

# Dual Reverse Attention Networks for Person Re-identification

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# Person Re-identification

Aims at retrieve images  
belonging to the same person identity to query

Given a person of interest,  
Re-id spots his appearance at:

other time

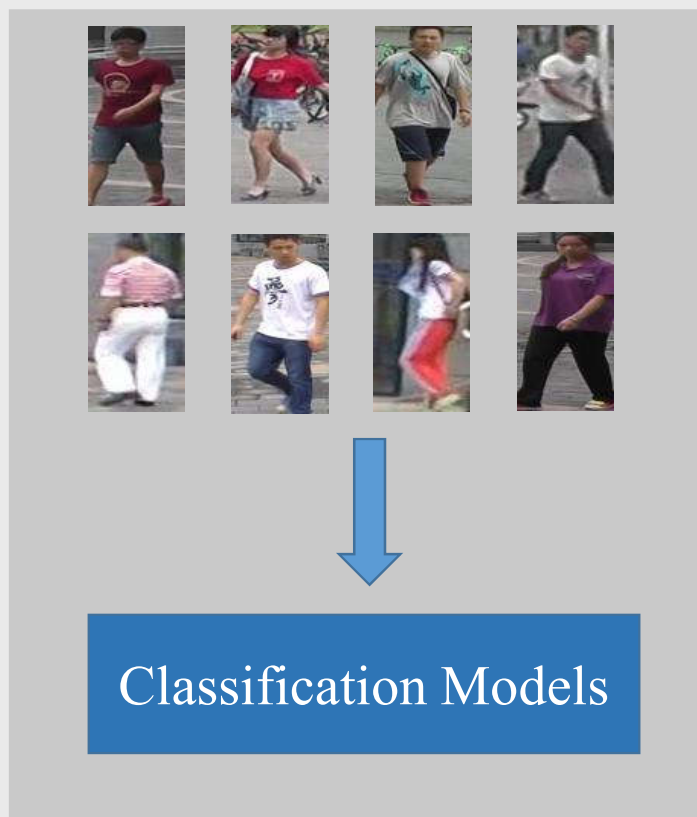
other location

other cameras

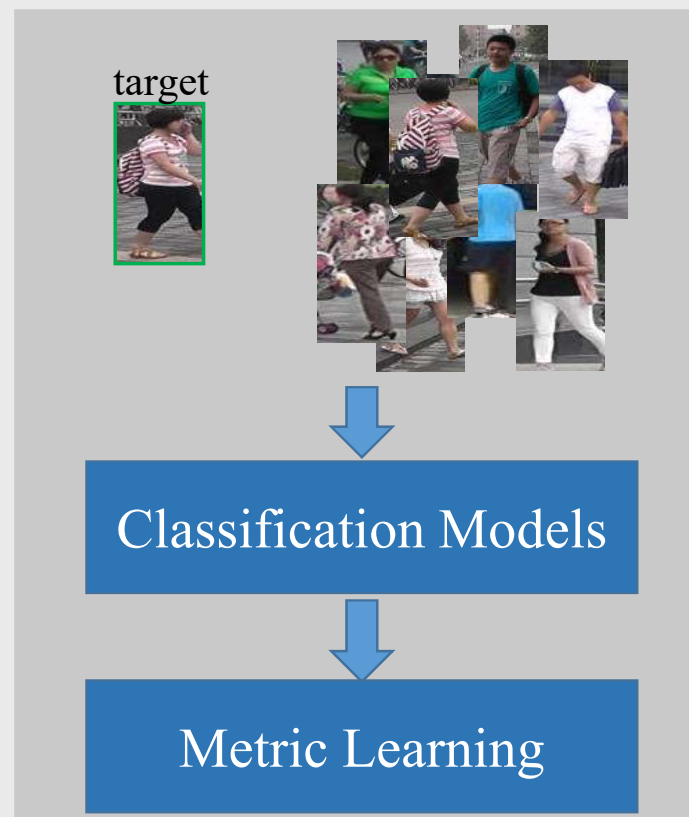


# Person Re-identification

training



testing



# Challenge

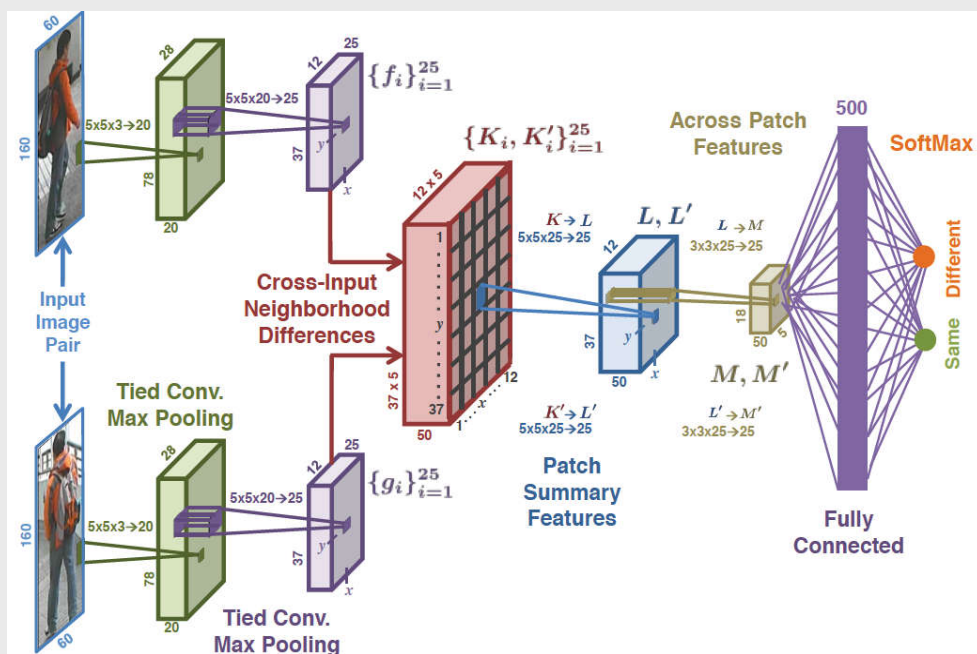
Due to pedestrian images being taken at different times and cameras, the environmental settings like **background clutter, illumination** as well as human attributes like **posture and clothing** are quite various.



This requires the Re-ID model to **be invariant to** visual cues, especially **hard examples** with complex deformation, occlusion and low resolution

# Existing Method : hard examples mining

## Offline mining



## Online mining

$$\mathcal{L}_{\text{BH}}(\theta; X) = \sum_{i=1}^{\overbrace{P \quad K}^{\text{all anchors}}} \sum_{a=1}^{\overbrace{K}^{\text{hardest positive}}} \left[ m + \max_{p=1 \dots K} D(f_{\theta}(x_a^i), f_{\theta}(x_p^i)) \right. \quad (5)$$

$$\left. - \min_{\substack{j=1 \dots P \\ n=1 \dots K \\ j \neq a}} D(f_{\theta}(x_a^i), f_{\theta}(x_n^j)) \right]_+$$

hardest negative

Ahmed E et. al, An improved deep learning architecture for person re-identification, in CVPR 2015

