

Relatively-Paired Space Analysis

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Multi-modality representation



Modality photo

Multi-modality representation



Modality photo



Modality sketch

Multi-modality representation



Modality photo



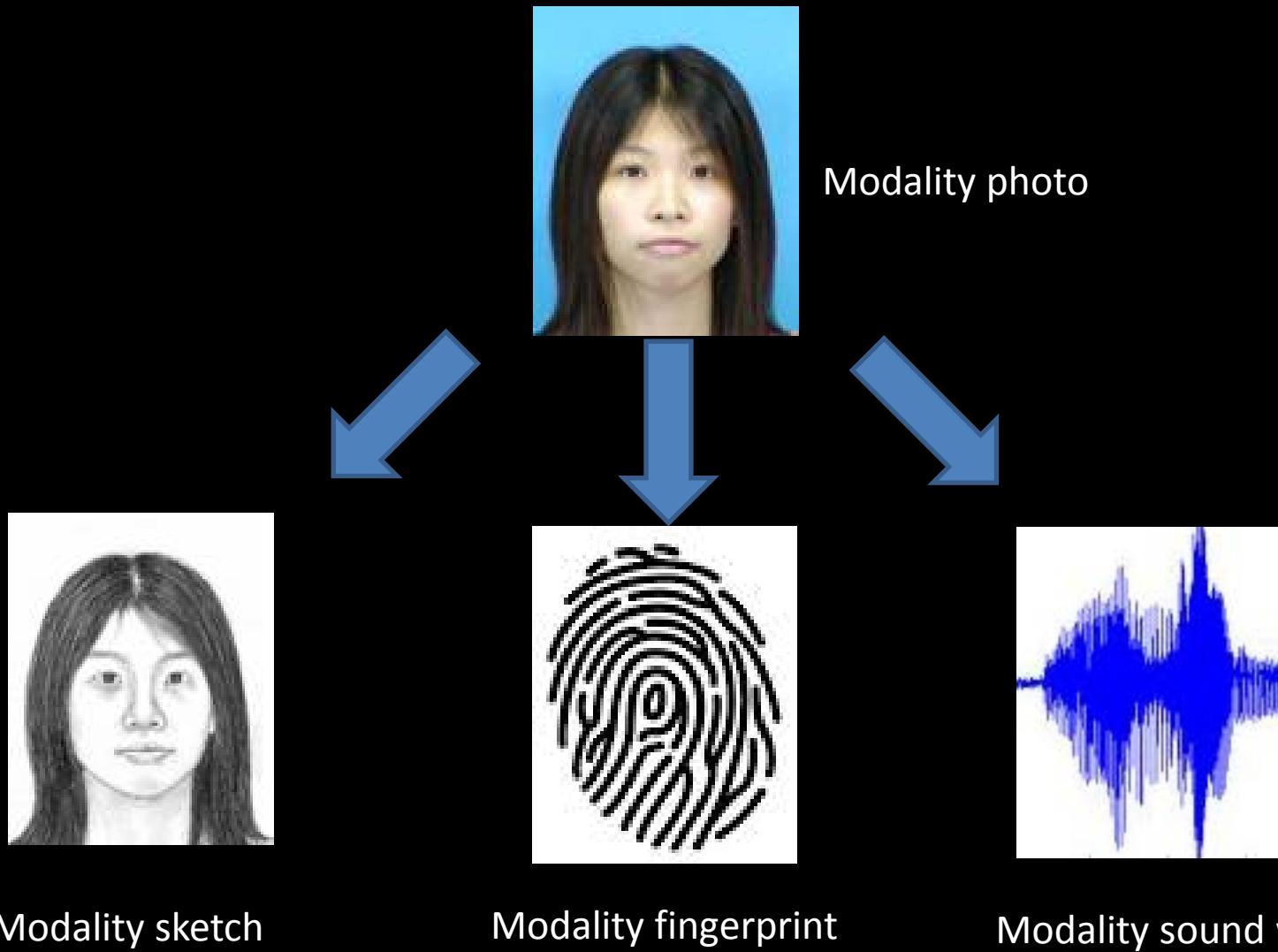
Modality sketch



Modality fingerprint



Multi-modality representation



Cross-modality pattern recognition



Gallery dataset with labels

Cross-modality pattern recognition



Gallery dataset with labels



Sketch query

Cross-modality pattern recognition



Gallery dataset with labels



How about KNN?

Cross-modality pattern recognition



Gallery dataset with labels



How about KNN?

Cross-modality pattern recognition



Gallery dataset with labels



How about KNN?

