Distance Metric Learning for Set-based Visual Recognition

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Outline

- Background
- Literature review
- Evaluations
- Summary

Face Recognition with Single Image

- Identification
  - Typical applications
    - Photo matching (1:N)
    - Watch list screening (1:N+1)
  - Performance metric
    - FR(@FAR)

- Verification
  - Typical applications
    - Access control (1:1)
    - E-passport (1:1)
  - Performance metric
    - ROC: FRR+FAR

Who is this celebrity?

Are they the same guy?

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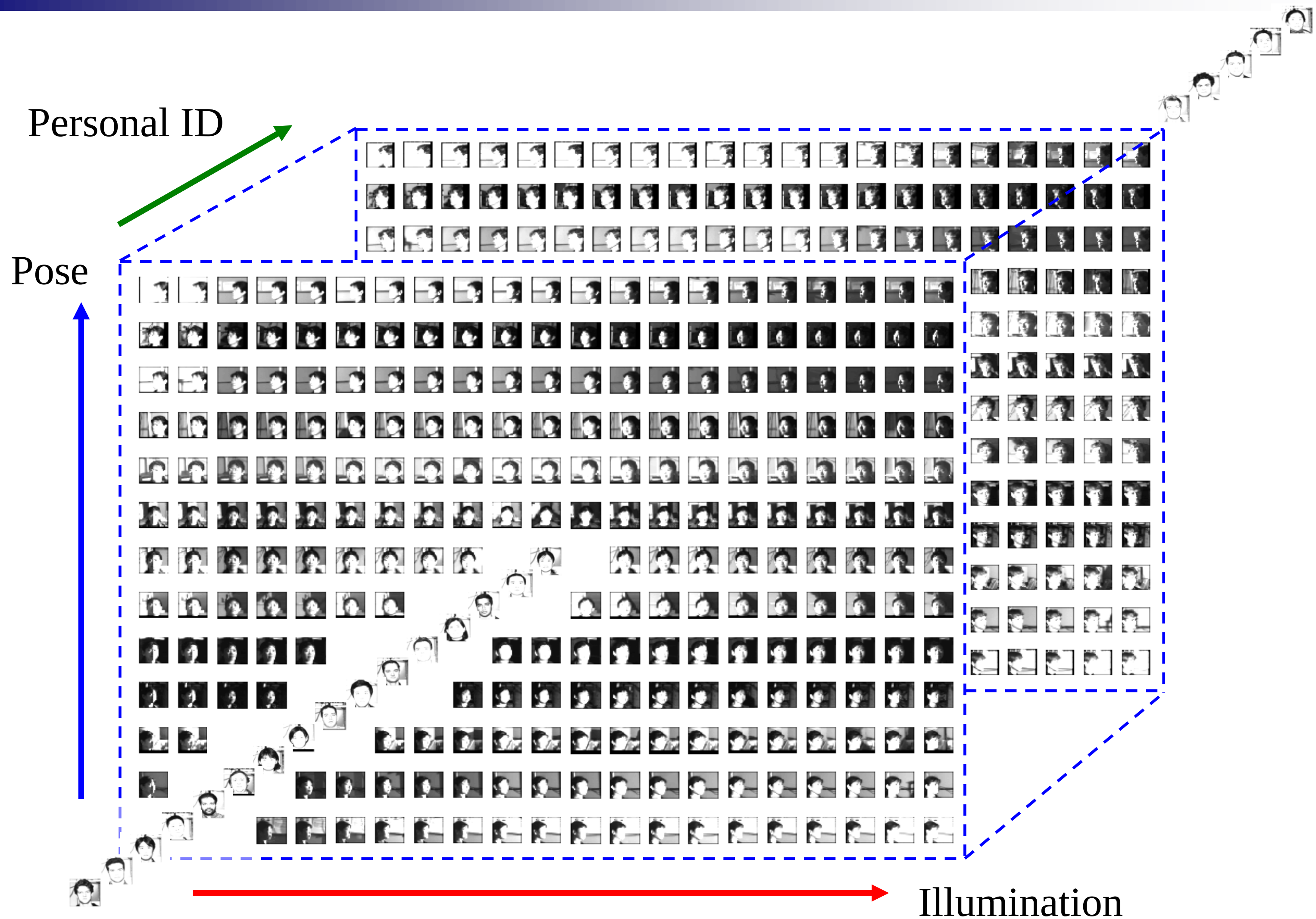
Challenges

Challenges



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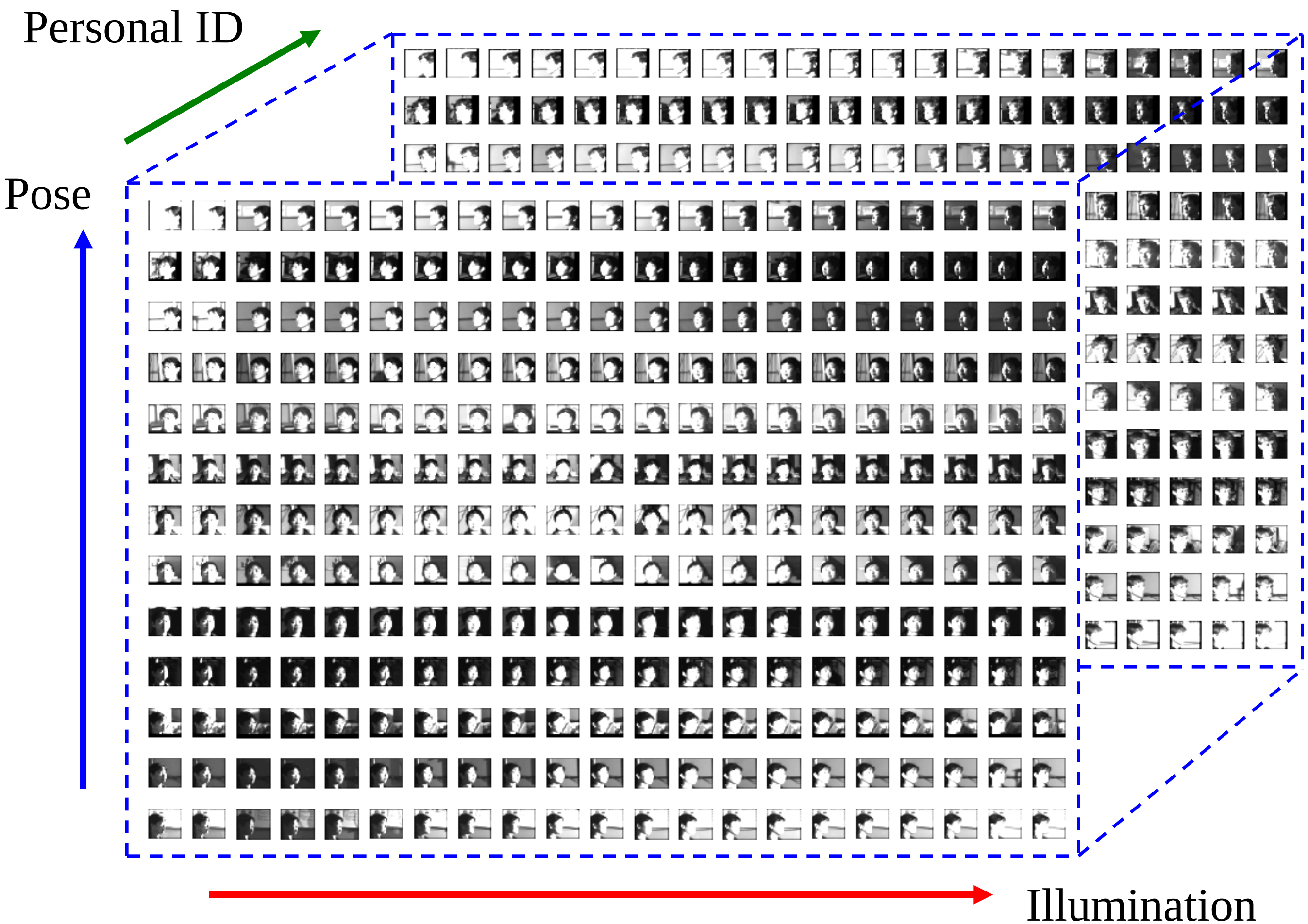
Challenges



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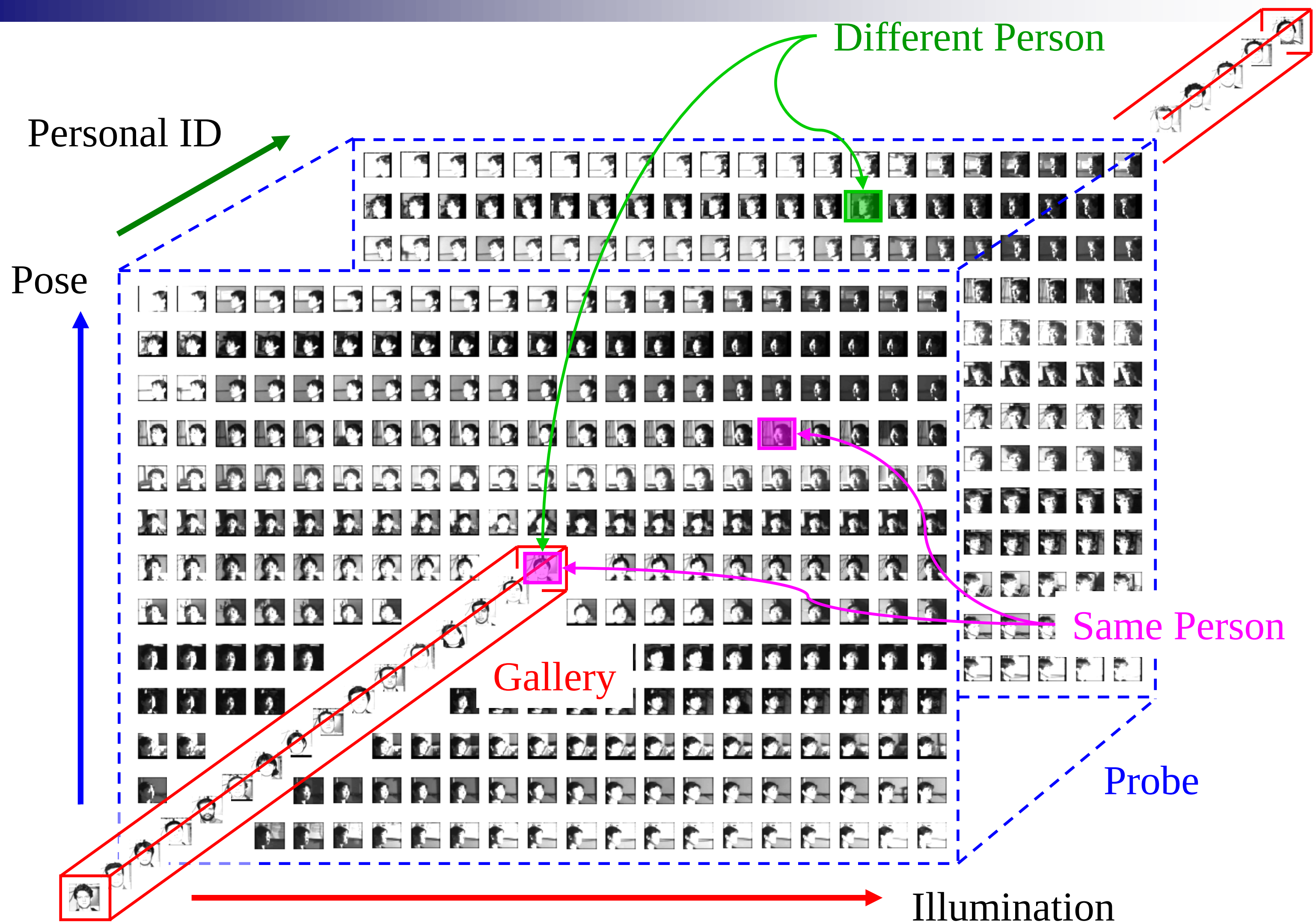
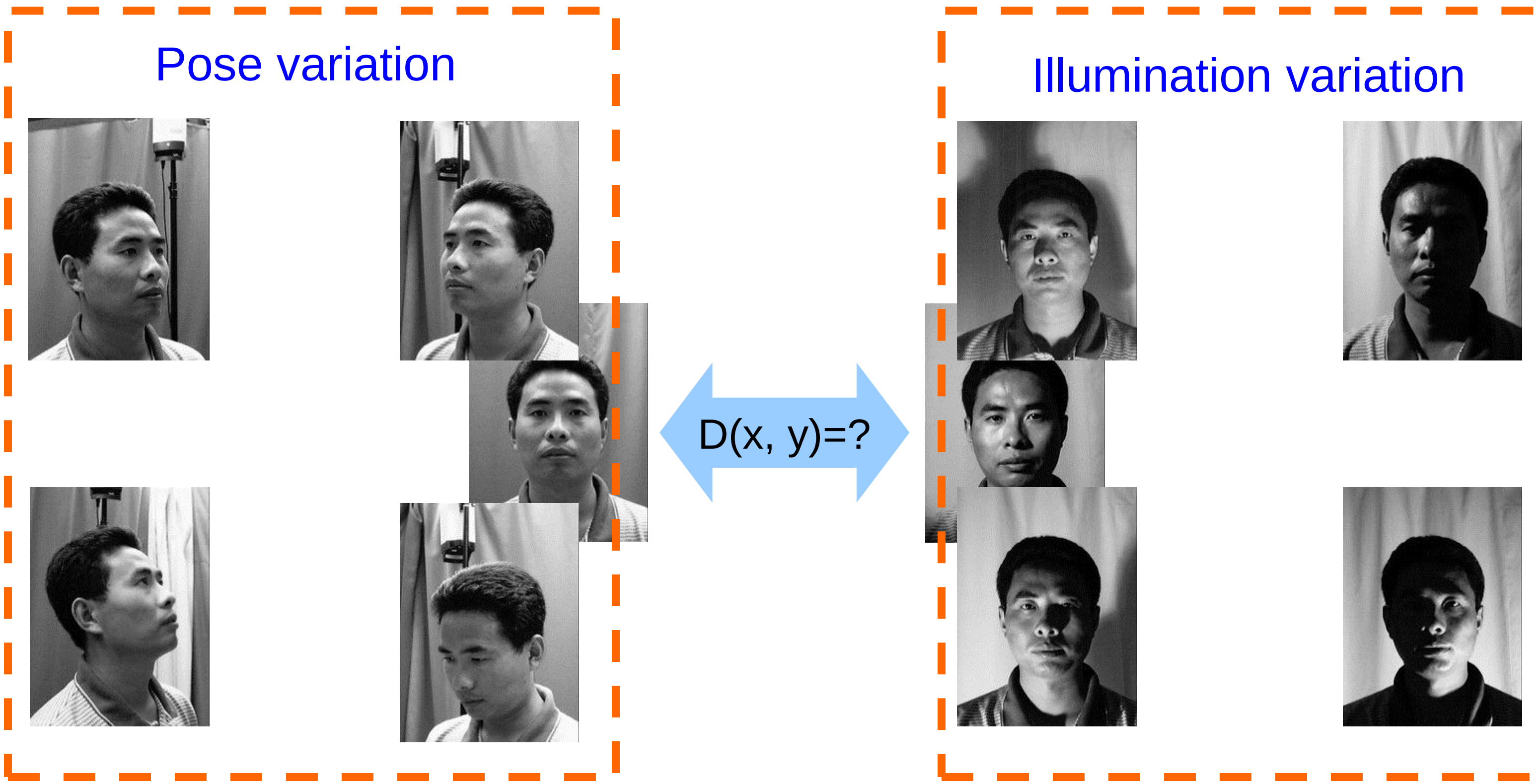
Challenges


Different Person
Personal ID
Pose
Same Person
Gallery
Probe
Illumination

Challenges

- Intra-class variation vs. inter-class variation
  - Distance measure →semantic meaning
  - Sample-based metric learning is made even harder



Face Recognition with Videos

- Video surveillance

Seeking missing children

Searching criminal suspects

http://www.youtube.com/watch?v=M80DXI932OE
http://www.youtube.com/watch?v=RfJsGeq0xRA#t=22

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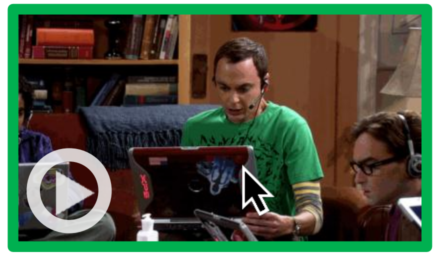
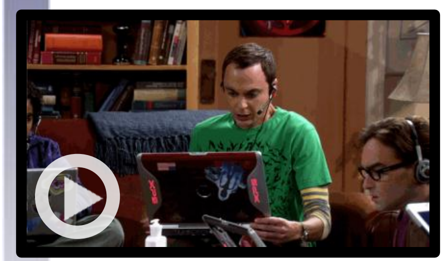
Face Recognition with Videos

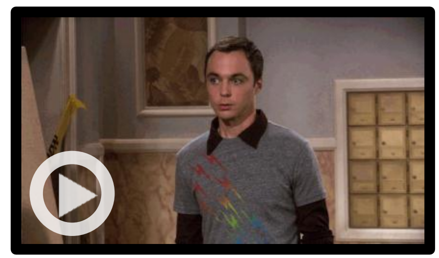
- Video shot retrieval

Smart TV-Series Character
Shots Retrieval System
"the Big Bang Theory"




S01E01: 10'48"

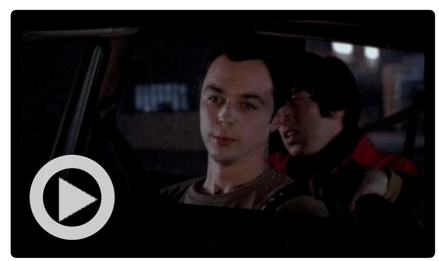

S01E06: 05'22"

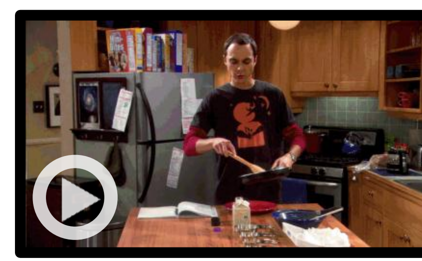

S01E02: 04'20"


S01E02: 00'21"


S01E03: 08'06"


S01E05: 09'23"


S01E01: 22'20"


S01E04: 03'42"

1 2 3 4 5 6 7 8 9 Next Page

Treating Video as Image Set

- A new & different problem
  - Unconstrained acquisition conditions
  - Complex appearance variations
  - Two phases: set modeling + set matching

New paradigm:
set-based metric learning

Outline

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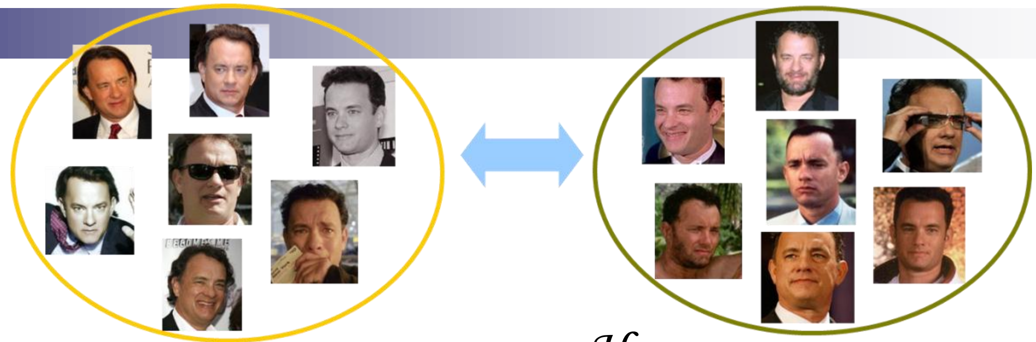
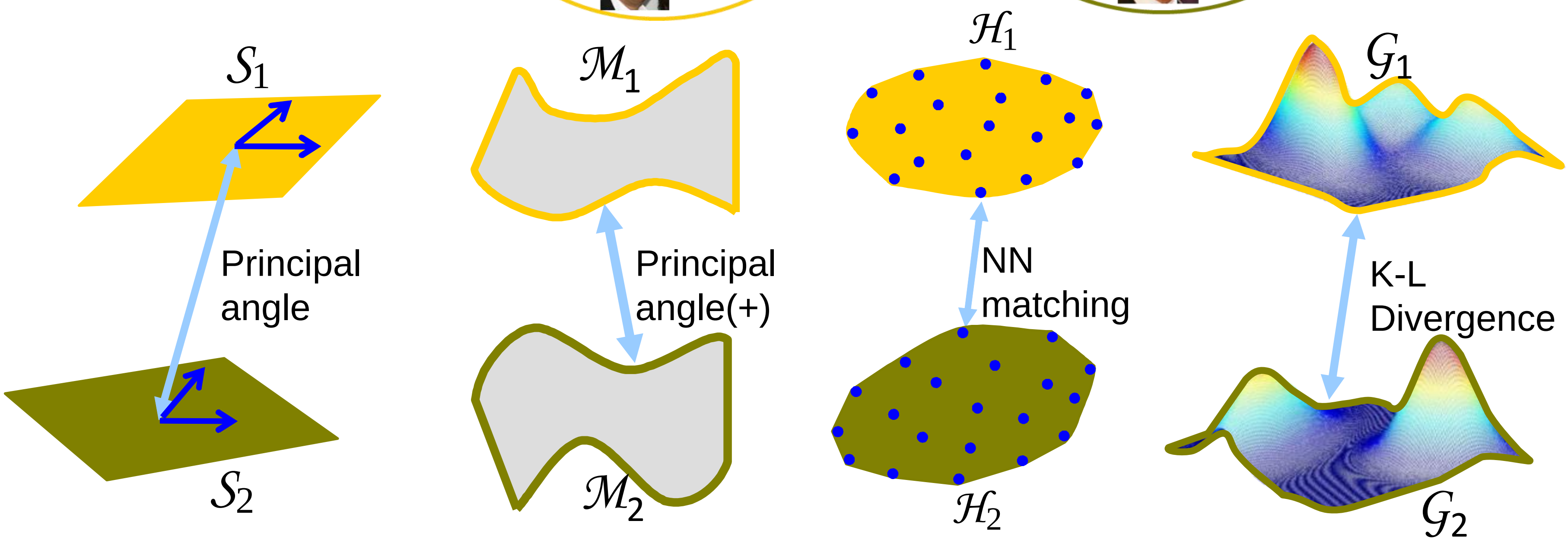
Overview of previous works

From the view of set modeling





◆Linear subspace
[Yamaguchi, FG'98]
[Kim, PAMI'07]
[Hamm, ICML'08]
[Huang, CVPR'15]

◆Nonlinear manifold
[Kim, BMVC'05]
[Wang, CVPR'08]
[Wang, CVPR'09]
[Chen, CVPR'13]
[Lu, CVPR'15]

◆Affine/Convex hull
[Cevikalp, CVPR'10]
[Hu, CVPR'11]
[Zhu, ICCV'13]

