Person Re-Identification:
Datasets and Representation Learning

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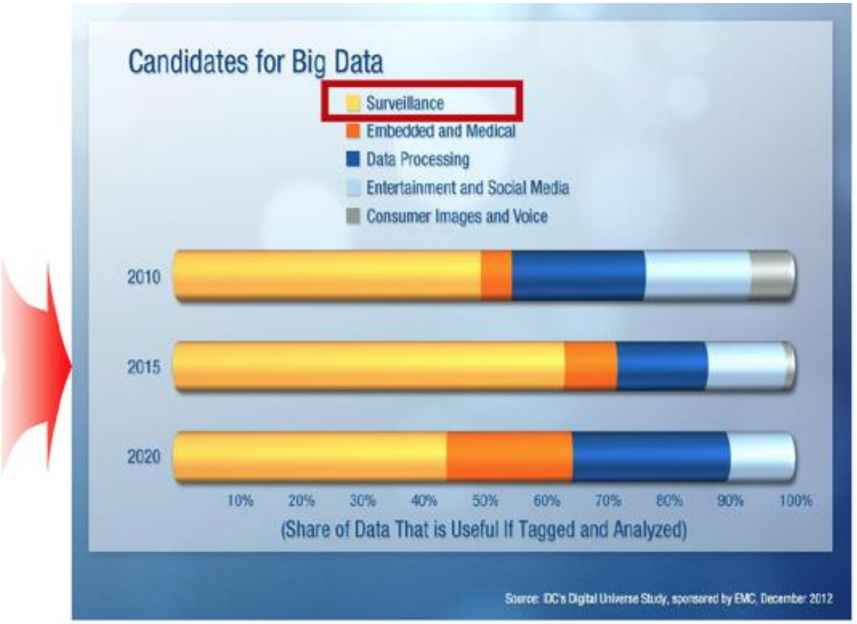
Cameras are Everywhere in Smart City

Large camera networks

Fast growth: millions of cameras deployed



Surveillance ~50% of all big data

Complicated and rich: cars, persons, etc.

Data ≠ Information: Visual Mining Needed

Boston 2013

Paris 2015

Person Detection
Re-Identification
Tracking
.....

London 2017

Las Vegas 2017

Person Re-Identification

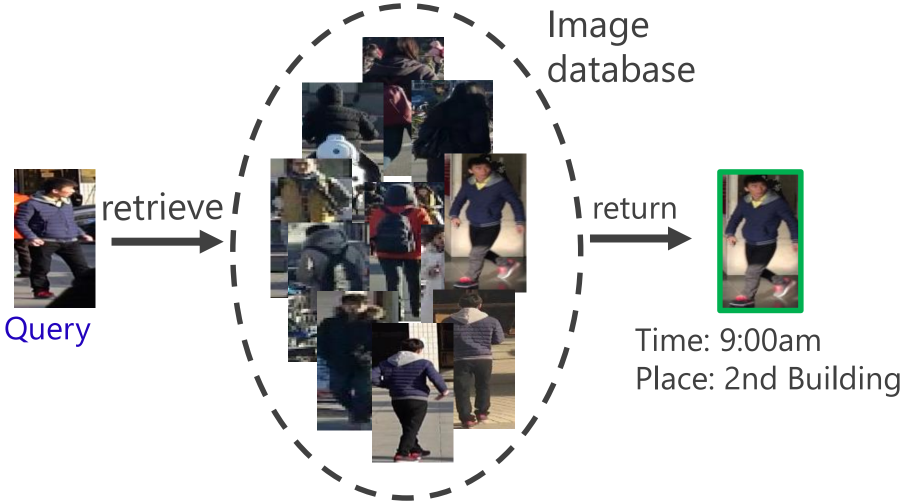
- Associate the same individuals across multiple cameras

  = Multi-camera tracking

Person Re-Identification

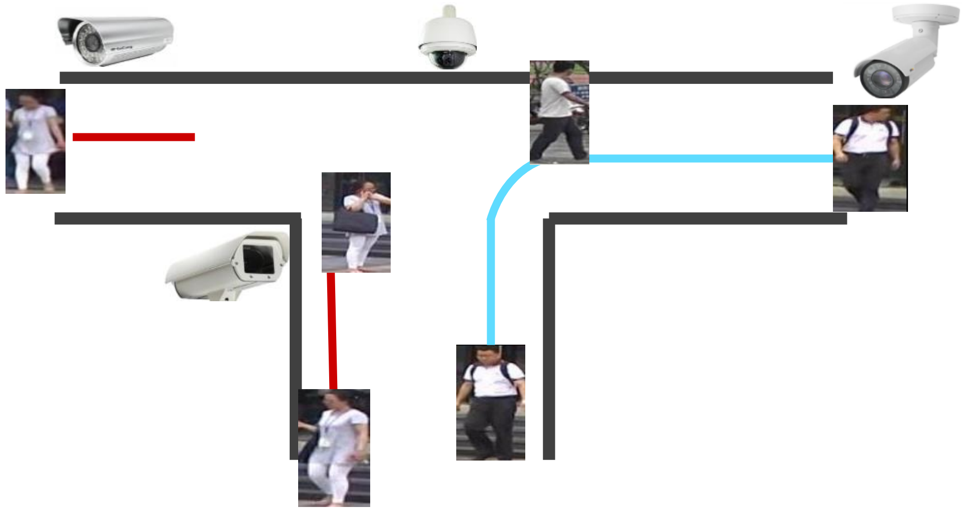
- Associate the tracks for a single camera
  - One person re-appears after a time
  - Target lost due to occlusion

Applications

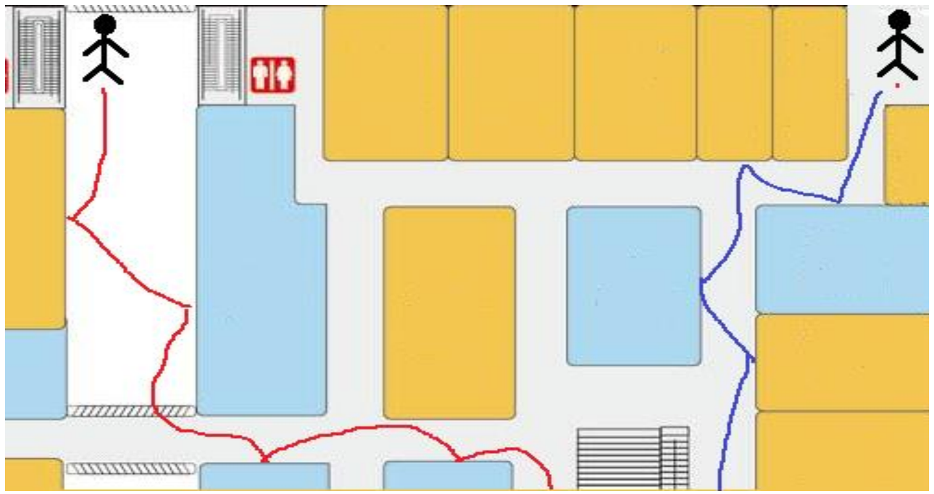


Person search

Event/action detection



Person counting by tracking



Behavior analysis

Hot Topics

- Datasets
  - Limited data scale/diversity
- Representations
  - Variable images: Low quality, part misalignment, ...
- Matching
  - Graph matching, Euclidean distance, ...
- Attributes
  - Mid-level information: Long sleeve, short hair, ...
- Loss
  - Pairwise loss, triplet loss, classification loss, ...
- …