Related Approaches

- Transform one modality into another



[Wang and Tang PAMI 2010, Zhou *et al.* CVPR 2012, Blanz et al. CVPR 2005]

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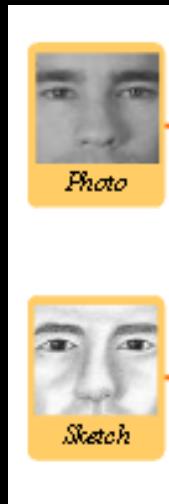
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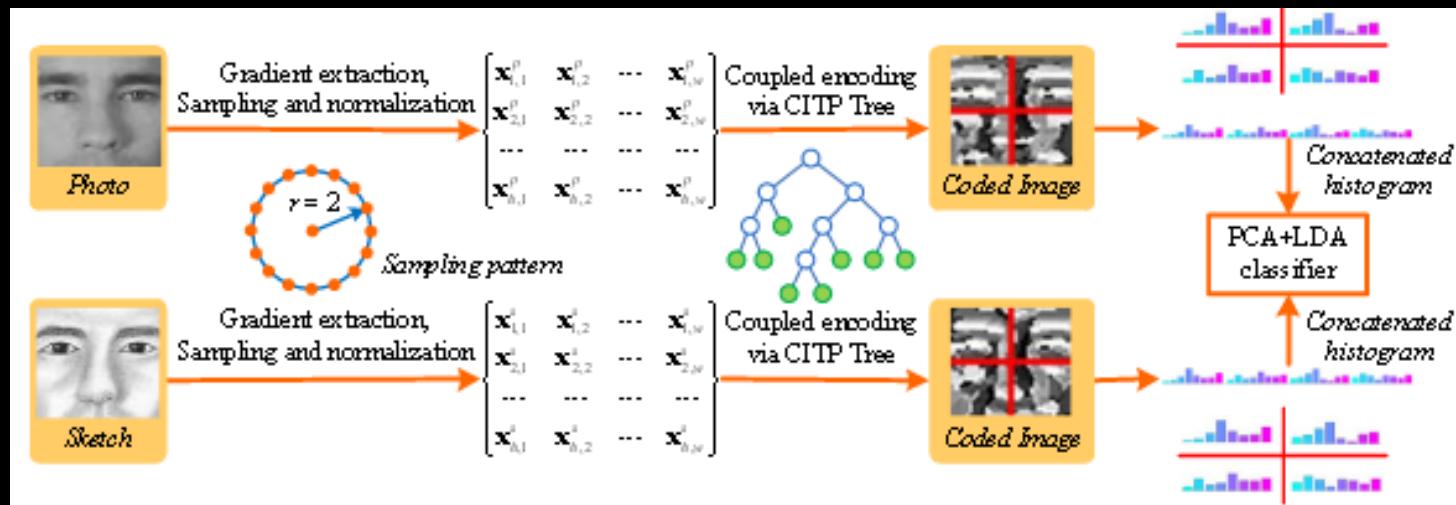
- Extract modality-invariant features



[Zhang *et al.* CVPR 2011]

