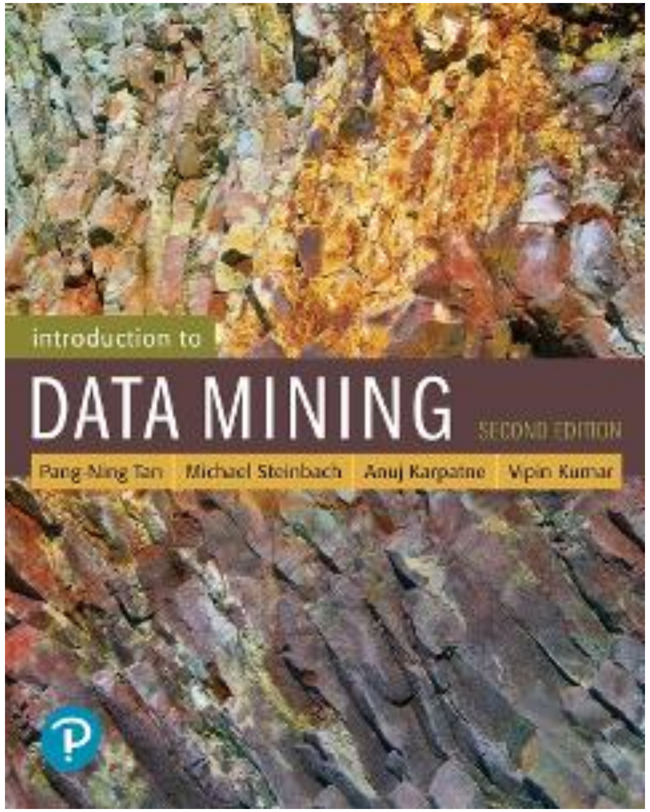


Summary

- Different models are based on different assumptions
- Different models provide different types of output (labeling/scoring)
- Different models consider outlier at different resolutions (global/local)
- Thus, different models will produce different results
- A thorough and comprehensive comparison between different models and approaches is still missing

References

- Anomaly Detection. Chapter 10. Introduction to Data Mining.
- Liu, Fei Tony; Ting, Kai Ming; Zhou, Zhi-Hua (December 2008). "Isolation Forest". 2008 Eighth IEEE International Conference on Data Mining: 413–422
- Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. ACM computing surveys (CSUR), 41(3), 1-58.



