

Learning Euclidean-to-Riemannian Metric for Point-to-Set Classification

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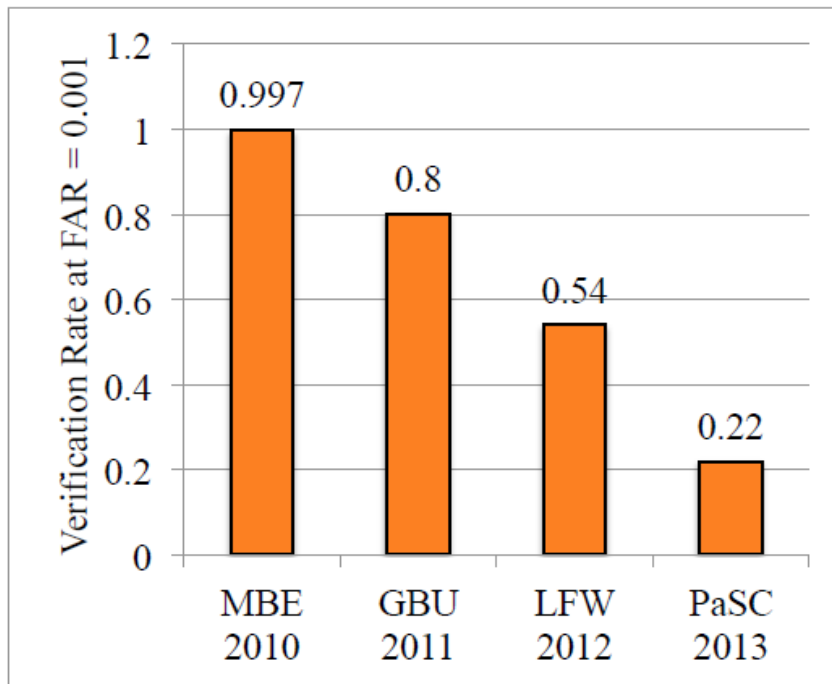


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Problem(1/3)

■ Face Recognition

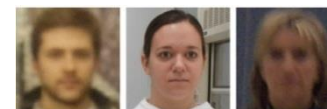
- From image-based to video-based setting



GBU (image)



LFW (image)



PaSC (video)

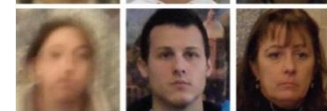


Figure: Performance progressively drops when shifting from controlled scenarios (**Image-based**) to uncontrolled point-and-shoot conditions (**video-based**). [Beveridge, BTAS'13]

Problem(2/3)

- Video-based FR
 - Video surveillance



Video frame of pair suspected in Boston attack

Query

Target



Video-to-Still (V2S)



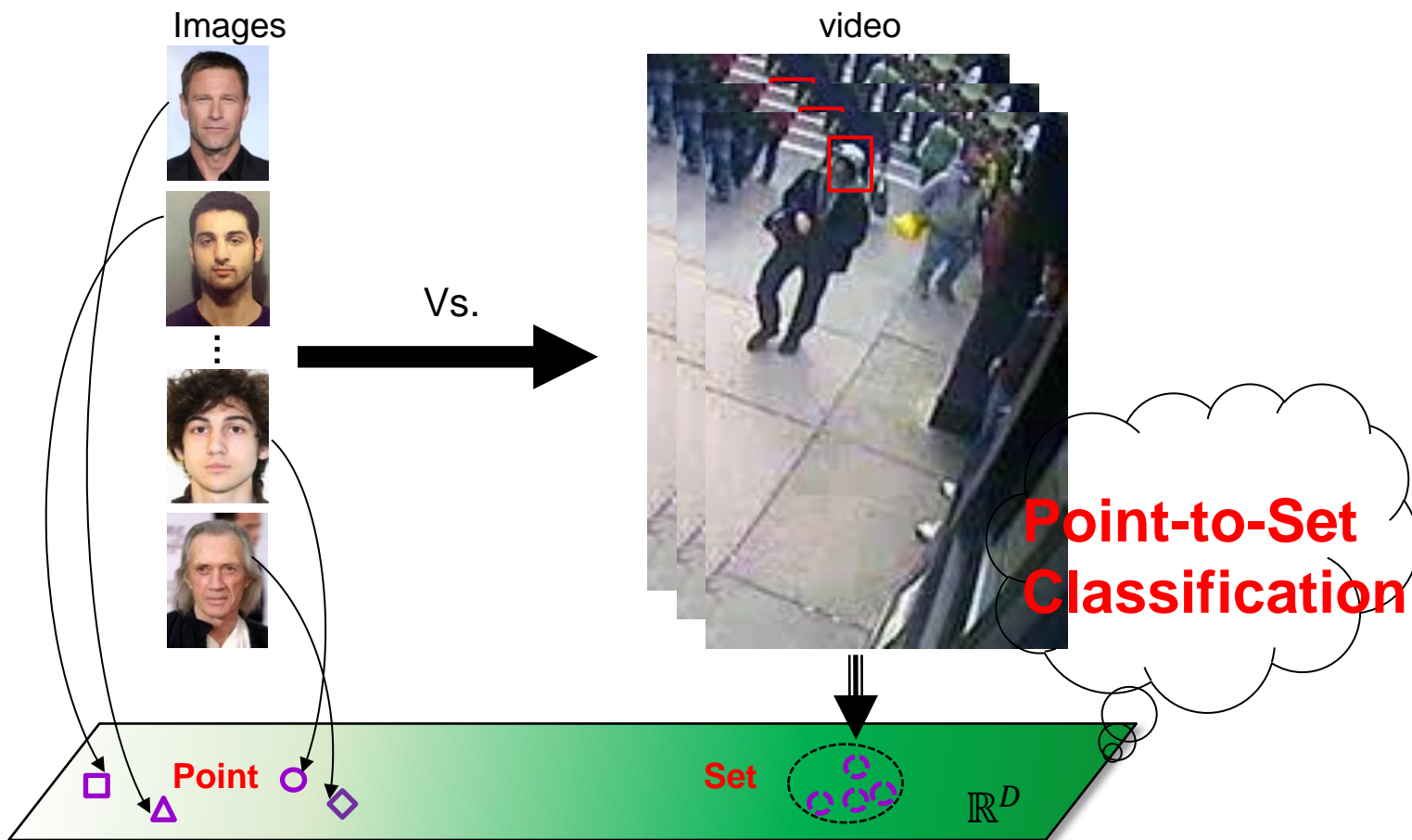
Still-to-Video (S2V)