Hot Topics

- Datasets
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  - Variable images: Low quality, part misalignment, …
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  - Mid-level information: Long sleeve, short hair, …
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  - Pairwise loss, triplet loss, classification loss, …
- …

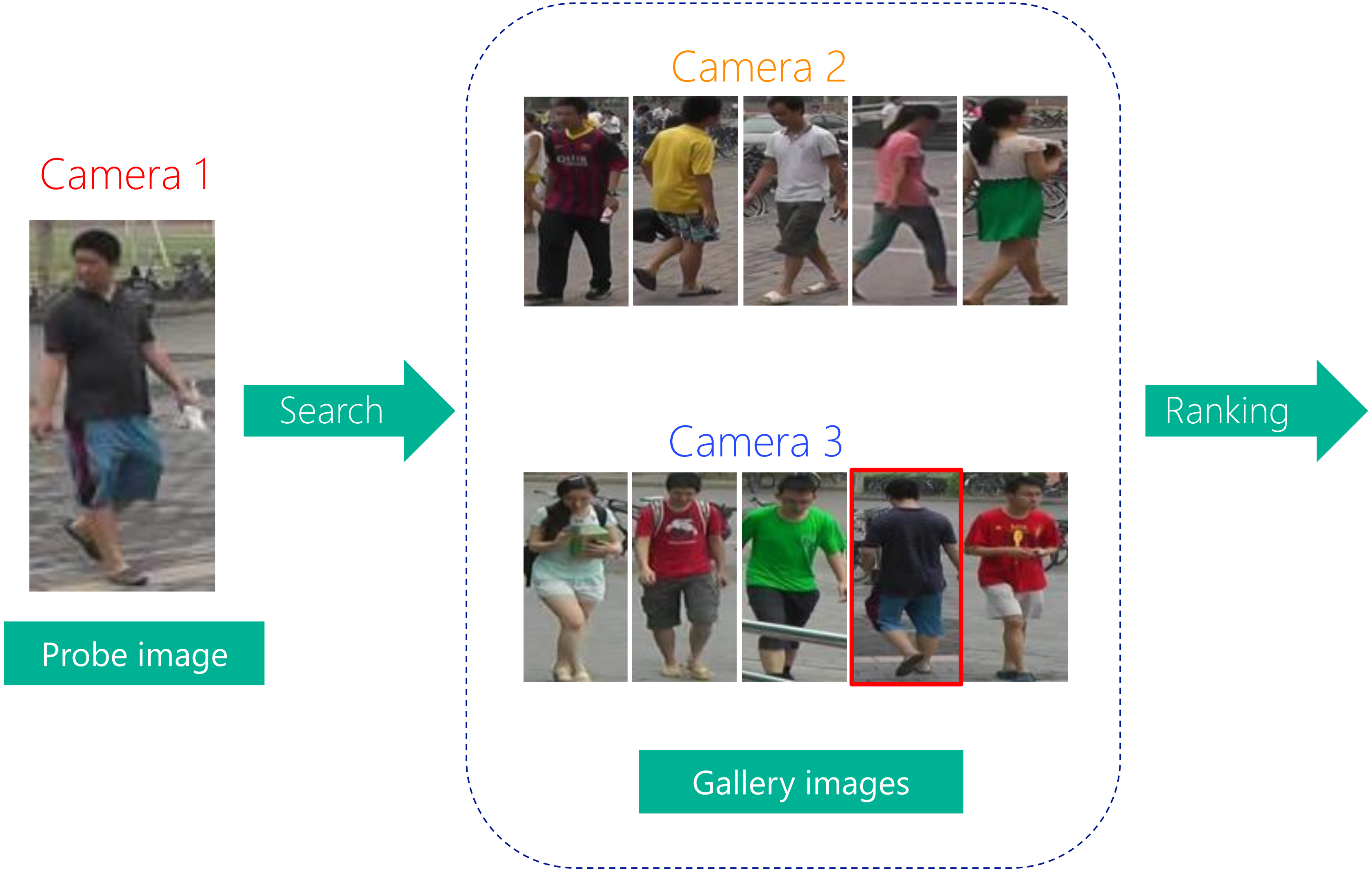
Session 1: Large-scale re-identification datasets

Liang Zheng, Liyue Shen, Lu Tian, Shengjin Wang, Jingdong Wang, Qi Tian: Scalable Person Re-identification: A Benchmark. ICCV 2015: 1116-1124
Liang Zheng, Zhi Bie, Yifan Sun, Jingdong Wang, Chi Su, Shengjin Wang, Qi Tian: MARS: A Video Benchmark for Large-Scale Person Re-identification. ECCV 2016

Real-world Setting

- Large scale
  - #Identities
  - #Box for each person
  - #Cameras
- Coverage/diverse
  - Weather/season
  - Scene
  - Time

Image-based ReID



The person in Probe
re-appears in Camera 3

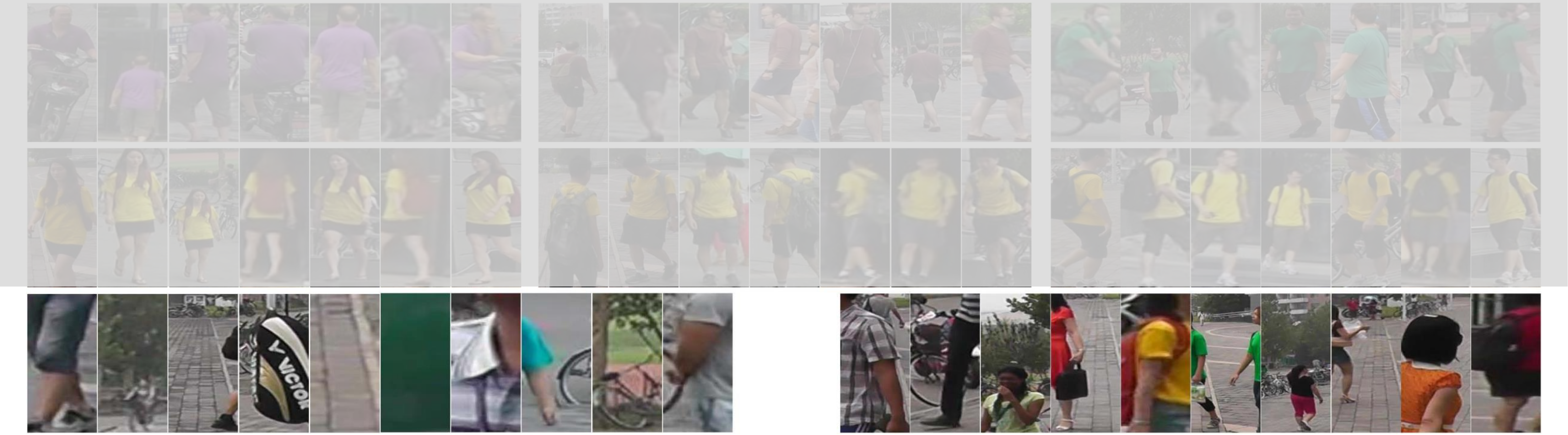
Market-1501

- DPM detector, multi-queries multi-groundtruths for each person
- 3368 queries, 14.8 cross camera groundtruths