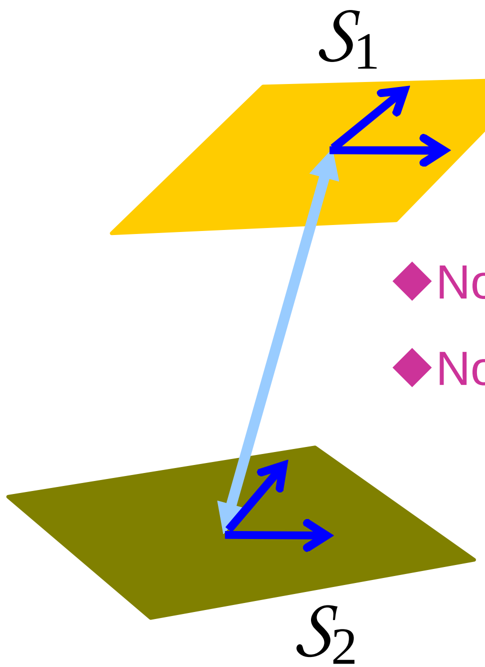
◆Statistics
[Shakhnarovich, ECCV'02]
[Arandjelović, CVPR'05]
[Wang, CVPR'12]
[Harandi, ECCV'14]
[Wang, CVPR'15]

Overview of previous works

- Set modeling
  - Linear subspace→Nonlinear manifold
  - Affine/Convex Hull (affine subspace)
  - Parametric PDFs → Statistics
- Set matching—basic distance
  - Principal angles-based measure
  - Nearest neighbor (NN) matching approach
  - K-L divergence→SPD Riemannian metric…
- Set matching—metric learning
  - Learning in Euclidean space
  - Learning on Riemannian manifold

Set model I: linear subspace

- Properties
  - PCA on the set of image samples to get subspace
  - Loose characterization of the set distribution region
  - Principal angles-based measure discards the varying importance of different variance directions
- Methods
  - MSM [FG'98]
  - DCC [PAMI'07]
  - GDA [ICML'08]
  - GGDA [CVPR'11]
  - PML [CVPR'15]
  - …



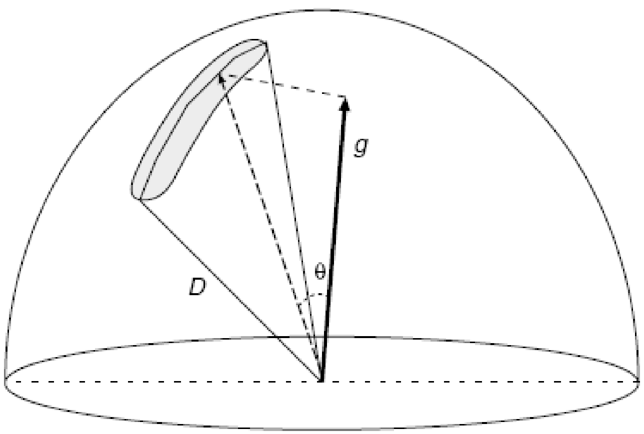
◆No distribution boundary

◆No direction difference

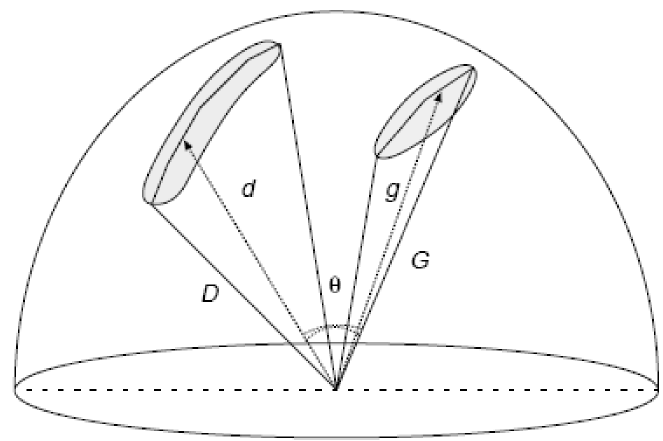
Set model I: linear subspace

- MSM (Mutual Subspace Method) [FG'98]
  - Pioneering work on image set classification
  - First exploit principal angles as subspace distance
  - Metric learning: N/A

$$cos^2\theta = \sup_{d\in D, g\in G, ||d||\neq 0, ||g||\neq 0} \frac{|(d,g)|^2}{||d||^2||g||^2}$$



subspace method



Mutual subspace method

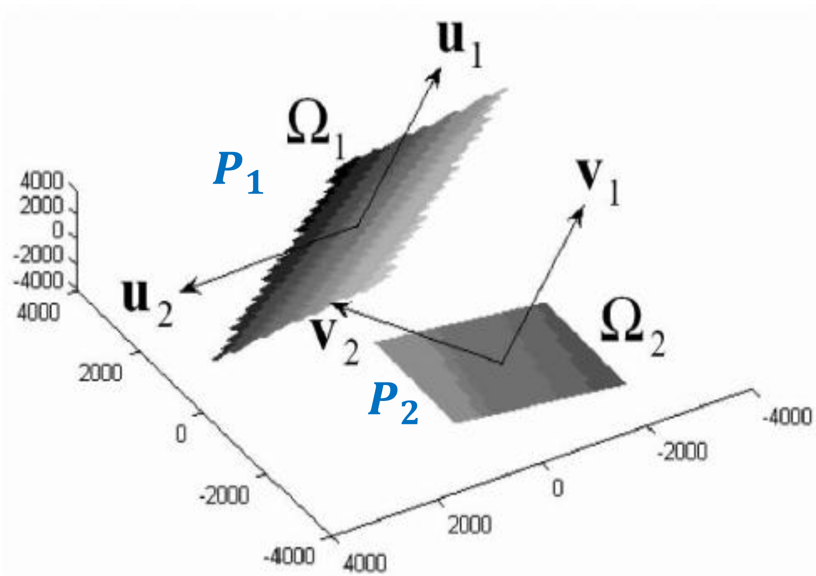
[1] O. Yamaguchi, K. Fukui, and K. Maeda. Face Recognition Using Temporal Image Sequence. *IEEE FG 1998.*

Set model I: linear subspace

- DCC (Discriminant Canonical Correlations) [PAMI'07]
  - Metric learning: in Euclidean space

Set 1: $\boldsymbol{X}_1$

Set 2: $\boldsymbol{X}_2$



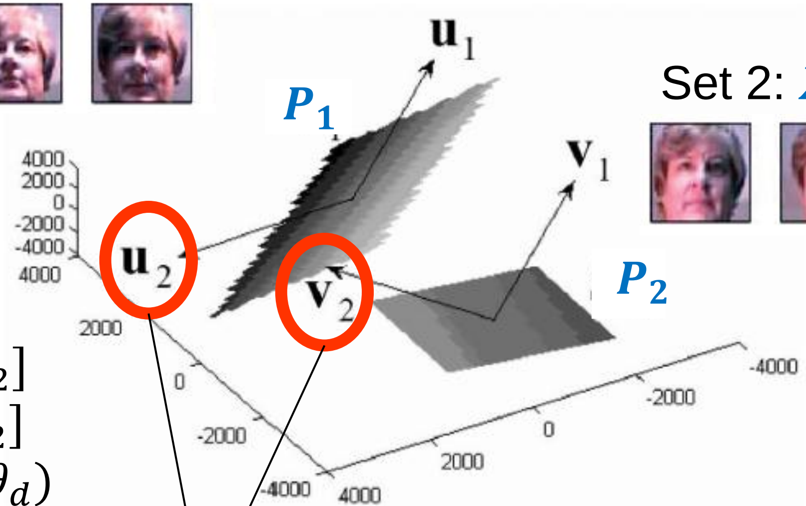
Linear subspace by:
orthonormal basis matrix
$\boldsymbol{X}_i\boldsymbol{X}_i^T \simeq \boldsymbol{P}_i\boldsymbol{\Lambda}_i\boldsymbol{P}_i^T$

[1] T. Kim, J. Kittler, and R. Cipolla. Discriminative Learning and Recognition of Image Set Classes Using Canonical Correlations. *IEEE T-PAMI, 2007.*

DCC

- Canonical Correlations/Principal Angles
  - Canonical vectors→common variation modes

Set 1: $\boldsymbol{X_1}$



Set 2: $\boldsymbol{X_2}$

$$\boldsymbol{P}_1^T\boldsymbol{P}_2 = \boldsymbol{Q}_{12}\boldsymbol{\Lambda}\boldsymbol{Q}_{21}^T$$
$$\boldsymbol{U} = \boldsymbol{P}_1\boldsymbol{Q}_{12} = [\boldsymbol{u}_1, \dots, \boldsymbol{u}_2]$$
$$\boldsymbol{V} = \boldsymbol{P}_2\boldsymbol{Q}_{21} = [\boldsymbol{v}_1, \dots, \boldsymbol{v}_2]$$
$$\boldsymbol{\Lambda} = diag(\cos\theta_1, \dots, \cos\theta_d)$$

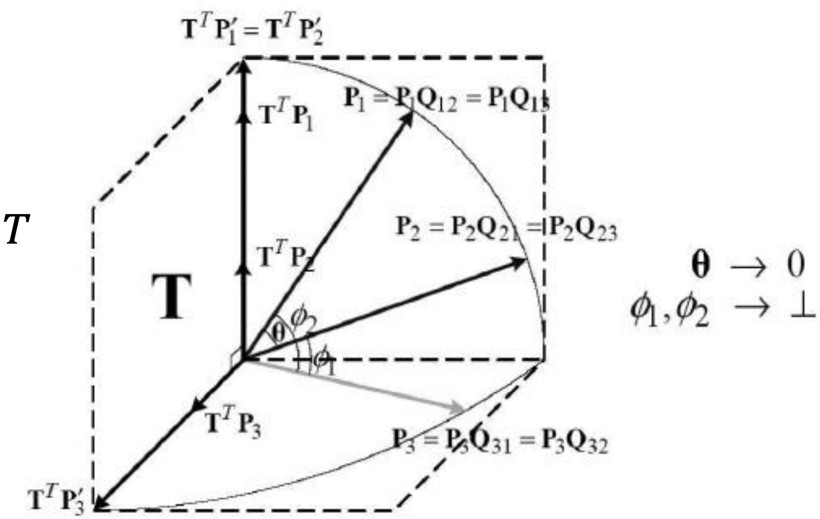
Canonical Correlation: $\cos\theta_i$

Principal Angles: θ_i

Canonical vectors

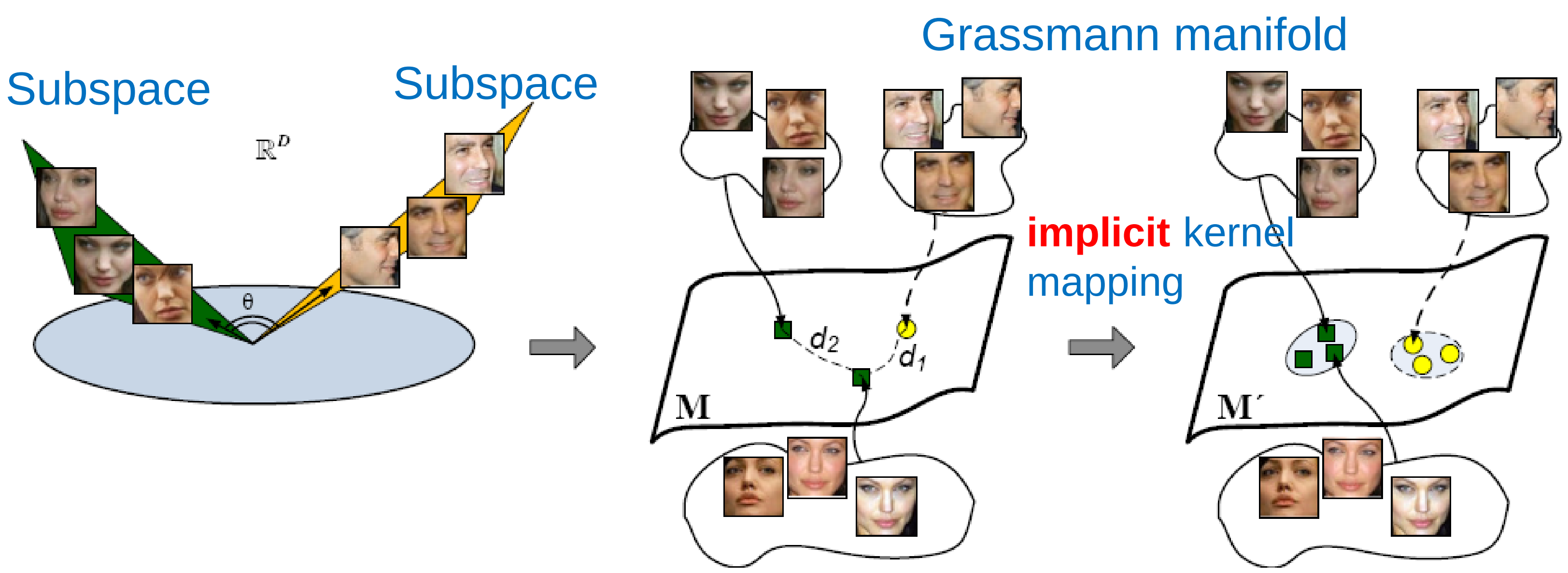
DCC

- Discriminative learning
  - Linear transformation
    - $\boldsymbol{T}$: $\boldsymbol{X}_i \longrightarrow \boldsymbol{Y}_i = \boldsymbol{T}^T\boldsymbol{X}_i$
  - Representation
    - $\boldsymbol{Y}_i\boldsymbol{Y}_i^T = (\boldsymbol{T}^T\boldsymbol{X}_i)(\boldsymbol{T}^T\boldsymbol{X}_i)^T$
      $\simeq (\boldsymbol{T}^T\boldsymbol{P}_i)\boldsymbol{\Lambda}_i(\boldsymbol{T}^T\boldsymbol{P}_i)^T$
  - Set similarity
    - $F_{ij} = \max_{\boldsymbol{Q}_{ij},\boldsymbol{Q}_{ji}} tr(M_{ij})$
      - $M_{ij} = \boldsymbol{Q}_{ij}^T\boldsymbol{P'}_i^T\boldsymbol{T}\boldsymbol{T}^T\boldsymbol{P}_j^T\boldsymbol{Q}_{ji}$
  - Discriminant function
    - $\boldsymbol{T} = \max_{arg\,\boldsymbol{T}} tr(\boldsymbol{T}^T\boldsymbol{S}_b\boldsymbol{T})\,/tr(\boldsymbol{T}^T\boldsymbol{S}_w\boldsymbol{T})$



Set model I: linear subspace

- GDA [ICML'08] / GGDA [CVPR'11]
  - Treat subspaces as points on Grassmann manifold
  - Metric learning: on Riemannian manifold



[1] J. Hamm and D. D. Lee. Grassmann Discriminant Analysis: a Unifying View on Subspace-Based Learning. *ICML 2008*.

[2] M. Harandi, C. Sanderson, S. Shirazi, B. Lovell. Graph Embedding Discriminant Analysis on Grassmannian Manifolds for Improved Image Set Matching. *IEEE CVPR 2011.*

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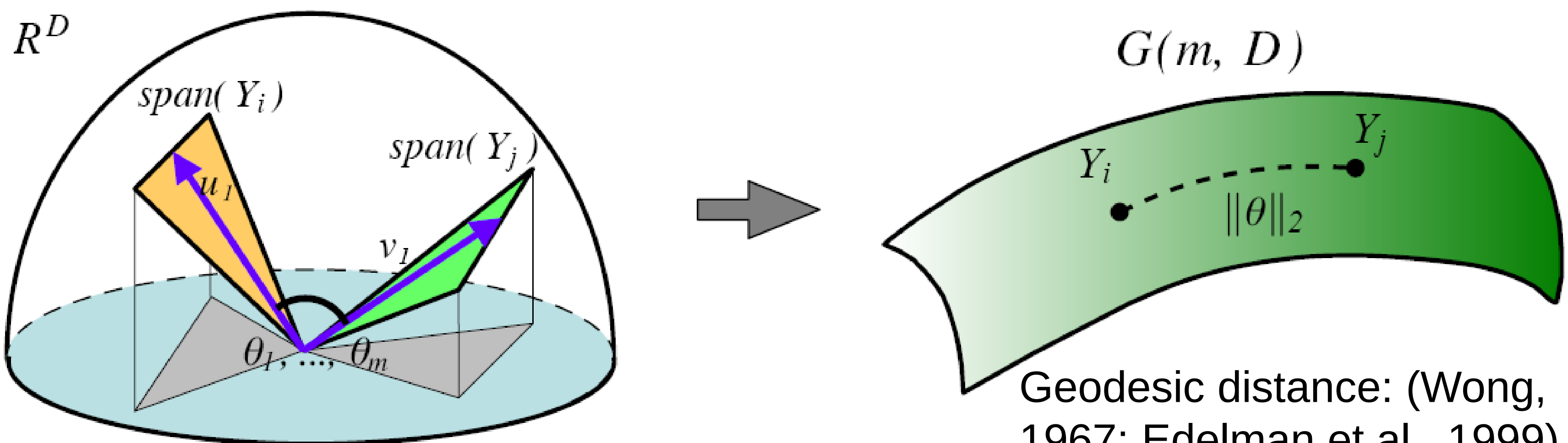
GDA/GGDA

- Projection metric
  - $d_P(\boldsymbol{Y}_1, \boldsymbol{Y}_2) = (\sum_i \sin^2 \theta_i)^{1/2} = 2^{-1/2} \| \boldsymbol{Y}_1 \boldsymbol{Y}_1^T - \boldsymbol{Y}_2 \boldsymbol{Y}_2^T \|_F$

θ_i: Principal angles



Geodesic distance: (Wong, 1967; Edelman et al., 1999)

$$d_G^2(\boldsymbol{Y}_1, \boldsymbol{Y}_2) = \sum_i \theta_i^2$$

GDA/GGDA

- Projection kernel
  - Projection embedding (isometric)
    - $\Psi_P: \mathcal{G}(m, D) \longrightarrow \mathbb{R}^{D\times D},\ span(\boldsymbol{Y}) \longrightarrow \boldsymbol{Y}\boldsymbol{Y}^T$
  - The inner-product of $\mathbb{R}^{D\times D}$
    - $tr((\boldsymbol{Y}_1\boldsymbol{Y}_1^T)(\boldsymbol{Y}_2\boldsymbol{Y}_2^T)) = \left\|\boldsymbol{Y}_1^T\boldsymbol{Y}_2\right\|_F^2$
  - Grassmann kernel (positive definite kernel)
    - $k_P(\boldsymbol{Y}_1, \boldsymbol{Y}_2) = \left\|\boldsymbol{Y}_1^T\boldsymbol{Y}_2\right\|_F^2$

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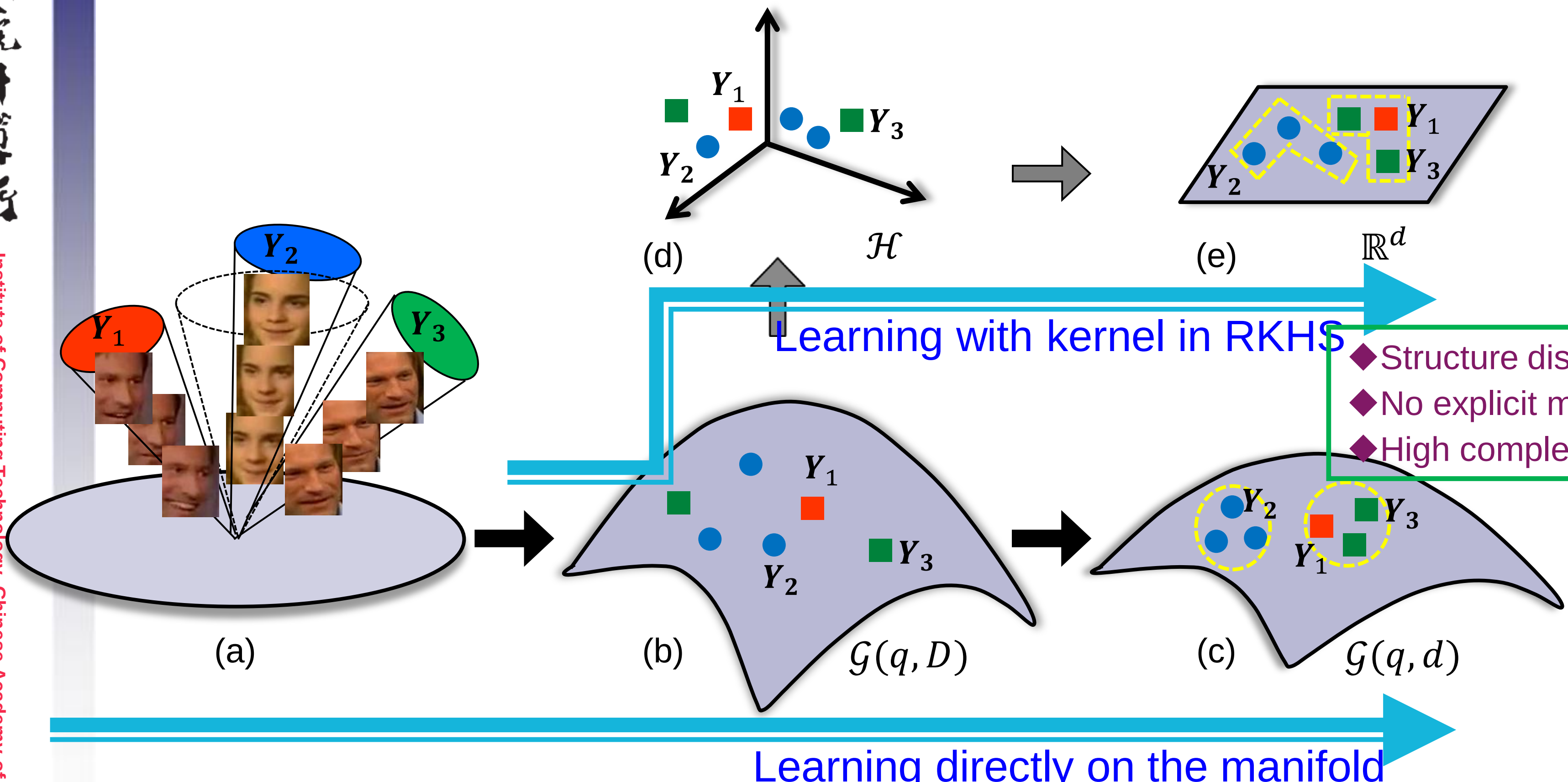
GDA/GGDA

- Discriminative learning
  - Classical kernel methods using the Grassmann kernel
    - e.g., Kernel LDA / kernel Graph embedding
  - $$\boldsymbol{\alpha}^{*} = \arg\max_{\boldsymbol{\alpha}} \frac{\boldsymbol{\alpha}^{T}\boldsymbol{K}\boldsymbol{W}\boldsymbol{K}\boldsymbol{\alpha}}{\boldsymbol{\alpha}^{T}\boldsymbol{K}\boldsymbol{K}\boldsymbol{\alpha}}$$

Grassmann kernel

Set model I: linear subspace

- PML (Projection Metric Learning) [CVPR'15]
  - Metric learning: on Riemannian manifold

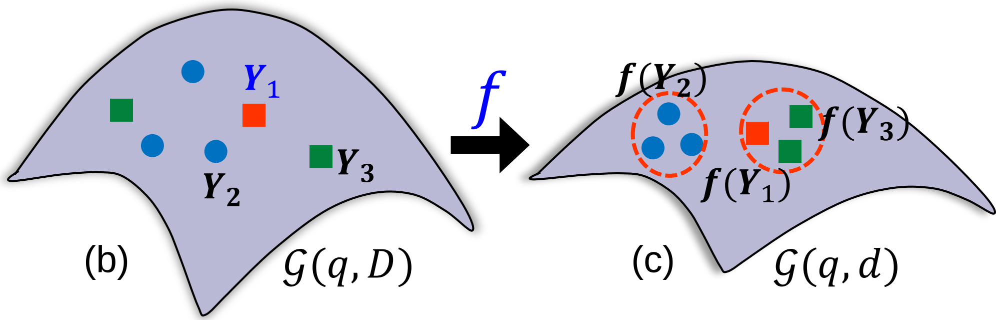


◆Structure distortion
◆No explicit mapping
◆High complexity

[1] Z. Huang, R. Wang, S. Shan, X. Chen. Projection Metric Learning on Grassmann Manifold with Application to Video based Face Recognition. *IEEE CVPR 2015.*

