

Manifold Learning

Nonlinear dimensionality reduction.

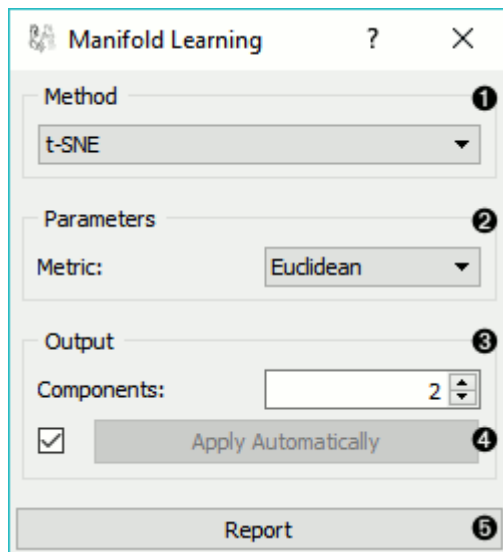
Inputs

- Data: input dataset

Outputs

- Transformed Data: dataset with reduced coordinates

Manifold Learning is a technique which finds a non-linear manifold within the higher-dimensional space. The widget then outputs new coordinates which correspond to a two-dimensional space. Such data can be later visualized with **Scatter Plot** or other visualization widgets.



1. Method for manifold learning:

- t-SNE
- MDS, see also MDS widget
- Isomap
- Locally Linear Embedding
- Spectral Embedding

2. Set parameters for the method:

- t-SNE (distance measures):
 - Euclidean distance
 - Manhattan

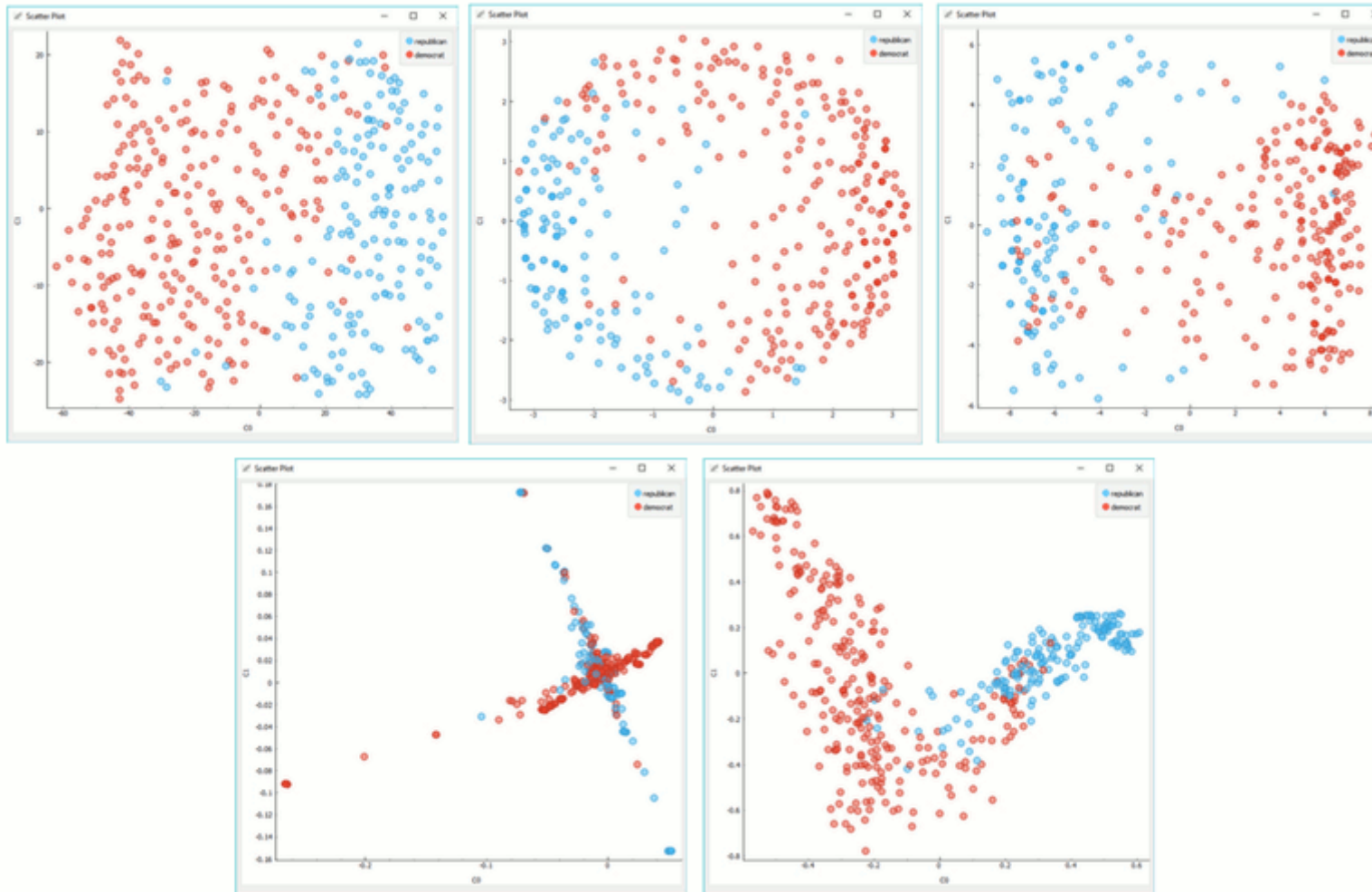
- *Chebyshev*
- *Jaccard*
- *Mahalanobis*
- *Cosine*
- MDS (iterations and initialization):
 - *max iterations*: maximum number of optimization interactions
 - *initialization*: method for initialization of the algorithm (PCA or random)
- Isomap:
 - number of *neighbors*
- Locally Linear Embedding:
 - *method*:
 - standard
 - modified
 - *hessian eigenmap*
 - local
 - number of *neighbors*
 - *max iterations*
- Spectral Embedding:
 - *affinity*:
 - nearest neighbors
 - RFB kernel

3. Output: the number of reduced features (components).

4. If *Apply automatically* is ticked, changes will be propagated automatically. Alternatively, click *Apply*.

5. Produce a report.

Manifold Learning widget produces different embeddings for high-dimensional data.



From left to right, top to bottom: t-SNE, MDS, Isomap, Locally Linear Embedding and Spectral Embedding.

Example

Manifold Learning widget transforms high-dimensional data into a lower dimensional approximation. This makes it great for visualizing datasets with many features. We used *voting.tab* to map 16-dimensional data onto a 2D graph. Then we used *Scatter Plot* to plot the embeddings.

