

# 高维数据中低维结构的可视探索

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LDSScanner: Exploratory Analysis of Low-Dimensional Structures in High-Dimensional Datasets

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<sup>1</sup>Central South University

<sup>2</sup>ZheJiang University

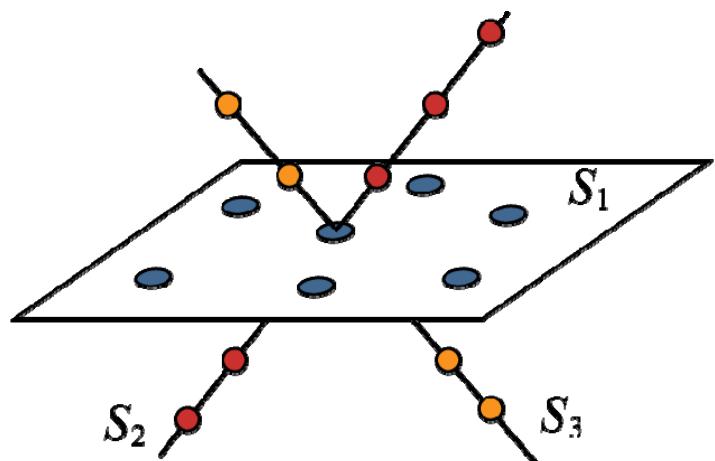
<sup>3</sup>Zhejiang University of Finance & Economics

<sup>4</sup>National University of Singapore

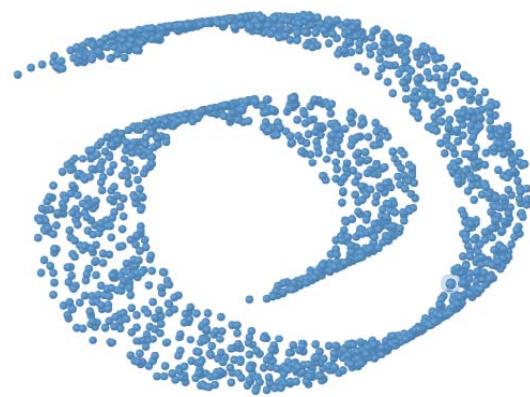
# 高维数据

- 通常指高维(Multidimensional)多元(Multivariate)数据
  - Multidimensional : 数据具有多个独立属性
  - Multivariate : 数据具有多个相关属性
- 可视分析中的定义
  - 维度太高，以致难以从中提取可理解的维度关联信息
  - 一般来说，高于10维的数据可称为高维数据
    - E. Bertini, A. Tatu, D. Keim. Quality Metrics in High-Dimensional Data Visualization: An overview and Systematization. IEEE Transactions on Visualization and Computer Graphics, 2011, 17(12): 2203-2212

# 高维数据中的低维结构



A dataset with three clusters, in a 2D **subspace**, and two 1-D **subspaces**, respectively.



Swiss roll in a 2D **manifold** embedded in 3D space.

# Motivation : 探索潜在的低维结构

- 给定一个未知的高维数据，如何探索其中潜在的低维结构？

HD dataset



# 降维/聚类 三个阶段中的可视化

Stage	Methods
Post-processing	Automatic models & Conventional Visualization
Intra-processing	Interactive subspace analysis
Pre-processing	

# 自动化降维/聚类方法

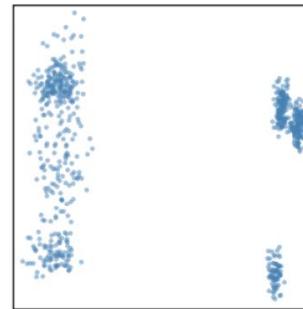
Number of Subspaces / Manifolds	Linear	Non-linear
Single	Linear DR	Manifold Learning
Multiple	Subspace Clustering	Manifold Clustering

# 如何选择模型？

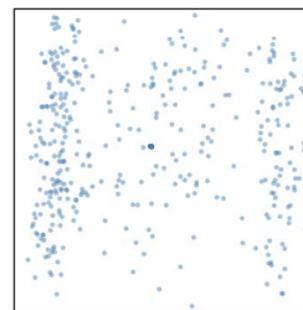
HD  
dataset



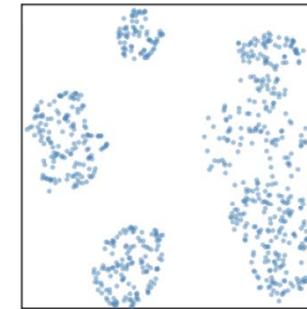
PCA



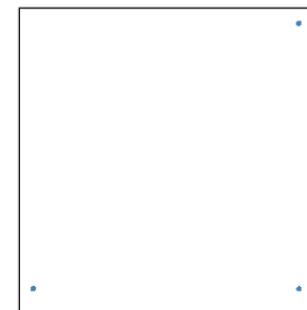
ISOMAP



t-SNE



LLE



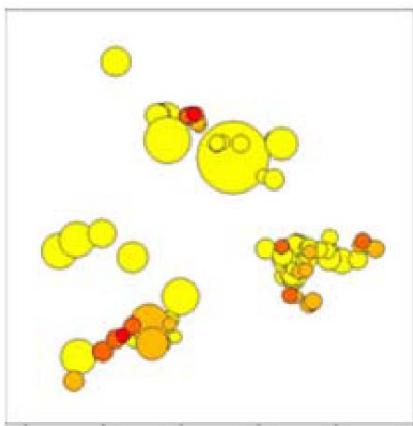
# 自动化降维/聚类方法

Number of Subspaces / Manifolds	Linear	Non-linear
Single	Linear DR	Manifold Learning
Multiple	<b>Subspace Clustering</b>	<b>Manifold Clustering</b>

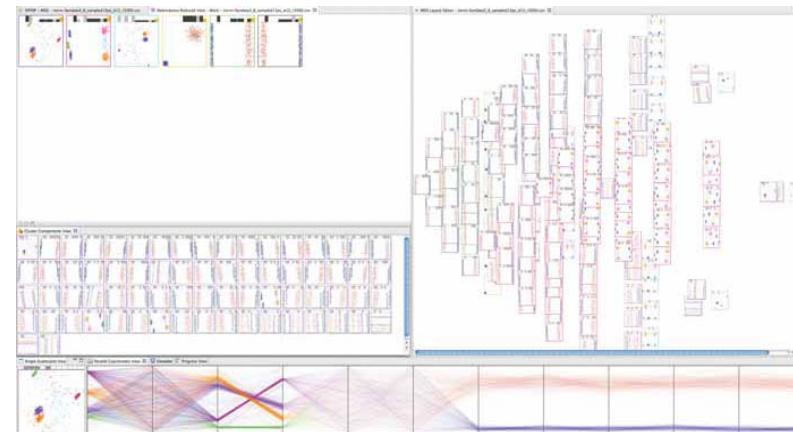
# 子空间聚类&流形聚类

- 需要输入先验信息/满足先验假设
  - 聚类个数
  - 本真维度
  - 聚类分布
- 可能产生大量冗余的结果
  - 难以理解
  - 难以解释

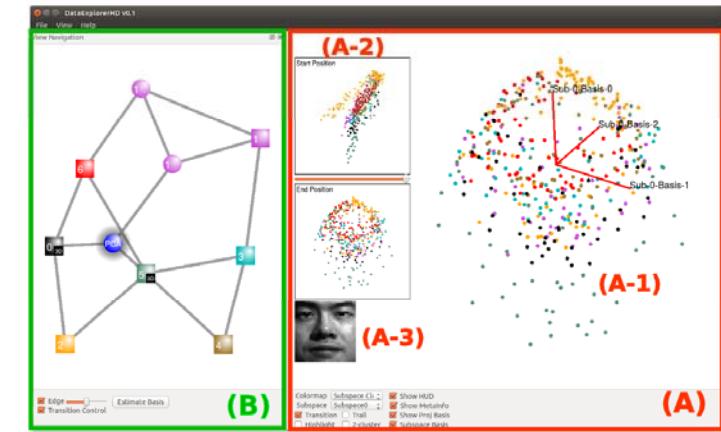
# 子空间聚类+可视化



I. Assent, et al. Visa:  
Visual subspace  
clustering analysis.  
SIGKDD, 2007.

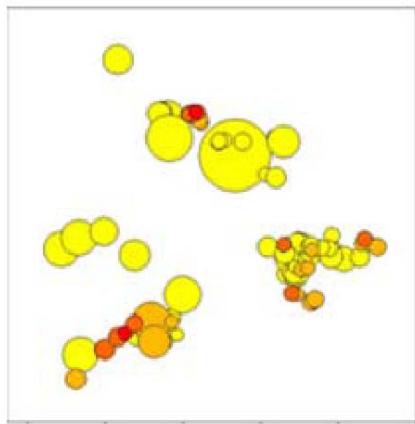


A. Tatu, et al. Subspace search and  
visualization to make sense of  
alternative clusterings in high-  
dimensional data. IEEE VAST, 2012.

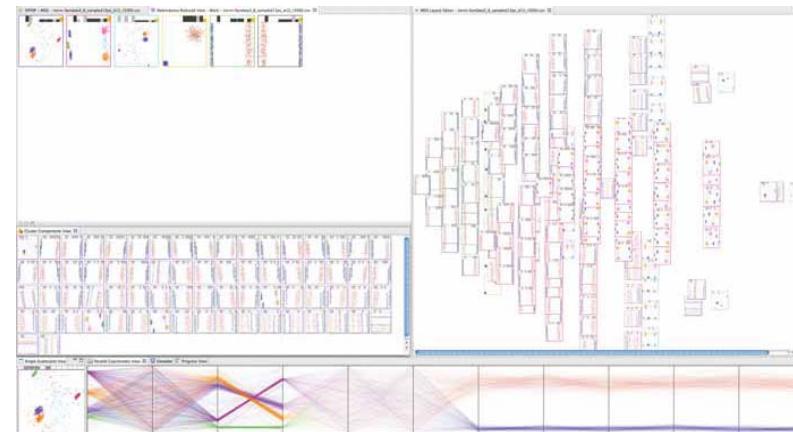


S. Liu, et al. Visual exploration of high-  
dimensional data through subspace  
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EuroVis, 2015.