Liang Zheng, Liyue Shen, Lu Tian, Shengjin Wang, Jingdong Wang, Qi Tian: Scalable Person Re-identification: A Benchmark. ICCV 2015: 1116-1124

500K Distractor Images

- Boxes from background + Boxes of persons not included in Market-1501



Liang Zheng, Liyue Shen, Lu Tian, Shengjin Wang, Jingdong Wang, Qi Tian: Scalable Person Re-identification: A Benchmark. ICCV 2015: 1116-1124

Image Datasets

Datasets	Market-1501	PRID 450S	RAiD	CUHK03	CUHK02	CUHK01	WARD	PRID 2011	CAVIAR	GRID	i-LIDS	VIPeR
time	2015	2014	2014	2014	2013	2012	2012	2011	2011	2009	2009	2007
#id	1,501	450	43	1,360	1,816	971	70	200	72	250	119	632
#boxes	32,668	900	6,920	13,164	7,264	1,942	4,786	1134	610	500	476	1,264
#distractors	2,793+500k	0	0	0	0	0	0	0	0	775	0	0
#cam	6	2	4	2	2×5	2	3	2	2	8	2	2
label	DPM	Hand	Hand	DPM	Hand	Hand	Hand	hand	Hand	Hand	Hand	Hand
evaluation	mAP+CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC

Enlarge the dataset

Image Datasets

Datasets	DukeMTMC-ReID	Market-1501	PRID 450S	RAiD	CUHK03	CUHK02	CUHK01	WARD	PRID 2011	CAVIAR	GRID	i-LIDS	VIPeR
time	2017	2015	2014	2014	2014	2013	2012	2012	2011	2011	2009	2009	2007
#id	1404	1,501	450	43	1,360	1,816	971	70	200	72	250	119	632
#boxes	36,003	32,668	900	6,920	13,164	7,264	1,942	4,786	1134	610	500	476	1,264
#distractors	408	2,793+500k	0	0	0	0	0	0	0	0	775	0	0
#cam	8	6	2	4	2	2×5	2	3	2	2	8	2	2
label	Hand	DPM	Hand	Hand	DPM	Hand	Hand	Hand	hand	Hand	Hand	Hand	Hand
evaluation	mAP+CMC	mAP+CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC	CMC

Enlarge the dataset

Video-based ReID

MARS

- Extension of Market-1501; 2009 queries, 3.7 groundgruths

Liang Zheng, Zhi Bie, Yifan Sun, Jingdong Wang, Chi Su, Shengjin Wang, Qi Tian: MARS: A Video Benchmark for Large-Scale Person Re-identification. ECCV 2016

Video Datasets

Datasets	MARS	iLIDS-VID	PRID-2011	3DPES	ETHZ
year	2016	2014	2011	2011	2007
#id	1,261	300	200	200	146
#tracklets	20,715	600	400	1,000	146
#Boxes	1,067,516	43,800	40,000	200k	8,580
#distractors	3,248	0	0	0	0
#cam	6	2	2	8	1
Label	DPM+GMMCP	Hand	Hand	Hand	Hand
Evaluation	mAP+CMC	CMC	CMC	CMC	CMC

Enlarge the dataset

Home Market-1501 Market-1501 Leaderboard Mars Mars Leaderboard FAQ

Leaderboard

Market-1501

The leaderboard

Baseline

Paper Name	Year	rank-1	rank-5	rank-10	rank-20	rank-30	rank-50	mAP	Notes
Scalable person re-identification: a benchmark [1]	2015	8.28	-	-	-	-	-	2.23	gBiCov [47], Euclidean distance, single query
		9.62	-	-	-	-	-	2.72	HistLBP [48], Euclidean distance, single query. Super thanks to Mengran Gou for sending us the evaluation results
		26.07	-	-	-	-	-	7.75	LOMO [49], Euclidean distance, single query
		35.84	52.40	60.33	67.64	71.88	75.80	14.75	BoW, Euclidean distance, single query
		44.36	60.24	66.48	73.25	76.19	79.69	19.42	BoW, Euclidean distance, multiple query
		34.00	-	-	-	-	-	15.66	BoW + LMNN, single query
		38.21	-	-	-	-	-	17.05	BoW + ITML, single query
		44.42	63.90	72.18	78.95	82.51	87.05	20.76	BoW + KISSME, single query
Person re-identification: Past, Present and Future [2]	2016	55.49	76.28	83.55	88.98	91.72	93.97	32.36	AlexNet identification model, using FC7 (4,096-dim) and Euclidean distance for testing, single query. This method is also used in [50, 51]
		73.90	87.68	91.54	94.80	96.02	97.21	47.78	ResNet-50 identification model, using Pool5 (2,048-dim) and Euclidean distance for testing, single query

430+ citations

Results of supervised approaches

Paper Name	Year	rank-1	rank-5	rank-10	rank-20	rank-30	rank-50	mAP	Notes
Multiregion Bilinear Convolutional Neural Networks for Person Re-Identification [3]	2015	66.36	85.01	90.17	-	-	-	41.17	Multiregion Bilinear DML, single query.

Home Market-1501 Market-1501 Leaderboard Mars Mars Leaderboard FAQ

Leaderboard

Mars

The leaderboard

Baseline

Paper Name	Year	MARS				Notes
		rank-1	rank-5	rank-20	mAP	
MARS: A Video Benchmark for Large-Scale Person Re-identification [1]	2016	2.6	6.4	12.4	0.8	HOG3D [11] + kissme [12], Euclidean distance, single query
		1.2	2.8	7.4	0.4	GEI [13] + kissme [12], single query.
		18.6	33.0	45.9	8.0	HistLBP [14] + XQDA [15], single query
		30.6	46.2	59.2	15.5	BoW [16] + kissme [12], single query
		60.0	77.9	87.9	42.4	IDE, average pooling, Euclidean distance, single query
		65.0	81.1	88.9	45.6	IDE + kissme, max pooling, Euclidean distance, single query
		68.3	82.6	89.4	49.3	IDE + kissme, max pooling, Euclidean distance, multiple query

Results of supervised approaches

Paper Name	Year	MARS				Notes
		rank-1	rank-5	rank-20	mAP	
Learning Compact Appearance Representation for Video-based Person Re-Identification [2]	2017	55.5	70.2	80.2	-	A frame selection step is used before feature pooling
Multi-Target Tracking in Multiple Non-Overlapping Cameras using Constrained Dominant Sets [3]	2017	68.22	-	-	-	The constrained dominant sets clustering (CDSC) method is proposed.
Re-ranking Person Re-identification with k-reciprocal Encoding [4]	2017	67.78	-	-	57.98	IDE (CaffeNet) + re-ranking, single query.
		73.94	-	-	68.45	IDE (ResNet50) + re-ranking, single query.