PML

- Explicit manifold to manifold mapping
  - $f(\boldsymbol{Y}) = \boldsymbol{W}^T\boldsymbol{Y} \in \mathcal{G}(q,d), \boldsymbol{Y} \in \mathcal{G}(q,D),\ d \leq D$



- Projection metric on target Grassmann manifold $\mathcal{G}(q,d)$
  - $d_p^2\left(f(\boldsymbol{Y}_\mathrm{i}), f(\boldsymbol{Y}_\mathrm{j})\right) = 2^{-1/2}\left\|(\boldsymbol{W}^T\boldsymbol{Y}_i')(\boldsymbol{W}^T\boldsymbol{Y}_i')^T - (\boldsymbol{W}^T\boldsymbol{Y}_j')(\boldsymbol{W}^T\boldsymbol{Y}_j')^T\right\|_F^2 = 2^{-1/2} tr\left(\boldsymbol{P}^T\boldsymbol{A}_{ij}\boldsymbol{A}_{ij}P\right)$
    - $\boldsymbol{A}_{ij} = (\boldsymbol{Y}_i'\boldsymbol{Y}_i'^T - \boldsymbol{Y}_j'\boldsymbol{Y}_j')^T$, $\boldsymbol{P} = \mathbf{WW}^T$ is a rank-d symmetric positive semidefinite (PSD) matrix of size $D \times D$ (similar form as Mahalanobis matrix)
    - $\boldsymbol{Y}_\mathrm{i}$ needs to be normalized to $\boldsymbol{Y}_i'$ so that the columns of $\boldsymbol{W}^T\boldsymbol{Y}_\mathrm{i}$ are orthonormal

PML

- Discriminative learning
  - Discriminant function
    - Minimize/Maximize the projection distances of any within-class/between-class subspace pairs
    - $J = \min \sum_{l_i = l_j} tr\left(\boldsymbol{P}^T \boldsymbol{A}_{ij} \boldsymbol{A}_{ij} \boldsymbol{P}\right) - \lambda \sum_{l_i \neq l_j} tr\left(\boldsymbol{P}^T \boldsymbol{A}_{ij} \boldsymbol{A}_{ij} \boldsymbol{P}\right)$

      within-class

      between-class
  - Optimization algorithm
    - Iterative solution for one of $\boldsymbol{Y}'$ and $\boldsymbol{P}$ by fixing the other
    - Normalization of $\boldsymbol{Y}$ by QR-decomposition
    - Computation of $\boldsymbol{P}$ by Riemannian Conjugate Gradient (RCG) algorithm on the manifold of PSD matrices

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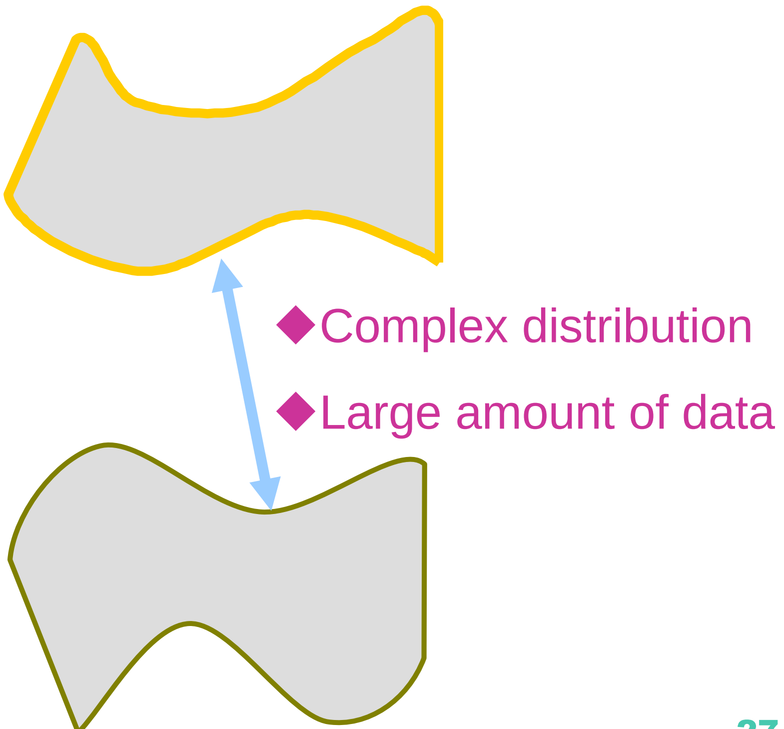
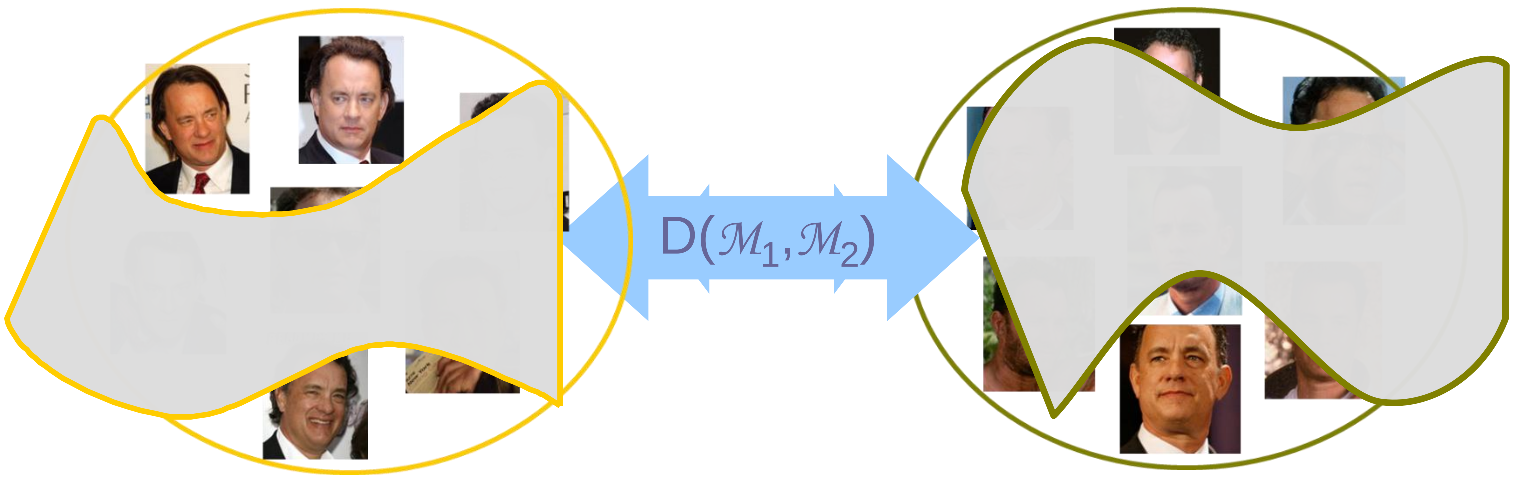
Set model II: nonlinear manifold

- Properties
  - Capture nonlinear complex appearance variation
  - Need dense sampling and large amount of data
  - Less appealing computational efficiency
- Methods
  - MMD [CVPR'08]
  - MDA [CVPR'09]
  - BoMPA [BMVC'05]
  - SANS [CVPR'13]
  - MMDML [CVPR'15]
  - …



Set model II: nonlinear manifold

- MMD (Manifold-Manifold Distance) [CVPR'08]
  - Set modeling with nonlinear appearance manifold
  - Image set classification →distance computation between two manifolds
  - Metric learning: N/A

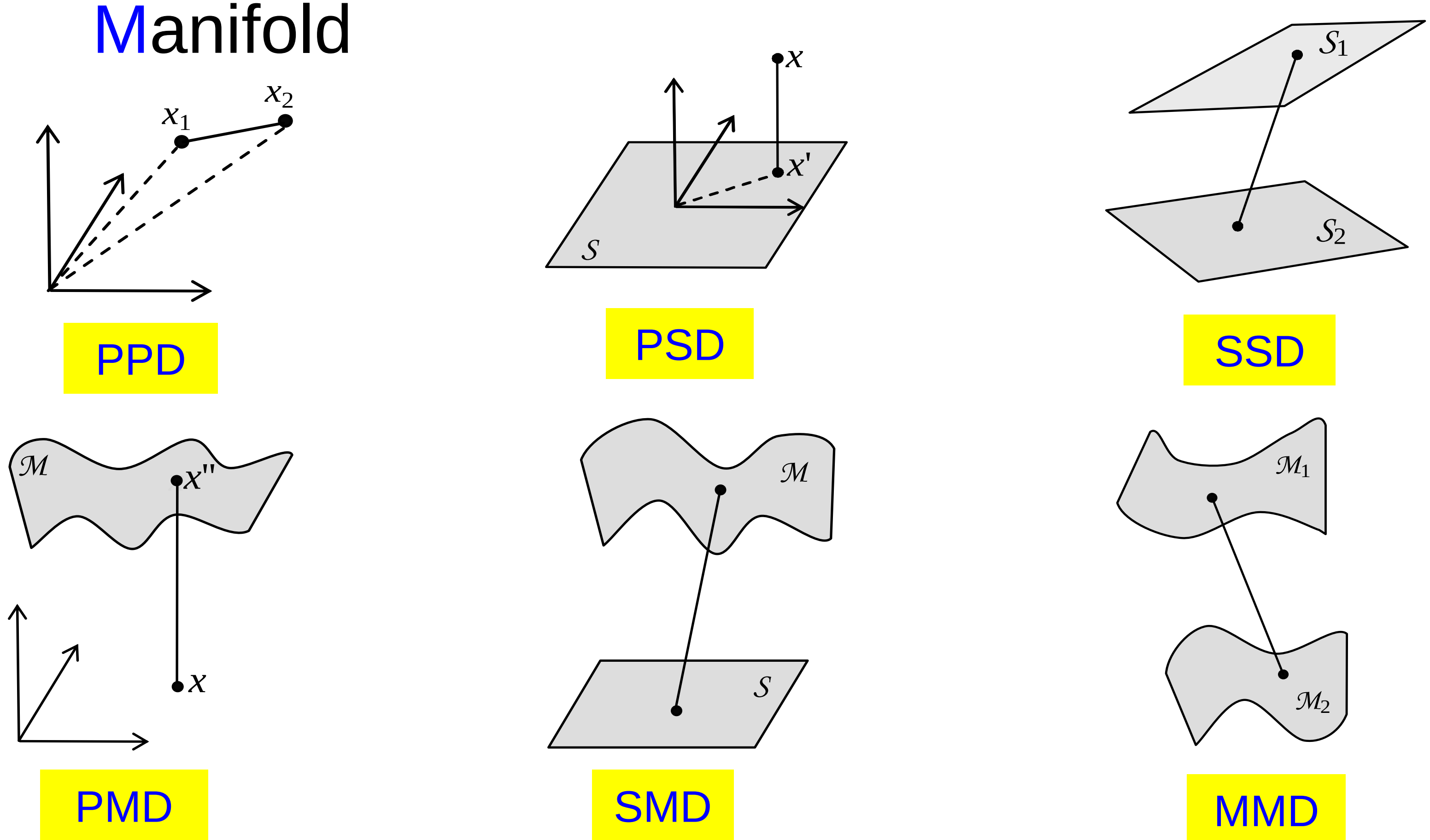


[1] R. Wang, S. Shan, X. Chen, W. Gao. Manifold-Manifold Distance with Application to Face Recognition based on Image Set. *IEEE CVPR 2008*. (Best Student Poster Award Runner-up)

[2] R. Wang, S. Shan, X. Chen, Q. Dai, W. Gao. Manifold-Manifold Distance and Its Application to Face Recognition with Image Sets. *IEEE Trans. Image Processing*, 2012.

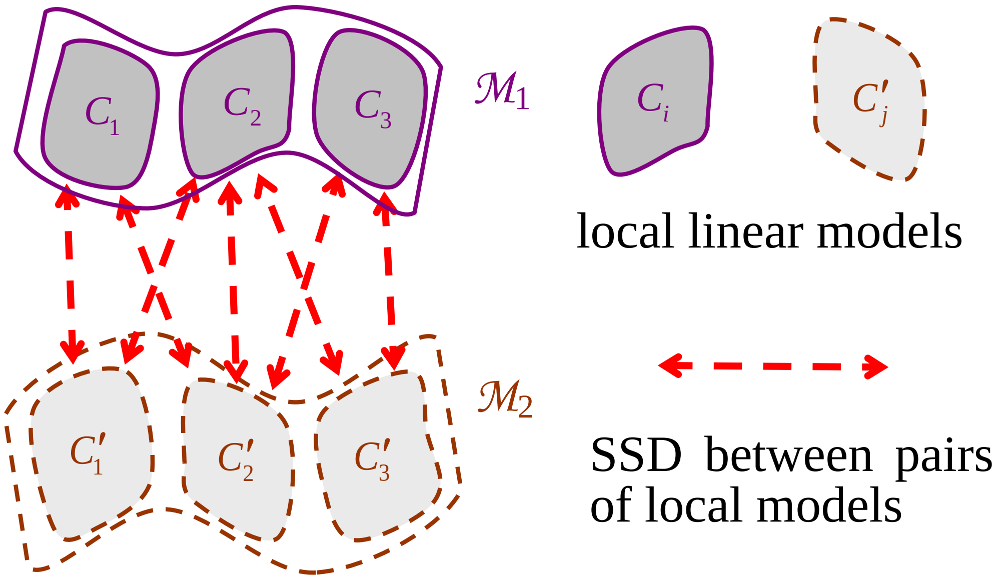
MMD

- Multi-level MMD framework
  - Three pattern levels: Point->Subspace->Manifold



MMD

Formulation & Solution



Three modules

- Local model construction
- Local model distance
- Global integration of local distances

$$d(\mathcal{M}_1, \mathcal{M}_2) = \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} d(C_i, C'_j)$$

$$s.t. \quad \sum_{i=1}^{m} \sum_{j=1}^{n} f_{ij} = 1, \quad f_{ij} \geq 0$$

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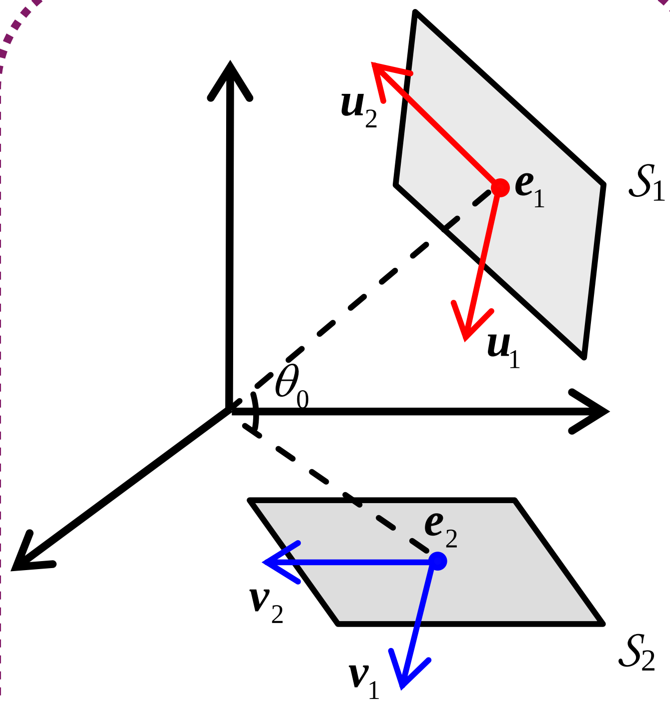
MMD

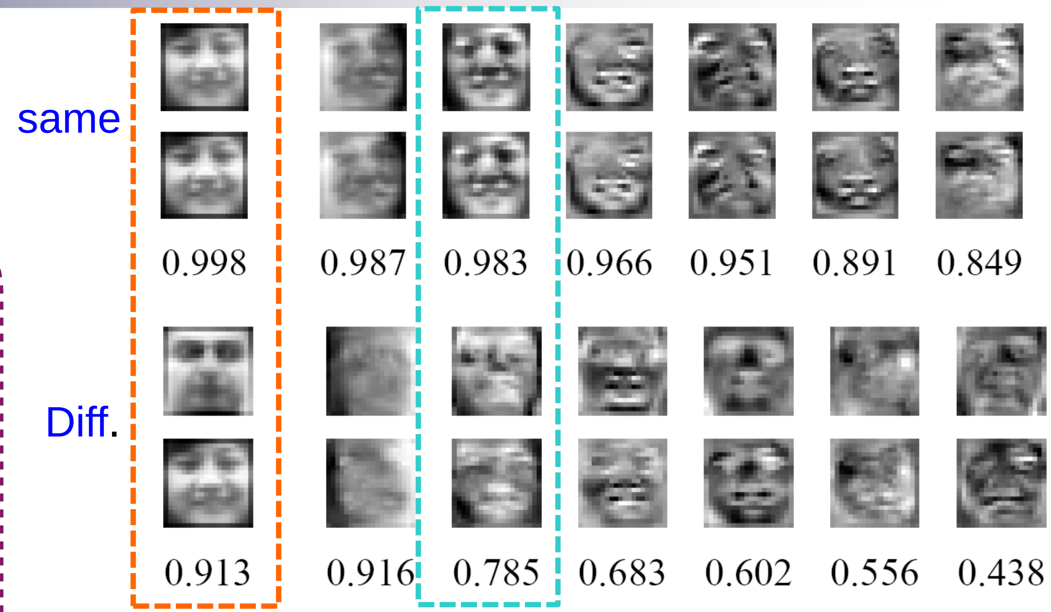
- Subspace-subspace distance (SSD)



mean (cosine correlation)

+

variance (canonical correlation)



$$d_E(S_1, S_2) = (1 - \cos^2\theta_0)^{1/2} = \sin\theta_0$$

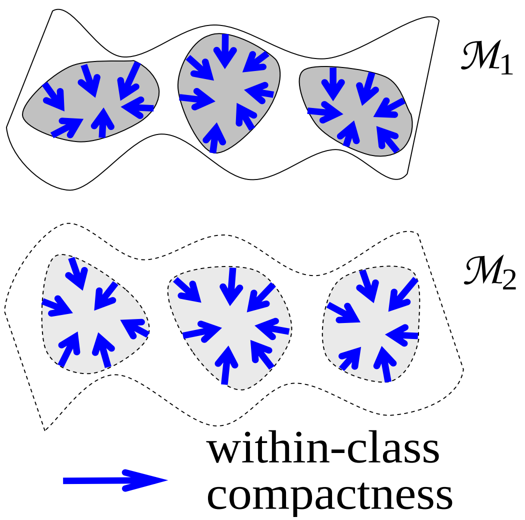
$$d_P(S_1, S_2) = (\sum_{k=1}^{r} \sin^2\theta_k)^{1/2} = (r - \sum_{k=1}^{r} \cos^2\theta_k)^{1/2}$$

$$d(S_1, S_2) = (\sin^2\theta_0 + \frac{1}{r}\sum_{k=1}^{r} \sin^2\theta_k)^{1/2}$$

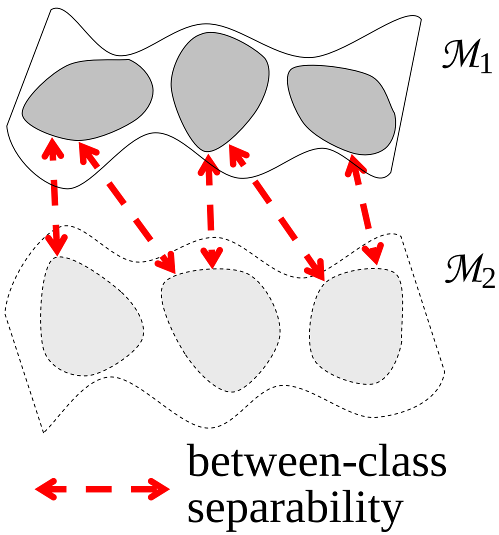
$$= (2 - \cos^2\theta_0 - \frac{1}{r}\sum_{k=1}^{r} \cos^2\theta_k)^{1/2}$$

Set model II: nonlinear manifold

- MDA (Manifold Discriminant Analysis) [CVPR'09]
  - Goal: maximize "manifold margin" under Graph Embedding framework
  - Metric learning: in Euclidean space
    - Euclidean distance between pair of image samples



Intrinsic graph



Penalty graph

[1] R. Wang, X. Chen. Manifold Discriminant Analysis. *IEEE CVPR 2009*.

MDA

- Optimization framework
  - Min. within-class scatter

Intrinsic graph

$$S_w = \sum_{m,n} \left\| \mathbf{v}^T \mathbf{x}_m - \mathbf{v}^T \mathbf{x}_n \right\|^2 w_{m,n} = 2\mathbf{v}^T X(D - W) X^T \mathbf{v}$$

  - Max. between-class scatter

Penalty graph

$$S_b = \sum_{m,n} \left\| \mathbf{v}^T \mathbf{x}_m - \mathbf{v}^T \mathbf{x}_n \right\|^2 w'_{m,n} = 2\mathbf{v}^T X(D' - W') X^T \mathbf{v}$$

  - Objective function
    - Global linear transformation

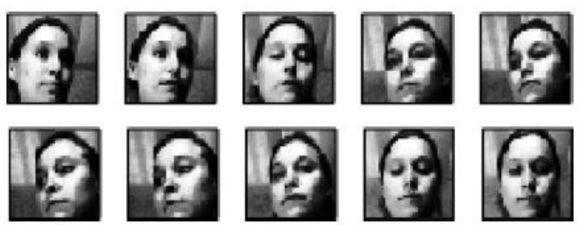
$$\text{Maximize } J(\mathbf{v}) = \frac{|S_b|}{|S_w|} = \frac{\mathbf{v}^T X(D' - W') X^T \mathbf{v}}{\mathbf{v}^T X(D - W) X^T \mathbf{v}}$$

    - Solved by generalized eigen-decomposition

Set model II: nonlinear manifold

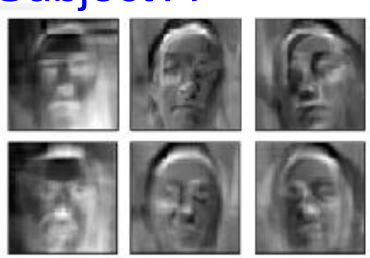
- BoMPA (Boosted Manifold Principal Angles) [BMVC'05]
  - Goal: optimal fusion of different principal angles
  - Exploit Adaboost to learn weights for each angle

$$\mathcal{M}(\Theta) = \mathrm{sign}\left[\sum_{i=1}^{N} w_i \mathcal{M}(\theta_i) - \frac{1}{2}\sum_{i=1}^{N} w_i\right]$$



Subject *A*

Subject *B*



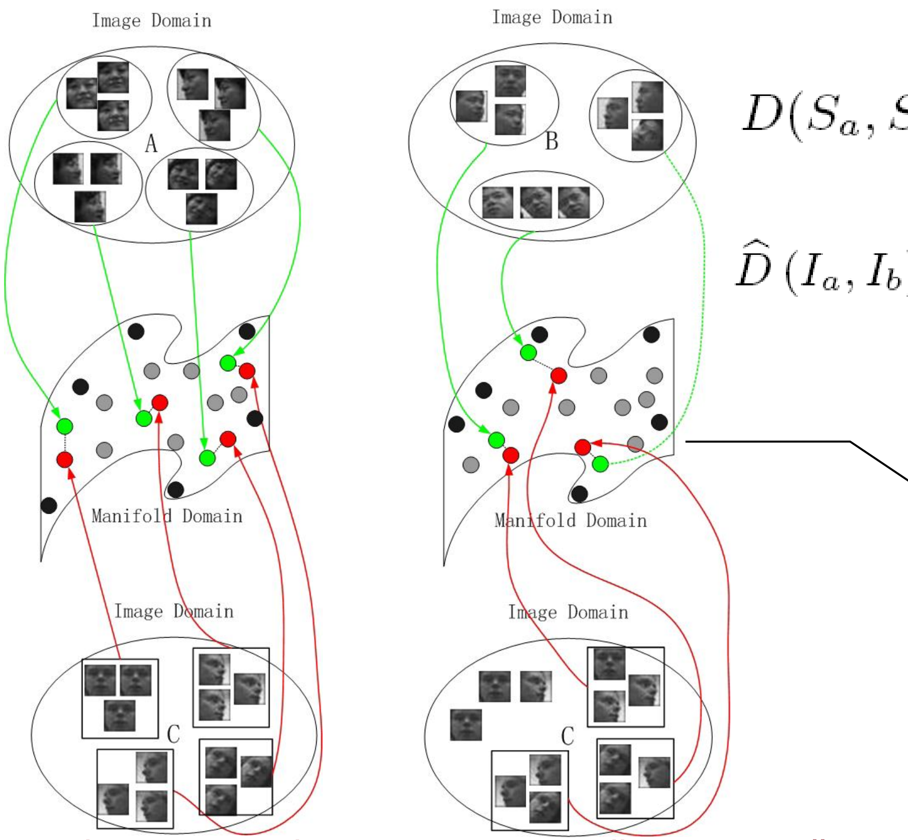
PA→similar (common illumination)

BoMPA→dissimilar

[1] T. Kim O. Arandjelovic, R. Cipolla. Learning over Sets using Boosted Manifold Principal Angles (BoMPA). *BMVC 2005*.