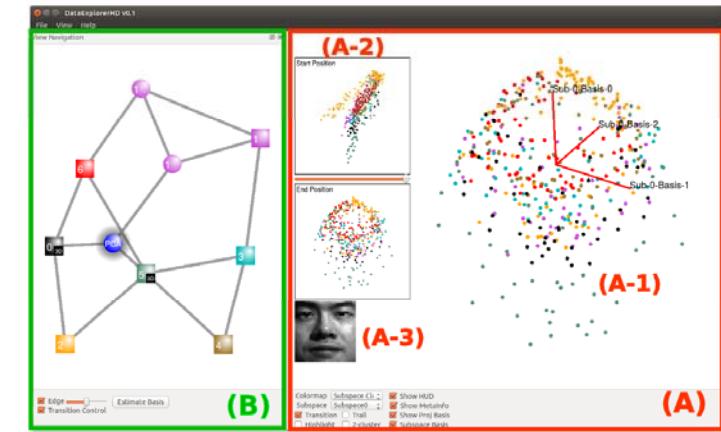
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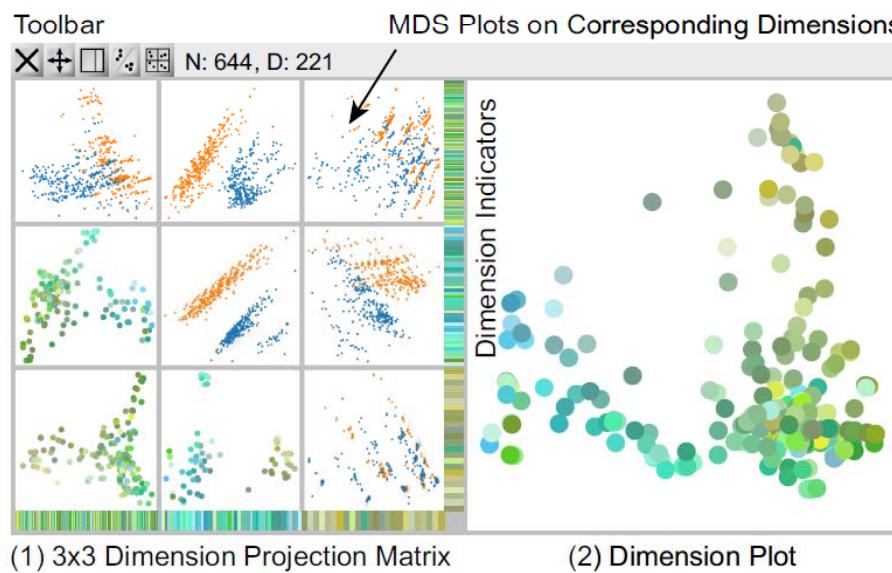
S. Liu, et al. Visual exploration of high-  
dimensional data through subspace  
analysis and dynamic projections.  
EuroVis, 2015.

仅仅对降维/聚类结果的结构进行分析，难以验证结果的正确性

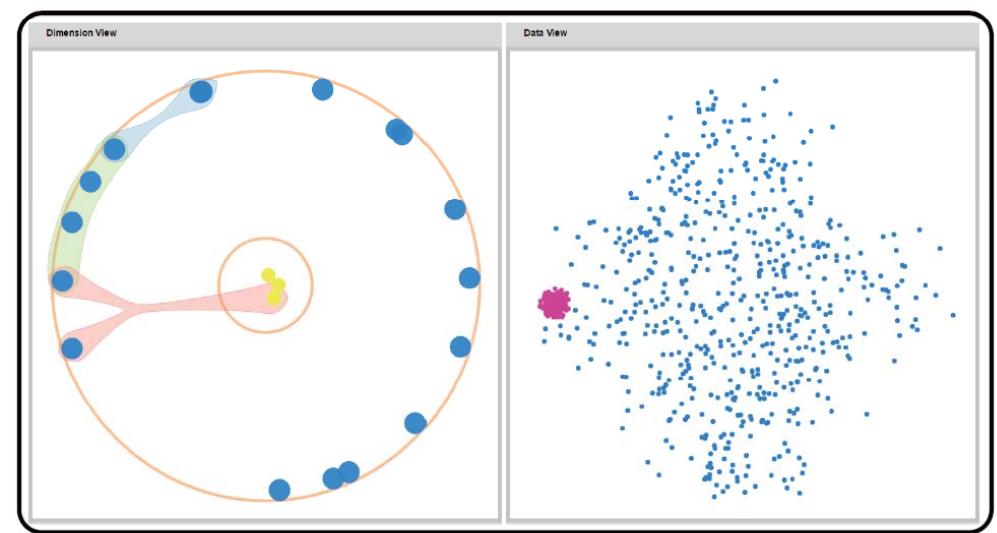
# 降维/聚类 三个阶段中的可视化

Stage	Methods	Limitation
Post-processing	Automatic models & Conventional Visualization	Blind model-choosing
Intra-processing	<b>Subspace exploration</b>	
Pre-processing		

# 子空间可视探索

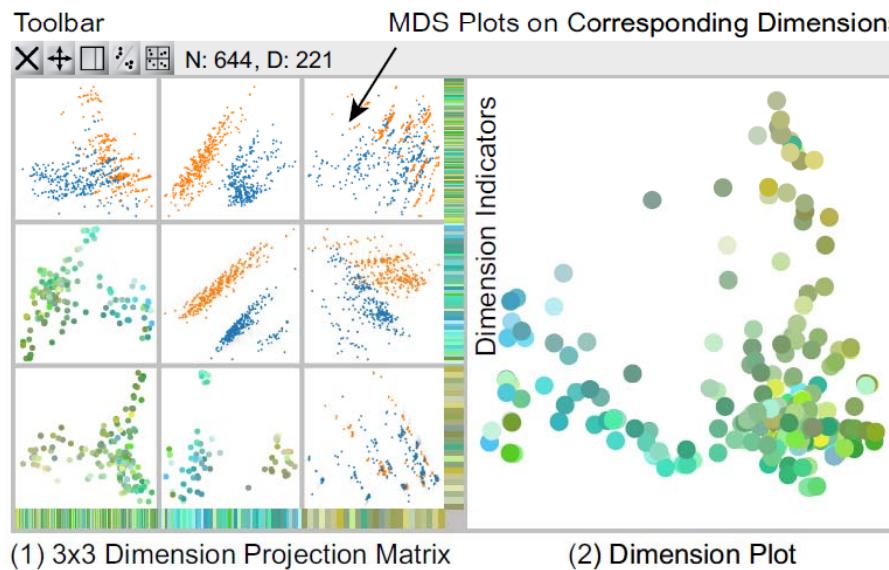


X. Yuan, et al. Dimension projection matrix/tree: Interactive subspace visual exploration and analysis of high dimensional data. IEEE TVCG. 2013.

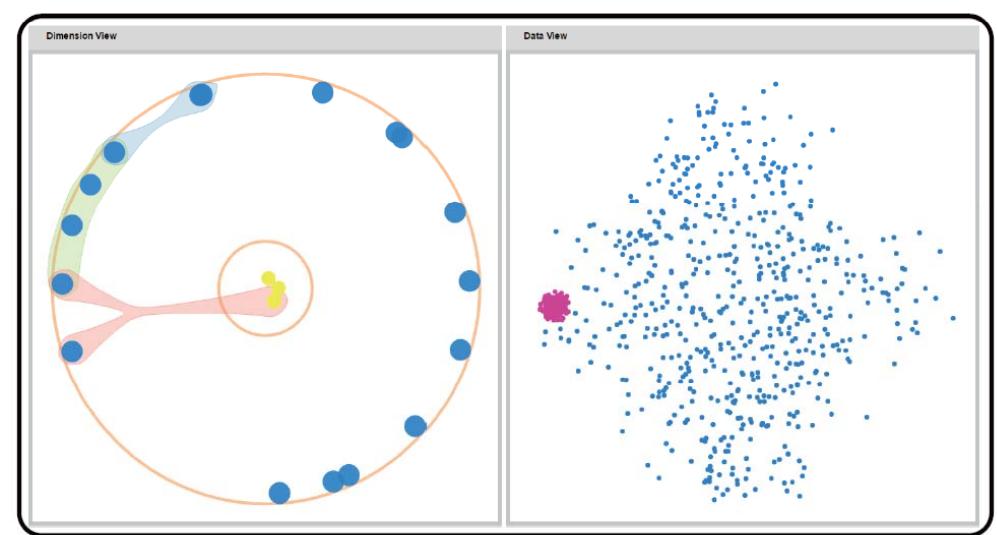


# 子空间可视探索

缺乏引导，冗长的试错循环



X. Yuan, et al. Dimension projection matrix/tree: Interactive subspace visual exploration and analysis of high dimensional data. IEEE TVCG. 2013.



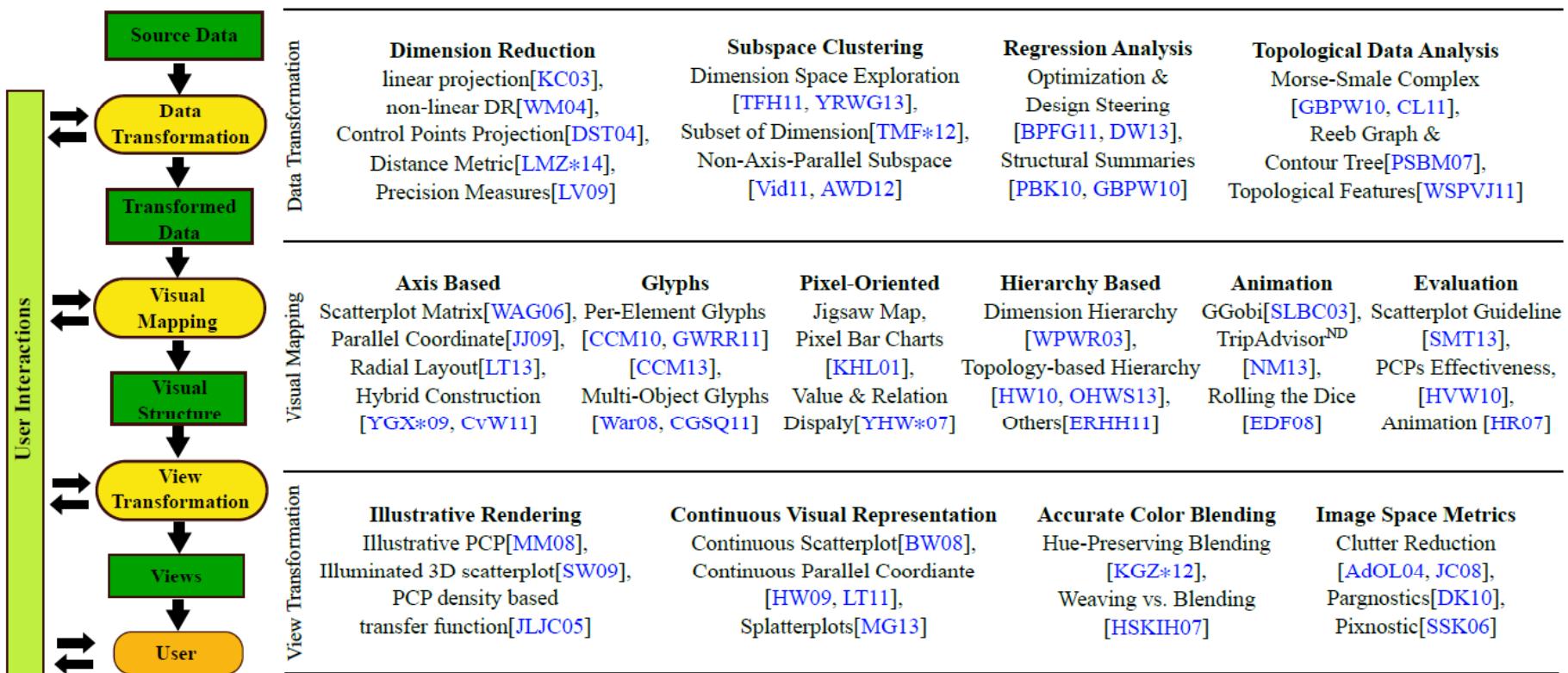
J. Xia, et al. Visual subspace clustering based on dimension relevance. JVLC. 2017

