



JHU vision lab

Low-Rank and Sparse Modeling for Visual Analytics

René Vidal (JHU), Ehsan Elhamifar (NEU),
Zhouchen Lin (PKU), Jiashi Feng (NUS),
Sheng Li (NEU), Yun Fu (NEU)



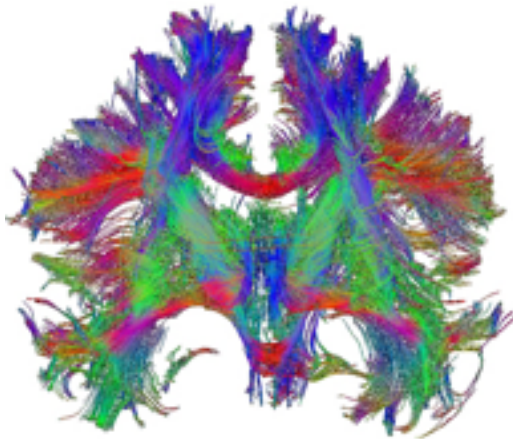
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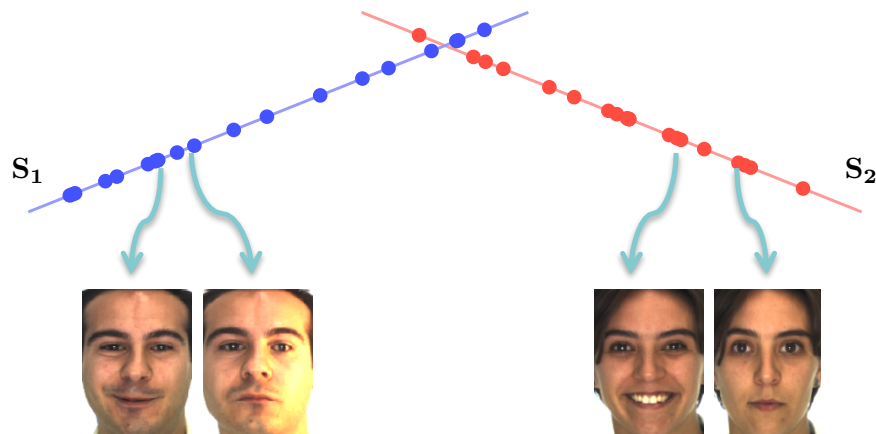
High-Dimensional Data

- In many areas, we deal with high-dimensional data
 - Computer vision
 - Medical imaging
 - Medical robotics
 - Signal processing
 - Bioinformatics

