IJCCI-NCTA

Neighborhood Function Design for Embedding in Reduced Dimension

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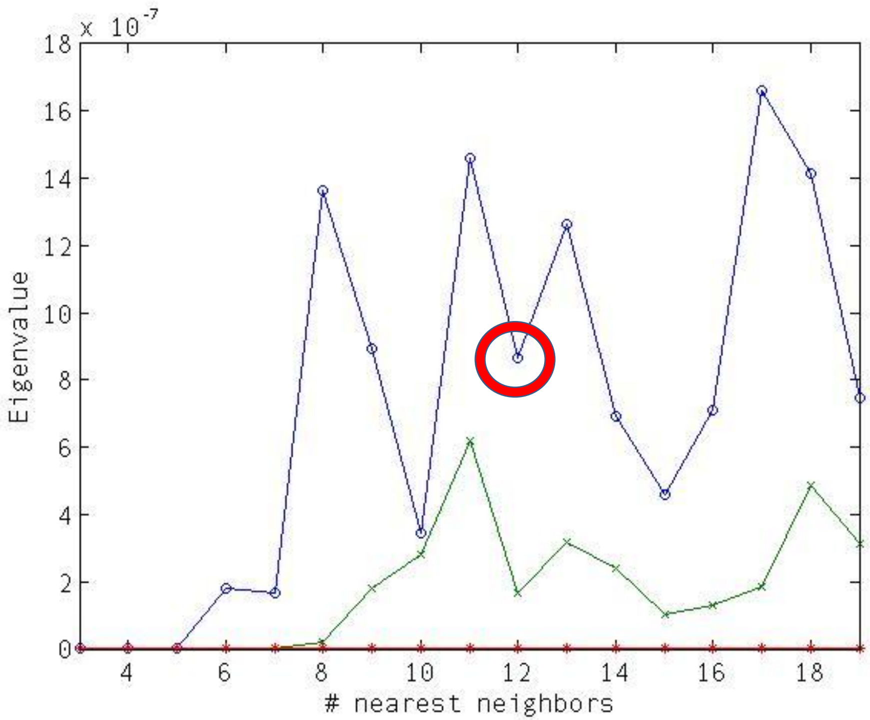
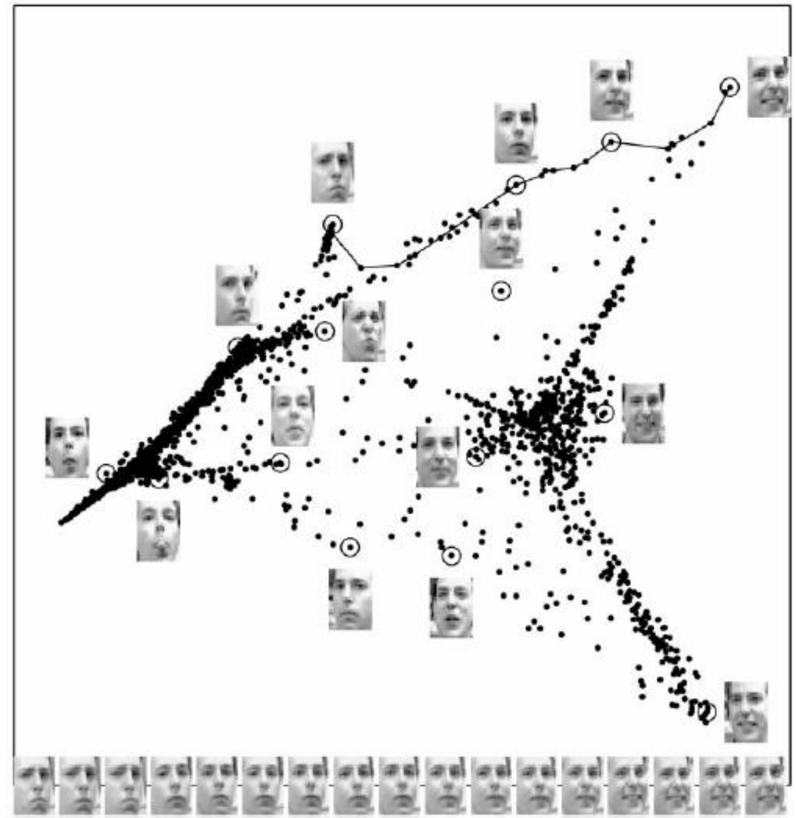
Motivation

LLE Eigenvalues



12-nn embedding



Why choosing 12-nn for example representation?

