

Nonlinear dimensionality reduction

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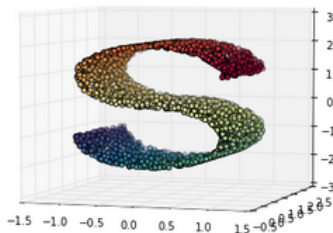
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Advantages of dimensionality reduction

- Reduce operational time and storage costs.
- Remove multi-collinearity in features.
- Visualize in 2D or 3D.

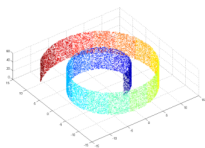
Non-linear dimensionality reduction

- Based on assumption that original data $x \in \mathbb{R}^D$ is distributed compactly on non-linear surface with dimensionality $d < D$.
- Let $y \in \mathbb{R}^d$ denote the coordinates of x on the surface.
- d is usually unknown.
- Sample dataset:

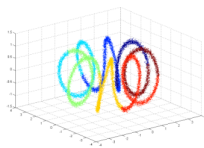


- Linear dimensionality reduction techniques will fail here.

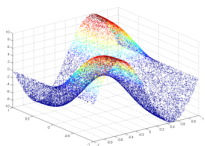
Typical datasets for dimensionality reduction evaluation



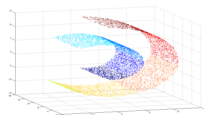
(a) Swiss roll dataset.



(b) Helix dataset.



(c) Twinpeaks dataset.



(d) Broken Swiss roll dataset.

Comment: true datasets have much more dimensions, more complex structure, errors, outliers, etc.

Categorization

Non-linear approaches of dimensionality reduction:

- preserving global properties
 - kernel PCA, autoencoders, MDS, ISOMAP, diffusion maps, MVU
- preserving local properties
 - LLE, LTSA
- global alignment of local linear models (not considered here)

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1 Global methods

2 Local methods

Multi-dimensional scaling

Multi-dimensional scaling

Map $x \rightarrow y$ preserving distances as much as possible.

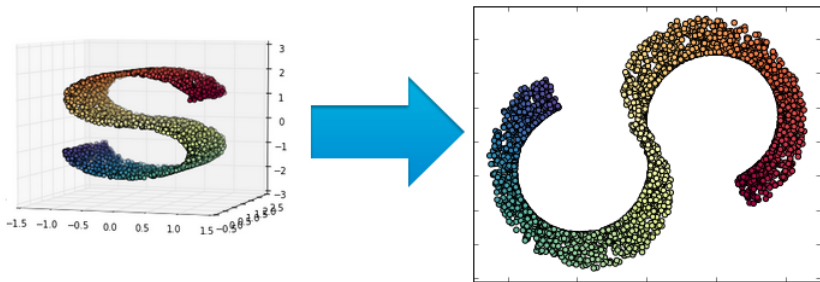
- Approaches:
 - absolute difference

$$\sum_{i,j} (\|x_i - x_j\| - \|y_i - y_j\|)^2 \rightarrow \min_Y$$

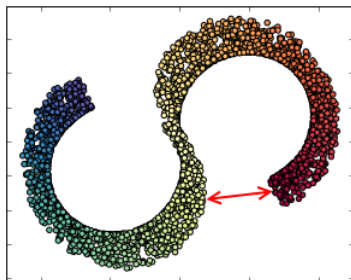
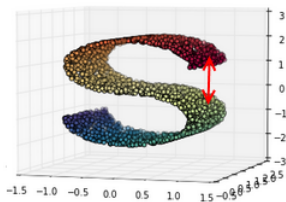
- relative difference (more attention to small distances)

$$\sum_{i,j} \frac{(\|x_i - x_j\| - \|y_i - y_j\|)^2}{\|x_i - x_j\|} \rightarrow \min_Y$$

Example



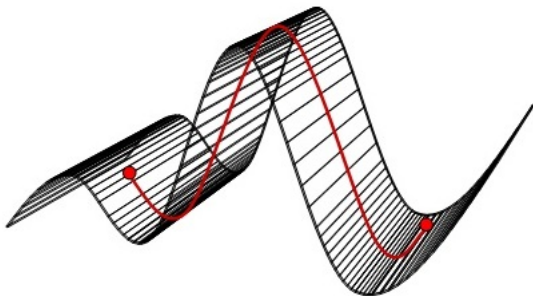
Analysis



Issue: small $\|x_i - x_j\|$ should not always imply small $\|y_i - y_j\|$.

Solution

Isomap: Map $x \rightarrow y$ preserving correspondence between distance in target space and geodesic distance along the surface in original space.



