

Machine Learning

Outlier Analysis

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Outlier Analysis

Informal definition (Hawkins)

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.

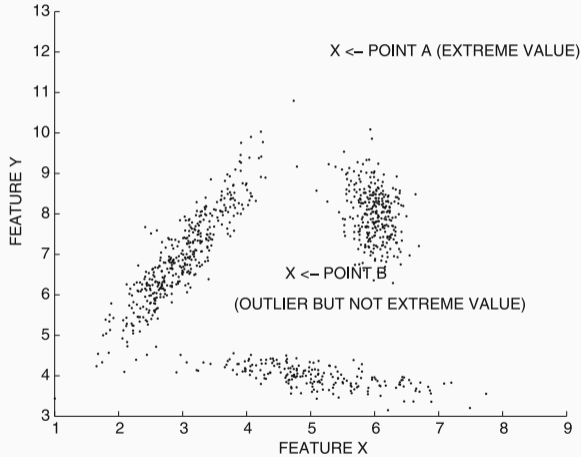
Outlier applications

- Data cleaning
 - An outlier represent a noise data.
- Credit card fraud
 - Credit card activity outside the usual pattern may represent an fraud.
- Network intrusion detection
 - Unusual records in traffic that do not follow the regular patterns.

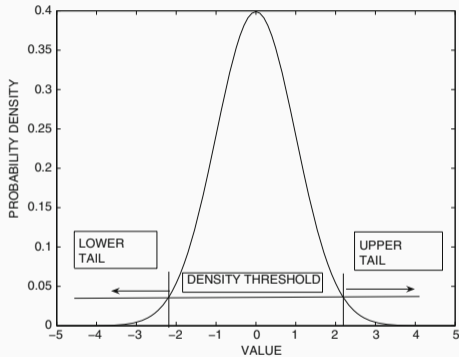
- Real-valued outlier score
 - A real value that represents the outlierness of a data point.
 - May be based on probability, distance measurement, etc.
- Binary label
 - Strict assignment of a outlier flag.
 - Contain less information than real-value score.
 - May be based on real-values with threshold.

- Extreme values
- Clustering models
- Distance-based models
- Density based models
- Probabilistic models
- Information-theoretic models

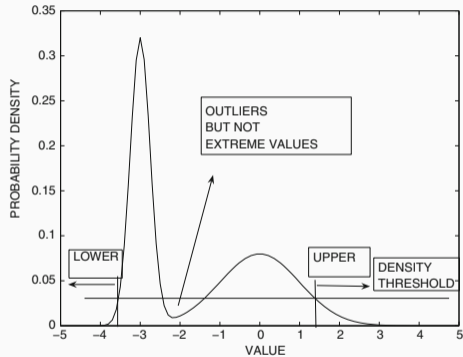
Outlier analysis - Extreme values - Example