Video-to-Video (V2V)

Problem(3/3)

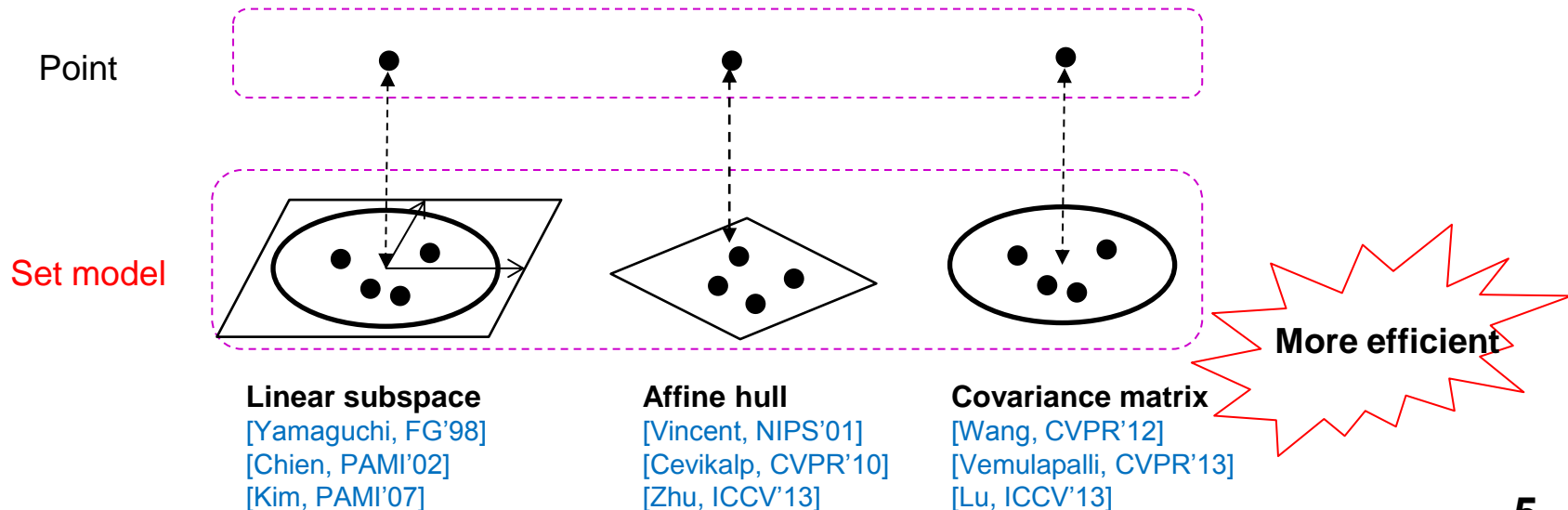
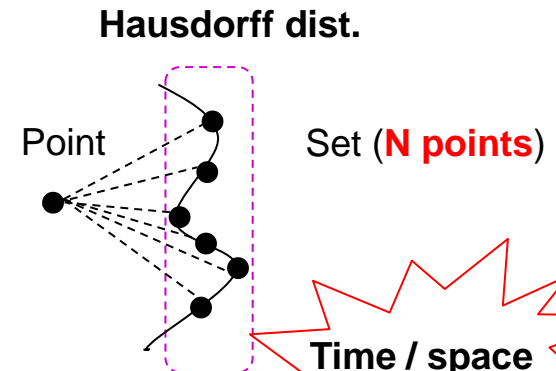
■ V2S/S2V FR



Motivation(1/2)

