APPLICATIONS OF GRAPH LAPLACEANS: Graph Embeddings, and Dimension Reduction

- **Graph Embeddings, vertex embeddings . The problem**
- **Use of Graph Laplaceans, Laplacean Eigenmaps**
- **Use of similarity graphs: Locally Linear Embeddings**
- **Explicit dimension reduction method: PCA**
- **Explicit graph-based dimension reduction method: LLP, ONPP.**

Graph embeddings

Vertex embedding: map every vertex x_i to a vector $y_i \in \mathbb{R}^d$

➤ Trivial use: visualize a graph ($d = 2$)

➤ Wish: mapping should preserve *similarities* in graph.

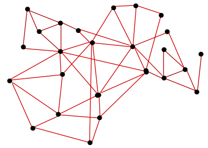
➤ Many applications [clustering, finding missing link, semi-supervised learning, community detection, ...]

➤ We will see two *nonlinear* classical methods: Eigenmaps, LLE ...

➤ ... and two linear (explicit) ones.

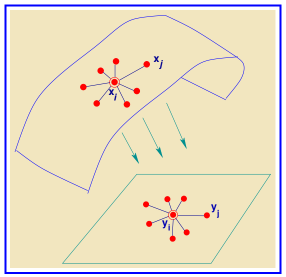
Given: a graph that models some data points $x_1, x_2, \cdots, x_n$ [simplest case: a kNN graph of $x_1, x_2, \cdots, x_n$]

Data: $X = [x_1, x_2, \cdots, x_n] \longrightarrow$ Graph:



➤ Graph captures similarities, closeness, ..., in data

Objective: Build a mapping of each vertex i to a data point $y_i \in \mathbb{R}^d$



➤ Many methods to do this. Eigenmaps is one of the best known

➤ Eigenmaps uses the *graph Laplacean*

➤ Recall: Graph Laplacean is a matrix defined by :

$$\boxed{L = D - W}$$

$$\begin{cases} w_{ij} \geq 0 \text{ if } j \in Adj(i) \\ w_{ij} = 0 \quad \text{else} \end{cases} \qquad D = \text{diag}\left[d_{ii} = \sum_{j \neq i} w_{ij} \right]$$

with $Adj(i)$ = neighborhood of i (excludes i)

➤ Remember that vertex i represents data item x_i. We will use i or x_i to refer to the vertex.

➤ We will find the y_i's by solving an optimization problem.

The Laplacean eigenmaps approach

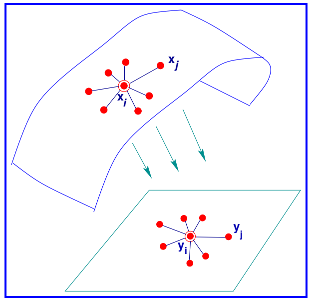
Laplacean Eigenmaps [Belkin-Niyogi '01] *minimizes*

$$\mathcal{F}(Y) = \sum_{i,j=1}^{n} w_{ij} \|y_i - y_j\|^2 \quad \text{subject to} \quad Y D Y^\top = I$$

Motivation: if $\|x_i - x_j\|$ is small (orig. data), we want $\|y_i - y_j\|$ to be also small (low-Dim. data)

➤ Original data used indirectly through its graph

➤ Objective function can be translated to a trace (see Property 3 in Lecture notes 9) and will yield a sparse eigenvalue problem



➤ Problem translates to:

$$\min_{\begin{cases} Y \in \mathbb{R}^{d\times n} \\ Y D\, Y^\top = I \end{cases}} \text{Tr}\left[Y(D-W)Y^\top \right] .$$

➤ Solution (sort eigenvalues increasingly):

$$(D - W)u_i = \lambda_i D u_i \ ; \quad y_i = u_i^\top; \quad i = 1, \cdots, d$$

➤ An $n \times n$ sparse eigenvalue problem [In 'sample' space]

➤ Note: can assume $D = I$. Amounts to rescaling data. Problem becomes

$$\boxed{(I - W)u_i = \lambda_i u_i \ ; \quad y_i = u_i^\top; \quad i = 1, \cdots, d}$$

Locally Linear Embedding (Roweis-Saul-00)

➤ LLE is very similar to Eigenmaps. Main differences:

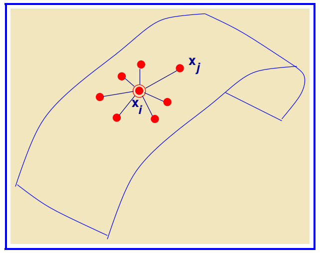
1) Graph Laplacean matrix is replaced by an 'affinity' graph

2) Objective function is changed: want to preserve graph

1. Graph: Each x_i is written as a convex combination of its k nearest neighbors:
$x_i \approx \Sigma w_{ij} x_j, \quad \sum_{j \in N_i} w_{ij} = 1$

➤ Optimal weights computed ('local calculation') by minimizing

$$\|x_i - \Sigma w_{ij} x_j\| \quad \text{for} \quad i = 1, \cdots, n$$



2. Mapping:

The y_i's should obey the same 'affinity' as x_i's $\rightsquigarrow$

Minimize:

$$\sum_i \left\| y_i - \sum_j w_{ij} y_j \right\|^2 \quad \text{subject to:} \quad Y \mathbb{1} = 0, \quad Y Y^\top = I$$