Related Approaches

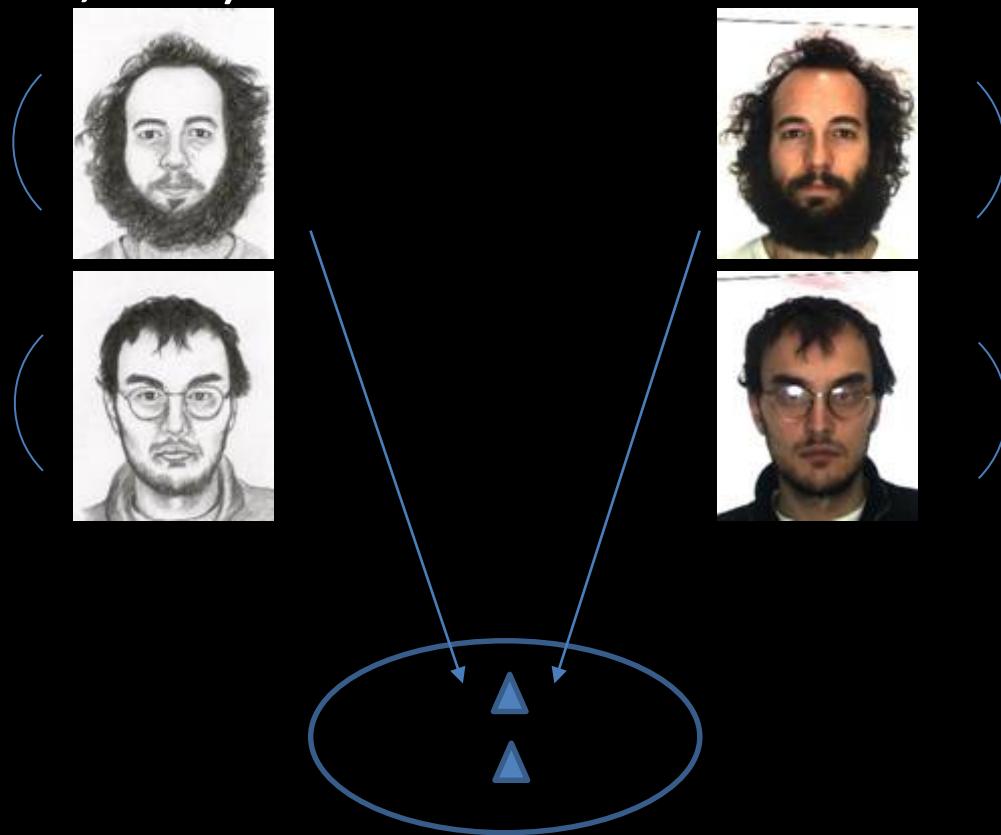
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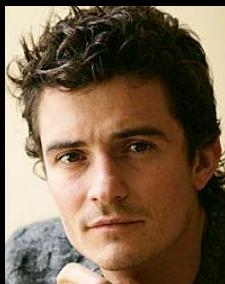
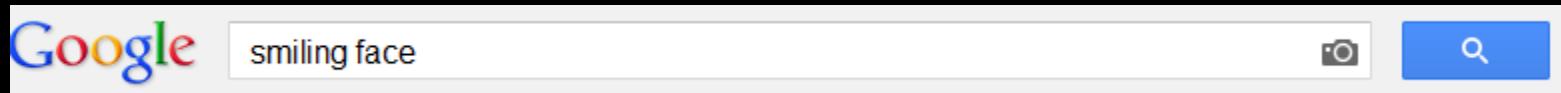
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Related Approaches

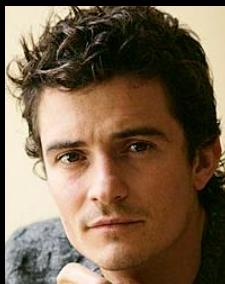
- Find a latent common space between different modalities using absolutely-paired observations (CCA, DCCA, PLS)



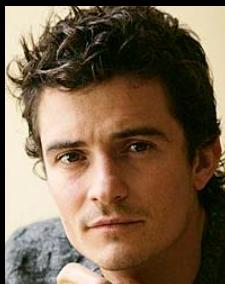
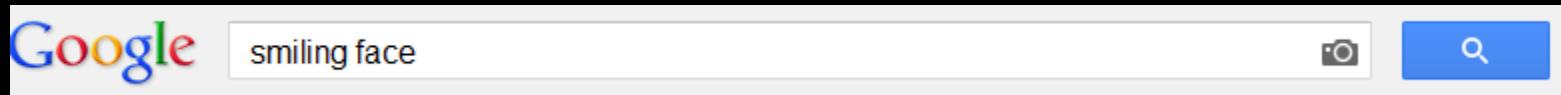
Relatively-Paired Scenario



Relatively-Paired Scenario



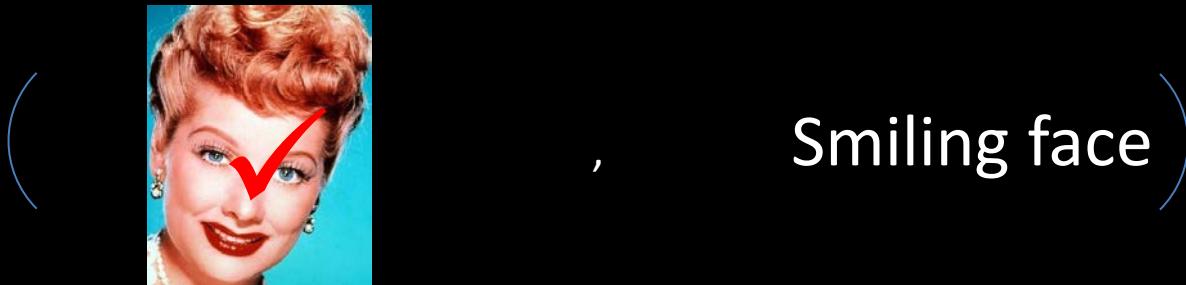
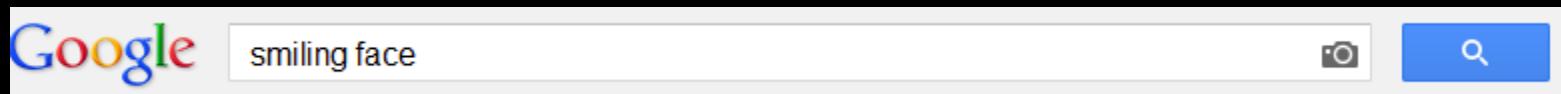
Relatively-Paired Scenario