Isomap

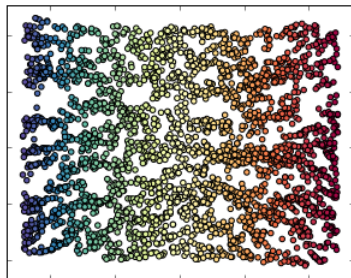
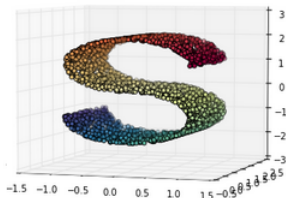
Isomap algorithm

- 1 Geodesic distance calculation:
 - 1 for each x_n find its K nearest neighbours
 - 2 build the pairwise distance matrix, filling distance between samples and their nearest neighbours.
 - 3 calculate all pairwise distances using shortest-path algorithm of Dijkstra or Floyd.
- 2 Apply MDS to match $\|x_i - x_j\|_G$ and $\|y_i - y_j\|$, where $\|\cdot\|_G$ is geodesic distance.

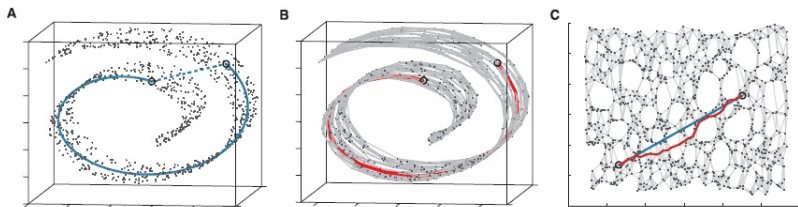
Issues of Isomap

- Noisy observations between distant parts of surfaces may make distant parts close
- Solutions:
 - remove observations with large total flows through them
 - remove nearest neighbours that violate local linearity
- Selection of K :
 - if too small, then poor approximation of geodesic distance
 - if too large, then increases chance of “short-circuiting” through noisy observations.

Example of ISOMAP



Example of ISOMAP



Picture source link.

Maximum variance unfolding

Maximum variance unfolding

Maximally unfold the transformations, preserving local geometry of data.

```
initialize neighbourhood graph  $G$  with edges being
the samples  $x_1, x_2, \dots, x_N$ 
```

```
for each  $x_n$ :
```

```
  for  $k = 1, 2, \dots, K$ :
```

```
    find  $k$ -th nearest neighbour  $x_{n_k}$  to  $x_n$ 
```

```
    add a link to  $G$  between  $x_n$  and  $x_{n_k}$ 
```

```
solve the optimization problem:
```

```
 $\sum_{i,j} \|y_i - y_j\|^2 \rightarrow \max$  subject to:  $\|y_i - y_j\|^2 = \|x_i - x_j\|^2 \forall (i,j) \in G$ 
```

Issue: noise sample may “short-circuit” leading to redundant constraint, which may prevent manifold unfolding.

Kernel PCA

- Like PCA, but input space is expanded with kernels
- Easy computation of projections of new points
- Issue: kernel selection.
 - linear (reduces to ordinary PCA)
 - Gaussian
 - polynomial

Diffusion maps

- 1 Construct proximity graph
 - nodes: observations
 - edge weight between x_i and x_j :

$$w_{ij} = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}$$

- 2 for each x_i outgoing probabilities set to normalized weights:

$$p_{ij}^{(1)} = \frac{w_{ij}}{\sum_k w_{ik}} \quad (1)$$

- 3 random walk with probabilities $p_{ij}^{(1)}$ stored in matrix $P^{(1)}$ is assumed.
- 4 based on random walk assumption, the probability of walking from x_i to x_j after T steps is:

$$p_{ij}^{(T)} = \underbrace{\{P^{(1)} \times \dots \times P^{(1)}\}}_{T \text{ times}}_{ij}$$

Diffusion maps

- Finally MDS is applied to match $\|y_i - y_j\|$ to *diffusion distance*:

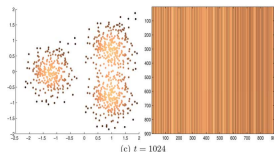
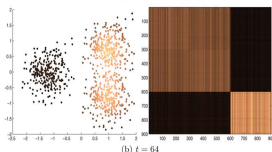
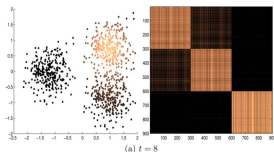
$$D^T(x_i, x_j) = \sqrt{\sum_k \frac{(p_{ik}^{(T)} - p_{jk}^{(T)})^2}{p_k}}$$

where $[p_1, p_2, \dots, p_N]$ is stationary distribution for Markov process with matrix $P^{(1)}$.

- p_i measures the probability to be at object i after big fixed number of trials.
- High p_k means that object k is central, connected to many objects.
- Normalization by p_k means that we are more interested in connection to distant isolated objects.

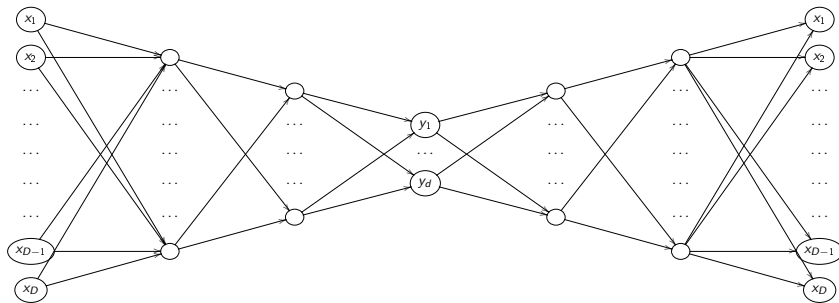
Discussion

- **Benefit:** distance between points is based on multiple paths through the graph - more robust to noise.
- Selection of T is important:
 - too small: method from global becomes local, matching distances between neighbouring points
 - too big: all points become equally similar
 - Example: 3 clusters with transition probabilities set with (1), color indicates $p(i|j)$ after t steps.