Set model II: nonlinear manifold

- SANS (Sparse Approximated Nearest Subspaces) [CVPR'13]
  - Goal: adaptively construct the nearest subspace pair
  - Metric learning: N/A



$$D(S_a, S_b) = ||\boldsymbol{U}_a - \boldsymbol{U}_b \boldsymbol{U}_b' \boldsymbol{U}_a||_F^2$$

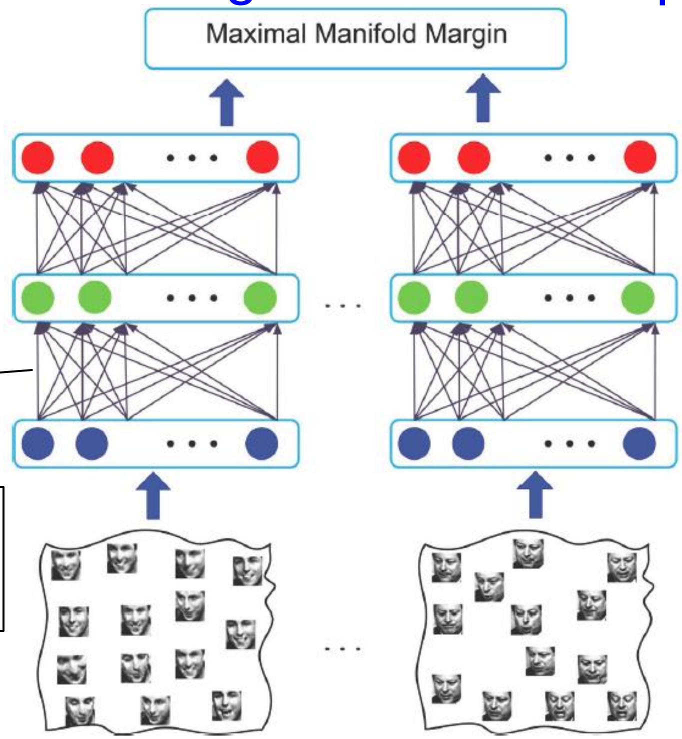
$$\widehat{D}\left(I_a, I_b\right) = \frac{1}{N_c} \sum_{k=1}^{N_c} D\left(s_k^a, s_k^b\right), \quad k \in [1, N_c]$$

◆**SSD** (Subspace-Subspace Distance): Joint sparse representation (JSR) is applied to approximate the nearest subspace over a Grassmann manifold.

[1] S. Chen, C. Sanderson, M.T. Harandi, B.C. Lovell. Improved Image Set Classification via Joint Sparse Approximated Nearest Subspaces. *IEEE CVPR 2013*.

Set model II: nonlinear manifold

- MMDML (Multi-Manifold Deep Metric Learning) [CVPR'15]
  - Goal: maximize "manifold margin" under Deep Learning framework
  - Metric learning: in Euclidean space



◆Class-specific DNN
◆Model nonlinearity

Objective function

$$D_1(h_{ci}^L) = \frac{1}{K_1}\sum_{p=1}^{K_1}\|h_{ci}^L - h_{cip}^L\|_2^2$$

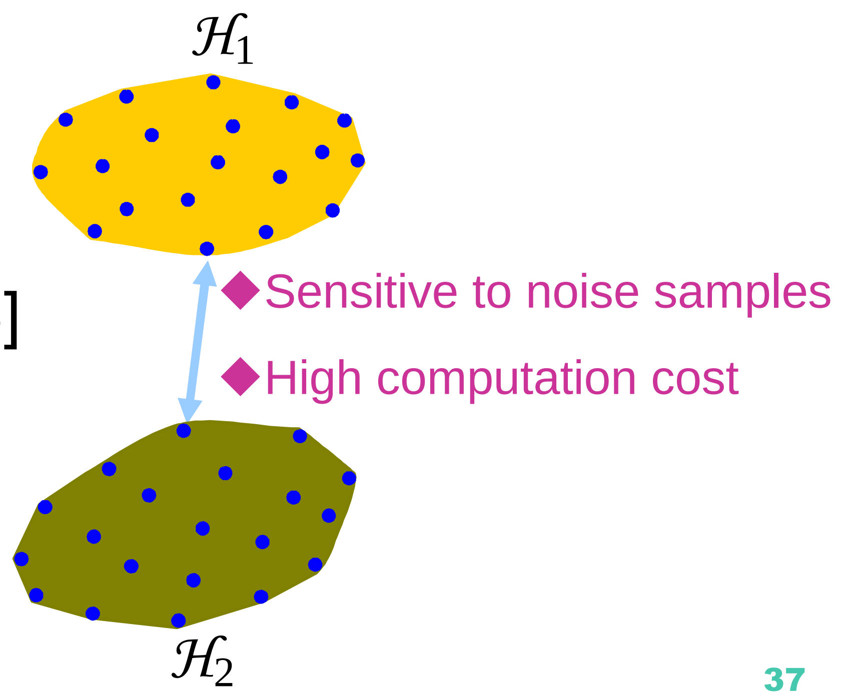
$$D_2(h_{ci}^L) = \frac{1}{K_2}\sum_{q=1}^{K_2}\|h_{ci}^L - h_{ciq}^L\|_2^2$$

$$\min_{f_c}\sum_{i=1}^{N_c}\left(D_1(h_{ci}^L) - D_2(h_{ci}^L)\right)$$

[1] J. Lu, G. Wang, W. Deng, P. Moulin, and J. Zhou. Multi-Manifold Deep Metric Learning for Image Set Classification. *IEEE CVPR 2015*.

Set model III: affine subspace

- Properties
  - Linear reconstruction using: mean + subspace basis
  - Synthesized virtual NN-pair matching
  - Less characterization of global data structure
  - Computationally expensive by NN-based matching
- Methods
  - AHISD/CHISD [CVPR'10]
  - SANP [CVPR'11]
  - PSDML/SSDML [ICCV'13]
  - …



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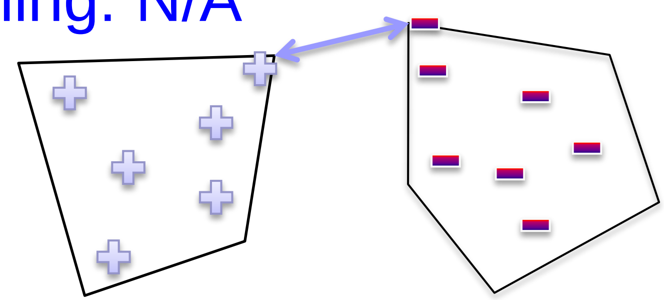
Set model III: affine subspace

- AHISD/CHISD [CVPR'10], SANP [CVPR'11]
  - NN-based matching using sample Euclidean distance
  - Metric learning: N/A



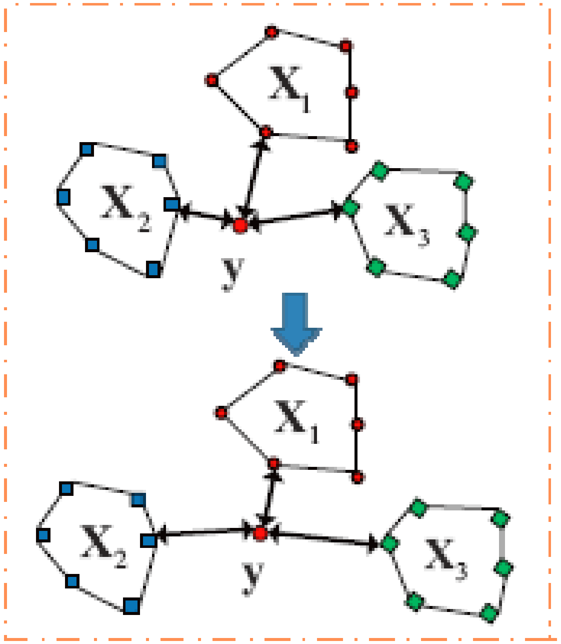
  - Subspace spanned by all the available samples $\boldsymbol{D} = \{d_1, \ldots, d_n\}$ in the set
    - Affine hull
      - $H(\boldsymbol{D}) = \{\boldsymbol{D\alpha} = \sum d_i \alpha_i \mid \sum \alpha_i = 1\}$
    - Convex hull
      - $H(\boldsymbol{D}) = \{\boldsymbol{D\alpha} = \sum d_i \alpha_i \mid \sum \alpha_i = 1, 0 \le \alpha_i \le 1\}$

[1] H. Cevikalp, B. Triggs. Face Recognition Based on Image Sets. *IEEE CVPR 2010.*

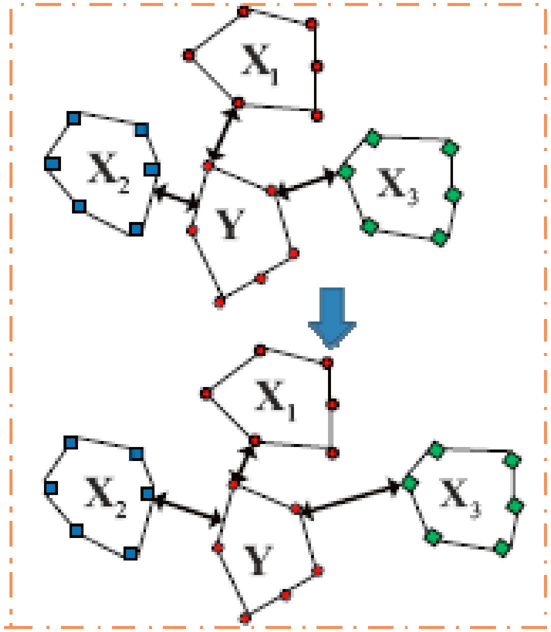
[2] Y. Hu, A.S. Mian, R. Owens. Sparse Approximated Nearest Points for Image Set Classification. *IEEE CVPR 2011.*

Set model III: affine subspace

- PSDML/SSDML [ICCV'13]
  - Metric learning: in Euclidean space



point-to-set distance metric learning (PSDML)



set-to-set distance metric learning (SSDML)

[1] P. Zhu, L. Zhang, W. Zuo, and D. Zhang. From Point to Set: Extend the Learning of Distance Metrics. *IEEE ICCV 2013.*

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PSDML/SSDML

- Point-to-set distance
  - Basic distance
    - $d^2(\boldsymbol{x}, \boldsymbol{D}) = min_{\boldsymbol{\alpha}} \|\boldsymbol{x} - H(\boldsymbol{D})\|_2^2 = min_{\boldsymbol{\alpha}} \|\boldsymbol{x} - \boldsymbol{D\alpha}\|_2^2$
      - Solution: Least Square Regression or Ridge Regression
  - Mahalanobis distance
    - $d_{\boldsymbol{M}}^2(\boldsymbol{x}, \boldsymbol{D}) = min \|\boldsymbol{P}(\boldsymbol{x} - \boldsymbol{D\alpha})\|_2^2 = (\boldsymbol{x} - \boldsymbol{D\alpha})^T \boldsymbol{P}^T \boldsymbol{P}(x - \boldsymbol{D\alpha}) = (\boldsymbol{x} - \boldsymbol{D\alpha})^T \boldsymbol{M}(\boldsymbol{x} - \boldsymbol{D\alpha})$

Projection matrix

PSDML/SSDML

- Point-to-set distance metric learning (PSDML)
  - SVM-based method

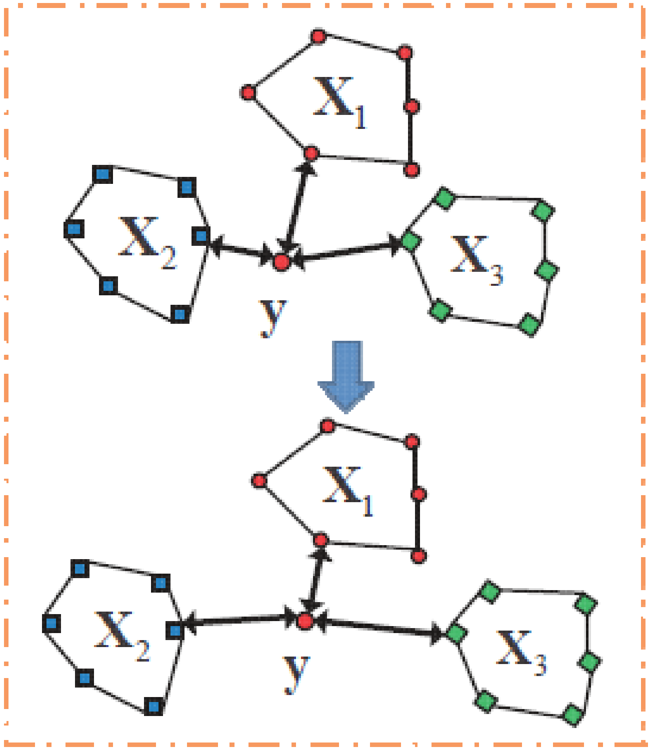
$$\min_{\boldsymbol{M},\boldsymbol{\alpha}_{l(\boldsymbol{x}_i)},\boldsymbol{\alpha}_j,\xi_{ij}^N,\xi_i^P,b} \|\boldsymbol{M}\|_F^2 + \nu\Big(\sum_{i,j}\xi_{i,j}^N + \sum_i \xi_i^P\Big)$$

$$s.t.\ d_M\big(\boldsymbol{x}_i,\boldsymbol{D}_j\big) + b \geq 1 - \xi_{ij}^N, j \neq l(\boldsymbol{x}_i);\ \text{(-)}$$

$$d_M\big(\boldsymbol{x}_i,\boldsymbol{D}_{l(\boldsymbol{x}_i)}\big) + b \leq -1 + \xi_i^P;\ \text{(+)}$$

$$\boldsymbol{M} \succcurlyeq 0, \forall i,j, \xi_{ij}^N \geq 0, \xi_i^P \geq 0$$

$$\begin{aligned} d_{\boldsymbol{M}}^2(\boldsymbol{x},\boldsymbol{D}) &= \min\|\boldsymbol{P}(\boldsymbol{x}-\boldsymbol{D}\boldsymbol{\alpha})\|_2^2 \\ &= (\boldsymbol{x}-\boldsymbol{D}\boldsymbol{\alpha})^T\boldsymbol{P}^T\boldsymbol{P}(x-\boldsymbol{D}\boldsymbol{\alpha}) \\ &= (\boldsymbol{x}-\boldsymbol{D}\boldsymbol{\alpha})^T\boldsymbol{M}(\boldsymbol{x}-\boldsymbol{D}\boldsymbol{\alpha}) \end{aligned}$$



PSDML/SSDML

- Set-to-set distance
  - Basic distance
    - $d^2(\boldsymbol{D}_1, \boldsymbol{D}_2) = min_{\boldsymbol{\alpha}_1,\boldsymbol{\alpha}_2} \|H(\boldsymbol{D}_1) - H(\boldsymbol{D}_1)\|_2^2 = min_{\boldsymbol{\alpha}_1,\boldsymbol{\alpha}_2} \|\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2\|_2^2$
      - Solution: **AHISD/CHISD [Cevikalp, CVPR’10]**
  - Mahalanobis distance
    - $d_{\boldsymbol{M}}^2(\boldsymbol{D}_1, \boldsymbol{D}_2) = min\|\boldsymbol{P}(\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2)\|_2^2 = (\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2)^T\boldsymbol{M}(\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2)$

PSDML/SSDML

- Set-to-set distance metric learning (SSDML)
  - SVM-based method

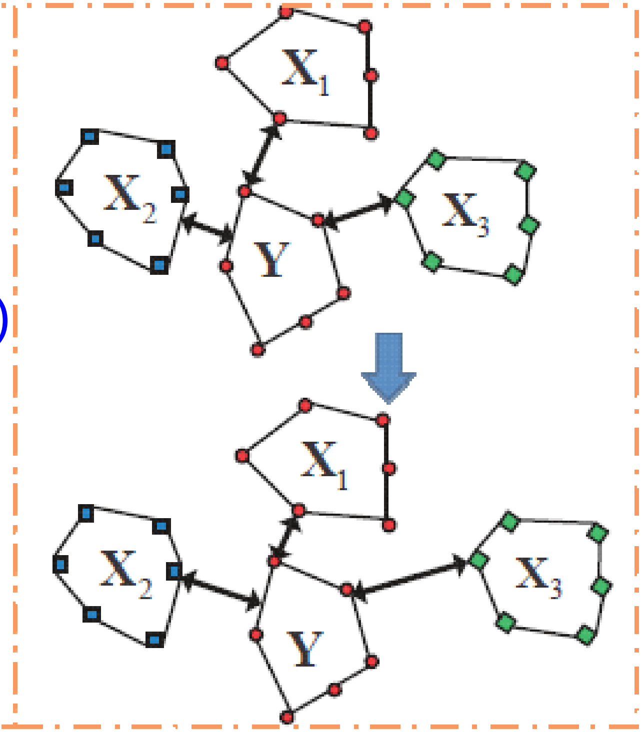
$$\min_{\boldsymbol{M},\boldsymbol{\alpha}_i,\boldsymbol{\alpha}_j,\boldsymbol{\alpha}_k,\xi_{ij}^N,\xi_{ik}^P,b} \|\boldsymbol{M}\|_F^2 + \nu\left(\sum_{i,j} \xi_{ij}^N + \sum_{i,k} \xi_{ik}^P\right)$$

$$s.t.\ d_M\left(\boldsymbol{D}_i, \boldsymbol{D}_j\right) + b \geq 1 - \xi_{ij}^N, l(\boldsymbol{D}_i) \neq l\left(\boldsymbol{D}_j\right); \text{(-)}$$

$$d_M(\boldsymbol{D}_i, \boldsymbol{D}_k) + b \leq -1 + \xi_{ik}^P, l(\boldsymbol{D}_i) = l(\boldsymbol{D}_k); \text{(+)}$$

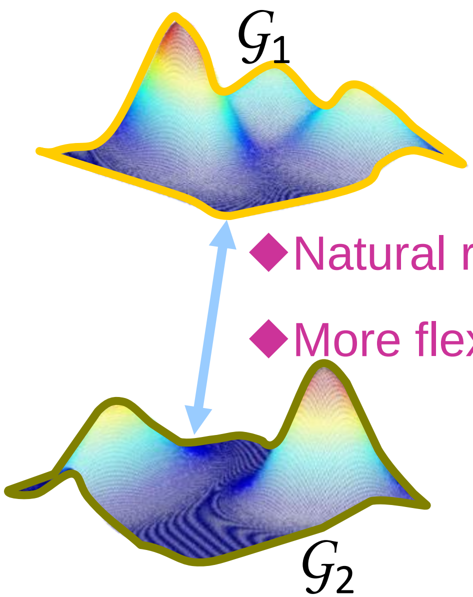
$$\boldsymbol{M} \succcurlyeq 0, \forall i, j, k, \xi_{ij}^N \geq 0, \xi_{ik}^P \geq 0$$

$$d_{\boldsymbol{M}}^2(\boldsymbol{D}_1, \boldsymbol{D}_2) = \min\|\boldsymbol{P}(\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2)\|_2^2$$
$$= (\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2)^T\boldsymbol{M}(\boldsymbol{D}_1\boldsymbol{\alpha}_1 - \boldsymbol{D}_2\boldsymbol{\alpha}_2)$$



Set model IV: statistics (COV+)

- Properties
  - The natural raw statistics of a sample set
  - Flexible model of multiple-order statistical information
- Methods
  - CDL [CVPR'12]
  - LMKML [ICCV'13]
  - DARG [CVPR'15]
  - SPD-ML [ECCV'14]
  - LEML [ICML'15]
  - LERM [CVPR'14]
  - HER [CVPR'15]
  - …



[Shakhnarovich, ECCV'02]
[Arandjelović, CVPR'05]

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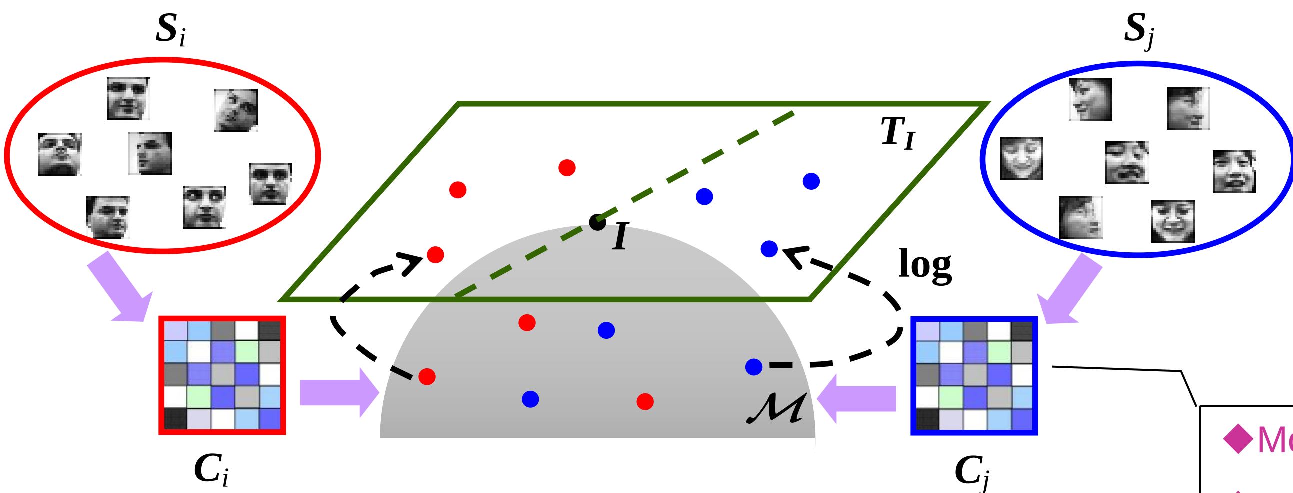
Set model IV: statistics (COV+)

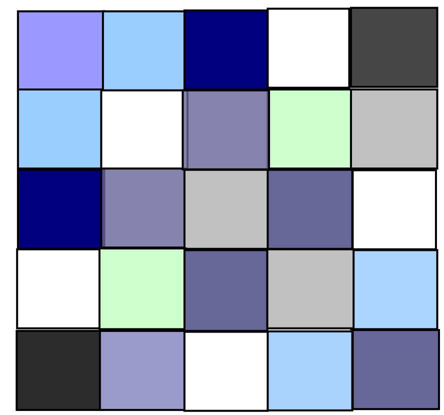
- CDL (Covariance Discriminative Learning) [CVPR'12]
  - Set modeling by Covariance Matrix (COV)
    - The 2nd order statistics characterizing set data variations
    - Robust to noisy set data, scalable to varying set size
  - Metric learning: on the SPD manifold



◆Model data variations
◆No assum. of data distr.