Exercises – Outlier Detection

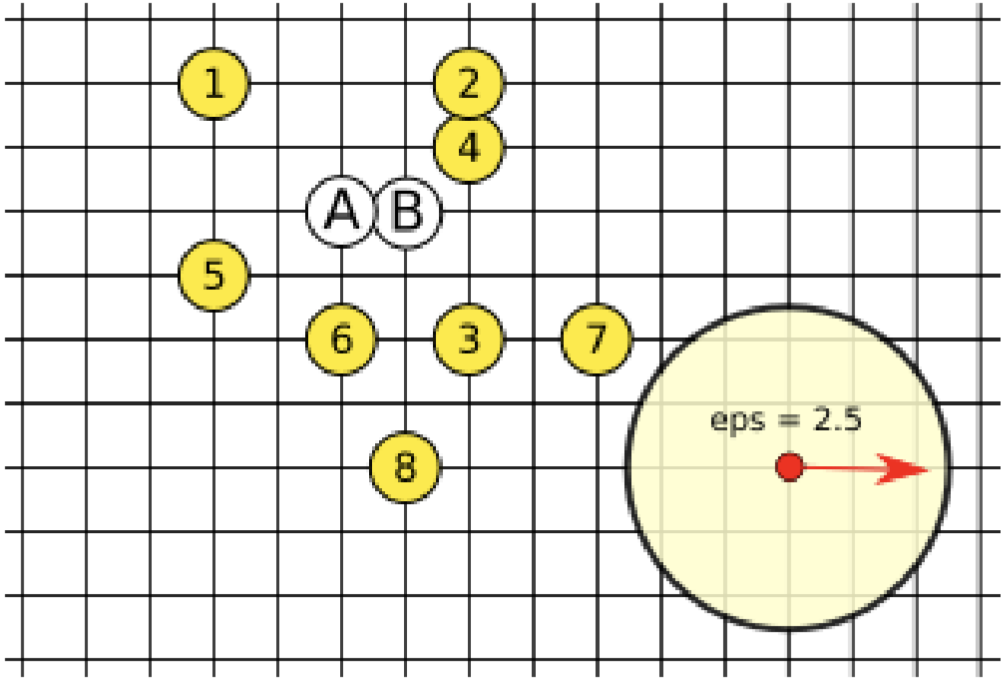
Outlier Detection – Exercise 1

Given the dataset of 10 points below, consider the outlier detection problem for points A and B, adopting the following three methods:

a) Distance-based: DB(ε,π) **(2 points)**
Are A and/or B outliers, if thresholds are forced to ε = 2.5 and π = 0.15 ? The point itself should not be counted.

b) Density-based: LOF **(2 points)**
Compute the LOF score for points A and B by taking k=2, i.e. comparing each point with its 2 NNs (not counting the point itself). In order to simplify the calculations, the reachability-distance used by LOF can be replaced by the simple Euclidean distance.

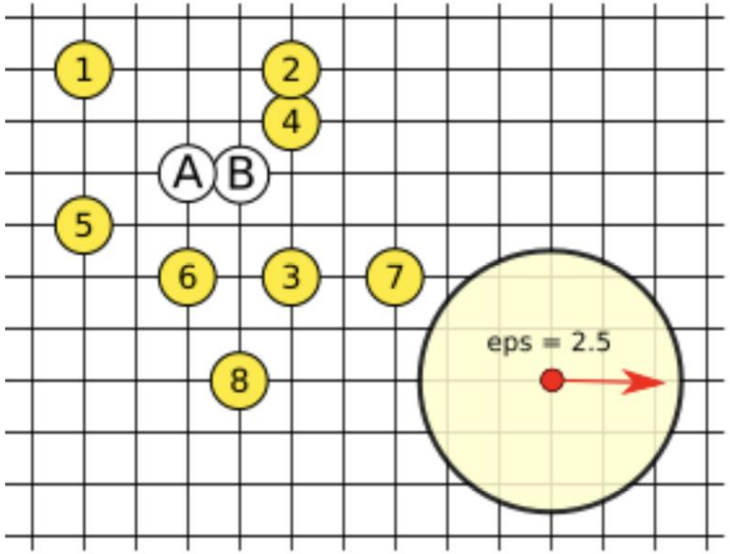
c) Depth-based **(2 points)**
Compute the depth score of all points.



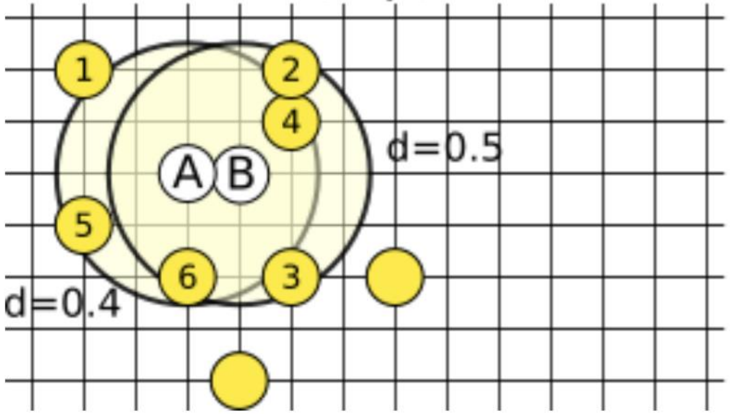
Outlier Detection – Exercise 1 – Solution

Distance-based

- No outliers because within their radius there are 0.4 and 0.5 points for A and B, respectively