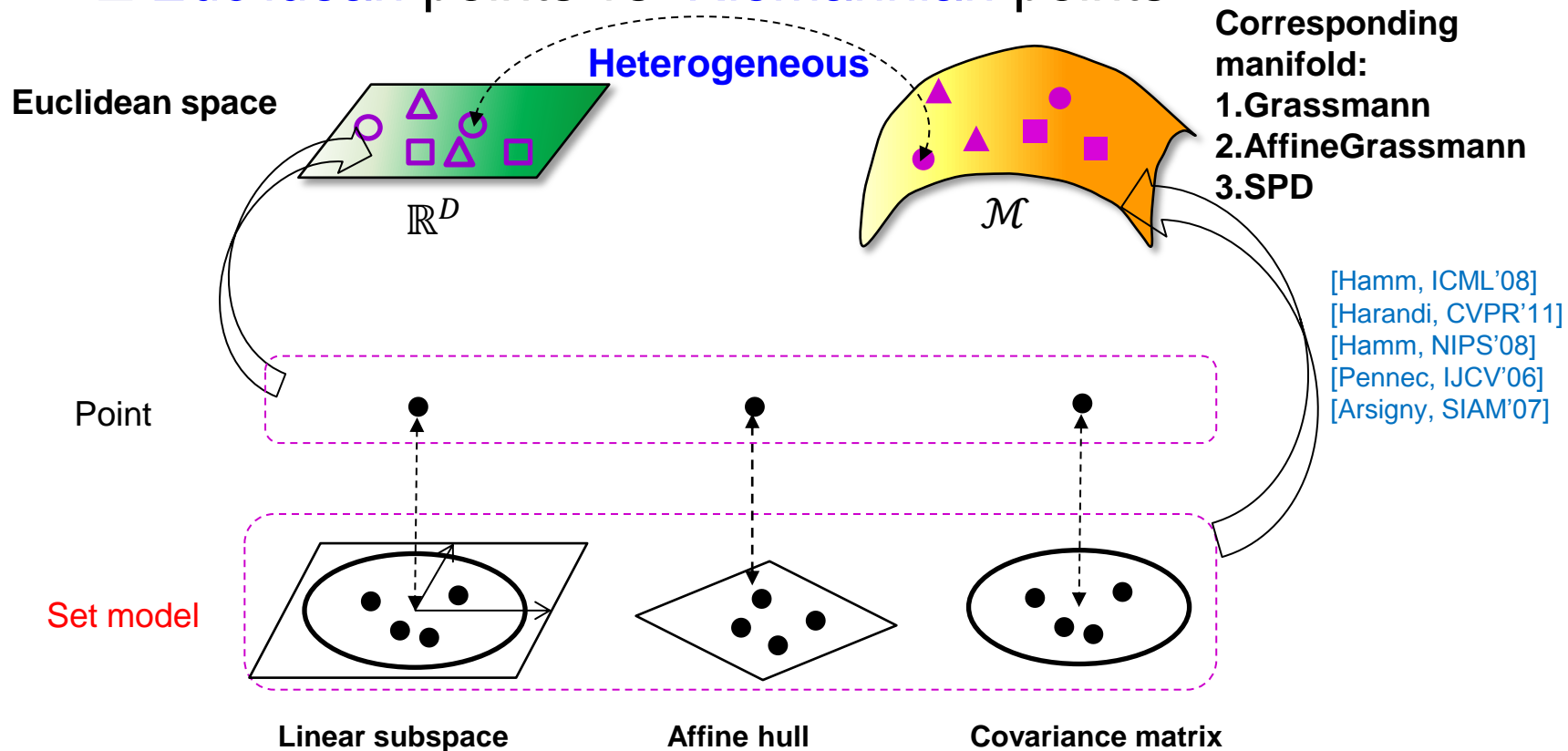
■ Point-to-Set Classification

- Match points against sets
 - Compare point with all points in set
 - 1-N Point to Point (P2P) matching
 - Compare point with **set model**
 - 1-1 Point to Set (P2S) matching



■ Point-to-Set Classification

□ Euclidean points vs. Riemannian points



Related Work(1/3)

- Grassmann manifold $\mathcal{G}(D', D)$
 - The space of linear subspaces
 - Each is represented by an orthonormal matrix $U \in \mathbb{R}^{D \times D'}$
 - Riemannian metric (projection metric) [Hamm et al., ICML'08]
 - $d^2(U_i, U_j) = 2^{-1/2} \|U_i U_i^T - U_j U_j^T\|_F$
- Affine Grassmann manifold $\mathcal{AG}(D', D)$
 - The space of affine subspaces
 - Each is represented by $U \in \mathbb{R}^{D \times D'}$ with mean value u
 - Riemannian metric (affine projection metric) [Hamm et al., NIPS'08]
 - $d^2(U_i, U_j) = 2^{-1/2} (\|U_i U_i^T - U_j U_j^T\|_F + \|(I - U_i U_i^T)u_i - (I - U_j U_j^T)u_j\|_F)$
- Symmetric Positive Define (SPD) manifold \mathcal{S}_{++}^D
 - The space of SPD matrices $C \in \mathbb{R}^{D \times D}$
 - Riemannian metric (Log-Euclidean metric) [Arsigny et al., SIAM'07]
 - $d^2(C_i, C_j) = \|\log(C_i) - \log(C_j)\|_F$



Related Work(2/3)

- Euclidean-to-Riemannian metric
 - Euclidean-to-Grassmannian
 - Point to Linear Subspace [Chien et al., PAMI'02]
 - $d(x_i, U_j) = \|x_i - U_j U_j^T x_i\|_F$
 - Euclidean-to-AffGrassmannian
 - Point to Affine Subspace [Vincent et al., NIPS'01]
 - $d(x_i, A_j) = \min_{\alpha} \|(U_j \alpha + u_j) - x_i\|_F$, α is a vector of free parameters that provides coordinates for points within the subspace
 - Euclidean-to-SPD
 - Point to Covariance Matrix (Mahalanobis distance)
 - $d^2(x_i, C_j) = \sqrt{(x_i - u_j)^T C_j^{-1} (x_i - u_j)}$



Related Work(3/3)

■ Point-to-set distance metric learning [zhu et al. , ICCV'13]

□ Point to affine subspace distance

- $d^2(\mathbf{x}, A(\mathbf{Y})) = \min \|\mathbf{x} - A(\mathbf{Y})\|_2^2$

- Affine hull: $A(\mathbf{Y}) = \mathbf{Y}\boldsymbol{\alpha} = \sum y_i \alpha_i$, s.t. $\sum \alpha_i = 1$

- spanned by all the available samples $\mathbf{Y} = [y_1, \dots, y_n]$ in the set

□ Mahalanobis distance

- $d_M^2(\mathbf{x}, \mathbf{D}) = \min \|\mathbf{W}(\mathbf{x} - \mathbf{Y}\boldsymbol{\alpha})\|_2^2 =$
 $(\mathbf{x} - \mathbf{Y}\boldsymbol{\alpha})^T \mathbf{W}^T \mathbf{W} (\mathbf{x} - \mathbf{Y}\boldsymbol{\alpha}) = (\mathbf{x} - \mathbf{Y}\boldsymbol{\alpha})^T \mathbf{M} (\mathbf{x} - \mathbf{Y}\boldsymbol{\alpha})$

Our Method(1/10)