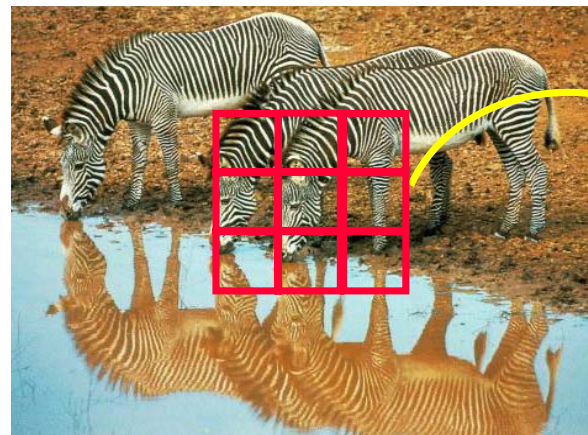


Low-Dimensional Manifolds

- Face clustering and classification



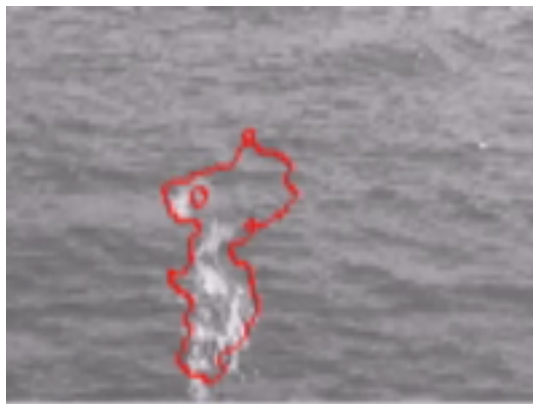
- Lossy image representation



- Motion segmentation



- DT segmentation

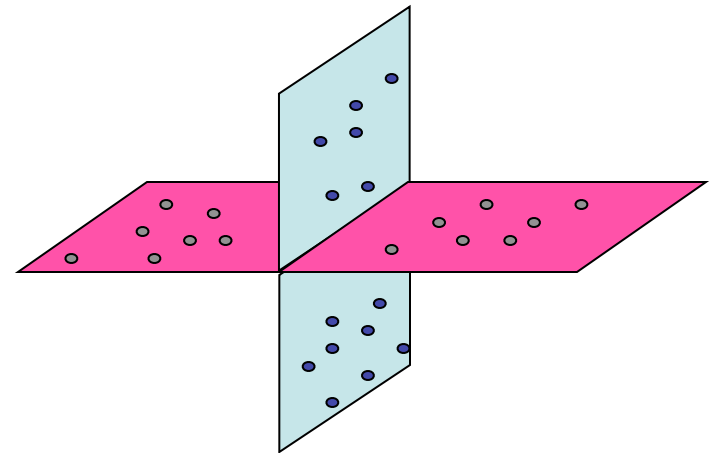


- Video segmentation



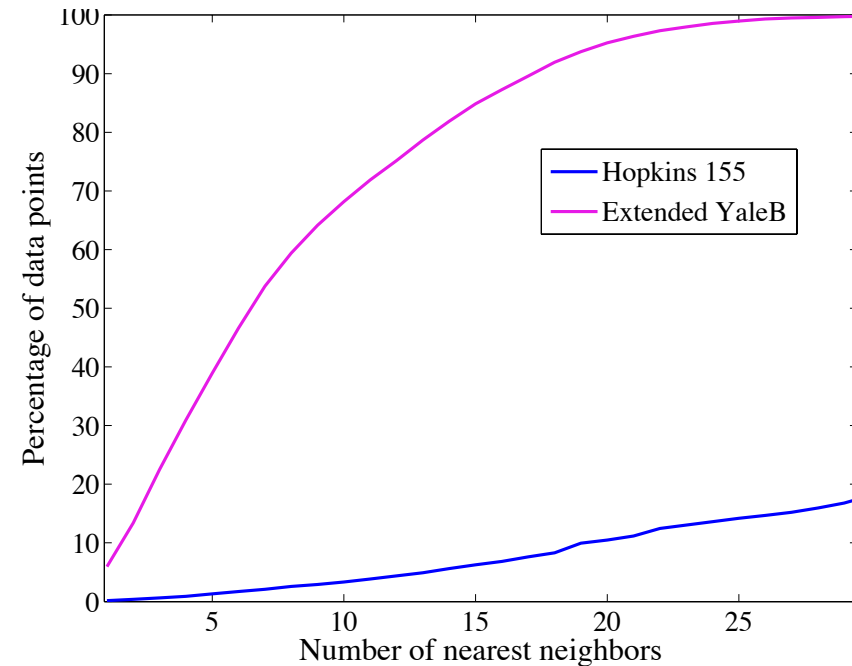
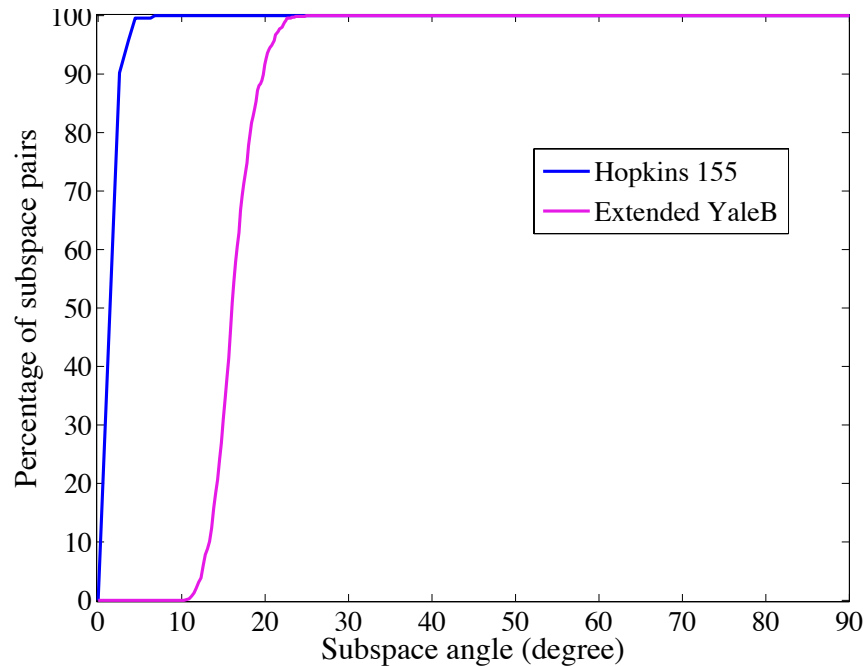
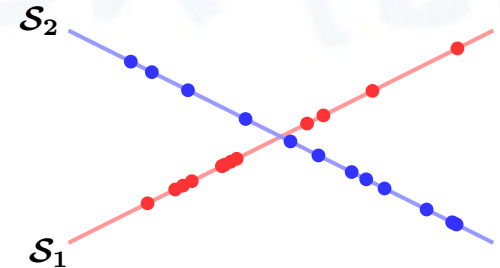
Subspace Clustering Problem