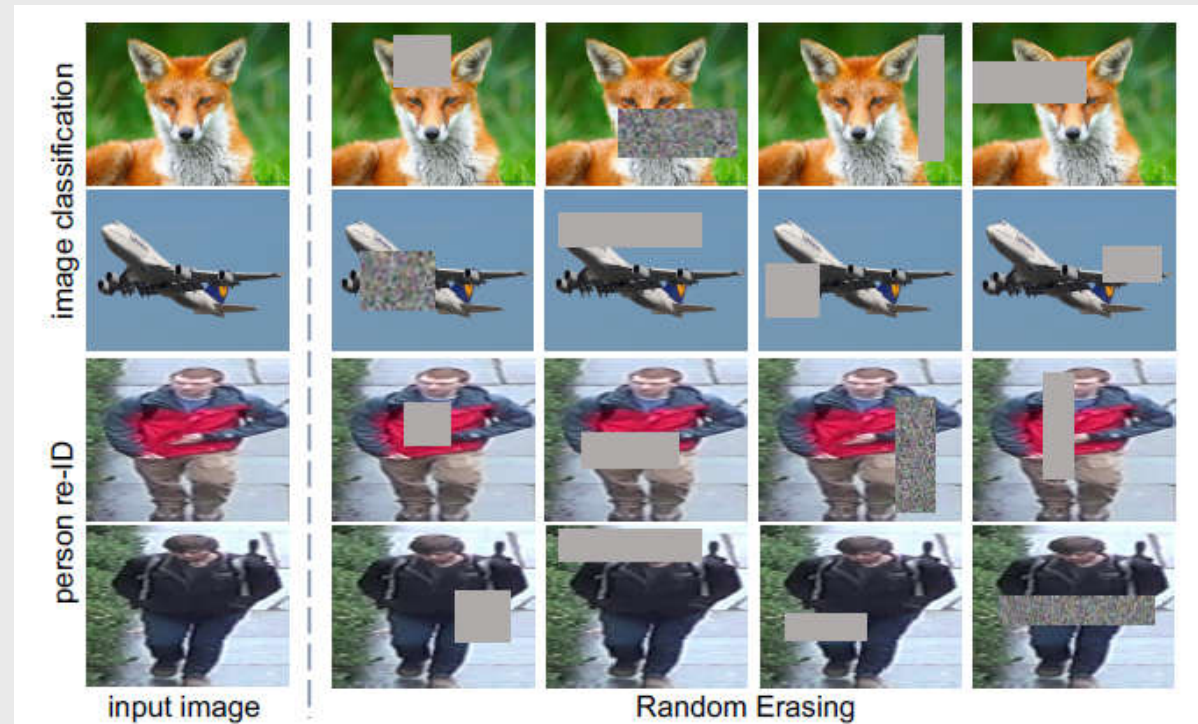
Hermans A et. al, In defense of the triplet loss for person re-identification, in arXiv 2017.



# Existing Method : hard examples generating

## Offline generating

## Online generating

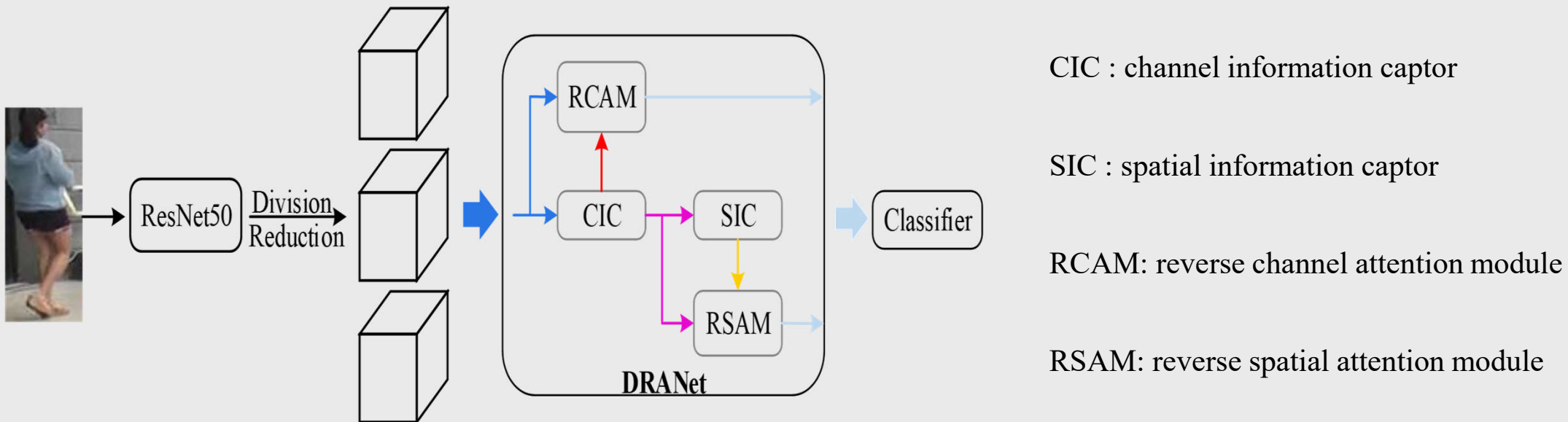


Zhuo Jiaxuan et. al, "Occluded person re-identification." in ICME 2018.