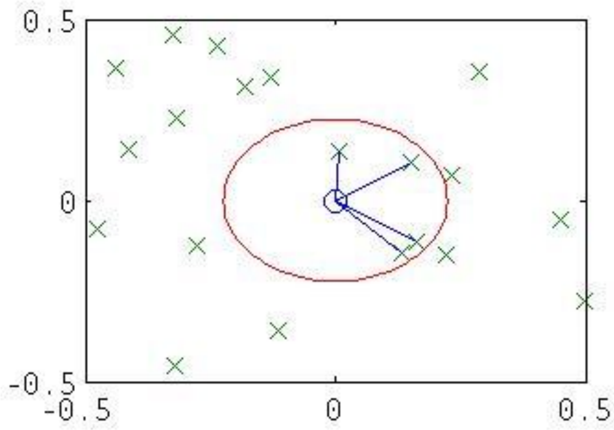
http://cs.nyu.edu/~roweis/lle/faces.html

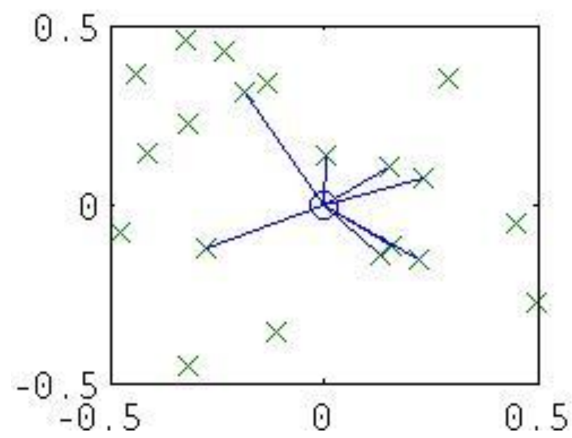
Outline

- Introduction
- Methods
- Experiments
- Results
- Discussion

Idea: Neighborhood Selection

- K-nearest neighbors
- ε-distance

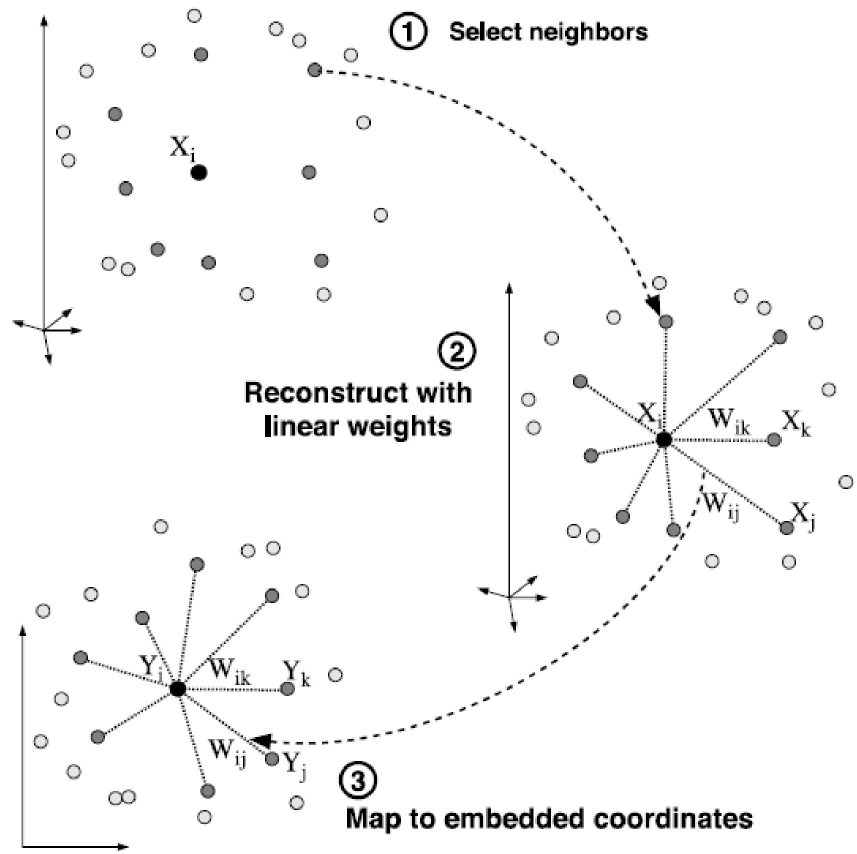




- Fractional nearest neighbors => k-nn + some number of connections selected from minimal distance within (k+1)-nn.

LLE Algorithm

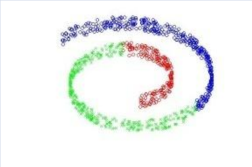
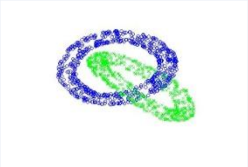
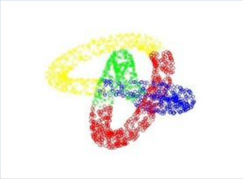
