|  |
| --- |
| tSNE |
| a parametric mapping between the high-dimensional data space and the low-dimensional latent space.  local structure of the data is preserved as well as possible in the latent space. |
| <https://scikit-learn.org/stable/modules/generated/sklearn.manifold.TSNE.html> |
| <https://lvdmaaten.github.io/tsne/>   * It is perfectly fine to run t-SNE ten times, and select the solution with the lowest KL divergence. * t-SNE does not retain distances but probabilities, so measuring some error between the Euclidean distances in high-D and low-D is useless. * It is possible that different runs give you different solutions. * The performance of t-SNE is fairly robust under different settings of the perplexity. Typical values for the perplexity range between 5 and 50. (is it is too high a ball shape output is created) * If data contains big numbers tsne may **report a very low error but the results look crappy** * If there was any problem check your data using PCA, maybe there is something wrong with the data set * it is not possible to embed test points in an existing map |
| Nonlinear Dimention reduction methods (NLDR)  ICA, PCA< FA, SVD, ISOMAP, t-SNE |
| parametric t-SNE |
| Comparision of manifold learning methods:  <https://scikit-learn.org/stable/auto_examples/manifold/plot_compare_methods.html#sphx-glr-auto-examples-manifold-plot-compare-methods-py> |
| Problem:   * Global structure is not explicitly preserved. This problem is mitigated by initializing points with PCA (using init='pca'). |
|  |
|  |