- Given a set of points lying in multiple subspaces, identify
 - The **number of subspaces** and their **dimensions**
 - A **basis** for each subspace
 - The **segmentation** of the data points
- Challenges
 - Model selection
 - Nonconvex
 - Combinatorial
- More challenges
 - Noise
 - Outliers
 - Missing entries



Subspace Clustering Problem: Challenges

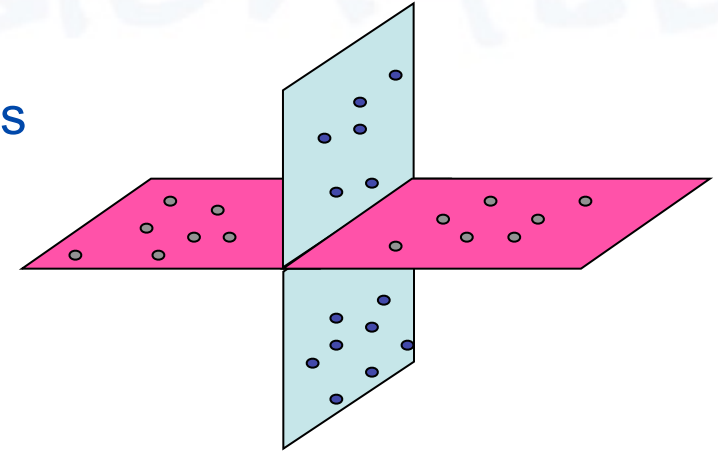
- Even more challenges
 - Angles between subspaces are small
 - Nearby points are in different subspaces



Prior Work: Iterative-Probabilistic Methods

- Approach

- Given segmentation, estimate subspaces
- Given subspaces, segment the data
- **Iterate** till convergence



- Representative methods

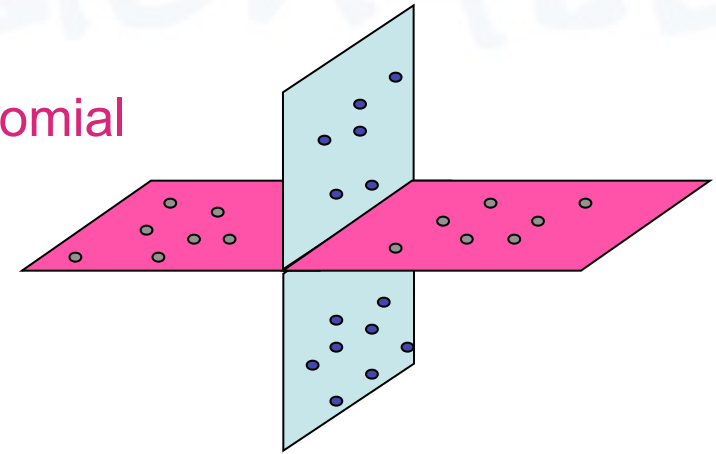
- **K-subspaces** (Bradley-Mangasarian '00, Kambhatla-Leen '94, Tseng'00, Agarwal-Mustafa '04, Zhang et al. '09, Aldroubi et al. '09)
- **Mixtures of PPCA** (Tipping-Bishop '99, Grubber-Weiss '04, Kanatani '04, Archambeau et al. '08, Chen '11)

Advantages	Disadvantages / Open Problems
Simple, intuitive	Known number of subspaces and dimensions
Missing data	Sensitive to initialization and outliers

Prior Work: Algebraic-Geometric Methods

- Approach

- Number of subspaces = degree of polynomial
- Subspaces = factors of polynomial



- Representative methods

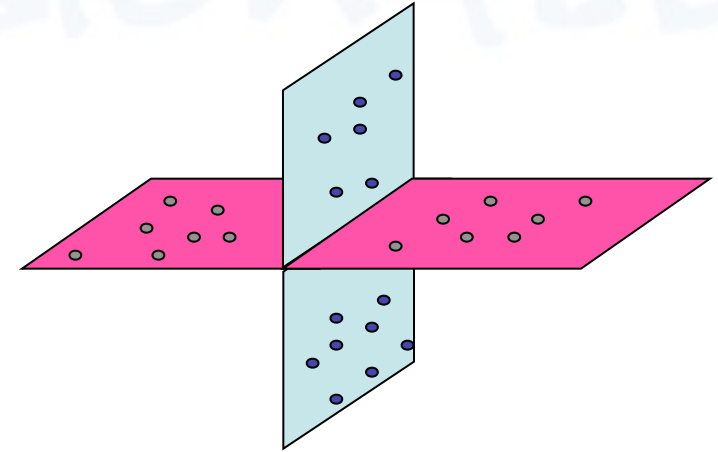
- **Factorization** (Boult-Brown'91, Costeira-Kanade'98, Gear'98, Kanatani et al.'01, Wu et al.'01, Sekmen'13)
- **GPCA** (Shizawa-Maze '91, Vidal et al. '03 '04 '05, Huang et al. '05, Yang et al. '05, Derksen '07, Ma et al. '08, Ozay et al. '10, Tsakiris-Vidal '14 '15)