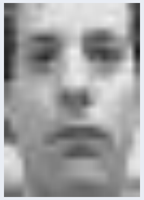
1. Select neighbors for each X.
2. Solve for reconstruction weights W.
3. Compute embedding coordinates Y using weights W. (Require d smallest positive eigenvalues.)



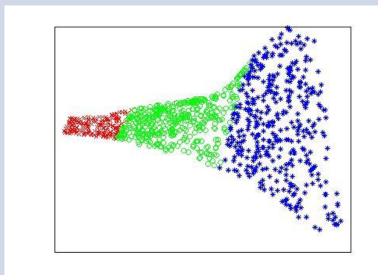
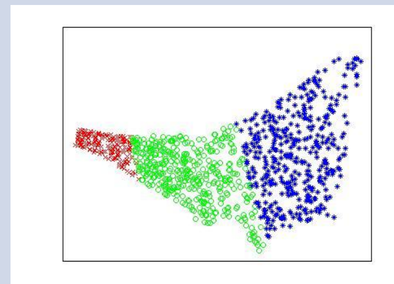
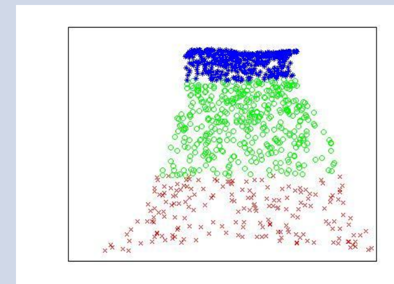
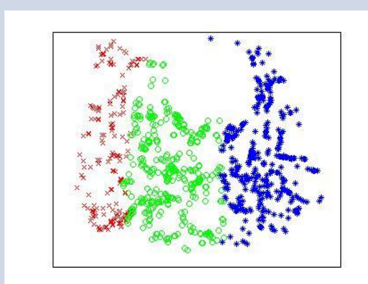
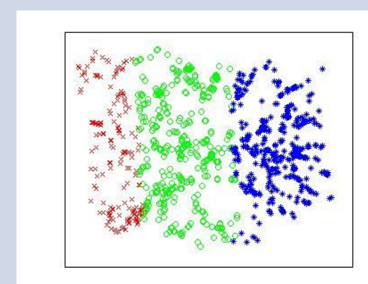
Isomap Algorithm

1. Construct neighborhood graph.
2. Compute shortest paths. (all-pair)
3. Construct d-dimensional embedding.
   (Require d largest eigenvalues.)

