Asymmetric Person Re-identification

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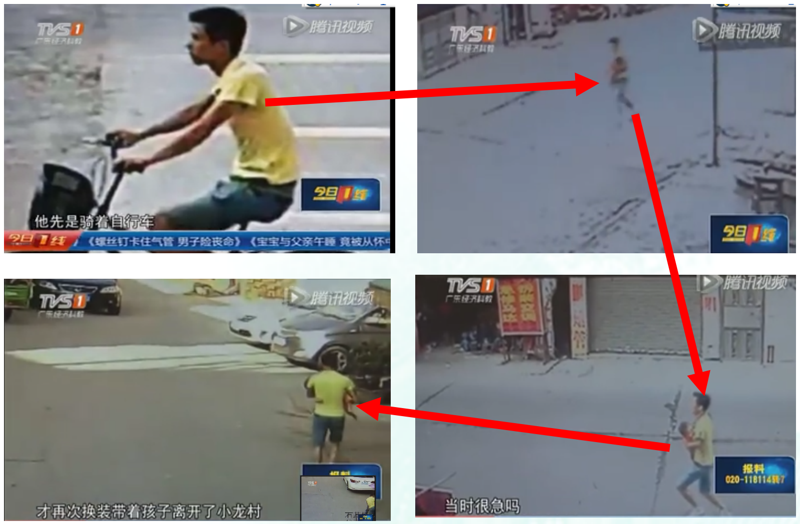
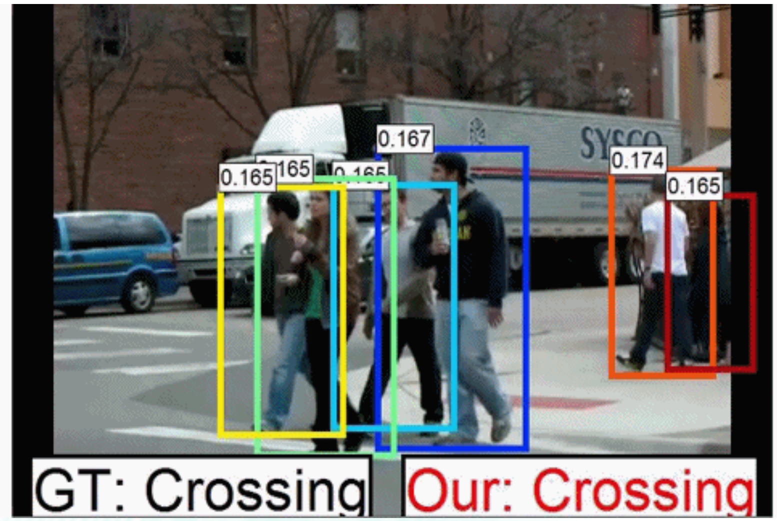
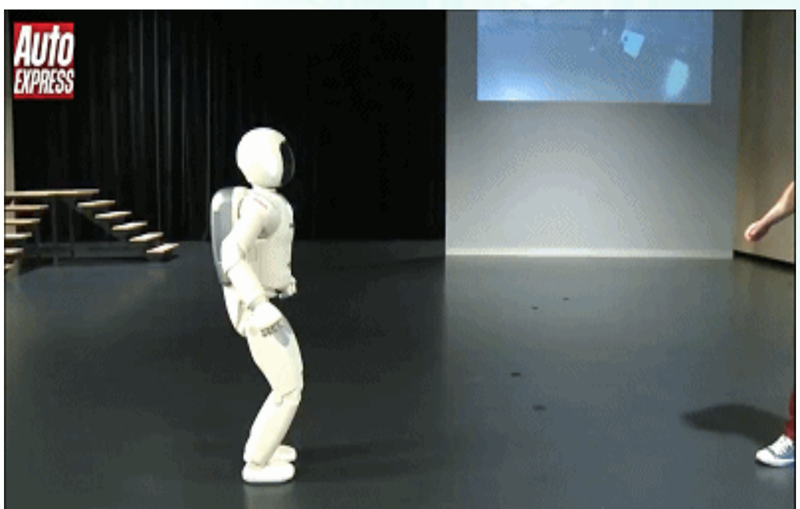
My Research