Advantages	Disadvantages / Open Problems
Closed form	Complexity
Arbitrary dimensions	Sensitive to noise, outliers, missing entries

Prior Work: Spectral-Clustering Methods

- Approach

- Data points = graph nodes
- Pairwise similarity = edge weights
- Segmentation = graph cut



- Representative methods

- **Local** (Zelnik-Manor '03, Yan-Pollefeys '06, Fan-Wu '06, Goh-Vidal '07, Sekmen'12)
- **Global** (Govindu '05, Agarwal et al. '05, Chen-Lerman '08, Lauer-Schnorr '09, Zhang et al. '10)

Advantages	Disadvantages / Open Problems
Efficient	Known number of subspaces and dimensions
Robust	Global methods are complex

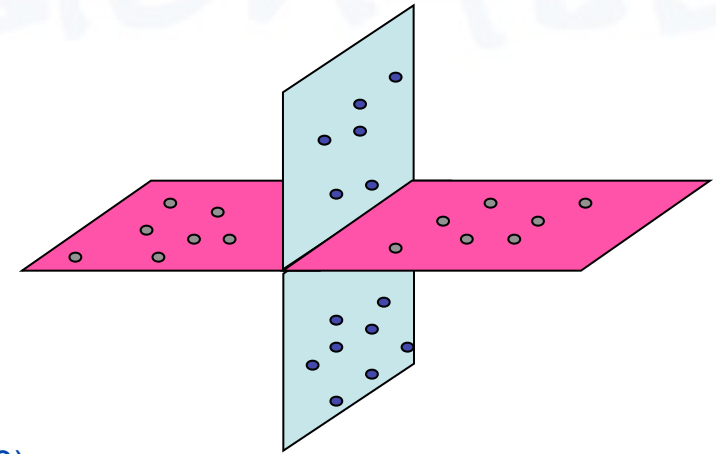
Prior Work: Sparse and Low-Rank Methods

- Approach

- Data are **self-expressive**
- Global affinity by **convex optimization**

- Representative methods

- **Sparse Subspace Clustering (SSC)**
(Elhamifar-Vidal '09 '10 '13, Candes-Soltanolkotabi '12 '13)
- **Low-Rank Subspace Clustering (LRR and LRSC)**
(Liu et al. '10 '13, Favaro-Vidal '11 '13)
- **Least Square Regression (LSR)** (Lu '12)
- **Sparse + Low-Rank** (Wang '13), **Sparse + Frobenius** (Dyer '13, You '16)



Advantages	Disadvantages / Open Problems
Efficient, Convex	Low-dimensional subspaces
Robust to noise/corruptions	Missing entries

Tutorial Objective

- Overview state-of-the-art sparse and low-rank subspace clustering methods
 - Representative methods and their theoretical properties
 - Optimization algorithms and their scalability
 - Applications in computer vision
- Unified framework

$$\min_{C, E} f(C) + \lambda g(E) \text{ s.t. } X = XC + E$$

- | | | |
|------------------------------------|-------------------------|---------------------------|
| – Sparse Subspace Clustering: | $f = l_1$ | $g = l_1 \text{ or Frob}$ |
| – Low Rank Representation: | $f = \text{nuclear}$ | $g = l_{21}$ |
| – Low Rank Subspace Clustering: | $f = \text{nuclear}$ | $g = l_1 \text{ or Frob}$ |
| – Elastic Net Subspace Clustering: | $f = l_1 + \text{Frob}$ | $g = l_1 \text{ or Frob}$ |

Tutorial Outline

- 08:30-08:45 Introduction to Subspace Clustering
- 08:45-10:00 Sparse Subspace Clustering
- 10:00-10:30 Coffee Break
- 10:30-12:00 Low Rank Subspace Clustering
- 12:00-02:00 Lunch Break
- 02:00-03:30 Algorithms & More Models
- 03:00-03:30 Coffee Break
- 03:30-05:00 Applications