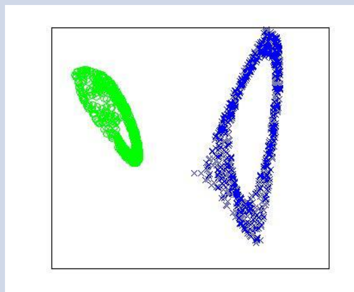
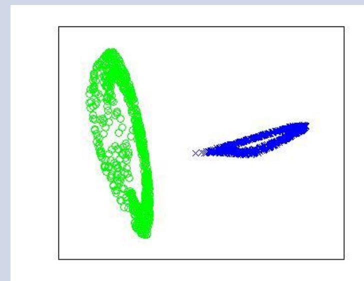
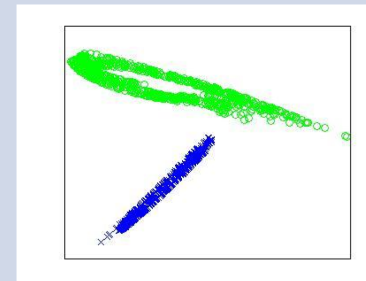
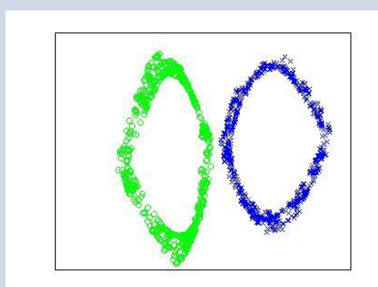
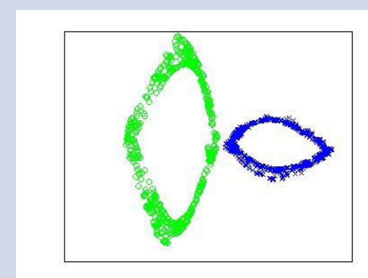
Experimental data

Dataset	Representation	Data Dimensions	Embedding Dimensions	Data Size
Swiss Roll		3	2	1000
Dual Tube		3	2	1500 (700+800)
Knot		3	2	2000
Face Dataset (true data)		560 (28x20)	2	1965

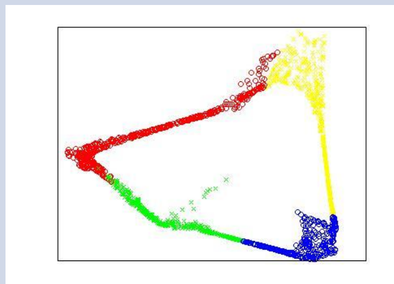
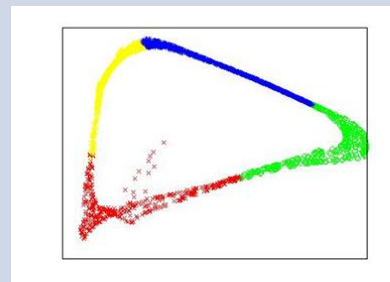
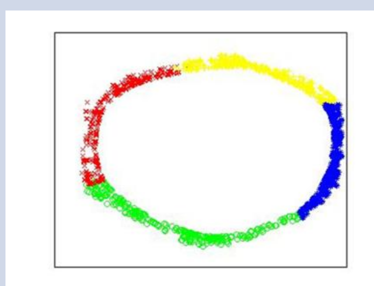
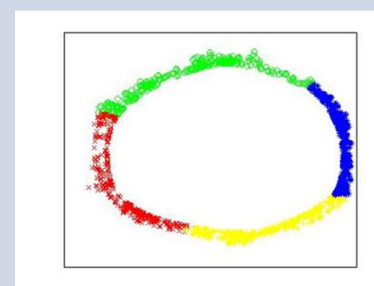
Embedding Result: Swiss Roll

Approach	K-nn	Frac-nn	ε-distance
LLE			
	7-nn	7.64-nn	$\varepsilon^2 = 21$
Isomap		N/A	
	7-nn	N/A	$\varepsilon^2 = 21$