150+ citations

Homepage:
https://jingdongwang2017.github.io/

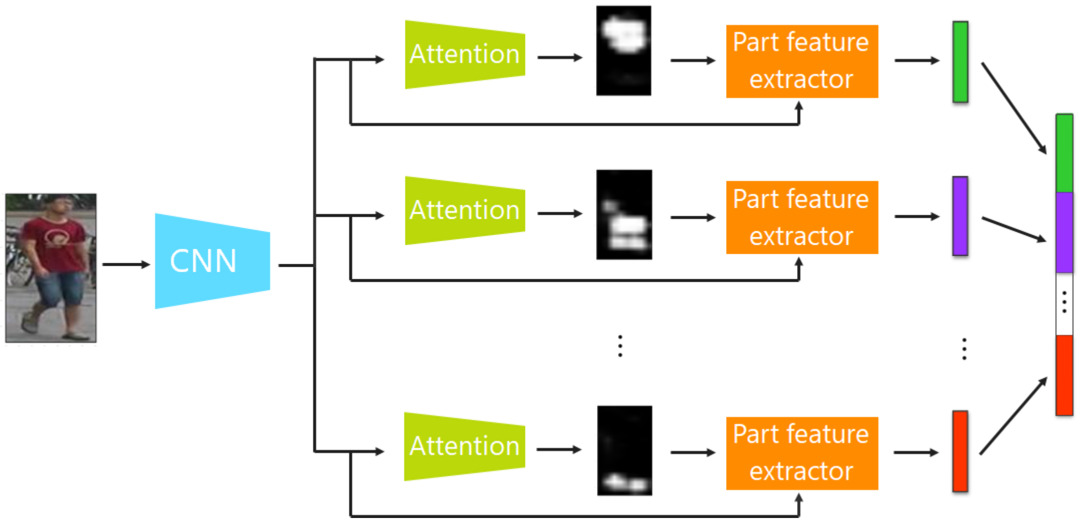
Real-world Setting

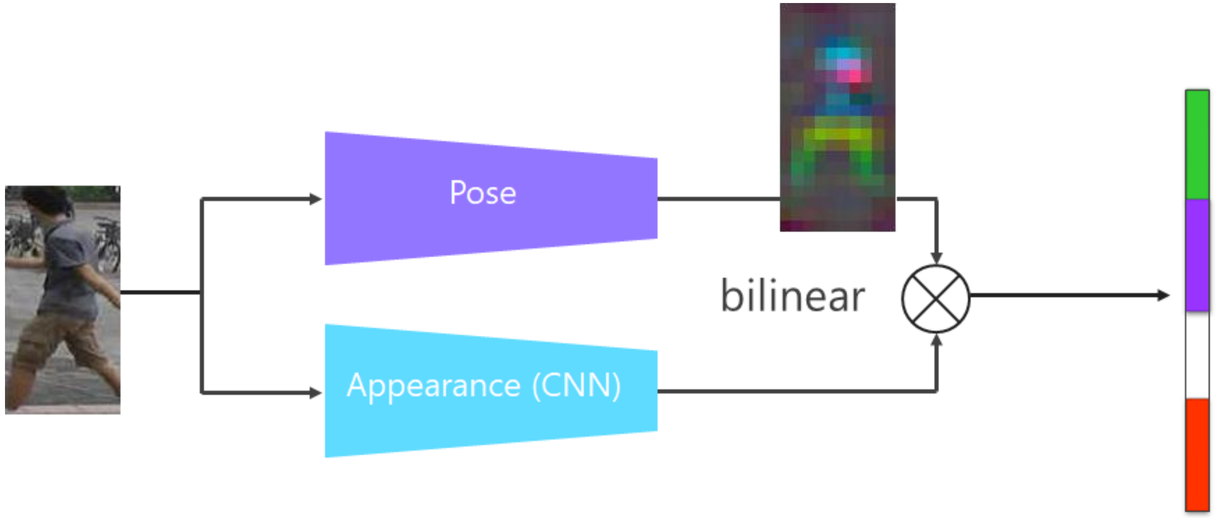
- Large scale
  - #Identities
  - #Box for each person
  - #Cameras
- Coverage/diverse
  - Weather/season
  - Scene
  - Time

Multi-scene and multi-time: indoor/outdoor, 1 month

Longhui Wei, Shiliang Zhang, Wen Gao, and Qi Tian. Person Transfer GAN to Bridge Domain Gap for Person Re-Identification. CVPR 2018:

Session 2: Part-Aligned Representation Learning





Liming Zhao, Xi Li, Yueting Zhuang, Jingdong Wang: Deeply-Learned Part-Aligned Representations for Person Re-identification. ICCV 2017

Yumin Suh, Jingdong Wang, Siyu Tang, Tao Mei and Kyoung Mu Lee: Part-Aligned Bilinear Representations for Person Re-identification. ECCV 2018

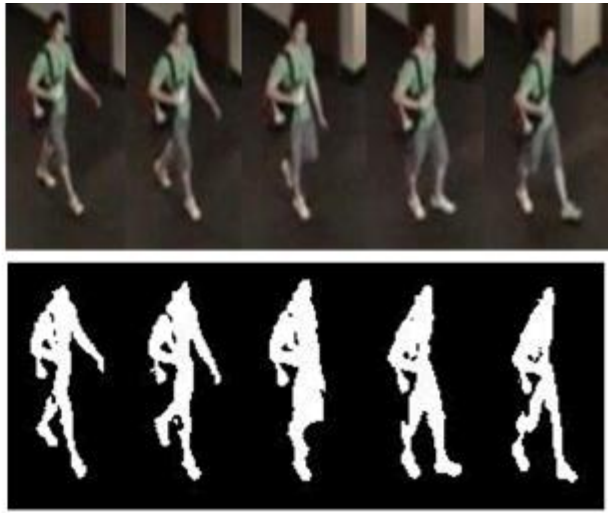
Solutions

- Biometric
  - Face
    - Frontal?
    - Enough resolution?

Solutions

- Biometric
  - Face
    - Frontal?
    - Enough resolution?

