Semi-Supervised Locally Linear Embedding (SSLLE)

Application & Sensitivity Analysis of Critical Hyperparameters

0 AGENDA

MANIFOLD LEARNING

Situation. Rapidly increasing amount of data thanks to novel applications and data sources

Problem. High data dimensionality detrimental to

→ Model functionality

→ Interpretability

→ Generalization ability

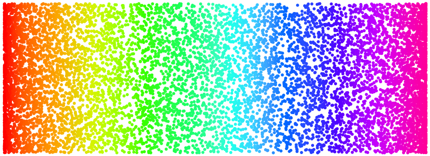
Manifold assumption. Data in high-dimensional observation space truly sampled from low-dimensional manifold

How to find a meaningful, structure-preserving embedding?

Formal goal of manifold learning.

→ **Given.** Data $\mathcal{X} = (\boldsymbol{x}_1, \boldsymbol{x}_2, ..., \boldsymbol{x}_N)$, with $\boldsymbol{x}_i \in \mathbb{R}^D \; \forall i \in \{1, 2, ..., N\}$ and $N, D \in \mathbb{N}$, supposedly lying on d-dimensional manifold $\mathcal{M}$
$\Rightarrow \psi : \mathcal{M} \rightarrow \mathbb{R}^d$ with $d \ll D, d \in \mathbb{N}$
$\Rightarrow \mathcal{X} \sim \mathcal{M} \subset \mathbb{R}^D$

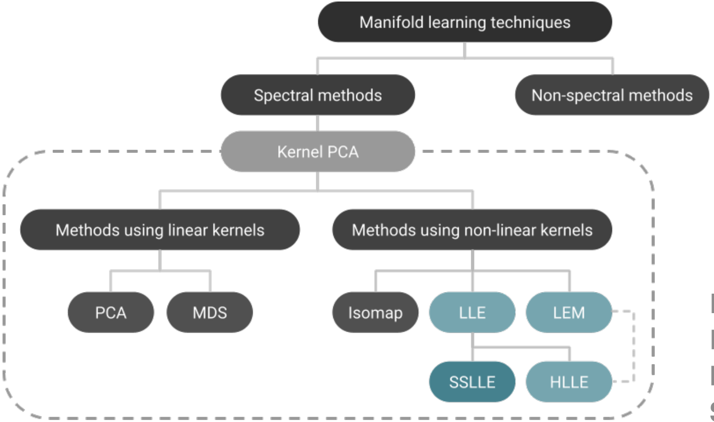
→ **Goal.** Find d-dimensional Euclidean representation
$\Rightarrow \mathcal{Y} = (\boldsymbol{y}_1, \boldsymbol{y}_2, ..., \boldsymbol{y}_N)$, with $\boldsymbol{y}_i = \psi(\boldsymbol{x}_i) \in \mathbb{R}^d \; \forall i \in \{1, 2, ..., N\}$.



2 LGML

TAXONOMY

Landscape. Various approaches, many of which may be translated into one another



LEM Laplacian eigenmaps
LLE Locally linear embedding
HLLE Hessian LLE
SSLLE Semi-supervised LLE

2 LGML CONCEPT

Idea. Capture intrinsic geometry, find principal axes of variability, retain most salient ones

Kernel PCA	LGML concept	LGML algorithm
Kernelization	Graph representation	Neighborhood construction
	Graph functional	Matrix representation
Eigenanalysis	Eigenanalysis	Eigenanalysis
Dimensionality reduction	Dimensionality reduction	Dimensionality reduction

CONCEPT

Graph representation. Construct skeletal model of the manifold in $\mathbb{R}^D$

Vertices. Given by observations
Edges. Present between neighboring points

- $\rightarrow$ Typically, *k*-neighborhoods
- $\rightarrow$ Edge weights determined by nearness

Graph functional. Belief about intrinsic manifold properties at the heart of each method

- $\rightarrow$ Local linearity LLE SSLLE
- $\rightarrow$ Smoothness LEM
- $\rightarrow$ Curvature HLLE
- $\rightarrow$ ...

3 TECHNIQUES

LLE

woteva

SSLLE

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NEIGHBORHOOD RELATIONS

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4 SENSITIVITY ANALYSIS

4.1 SETUP SCENARIOS

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EVALUATION

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FOO

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5 DISCUSSION

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REFERENCES

G. Randauthor (2021): Most Relevant Shit, THE Journal, frontpage (what else)