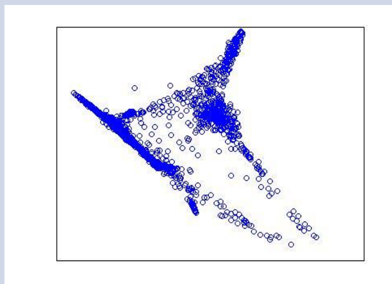
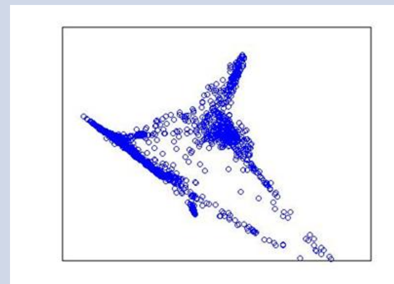
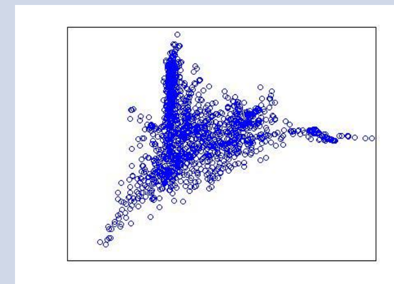
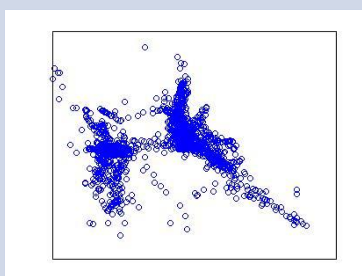
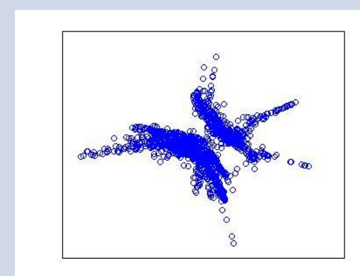
Embedding Result: Dual Tube

Approach	K-nn	Frac-nn	ε-distance
LLE			
	11-nn	11.64-nn	$\varepsilon^2 = 0.0575$
Isomap		N/A	
	12-nn	N/A	$\varepsilon^2 = 0.065$

Embedding Result: Knot

Approach	K-nn	Frac-nn	ε-distance
LLE			
	7-nn	8.6-nn	$\varepsilon^2 = 0.384$
Isomap		N/A	
	6-nn	N/A	$\varepsilon^2 = 0.42$

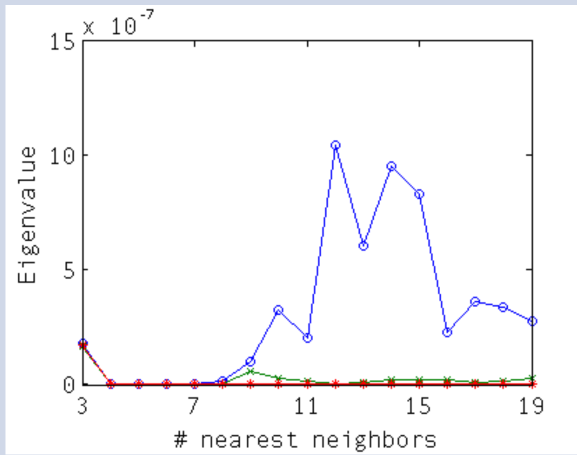
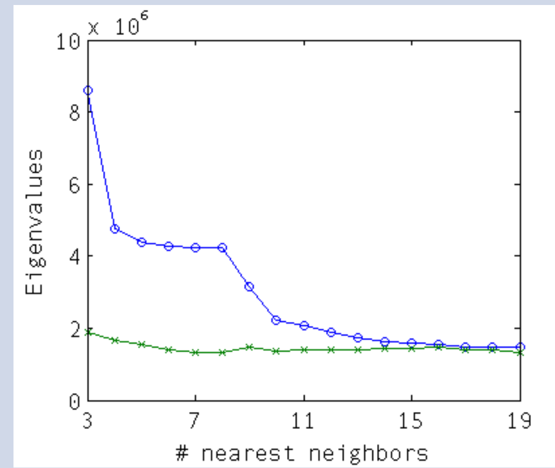
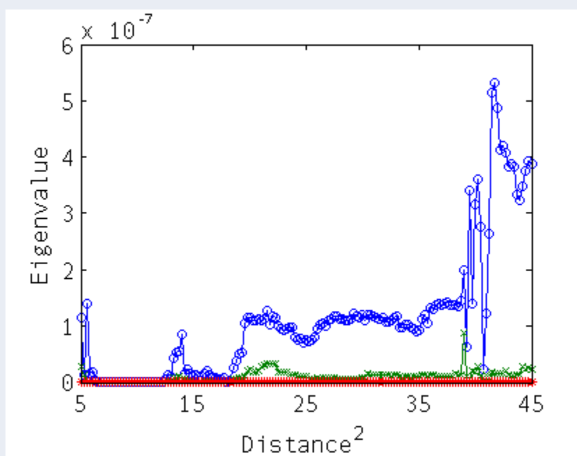
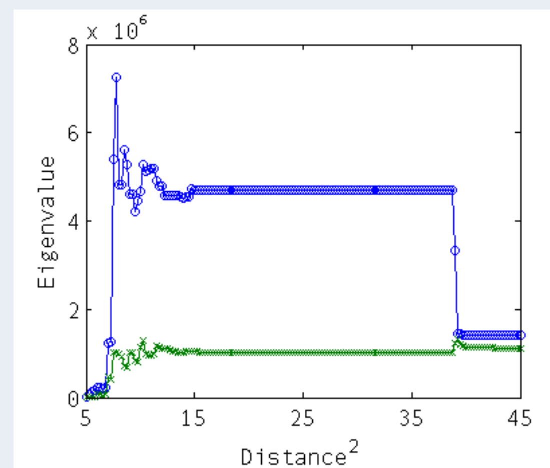
Embedding Result: Face dataset