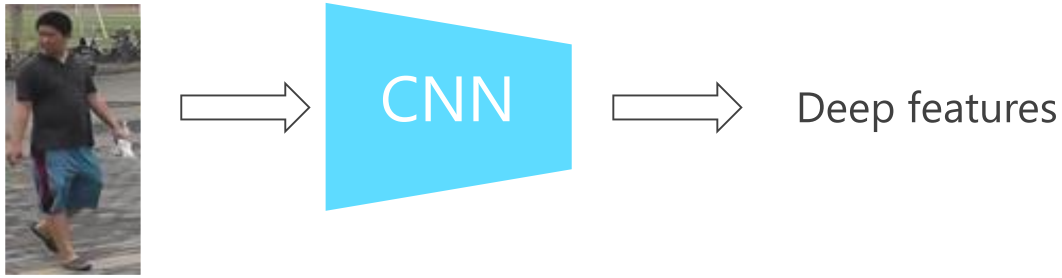
  - Gait
    - Silhouette extraction is not easy



Solutions

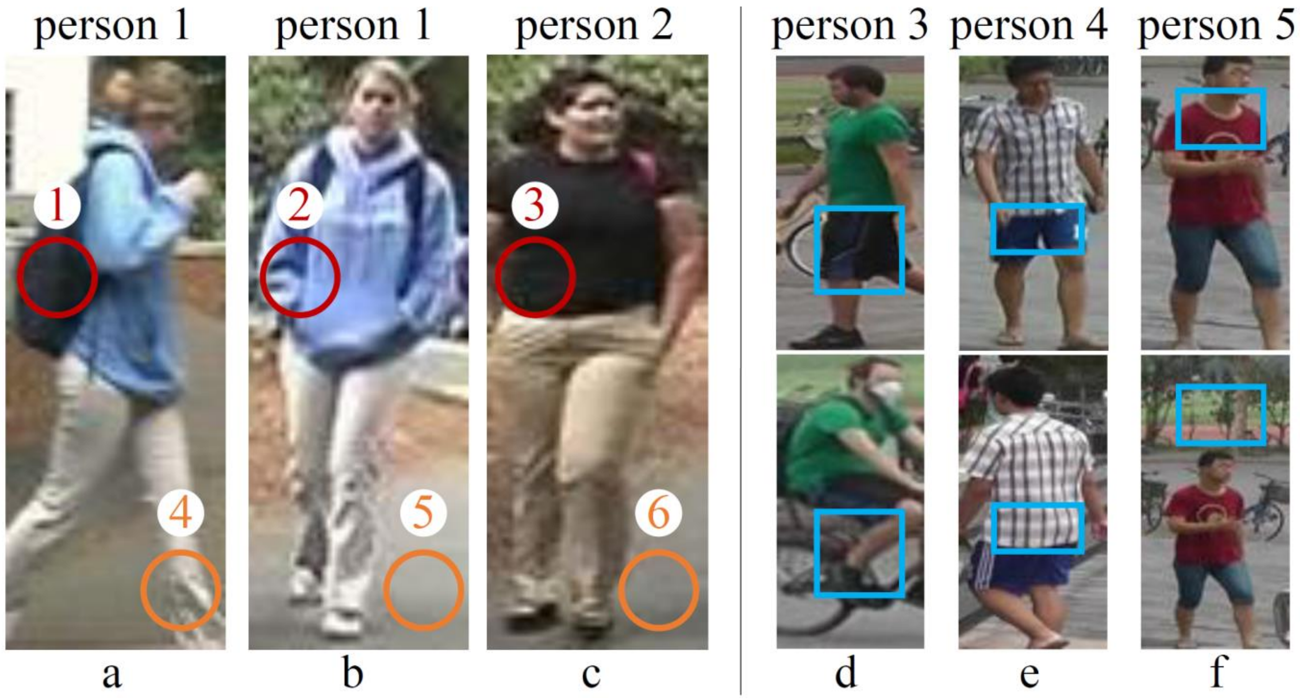
- Appearance
  - Clothing color, texture

  - Deep learning



Our motivation

- Human re-identifies persons by comparing body parts
- Comparison on the same spatial position is not reliable