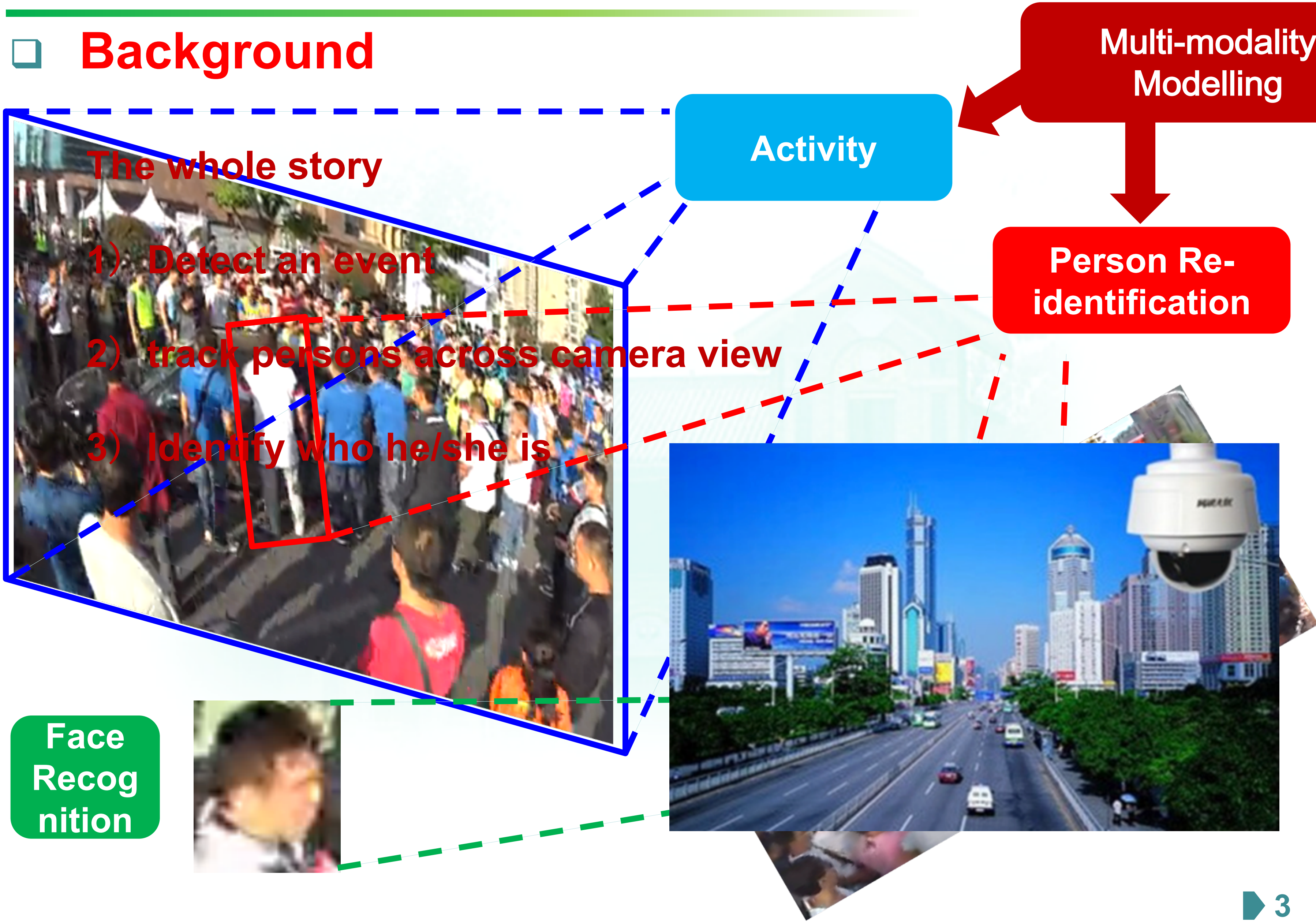




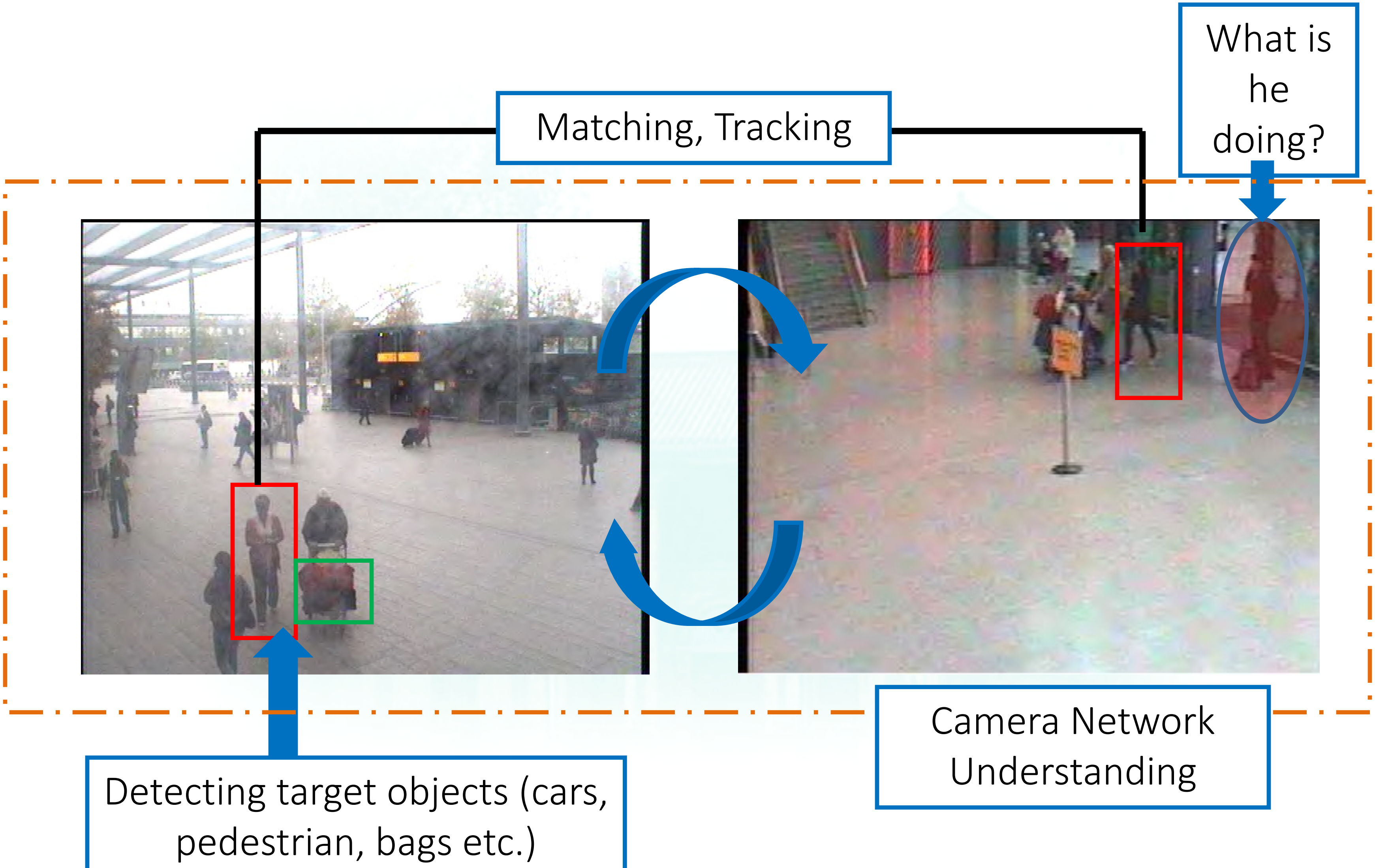
面向视觉对象关联的机器学习建模

Human Identification & Activity Understanding

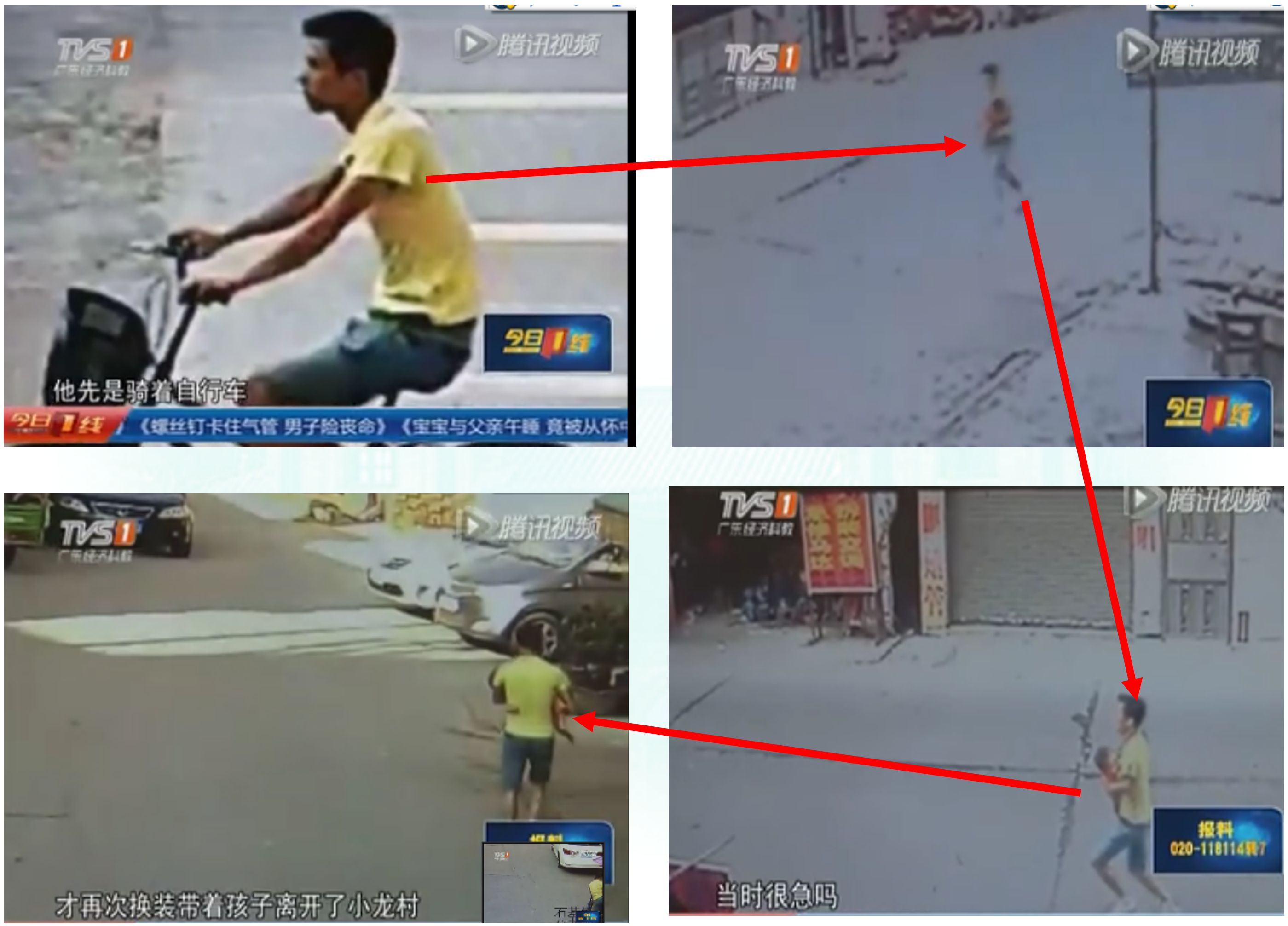
Background



Person Re-identification



Person Re-identification



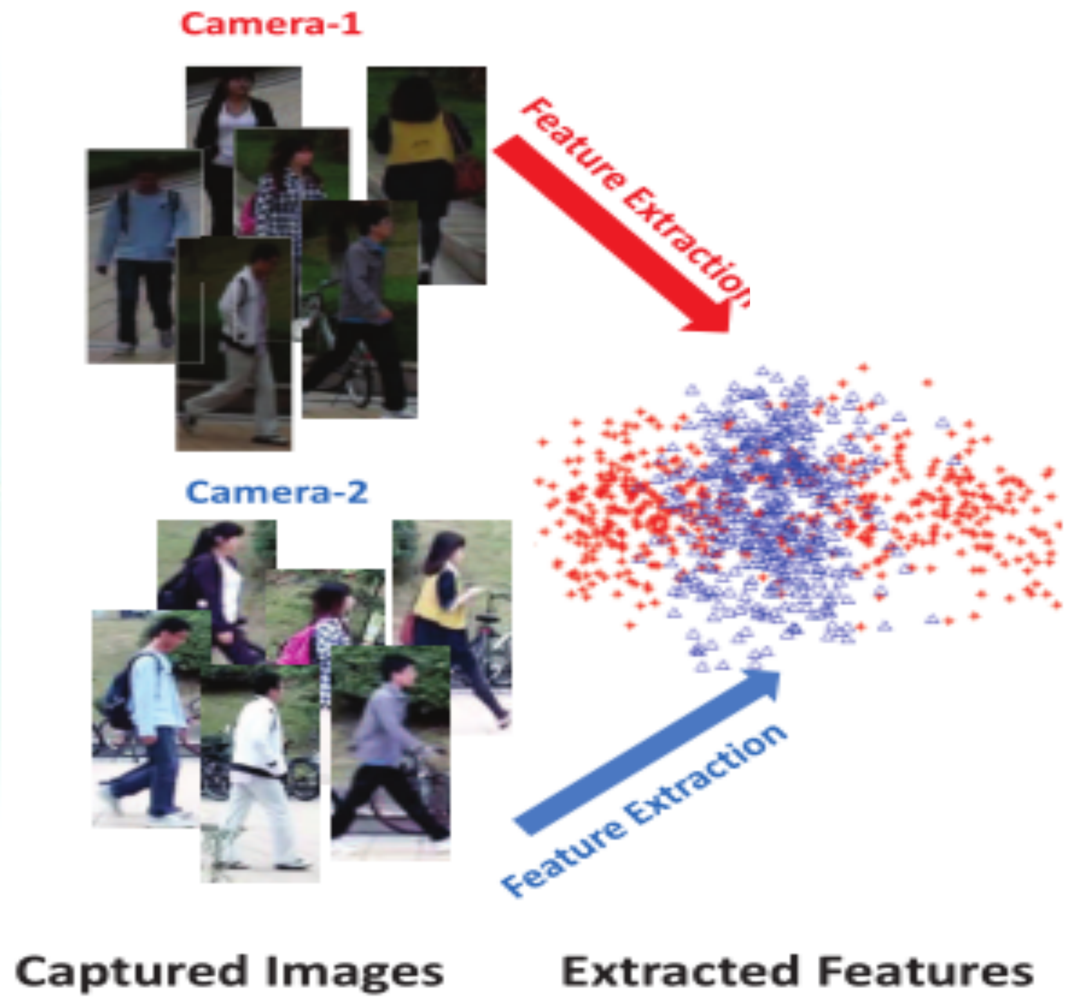
Person Re-identification: Challenges

- **Some Main Variations**

View | Lighting | Occlusion | Low Resolution | Clothing Change

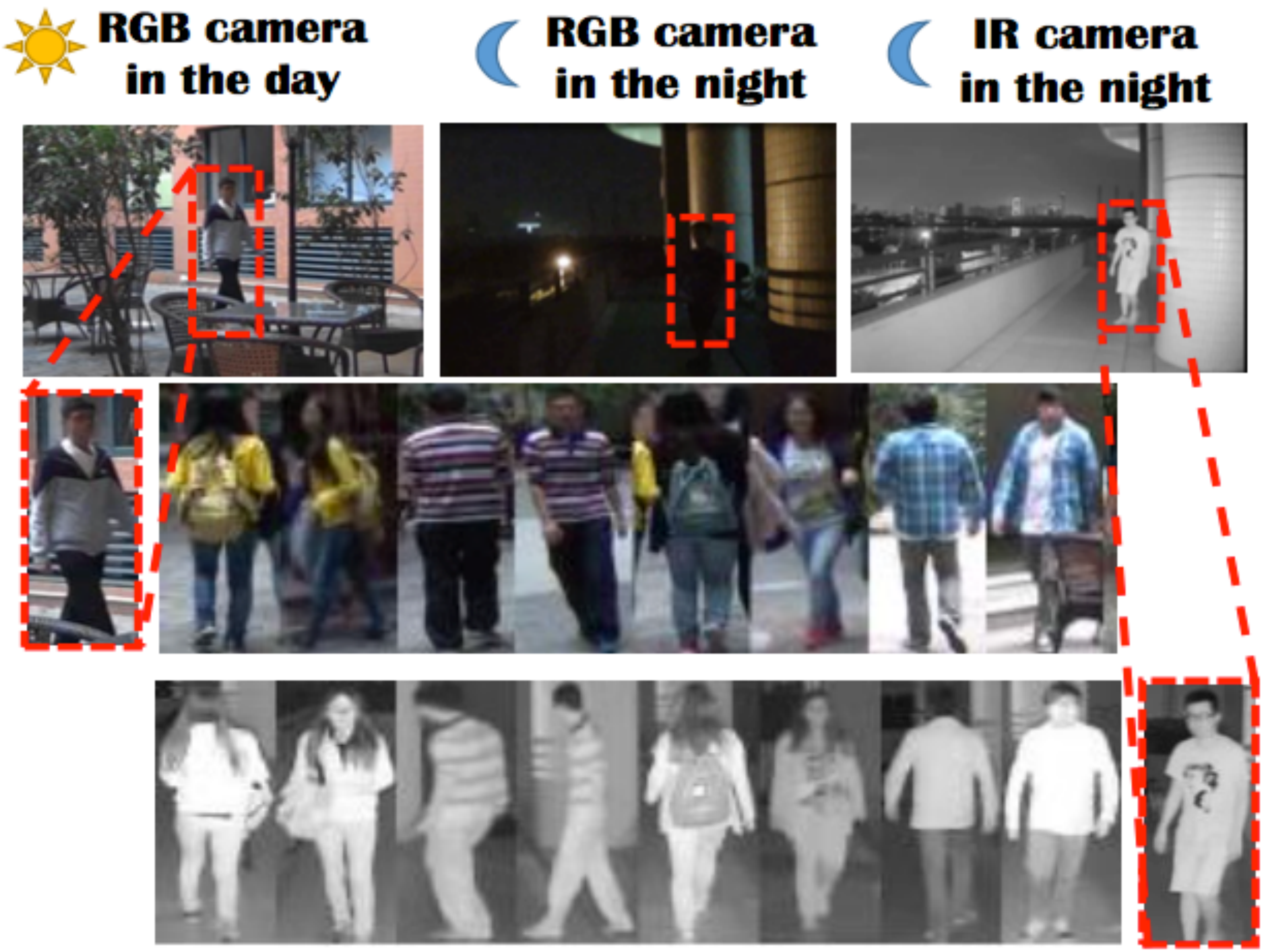
Person Re-ID vs. Cross-Modality

- View Bias



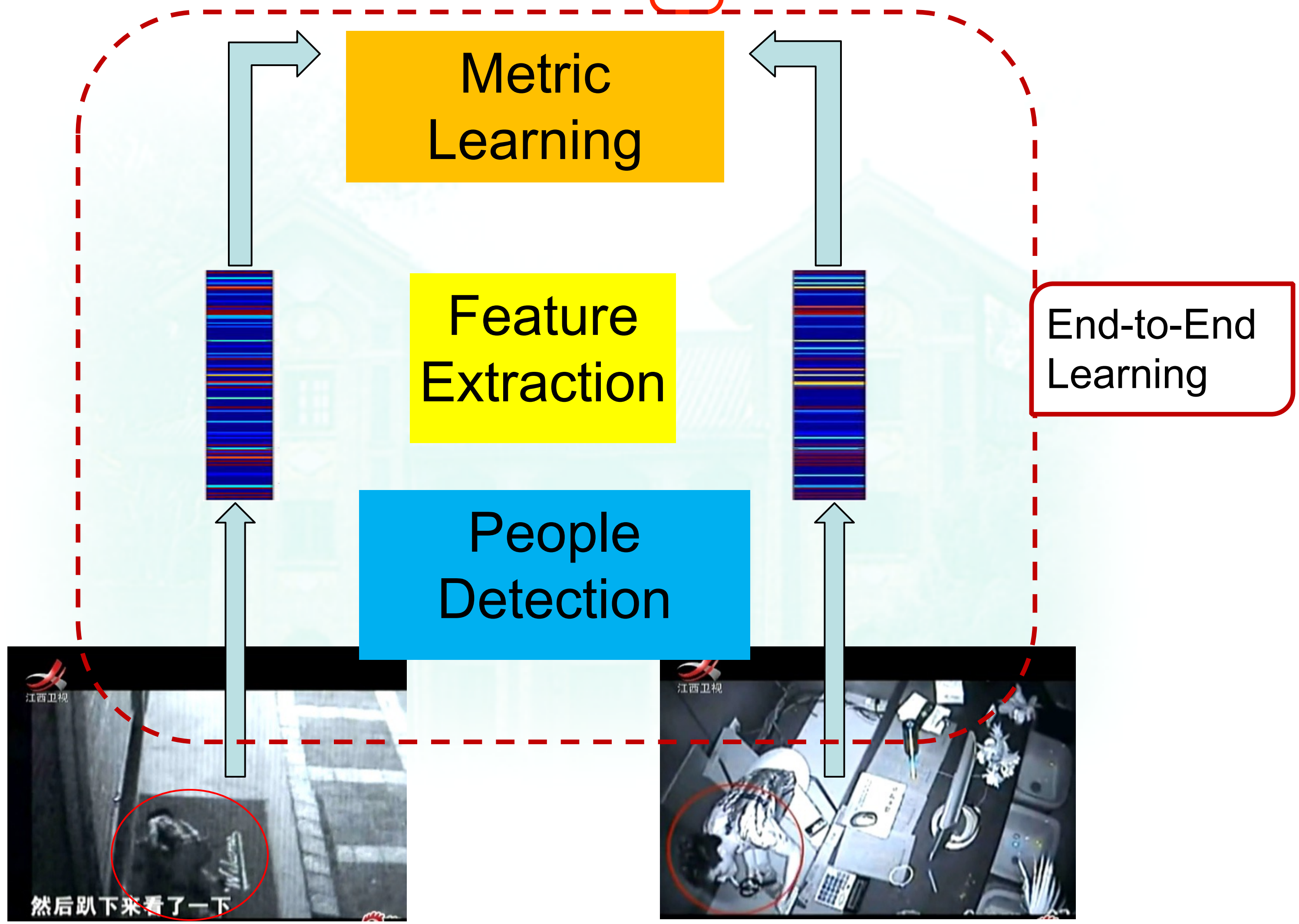
Person Re-ID vs. Cross-Modality

- Matching between Heterogeneous Images



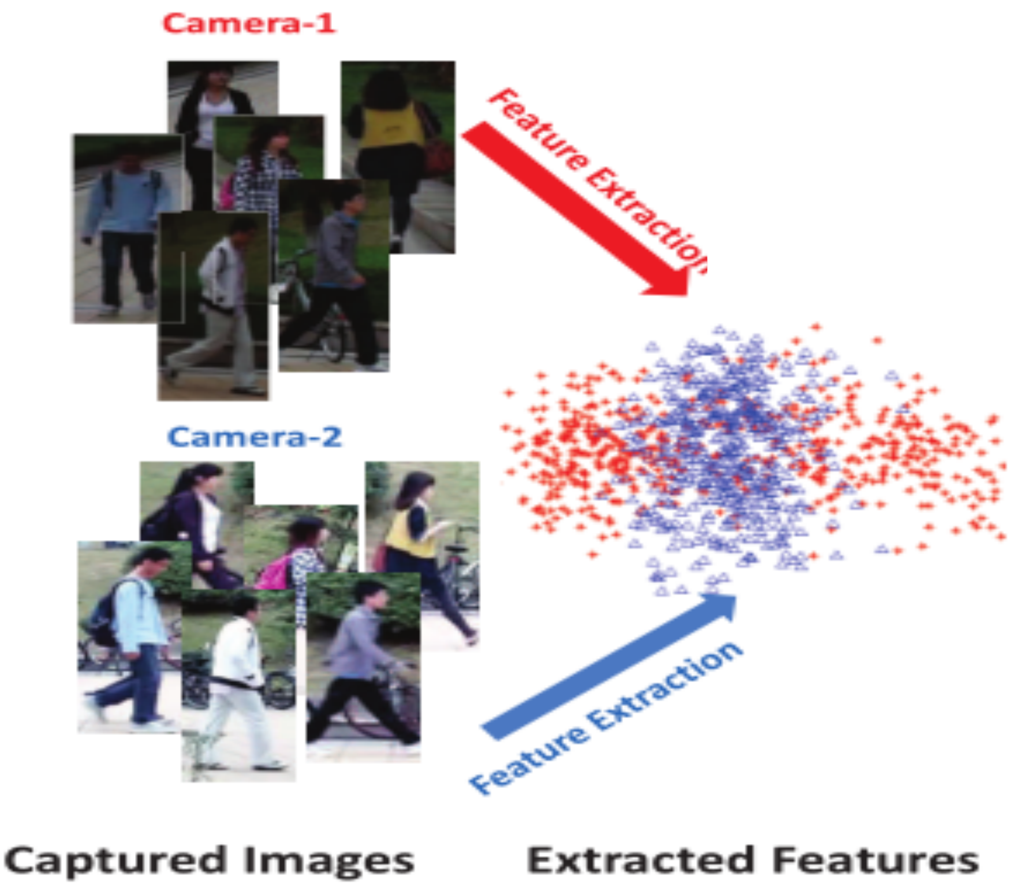
Person Re-identification: Metric Learning

$$\mathcal{D}_{\mathbf{M}}(\vec{x}_i,\vec{x}_j) = (\vec{x}_i-\vec{x}_j)^\top \boxed{\mathbf{M}}(\vec{x}_i-\vec{x}_j)$$



How to alleviate view bias across camera views?