Approach	K-nn	Frac-nn	ε-distance
LLE			
	12-nn	12.33-nn	$\varepsilon^2 = 3.45$
Isomap		N/A	
	9-nn	N/A	$\varepsilon^2 = 6$

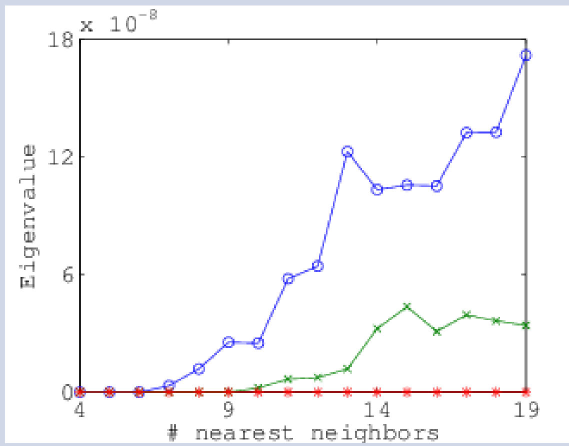
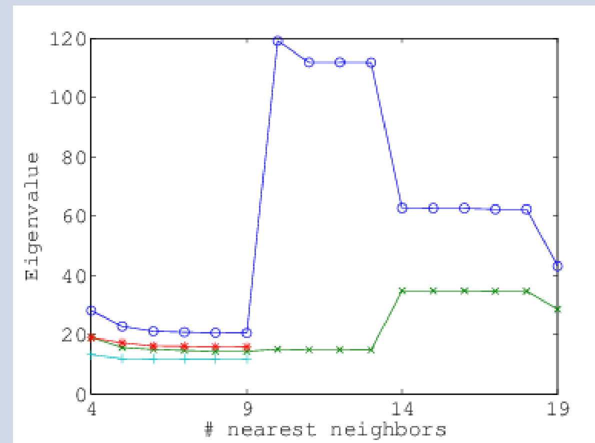
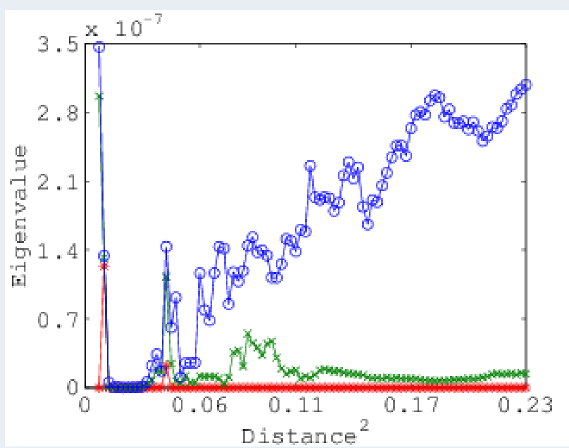
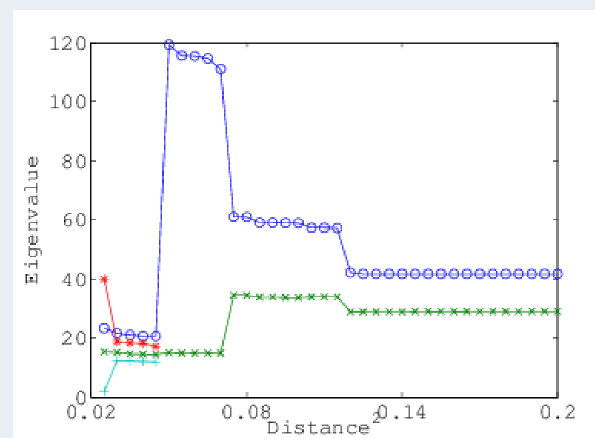
Eigenvalue trends