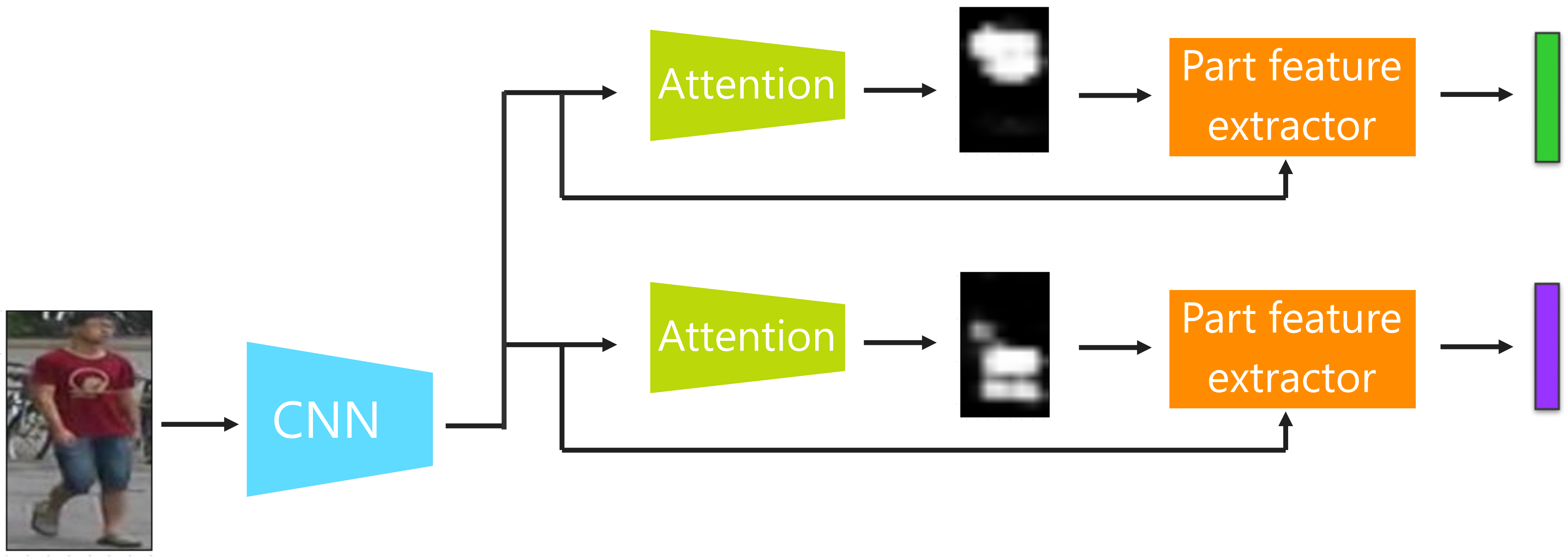


Deeply-Learned Part-Aligned Representations

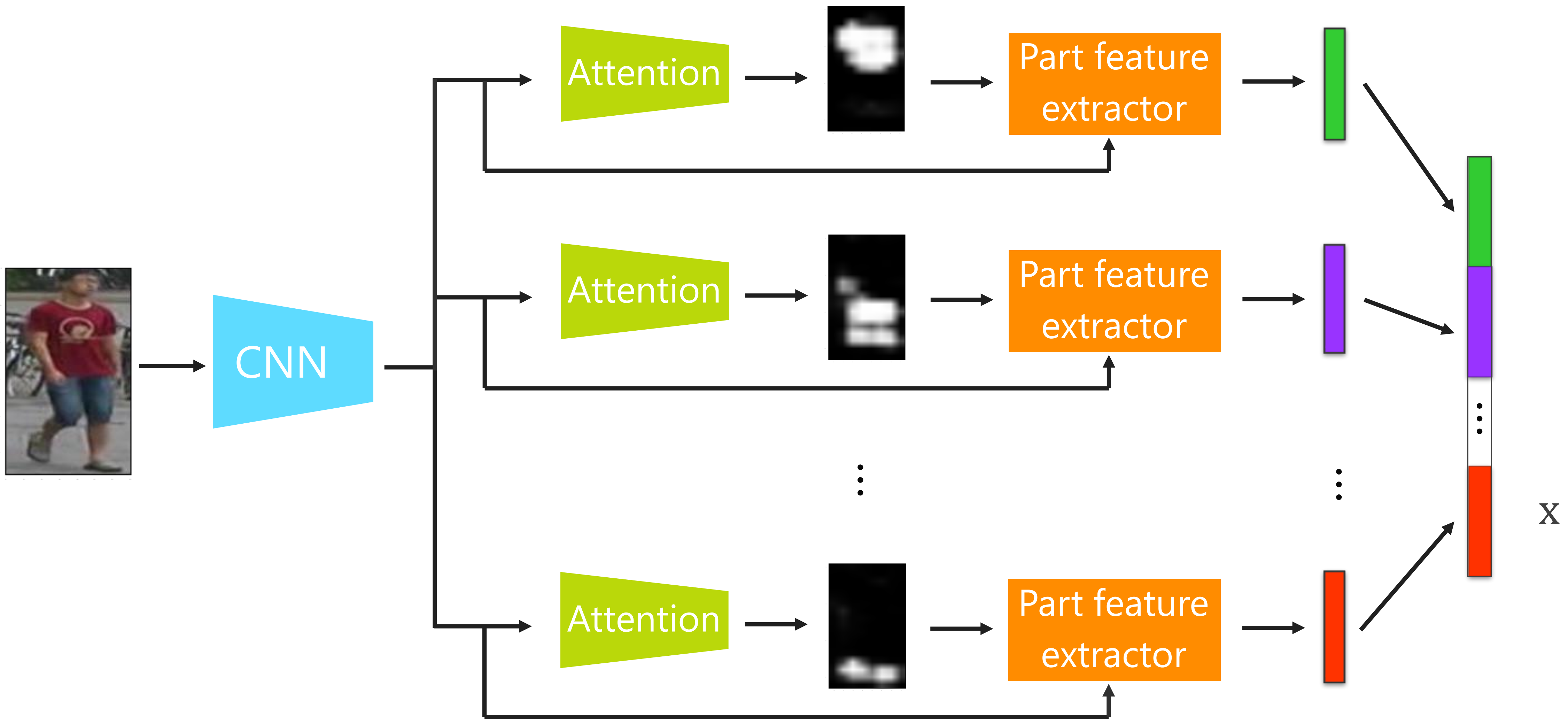
- An end-to-end solution to
  - Learn the discriminative parts (attention maps) *w/o part annotation*
  - Weak supervision: person matching as the target

Liming Zhao, Xi Li, Yueting Zhuang, Jingdong Wang: Deeply-Learned Part-Aligned Representations for Person Re-identification. ICCV 2017

Pipeline


CNN
Attention
Part feature extractor
Attention
Part feature extractor

Pipeline


CNN
Attention
Attention
Attention
Part feature extractor
Part feature extractor
Part feature extractor
x

Optimization Loss

- Rank loss: Triplet hinge loss

$$l(\mathrm{x}, \mathrm{x}^+, \mathrm{x}^-) = [d(\mathrm{x}, \mathrm{x}^+) - d(\mathrm{x}, \mathrm{x}^-) + 1]_+$$

$$[y]_+ = \begin{cases} y, if\ y > 0 \\ 0, if\ y \leq 0 \end{cases}$$

Fast Gradient Computation

- Euclidean distance

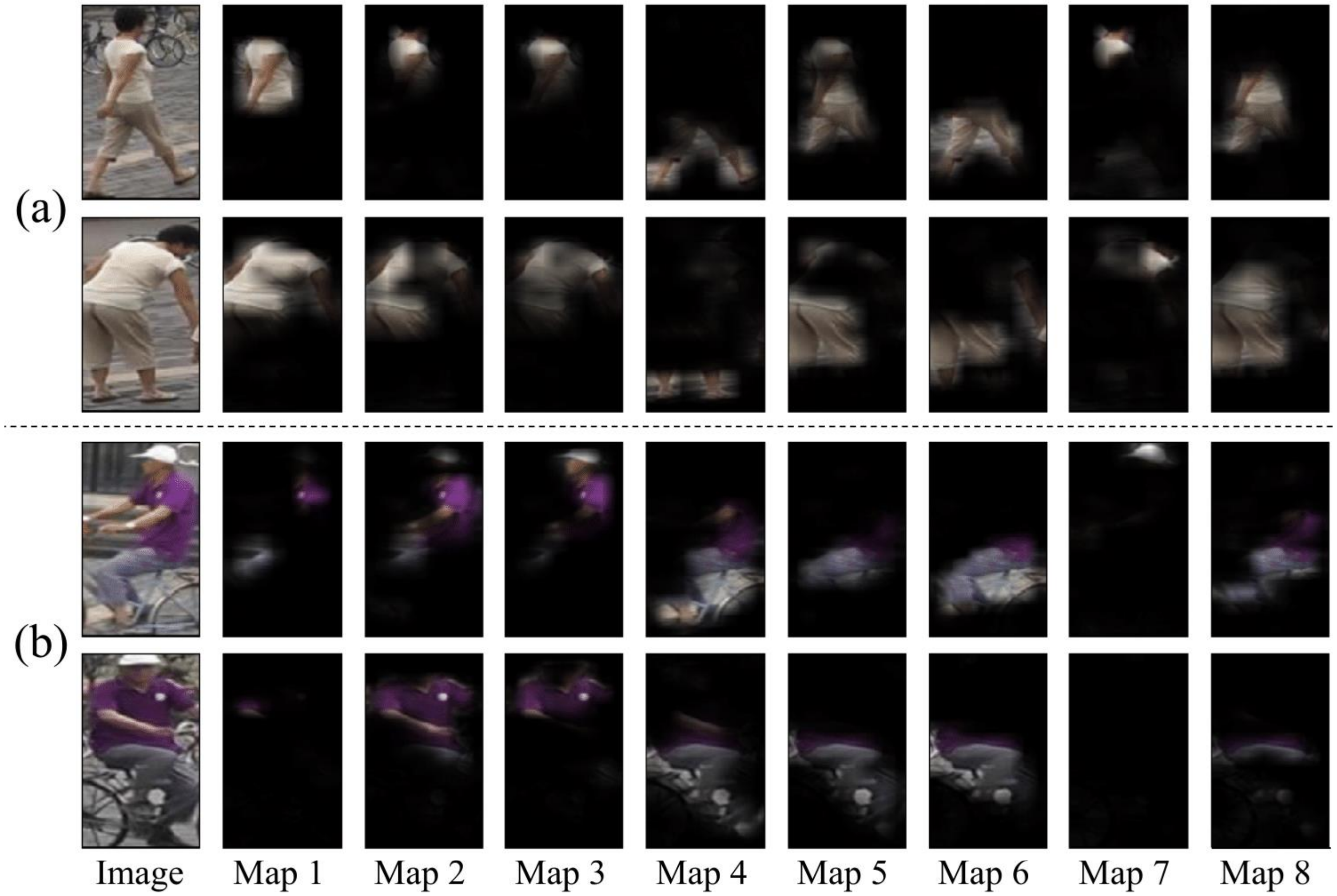
$$d(\mathrm{x}, \mathrm{y}) = |\mathrm{x} - \mathrm{y}|_2^2$$