Our Approach



Learning universal feature transformation

Learning view-specific feature transformation

Asymmetric Metric

$$d(x_i, x_j) = \sqrt{(x_i - x_j)^T \mathrm{M} (x_i - x_j)}$$
$$= ||U^T x_i - U^T x_j||_2,$$

Learn different feature transformation for different camera views

Pseudometric

$$d(\{x_i^p, p\}, \{x_j^q, q\}) = ||U^{pT} x_i^p - U^{qT} x_j^q||_2$$
$$U^p \neq U^q$$

Non-negativity

Symmetry

$$\begin{aligned} d(\{x_i^p, p\}, \{x_j^q, q\}) &= ||U^{pT} x_i^p - U^{qT} x_j^q||_2 \\ &= ||U^{qT} x_j^q - U^{pT} x_i^p||_2 \\ &= d(\{x_j^q, q\}, \{x_i^p, p\}), \end{aligned}$$

Triangle Inequality

$$\begin{aligned} &||U^{rT} x_k^r - U^{qT} x_j^q||_2 \leq \\ &\quad ||U^{rT} x_k^r - U^{pT} x_i^p||_2 + ||U^{pT} x_i^p - U^{qT} x_j^q||_2. \end{aligned}$$

Coincidence

$$d(\{x^p, p\}, \{x^q, q\}) = 0$$

$$\cancel{U}^{pT} x^p = \cancel{U}^{qT} x^q \quad \longleftarrow \quad U^{pT} x^p = U^{qT} x^q$$

$$||U^p - U^q||_F^2 \downarrow$$

Asymmetric Metric for RE-ID

RE-ID Reformulation by Augmentation

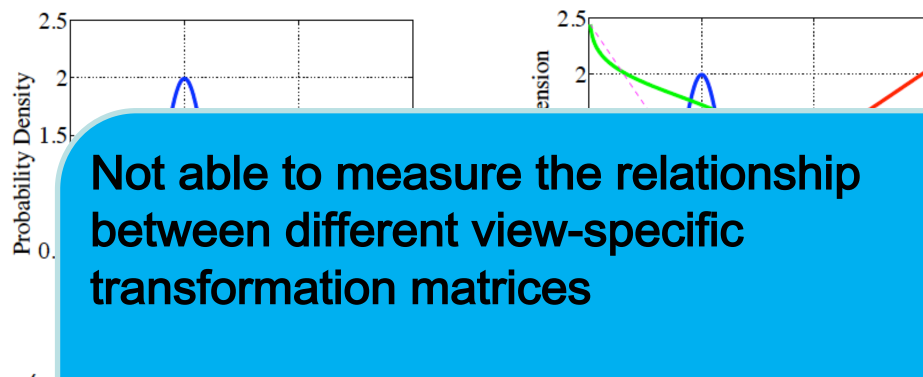
$$\tilde{\boldsymbol{X}}^a_{\text{zp}} = \begin{bmatrix} \boldsymbol{I}_{d\times d} \\ \boldsymbol{O}_{d\times d} \end{bmatrix} \boldsymbol{X}^a, \qquad \tilde{\boldsymbol{X}}^b_{\text{zp}} = \begin{bmatrix} \boldsymbol{O}_{d\times d} \\ \boldsymbol{I}_{d\times d} \end{bmatrix} \boldsymbol{X}^b$$

$$\hat{\boldsymbol{W}} = \min_{\boldsymbol{W}} f_{\text{obj}}(\boldsymbol{W}^\top \tilde{\boldsymbol{X}}_{\text{zp}})$$

$$\hat{\boldsymbol{W}} = [(\hat{\boldsymbol{W}}^a)^\top, (\hat{\boldsymbol{W}}^b)^\top]^\top$$

View-specific transformation

$$\hat{\boldsymbol{W}}^\top \tilde{\boldsymbol{X}}^a_{\text{zp}} = (\hat{\boldsymbol{W}}^a)^\top \boldsymbol{X}^a$$
$$\hat{\boldsymbol{W}}^\top \tilde{\boldsymbol{X}}^b_{\text{zp}} = (\hat{\boldsymbol{W}}^b)^\top \boldsymbol{X}^b.$$



(a

Fig.
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by the solid red line. The two dashed lines imply feature projection operation. Note that the probability density axis is not plotted in (b) for demonstration simplicity.

Not able to measure the relationship between different view-specific transformation matrices

Do not constraint the discrepancy between feature transformation across view: **Coincidence**

Yingcong Chen, Xiatian Zhu, Wei-Shi Zheng*, and Jian-Huang Lai. Person Re-Identification by Camera Correlation Aware Feature Augmentation. IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI), 2017.

Asymmetric Metric for RE-ID

Adaptive feature augmentation

$$\tilde{\boldsymbol{X}}^a_{\text{zp}} = \begin{bmatrix} \boldsymbol{I}_{d\times d} \\ \boldsymbol{O}_{d\times d} \end{bmatrix} \boldsymbol{X}^a, \qquad \tilde{\boldsymbol{X}}^b_{\text{zp}} = \begin{bmatrix} \boldsymbol{O}_{d\times d} \\ \boldsymbol{I}_{d\times d} \end{bmatrix} \boldsymbol{X}^b$$

$$\Downarrow \qquad\qquad \Downarrow$$

generalised

$$\tilde{\boldsymbol{X}}^a_{\text{craft}} = \begin{bmatrix} \boldsymbol{R} \\ \boldsymbol{M} \end{bmatrix} \boldsymbol{X}^a, \qquad \tilde{\boldsymbol{X}}^b_{\text{craft}} = \begin{bmatrix} \boldsymbol{M} \\ \boldsymbol{R} \end{bmatrix} \boldsymbol{X}^b$$

$$f_a(\tilde{\boldsymbol{X}}^a_{\text{craft}}) = \boldsymbol{W}^\top \tilde{\boldsymbol{X}}^a_{\text{craft}} = (\boldsymbol{R}^\top \boldsymbol{W}^a + \boldsymbol{M}^\top \boldsymbol{W}^b)^\top \boldsymbol{X}^a$$

$$f_b(\tilde{\boldsymbol{X}}^b_{\text{craft}}) = \boldsymbol{W}^\top \tilde{\boldsymbol{X}}^b_{\text{craft}} = (\boldsymbol{M}^\top \boldsymbol{W}^a + \boldsymbol{R}^\top \boldsymbol{W}^b)^\top \boldsymbol{X}^b$$

control the discrepancy Between f_a and f_b

Yingcong Chen, Xiatian Zhu, Wei-Shi Zheng*, and Jian-Huang Lai. Person Re-Identification by Camera Correlation Aware Feature Augmentation. IEEE Trans. on Pattern Analysis and Machine Intelligence (PAMI), 2017.

Asymmetric Metric for RE-ID

Learning:

Camera coRrelation Aware Feature augmenTation (CRAFT)

$$\hat{\boldsymbol{W}} = \arg\min_{\boldsymbol{W}} f_{\text{obj}}(\boldsymbol{W}^\top \tilde{\boldsymbol{X}}_{\text{craft}}) + \lambda \text{tr}(\boldsymbol{W}^\top \boldsymbol{C}\boldsymbol{W})$$

Generalize any symmetric metric learning models to asymmetric ones: e.g. MFA

$1 + \eta_{\text{ridge}}$

$$\min_{\boldsymbol{H}} \sum_{i \neq j} A^c_{ij} ||\boldsymbol{H}^\top(\ddot{\boldsymbol{x}}_i - \ddot{\boldsymbol{x}}_j)||_2^2 + \lambda \text{tr}(\boldsymbol{H}^\top \boldsymbol{H})$$

$$\text{s.t.} \sum_{i \neq j} A^p_{ij} ||\boldsymbol{H}^\top(\ddot{\boldsymbol{x}}_i - \ddot{\boldsymbol{x}}_j)||_2^2 = 1,$$

$\gamma \quad = ||\boldsymbol{W}^c$

$= \text{tr}(\boldsymbol{W}$

$= (1 + \eta_{\text{ridge}})\text{tr}(\boldsymbol{W}^\top \boldsymbol{C}\boldsymbol{W}).$

Reduce

nce

$$A^c_{ij} = \begin{cases} 1 & \text{if } i \in N^+_{k_1}(j) \text{ or } j \in N^+_{k_1}(i) \\ 0 & \text{otherwise,} \end{cases}$$

ction

a strictly convex function $\mathcal{F} : \mathbb{R}^{d \times c} \to \mathbb{R}$

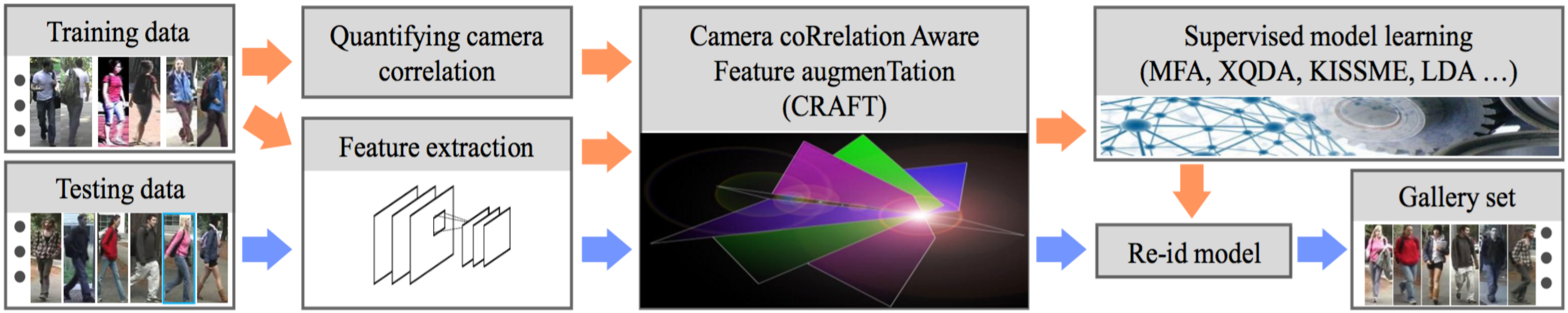
$$A^p_{ij} = \begin{cases} 1 & \text{if } (i,j) \in P_{k_2}(y_i) \text{ or } (i,j) \in P_{k_2}(y_j) \\ 0 & \text{otherwise,} \end{cases}$$

$\boldsymbol{U}^p - \boldsymbol{U}^q)$

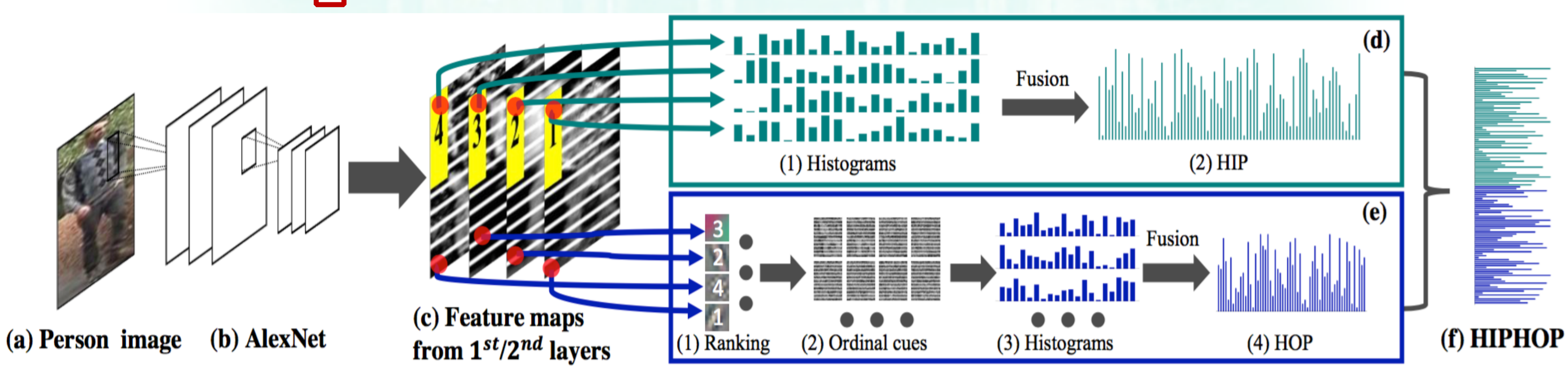
$||\boldsymbol{U}^p - \boldsymbol{U}^q||_F^2$

Asymmetric Metric for RE-ID

❑ A framework



to extract domain-generic and more view invariant person features



Asymmetric Metric for RE-ID

Evaluation: augmentation or not augmentation?

Dataset	VIPeR [30]				CUHK01 [31]				CUHK03 [26]				Market-1501 [33]				QMUL GRID [32]			
Rank (%)	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20
OriFeat	43.3	72.7	84.1	93.4	64.3	85.1	90.6	94.6	63.4	88.0	93.0	96.1	65.4	84.0	89.3	93.1	21.0	42.9	53.0	62.7
+ Kernelization	47.0	75.4	86.8	94.4	69.5	89.3	93.5	96.5	78.6	94.9	96.8	98.4	66.0	84.4	89.3	93.2	19.0	42.2	51.9	61.4
ZeroPad [71]	37.5	69.9	82.8	92.1	66.4	85.8	90.5	94.7	76.0	91.9	94.8	95.3	38.2	62.5	71.7	80.0	7.2	26.0	40.3	55.8
+ Kernelization	40.0	72.8	85.0	93.4	71.8	89.6	93.8	96.5	80.0	92.7	94.4	95.3	49.5	72.4	80.0	85.8	6.1	21.8	36.3	51.4
BaseFeatAug [69]	45.5	76.1	87.4	95.1	59.0	81.1	87.0	92.4	78.3	94.6	97.3	98.9	65.3	83.6	88.8	92.6	20.1	47.6	58.8	70.0
+ Kernelization	47.3	77.8	89.0	95.2	63.0	83.5	89.0	93.6	83.4	97.0	98.1	99.1	65.3	83.6	88.8	92.6	20.1	47.6	58.8	70.0
CRAFT	47.8	77.1	87.8	95.1	70.0	87.4	92.0	95.5	78.5	94.7	97.5	98.9	67.9	85.1	90.0	93.4	25.4	50.2	61.8	74.2
+ Kernelization	50.3	80.0	89.6	95.5	74.5	91.2	94.8	97.1	84.3	97.1	98.3	99.1	68.7	87.1	90.8	94.0	22.4	49.9	61.8	71.7

Evaluation: augmentation vs. domain adaptation

Comparison between CRAFT and domain adaptation.