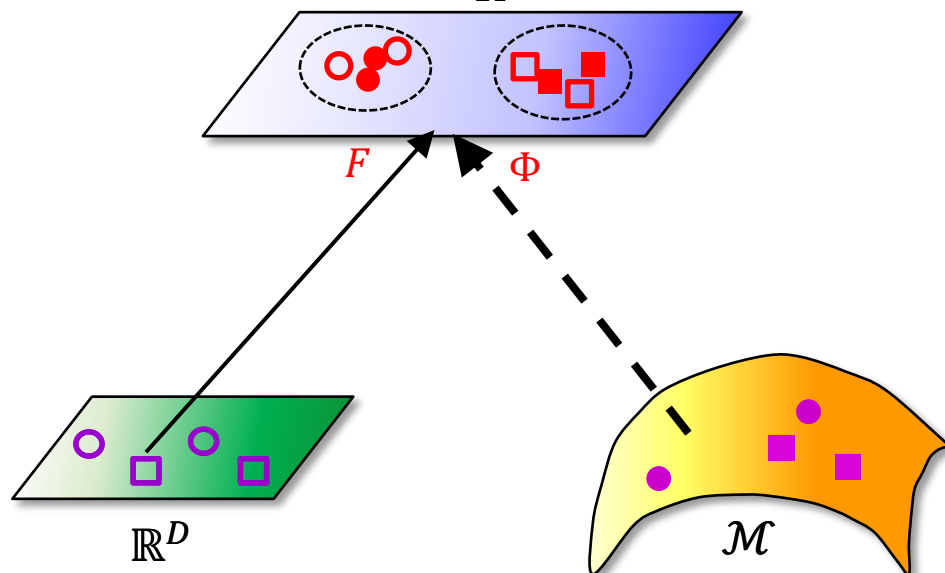
■ Basic idea

□ Reduce Euclidean-to-Riemannian metric to classical Euclidean metric

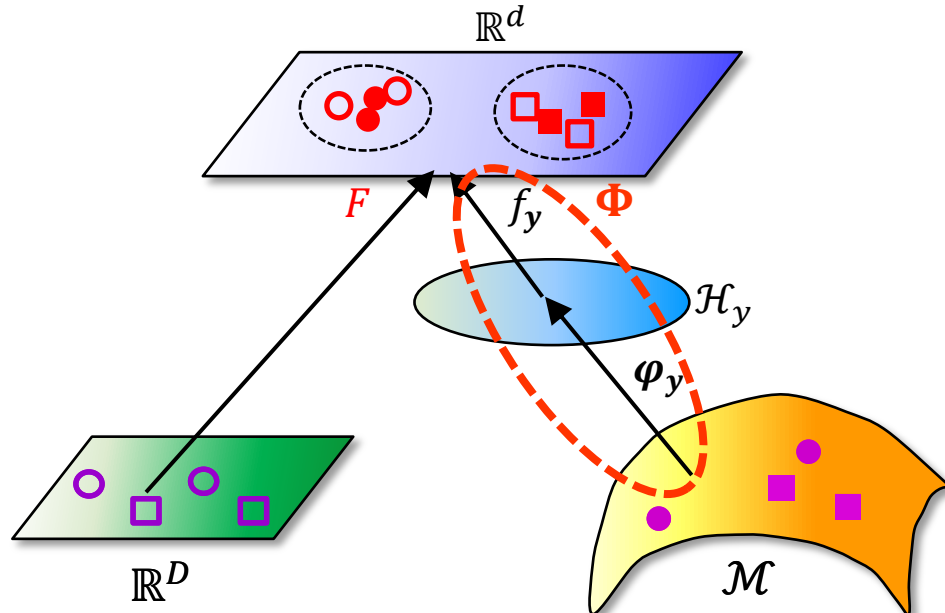
■ Seek maps F, Φ to a common Euclidean subspace

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

\mathbb{R}^d

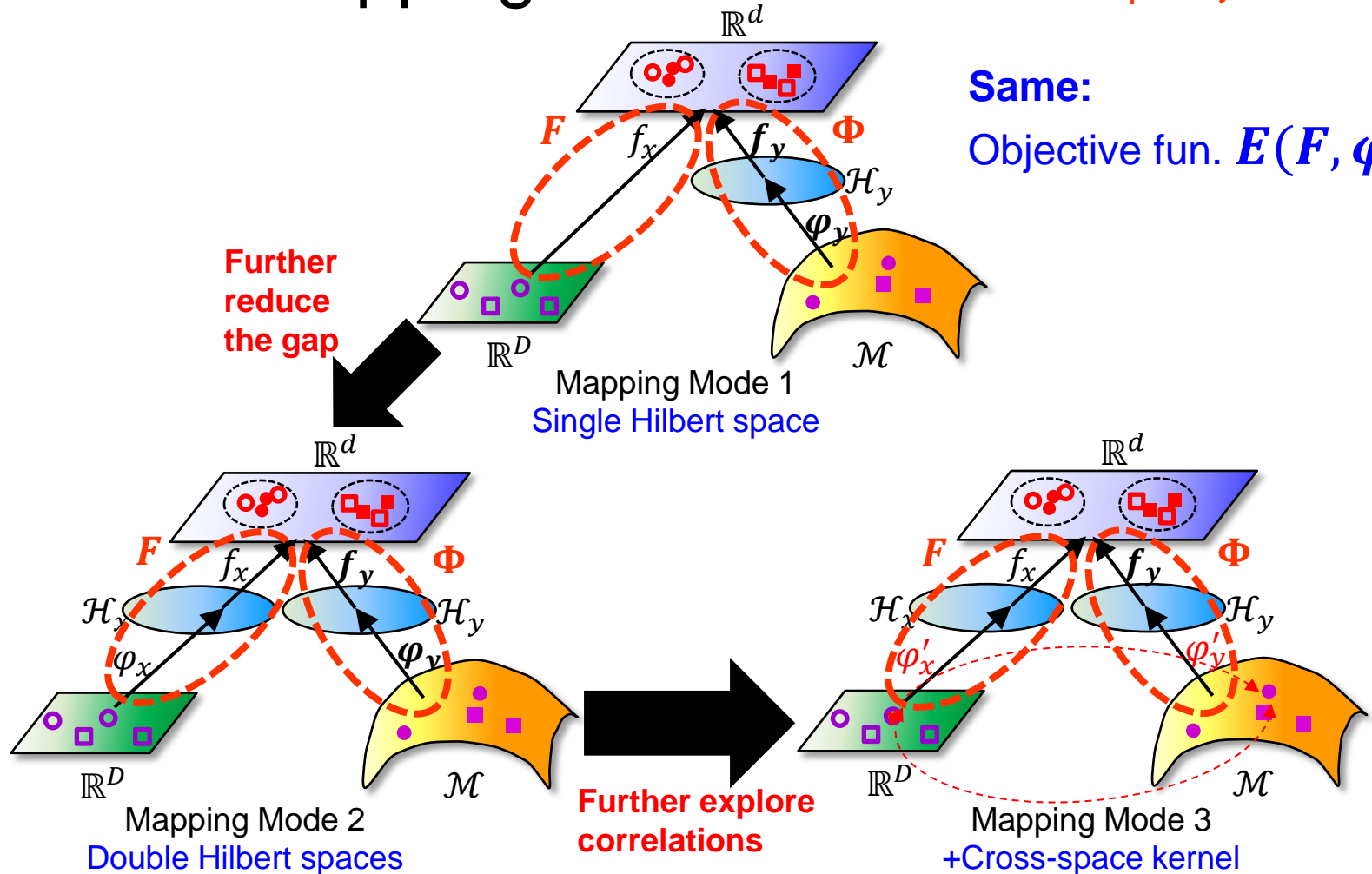


- Basic idea
 - Bridge Euclidean-to-Riemannian gap
 - Hilbert space embedding
 - Adhere to Euclidean geometry
 - Encode the Riemannian geometry
 - Riemannian metric based kernel function



