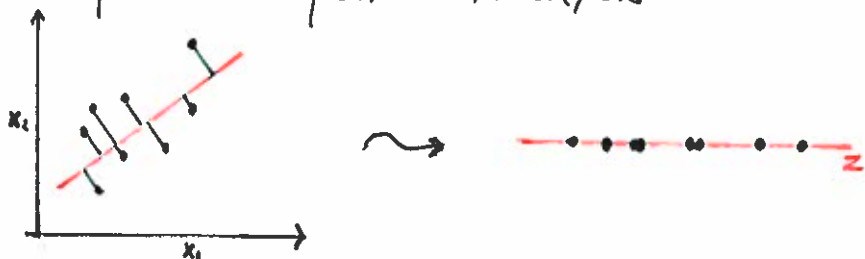


# Dimensionality reduction

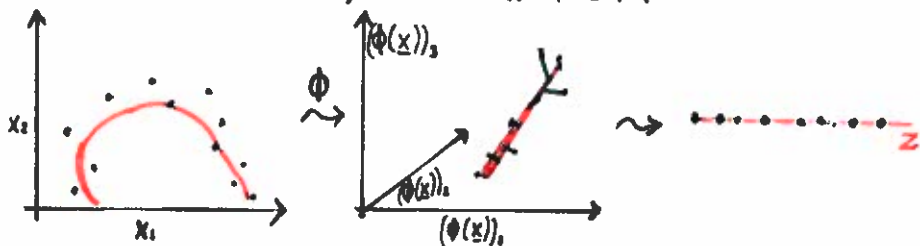
- Linear:

- Principal Component Analysis



- Nonlinear:

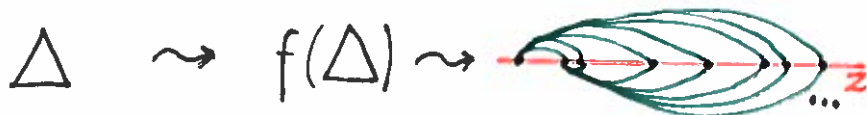
- Nonlinear PCA, kernel PCA



- Metric MDS



- Nonmetric MDS



- Classical MDS (= "classical scaling")

Precise numerical values taken into account

Assumption:  $\Delta$  directly represents Euclidean distances between hypothetical points

$z_1, \dots, z_n \in \mathbb{R}^k$ ,  $k$  unknown

$\leadsto$  Apply "PCA from distances" procedure  
(use Gram matrix  $G = -\frac{1}{2} C_n \Delta C_n$ ,  
calculate  $Z$ )

But: If assumption violated:

some eigenvalues  $\tilde{\lambda}_j$  can be negative

$\leadsto$  discard corresponding EV

Optimisation problem:

$$Z = \underset{M}{\text{minimise}} \left\| \left( -\frac{1}{2} C_n \Delta C_n \right) - M^T M \right\|_F$$