Dataset	VIPeR [30]				CUHK01 [31]				CUHK03 [26]				Market-1501 [33]				QMUL GRID [32]			
Rank (%)	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20
TCA [63]	11.1	23.4	31.0	38.5	7.0	16.4	22.2	30.1	5.5	16.2	26.4	42.8	8.9	18.7	24.1	30.1	9.8	22.2	29.8	38.3
TFLDA [64]	46.4	75.8	86.7	93.9	69.6	88.7	92.8	96.2	76.7	94.4	96.5	98.0	62.5	81.3	87.0	91.6	19.5	42.5	51.6	61.8
CRAFT	**50.3**	**80.0**	**89.6**	**95.5**	**74.5**	**91.2**	**94.8**	**97.1**	**84.3**	**97.1**	**98.3**	**99.1**	**68.7**	**87.1**	**90.8**	**94.0**	**22.4**	**49.9**	**61.8**	**71.7**

Evaluation: whether using Camera View Discrepancy

Evaluating the effect of our CVD regularization.

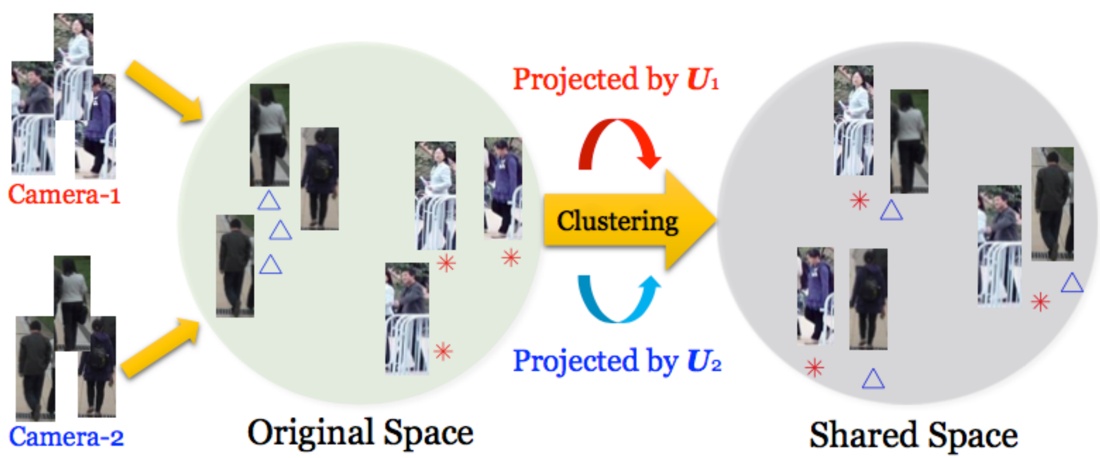
Dataset	VIPeR [30]				CUHK01 [31]				CUHK03 [26]				Market-1501 [33]				QMUL GRID [32]			
Rank (%)	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20
CRAFT(no γ_{cvd})	46.3	77.9	88.1	95.4	73.8	90.6	94.2	96.9	83.9	97.0	98.2	**99.1**	66.6	85.9	90.7	93.7	15.8	45.0	57.7	60.0
CRAFT	**50.3**	**80.0**	**89.6**	**95.5**	**74.5**	**91.2**	**94.8**	**97.1**	**84.3**	**97.1**	**98.3**	**99.1**	**68.7**	**87.1**	**90.8**	**94.0**	**22.4**	**49.9**	**61.8**	**71.7**

Does the Asymmetric Metric Modelling Work for other setting: unsupervised, semi-supervised, …..

Asymmetric Metric for RE-ID: Unsupervised

Unsupervised Learning

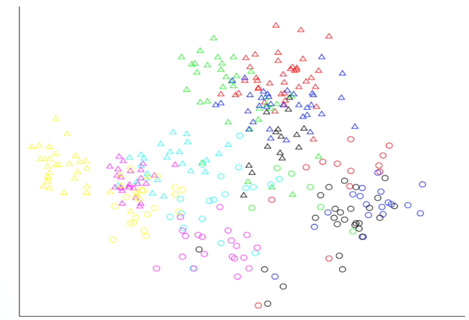
- Clustering-based Asymmetric MEtric Learning (CAMEL)



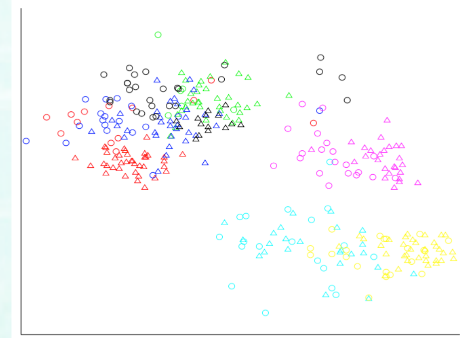
$$\min_{U^1,\cdots,U^V} \mathcal{F}_{obj} = \frac{1}{N}\sum_{k=1}^{K}\sum_{i\in\mathcal{C}_k}\|\boldsymbol{U}^{p\mathrm{T}}\mathbf{x}_i^p - \mathbf{c}_k\|^2 + \lambda\sum_{p\neq q}\|\boldsymbol{U}^p - \boldsymbol{U}^q\|_F^2$$

$$s.t. \qquad \boldsymbol{U}^{p\mathrm{T}}\boldsymbol{\Sigma}^p\boldsymbol{U}^p = \boldsymbol{I} \quad (p = 1,\cdots,V),$$

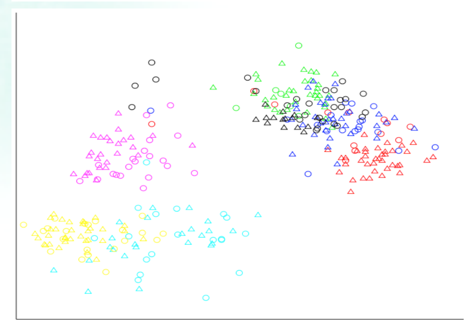
Hongxing Yu, Ancong Wu, Wei-Shi Zheng*. Cross-view Asymmetric Metric Learning for Unsupervised Person Re-identification. In IEEE Conf. on Computer Vision (ICCV), 2017.



(a) Original Feature Distribution



(b) Middle Stage of CAMEL

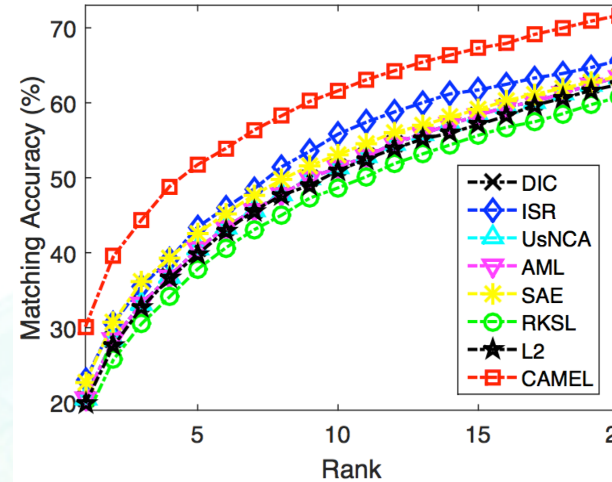


(c) Convergence Stage of CAMEL

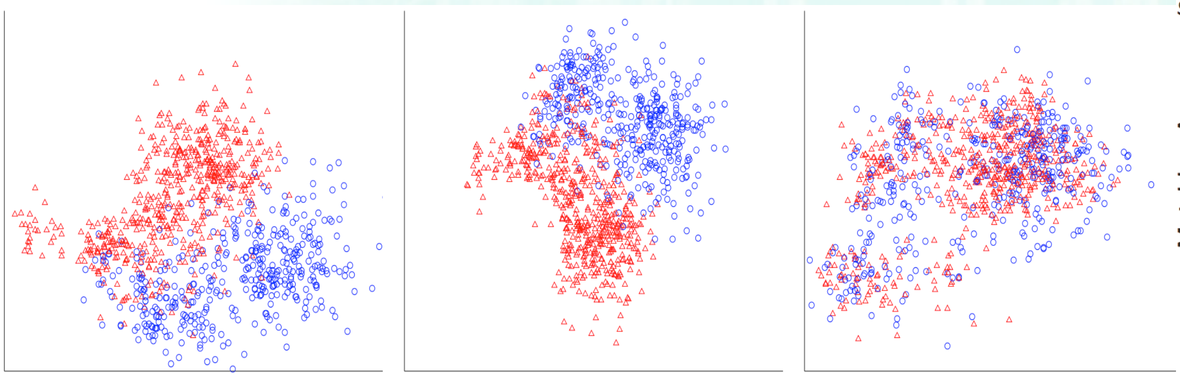
Asymmetric Metric for RE-ID: Unsupervised

Unsupervised Learning

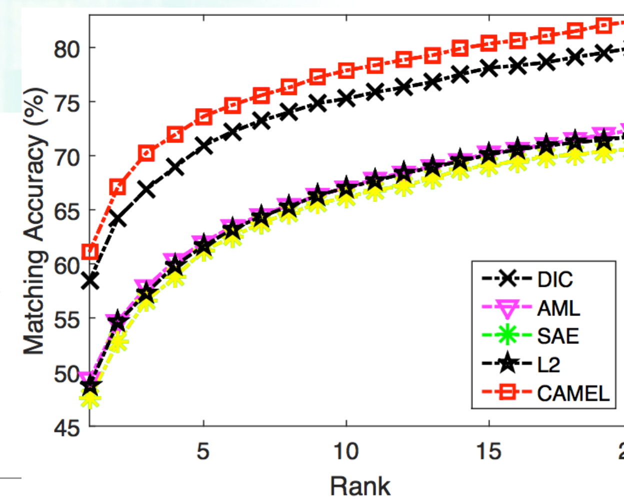
Dataset	VIPeR	CUHK01	CUHK03	SYSU	Market	ExMarket
Setting	SS	SS/MS	SS/MS	SS/MS	MS	MS
Dic [12]	32.9	49.1/52.2	23.8/29.2	20.5/26.0	57.5(28.8)	58.4(26.9)
ISR [20]	29.2	45.1/46.3	27.1/35.6	23.0/33.4	25.6(8.8)	-
RKSL [29]	27.0	38.6/40.4	20.8/26.9	17.8/22.3	41.4(17.9)	-
SAE [14]	25.1	39.2/41.9	19.3/24.4	22.7/27.6	46.8(20.3)	47.5(19.4)
L_2	23.2	40.3/43.1	20.5/26.1	19.9/24.1	47.9(19.9)	49.3(18.6)
AML [33]	23.6	37.6/39.9	18.7/23.6	20.5/24.9	47.9(19.9)	49.3(18.6)
UsNCA [24]	23.6	37.6/39.9	18.8/23.7	20.2/24.1	47.9(19.9)	-
CAMEL	**33.5**	**55.8/59.1**	**30.1/37.9**	**31.2/37.8**	**61.2(31.4)**	**61.1(29.1)**



(d) SYSU



(a) Original Feature Distribution (b) After Symmetric Metric (c) After Asymmetric Metric



(f) ExMarket

Asymmetric Metric for RE-ID: Fast

- FAST Re-ID
  - Learning view-specific hash code for each camera

$$f_p(\boldsymbol{x}_i^p) = \boldsymbol{x}_i^p \boldsymbol{W}_p, \qquad f_g(\boldsymbol{x}_j^g) = \boldsymbol{x}_j^g \boldsymbol{W}_g$$

$$\boldsymbol{B}_p = \mathrm{sign}(\boldsymbol{X}_p \boldsymbol{W}_p) \in \{-1, 1\}^{n_p \times c},$$
$$\boldsymbol{B}_g = \mathrm{sign}(\boldsymbol{X}_g \boldsymbol{W}_g) \in \{-1, 1\}^{n_g \times c},$$

Xiatian Zhu, Botong Wu, Dongcheng Huang, Wei-Shi Zheng*. Fast Open-World Person Re-Identification. IEEE Transactions on Image Processing, 2017.

Wei-Shi Zheng, Shaogang Gong, and Tao Xiang. Towards Open-World Person Re-Identification by One-Shot Group-based Verification. IEEE Transactions on Pattern Analysis and Machine Intelligence (PAMI), vol. 38, no. 3, pp. 591-606, 2016.

Asymmetric Metric for RE-ID: Fast

Idea of the Formulation

$$\underbrace{\left(\|\boldsymbol{B}_p - \boldsymbol{X}_p\boldsymbol{W}_p\|_F^2 + \|\boldsymbol{B}_g - \boldsymbol{X}_g\boldsymbol{W}_g\|_F^2\right)}_{\text{Quantisation loss}} +$$

Cross-view Identity Verification Regularisation

$$l_{\text{ie}}(y_i, U^\top b_i) = \|U\|_F^2 + \eta_{\text{hinge}} \sum_{i=1}^{n} \varepsilon_i$$

$$\text{s.t.} \quad \forall i, j \quad u_{k_i}^\top b_i - u_j^\top b_i + y_{i,j} \geq 1 - \varepsilon_i, \quad \varepsilon_i \geq 0$$

$+$

Cross-view Identity Correlation Hashing

$$\text{cosine}(f_p(\boldsymbol{x}_i^p), f_g(\boldsymbol{x}_j^g)) = \frac{f_p(\boldsymbol{x}_i^p)(f_g(\boldsymbol{x}_j^g))^\top}{\|f_p(\boldsymbol{x}_i^p)\|_2 \|f_g(\boldsymbol{x}_j^g)\|_2}$$

$$= \frac{\boldsymbol{x}_i^p \boldsymbol{W}_p \boldsymbol{W}_g^\top \boldsymbol{x}_j^{g\top}}{\sqrt{\boldsymbol{x}_i^p \boldsymbol{W}_p \boldsymbol{W}_p^\top \boldsymbol{x}_i^{p\top}} \sqrt{\boldsymbol{x}_j^g \boldsymbol{W}_g \boldsymbol{W}_g^\top \boldsymbol{x}_j^{g\top}}}.$$

$\times$

View Context Discrepancy Regularisation

$$R_{\text{vcd}} = \|\boldsymbol{W}_p - \boldsymbol{W}_g\|_F^2.$$

Asymmetric Metric for RE-ID: Fast

- FAST Re-ID
  - Comparison to other related Hashing functions

TABLE III: Comparing state-of-the-art hashing methods. (Metrics: TTR (%) at varying FTRs (%), and mAP (%).)