在建模之前，能否对数据进行预审察，  
探索其潜在的低维结构？

# 降维/聚类 三个阶段中的可视化

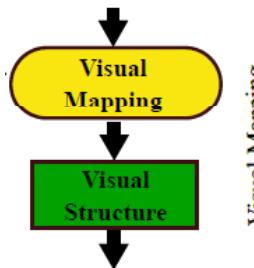
Stage	Methods	Limitation
Post-processing	Automatic models & Conventional Visualization	Blind model-choosing
Intra-processing	Subspace exploration	Trail-and-error
Pre-processing	<b>Exploratory Analysis ?</b>	

# 高维数据可视化技术分类

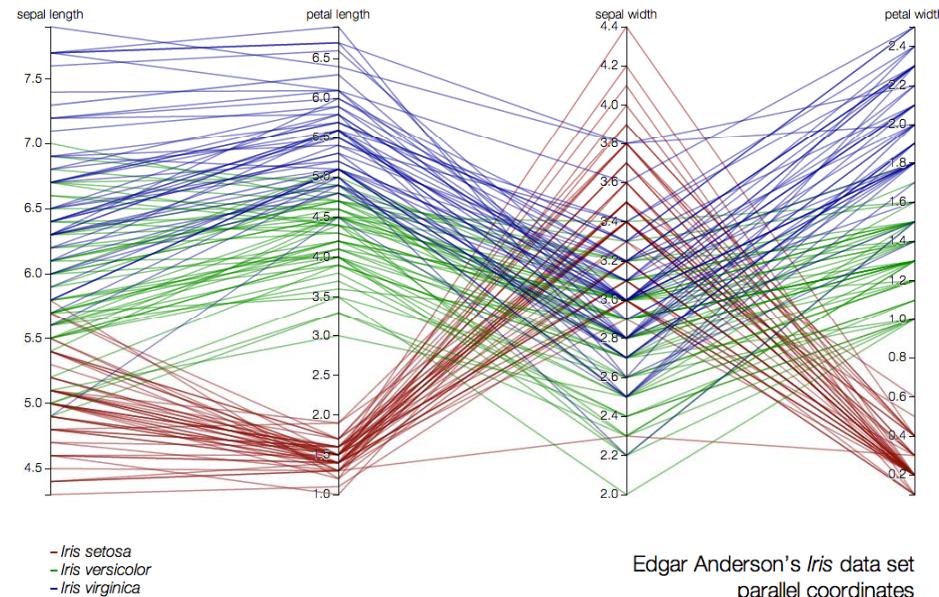
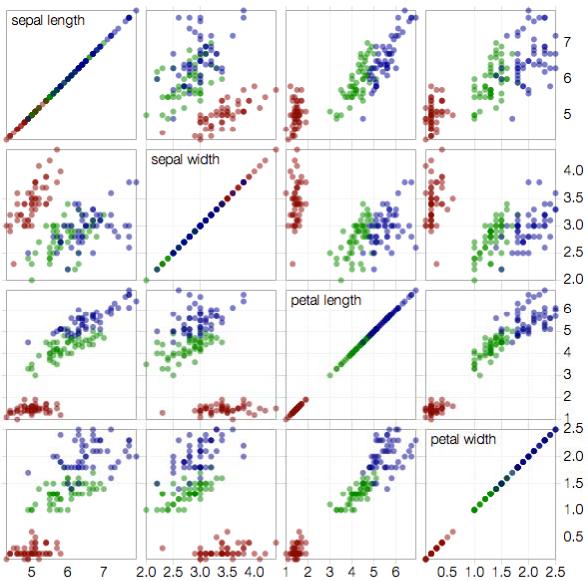


-Shusen Liu, Dan Maljovec, Bei Wang, Peer-Timo Bremer, and Valerio Pascucci. Visualizing High-Dimensional Data: Advances in the Past Decade. *IEEE Transactions on Visualization and Computer Graphics* 23(3), 1249-1268, 2017.

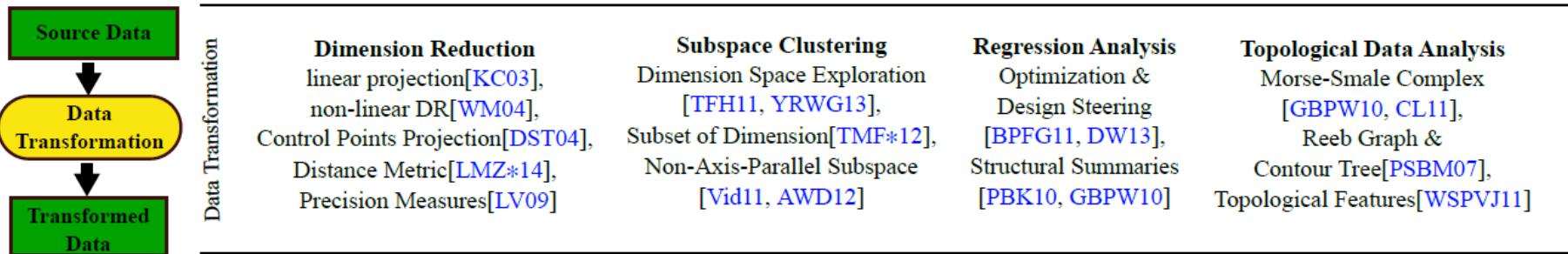
# Visual Mapping



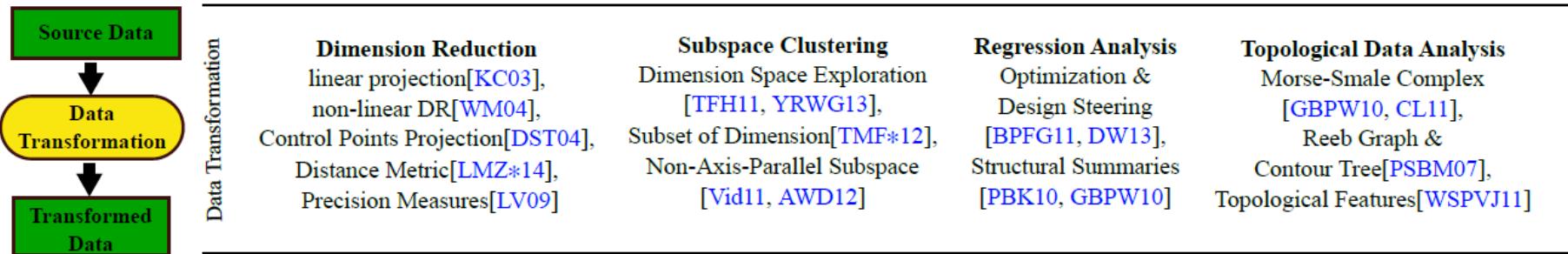
	Axis Based	Glyphs	Pixel-Oriented	Hierarchy Based	Animation	Evaluation
Visual Mapping	<ul style="list-style-type: none"> <li>Scatterplot Matrix [WAG06]</li> <li>Parallel Coordinate [JJ09]</li> <li>Radial Layout [LT13]</li> <li>Hybrid Construction [YGX*09, CvW11]</li> </ul>	<ul style="list-style-type: none"> <li>Per-Element Glyphs [CCM10, GWRR11]</li> <li>[CCM13]</li> <li>Multi-Object Glyphs [War08, CGSQ11]</li> </ul>	<ul style="list-style-type: none"> <li>Jigsaw Map, Pixel Bar Charts [KHL01]</li> <li>Value &amp; Relation Dispaly [YHW*07]</li> </ul>	<ul style="list-style-type: none"> <li>Dimension Hierarchy [WPWR03]</li> <li>Topology-based Hierarchy [HW10, OHWS13]</li> <li>Others [ERHH11]</li> </ul>	<ul style="list-style-type: none"> <li>GGobi [SLBC03]</li> <li>TripAdvisor<sup>ND</sup> [NM13]</li> <li>Rolling the Dice [EDF08]</li> </ul>	<ul style="list-style-type: none"> <li>Scatterplot Guideline [SMT13]</li> <li>PCPs Effectiveness, [HVW10]</li> <li>Animation [HR07]</li> </ul>