Outlier analysis - Extreme values - Univariate

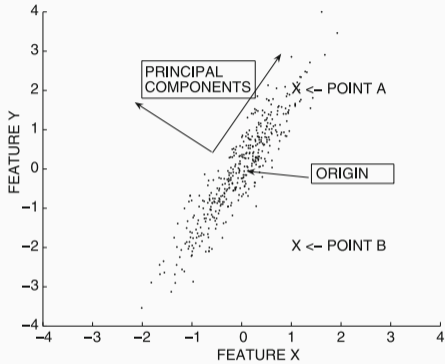


(a) Symmetric distribution

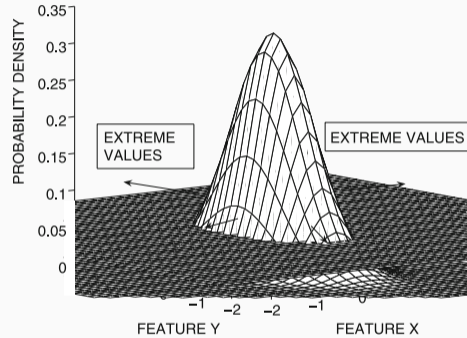


(b) Asymmetric distribution

Outlier analysis - Extreme values - Multivariate

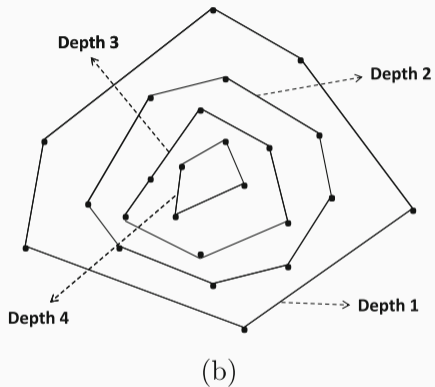
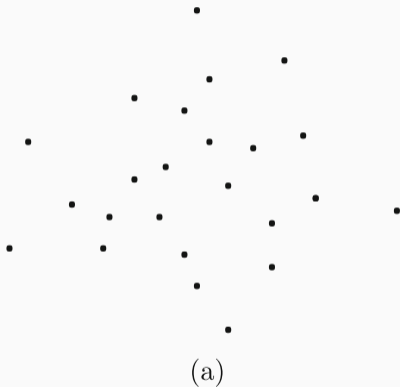


(a) Multivariate extreme values

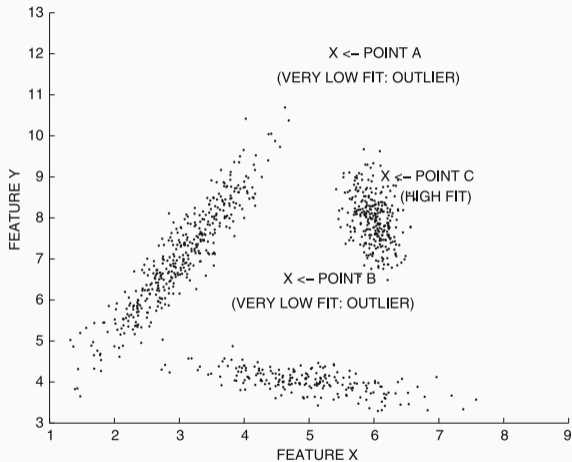


(b) Multivariate extreme values
(probabilistic interpretation)

Outlier analysis - Extreme values - Depth-based



Outlier analysis - Probability values - Likelihood

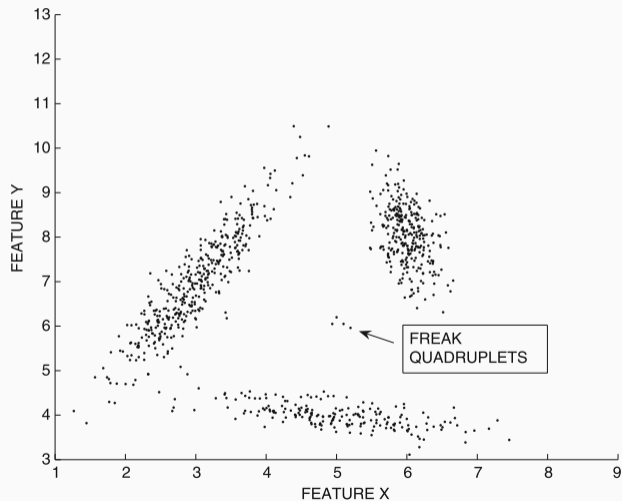


Outlier analysis - Distance-based detection

The distance-based outlier score of an object O is its distance to its k -th nearest neighbor.

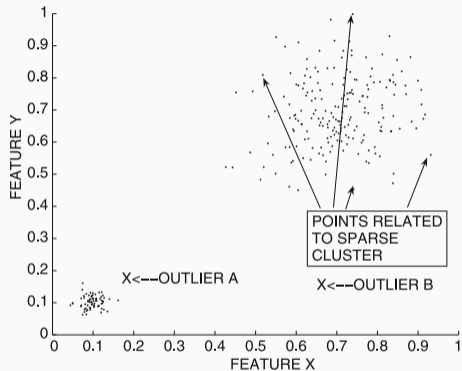
- The definition is based on the user defined k .
- The $k > 1$ helps to remove a group of outliers.
- Outlier detection methods use finer granularity than clustering methods.
- The ambient noise has lower k -nearest neighbor distance than truly isolated anomaly.
- The better granularity brings higher computational complexity.
- The speed-up techniques are used:
 - Index structures
 - Pruning tricks.