[1] R. Wang, H. Guo, L.S. Davis, Q. Dai. Covariance Discriminative Learning: A Natural and Efficient Approach to Image Set Classification. *IEEE CVPR 2012*.

Set modeling by Covariance Matrix



◆Image set: *N* samples with *d*-dimension image feature

$$\boldsymbol{X} = [\boldsymbol{x}_1, \boldsymbol{x}_2, \ldots, \boldsymbol{x}_N]_{d \times N}$$

◆COV: *d*d* symmetric positive definite (SPD) matrix*

$$\boldsymbol{C} = \frac{1}{N-1}\sum_{i=1}^{N}(\boldsymbol{x}_i - \bar{\boldsymbol{x}})(\boldsymbol{x}_i - \bar{\boldsymbol{x}})^T$$

*: *use regularization to tackle singularity problem*

CDL

- Set matching on COV manifold
  - Riemannian metrics on the SPD manifold
    - Affine-invariant distance (AID) [1]

$$d^2(C_1, C_2) = \sum_{i=1}^{d} \ln^2 \lambda_i(C_1, C_2)$$

or

$$d^2(C_1, C_2) = \left\| \log_I (C_1^{-1/2} C_2 C_1^{-1/2}) \right\|_F^2$$

    - Log-Euclidean distance (LED) [2]

$$d(C_1, C_2) = \left\| \log_I (C_1) - \log_I (C_2) \right\|_F$$

High computational burden

More efficient, more appealing

[1] W. Förstner and B. Moonen. A Metric for Covariance Matrices. *Technical Report* 1999.

[2] V. Arsigny, P. Fillard, X. Pennec and N. Ayache. Geometric Means In A Novel Vector Space Structure On Symmetric Positive-Definite Matrices. *SIAM J. MATRIX ANAL. APPL*. Vol. 29, No. 1, pp. 328-347, 2007.

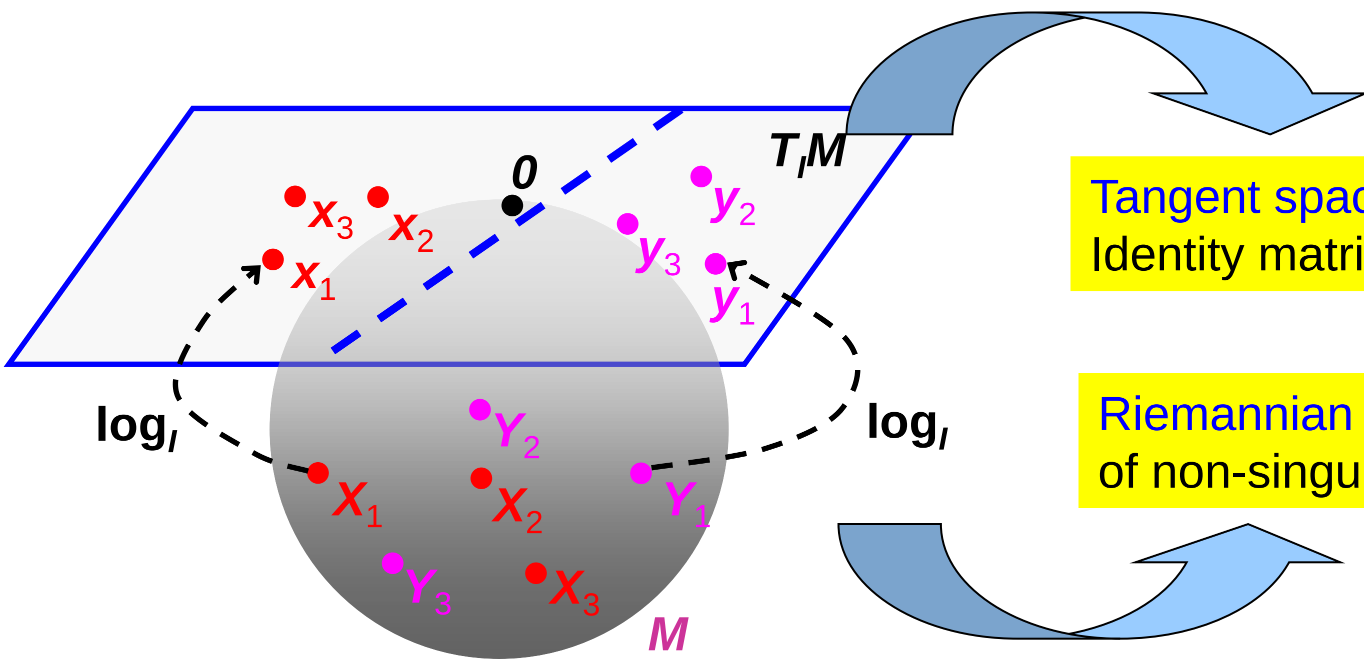
CDL

- Set matching on COV manifold (cont.)
  - Explicit Riemannian kernel feature mapping with LED

$$\Psi_{log}: \quad C \to \log_I(C), \quad (\mathcal{M} \mapsto R^{d\times d})$$

$$k_{log}(C_1, C_2) = trace[\log_I(C_1)\cdot \log_I(C_2)]$$

Mercer's theorem

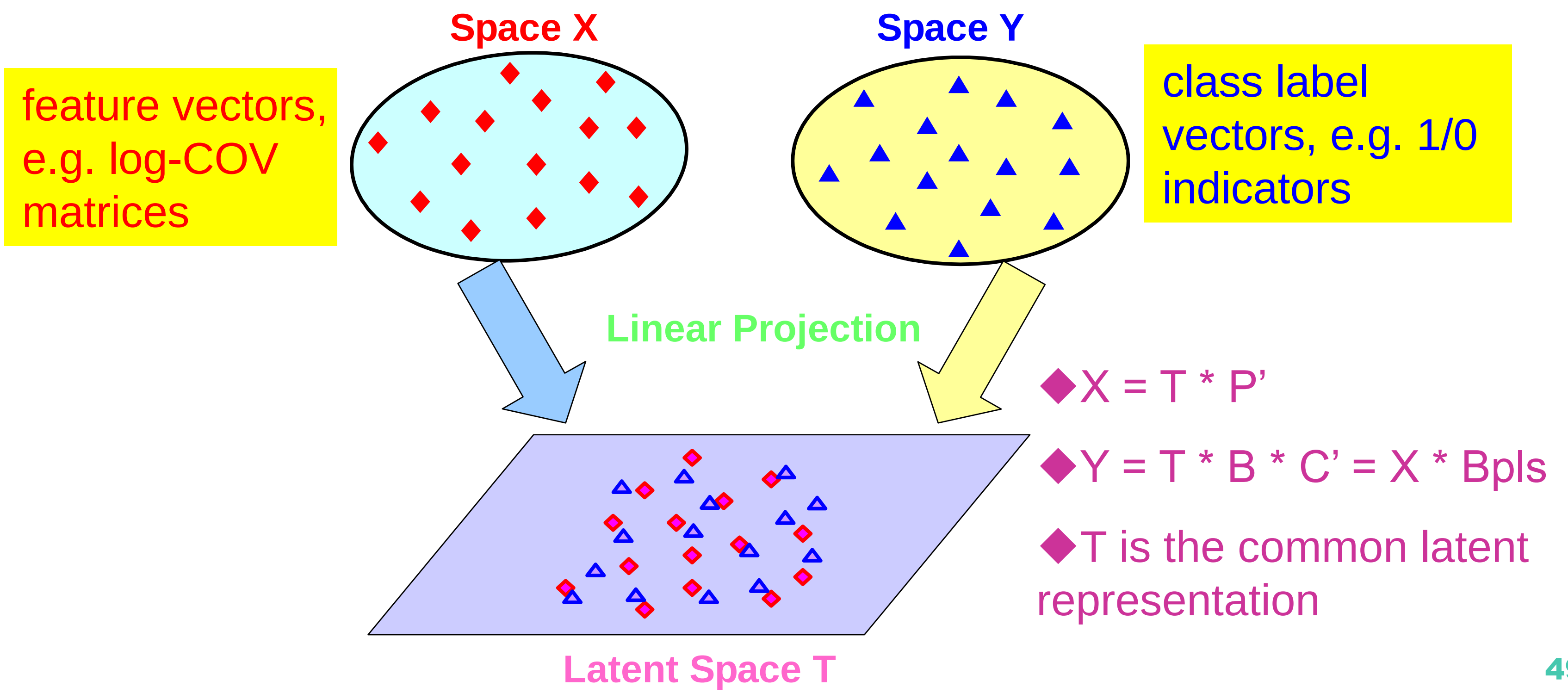


Tangent space at Identity matrix ***I***

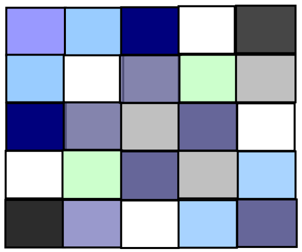
Riemannian manifold of non-singular COV

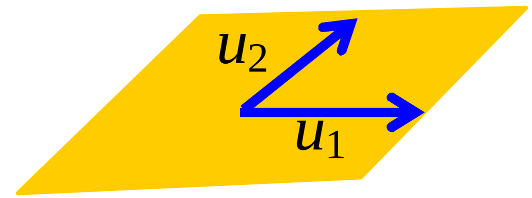
CDL

- Discriminative learning on COV manifold
  - Partial Least Squares (PLS) regression
  - Goal: Maximize the covariance between observations and class labels



CDL vs. GDA





- COV→SPD manifold
  - Model

$$C = \frac{1}{N-1}\sum_{i=1}^{N}(x_i - \bar{x})(x_i - \bar{x})^T$$

  - Metric

$$d(C_1, C_2) = \left\| \log_I(C_1) - \log_I(C_2) \right\|_F$$

$$\Rightarrow \log_I(C) = U \log_I(\Lambda) U^T$$

  - Kernel

$$\Psi_{log} : \ C \rightarrow \log_I(C), \ (\mathcal{M} \mapsto R^{d\times d})$$

- Subspace→Grassmannian
  - Model

$$C = U \Lambda U^T$$

$$\Rightarrow U = [u_1, u_2, \ldots, u_m]_{D\times m}{*}$$

  - Metric

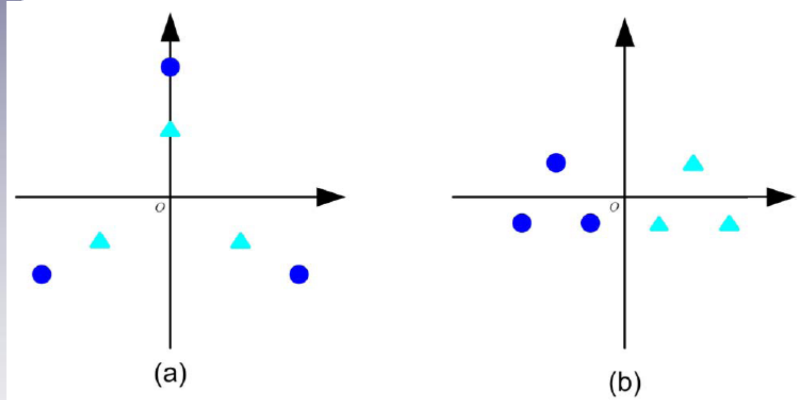
$$d_{proj}(U_1, U_2) = 2^{-1/2} \left\| U_1 U_1^T - U_2 U_2^T \right\|_F$$

  - Kernel

$$\Psi_{proj} : \ U \rightarrow UU^T, \ \mathcal{G}(m, D) \rightarrow R^{d\times d}$$

Set model IV: statistics (COV+)

- LMKML (Localized Multi-Kernel Metric Learning) [ICCV'13]
  - Exploring multiple order statistics
    - Data-adaptive weights for different types of features
    - Ignoring the geometric structure of 2nd/3rd-order statistics
  - Metric learning: in Euclidean space



Complementary information
(mean vs. covariance)

1st / 2nd / 3rd-order statistics

$$m = \frac{1}{n}\sum_{i-1}^{n} x_i \qquad C = \frac{1}{n-1}\sum_{i=1}^{n}\sum_{j=1}^{n}(x_i - m)(x_j - m)^T$$

$$\mathcal{T} = C \otimes m$$

Objective function

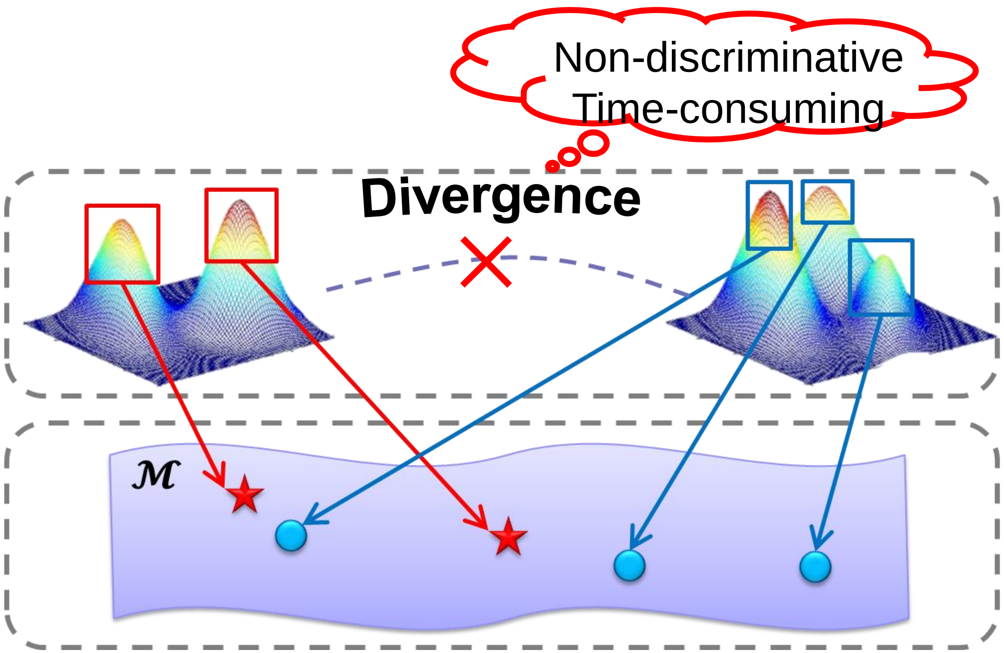
$$d(S_i, S_j) = \sum_{p=1}^{P} \eta_p(\phi_i^p)(\phi_i^p - \phi_j^p)^T M(\phi_i^p - \phi_j^p)\eta_p(\phi_j^p)$$

$$\max_M J = \sum_{\substack{i,j=1 \\ (S_i,S_j)\in C^-}}^{N} \frac{d(S_i, S_j)}{N_{C-}} - \sum_{\substack{i,j=1 \\ (S_i,S_j)\in C^+}}^{N} \frac{d(S_i, S_j)}{N_{C+}}$$

[1] J. Lu, G. Wang, and P. Moulin. Image Set Classification Using Holistic Multiple Order Statistics Features and Localized Multi-Kernel Metric Learning. *IEEE ICCV 2013*.

Set model IV: statistics (COV+)

- DARG (Discriminant Analysis on Riemannian manifold of Gaussian distributions) [CVPR'15]
  - Set modeling by mixture of Gaussian distribution (GMM)
    - Naturally encode the 1st order and 2nd order statistics
  - Metric learning: on Riemannian manifold



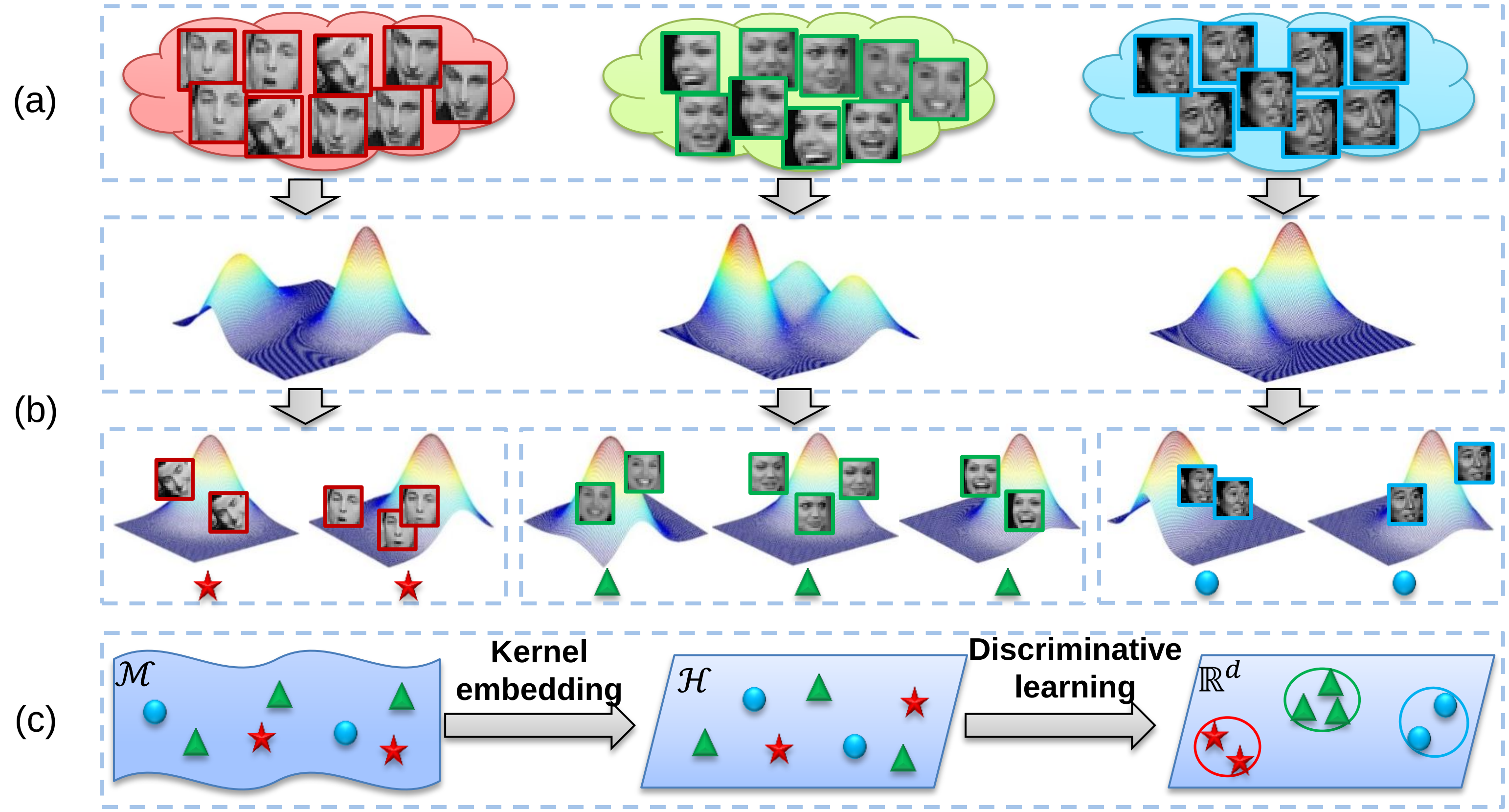
[Shakhnarovich, ECCV'02]
[Arandjelović, CVPR'05]

$\mathcal{M}$: Riemannian manifold of Gaussian distributions

[1] W. Wang, R. Wang, Z. Huang, S. Shan, X. Chen. Discriminant Analysis on Riemannian Manifold of Gaussian Distributions for Face Recognition with Image Sets. *IEEE CVPR 2015*.