- Gradient is decomposed:

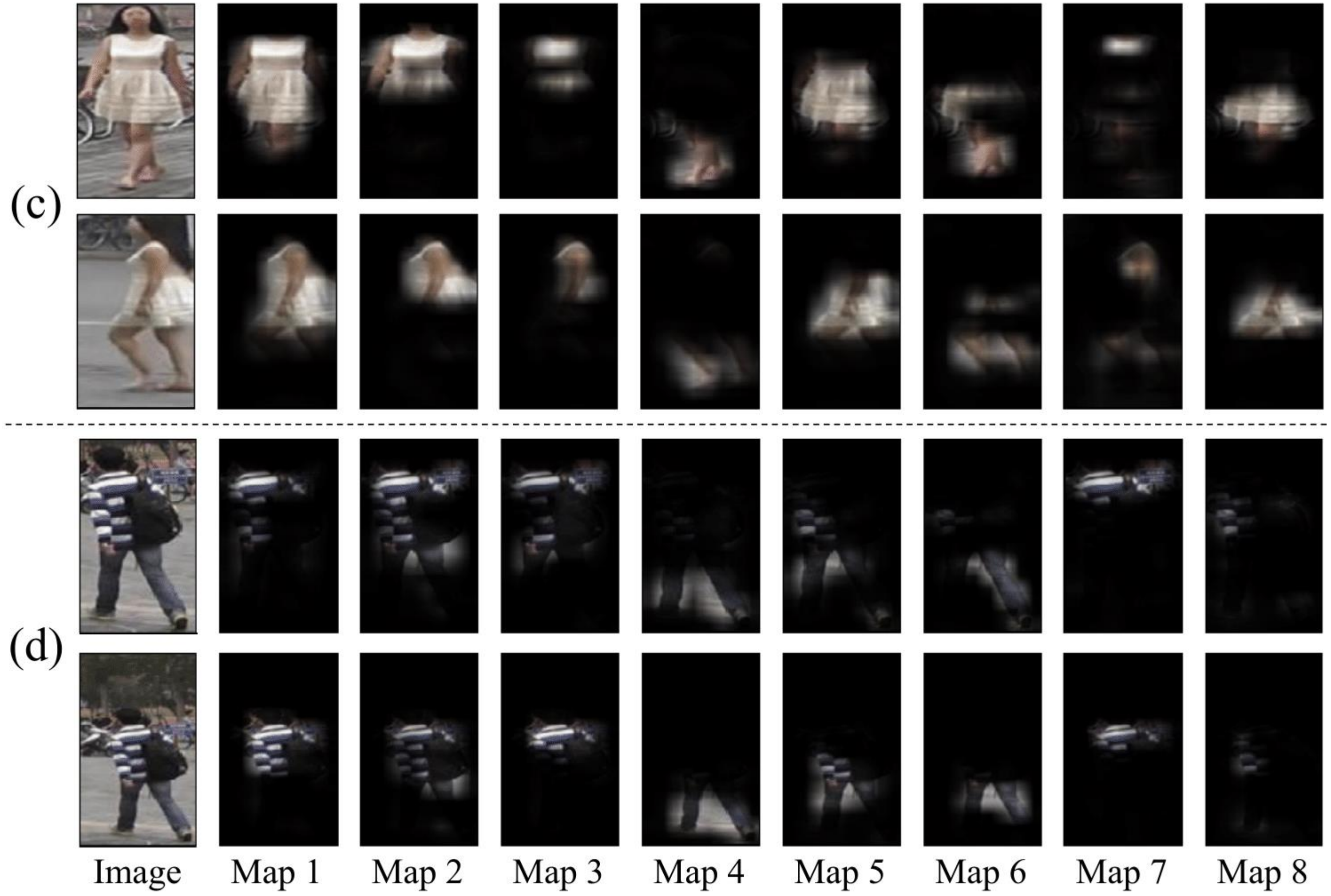
$$\frac{\partial l}{\partial \theta} = \delta_{l>0} \times 2 \left[\frac{\partial \mathrm{x}}{\partial \theta} (\mathrm{x}^- - \mathrm{x}^+) + \frac{\partial \mathrm{x}^+}{\partial \theta} (\mathrm{x}^+ - \mathrm{x}) + \frac{\partial \mathrm{x}^-}{\partial \theta} (\mathrm{x} - \mathrm{x}^-) \right]$$

- #(gradient computation) is linear w.r.t. #(minibatch samples) other than cubic

Parts are well aligned



Parts are well aligned



Experiments

- Datasets
  - Market-1501
  - CUHK03
  - CUHK01
- Evaluation metric
  - Cumulative matching characteristics (CMC) at Rank position
  - MAP

The Effect of #Parts

#parts	rank-1	rank-5	rank-10	rank-20
1	77.7	95.6	98.4	**99.7**
2	80.4	96.7	98.4	99.4
4	82.0	96.7	**98.8**	**99.7**
8	**83.8**	96.9	98.3	**99.7**
12	83.6	**97.3**	**98.8**	99.6