Zhong Z et al., Random erasing data augmentation in arXiv 2017

# Proposed Framework

- Hard examples generating in the convolutional space
- Powered by reverse attention modules



**Fig. 1.** Illustration of Dual Reverse Attention Networks(DRANet).

# Proposed Framework

$$m = f_{eq}(g) = \sigma(W_1 \delta(W_0 g))$$

$$B = A \cdot m$$

$$\bar{m} = (1 - m)^{\alpha_c}$$

$$C = A \cdot \bar{m} = A \cdot (1 - m)^{\alpha_c}$$

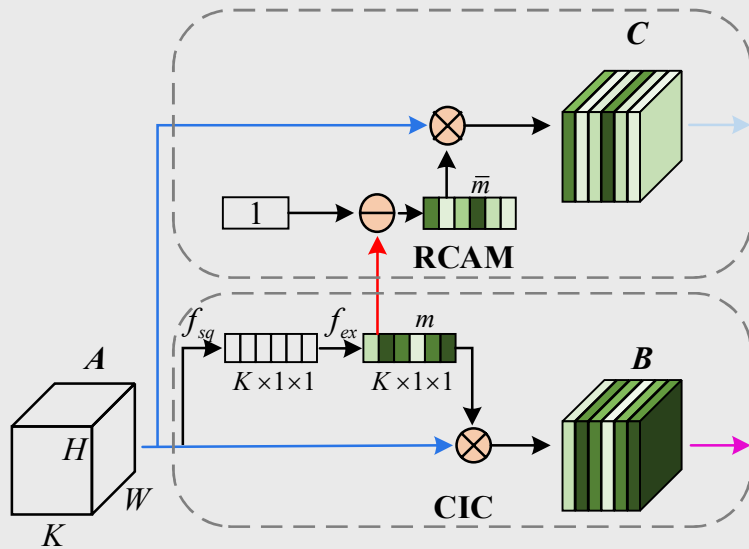


Fig. 2. Illustration of generating channel hard examples.

$$H_n = f_{1 \times 1}(f_{3 \times 3}(\mathbf{B}))[n, :, :]$$

$$\bar{H}_n = (1 - H_n)^{\alpha_s}$$

$$D = \mathbf{B} \cdot \bar{H}_n = \mathbf{B} \cdot (1 - H_n)^{\alpha_s}$$

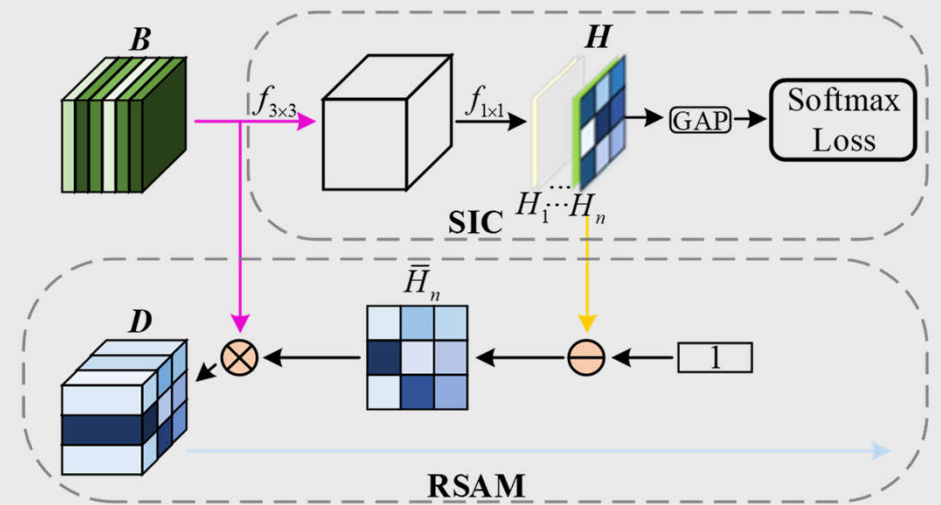


Fig. 3. Illustration of generating spatial hard examples.