Dataset	CUHK03 [39]						SYSU [36]						Market-1501 [40]					
Metric	Individual Verification					mAP	Individual Verification					mAP	Individual Verification					mAP
	1%	5%	10%	20%	30%	(%)	1%	5%	10%	20%	30%	(%)	1%	5%	10%	20%	30%	(%)
LSH [25]	15.03	34.87	48.12	64.66	75.20	1.91	21.21	43.73	57.42	72.17	81.17	5.48	37.00	61.56	73.43	85.12	90.92	8.28
SH [27]	11.97	27.8	39.99	54.73	65.35	1.49	17.60	34.21	45.63	60.14	70.27	4.18	38.54	58.69	69.47	80.71	86.75	9.29
SGH [65]	16.95	37.37	50.71	66.45	76.76	2.36	27.18	49.21	61.74	75.34	82.92	8.03	37.75	63.16	75.05	86.13	91.76	8.69
ITQ [66]	17.31	39.29	53.06	69.12	80.24	2.70	26.51	49.55	63.18	77.04	84.87	7.47	40.72	67.17	78.67	88.51	93.41	10.84
CCA+ITQ [66]	28.11	51.15	65.05	78.95	86.37	4.28	50.50	73.75	83.16	91.08	94.67	18.12	57.75	80.30	87.53	93.47	96.17	15.02
KSH [30]	32.29	57.54	69.78	81.73	88.96	5.49	53.23	77.28	85.88	92.62	95.62	22.29	59.03	81.83	89.01	94.26	96.41	17.34
FH [68]	20.01	40.07	52.32	67.35	77.39	1.03	29.48	50.56	62.42	75.58	83.65	8.07	28.24	48.88	60.59	73.92	81.61	5.07
SDH [31]	38.80	66.82	78.83	88.15	93.03	7.31	46.09	72.34	82.76	90.75	94.51	17.99	58.03	81.26	88.22	94.16	96.29	15.57
COSDISH [69]	13.19	29.18	40.33	56.88	68.23	1.55	38.04	61.43	72.73	83.95	89.38	11.51	39.29	62.26	73.49	83.68	89.04	8.44
CMSSH [48]	10.46	32.46	49.80	68.67	80.45	1.25	11.06	33.76	50.51	70.55	82.29	3.18	8.88	29.25	46.49	67.02	79.56	1.55
CVH [47]	2.83	10.09	17.81	31.05	42.51	0.39	5.76	19.67	31.77	49.33	62.21	1.30	3.51	13.38	22.62	37.31	50.55	0.53
CMFH [71]	11.85	31.23	46.40	64.63	75.56	1.27	25.73	54.24	68.73	82.09	89.14	6.32	24.96	52.96	67.52	81.62	89.11	4.07
SCM [51]	5.43	17.84	28.77	44.72	58.70	0.59	14.83	32.93	45.22	60.35	70.95	3.92	13.41	31.49	43.44	58.75	69.09	2.04
SePH [70]	26.98	52.69	65.88	79.29	86.24	4.18	37.15	64.01	75.75	86.09	91.56	13.56	41.88	70.39	80.72	88.89	93.09	8.80
X-ICE(hinge)	49.67	**79.60**	**89.50**	**96.09**	**98.48**	**11.66**	61.86	84.10	91.47	**96.35**	**98.26**	**29.93**	**66.52**	**88.03**	**93.66**	**97.15**	98.55	**21.47**
X-ICE(reg)	**49.96**	78.18	88.96	95.88	97.98	11.23	**63.13**	**84.86**	**91.52**	96.17	98.08	29.44	64.18	86.98	92.91	97.09	**98.59**	20.68
Metric	Set Verification					mAP	Set Verification					mAP	Set Verification					mAP
LSH [25]	4.81	13.97	21.83	35.01	45.88	1.91	7.25	18.13	27.35	41.18	52.31	5.48	17.17	33.22	43.85	57.75	67.36	8.28
SH [27]	3.91	12.00	19.93	31.72	43.41	1.49	7.22	16.36	24.39	36.62	46.96	4.18	21.52	36.77	46.41	58.33	68.00	9.29
SGH [65]	5.42	14.34	22.87	36.84	48.89	2.36	10.20	22.06	31.91	46.08	56.88	8.03	16.59	34.04	45.33	59.12	69.60	8.69
ITQ [66]	5.45	14.9	23.96	37.95	49.51	2.70	8.81	21.47	31.42	45.82	56.73	7.47	17.39	35.66	47.25	60.90	70.46	10.84
CCA+ITQ [66]	10.52	23.86	34.05	49.95	59.58	4.28	21.08	42.10	53.63	67.05	75.76	18.12	18.30	45.05	60.16	73.75	81.38	15.02
KSH [30]	11.65	27.43	38.19	52.68	63.62	5.49	22.07	43.13	55.44	69.26	77.25	22.29	21.74	47.36	61.28	74.78	82.22	17.34
FH [68]	7.66	17.92	26.82	40.15	52.08	1.03	12.82	26.19	35.86	48.86	59.28	8.07	13.32	27.17	36.78	50.13	60.84	5.07
SDH [31]	13.59	31.37	43.59	60.08	70.34	7.31	15.46	36.48	49.00	63.30	72.79	17.99	20.95	47.01	61.17	75.19	82.16	15.57
COSDISH [69]	5.07	13.37	21.71	34.27	43.74	1.55	16.86	33.10	43.36	57.20	66.38	11.51	15.80	35.00	46.81	60.49	69.66	8.44
CMSSH [48]	2.32	10.32	19.42	32.44	45.06	1.25	2.66	11.13	19.29	33.87	46.11	3.18	2.20	8.93	17.42	31.57	44.29	1.55
CVH [47]	1.31	5.62	12.06	23.29	32.45	0.39	1.75	7.65	14.44	27.18	38.12	1.30	1.57	6.83	12.83	24.39	35.74	0.53
CMFH [71]	3.49	11.91	20.06	34.46	45.35	1.27	7.25	21.42	32.99	48.97	60.98	6.32	7.95	22.60	33.55	48.81	60.49	4.07
SCM [51]	1.91	7.64	14.74	27.22	37.74	0.59	5.75	15.55	23.82	37.04	48.23	3.92	5.29	15.23	23.20	36.53	47.93	2.04
SePH [70]	9.64	23.22	33.51	49.79	60.94	4.18	12.40	30.40	42.85	57.81	67.73	13.56	11.78	32.98	46.91	63.28	73.64	8.80
X-ICE(hinge)	**16.41**	**37.50**	**50.14**	**66.56**	**77.30**	**11.66**	23.32	46.84	60.48	74.20	82.37	**29.93**	**26.81**	**52.73**	**66.47**	**79.66**	**86.16**	**21.47**
X-ICE(reg)	16.37	37.36	49.71	65.49	76.03	11.23	**25.94**	**49.94**	**62.59**	**75.91**	**83.30**	29.44	22.27	48.12	62.87	77.13	84.55	20.68

Asymmetric Metric for RE-ID: Fast

FAST Re-ID

- When using more powerful features?

TABLE IX: Evaluating the effect of different visual features. (Metrics: TTR (%) at FTR = 1%, and mAP (%). IV: Individual Verification, SV: Set Verification.)

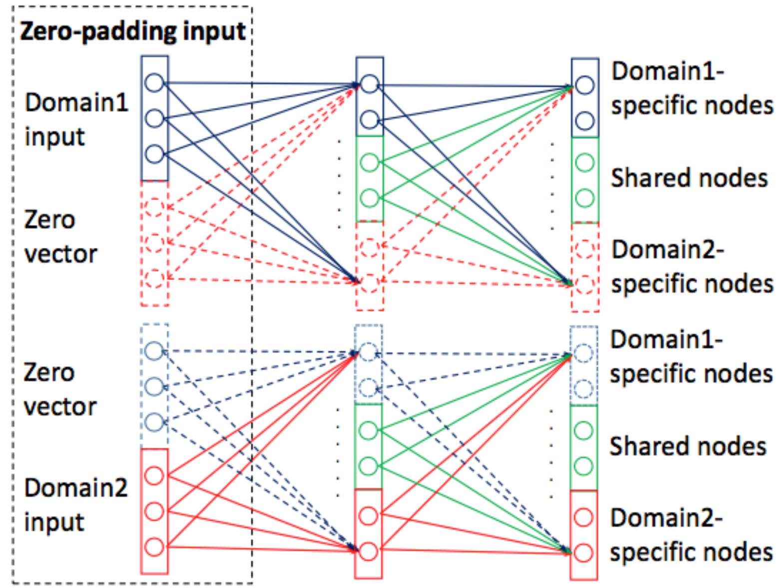
Method	Feature	CUHK03 [39]			SYSU [36]			Market-1501 [40]		
		IV	SV	mAP	IV	SV	mAP	IV	SV	mAP
DCNN [74]	Deep	47.87	14.38	13.62	58.77	19.64	29.69	78.37	31.58	33.65
KSH [30]	LOMO	32.29	11.65	5.49	53.23	22.07	22.29	59.03	21.74	17.34
	Deep	51.08	**19.00**	14.77	60.38	21.55	31.54	79.50	34.39	34.96
SDH [31]	LOMO	38.80	13.59	7.31	46.09	15.46	17.99	58.03	20.95	15.57
	Deep	36.88	15.93	9.11	52.93	16.60	22.23	71.00	35.61	26.73
X-ICE(hinge)	LOMO	49.67	16.41	11.66	61.86	23.32	29.93	66.52	26.81	21.47
	Deep	51.79	18.29	**15.33**	63.08	23.35	32.95	**80.90**	**41.52**	**37.34**
X-ICE(reg)	LOMO	49.96	16.37	11.23	63.13	25.94	29.44	64.18	22.27	20.68
	Deep	**52.62**	17.63	15.21	**64.05**	**24.57**	**33.07**	80.37	41.01	37.23

How to match heterogeneous person images across camera views?

Asymmetric Metric for RE-ID: RGB-Infrared

Cross-Modality Learning: RGB-IR RE-ID

- Deep zero-padding



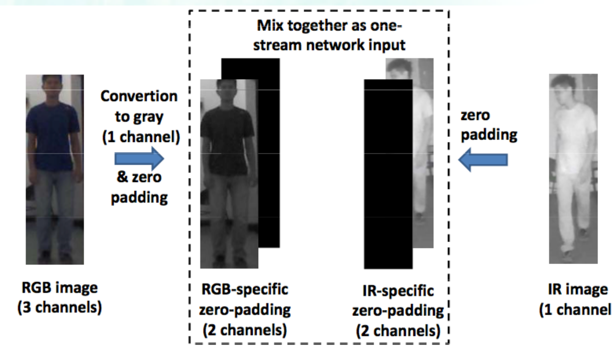
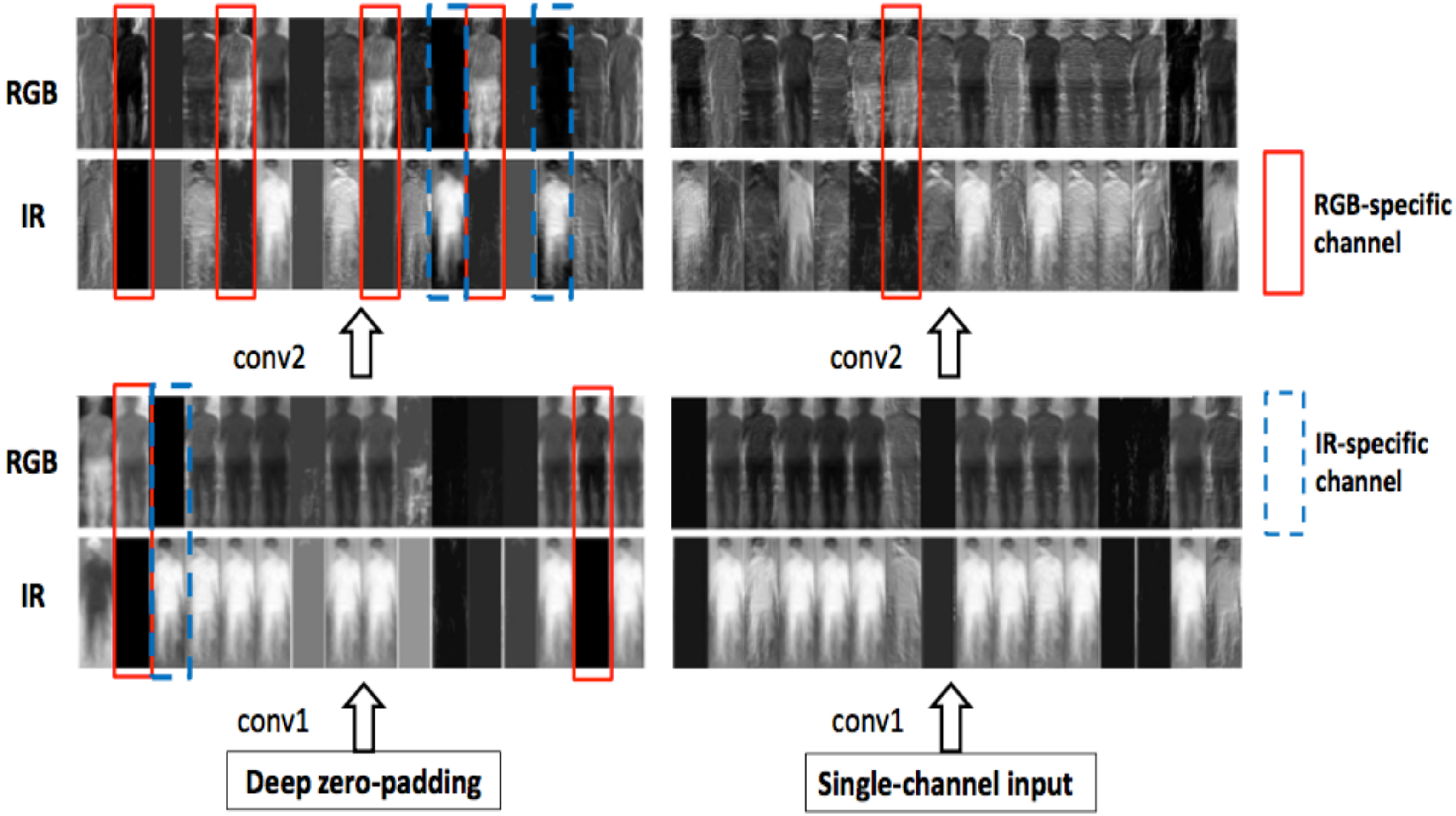


Figure 6. Deep zero-padding for RGB and infrared (IR) images.