# Data Transformation



# Data Transformation



可视分析设计由任务驱动

# 分析目标

- 探索潜在的低维结构
- 为选择/使用/调整 自动化模型提供信息

# Overview

## Analysis Tasks

T1: NO. of clusters

T2: Linear or Non-linear

T3: Intrinsic dimensionality

T4: Distribution

T5: Locality Assumption

## Data/Feature Abstraction

Partition

Geodesic distance

Local tangent space

LTS Diversity

k-neighborhood locality

## Visual Design

LTSD-GD View

T-SNE View

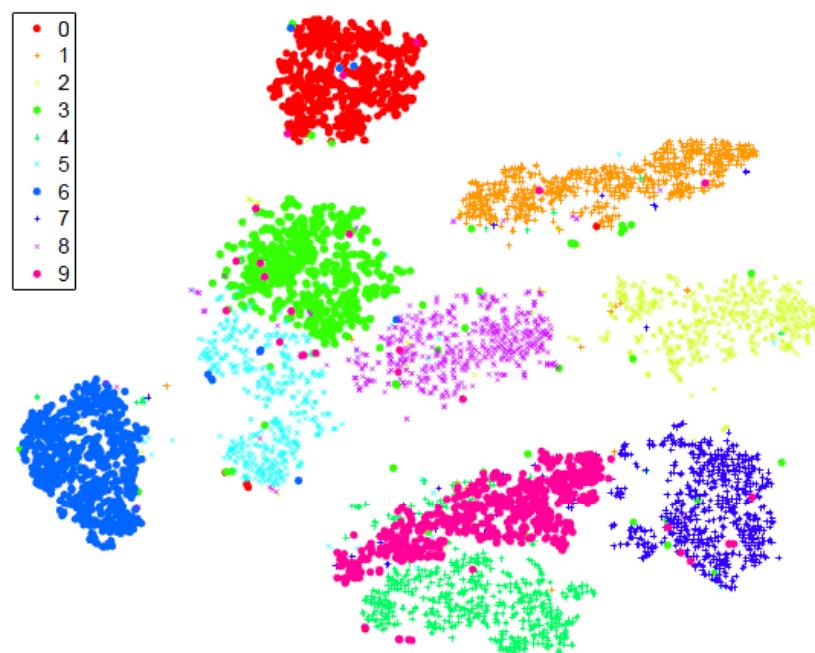
Est. Local dimensionality

Scree plot of point-wise LTSs

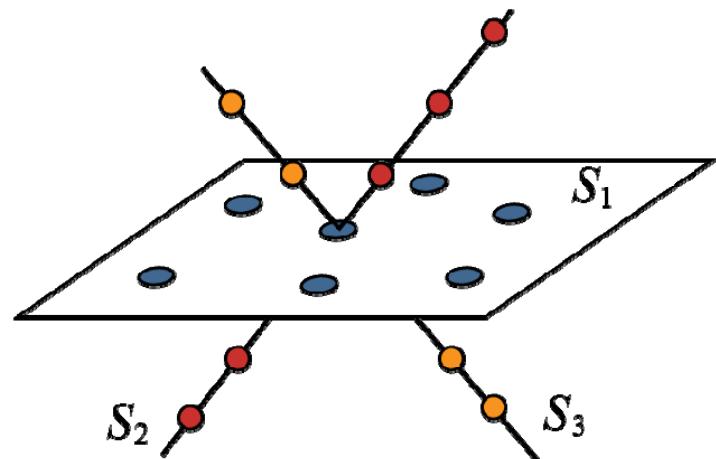
Scree plot of structures

Identified structures view

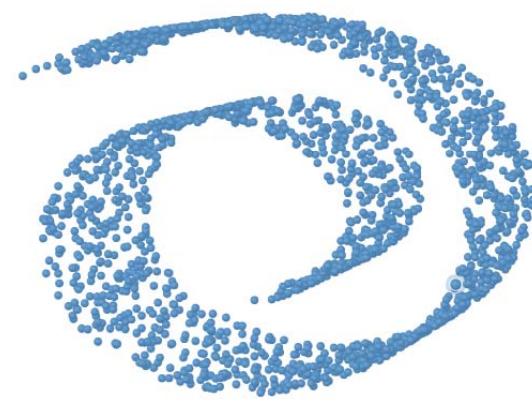
# 分析任务一：低维结构（聚类）的个数



## 分析任务二：低维结构是线性还是非线性？



线性子空间



流形

## 分析任务三：低维结构的本真维度

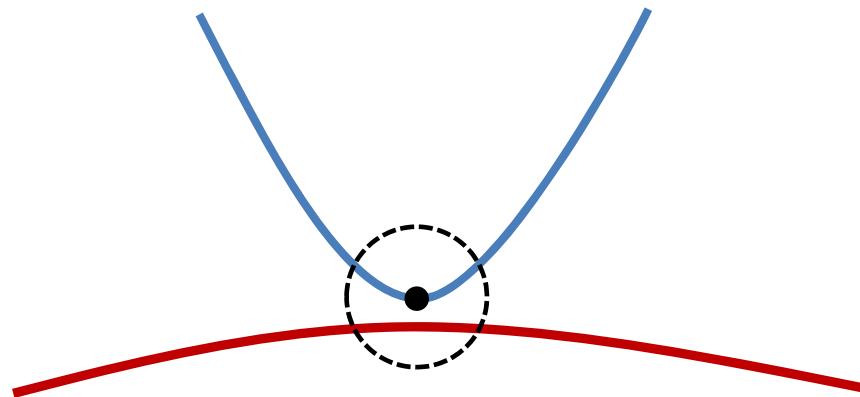
- 大量的子空间聚类/流形聚类方法需要本真维度作为算法的输入
- 先验信息？试错？

## 分析任务四：低维结构的分布情况

- 低维结构之间的距离
- 低维结构所在空间之间的距离
- 低维结构之间是否交叉

# 分析任务五：局部性假设是否成立

- 局部性假设：流形上一点，与其邻域内所有的点都位于同一个流形上

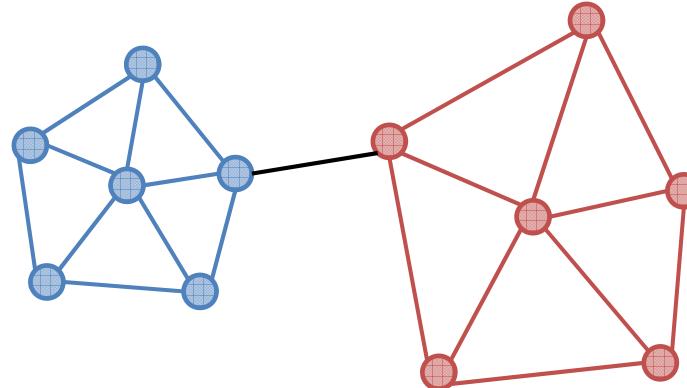


# 低维结构的表达

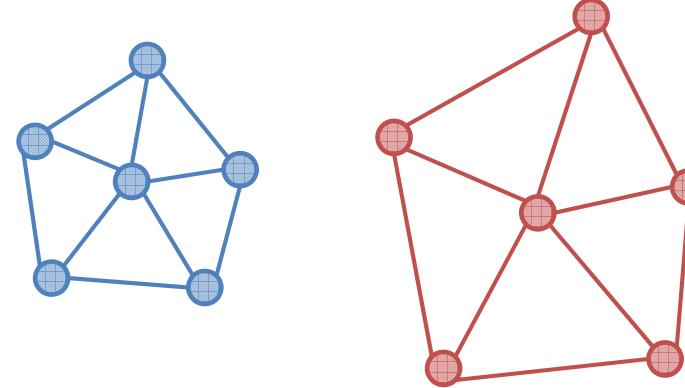
- 子空间
  - 基于线性系统的表达
- 流形
  - 邻域图（来自流形学习方法）
- 给定一个未知数据集
  - 需要一个统一的表达
  - 邻接图

# 特征提取: 分割

- Shared Nearest Neighbors (SNN) graph

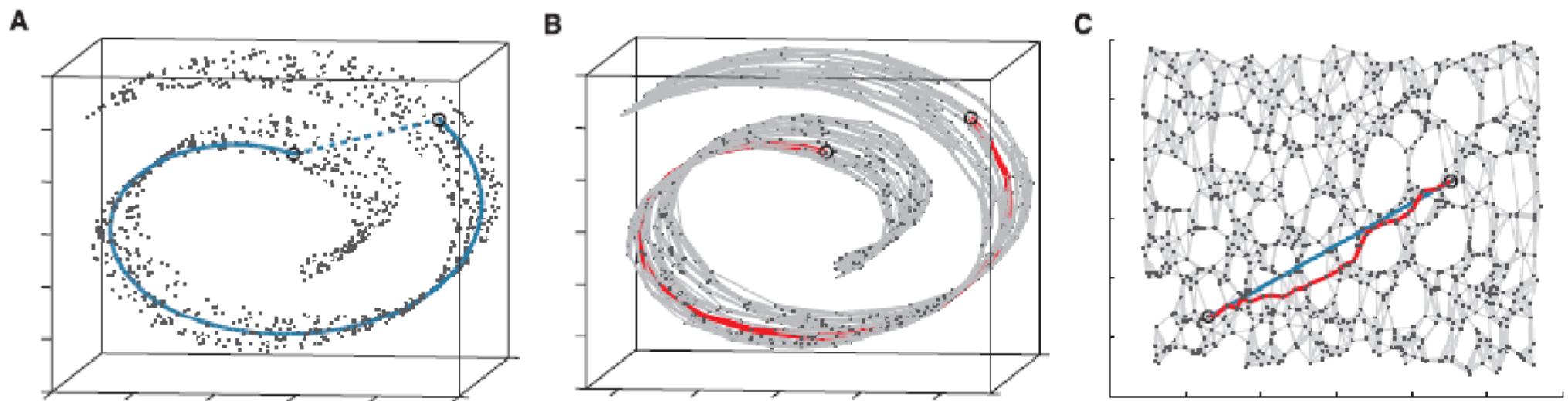


k-NN



SNN

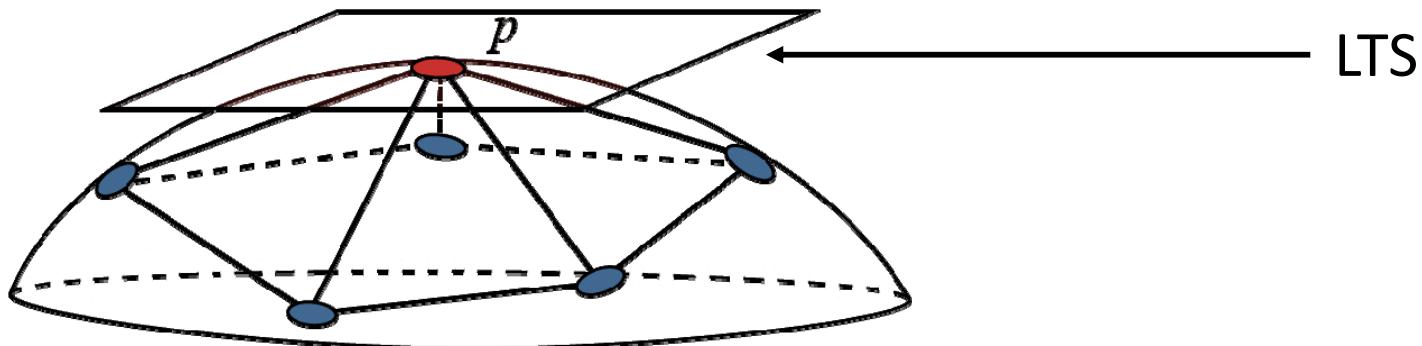
# 特征提取: 测地距离



-Joshua B. Tenenbaum, et al. A Global Geometric Framework for Nonlinear Dimensionality Reduction. Science. 2000.

# 特征提取: Local Tangent Space (LTS)

- Locality assumption: for each point, there is a small neighborhood, which contains only points of the same manifold

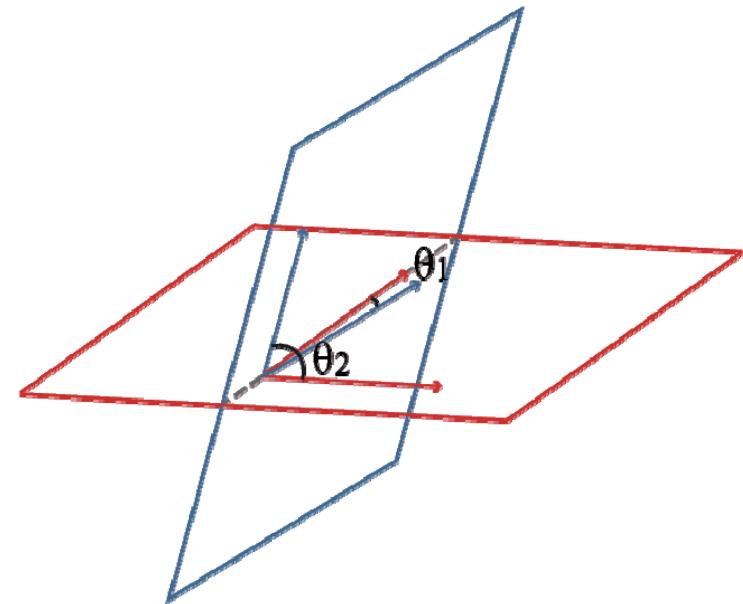


- The local tangent space is fit by  $k$ -nearest neighbors (SVD)

# 特征提取: Local Tangent Space Divergence (LTSD)

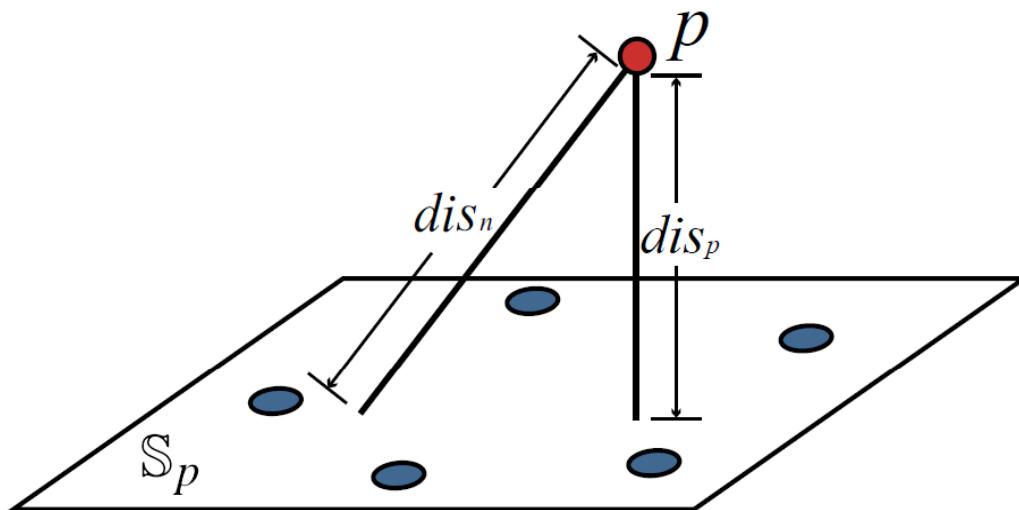
- A divergence measurement between two subspaces
- It is defined by the principal angles between two subspaces

$$1 - \sqrt{\frac{\cos^2 \theta^{(1)} + \dots + \cos^2 \theta^{(d_p \wedge d_q)}}{d_p \wedge d_q}}$$