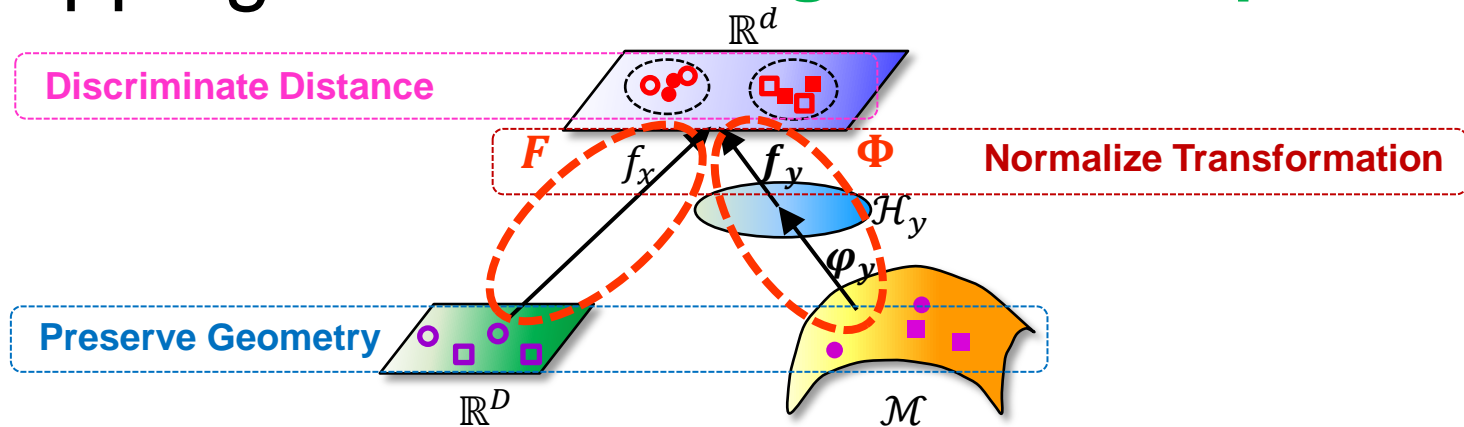
Our Method(3/10)

Three Mapping Modes



Our Method(4/10)

Mapping 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:

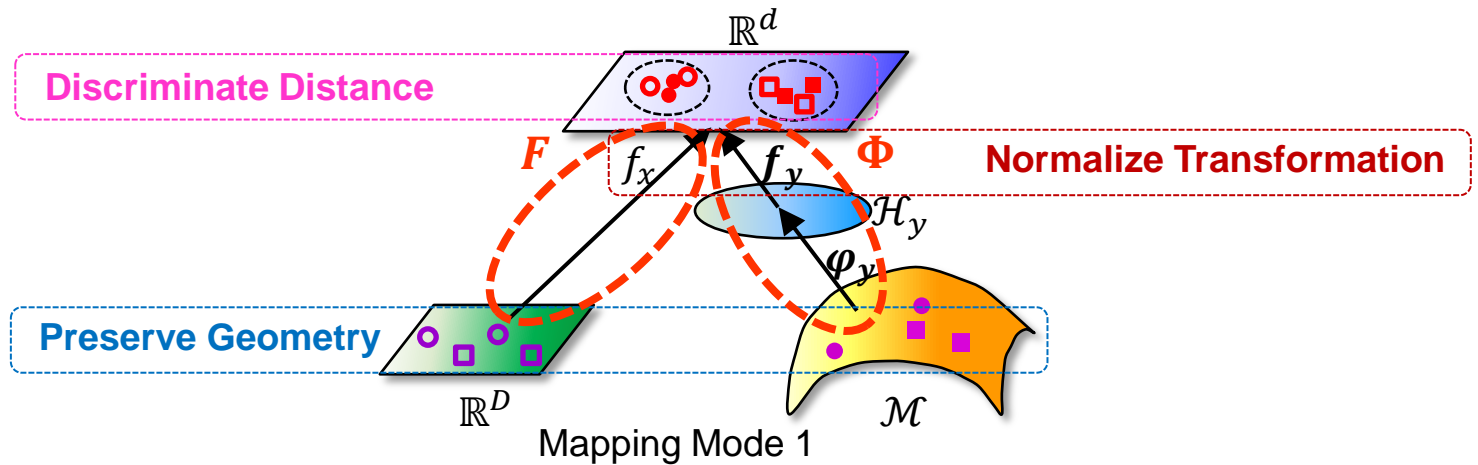
$$d(x_i, y_j) = \sqrt{(F(x_i) - \Phi(y_j))^T (F(x_i) - \Phi(y_j))}$$

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

Our Method(5/10)



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

Objective fun.: $E(F, \Phi) = \min_{F, \Phi} \{ \boxed{D(F, \Phi)} + \lambda_1 \boxed{G(F, \Phi)} + \lambda_2 \boxed{T(F, \Phi)} \}$