Ancong Wu, Wei-Shi Zheng*, Hongxing Yu, Shaogang Gong, Jianhuang Lai. RGB-Infrared Cross-Modality Person Re-Identification. In IEEE Conf. on Computer Vision (ICCV), 2017.

Asymmetric Metric for RE-ID: RGB-Infrared

- Cross-Modality Learning: RGB-IR RE-ID



Asymmetric Metric for RE-ID: RGB-Infrared

❑ Cross-Modality Learning: RGB-IR RE-ID

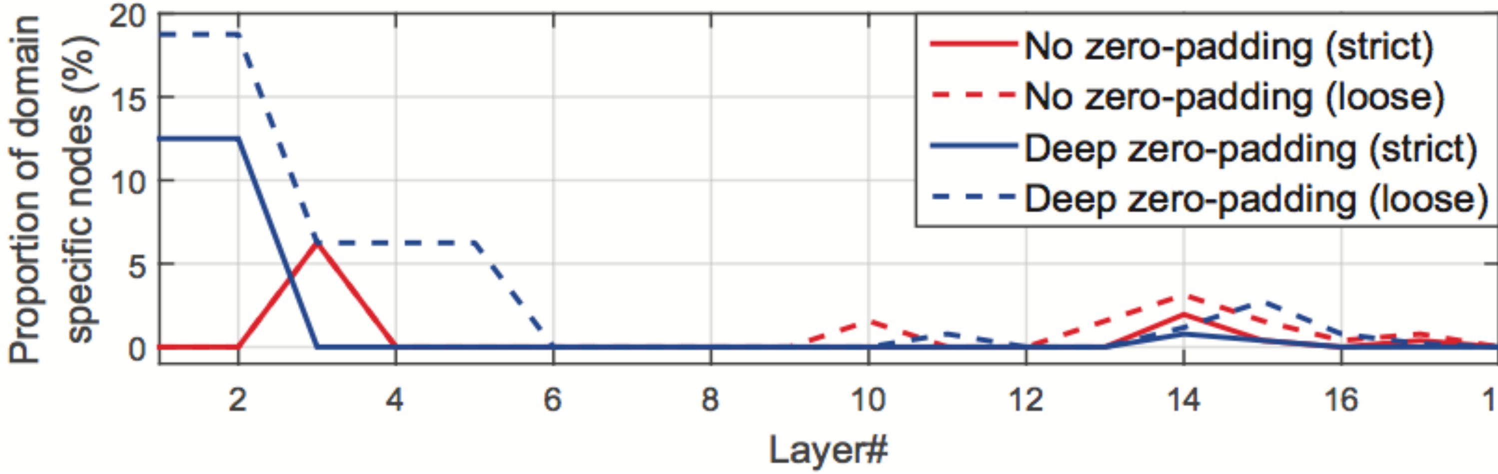


Figure 8. Relation between proportion of domain-specific nodes and layer depth. The x-axis denotes layer depth from bottom to top of the network, and the y-axis denotes the proportion of domain-specific nodes. The strict threshold is $T = 0.01\ std(x_i^{(l)})$ and the loose threshold is $T = 0.05\ std(x_i^{(l)})$ ($std(x_i^{(l)})$ is the standard deviation of the output of the i-th node in layer l). Generally, the proportion of domain-specific nodes using deep zero-padding is higher than that without zero-padding.

Asymmetric Metric for RE-ID: RGB-Infrared

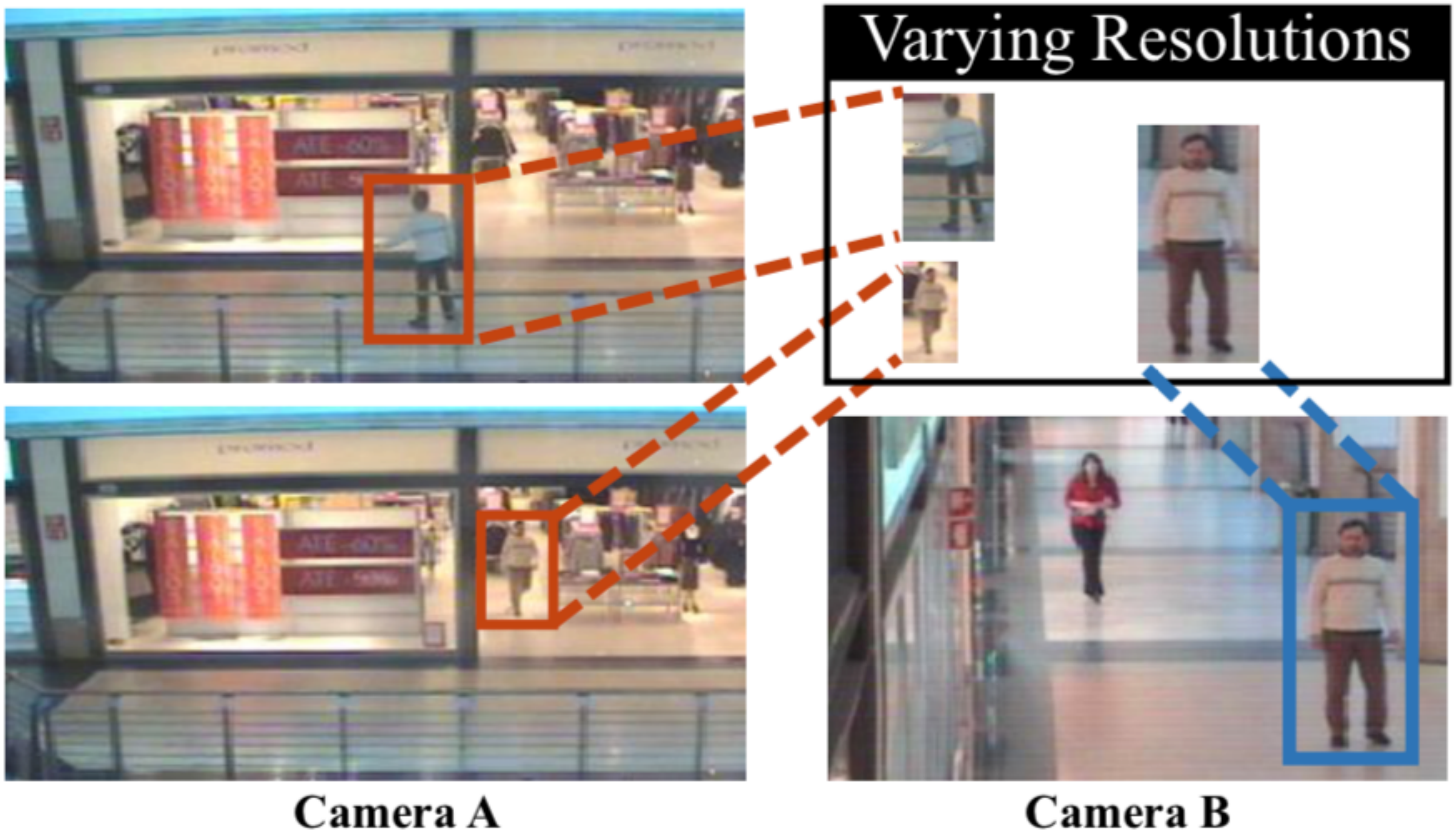
Cross-Modality Learning: RGB-IR RE-ID

- SYSU RGB-IR Re-ID Dataset

Feature	Metric	All-search								Indoor-search							
		Single-shot				Multi-shot				Single-shot				Multi-shot			
		r1	r10	r20	mAP	r1	r10	r20	mAP	r1	r10	r20	mAP	r1	r10	r20	mAP
One-stream network (deep zero-padding)	Euclidean	**14.80**	**54.12**	**71.33**	**15.95**	**19.13**	**61.40**	**78.41**	**10.89**	**20.58**	**68.38**	**85.79**	**26.92**	**24.43**	**75.86**	**91.32**	**18.64**
One-stream network	Euclidean	12.04	49.68	66.74	13.67	16.26	58.14	75.05	8.59	16.94	63.55	82.10	22.95	22.62	71.74	87.82	15.04
Asymmetric FC layer network	Euclidean	9.30	43.26	60.38	10.82	13.06	52.11	69.52	6.68	14.59	57.94	78.68	20.33	20.09	69.37	85.80	13.04
Lin's	GSM	5.29	33.71	52.95	8.00	6.19	37.15	55.66	4.38	9.46	48.98	72.06	15.57	11.36	51.34	73.41	9.03
HIPHOP	CRAFT	1.80	14.56	26.29	3.40	1.92	16.00	28.31	1.77	2.86	23.40	41.94	7.16	3.01	25.53	44.97	3.43
HOG	Euclidean	2.76	18.25	31.91	4.24	3.82	22.77	37.63	2.16	3.22	24.68	44.52	7.25	4.75	29.06	49.38	3.51
	KISSME	2.12	16.21	29.13	3.53	2.79	18.23	31.25	1.96	3.11	25.47	46.47	7.43	4.10	29.32	50.59	3.61
	LFDA	2.33	18.58	33.38	4.35	3.82	20.48	35.84	2.20	2.44	24.13	45.50	6.87	3.42	25.27	45.11	3.19
	CCA	2.74	18.91	32.51	4.28	3.25	21.82	36.51	2.04	4.38	29.96	50.43	8.70	4.62	34.22	56.28	3.87
	CDFE	2.09	16.68	30.51	3.75	2.47	19.11	34.11	1.86	2.80	23.39	44.46	6.91	3.28	27.31	48.61	3.24
	GMA	1.07	10.42	20.91	2.52	1.03	10.29	20.73	1.39	1.84	17.97	36.14	5.64	1.80	18.10	35.79	2.63
	SCM	1.86	15.16	28.27	3.57	2.40	17.45	31.22	1.66	3.30	25.82	46.23	7.52	3.90	28.84	51.64	3.22
	CRAFT	2.59	17.93	31.50	4.24	3.58	22.90	38.59	2.06	3.03	24.07	42.89	7.07	4.16	27.75	47.16	3.17
LOMO	Euclidean	1.75	14.14	26.63	3.48	1.96	15.06	27.30	1.85	2.24	22.53	41.53	6.64	2.24	22.79	41.80	3.31
	KISSME	2.23	18.95	32.67	4.05	2.65	20.36	34.78	2.45	3.83	31.09	52.86	8.94	4.46	34.35	58.43	4.93
	LFDA	2.98	21.11	35.36	4.81	3.86	24.01	40.54	2.61	4.81	32.16	52.50	9.56	6.27	36.29	58.11	5.15
	CCA	2.42	18.22	32.45	4.19	2.63	19.68	34.82	2.15	4.11	30.60	52.54	8.83	4.86	34.40	57.30	4.47
	CDFE	3.64	23.18	37.28	4.53	4.70	28.23	43.05	2.28	5.75	34.35	54.90	10.19	7.36	40.38	60.33	5.64
	GMA	1.04	10.45	20.81	2.54	0.99	10.50	21.06	1.47	1.79	17.90	36.01	5.63	1.71	18.11	36.17	2.88
	SCM	1.54	14.12	26.27	3.34	1.66	15.17	28.41	1.57	2.86	24.34	44.53	7.06	2.89	25.81	48.33	3.02
	CRAFT	2.34	18.70	32.93	4.22	3.03	21.70	37.05	2.13	3.89	27.55	48.16	8.37	2.45	20.20	38.15	2.69