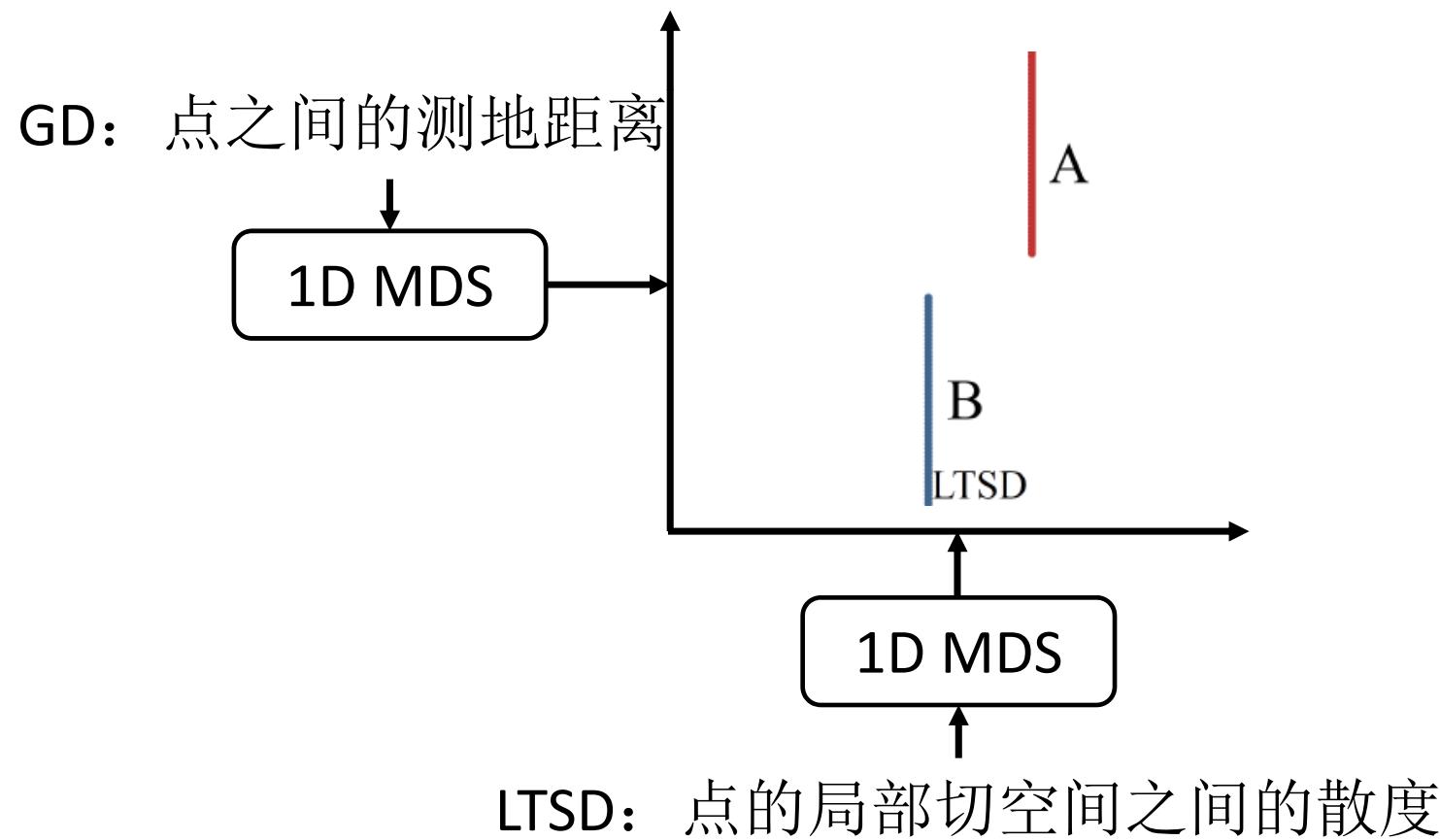


# 特征提取：局部性估计

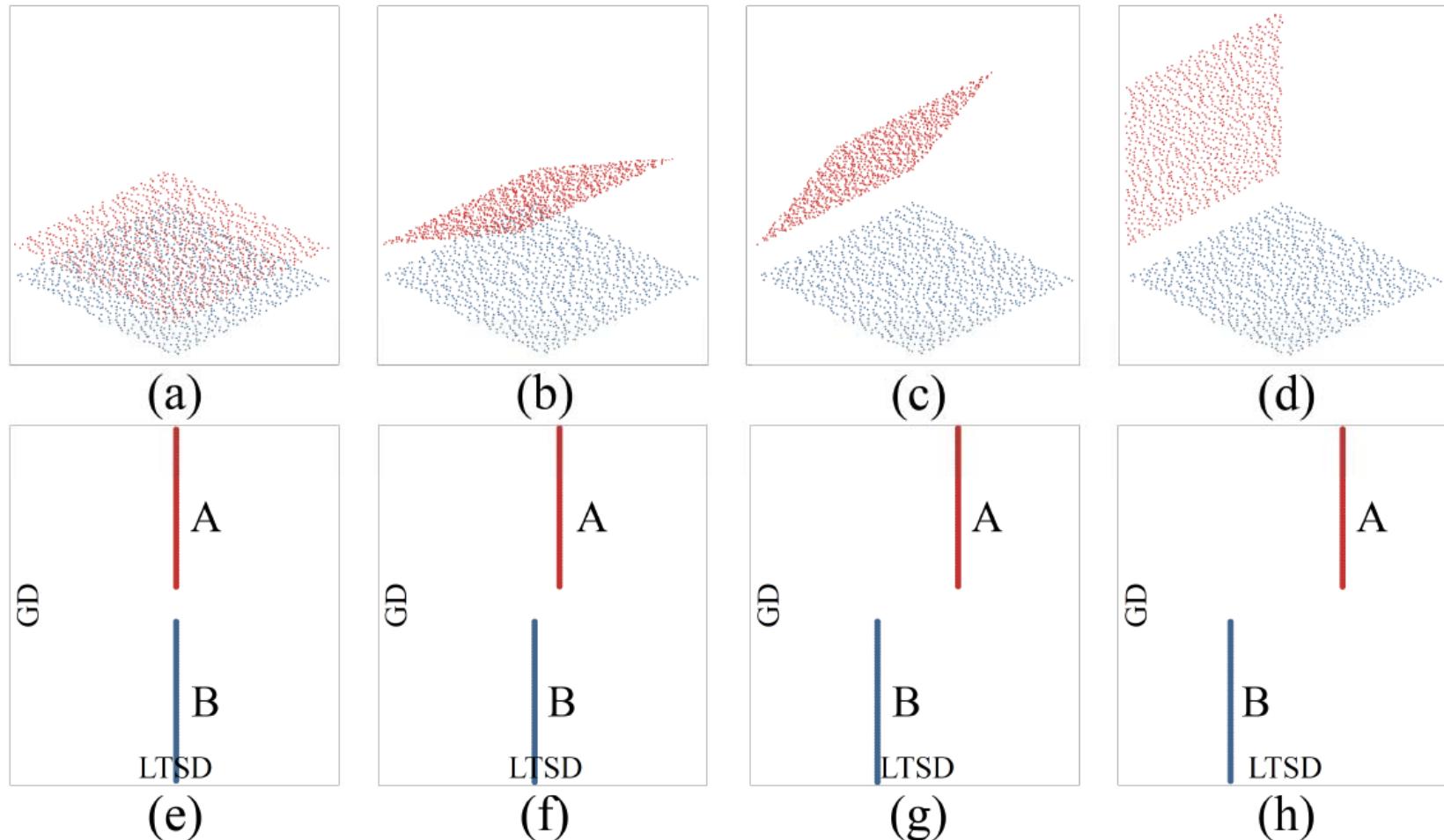
- k-neighborhood locality
  - The locality assumption may not hold due to noise and complicated structure, e.g. intersection.