- Embedding data to fixed number of dimensions (Ex: 2).
- Using different neighborhood functions and parameters.
- Meaning for large changes for specific parameters.

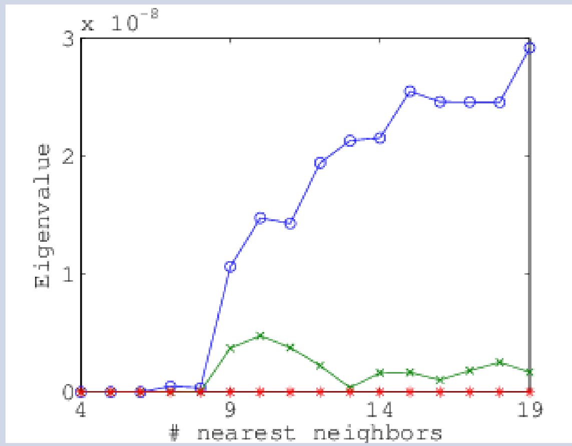
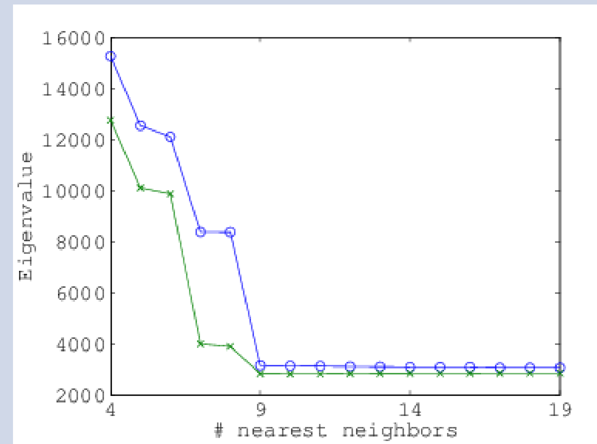
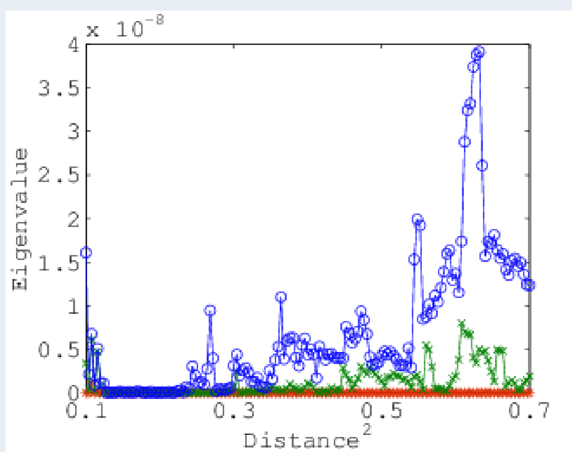
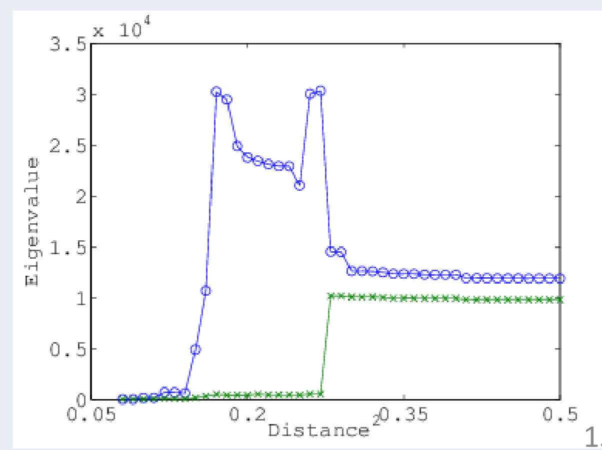
Eigenvalues Result for Swiss Roll

