

Homework 8. Generalized LLE in Manifold Learning

Instructor: Yuan Yao

Due: Tuesday May 3, 2016

The problem below marked by * is optional with bonus credits.

1. *Manifold Learning*: The following codes by Todd Wittman contain major manifold learning algorithms talked on class.

`http://math.stanford.edu/~yuany/course/data/mani.m`

Precisely, eight algorithms are implemented in the codes: MDS, PCA, ISOMAP, LLE, Hessian Eigenmap, Laplacian Eigenmap, Diffusion Map, and LTSA. The following nine examples are given to compare these methods,

- (a) Swiss roll;
- (b) Swiss hole;
- (c) Corner Planes;
- (d) Punctured Sphere;
- (e) Twin Peaks;
- (f) 3D Clusters;
- (g) Toroidal Helix;
- (h) Gaussian;
- (i) Occluded Disks.

Run the codes for each of the nine examples, and analyze the phenomena you observed.

* Moreover if possible, make an implementation of Vector Diffusion Map (Laplacian) to reconstruct Swiss roll etc., and compare it against others. Note that LTSA looks for the following coordinates,

$$\min_Y \sum_{i \sim j} \|y_i - U_i U_j^T y_j\|^2$$

where U_i is a local PCA basis for tangent space at point $x_i \in \mathbb{R}^p$; in a contrast, vector connection Laplacian looks for:

$$\min_Y \sum_{i \sim j} \|y_i - O_{ij} y_j\|^2, \quad O_{ij} = \arg \min_O \|U_i - O_{ij} U_j\|^2$$

where O_{ij} is an isometry (parallel transportation) from the tangent space at point x_j to the tangent space at point x_i , whose solution is given by the lower eigenvectors of the following vector connection Laplacian

$$L_{ij} = \begin{cases} -w_{ij} O_{ij}, & i \neq j \\ \sum_j w_{ij} I, & i = j. \end{cases}$$

Here $w_{ij} = w_{ji}$ defines the similarity (neighborhood) between point x_i and x_j . For details, please refer to the paper by Amit Singer and Hau-Tieng Wu, *Vector diffusion maps and the connection laplacian*, Comm. Pure Appl. Math. 65 (2012), no. 8, 10671144. You may try Hau-Tieng Wu's matlab codes on VDM from the following website

<https://sites.google.com/site/hautiengwu/home/download>