Solution:

$$\boxed{(I - W^\top)(I - W)u_i = \lambda_i u_i; \qquad y_i = u_i^\top .}$$

➤ $(I - W^\top)(I - W)$ replaces the graph Laplacean of eigenmaps

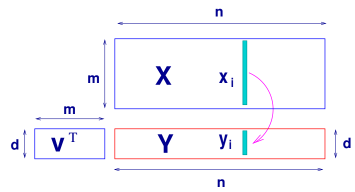
Implicit vs explicit mappings

➤ Background: Principal Component Analysis (PCA)

Dimension reduction via PCA: We are given a data set $X = [x_1, x_2, \ldots, x_n]$, and want a linear mapping from X to Y, expressed as:

$$\boxed{Y = V^\top X} \qquad X \in \mathbb{R}^{m\times n}; \quad V \in \mathbb{R}^{m\times d} \quad \to \quad Y \in \mathbb{R}^{d\times n}$$

➤ m-dimens. objects (x_i) 'flattened' to d-dimens. space (y_i)



➤ In PCA V is orthogonal ($V^TV = I$)

➤ In *Principal Component Analysis* $V \in \mathbb{R}^{m\times d}$ is computed to maximize variance of projected data:

$$\max_{V \;;\; V^\top V = I} \sum_{i=1}^{d} \left\| y_i - \frac{1}{n}\sum_{j=1}^{n} y_j \right\|_2^2, \quad y_i = V^\top x_i.$$

➤ Leads to maximizing

$$\text{Tr}\left[V^\top (X - \mu e^\top)(X - \mu e^\top)^\top V\right], \quad \mu = \tfrac{1}{n}\Sigma_{i=1}^{n} x_i$$

➤ Solution $V = \{$ dominant eigenvectors $\}$ of the covariance matrix

Explicit (linear) vs. Implicit (nonlinear) mappings:

➤ In PCA the mapping Φ from high-dimensional space ($\mathbb{R}^m$) to low-dimensional space ($\mathbb{R}^d$) is explicitly known:

$$y = \Phi(x) \equiv V^T x$$

➤ In Eigenmaps and LLE we only know

$$y_i = \phi(x_i), i = 1, \cdots, n$$

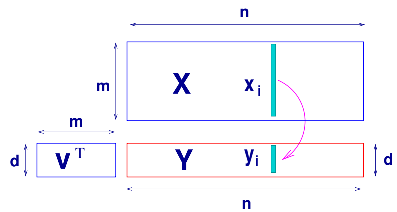
➤ Mapping ϕ is now implicit: Very difficult to compute $\phi(x)$ for an x that is not in the sample (i.e., not one of the x_i's)

➤ Inconvenient for classification. Thus is known as the "The out-of-sample extension" problem

Locally Preserving Projections (He-Niyogi-03)

➤ LPP is a linear dimensionality reduction technique

➤ Recall the setting:
Want $V \in \mathbb{R}^{m\times d}$; $Y = V^\top X$



➤ Starts with the same neighborhood graph as Eigenmaps: $L \equiv D - W$ = graph 'Laplacean'; with $D \equiv diag(\{\Sigma_i w_{ij}\})$.

➤ Optimization problem is to solve

$$\min_{Y \in \mathbb{R}^{d\times n},\ YDY^\top = I} \quad \Sigma_{i,j} w_{ij} \|y_i - y_j\|^2, \quad Y = V^\top X.$$

➤ Difference with eigenmaps: Y is an explicit projection of X

➤ Solution (sort eigenvalues increasingly)

$$XLX^\top v_i = \lambda_i XDX^\top v_i \quad y_{i,:} = v_i^\top X$$

➤ Note: essentially same method in [Koren-Carmel'04] called 'weighted PCA' [viewed from the angle of improving PCA]

ONPP (Kokiopoulou and YS '05)

➤ Orthogonal Neighborhood Preserving Projections

➤ A linear (orthogonoal) version of LLE obtained by writing Y in the form $Y = V^\top X$

➤ Same graph as LLE. Objective: preserve the affinity graph (as in LLE) *but* with the constraint $Y = V^\top X$

➤ Problem solved to obtain mapping:

$$\min_V \mathrm{Tr}\left[V^\top X(I - W^\top)(I - W)X^\top V\right]$$
s.t. $V^T V = I$

➤ In LLE replace $V^\top X$ by Y

More recent methods

➤ Quite a bit of recent work - e.g., methods: node2vec, DeepWalk, GraRep, ...

See the following papers:

[1] *William L. Hamilton, Rex Ying, and Jure Leskovec* *Representation Learning on Graphs: Methods and Applications* arXiv:1709.05584v3

[2] *Shaosheng Cao, Wei Lu, and Qiongkai Xu* *GraRep: Learning Graph Representations with Global Structural Information*, CIKM, ACM Conference on Information and Knowledge Management, 24

[3] *Amr Ahmed, Nino Shervashidze, and Shravan Narayanamurthy*, *Distributed Large-scale Natural Graph Factorization* [Proc. WWW 2013, May 1317, 2013, Rio de Janeiro, Brazil]

... among many others