DARG

■ Framework



$\mathcal{M}$: Riemannian manifold of Gaussian distributions
$\mathcal{H}$: high-dimensional reproducing kernel Hilbert space (RKHS)
$\mathbb{R}^d$: target lower-dimensional discriminant Euclidean subspace

- Kernels on the Gaussian distribution manifold
  - kernel based on Lie Group
    - Distance based on Lie Group (LGD)

$$LGD(P_i, P_j) = \left\| \log(P_i) - \log(P_j) \right\|_F ,$$

SPD matrix according to information geometry

$$g \sim N(x|\mu, \Sigma) \longmapsto P = |\Sigma|^{-\frac{1}{d+1}} \begin{pmatrix} \Sigma + \mu\mu^T & \mu \\ \mu^T & 1 \end{pmatrix}$$

    - Kernel function

$$K_{\mathrm{LGD}}(g_i, g_j) = \exp\left(-\frac{LGD^2(P_i, P_j)}{2t^2}\right)$$

DARG

- Kernels on the Gaussian distribution manifold
  - kernel based on Lie Group
  - kernel based on MD and LED
    - Mahalanobis Distance (MD) between mean

$$MD(\mu_i,\mu_j)=\sqrt{(\mu_i-\mu_j)^T(\Sigma_i^{-1}+\Sigma_j^{-1})(\mu_i-\mu_j)}$$

    - LED between covariance matrix

$$LED(\Sigma_i,\Sigma_j)=\|\log(\Sigma_i)-\log(\Sigma_j)\|_F$$

    - Kernel function

$$K_{MD+LED}(g_i,g_j)=\gamma_1 K_{MD}(\mu_i,\mu_j)+\gamma_2 K_{LED}(\Sigma_i,\Sigma_j)$$

$$K_{MD}(\mu_i,\mu_j)=\exp\left(-\frac{\mathrm{MD}^2(\mu_i,\mu_j)}{2t^2}\right)$$

$$K_{LED}(\Sigma_i,\Sigma_j)=\exp\left(-\frac{LED^2(\Sigma_i,\Sigma_j)}{2t^2}\right)$$

γ_1,γ_2 are the combination coefficients

DARG

- Discriminative learning
  - Weighted KDA (kernel discriminant analysis)
    - incorporating the weights of Gaussian components

$$J(\alpha) = \frac{|\alpha^T \boldsymbol{B} \alpha|}{|\alpha^T \boldsymbol{W} \alpha|}$$

$$\boldsymbol{W} = \sum_{i=1}^{C} \frac{1}{\omega_i} \sum_{j=1}^{N_i} w_j^{(i)} (k_j^i - m_i)(k_j^i - m_i)^T$$

$$\boldsymbol{B} = \sum_{i=1}^{C} N_i (m_i - m)(m_i - m)^T$$

$$m_i = \frac{1}{N_i \omega_i} \sum_{j=1}^{N_i} w_j^i k_j^i \,, \mathrm{m} = \frac{1}{N_i} \sum_{i=1}^{C} \frac{1}{\omega_i} \sum_{j=1}^{N_i} w_j^i k_j^i$$

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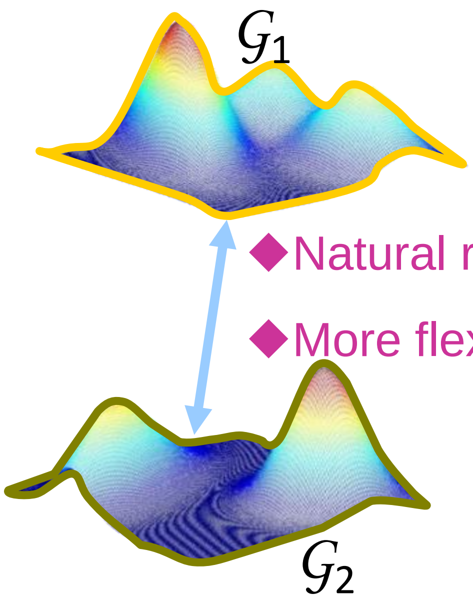
Set model IV: statistics (COV+)

- Properties
  - The natural raw statistics of a sample set
  - Flexible model of multiple-order statistical information
- Methods
  - CDL [CVPR'12]
  - LMKML [ICCV'13]
  - DARG [CVPR'15]
  - SPD-ML [ECCV'14]
  - LEML [ICML'15]
  - LERM [CVPR'14]
  - HER [CVPR'15]
  - …



◆Natural raw statistics

◆More flexible model

[Shakhnarovich, ECCV'02]
[Arandjelović, CVPR'05]

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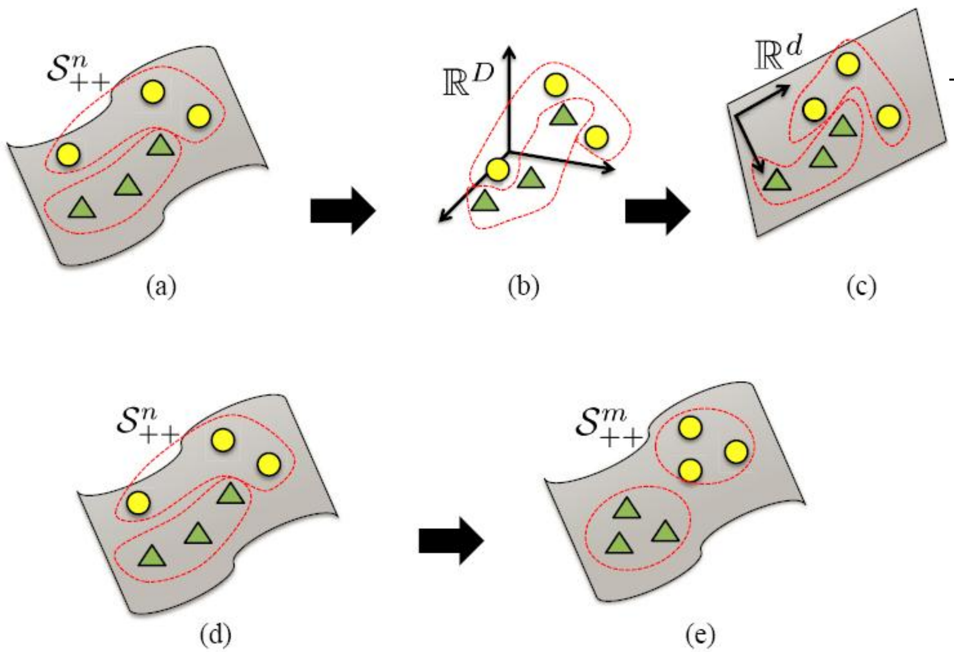
Set model IV: statistics (COV+)

- SPD-ML (SPD Manifold Learning) [ECCV'14]
  - Pioneering work on explicit manifold-to-manifold dimensionality reduction
  - Metric learning: on Riemannian manifold

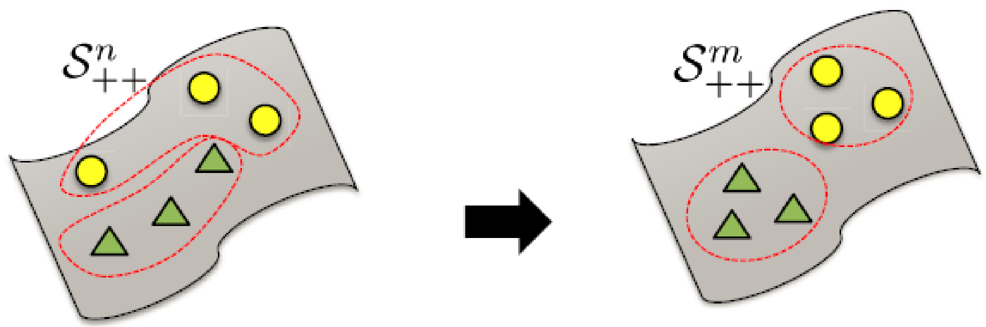


◆Structure distortion
◆No explicit mapping

[1] M. Harandi, M. Salzmann, R. Hartley. From Manifold to Manifold: Geometry-Aware Dimensionality Reduction for SPD Matrices. *ECCV 2014.*

SPD-ML

- SPD manifold dimensionality reduction
  - Mapping function: $f: \mathcal{S}_{++}^{n} \times \mathbb{R}^{n\times m} \rightarrow \mathcal{S}_{++}^{m}$
    - $f\left(\boldsymbol{X}, \widetilde{\boldsymbol{W}}\right) = \widetilde{\boldsymbol{W}}^{T}\boldsymbol{X}\widetilde{\boldsymbol{W}} \in \mathcal{S}_{++}^{m} \succ 0,\ \boldsymbol{X} \in \mathcal{S}_{++}^{n},\ \widetilde{\boldsymbol{W}} \in \mathbb{R}^{n\times m}$ (full rank)



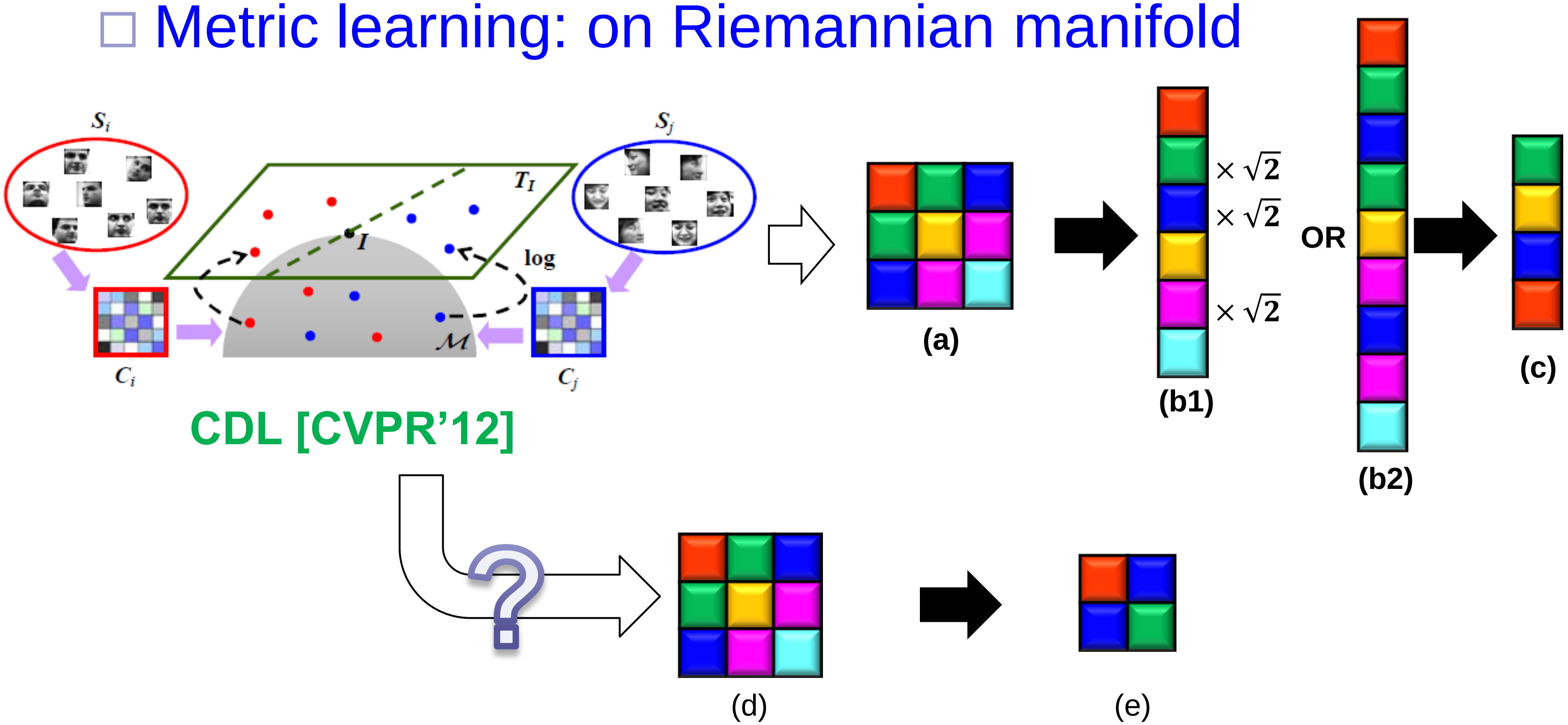
- Affine invariant metrics: AIRM / Stein divergence on target SPD manifold $\mathcal{S}_{++}^{m}$
  - $\delta^{2}\left(\widetilde{\boldsymbol{W}}^{T}\boldsymbol{X}_{i}\widetilde{\boldsymbol{W}}, \widetilde{\boldsymbol{W}}^{T}\boldsymbol{X}_{i}\widetilde{\boldsymbol{W}}\right) = \delta^{2}\left(\boldsymbol{W}^{T}\boldsymbol{X}_{i}\boldsymbol{W}, \boldsymbol{W}^{T}\boldsymbol{X}_{j}\boldsymbol{W}\right)$
    - $\widetilde{\boldsymbol{W}} = \boldsymbol{M}\boldsymbol{W},\ \boldsymbol{M} \in GL(n),\ \boldsymbol{W} \in \mathbb{R}^{n\times m},\ \boldsymbol{W}^{T}\boldsymbol{W} = \boldsymbol{I}_{m}$

SPD-ML

- Discriminative learning
  - Discriminant function
    - Graph Embedding formalism with an affinity matrix that encodes intra-class and inter-class SPD distances
    - $\min L(\boldsymbol{W}) = \min \sum_{ij} \boldsymbol{A}_{ij} \delta^2(\boldsymbol{W}^T \boldsymbol{X}_i \boldsymbol{W}, \boldsymbol{W}^T \boldsymbol{X}_j \boldsymbol{W})$
      - $s.t. \boldsymbol{W}^T \boldsymbol{W} = \boldsymbol{I}_m$ (orthogonality constraint)
  - Optimization
    - Optimization problems on Stiefel manifold, solved by nonlinear Conjugate Gradient (CG) method

Set model IV: statistics (COV+)

- LEML (Log-Euclidean Metric Learning) [ICML'15]
  - Learning tangent map by preserving matrix symmetric structure
  - Metric learning: on Riemannian manifold



[1] Z. Huang, R. Wang, S. Shan, X. Li, X. Chen. Log-Euclidean Metric Learning on Symmetric Positive Definite Manifold with Application to Image Set Classification. *ICML 2015*.

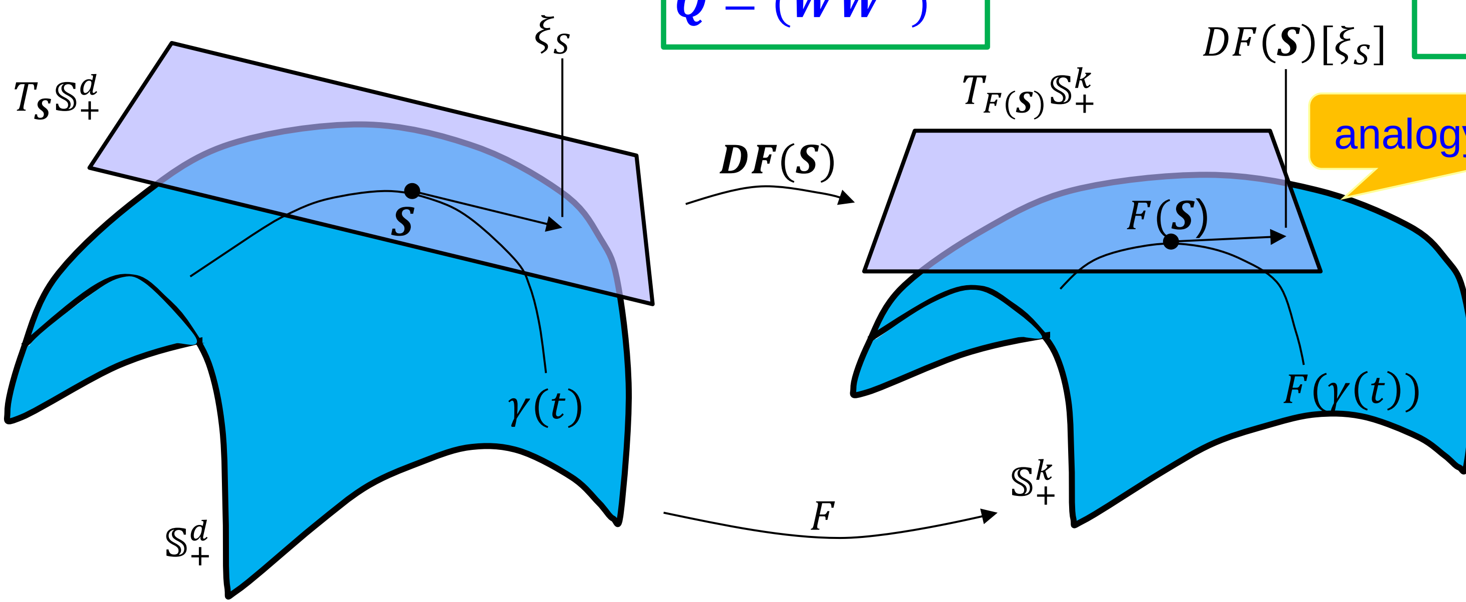
LEML

- SPD tangent map learning
  - Mapping function: DF: $f(\log(\boldsymbol{S})) = \boldsymbol{W}^T \log(\boldsymbol{S})\boldsymbol{W}$
    - $\boldsymbol{W}$ is column full rank
  - Log-Euclidean distance in the target tangent space
    - $d_{LED}\left(f(\boldsymbol{T}_i), f(\boldsymbol{T}_j)\right) = ||\boldsymbol{W}^T\boldsymbol{T}_i\boldsymbol{W} - \boldsymbol{W}^T\boldsymbol{T}_j\boldsymbol{W}||_F$

$$= tr(\boldsymbol{Q}(\boldsymbol{T}_i - \boldsymbol{T}_j)(\boldsymbol{T}_i - \boldsymbol{T}_j))$$

$\boldsymbol{Q} = (\boldsymbol{W}\boldsymbol{W}^T)^2$

$\boldsymbol{T} = \log(\boldsymbol{S})$



analogy to 2DPCA

LEML

- Discriminative learning
  - Objective function
    - $\arg\min_{Q,\xi} D_{ld}(\boldsymbol{Q}, \boldsymbol{Q_0}) + \eta D_{ld}(\boldsymbol{\xi}, \boldsymbol{\xi_0})$

$$\text{s.t.}, \operatorname{tr}\left(\boldsymbol{Q}\boldsymbol{A}_{ij}^{T}\mathbf{A}_{ij}\right) \leq \xi_{\boldsymbol{c}(i,j)}, (i,j) \in \boldsymbol{S}$$

$$\operatorname{tr}\left(\boldsymbol{Q}\boldsymbol{A}_{ij}^{T}\mathbf{A}_{ij}\right) \geq \xi_{\boldsymbol{c}(i,j)}, (i,j) \in \boldsymbol{D}$$

    - $\mathbf{A}_{ij} = \log(\boldsymbol{C}_i) - \log(\boldsymbol{C}_j)$, D_{ld}: LogDet divergence
  - Optimization
    - Cyclic Bregman projection algorithm [Bregman’1967]

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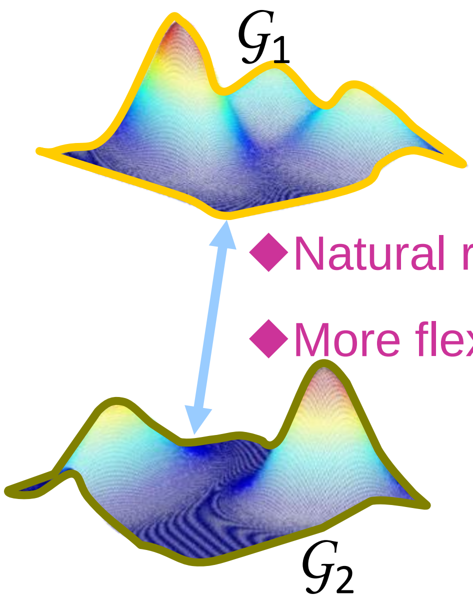
Set model IV: statistics (COV+)

- Properties
  - The natural raw statistics of a sample set
  - Flexible model of multiple-order statistical information
- Methods
  - CDL [CVPR'12]
  - LMKML [ICCV'13]
  - DARG [CVPR'15]
  - SPD-ML [ECCV'14]
  - LEML [ICML'15]
  - LERM [CVPR'14]
  - HER [CVPR'15]
  - …



◆Natural raw statistics

◆More flexible model

[Shakhnarovich, ECCV'02]
[Arandjelović, CVPR'05]

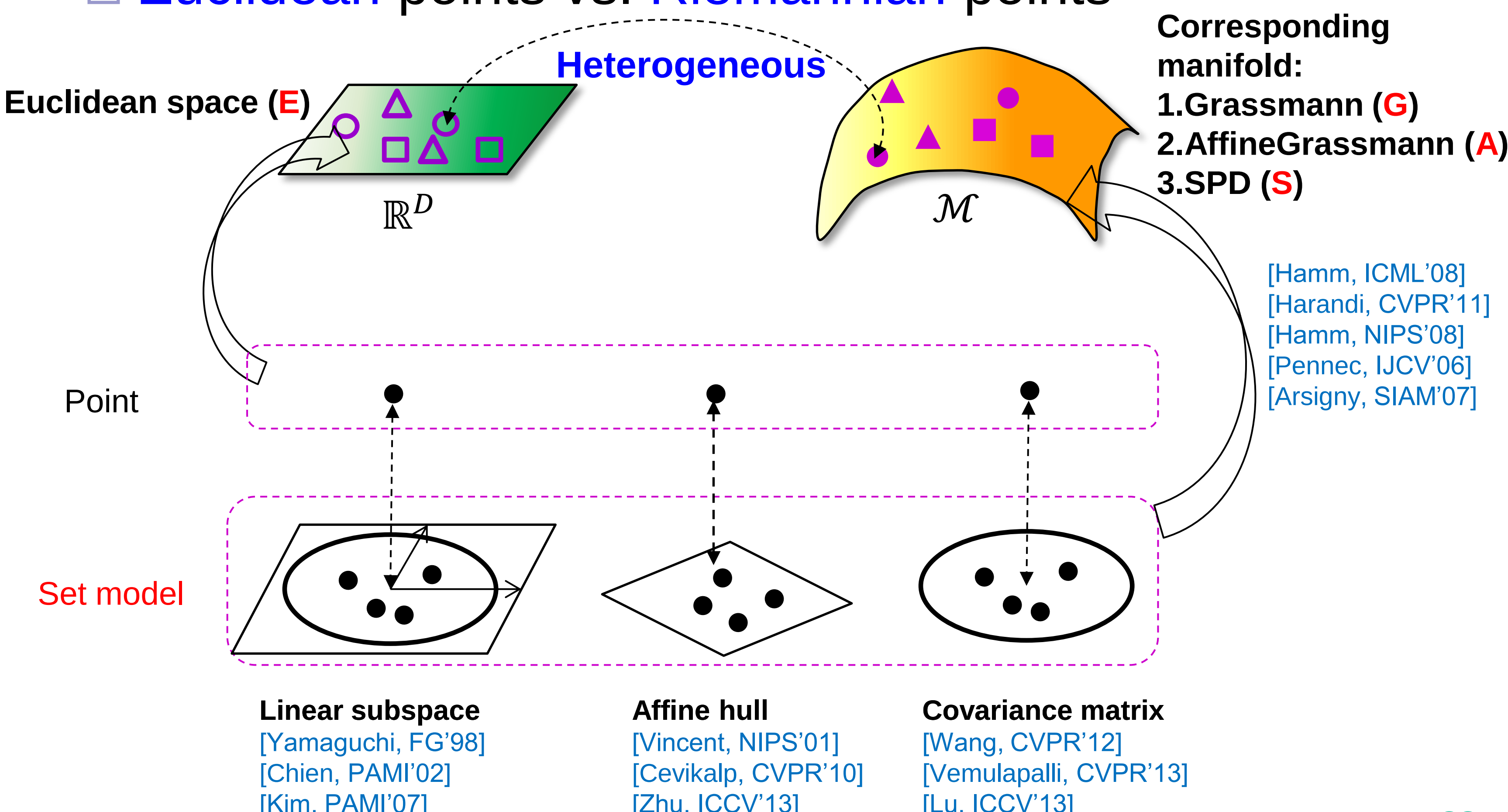
Set model IV: statistics (COV+)

- LERM (Learning Euclidean-to-Riemannian Metric) [CVPR'14]
  - Application scenario: still-to-video face recognition
  - Metric learning: cross Euclidean space and Riemannian manifold

[1] Z. Huang, R. Wang, S. Shan, X. Chen. Learning Euclidean-to-Riemannian Metric for Point-to-Set Classification. *IEEE CVPR 2014*.