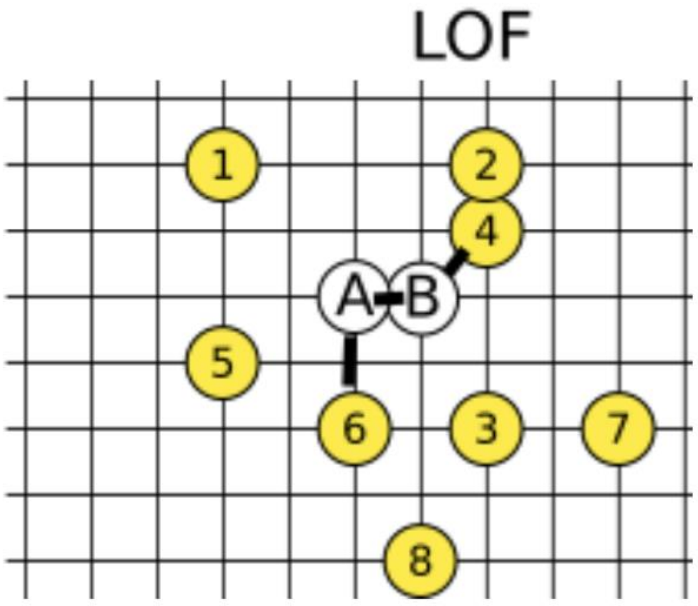
DB(e,p)



Outlier Detection – Exercise 1 – Solution

Density-based

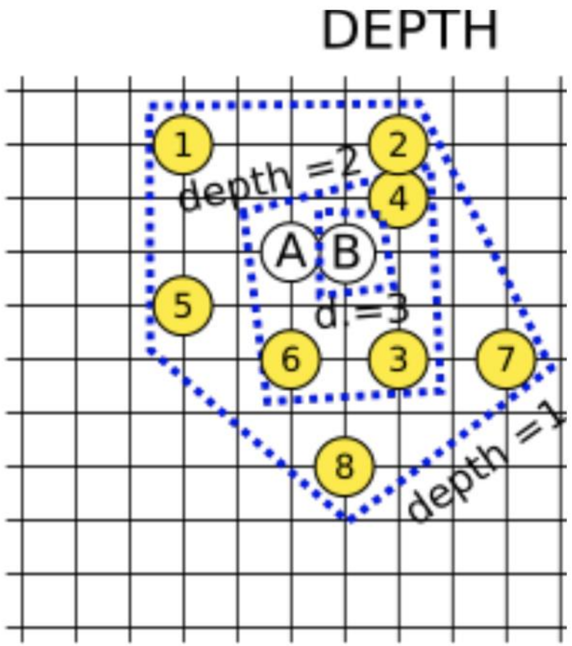
- LRD(A) = 1/ [(1 + 2)/2] = 0.666
- LRD(B) = 1/ [(1 + √2)/2] = 0.828
- LRD(6) = 1/ [(2 + 2)/2] = 0.500
- LOF(A) = ([LRD(B) + LRD(6)]/2) / LRD(A) = [(0.828 + 0.500) / 2] / 0.666 = 1.003
- LRD(4) = 1/ [(1 + √2)/2] = 0.828
- LOF(B) = ([LRD(A) + LRD(4)]/2) / LRD(B) = [(0.666 + 0.828) / 2] / 0.828 = 0.902
- Both are smaller or very close to 1, so they are most likely no outliers.