Asymmetric Modeling for Low-resolution Person Re-identification

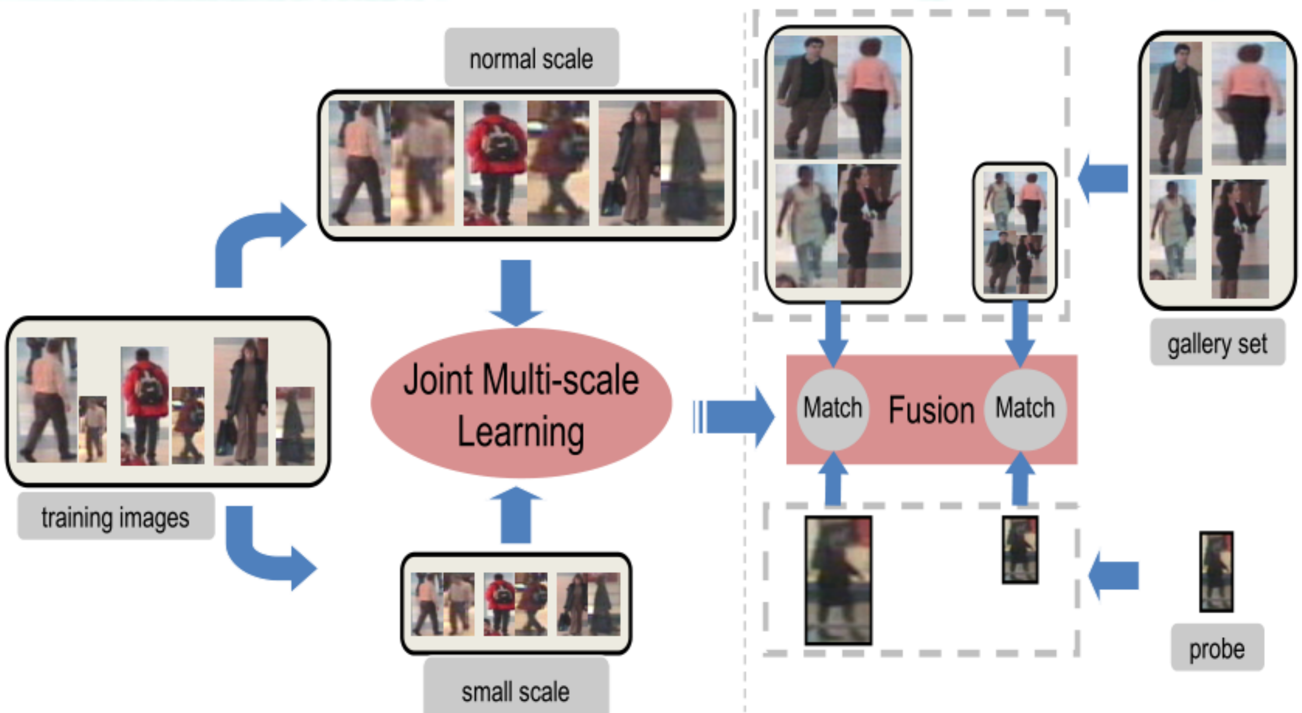
Asymmetric Modeling for RE-ID: Low



Asymmetric Modeling for RE-ID: Low

Low-resolution Re-ID

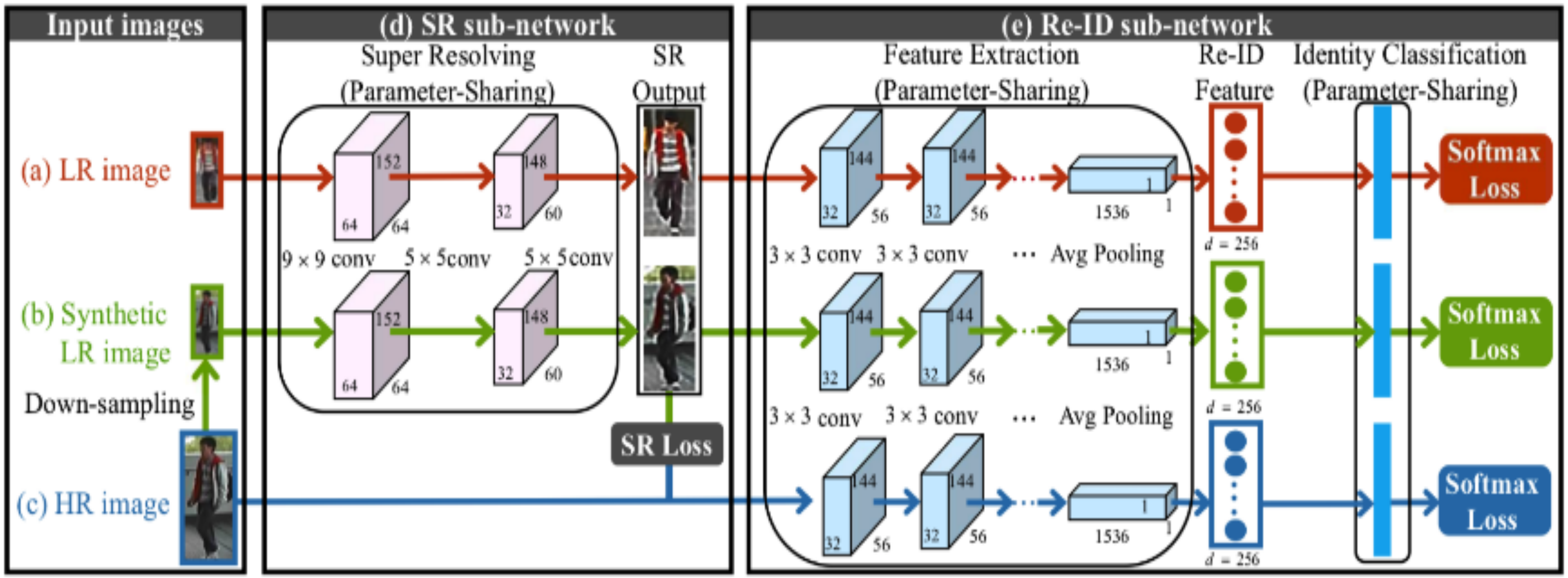
- JUDEA : joint multi-scale discriminant component analysis



Xiang Li, Wei-Shi Zheng*, Xiaojuan Wang, Tao Xiang, Shaogang Gong. Multi-scale Learning for Low-resolution Person Re-identification. IEEE Conf. on Computer Vision (ICCV), 2015.

Asymmetric Modeling for RE-ID: Low

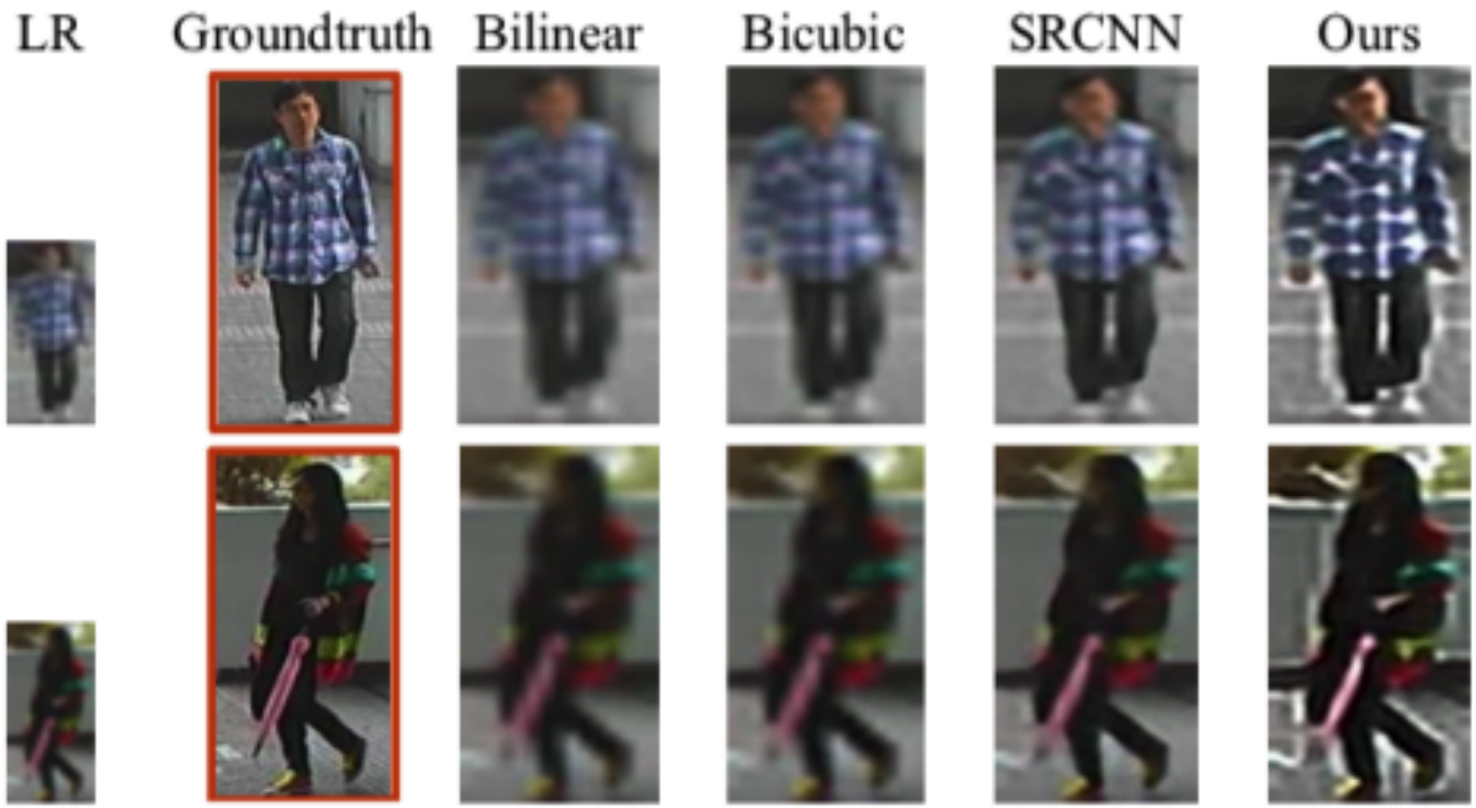
- Super- resolution and Identity joiNt learninG (SING)



Jiening Jiao, Wei-Shi Zheng*, Ancong Wu, Xiatian Zhu, and Shaogang Gong. Deep Low-resolution Person Re-identification. AAAI 2018

Asymmetric Modeling for RE-ID: Low

- Enhance Local Edge Features



Asymmetric Modeling for RE-ID: Low

❑ Results

Table 1: Comparing state-of-the-art LR re-id methods (%). The 1st/2nd best results are indicated in red/blue.

CAVIAR	r=1	r=5	r=10	r=20
JUDEA	**22.0**	**60.1**	**80.8**	**98.1**
SLD^{2}L	18.4	44.8	61.2	83.6
SDF	14.3	37.5	62.5	95.2
SING	**33.5**	**72.7**	**89.0**	**98.6**
MLR-CUHK03	r=1	r=5	r=10	r=20
JUDEA	**26.2**	**58.0**	**73.4**	**87.0**
SLD^{2}L	-	-	-	-
SDF	22.2	48.0	64.0	80.0
SING	**67.7**	**90.7**	**94.7**	**97.4**
MLR-SYSU	r=1	r=5	r=10	r=20
JUDEA	18.3	**41.9**	**54.5**	**68.0**
SLD^{2}L	**20.3**	34.8	43.4	55.4
SDF	13.3	26.7	42.9	66.7
SING	**50.7**	**75.4**	**83.1**	**88.1**
MLR-VIPeR	r=1	r=5	r=10	r=20
JUDEA	**26.0**	**55.1**	**69.2**	**82.3**
SLD^{2}L	20.3	44.0	62.0	**78.2**
SDF	9.52	38.1	52.4	68.0
SING	**33.5**	**57.0**	**66.5**	76.6

Table 2: C

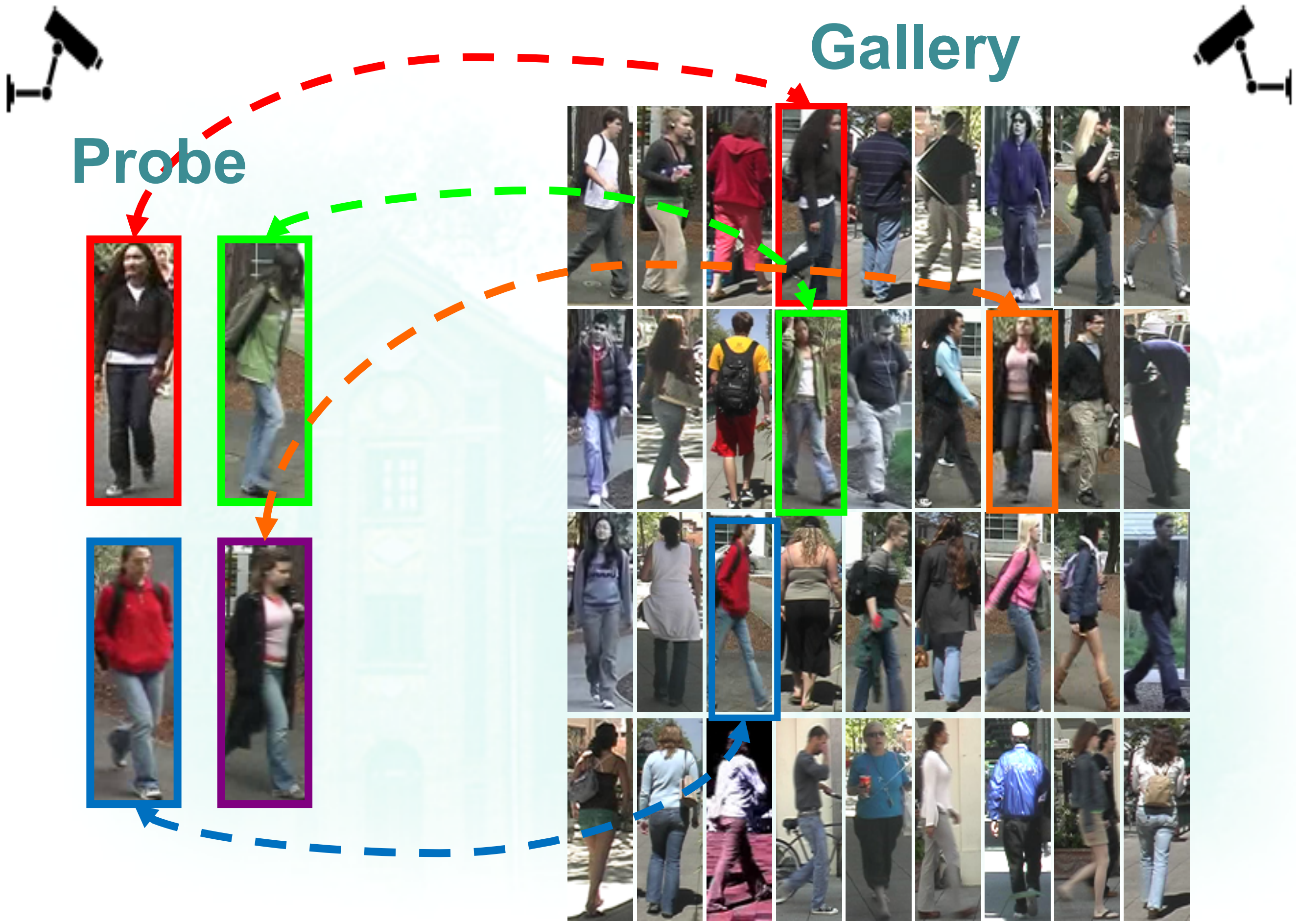
Super-Resolution Method	Re-ID Method
Bilinear	XQDA
Bicubic	XQDA
SRCNN	XQDA
Bilinear	NFST
Bicubic	NFST
SRCNN	NFST
Bilinear	DGD
Bicubic	DGD
SRCNN	DGD
SING	

(%).