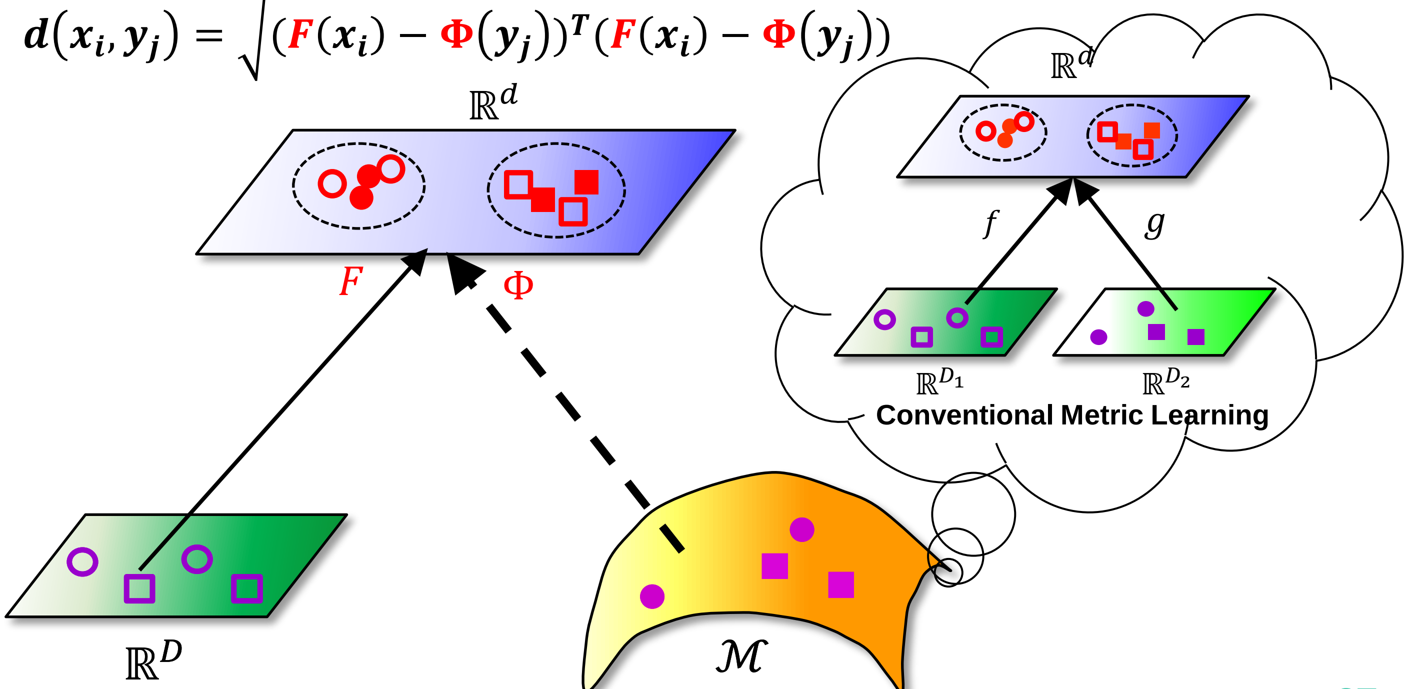
LERM

- Point-to-Set Classification
  - Euclidean points vs. Riemannian points



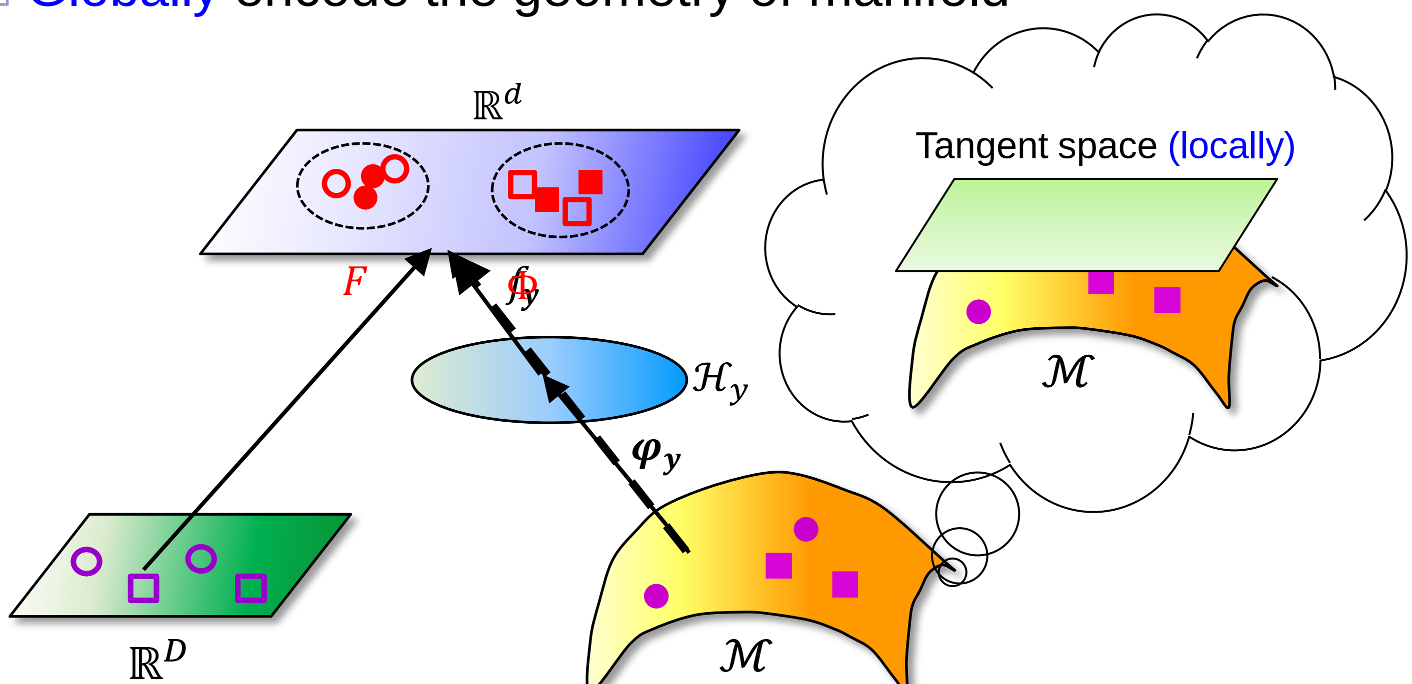
LERM

- Basic idea
  - Reduce Euclidean-to-Riemannian metric to classical Euclidean metric
    - Seek maps F, Φ to a common Euclidean subspace
      - $d(x_i, y_j) = \sqrt{(F(x_i) - \Phi(y_j))^T (F(x_i) - \Phi(y_j))}$



LERM

- Basic idea
  - Bridge Euclidean-to-Riemannian gap
    - Hilbert space embedding
      - Adhere to Euclidean geometry
      - Globally encode the geometry of manifold



LERM

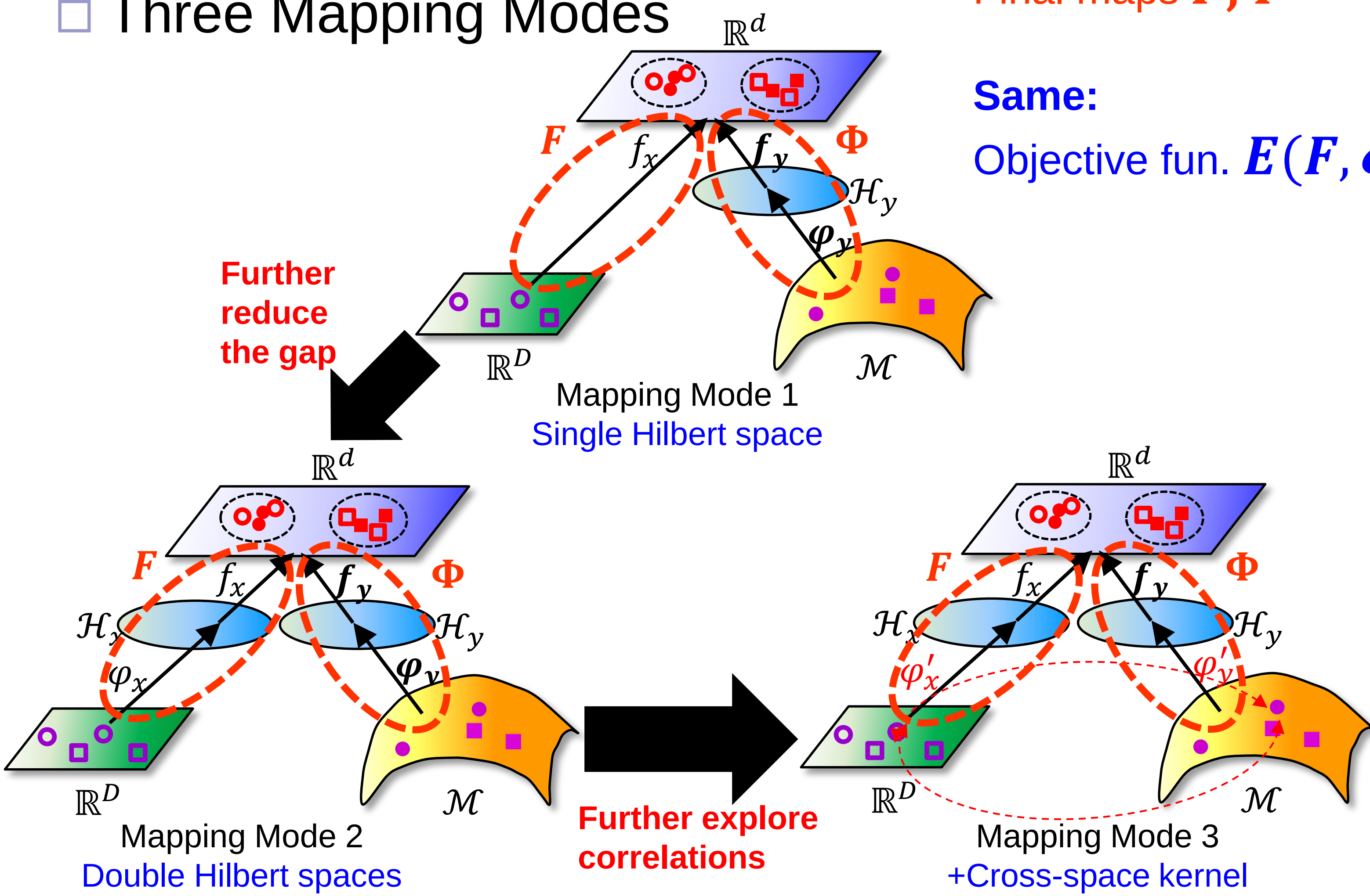
- Formulation
  - Three Mapping Modes

Different:

Final maps $\boldsymbol{F}, \boldsymbol{\Phi}$

Same:

Objective fun. $\boldsymbol{E}(\boldsymbol{F}, \boldsymbol{\varphi})$



LERM

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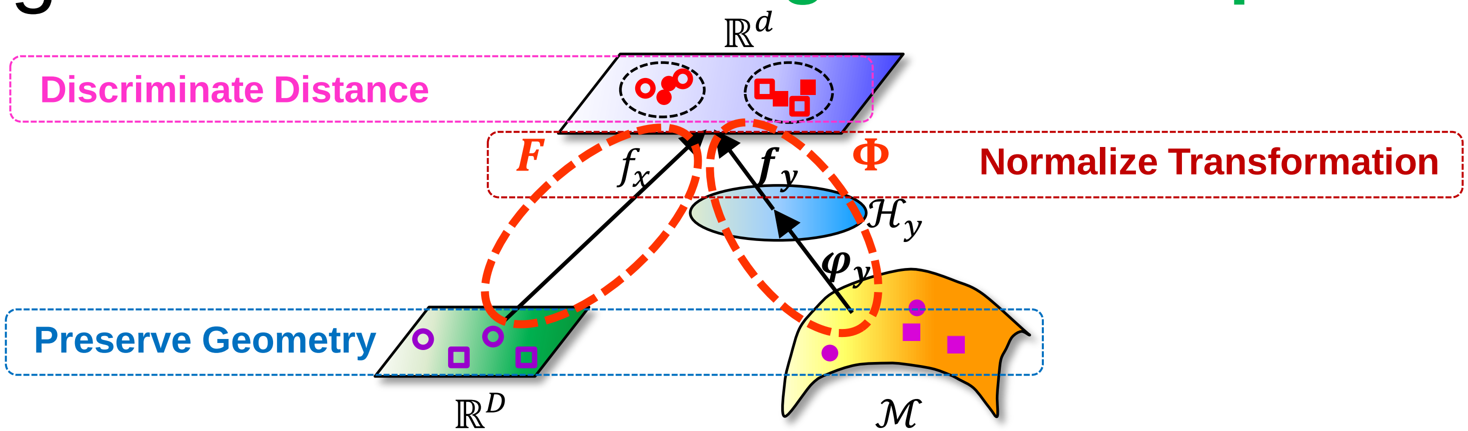
- e.g. Mode 1

Single Hilbert space



Final maps:

$$F = f_x = W_x^T X$$

$$\Phi = f_y \circ \varphi_y = W_y^T K_y$$

$$\langle \varphi_{y_i}, \varphi_{y_j} \rangle = K_y(i,j)$$

$$K_y(i,j) = \exp(-d^2(y_i, y_j)/2\sigma^2)$$

Riemannian metrics [ICML'08, NIPS'08, SIAM'06]

Distance metric:

$$d(x_i, y_j) = \sqrt{(F(x_i) - \Phi(y_j))^T (F(x_i) - \Phi(y_j))}$$

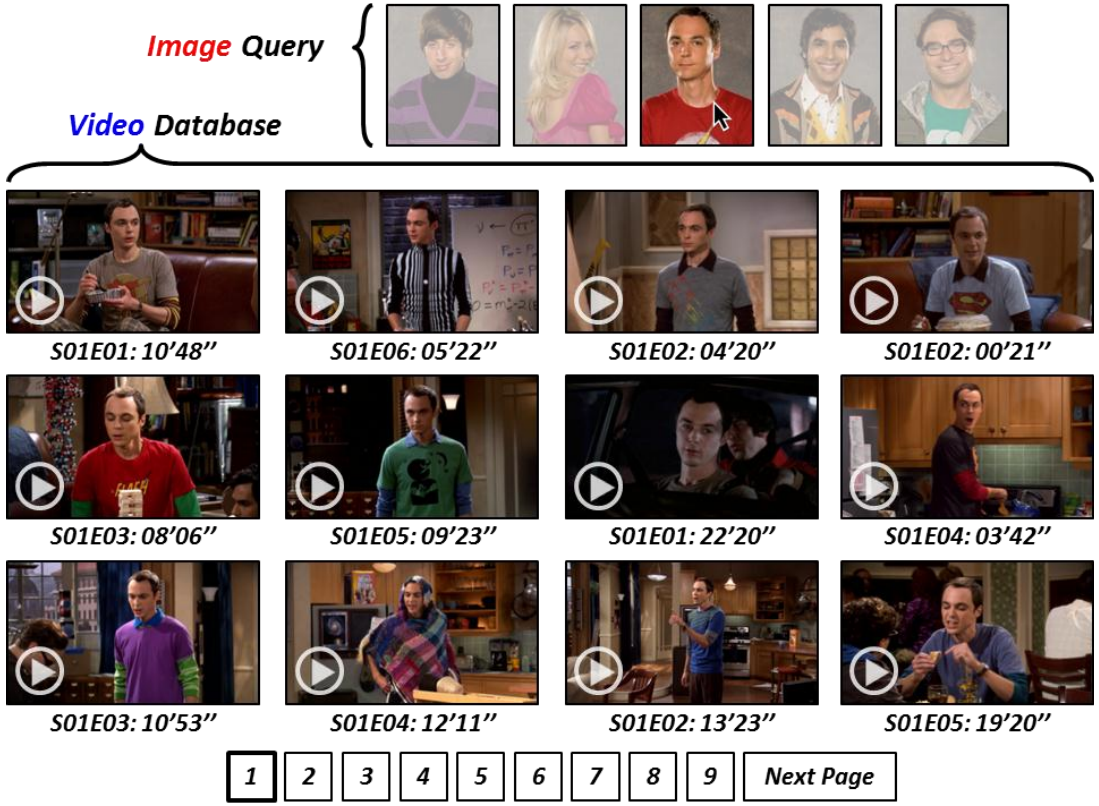
Objective function: $E(F, \varphi)$

$$\min_{F,\Phi} \{ \boxed{D(F,\Phi)} + \lambda_1 \boxed{G(F,\Phi)} + \lambda_2 \boxed{T(F,\Phi)} \}$$

Distance Geometry Transformation

Set model IV: statistics (COV+)

- HER (Hashing across Euclidean and Riemannian) [CVPR'15]
  - Application scenario: video-based face retrieval
  - Metric learning: hamming distance learning across heter. spaces



[1] Y. Li, R. Wang, Z. Huang, S. Shan, X. Chen. Face Video Retrieval with Image Query via Hashing across Euclidean Space and Riemannian Manifold. *IEEE CVPR 2015*.

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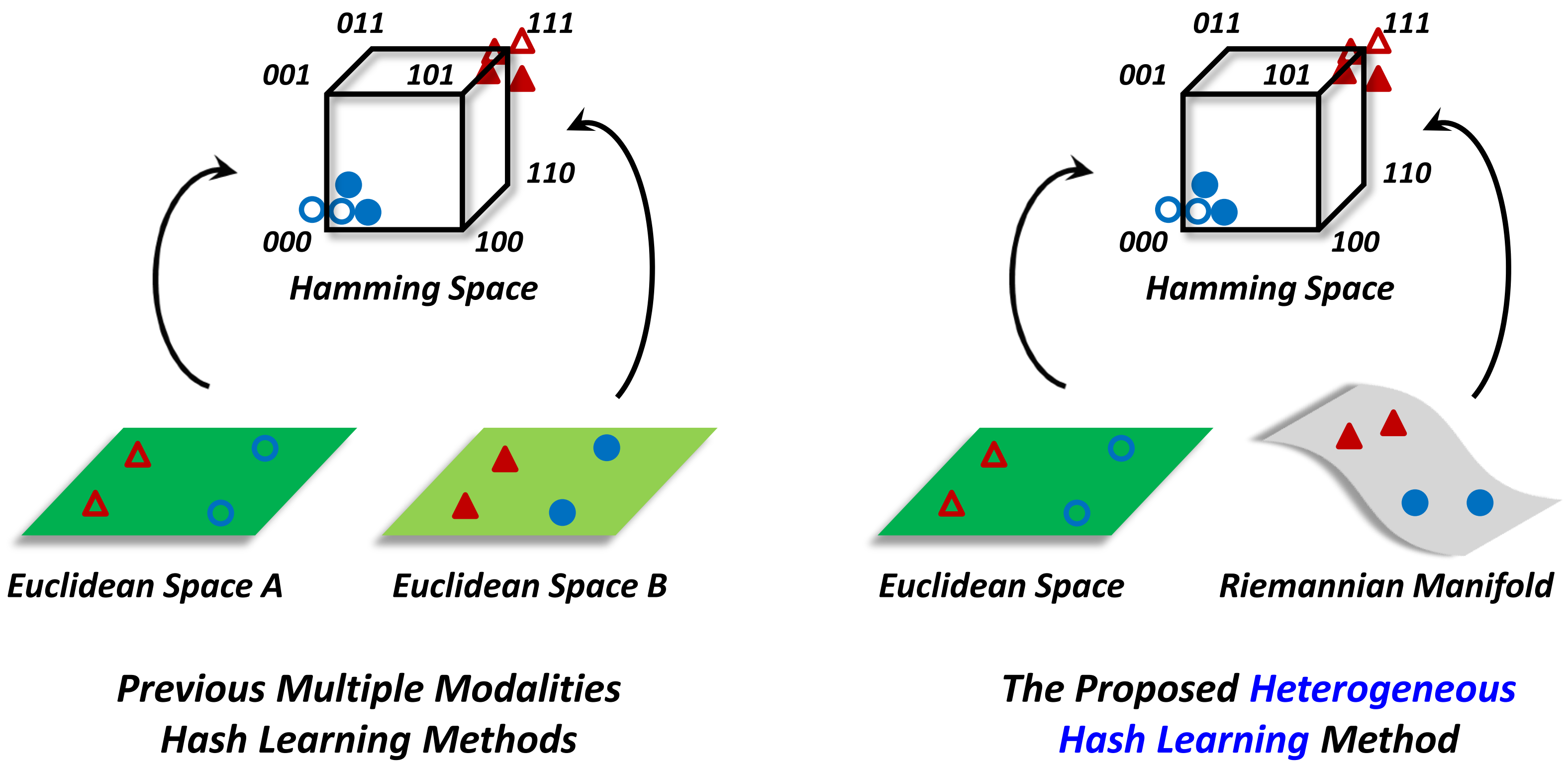
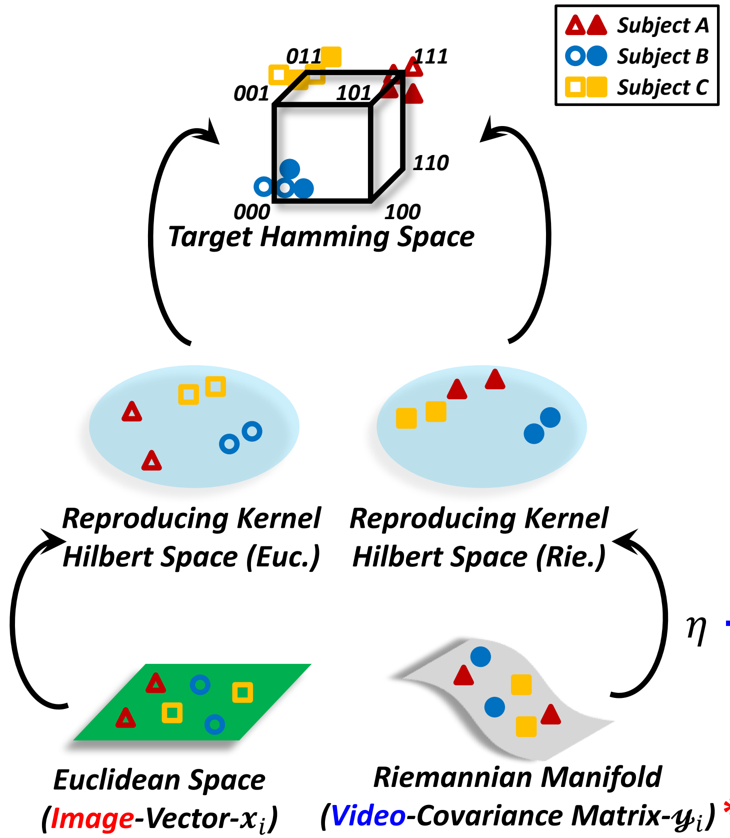
HER

- Heterogeneous Hash Learning



HER

- Two-Stage Architecture
  - Stage-1: kernel mapping



Euclidean Kernel (Image)

$$K_e^{ij} = \exp(-\frac{\|x_i - x_j\|_2^2}{2\sigma_e^2})$$

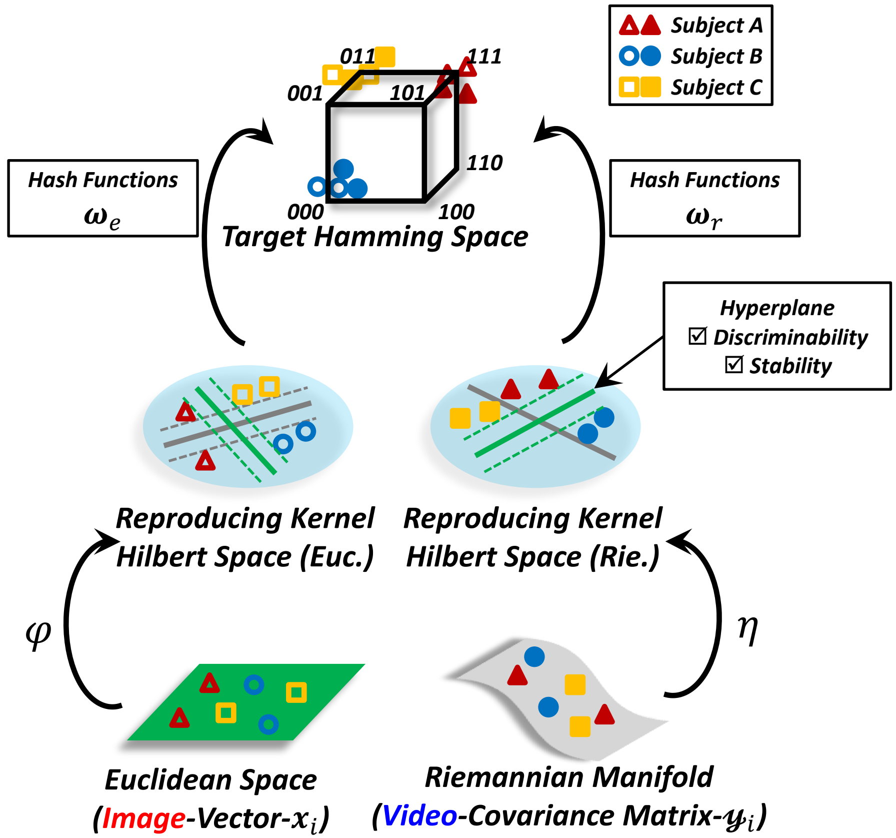
Riemannian Kernel (Video)

$$K_r^{ij} = \exp(-\frac{\|\log(\mathcal{Y}_i) - \log(\mathcal{Y}_j)\|_F^2}{2\sigma_r^2})$$

[*] Y. Li, R. Wang, Z. Cui, S. Shan, X. Chen. Compact Video Code and Its Application to Robust Face Retrieval in TV-Series. *BMVC 2014*. (**: **CVC** method for video-video face retrieval)