Relatively-Paired Scenario



Relatively-Paired Scenario



Relatively-Paired Scenario



(

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Smiling face)

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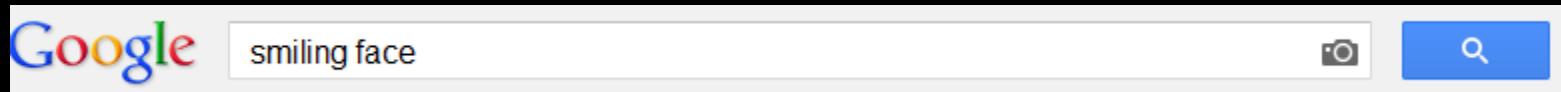
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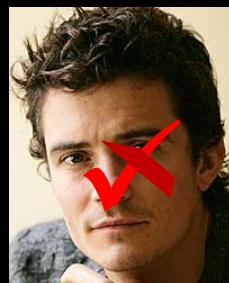
Smiling face)



Relatively-Paired Scenario



(Smiling face)



(Smiling face)



(Smiling face)

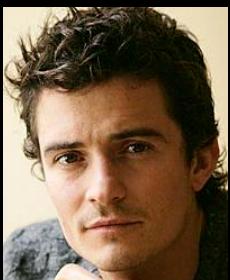
Exploit distance

Exploit distance

Distance ( , Smiling face)

Exploit distance

Distance ( , Smiling face)

Distance ( , Smiling face)



Exploit distance

Distance (, Smiling face)



Distance (, Smiling face)



Distance (, Smiling face)



Exploit distance

Distance ( , Smiling face)

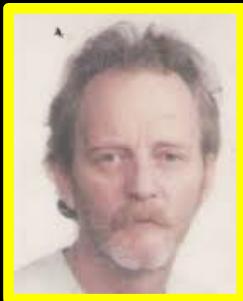


How to define distance?

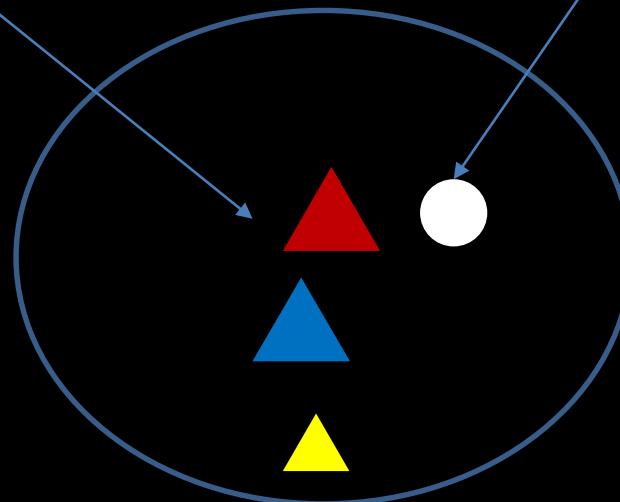
Distance ( , Smiling face)