	LLE	Isomap
K-nn		
ε-distance		

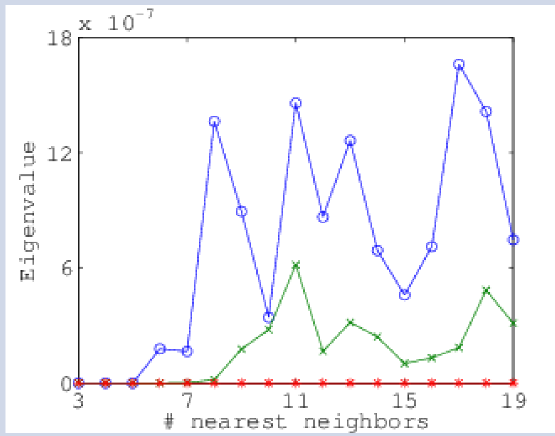
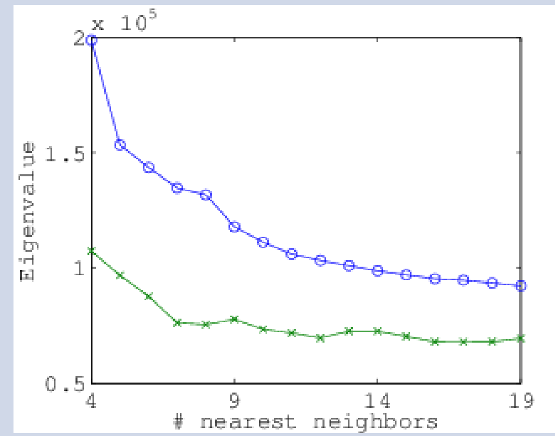
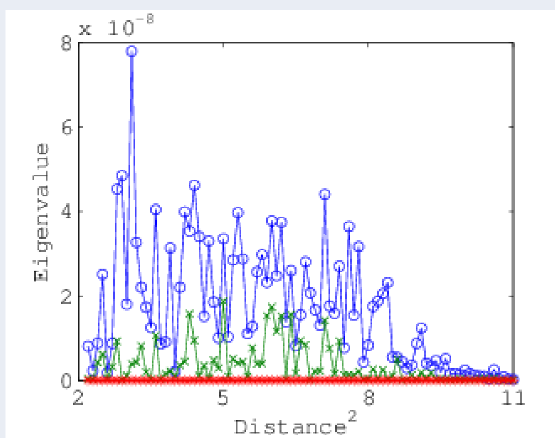
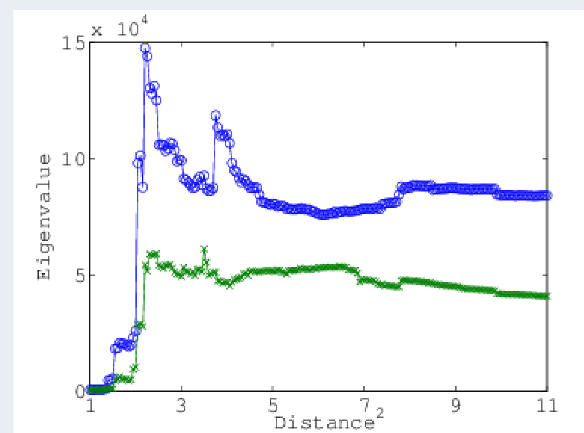
Eigenvalues Result for Dual Tube

	LLE	Isomap
K-nn		
ε-distance		

Eigenvalues Result for Knot

	LLE	Isomap
K-nn		
ε-distance		

Eigenvalues Result for Face dataset

	LLE	Isomap
K-nn		
ε-distance		

Discussion

- Comparison between k-nn and ε-distance.
- Difference between LLE and Isomap.
- From eigenvalues to embeddings.

New approaches after observations from eigenvalues:

1. Qualitative ensemble behaviors.
2. Recommend parameters of interest.

Thanks for your attention.