Outliers

Outlier detection widget.

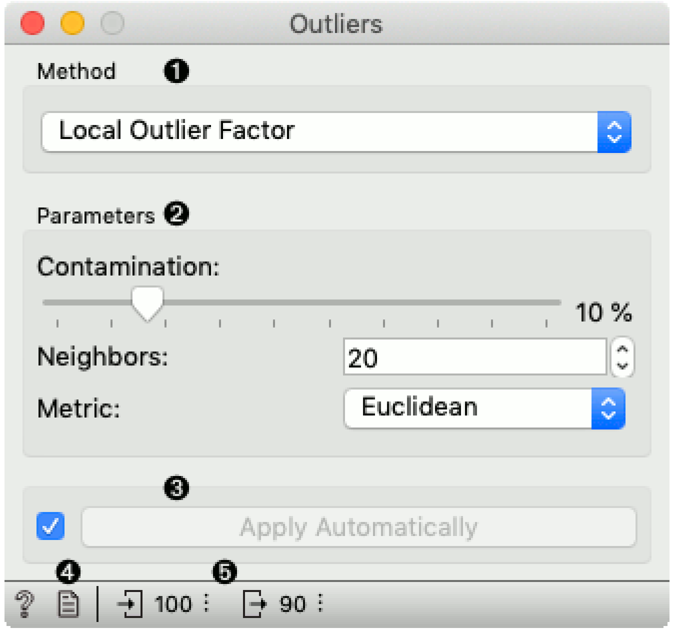
Inputs

- Data: input dataset

Outputs

- Outliers: instances scored as outliers
- Inliers: instances not scored as outliers
- Data: input dataset appended *Outlier* variable

The **Outliers** widget applies one of the four methods for outlier detection. All methods apply classification to the dataset. *One-class SVM with non-linear kernels (RBF)* performs well with non-Gaussian distributions, while *Covariance estimator* works only for data with Gaussian distribution. One efficient way to perform outlier detection on moderately high dimensional datasets is to use the *Local Outlier Factor* algorithm. The algorithm computes a score reflecting the degree of abnormality of the observations. It measures the local density deviation of a given data point with respect to its neighbors. Another efficient way of performing outlier detection in high-dimensional datasets is to use random forests (*Isolation Forest*).

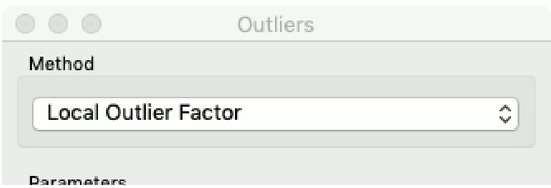


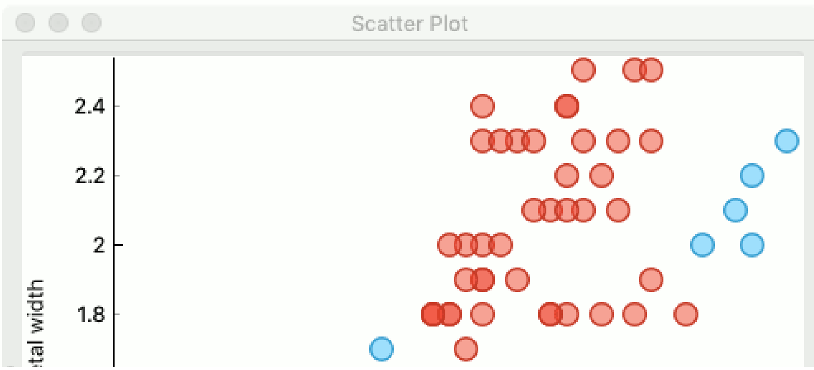
1. Method for outlier detection:

  - One Class SVM
  - Covariance Estimator
  - Local Outlier Factor
  - Isolation Forest
2. Set parameters for the method:
   - **One class SVM with non-linear kernel (RBF)**: classifies data as similar or different from the core class:
     - *Nu* is a parameter for the upper bound on the fraction of training errors and a lower bound of the fraction of support vectors
     - *Kernel coefficient* is a gamma parameter, which specifies how much influence a single data instance has
   - **Covariance estimator**: fits ellipsis to central points with Mahalanobis distance metric:
     - *Contamination* is the proportion of outliers in the dataset
     - *Support fraction* specifies the proportion of points included in the estimate
   - **Local Outlier Factor**: obtains local density from the k-nearest neighbors:
     - *Contamination* is the proportion of outliers in the dataset
     - *Neighbors* represents number of neighbors
     - *Metric* is the distance measure
   - **Isolation Forest**: isolates observations by randomly selecting a feature and then randomly selecting a split value between the maximum and minimum values of the selected feature:
     - *Contamination* is the proportion of outliers in the dataset
     - *Replicabe training* fixes random seed
3. If *Apply automatically* is ticked, changes will be propagated automatically. Alternatively, click *Apply*.
4. Produce a report.
5. Number of instances on the input, followed by number of instances scored as inliers.

Example

Below is an example of how to use this widget. We used subset (*versicolor* and *virginica* instances) of the *Iris* dataset to detect the outliers. We chose the *Local Outlier Factor* method, with *Euclidean* distance. Then we observed the annotated instances in the Scatter Plot widget. In the next step we used the *setosa* instances to demonstrate novelty detection using Apply Domain widget. After concatenating both outputs we examined the outliers in the *Scatter Plot (1)*.






Contamination:
10 %
Neighbors:
20
Metric:
Euclidean
Apply Automatically
100
90
outliers.ows
File
Data
Select Rows
Matching Data → Data
Outliers
Data
Scatter Plot
Data → Primary Data
Concatenate
Data
Scatter Plot (1)
Unmatched Data → Data
Data → Template Data
Transformed Data → Additional Data
Apply Domain
1.6
1.4
1.2
1
3
4
5
6
petal length
Yes
No
Select Rows
Conditions
iris
is one of
Iris-versicolor, Iris-virg...
Add Condition
Add All Variables
Remove All
Data
In: ~150 rows, 5 variables
Out: ~100 rows, 5 variables
Purging
Remove unused features
Remove unused classes
Send Automatically
Scatter Plot (1)
petal width
2.4
2.2
2
1.8
1.6
1.4
1.2
1
0.8
0.6
0.4
0.2
1
2
3
4
5
6
7
Yes
No


petal length
150