$$\text{s.t. rank}(M^T M) = k$$

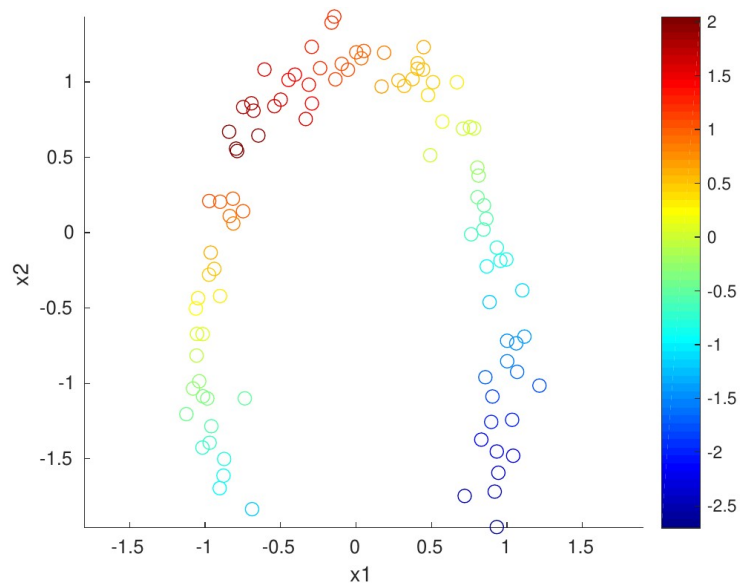
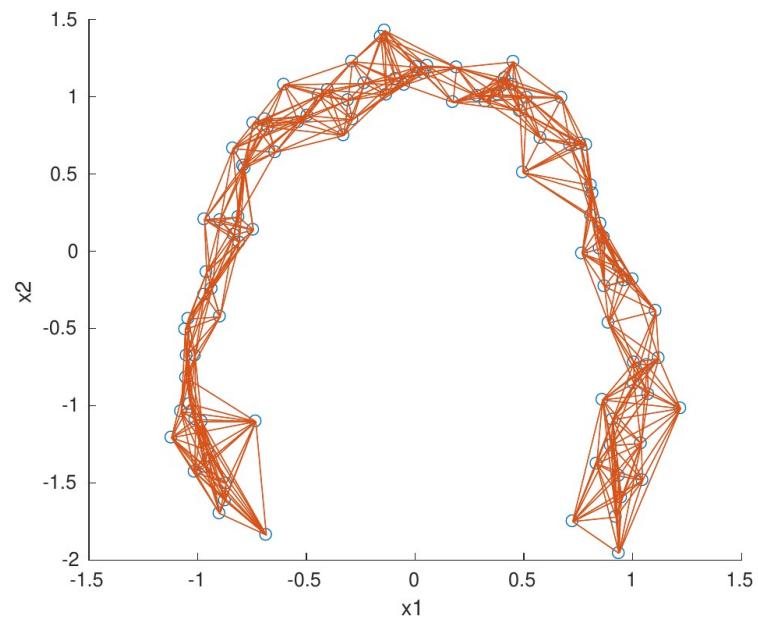
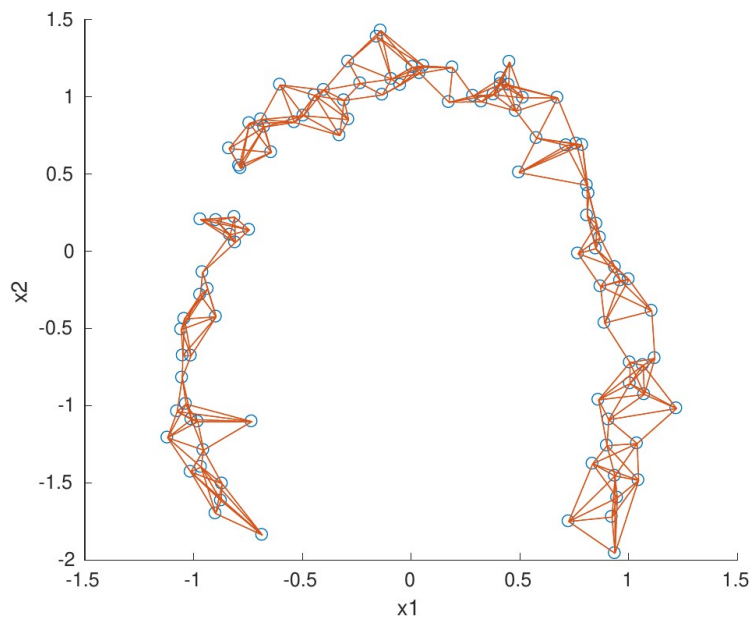
Isomap

Classical MDS with particular  $\Delta$ :

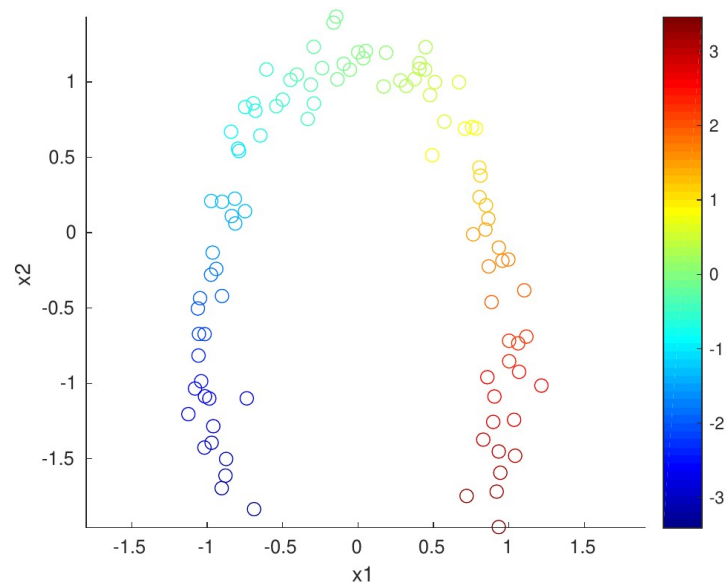
For  $\underline{x}_i, \underline{x}_j \in \mathbb{R}^d$ :

$\delta_{ij}$  = shortest distance when travelling  
from one neighbouring data point  
to the next, where neighbourhood  
defined by  $m$ -nearest neighbours  
( $m$ -NN)