[Link to picture source](#)

Autoencoders



- feed-forward neural network, trained to reproduce input with MSE loss.
- D input and D output nodes
- d nodes in the central layer
- User-defined number of layers and nodes

Autoencoders

- Benefits: can map new points to reduced space
- Issues:
 - optimization may get stuck in local optima
 - slow convergence (can be improved with specific starting weights)
 - unfeasible to apply to high d (too many connections).

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1 Global methods

2 Local methods

Local linear embedding

Local linear embedding

Method preserves reconstruction weights of objects through their nearest neighbors.

INPUT:

training sample x_1, x_2, \dots, x_N
 number of neighbours K

ALGORITHM:

for each x_i :

find its K nearest neighbours: $x_{i(1)}, x_{i(2)}, \dots, x_{i(K)}$

find weights to reconstruct x_i using its neighbours:

$$x_i \approx \sum_{k=1}^K w_{ik} x_{i(k)}$$

solve optimization problem: $\sum_{n=1}^N (y_i - \sum_{k=1}^K w_{ik} y_{ik})^2 \rightarrow \max_Y$

OUTPUT: reduced space representation: y_1, y_2, \dots, y_N .

Laplacian eigenmaps

Laplacian eigenmaps

Forces distances of points with nearest neighbours to be smaller.

INPUT:

training sample x_1, x_2, \dots, x_N
 number of neighbours K

ALGORITHM:

for each x_i :

find its K nearest neighbours: $x_{i(1)}, x_{i(2)}, \dots, x_{i(K)}$

for each nearest neighbour $j=i(1), i(2), \dots, i(K)$:

calculate distance-based weights: $w_{ij} = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}$

solve optimization problem:

$$\sum_{n=1}^N \sum_{i=1}^N \sum_{j \in \{i(1), \dots, i(K)\}} w_{ij} (y_i - y_j)^2 \rightarrow \min_Y$$

OUTPUT: reduced space representation: y_1, y_2, \dots, y_N .

Comments on local methods

- short-circuiting affects only local points in space
- local method, relying on K-NN \Rightarrow prone to curse of dimensionality
- prone to overfitting on outliers (when they become nearest neighbors)

Properties

Technique	Convex	Parameters	Computational	Memory
PCA	yes	none	$O(D^3)$	$O(D^2)$
MDS	yes	none	$O(N^3)$	$O(N^2)$
Isomap	yes	K	$O(N^3)$	$O(N^2)$
MVU	yes	K	$O((NK)^3)$	$O((NK)^3)$
Kernel PCA	yes	kernel	$O(N^3)$	$O(N^2)$
Diffusion maps	yes	σ, T	$O(N^3)$	$O(N^2)$
Autoencoders	no	network shape	$O(INW)$	$O(W)$
<i>LLE</i>	yes	K	$O(pN^2)$	$O(pN^2)$
<i>Laplacian eigenmaps</i>	yes	K, σ	$O(pN^2)$	$O(pN^2)$

D - input dimension, N - sample size, K - number of nearest neighbors, σ - smoothing parameter of Gaussian kernel, W number of weights in neural network, I - number of iterations (optimization passes), p - the fraction of non-zero entries in the weight matrix.

Comment: PCA is the most efficient, then come local methods (italic) and finally global methods.

Other

- **Problem of transforming new previously unobserved samples.**
 - direct for PCA, Kernel PCA, autoencoders
 - only approximations possible for other methods ().
- **Selection of target dimensionality d :**
 - Cross-validation of the original task (e.g. classification)
 - How many components of local PCA explain most of the variance?
 - The growth rate of number of objects falling inside a growing hypersphere with center x : $\#\{x_i : \|x_i - x\| \leq R\}$
 - for d -dimensional manifold it should grow $\propto R^d$.
 - etc.

Conclusion

- L.J.P. van der Maaten, E.O. Postma, H.J. van den Herik. Dimensionality Reduction: A Comparative Review. Working paper. 2008.
 - Extensive comparison of different dimensionality reduction methods.
 - Non-linear techniques perform better than PCA on simulated data
 - PCA wins most of the time on real data
 - Problems:
 - global methods: short-circuiting
 - nearest neighbours based methods: curse of dimensionality, overfitting to outliers
 - unstable optimization for local methods: they reduce to eigenproblems, frequently $\lambda_{max}/\lambda_{min} \gg 1$.
 - suboptimal local optima for autoencoders.
- Dimensionality reduction is an actively developing field.

Extra

- Landmark algorithm
- Local linear projection (with PCA)
 - show ipynb example