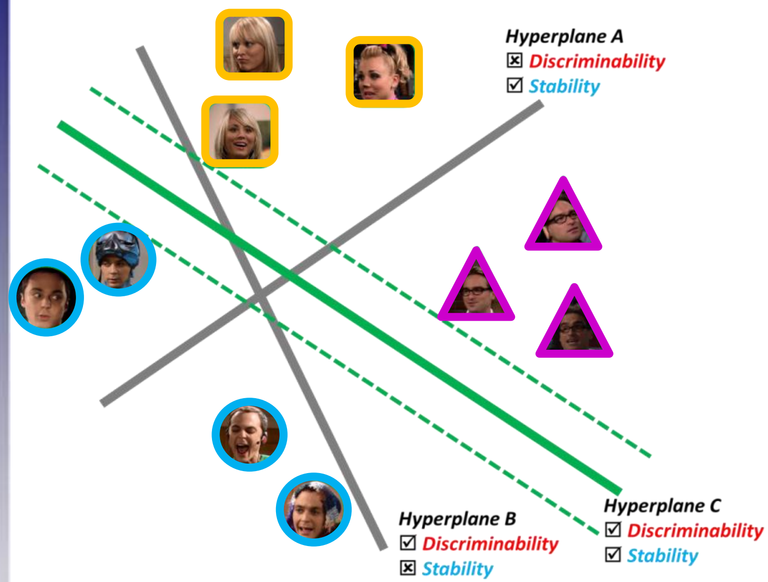
HER

- Two-Stage Architecture
  - Stage-2: binary encoding



HER

- Binary encoding [Rastegari, ECCV'12]



Discriminability

$$E_e = \sum_{c\in\{1:C\}} \sum_{m,n\in c} d(\boldsymbol{B}_e^m, \boldsymbol{B}_e^n) - \lambda_e \sum_{\substack{c_1\in\{1:C\}\\ p\in c_1}} \sum_{\substack{c_2\in\{1:C\}\\ c_1\neq c_2, q\in c_2}} d\left(\boldsymbol{B}_e^p, \boldsymbol{B}_e^q\right)$$

$$E_r = \sum_{c\in\{1:C\}} \sum_{m,n\in c} d(\boldsymbol{B}_r^m, \boldsymbol{B}_r^n) - \lambda_r \sum_{\substack{c_1\in\{1:C\}\\ p\in c_1}} \sum_{\substack{c_2\in\{1:C\}\\ c_1\neq c_2, q\in c_2}} d\left(\boldsymbol{B}_r^p, \boldsymbol{B}_r^q\right)$$

$$E_{er} = \sum_{c\in\{1:C\}} \sum_{m,n\in c} d(\boldsymbol{B}_e^m, \boldsymbol{B}_r^n) - \lambda_{er} \sum_{\substack{c_1\in\{1:C\}\\ p\in c_1}} \sum_{\substack{c_2\in\{1:C\}\\ c_1\neq c_2, q\in c_2}} d\left(\boldsymbol{B}_e^p, \boldsymbol{B}_r^q\right)$$

Objective Function

$$\min_{\omega_e,\omega_r,\xi_e,\xi_r,\boldsymbol{B}_e,\boldsymbol{B}_r} \boxed{\lambda_1 E_e + \lambda_2 E_r + \lambda_3 E_{er}} + \boxed{\gamma_1 \sum_{k\in\{1:K\}} \left\|\boldsymbol{\omega}_e^k\right\|^2 + C_1 \sum_{\substack{k\in\{1:K\}\\ i\in\{1:N\}}} \xi_e^{ki}} + \boxed{\gamma_2 \sum_{k\in\{1:K\}} \left\|\boldsymbol{\omega}_r^k\right\|^2 + C_2 \sum_{\substack{k\in\{1:K\}\\ i\in\{1:N\}}} \xi_r^{ki}}$$

s.t.

$$\boldsymbol{B}_e^{ki} = sgn\left(\boldsymbol{\omega}_e^{k^T} \varphi(\boldsymbol{x}_i)\right), \forall k \in \{1{:}K\}, \forall i \in \{1{:}N\}$$

$$\boldsymbol{B}_r^{ki} = sgn\left(\boldsymbol{\omega}_r^{k^T} \eta(\boldsymbol{y}_i)\right), \forall k \in \{1{:}K\}, \forall i \in \{1{:}N\}$$

$$\boldsymbol{B}_r^{ki}\left(\boldsymbol{\omega}_e^{k^T} \varphi(\boldsymbol{x}_i)\right) \geq 1 - \xi_e^{ki}, \xi_e^{ki} > 0, \forall k \in \{1{:}K\}, \forall i \in \{1{:}N\}$$

$$\boldsymbol{B}_e^{ki}\left(\boldsymbol{\omega}_r^{k^T} \eta(\boldsymbol{y}_i)\right) \geq 1 - \xi_r^{ki}, \xi_r^{ki} > 0, \forall k \in \{1{:}K\}, \forall i \in \{1{:}N\}$$

Discriminability (LDA)

Stability (SVM)

Compatibility (Cross-training)

Outline

- Background
- Literature review
- Evaluations
- Summary

Evaluations

- Two YouTube datasets
  - YouTube Celebrities (YTC) [Kim, CVPR'08]
    - 47 subjects, 1910 videos from YouTube
  - YouTube FaceDB (YTF) [Wolf, CVPR'11]
    - 3425 videos, 1595 different people

YTC

YTF

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Evaluations

- COX Face [Huang, ACCV'12/TIP'15]
  - 1,000 subjects
    - each has 1 high quality images, 3 unconstrained video sequences

Images

Videos

http://vipl.ict.ac.cn/resources/datasets/cox-face-dataset/cox-face

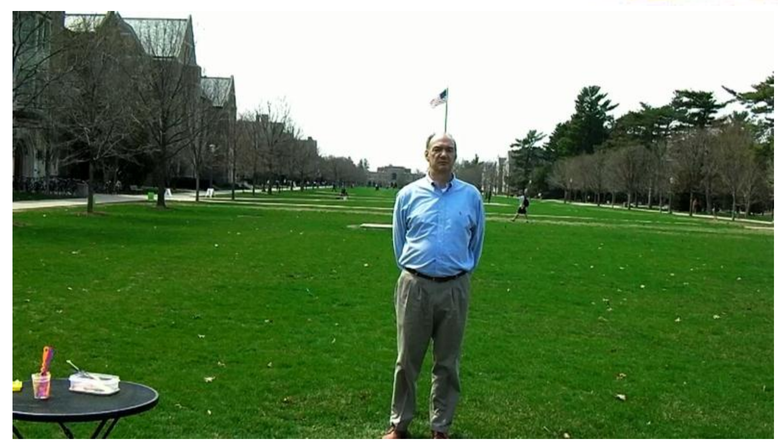
Evaluations

- PaSC [Beveridge, BTAS’13]
  - Control videos
    - 1 mounted video camera
    - 1920*1080 resolution
  - Handheld videos
    - 5 handheld video cameras
    - 640*480~1280*720 resolutic

Table 2. Summary of Video PaSC Data.

Number of Subjects	265
Total Videos	2,802
Total Control Videos	1,401
Total Handheld Videos	1,401
Control Videos per Subject	4 to 7
Handheld Videos per Subject	4 to 7
Number of Locations	6

Control video



Handheld video

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Evaluations

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■ Results (*reported in our DARG paper**)

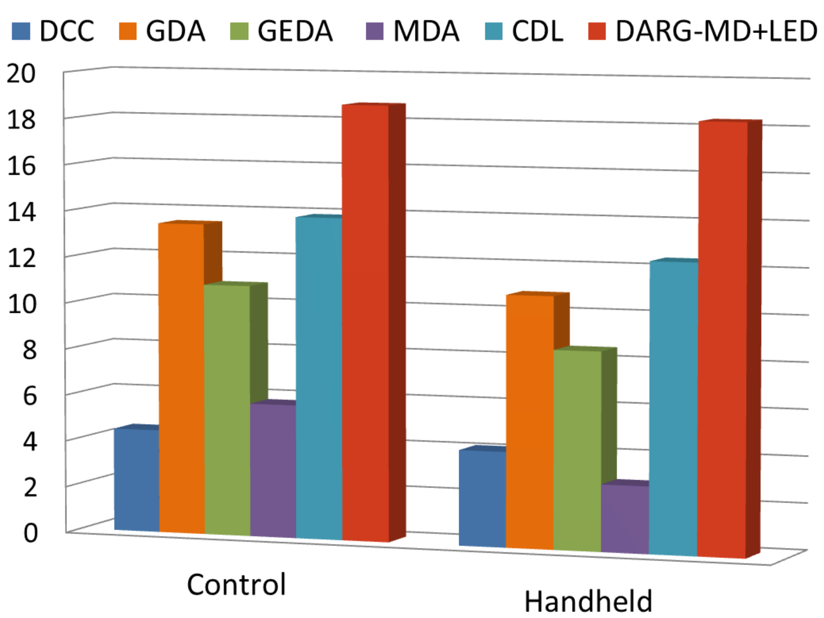
Method	YTC	COX					
		COX-11	COX-12	COX-23	COX-21	COX-31	COX-32
CHISD [CVPR'10]	66.46	56.87	30.10	14.80	44.37	26.44	13.68
GDA [CVPR'08]	65.91	72.26	80.70	74.36	71.44	81.99	77.57
GGDA [CVPR'11]	66.83	76.73	83.80	76.59	72.56	82.84	79.99
MMD [CVPR'08]	65.30	38.29	30.34	15.24	34.86	22.21	11.44
MDA [CVPR'09]	66.98	65.82	63.01	36.17	55.46	43.23	29.70
SGM [ECCV'02]	52.00	26.74	14.32	12.39	26.03	19.21	10.50
MDM [CVPR'05]	62.12	30.70	24.98	14.30	28.90	31.72	19.30
CDL [CVPR'12]	69.70	78.37	85.25	79.74	75.59	85.83	81.87
DARG-KLD	72.21	71.93	80.11	73.65	70.87	81.03	76.99
DARG-LGD	68.72	76.74	84.99	78.02	72.93	83.88	81.54
DARG-MD+LED	**77.09**	**83.71**	**90.13**	**85.08**	**81.96**	**89.99**	**88.35**

[*] W. Wang, R. Wang, Z. Huang, S. Shan, X. Chen. Discriminant Analysis on Riemannian Manifold of Gaussian Distributions for Face Recognition with Image Sets. *IEEE CVPR 2015*.

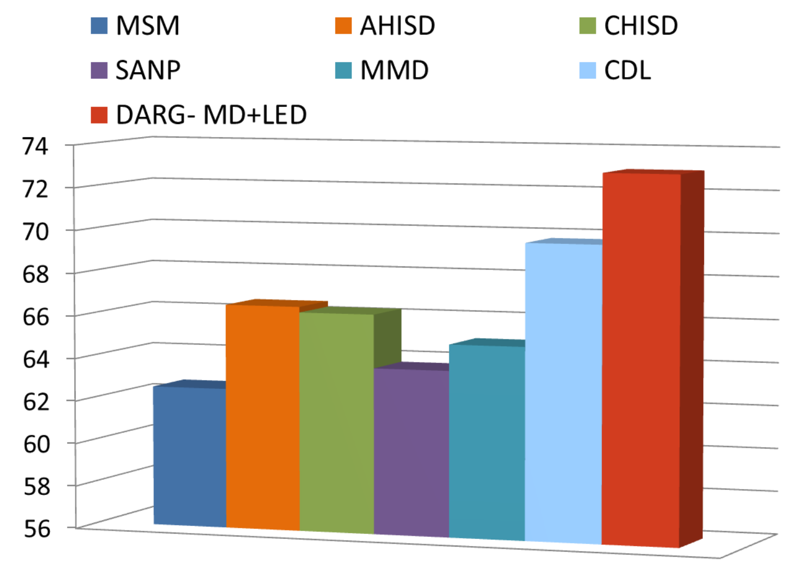
Evaluations

- Results (*reported in our DARG paper**)

VR@FAR=0.01 on PaSC



AUC on YTF



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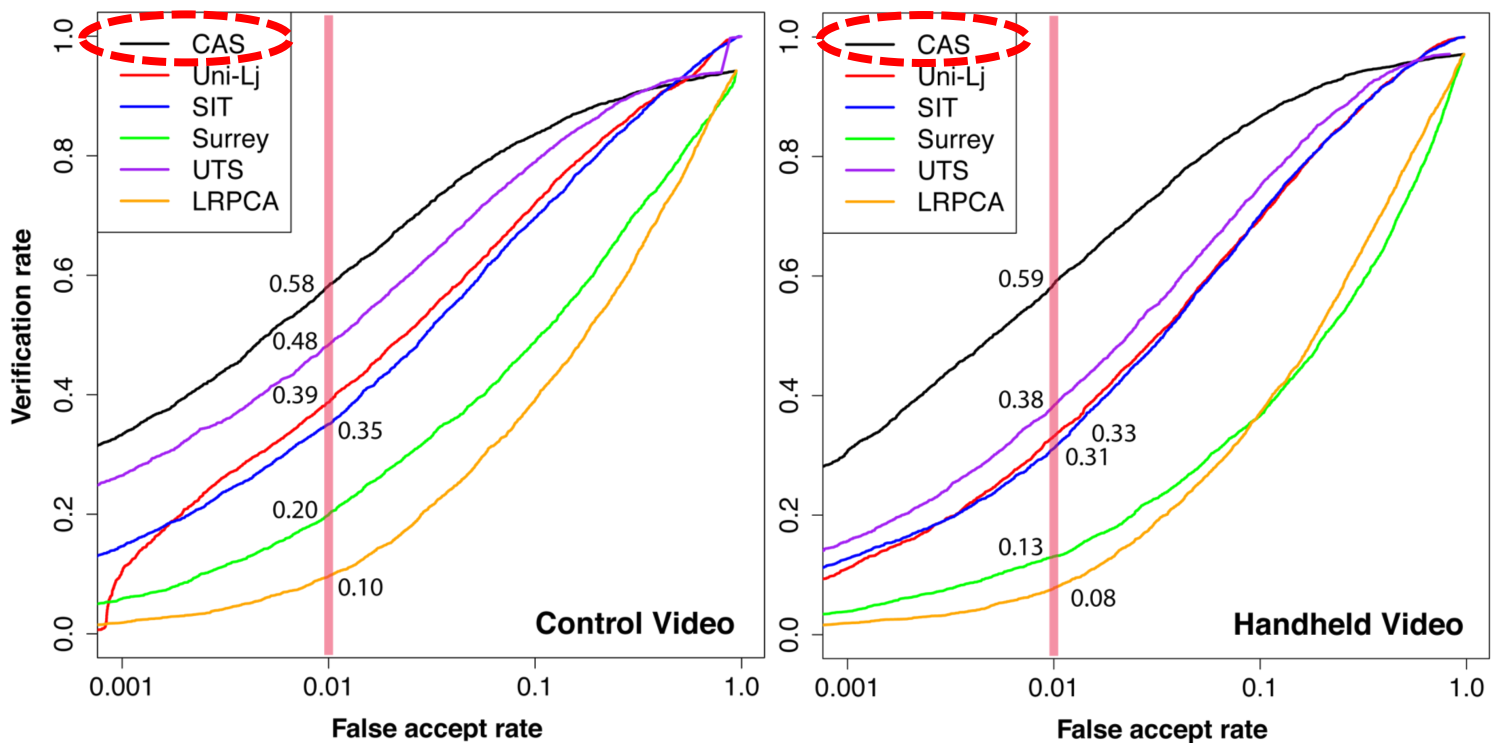
Evaluations

- Performance on PaSC Challenge (IEEE FG'15)
  - HERML-DeLF
    - DCNN learned image feature
    - Hybrid Euclidean and Riemannian Metric Learning*



[*] Z. Huang, R. Wang, S. Shan, X. Chen. Hybrid Euclidean-and-Riemannian Metric Learning for Image Set Classification. *ACCV 2014*. (**: the key reference describing the method used for the challenge)

Evaluations

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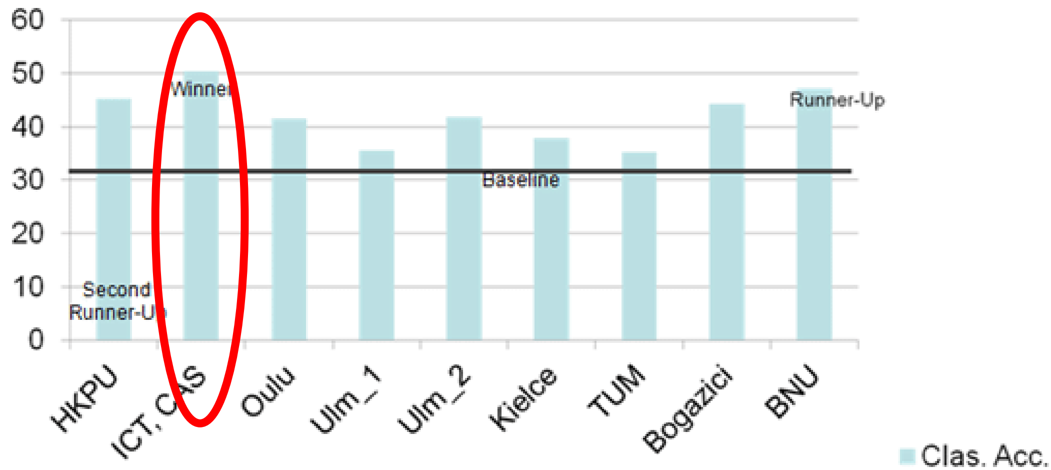
- Performance on EmotiW Challenge (ACM ICMI'14)*
  - Combination of multiple statistics for video modeling
  - Learning on the Riemannian manifold

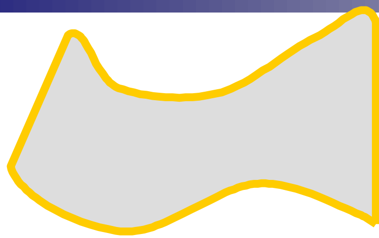


[*] M. Liu, R. Wang, S. Li, S. Shan, Z. Huang, X. Chen. Combining Multiple Kernel Methods on Riemannian Manifold for Emotion Recognition in the Wild. *ACM ICMI 2014*.

Outline

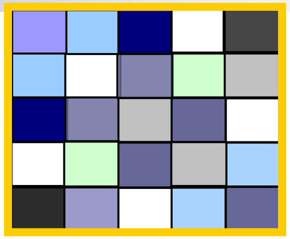
- Background
- Literature review
- Evaluations
- Summary

Route map of our methods



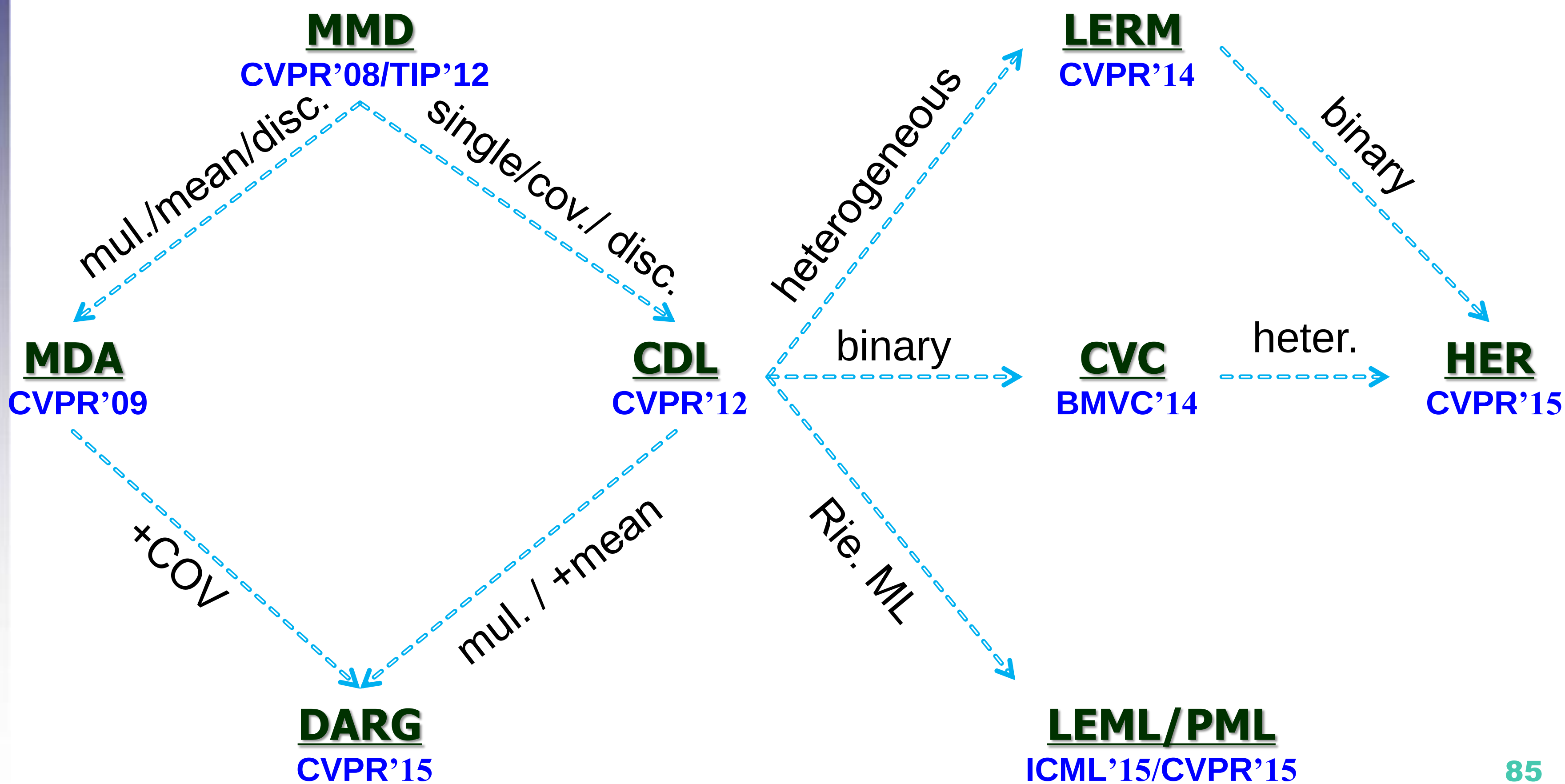
Appearance manifold

- Complex distribution
- Large amount of data



Covariance matrix

- Natural raw statistics
- No assum. of data dist.



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Summary

- What we learn from current studies
  - Set modeling
    - Linear(/affine) subspace → Manifold → Statistics
  - Set matching
    - Non-discriminative → Discriminative
  - Metric learning
    - Euclidean space → Riemannian manifold
- Future directions
  - More flexible set modeling for different scenarios
  - Multi-model combination
  - Learning method should be more efficient
  - Set-based vs. sample-based?

Additional references (not listed above)

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- [Chien, PAMI'02] J. Chien and C. Wu. Discriminant waveletfaces and nearest feature classifiers for face recognition. *IEEE T-PAMI 2002*.
- [Rastegari, ECCV'12] M. Rastegari, A. Farhadi, and D. Forsyth. Attribute discovery via predictable discriminative binary codes. *ECCV 2012*.
- [Shakhnarovich, ECCV'02] G. Shakhnarovich, J. W. Fisher, and T. Darrell. Face Recognition from Long-term Observations. *ECCV 2002*.
- [Vemulapalli, CVPR'13] R. Vemulapalli, J. K. Pillai, and R. Chellappa. Kernel learning for extrinsic classification of manifold features. *IEEE CVPR 2013*.
- [Vincent, NIPS'01] P. Vincent and Y. Bengio. K-local hyperplane and convex distance nearest neighbor algorithms. *NIPS 2001*.

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Codes of our methods available at: http://vipl.ict.ac.cn/resources/codes