# Isomap



(a) 5 neighbours



(b) 10 neighbours

# Uniform Manifold Approximation and Projection (UMAP)

Nearest neighbour-based graph dimensionality reduction method (like Isomap)

For Isomap: used graph to transform data to  $\Delta$

For UMAP: calculate a graph for data  $\tilde{X}$  and for each potential  $Z$ ; minimise graph distance

Graph construction: for given  $Y = (y_1, \dots, y_n)$   
m-NN graph for  $Y$ ; add weights to each edge:  
 $w_i^{(y)}(y_i, y_j) = \exp\left(-\frac{\|y_i - y_j\| - p_i}{\epsilon_i}\right)$

where  $\epsilon_i$ : diameter of neighbourhood

$p_i$ : distance to nearest neighbour

Weight: "Probability that edge exists"

"Make data uniform on manifold"

$\rightarrow$  two weights per edge - can be asymmetric

$\rightarrow$  set  $w^{(y)}(y_i, y_j) = w_i^{(y)}(y_i, y_j) + w_j^{(y)}(y_i, y_j)$   
 $- w_i^{(y)}(y_i, y_j) w_j^{(y)}(y_i, y_j)$

"Probability that at least one of the edges exists"

$\rightarrow$  Weight matrix  $(W^{(y)})_{i,j} = w^{(y)}(y_i, y_j)$

- Calculate  $W^{(x)}$  for given data  $X$
- Calculate  $W^{(z)}$  for potential  $Z$
- Calculate cross-entropy between  $W^{(\tilde{x})}$  and  $W^{(z)}$ :

$$C(W^{(\tilde{x})}, W^{(z)}) = \sum_{i < j} w_{ij}^{(\tilde{x})} \log\left(\frac{w_{ij}^{(\tilde{x})}}{w_{ij}^{(z)}}\right) + (1 - w_{ij}^{(\tilde{x})}) \log\left(\frac{1 - w_{ij}^{(\tilde{x})}}{1 - w_{ij}^{(z)}}\right)$$

Optimisation problem:

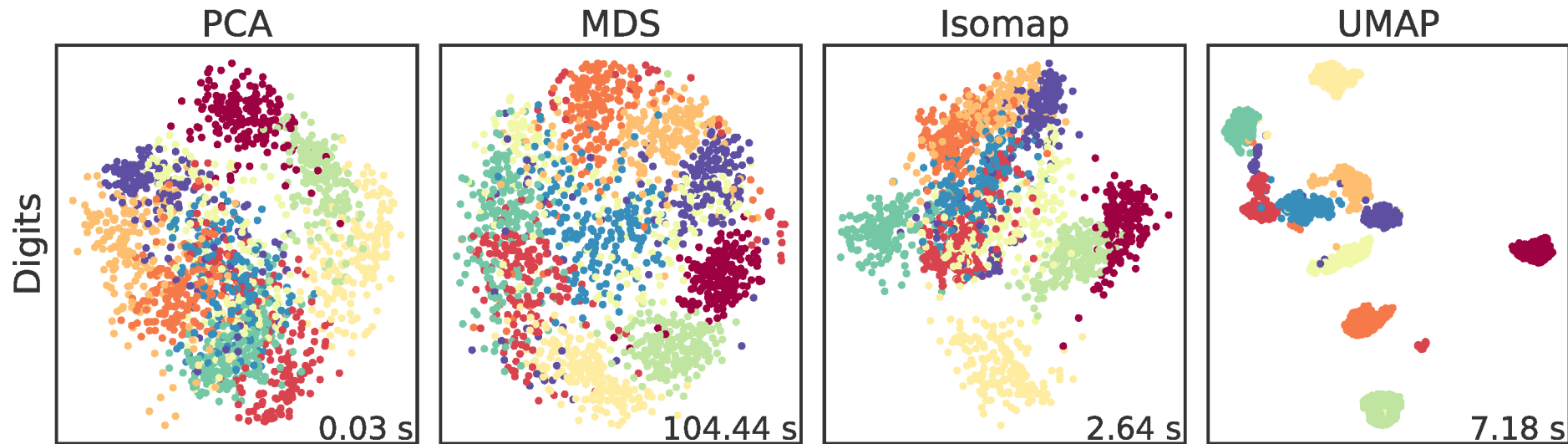
$$\underset{Z}{\text{minimise}} \ C(W^{(\tilde{x})}, W^{(z)})$$

Optimise via gradient descent

Recent method:

McInner, Healy & Melville 2018

# Comparison on Handwritten Digits



Adapted from <https://umap-learn.readthedocs.io/>