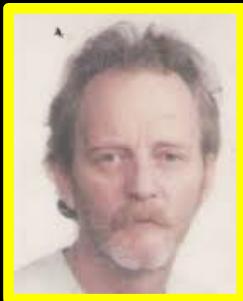
Relatively-Paired Space Analysis



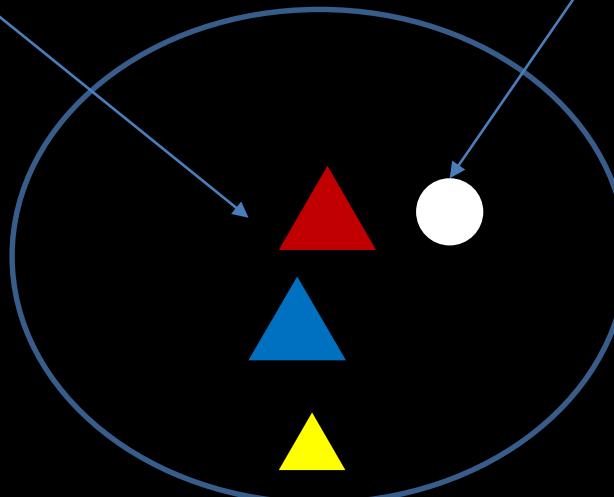
Smiling face



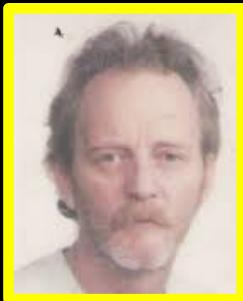
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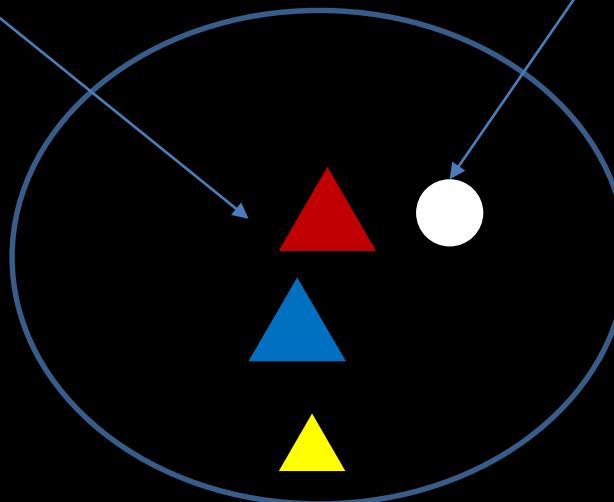
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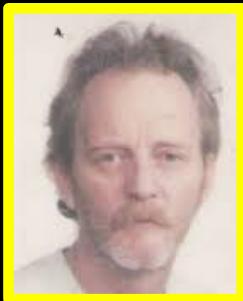
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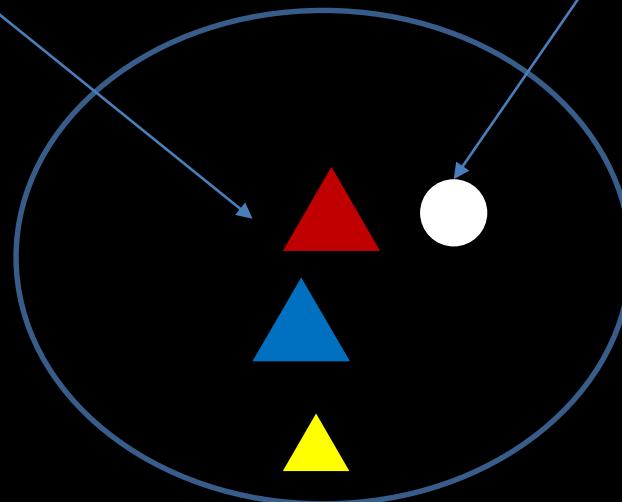
Smiling face



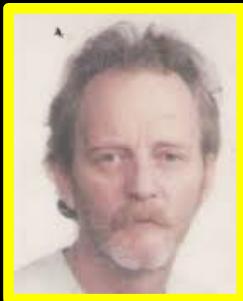