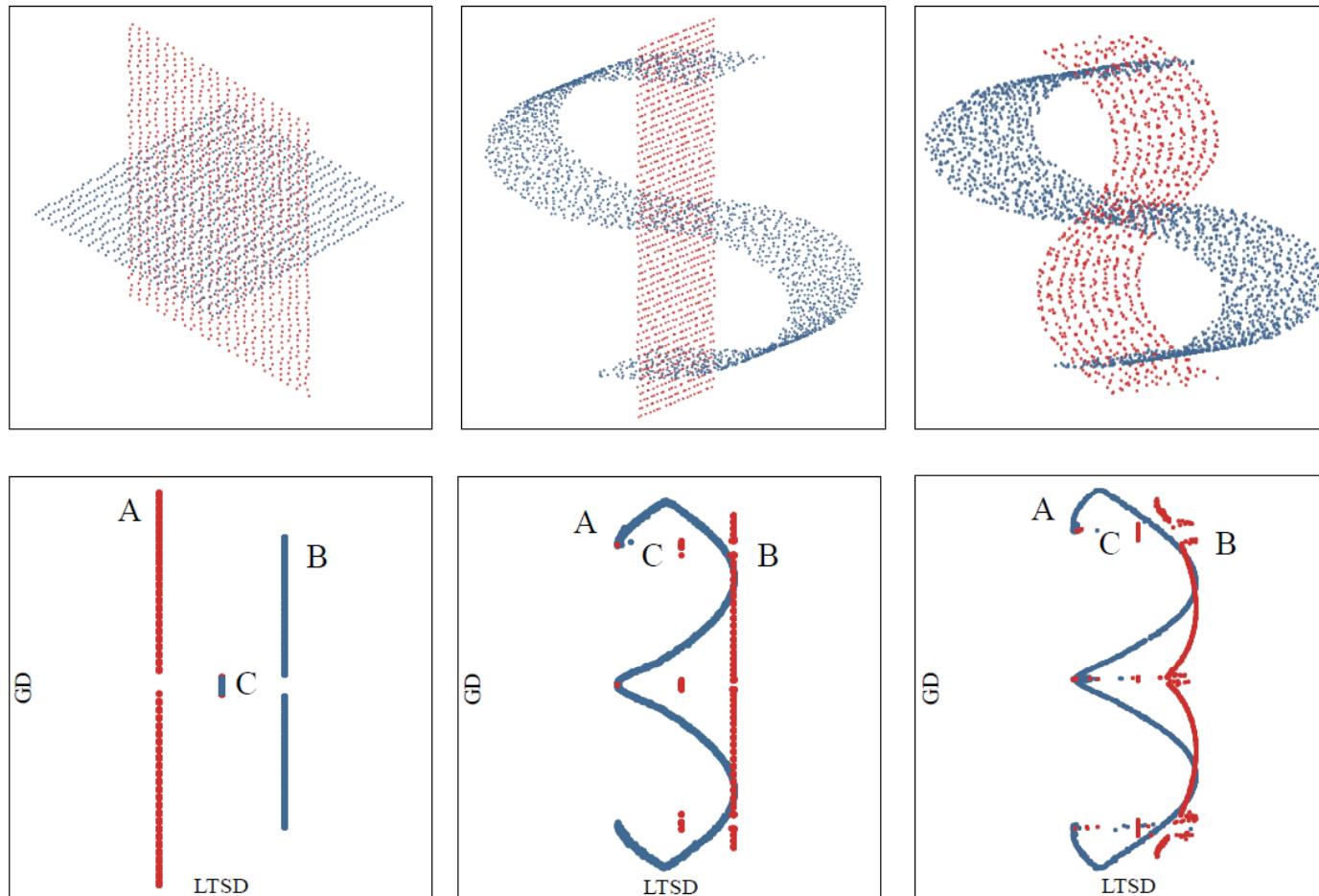
# The LTSD-GD view



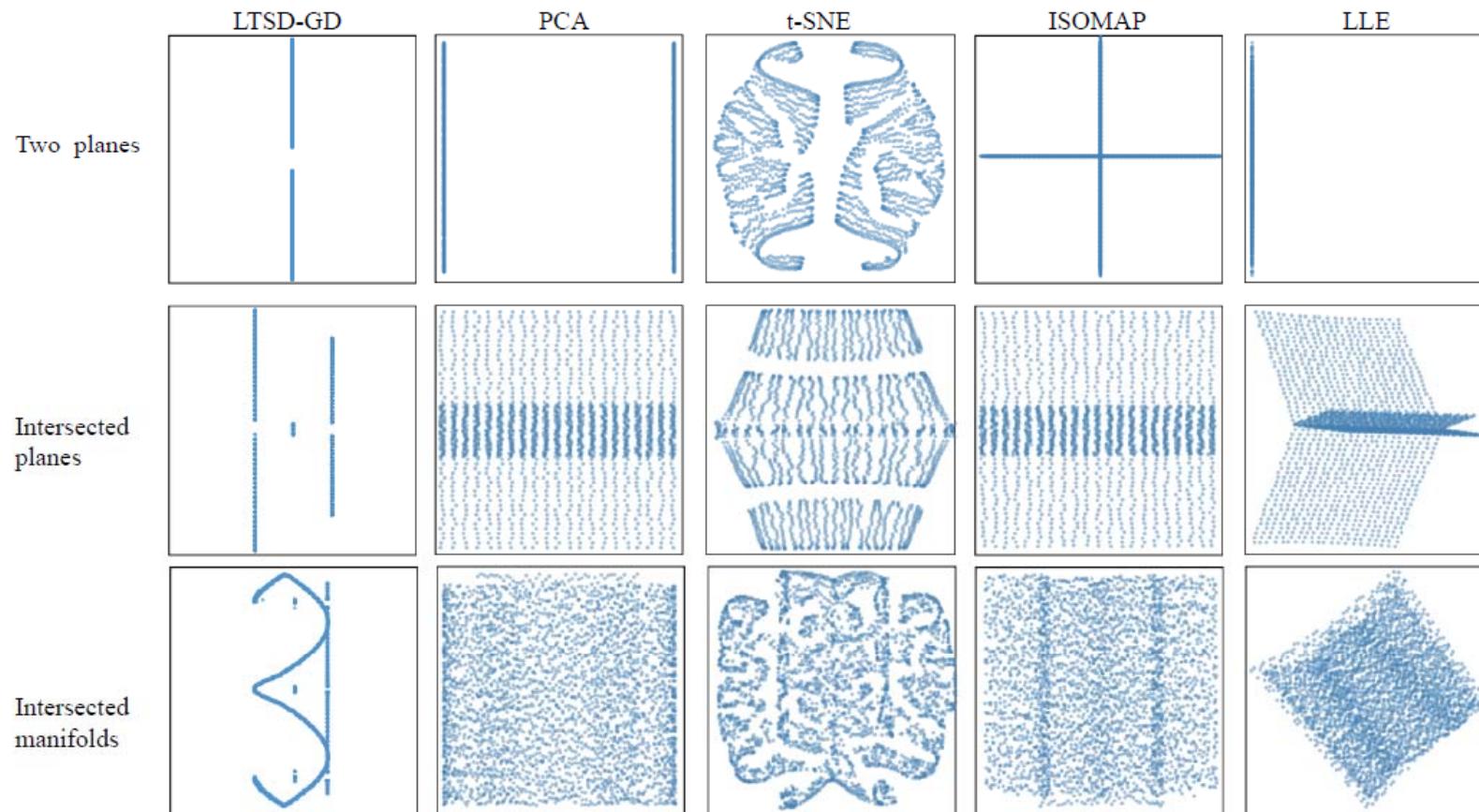
# LTSD-GD 视图：两个子空间



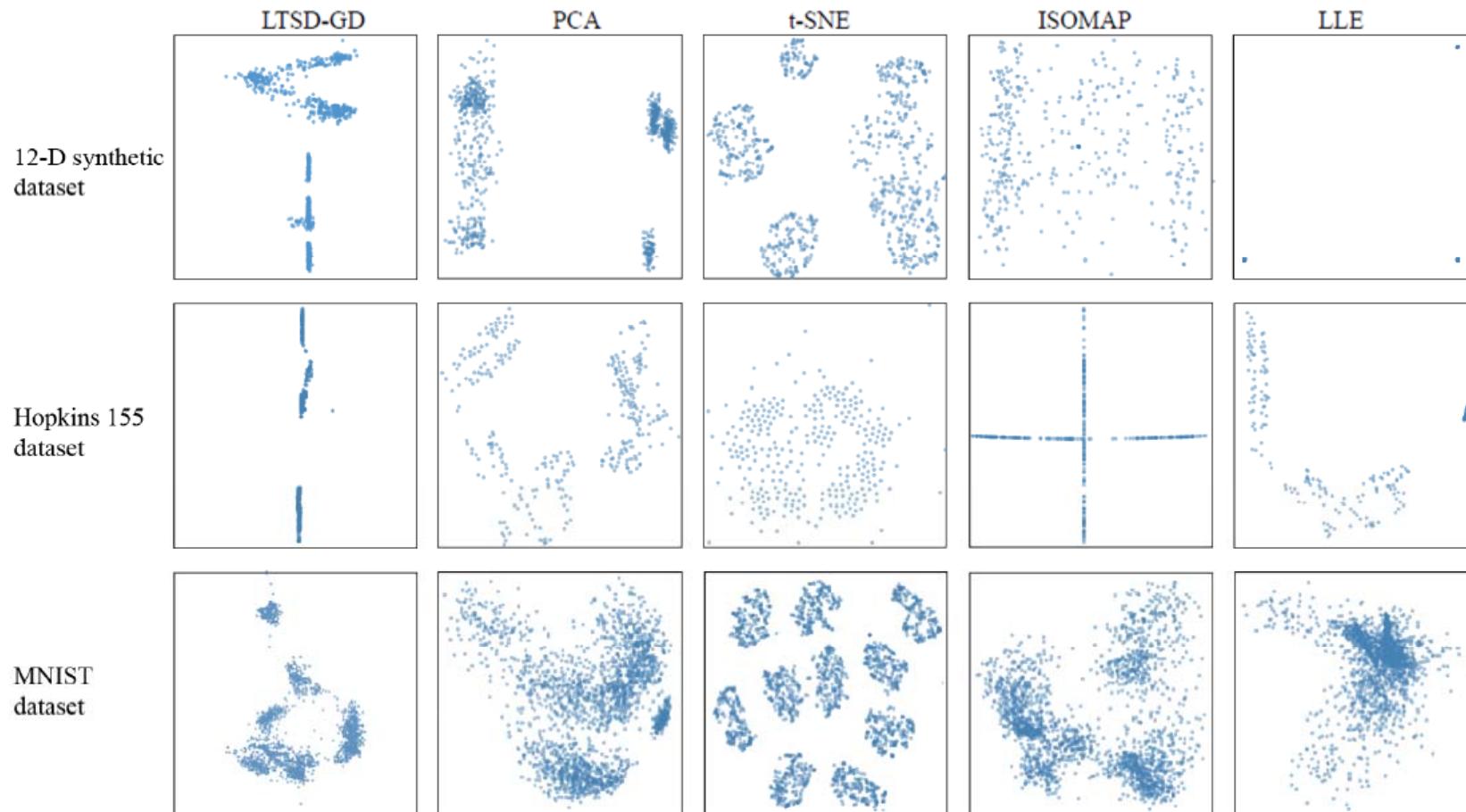
# LTSD-GD 视图：两个相交的流形



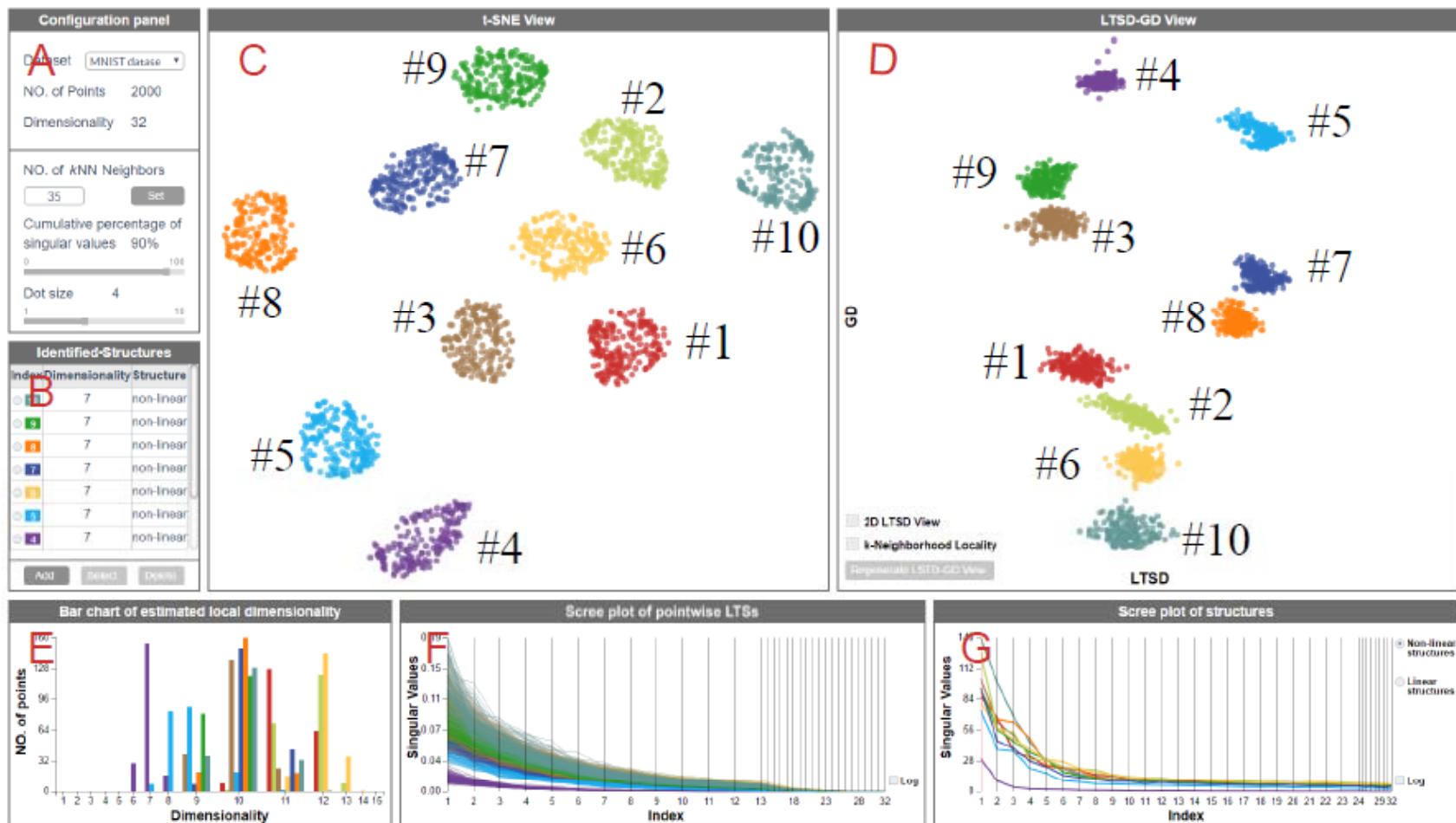
# Comparisons



# Comparisons



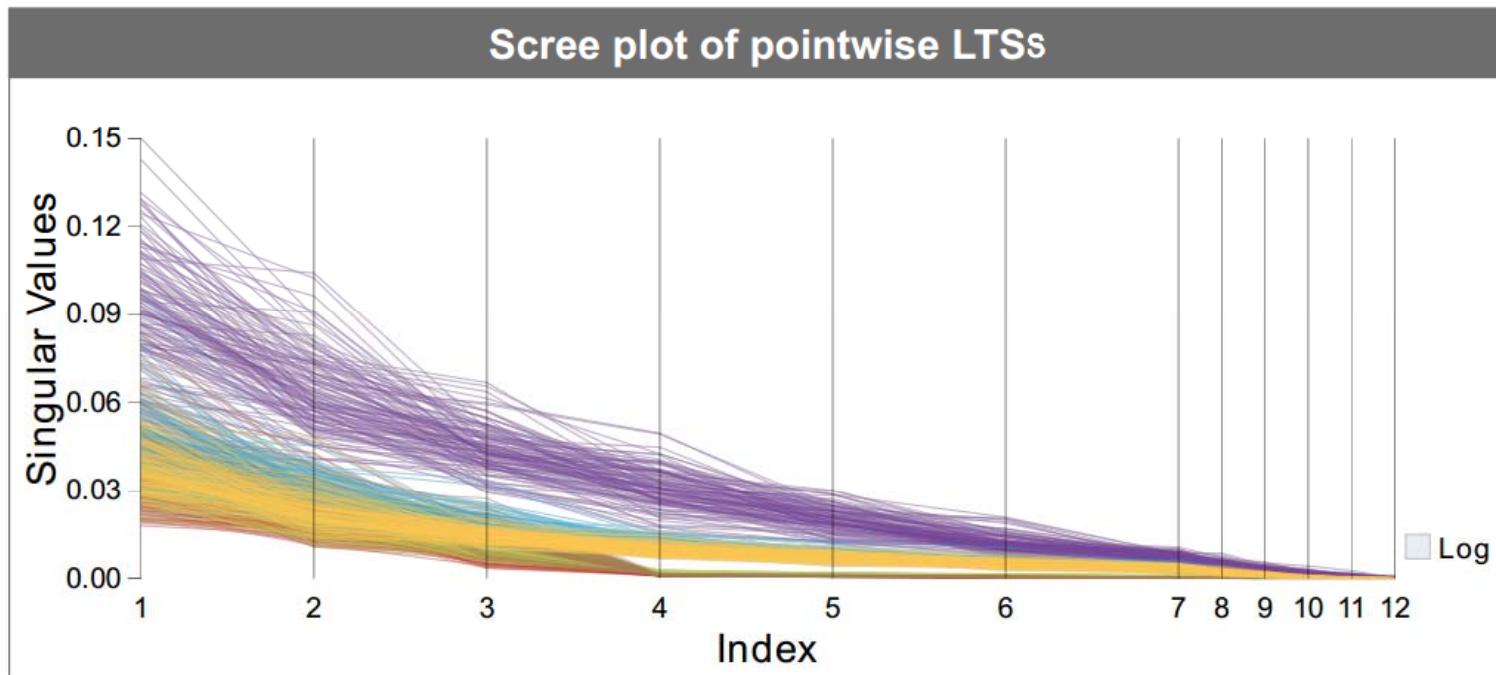
# Visual analysis interface



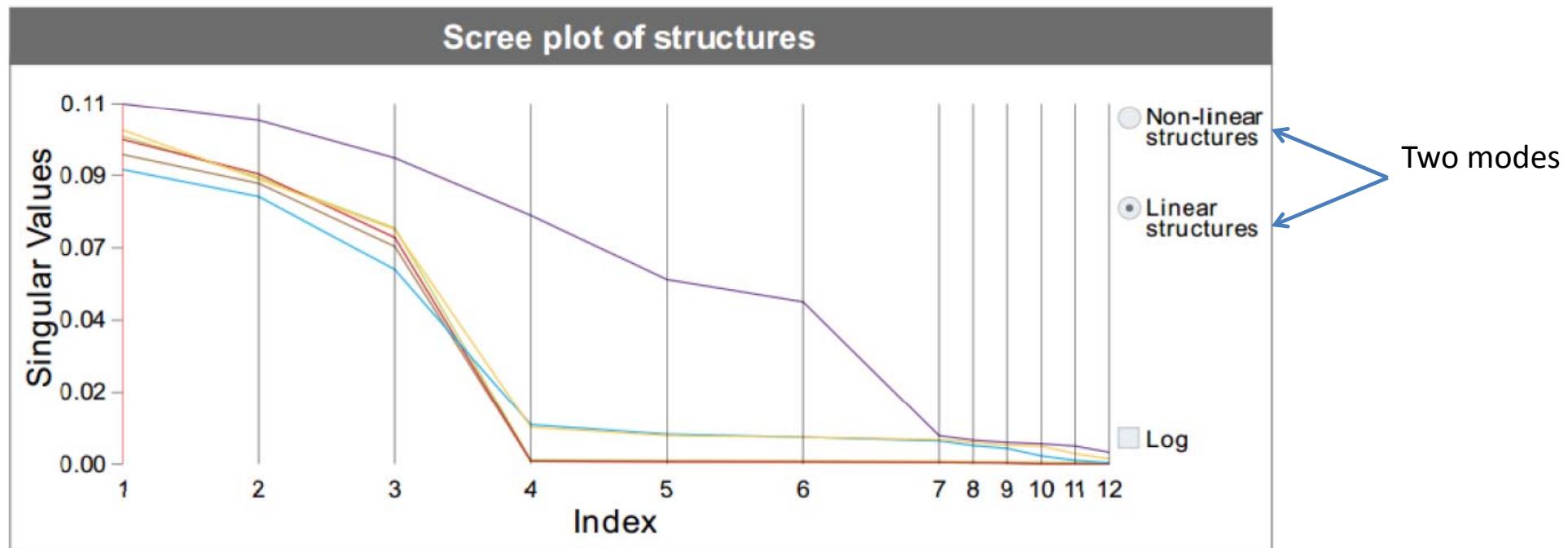
# t-SNE view

- 提供聚类信息