Distance
Geometry
Transformation

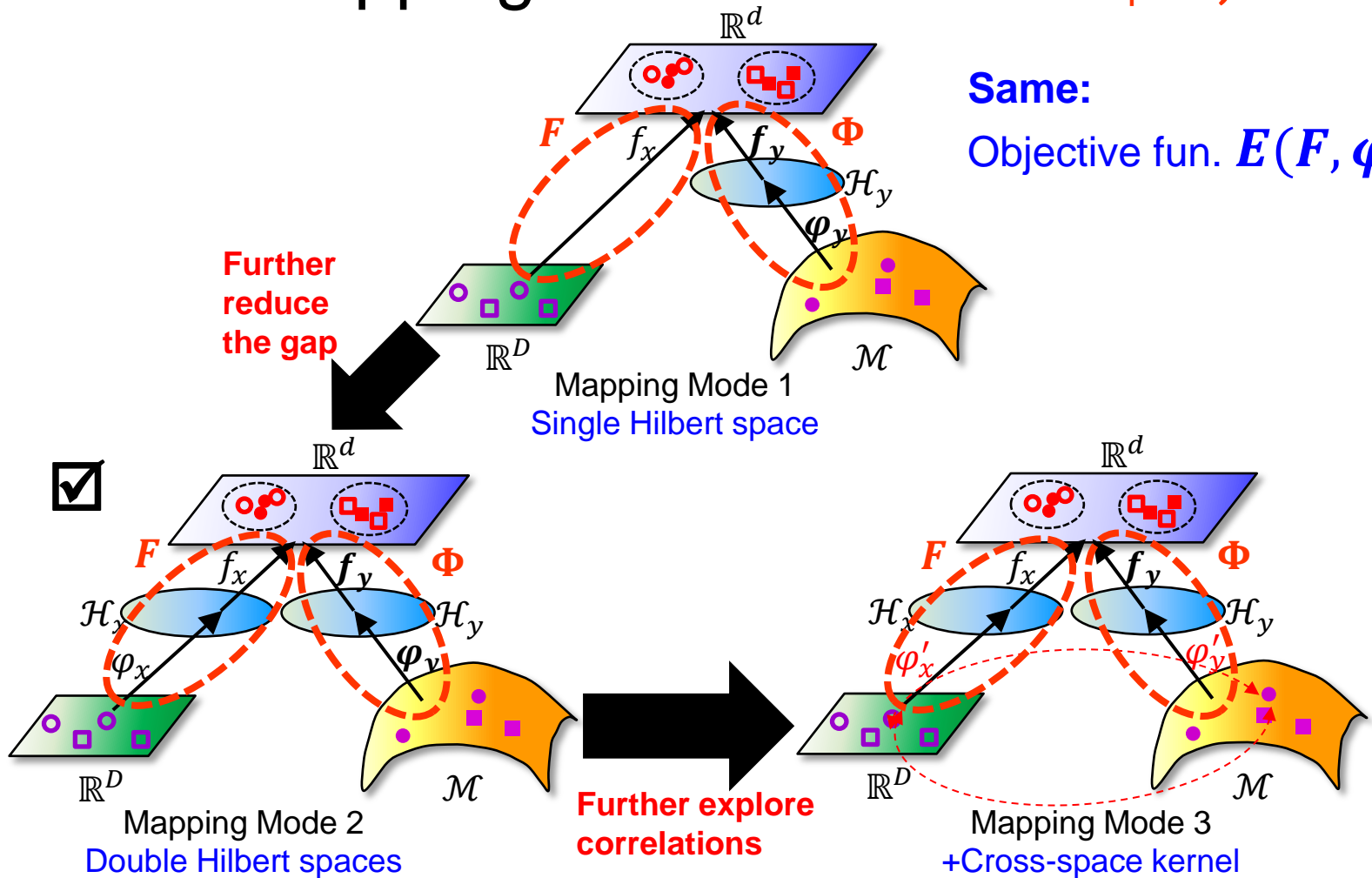
$$D = \frac{1}{2} \sum \sum \text{sgn}(l_i^x, l_j^y) d^2(x_i, y_j)$$

$$G_x = \frac{1}{2} \sum \sum e^{-\frac{\|x_i - x_j\|^2}{\sigma_x^2}} d_x^2(x_i, x_j)$$

$$T = \frac{1}{2} (\|F(X)\|_F^2 + \|\Phi(Y)\|_F^2)$$

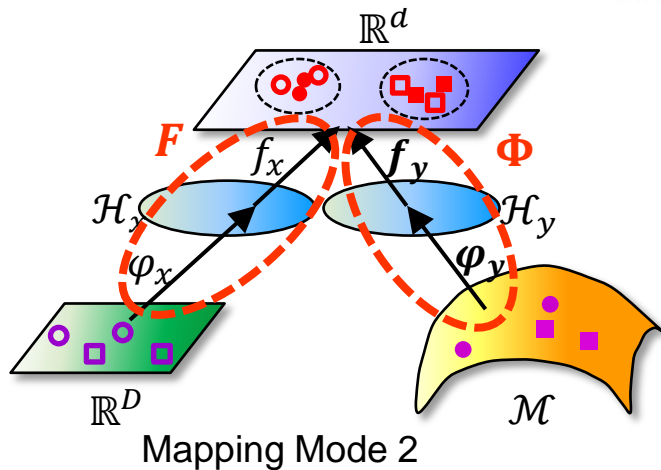
Our Method(6/10)

Three Mapping Modes



■ Mapping Mode 2

Further reduce the E-R gap with double Hilbert spaces



Final maps:

$$F = f_x \circ \varphi_x = W_x^T K_x$$

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

$$K_x(i, j) = \exp(-\|x_i - x_j\|_2^2 / 2\sigma^2)$$

Classical Euclidean distance

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

Distance metric :