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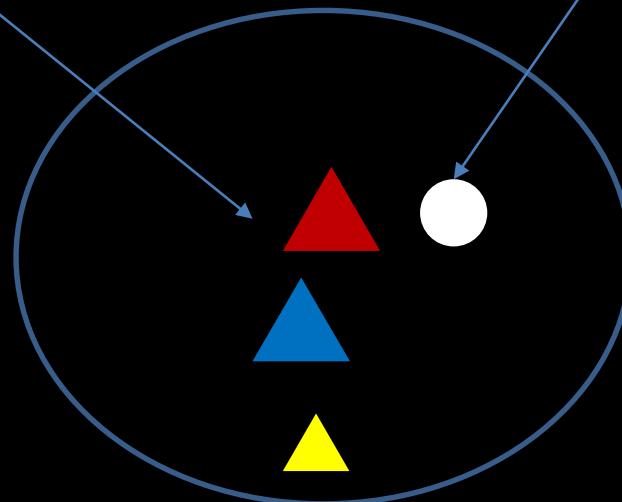
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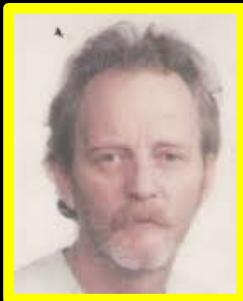
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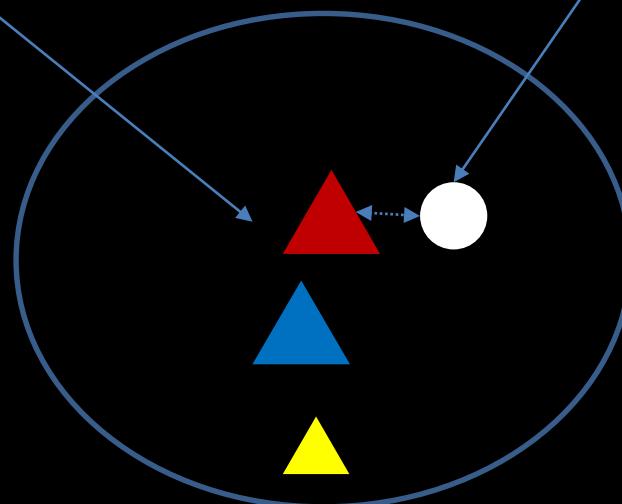
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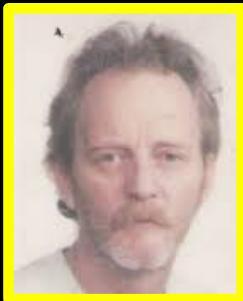
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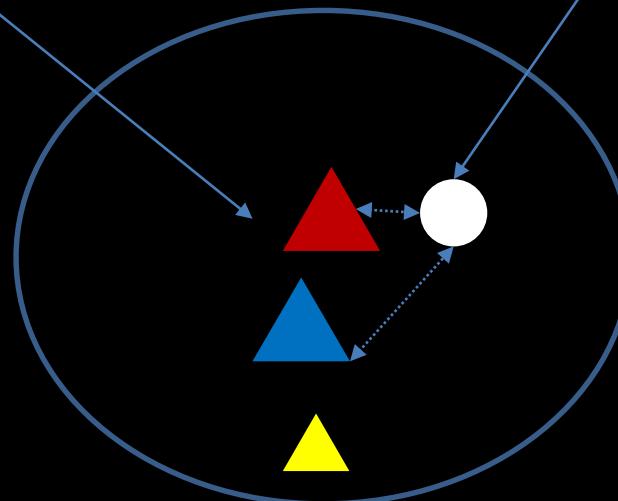
Smiling face