- 需要比较少的先验信息
  - 仅需要满足局部性假设

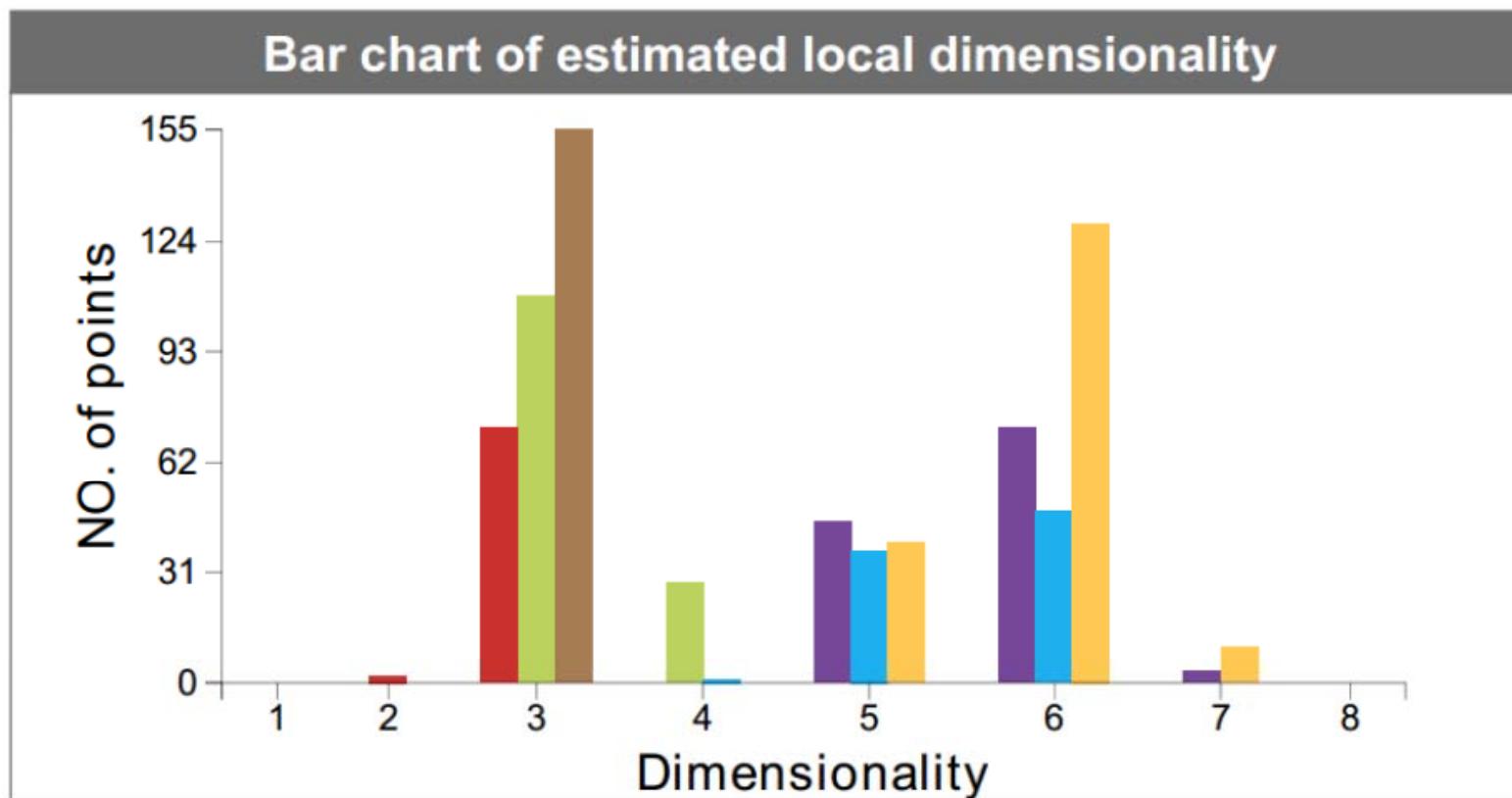
# Scree plot of pointwise LTSs



# Scree plot of structures

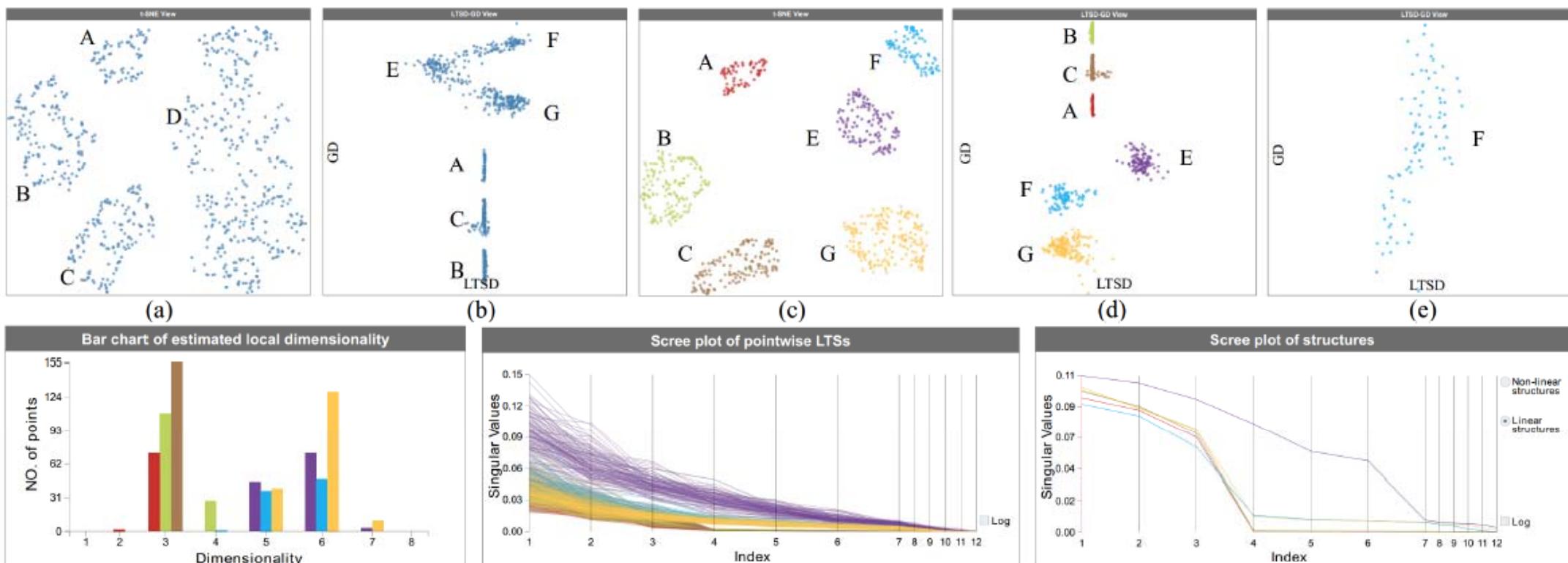


# Bar chart of estimated local dimensionality



# Case study: the synthetic 12-D dataset

12D, 750 points, in six clusters

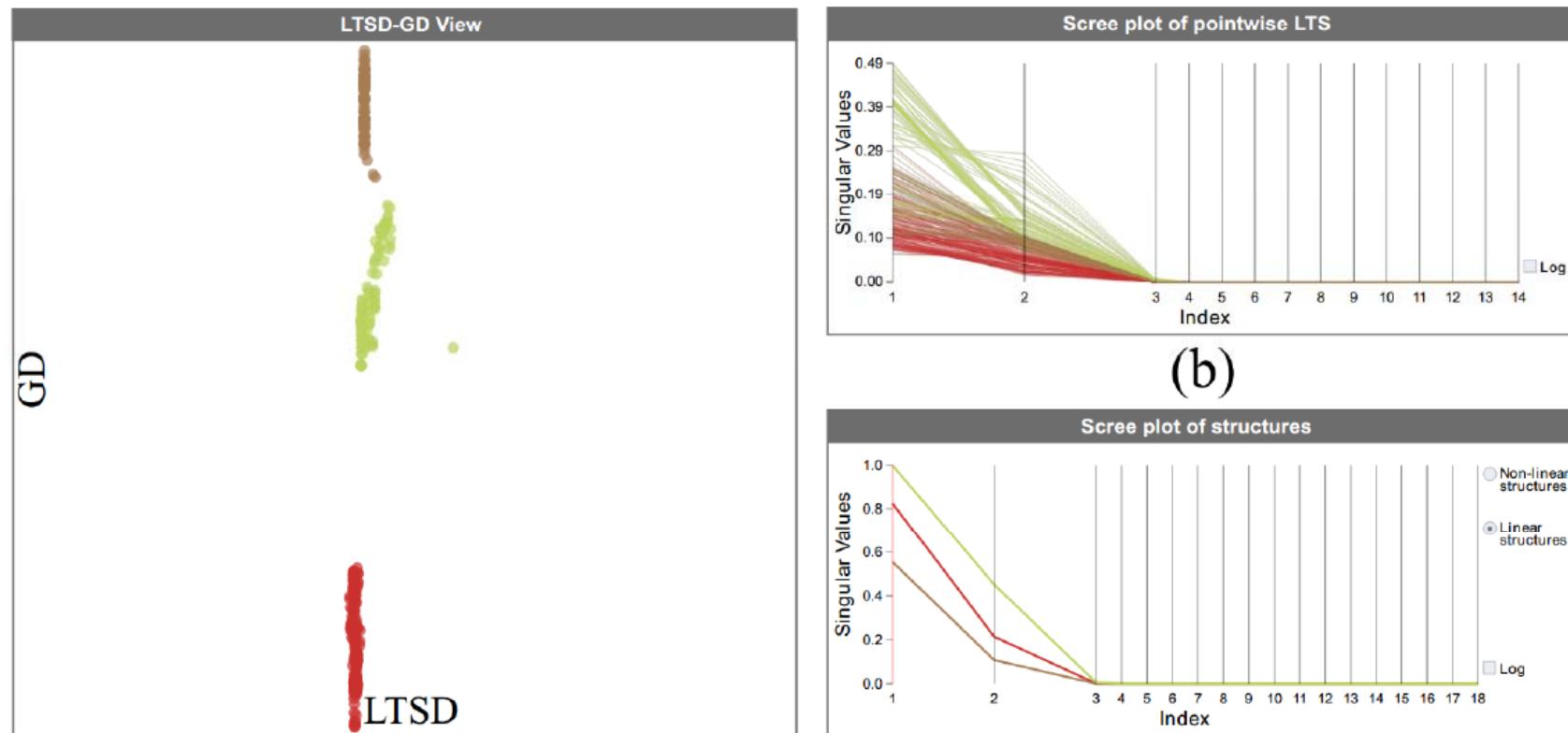


# Exploring The Synthetic 12D Data

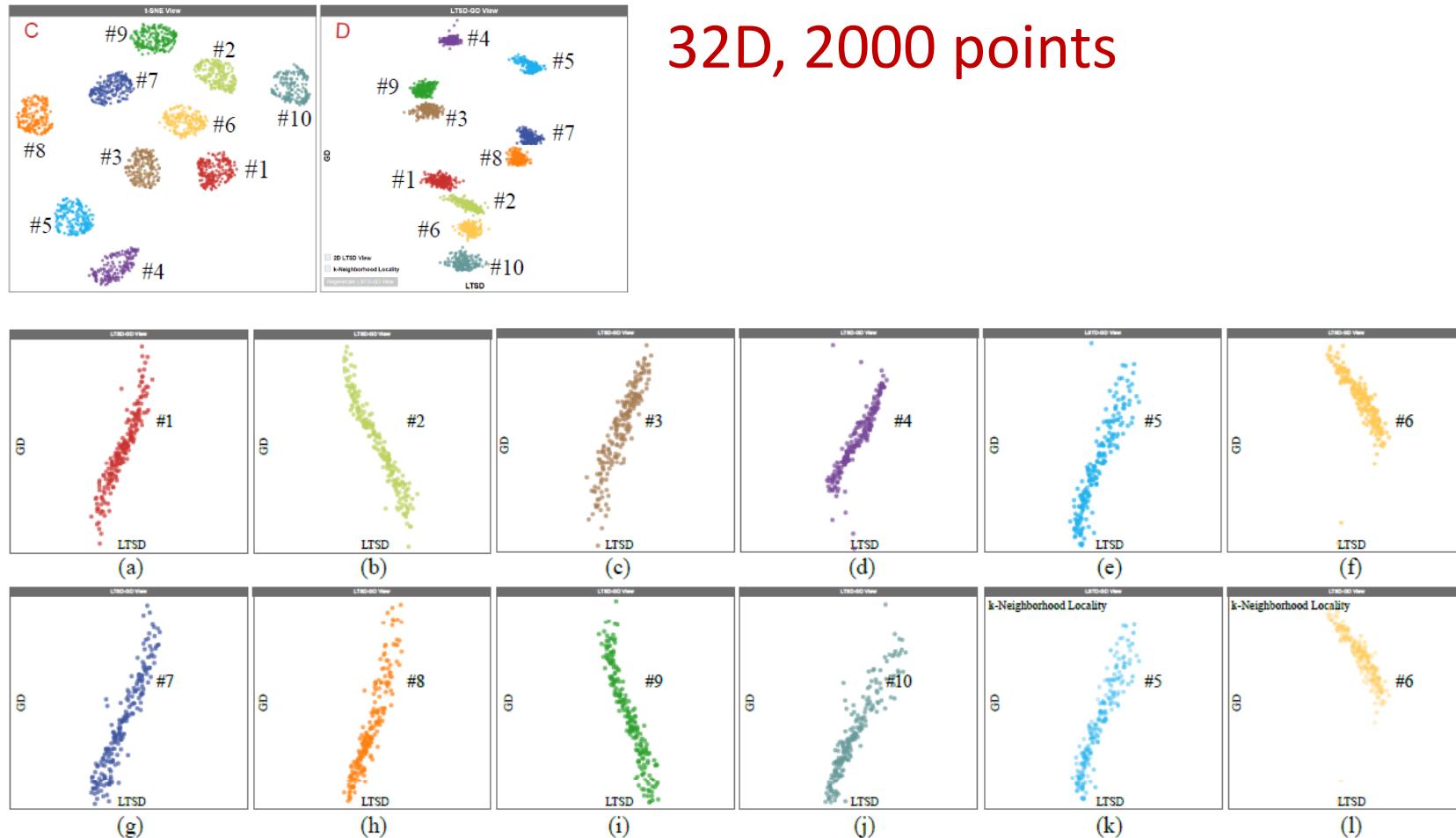
750 points, 12 dimensions (in 6 Gaussian clusters)

# Case study: the Hopkins 155 dataset

62D, 297 points



# Case study: the MNIST dataset



# 总结

- 提出了一种新的高维数据二维映射方法，以揭示潜在的低维结构
- 提出了一个对高维数据中潜在低维结构进行预审查的方法

# 正在进行的工作

- 大规模高维数据可视分析
- 面向领域问题的高维数据可视分析

# 谢谢！

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个人主页 : <http://faculty.csu.edu.cn/xiajiazhi>