Outlier analysis - Distance-based detection

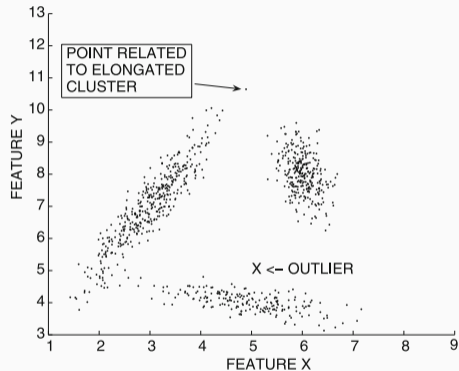


- Sampling methods
 - A sample S of size s is sampled from data.
 - Distances between all pairs from D and S are computed.
 - The complexity is $O(n \cdot s) \ll O(n^2)$.
 - The top r ranked outlier in sample S is determined.
 - The score of the r th ranked outlier is the lower bound L over the the whole dataset.
 - The upper bound $V^k(X)$ for each point $X \in D - S$ is known from distances of pairs.
 - When $V^k(X)$ is not larger than the lower bound L the point X may be excluded from the testing.
 - Large number of points is removed due to this condition.
 - The remaining points $R \subseteq D - S$ is tested by outlier measure.
 - The proper ordering of R and $D - S$ may significantly improve the speed of the algorithm.

Outlier analysis - Distance-based detection - Local distance correction



(a) Varying cluster density



(b) Varying cluster shape

- Local outlier factor (LOF)
 - Adjusting the local variations in cluster density by normalization of distanced with the average point-specific distances in a data locality.
 - This approach solves the varying cluster density situation.
 - For a given point X the $V^k(X)$ is its distance to its k -nearest neighbor.
 - The $L_k(X)$ is the set of points within the k -nearest neighbor distance of X .
 - The number of points in $L_k(X)$ is k or more.
 - The reachability distance is defined as

$$R_k(X, Y) = \max\{\text{Dist}(X, Y), V^k(Y)\}$$

- The average reachability distance of X with respect to $L_k(X)$ is then

$$AR_k(X) = \text{MEAN}_{Y \in L_k(X)} R_k(X, Y)$$

- The Local Outlier Factor LOF_k is then

$$LOF_k(X) = \text{MEAN}_{Y \in L_k(X)} \frac{AR_k(X)}{AR_k(Y)}$$

- Instance-Specific Mahalanobis distance
 - The goal is to deal with the varying cluster shape.
 - A k -local neighborhood $L_k(X)$ with respect to the cluster shape have to be defined.
 - $L_k(X)$ is constructed with the single-linkage agglomerative approach around the point X .
 - A mean $\mu_k(X)$ and the covariance matrix $\Sigma_k(X)$ are computed.
 - The distance $LMaha_k(X)$ then represent the outlier score.

$$LMaha_k(X) = Maha(X, \mu_k(X), \Sigma_k(X))$$

Outlier analysis - Density based methods

- The idea is similar to the density-based clustering.
- The main difference is that only the non-dense regions are detected.
- The points in sparse regions are reported as outliers.
- Histogram-based technique
 - Popular method for univariate data.
 - Represents the statistical distribution of points.
 - Difficult to adapt to varying density in different data locality.
 - Difficult to adapt this method to higher dimensions.
- Grid-based techniques
 - The space is partitioned into p equi-width ranges.
 - The sparse regions with the density less than τ are reported as outliers.
 - It is difficult to select proper p .
 - The τ may be defined using univariate extreme value analysis.
 - Outlier groups may not be reported because the cluster shapes are not recognized.

- Kernel-based density estimation
 - Similarly to Histogram- or Grid-based methods a local density is detected.
 - The density in each point is computed as smoothed values of a kernel functions associated with each data point.

$$f(X) = \frac{1}{n} \sum_{i=1}^n K_h(X - X_i)$$

- The h is a parameter of a function.
- typical choice is the Gaussian kernel with the width h .

$$K_h(X - X_i) = \left(\frac{1}{\sqrt{2\pi}h} \right)^d \cdot e^{-\|X - X_i\|^2 / (2h^2)}$$

Questions?