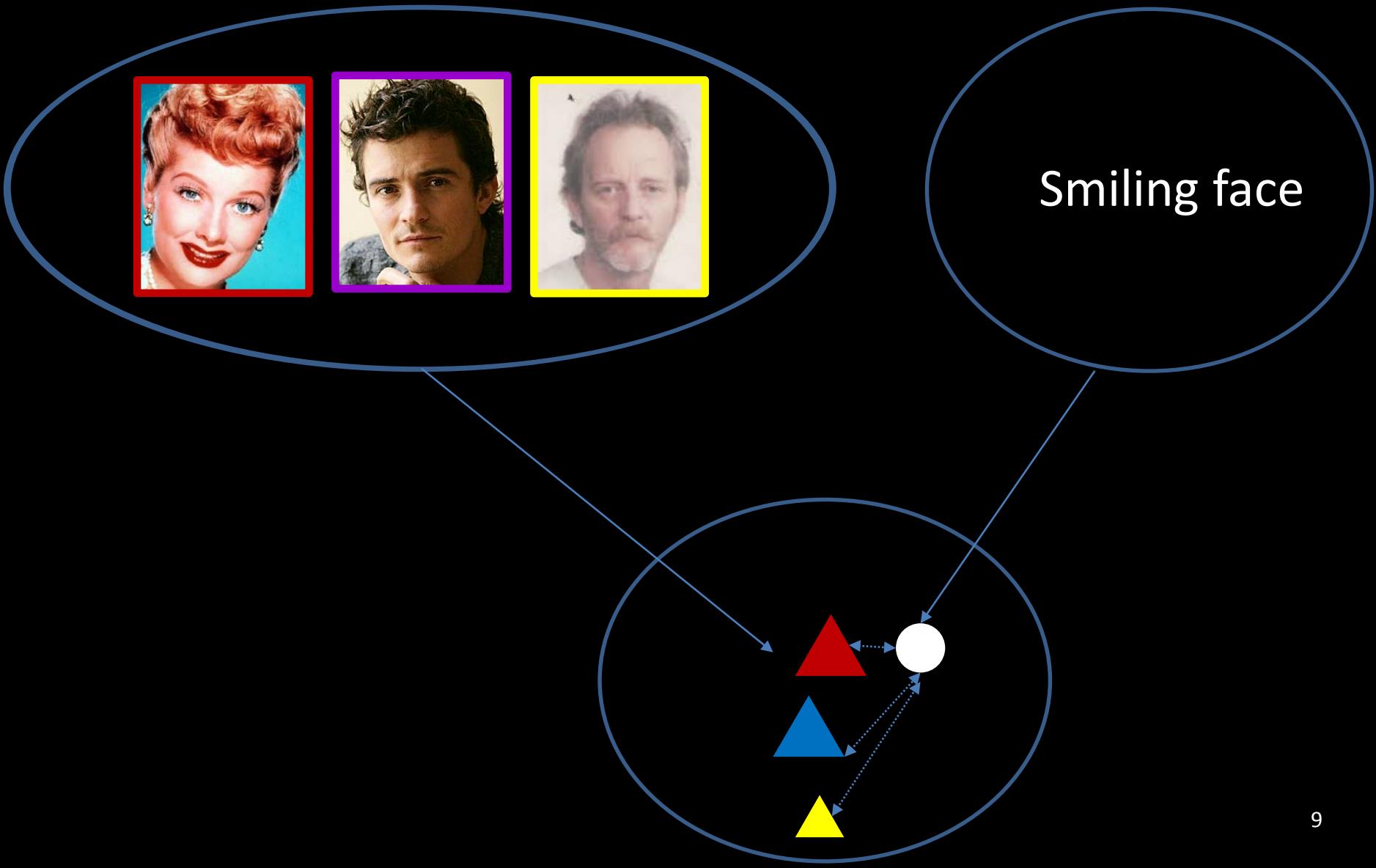
Relatively-Paired Space Analysis



Smiling face



Relatively-Paired Space Analysis



Relatively-Paired Space Analysis

$$\min \| A \|^2_F + \gamma \sum \ell(x_i, x_j, x_k)$$

Relatively-Paired Space Analysis

$$\min \boxed{\| A \|_F^2} + \gamma \sum \ell(x_i, x_j, x_k)$$

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$$A = W^T W, W = [W_1, \dots, W_M]$$

Relatively-Paired Space Analysis

$$\min \| A \|_F^2$$

+

$$\gamma \sum \ell(x_i, x_j, x_k)$$

$$A = W^T W, W = [W_1, \dots, W_M]$$

$$(1 - Tr(AC_{ijk}))_+$$
$$C_{ijk} = C_{ik} - C_{ij}$$

$$C_{ij} = (A_{\Omega_{t_i}} x_i - A_{\Omega_{t_j}} x_j) \left(A_{\Omega_{t_i}} x_i - A_{\Omega_{t_j}} x_j \right)^T$$

$$W_{\Omega_m} = WA_{\Omega_m}$$

Relatively-Paired Space Analysis

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Primal problem

$$\min \| A \|_F^2 + \gamma \sum (1 - \text{Tr}(AC_{ijk}))_+$$

Relatively-Paired Space Analysis

Dual problem

$$\begin{aligned} \min \frac{1}{2} \| Z + \sum u_{ijk} C_{ijk} \|_F - \sum u_{ijk} \\ s.t. Z \geq 0, 0 \leq u \leq \frac{\gamma}{m} \end{aligned}$$

Repeat

Fixing u , optimize Z

Fixing Z , optimize u

Until convergence

Relatively-Paired Space Analysis

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Relatively-Paired Space Analysis

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Time complexity $A = O(td^3)$

Experimental Results

- Feature fusion

Dataset: UCI Multiple Features dataset with six features, Fou, Fac, Kar, Pix, Zer and Mor

How to fuse: sum of projection of paired feature from different modalities

How to evaluate: Mean recognition rates of 1-NN in the latent common space over 10 times

Recognition rates on Multiple Features Dataset.

Pairs	DCCA	bgCCA	bgDCCA	bsCCA	bsDCCA	PLS	RCE	RPSA
Fac Fou	0.89	0.86	0.89	0.84	0.88	0.94	0.95	0.97
Fac Kar	0.98	0.95	0.98	0.93	0.98	0.94	0.98	0.98
Fac Pix	0.97	0.86	0.97	0.86	0.97	0.94	0.95	0.98
Fac Zer	0.88	0.86	0.88	0.84	0.87	0.96	0.97	0.97
Fac Mor	0.82	0.75	0.82	0.74	0.81	0.88	0.88	0.92
Fou Kar	0.90	0.90	0.90	0.88	0.89	0.97	0.96	0.97
Fou Pix	0.89	0.77	0.89	0.74	0.87	0.98	0.95	0.98
Fou Zer	0.83	0.82	0.83	0.80	0.81	0.81	0.85	0.85
Fou Mor	0.77	0.75	0.77	0.74	0.76	0.44	0.80	0.74
Kar Pix	0.95	0.94	0.95	0.93	0.94	0.98	0.96	0.97
Kar Zer	0.88	0.90	0.88	0.89	0.86	0.83	0.96	0.94
Kar Mor	0.80	0.77	0.80	0.76	0.79	0.62	0.86	0.84
Pix Zer	0.87	0.83	0.87	0.80	0.86	0.84	0.94	0.95
Pix Mor	0.79	0.73	0.79	0.71	0.77	0.71	0.84	0.88
Zer Mor	0.75	0.72	0.75	0.70	0.74	0.72	0.77	0.72