Outlier Detection – Exercise 1 – Solution

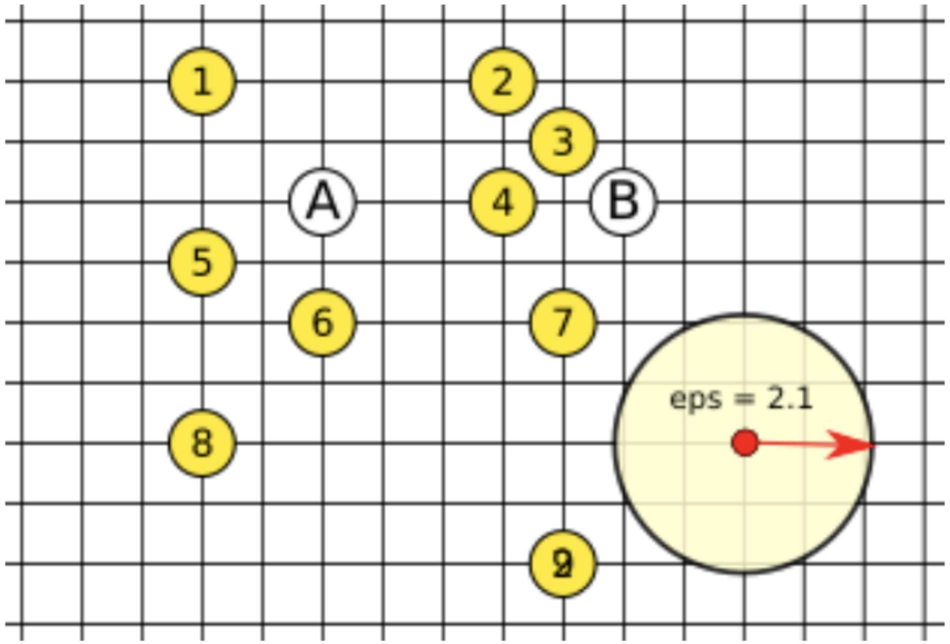
Depth-based

- A is an outlier for depth = 2
- For depth <= 1 neither A or B are outliers



Outlier Detection – Exercise 2

Given the dataset of 10 points below, consider the outlier detection problem for points A and B, adopting the following three methods:

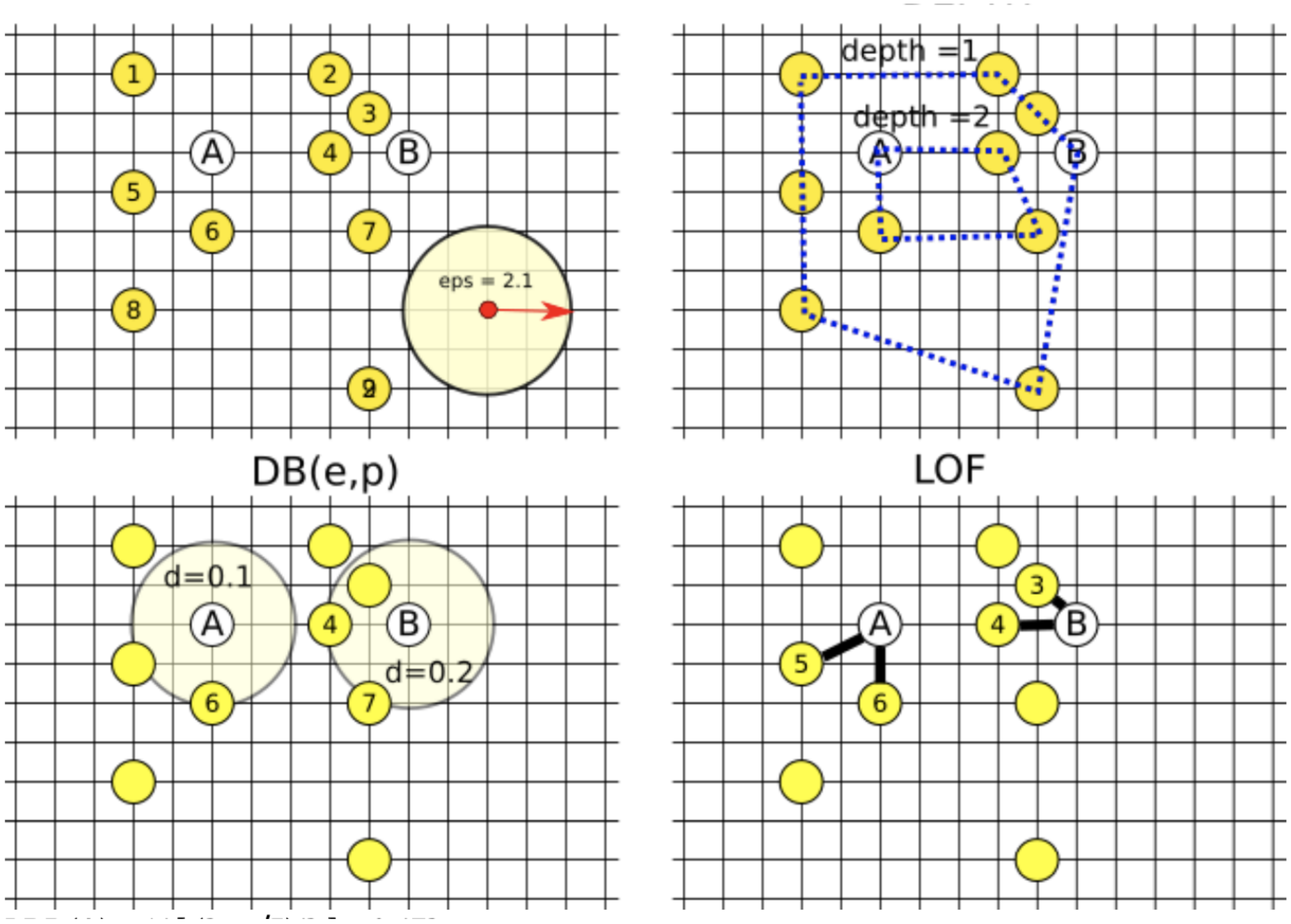


a) Distance-based: DB(ε,π) **(2 points)**
Are A and/or B outliers, if thresholds are forced to ε = 2.1 and π = 0.15 ? The point itself should not be counted.

b) Density-based: LOF **(2 points)**
Compute the LOF score for points A and B by taking k=2, i.e. comparing each point with its 2 NNs (not counting the point itself). In order to simplify the calculations, the reachability-distance used by LOF can be replaced by the simple Euclidean distance.

c) Depth-based **(2 points)**
Compute the depth score of all points. Are A and/or B outliers of depth 1?

Outlier Detection – Exercise 2 – Solution



LRD(A) = 1/ [(2 + √5)/2] = 0.472

LRD(5) = 1/ [(√5 + √5)/2] = 0.447

LRD(6) = 1/ [(2 + √5)/2] = 0.472

LOF(A) = ([LRD(5) + LRD(6)]/2) / LRD(A)
= [(0.472 + 0.447) / 2] / 0.472 = 0.973

LRD(B) = 1/ [(2 + √2)/2] = 0.586

LRD(3) = 1/ [(√2 + √2 + √2)/3] = 0.707

LRD(4) = 1/ [(2 + 2 + √2)/3] = 0.554

LOF(B) = ([LRD(3) + LRD(4)]/2) / LRD(B)
= [(0.707 + 0.554) / 2] / 0.586 = 0.929

Outlier Detection – Exercise 3

Given the dataset of 10 points below (A, B, 1, 2, …, 8), consider the outlier detection problem for points A and B, adopting the following three methods:

a) Distance-based: DB(ε,π) (2 points)
Are A and/or B outliers, if thresholds are forced to ε = 2.5 and π = 0.3? Show the density of the two points. (Notice: in computing the density of a point P, P itself should not be counted as neighbour).

b) Density-based: LOF **(3 points)**
Compute the LOF score for points A and B by taking k=2, i.e. comparing each point with its 2-NNs (not counting the point itself). In order to simplify the calculations, the reachability-distance used by LOF can be replaced by the simple Euclidean distance.

c) Depth-based **(1 points)**
Compute the depth score of all points.