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

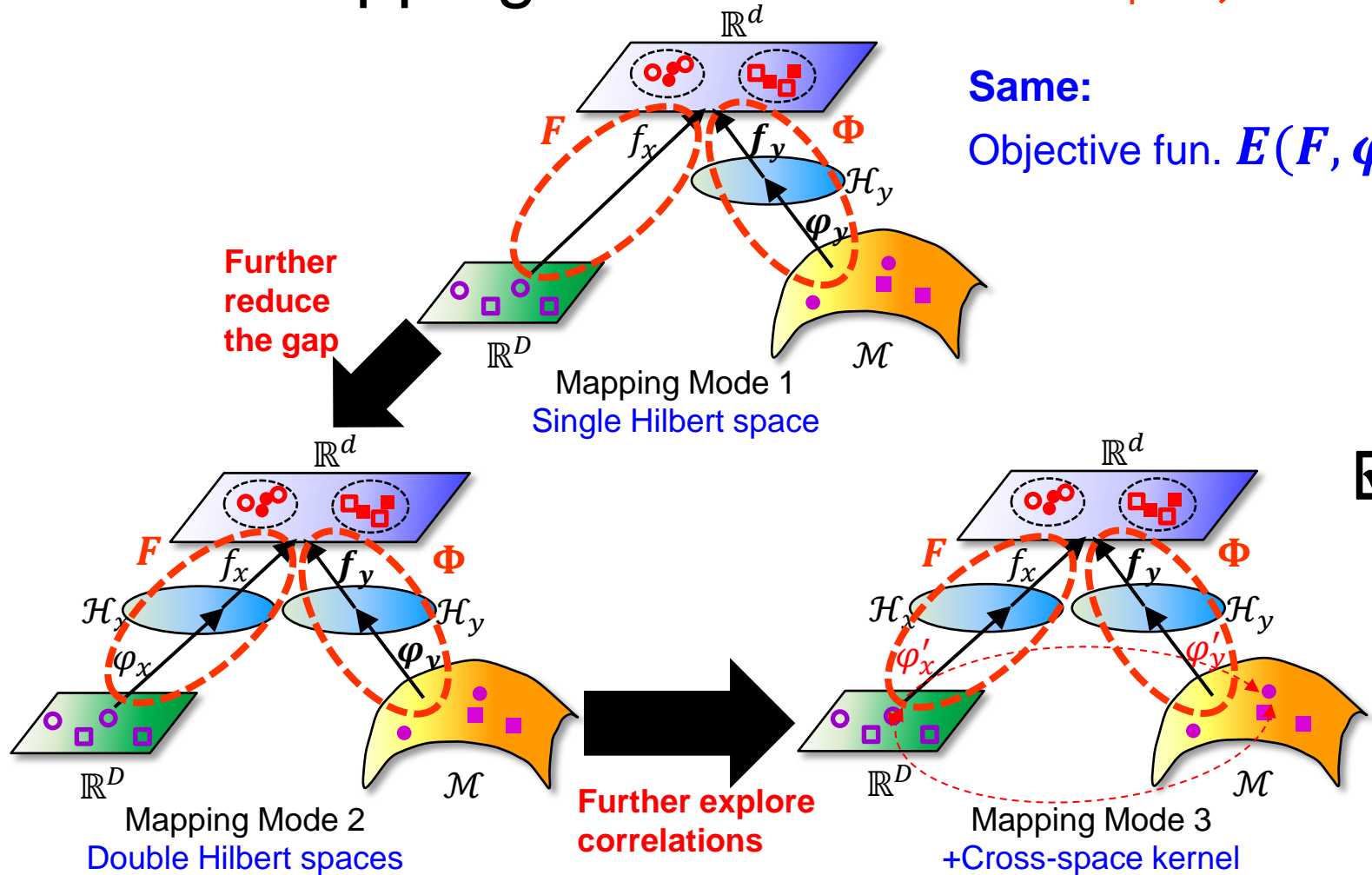
Objective function: $E(F, \Phi)$

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

Distance Geometry Transformation

Our Method(8/10)

■ Three Mapping Modes



■ Mapping Mode 3

Final Maps:

$$F = f_x \circ \varphi'_x = W_x^T [K_x, K_{xy}]$$

$$\Phi = f_y \circ \varphi'_y = W_y^T [K_y, K_{xy}^T]$$

$$K_x(i, j) = \exp(-\|x_i - x_j\|_2^2 / 2\sigma^2)$$

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

$$K_{xy}(i, j) = \exp(-d^2(x_i, y_j) / 2\sigma^2)$$

Further correlate the double Hilbert spaces with cross-space kernel

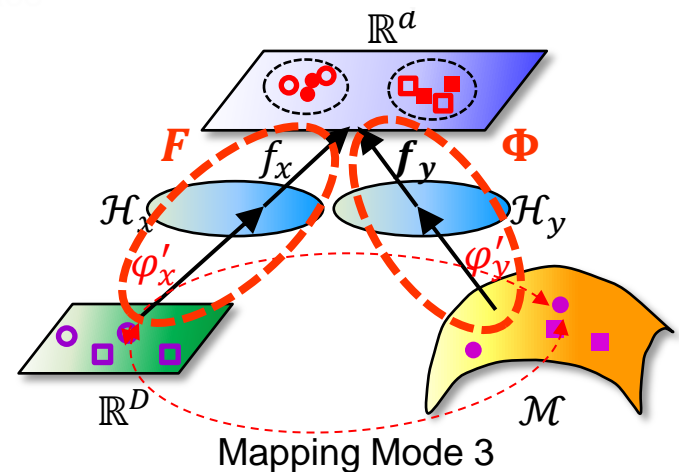
Point-to-Set (E-R) distance
[PAMI'02, NIPS'01, Mahalanobis]

Distance metric:

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

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

$$\min_{F, \Phi} \{ \underbrace{D(F, \Phi)}_{\text{Distance}} + \lambda_1 \underbrace{G(F, \Phi)}_{\text{Geometry}} + \lambda_2 \underbrace{T(F, \Phi)}_{\text{Transformation}} \}$$



■ Optimization of the objective functions

□ Iterative optimization

■ CCA-like Initialization

- $\max_{W_x, W_y} \{D^b(W_x, W_y) + \lambda_1 G^b(W_x, W_y)\}$
- s. t. $D^w(W_x, W_y) + \lambda_1 G^w(W_x, W_y) = 1$

D^b, G^b : the **between-class** template of D, G

D^w, G^w : the **within-class** template of D, G

■ Alternately updating (gradient descent)

- Fix W_y to update W_x
 - $W_x = ?$
- Fix W_x to update W_y
 - $W_y = ?$

$$F = f_x \circ \varphi_x = W_x^T K_x$$

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

- Video face datasets
 - YouTube Celebrities [Kim, CVPR'08]
 - 47 subjects
 - 1,910 videos from YouTube, images selected from videos



Images

Videos

- COX video face database
 - <http://vipl.ict.ac.cn/resources/datasets/cox-face-dataset>
- Features of COX
 - 1000 subjects, each
 - 1 high quality still image
 - 3 low quality video clips from 3 camcorders
 - (Intended to) simulate video surveillance
 - Evaluation protocols



(a) Still image



(b) Video clip1



(c) Video clip2



(d) Video clip3



Experiments(3/7)

- Comparative Methods
 - Point-to-Point (**P2P**) metric learning methods
 - NCA [Goldberger, NIPS'04]
 - ITML [Davis, ICML'07]
 - LMNN [Weinberger, JMLR'09]
 - Point-to-Set (**P2S**) matching methods
 - NFS [Chien, PAMI'02]
 - HKNN [Vincent, NIPS'01]
 - PSDML [Zhu, ICCV'13]
 - Kernelized Multiview Learning (**KML**) methods
 - KPLS [Sharma, CVPR'11]
 - KCCA [Hardoon, Neural Comp.'04]
 - KGMLDA [Sharma, CVPR'12]

Experiments(4/7)