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Experimental Results

- Cross-pose face recognition

Dataset: CMUPIE with 68 subjects and 13 poses

How to evaluate: Mean recognition rates of 1-NN in the latent common space

Mean recognition rates for frontal faces (c27) gallery.					
Gallery	Probe	Method	Accuracy	Method	Accuracy
c27	c05/37/25/22/29/11/14/34	PGFR	0.86	RPSA	0.94
c27	c05/22	TFA	0.95	RPSA	0.93
c27	c05/29/37/11/07/09	LLR	0.95	RPSA	1.00
c27	c05/29/37/11/07/09	ELF	0.90	RPSA	1.00
c27	c05/29/37/11/07/09/02/14/22/34/25/31	PLS	0.94	RPSA	0.95

[Liu and Chen CVPR 2005, Prince *et al.* PAMI 2008, Chai et al. TIP 2005, Gross et al. PAMI 2004, Sharma and Jacobs CVPR 2011]

Experimental Results

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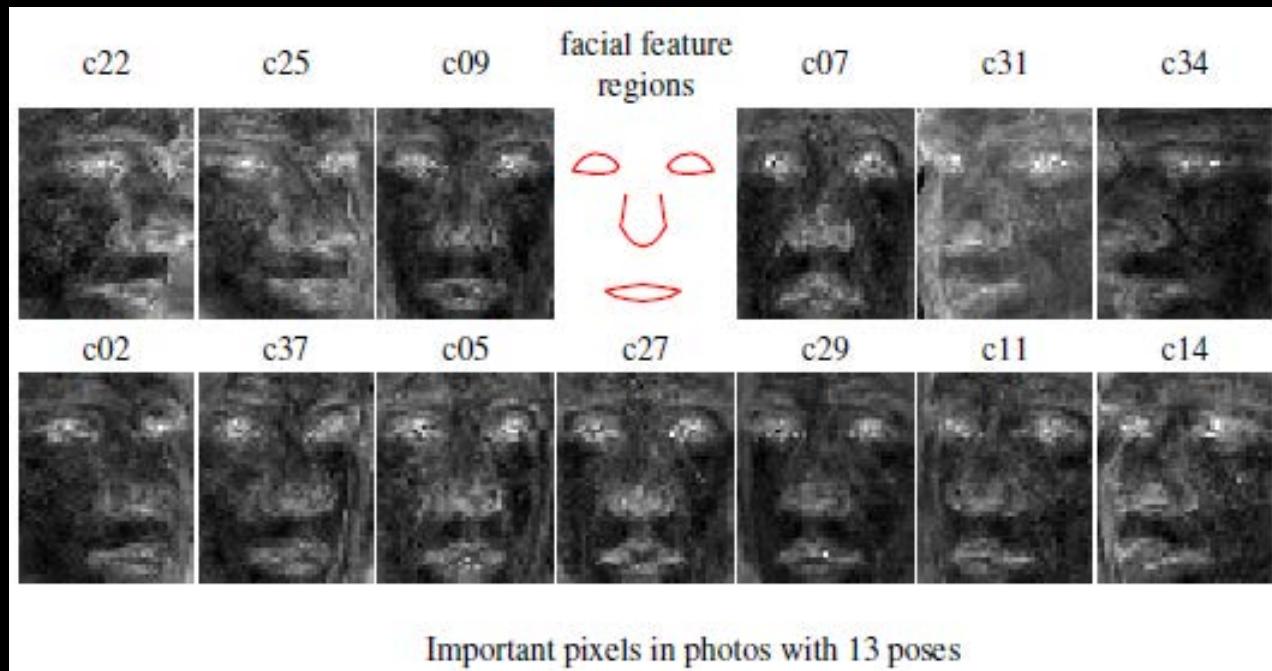
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[Liu and Chen CVPR 2005, Prince *et al.* PAMI 2008, Chai et al. TIP 2005, Gross et al. PAMI 2004, Sharma and Jacobs CVPR 2011]

Experimental Results

- Visualization



Conclusion

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- RPSA is a general framework used in any pattern recognition across modality

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- RPSA learns a latent space according to relatively-paired observations
- RPSA is a general framework used in any pattern recognition across modality
- RPSA achieves state-of-art results

Thanks for your attention.

Questions?

The code is available online
(<http://i.cs.hku.hk/~zhkuang/Software.html>)