# Experiment results

## Comparison with the State-of-the-art

**Table 1.** Evaluation on Market-1501.

Method	rank1	rank5	rank10	mAP
DLPAR [10]	81.0	92.0	94.7	63.4
SVDNet [23]	82.3	92.3	95.2	62.1
Triplet Loss [4]	84.9	94.2	-	69.1
IDE+RE [9]	85.2	-	-	68.3
AOS [21]	86.5	-	-	70.4
HA-CNN[11]	91.2	-	-	75.7
PCB [22]	92.3	97.2	98.2	77.4
Ours (DRANet)	<b>92.9</b>	<b>97.2</b>	<b>98.3</b>	<b>79.7</b>

**Table 2.** Evaluation on DukeMTMC-reID.

Method	rank1	mAP
IDE+RE [9]	74.2	56.2
SVDNet [23]	76.7	56.8
AOS [21]	79.2	62.1
HA-CNN [11]	80.5	63.8
PCB [22]	81.7	66.1
Ours (DRANet)	<b>84.3</b>	<b>69.5</b>

**Table 3.** Evaluation on CUHK03

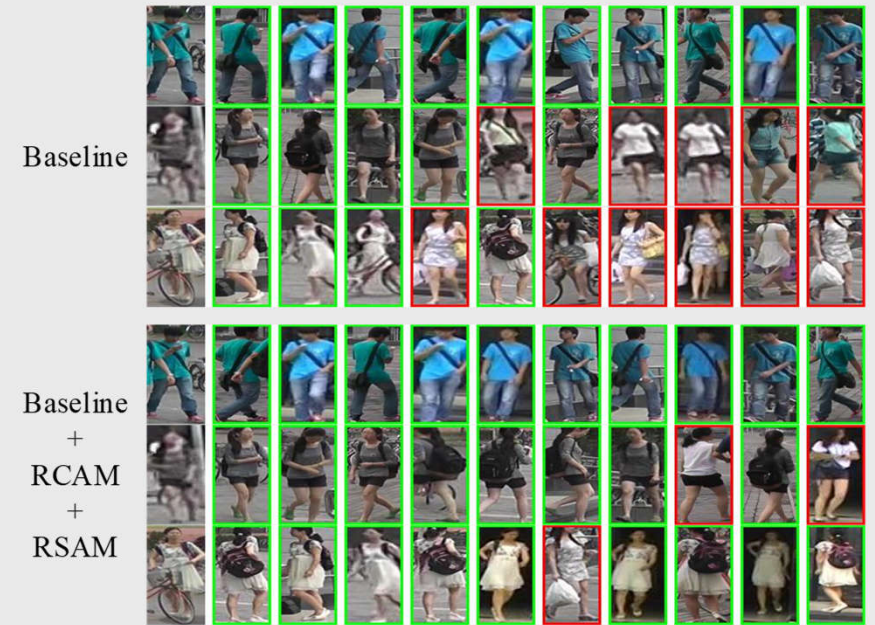
Method	Rank1	mAP
IDE+RE [9]	41.5	36.8
SVDNet [23]	41.5	37.3
HA-CNN [11]	41.7	38.6
AOS [21]	47.1	43.3
PCB [22]	59.7	53.2
Ours (DRANet)	<b>61.7</b>	<b>58.6</b>

# Experiment results

## Comparison with the baseline

**Table 4.** Comparison of different reverse attention modules

Dataset	Method	rank1	rank5	mAP
Market-1501	Baseline	91.5	96.6	77.5
	Baseline+RCAM	92.7	96.9	79.5
	Baseline+RSAM	92.1	96.6	79.4
	Baseline+RCAM+RSAM	<b>92.9</b>	<b>97.2</b>	<b>79.7</b>
DukeMTMC-reID	Baseline	81.3	89.0	65.5
	Baseline+RCAM	82.8	91.4	68.2
	Baseline+RSAM	84.0	<b>91.8</b>	<b>70.2</b>
	Baseline+RCAM+RSAM	<b>84.3</b>	90.7	69.5
CUHK03	Baseline	55.1	73.2	52.1
	Baseline+RCAM	58.6	77.6	56.3
	Baseline+RSAM	59.9	<b>78.5</b>	58.1
	Baseline+RCAM+RSAM	<b>61.7</b>	78.1	<b>58.6</b>



**Fig. 4.** Ranking list of whether using RCAM and RSAM.

# Main Contribution

- Hard examples generating in the convolutional feature space
- A novel dual reverse attention networks (DRANet)

**Thank You**