- V2S/S2V FR
 - YouTube dataset

Methods		Probe-Gallery; Average rank-1 recognition rate	
		Video-to-Still	Still-to-Video
P2P	NCA [NIPS'04]	51.74±3.11	60.35±3.09
	ITML [ICML'07]	47.62±1.73	59.72±4.27
	LMNN [JMLR'09]	55.02±2.71	70.99±3.25
P2S	NFS [PAMI'02]	53.27±2.75	60.21±5.99
	HKNN [NIPS'01]	36.94±2.71	48.01±4.80
	PSDML [ICCV'13]	55.30 ±1.90	61.21±5.24
KML	KPLS [CVPR'11]	54.02±2.61	64.89±5.18
	KCCA [Neural Comp.'04]	55.80±3.12	67.80±3.71
	KGMLDA [CVPR'12]	58.19±4.00	89.36±6.88
Ours	LERM	69.11±2.99	96.60±3.36

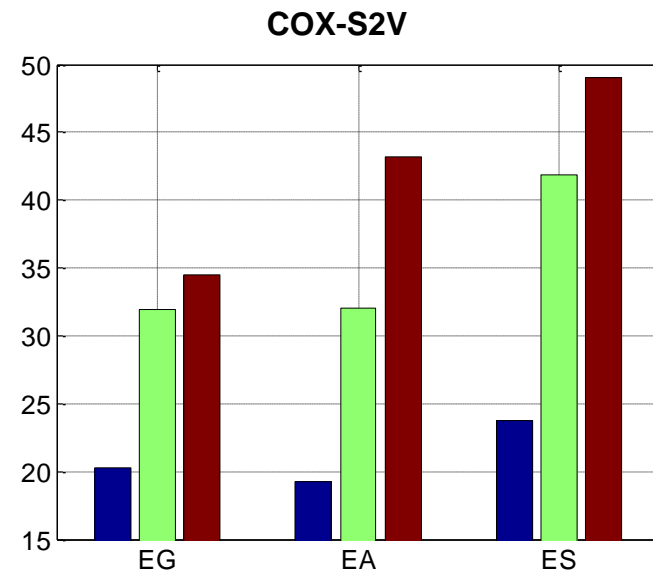
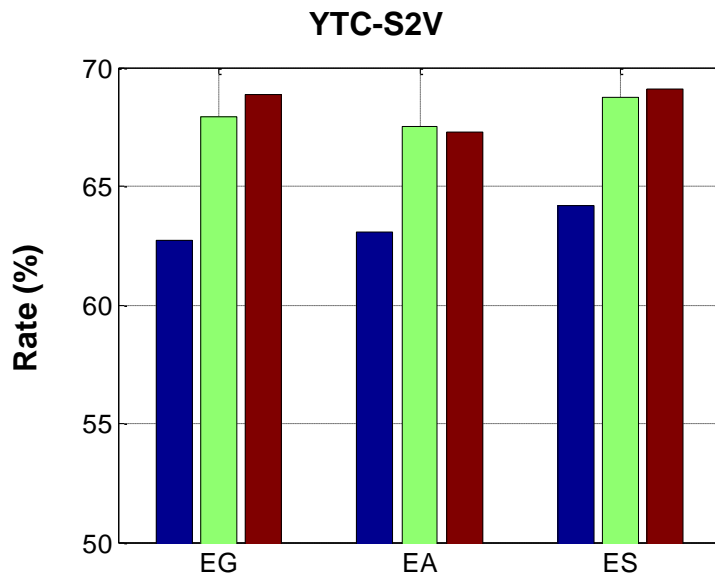
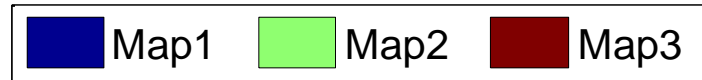
Experiments(5/7)

- V2S/S2V FR
 - COX Face dataset

Methods		Probe-Gallery; Average rank-1 recognition rate					
		V1-S	V2-S	V3-S	S-V1	S-V2	S-V3
P2P	NCA [NIPS'04]	39.14	31.57	57.57	37.71	32.14	58.86
	ITML [ICML'07]	19.83	18.20	36.63	26.66	25.21	47.57
	LMNN [JMLR'09]	34.44	30.03	58.06	37.84	35.77	63.33
P2S	NFS [PAMI'02]	9.99	5.90	22.23	11.64	6.51	31.67
	HKNN [NIPS'01]	4.70	3.70	12.70	6.34	4.64	20.41
	PSDML [ICCV'13]	12.14	9.43	25.43	7.04	4.14	29.86
KML	KPLS [CVPR'11]	20.21	16.21	27.23	14.83	11.61	23.99
	KCCA [Neural Comp.'04]	38.60	33.20	53.26	36.39	30.87	50.96
	KGMLDA [CVPR'12]	41.89	38.29	52.87	38.03	33.29	50.06
Ours	LERM	45.71	42.80	58.37	49.07	44.16	63.83

■ Different mapping modes

Map3 > Map2 > Map1



Set models:

- EG: Euclidean-to-Grassmannian ([linear subspace](#))
- EA: Euclidean-to-AffineGrassmannian ([affine subspace](#))
- ES: Euclidean-to-SPD ([covariance matrix](#))

Experiments(7/7)

- Running time (seconds) on YouTube

Methods		Training	Test
P2P	NCA [NIPS'04]	7761	0.165
	ITML [ICML'07]	523.2	0.394
	LMNN [JMLR'09]	282.4	0.162
P2S	PSDML [ICCV'13]	55.78	0.016
	LERM	3.615	0.032

Note: The running time in test is average per testing video



Conclusion

- V2S/S2V FR → Point-to-set classification
⇒ Euclidean-to-Riemannian matching
- Conventional metric learning
⇒ Euclidean-to-Riemannian Metric Learning
- Impressively improvement and much higher efficiency



Future work

- This framework may be also **applied in many other CV tasks**, e.g., image-to-set object categorization, image-to-video face retrieval
- This framework can be extended for **metrics between sets with application to V2V FR**



Take home message

- Learning Euclidean-to-Riemannian Metric (LERM) for point-to-set classification

Get a copy of COX face dataset for video-based (V2S/S2V/V2V) face recognition!

Data and code are available online!

<http://vipl.ict.ac.cn/resources>

Thank you!

Q&A



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