	MLR-VIPeR		
	r=5	r=10	r=20
5	65.7	78.5	89.7
3	66.0	78.9	89.3
5	65.1	78.9	89.8
7	**68.4**	**81.0**	**90.4**
2	**67.9**	**80.3**	**90.7**
5	67.1	79.5	90.1
1	45.9	56.6	67.7
)	51.3	59.2	69.3
3	48.4	57.3	66.5
5	57.0	66.5	76.6

Asymmetric Modeling for Transfer Person Re-identification

Person Re-identification: Labelling

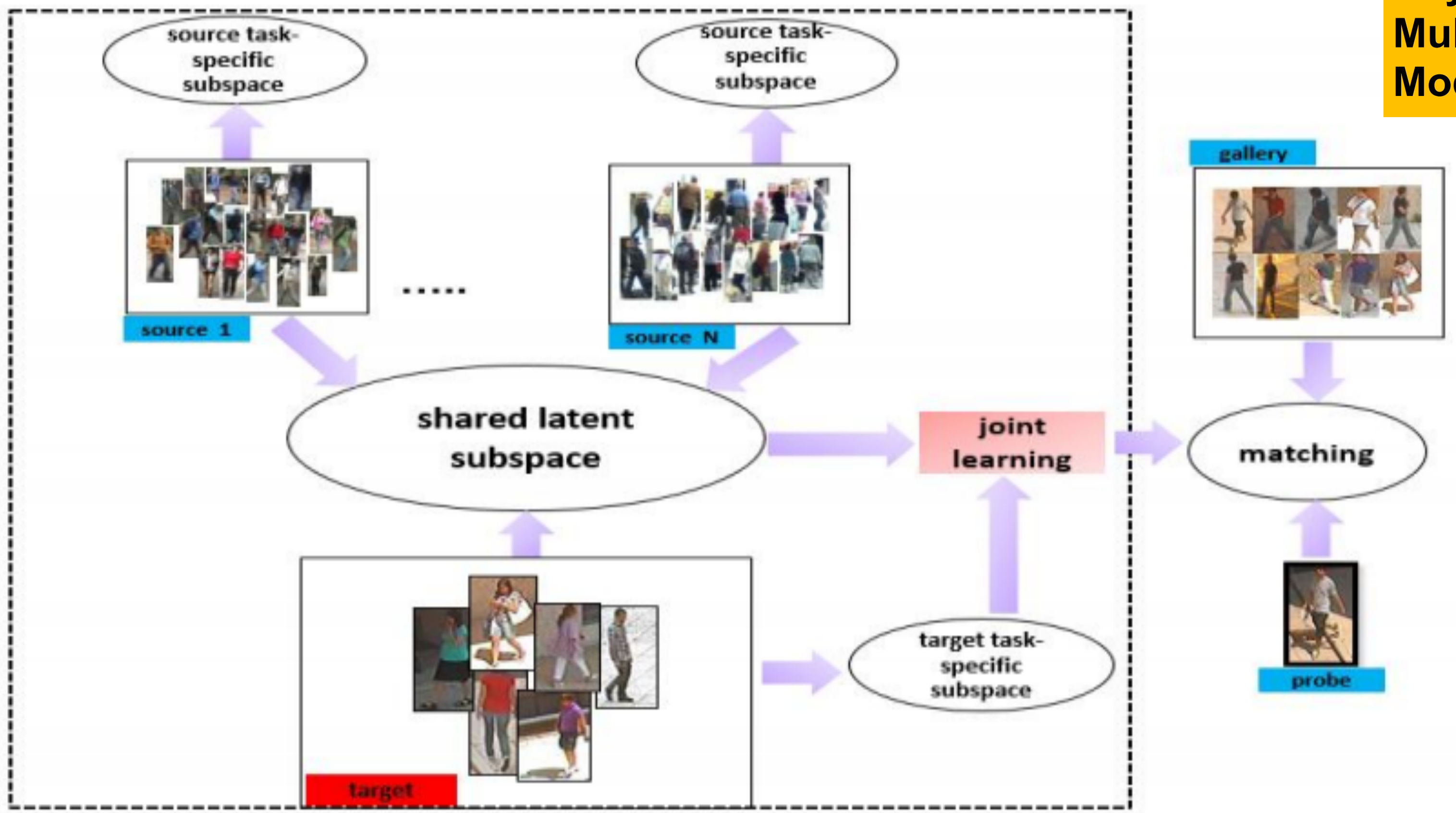


Labelling images across camera views is costly

Asymmetric Metric for RE-ID: Transfer

❑ Transfer Re-ID

An Asymmetric Multi-task Modelling



Xiaojuan Wang, Wei-Shi Zheng*, Xiang Li, and Jianguo Zhang. Cross-scenario Transfer Person Re-identification. IEEE Transactions on Circuits and Systems for Video Technology, vol. 26, no. 8, pp. 1447-1460, 2016.

Asymmetric Metric for RE-ID: Transfer

source task-specific subspace:

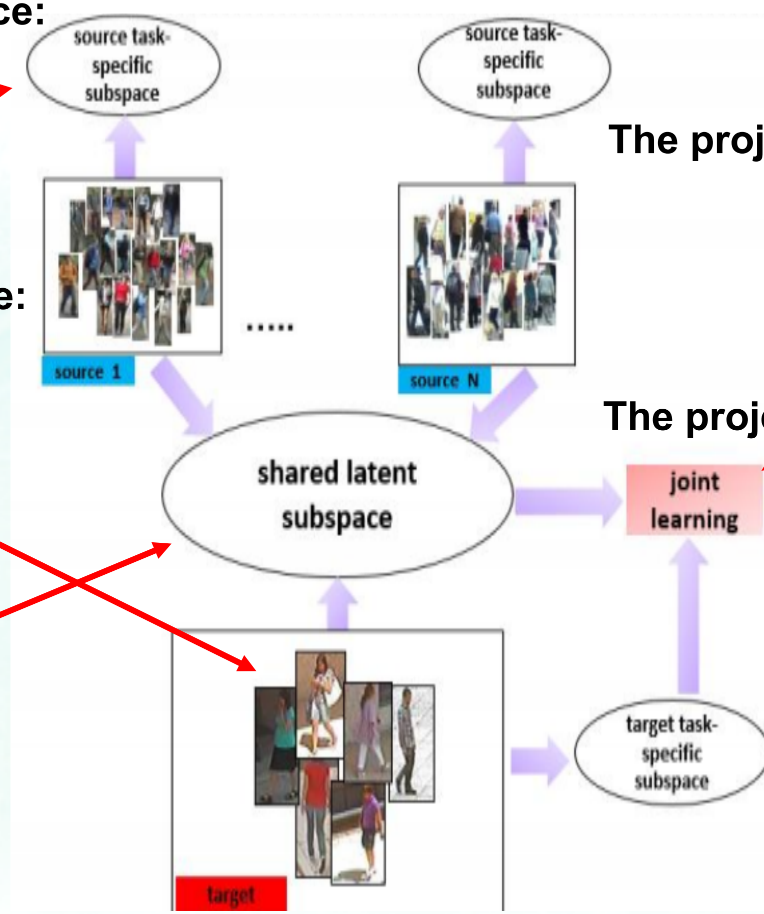
$$W_s \in R^{d \times r}$$

target task-specific subspace:

$$W_t \in R^{d \times r}$$

shared latent subspace:

$$W_0 \in R^{d \times r}$$



The projection of a target sample x_t

$$z_t = ((1-\beta)\boxed{W_0} + \beta W_t)' x_t$$

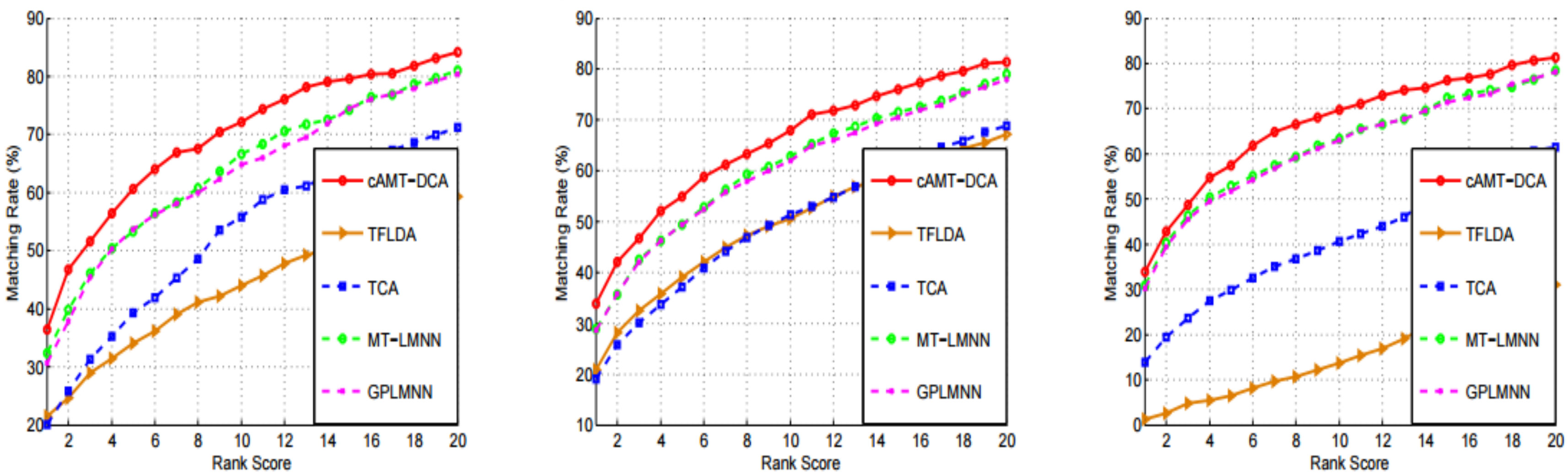
The projection of a source sample x_s

$$z_s = ((1-\beta)\boxed{W_0} + \beta W_s)' x_s$$

$$\max_{\mathbf{W}_1, \mathbf{W}_2} \frac{\mathrm{tr}((1-\gamma)\mathbf{W}_1' \mathbf{S}_b^s \mathbf{W}_1 + \gamma \mathbf{W}_2' \mathbf{S}_b^t \mathbf{W}_2)}{\mathrm{tr}((1-\gamma)\mathbf{W}_1' \mathbf{S}_w^s \mathbf{W}_1 + \gamma \mathbf{W}_2' \mathbf{S}_w^t \mathbf{W}_2)}$$

Asymmetric Metric for RE-ID: Transfer

Compared methods: TCA (Pan et al.), TFLDA (Si et al.), MT-LMNN (Parameswaran et al.), GPLMNN (Yang et al,)



(a) VIPeR→i-LIDS (b) 3DPeS→i-LIDS (c) CAVIAR→i-LIDS

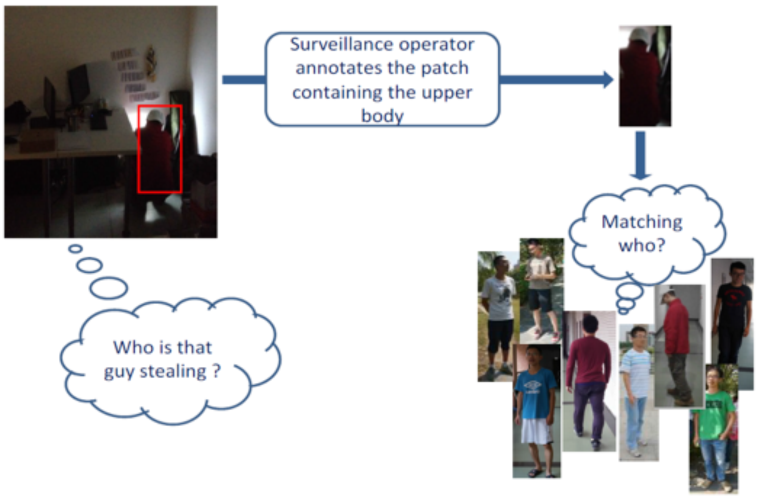
Figure 5: Matching rates of cAMT-DCA, multi-task methods and domain adaptation methods, with i-LIDS as target dataset. Two sample images ($p = 2$) are used for each target person.

dataset	VIPeR	3DPeS	i-LIDS	CAVIAR
number of persons	632	192	119	72
number of images	1264	1011	476	1220
location (scenario)	street	campus	airport	shopping mall

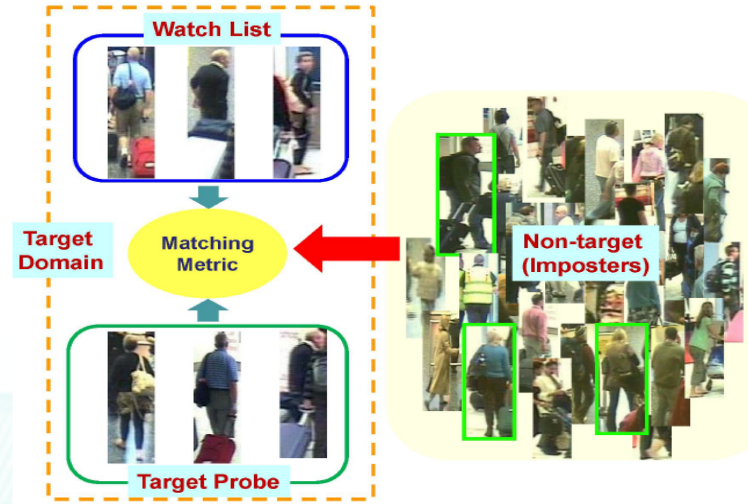
Table 1: Summary of datasets used in the experiments.

Asymmetrical RE-ID: More

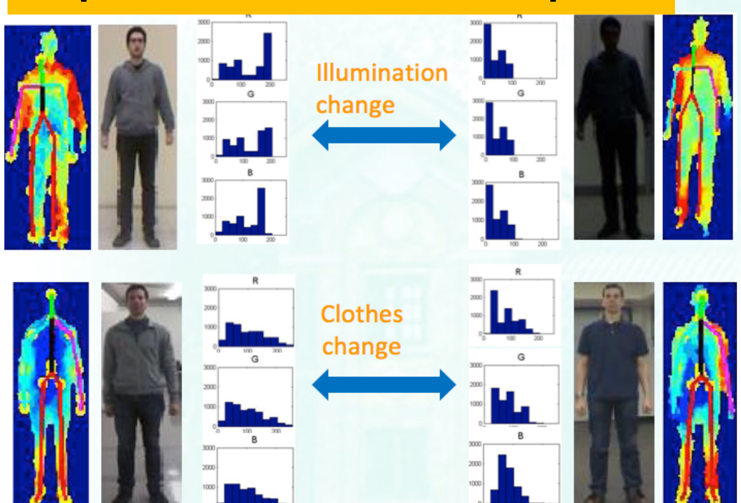
Partial RE-ID: local vs. global



Open-world RE-ID: target vs. source



Depth RE-ID: RGB to Depth



Wei-Shi Zheng, Xiang Li, Tao Xiang, Shengcai Liao, JianHuang Lai, Shaogang Gong. Partial Person Re-identification. ICCV, 2015.

Wei-Shi Zheng, Shaogang Gong, and Tao Xiang. Towards Open-World Person Re-Identification by One-Shot Group-based Verification. IEEE TPAMI, 2016.

Ancong Wu, Wei-Shi Zheng*, and Jian-Huang Lai. Robust Depth-based Person Re-identification. IEEE TIP, 2017

Summary

Modelling with Multiple Modalities:
Machine Learning for Cross-Modality

Asymmetric Modelling

- **Asymmetric Metric Learning**
- **Asymmetric Binary code Learning**
- **Cross-scenario Transfer Learning**
- **Unsupervised Learning**
- **Deep Learning**

Person Re-identification

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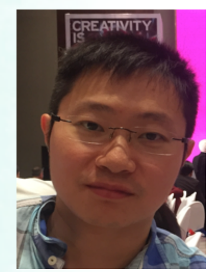
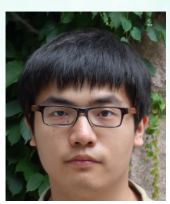
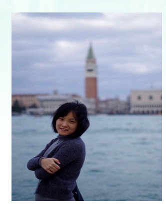


Thanks to my students

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