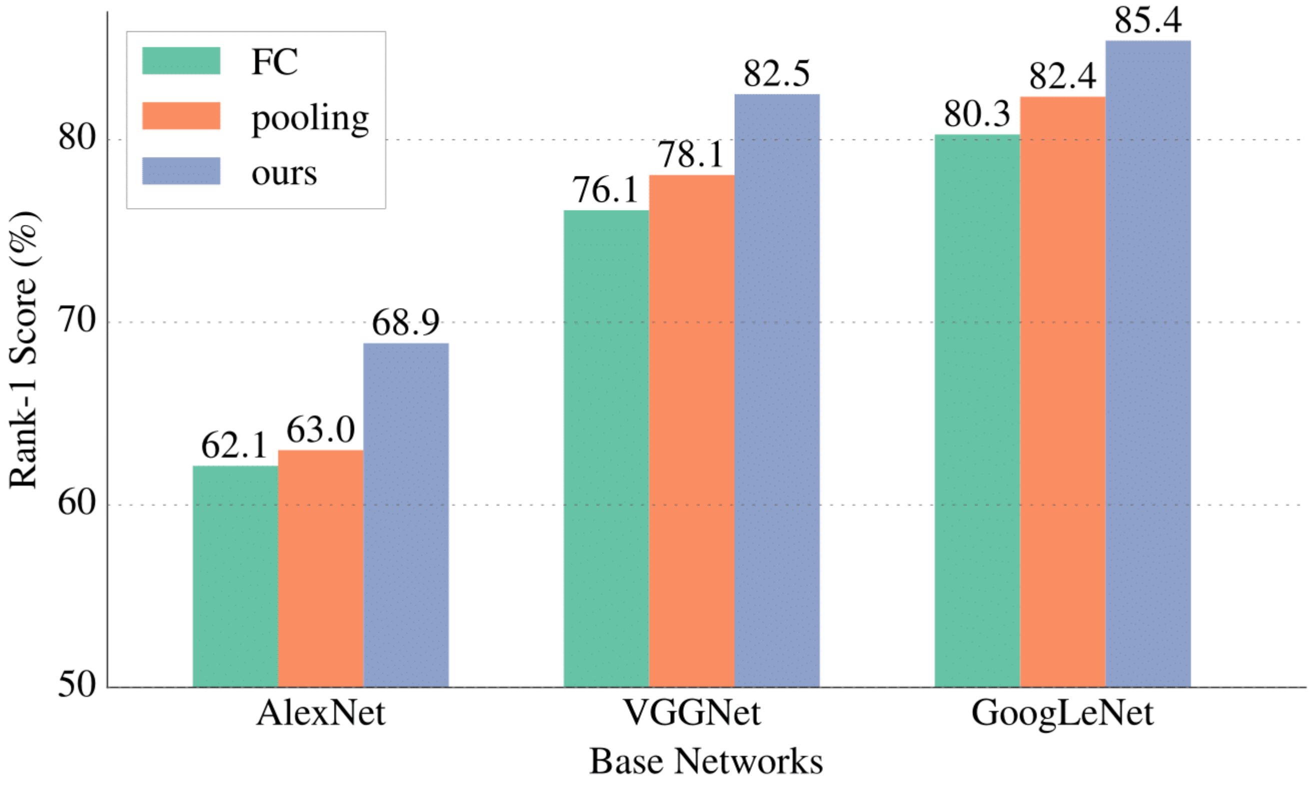
The Effect of Attention

Dataset	Method	rank-1	rank-5	rank-10	mAP
Market-1501	ours	**81.0**	**92.0**	**94.7**	**63.4**
	FC	75.9	89.3	92.9	54.3
	pooling	75.9	89.0	92.2	55.6
CUHK03	ours	**85.4**	**97.6**	**99.4**	**90.9**
	FC	80.3	95.5	98.6	87.3
	pooling	82.4	96.8	99.0	88.9

Comparison to spatial partition

Dataset	Method	rank-1	rank-5	rank-10	rank-20
Market-1501	ours	**81.0**	**92.0**	**94.7**	**96.4**
	stripe	74.1	89.0	92.3	95.1
	grid	73.4	88.2	91.8	94.4
CUHK03	ours	**85.4**	**97.6**	**99.4**	**99.9**
	stripe	81.4	97.1	99.3	99.7
	grid	78.2	96.7	99.2	99.8

Stable improvement over different base nets



Experimental Results

- Market-1501
  - Training 750 identities; testing 751 identities
  - 3,368 queries; 15,913 galleries (2,798 distractors)

	rank-1	rank-5	rank-10	mAP
BoW (ICCV 2015)	35.84	52.40	60.33	14.75
PersonNet (Arxiv 2016)	37.21	-	-	18.57
Deep Attributes (ECCV 2016)	39.40	-	-	19.60
LOMO Feature(CVPR 2015)	43.79	-	-	22.22
WARCA Metric (ECCV 2016)	45.16	68.23	76.00	-
Bilinear CNN (Arxiv 2015)	45.58	67.00	76.00	26.11
Null Space (CVPR 2016)	55.43	-	-	29.87
Gated Siamese CNN (ECCV 2016)	65.88	-	-	39.55
Our Method	81.15	92.25	94.92	63.69

Experimental Results

- CUHK03
  - Training 1160 identities; testing 100 identities
  - Randomly split training and testing sets

	rank-1	rank-5	rank-10	rank-20
DeepReID (CVPR 2014)	20.65	51.32	68.74	83.06
LOMO Feature (CVPR 2015)	52.20	82.23	92.14	96.25
Improved Deep (CVPR 2015)	54.74	86.42	93.88	98.10
Null Space (CVPR 2016)	58.90	85.60	92.45	96.30
Bilinear CNN (Arxiv 2015)	63.87	91.43	95.85	98.56
PersonNet (Arxiv 2016)	64.80	89.40	94.92	98.20
Gated Siamese CNN (ECCV 2016)	68.10	88.10	94.60	-
WARCA Metric (ECCV 2016)	78.38	94.50	97.52	99.11
Our Method	85.43	97.57	99.36	99.86

Experimental Results

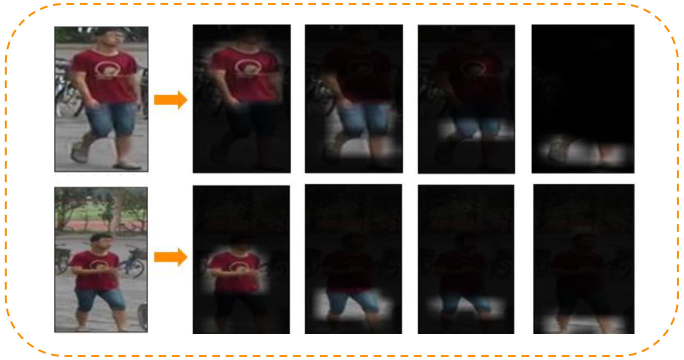
- CUHK01
  - The CUHK01 data set has 971 identities
  - 2 images per person in each view/camera
  - 486 test IDs; 485 for training

	rank-1	rank-5	rank-10	rank-20
Salience Matching (ICCV 2013)	28.45	45.85	55.67	67.95
Improved Deep (CVPR2015)	47.53	71.60	80.25	87.45
LOMO Feature (CVPR 2015)	63.21	83.89	90.04	94.16
Null Space (CVPR 2016)	64.98	84.96	89.92	94.36
WARCA Metric (ECCV 2016)	65.64	85.34	90.48	95.04
Our Method	71.40	89.80	94.52	97.31

Pose-guided Part-Aligned Representation

- Attention
  - Weak-supervision
  - w/o pose

Attention maps



Chi Su, Jianing Li, Shiliang Zhang, Junliang Xing, Wen Gao, Qi Tian: Pose-Driven Deep Convolutional Model for Person Re-identification. ICCV 2017: 3980-3989

Longhui Wei, Shiliang Zhang, Hantao Yao, Wen Gao, Qi Tian: GLAD: Global-Local-Alignment Descriptor for Pedestrian Retrieval. ACM Multimedia 2017: 420-428

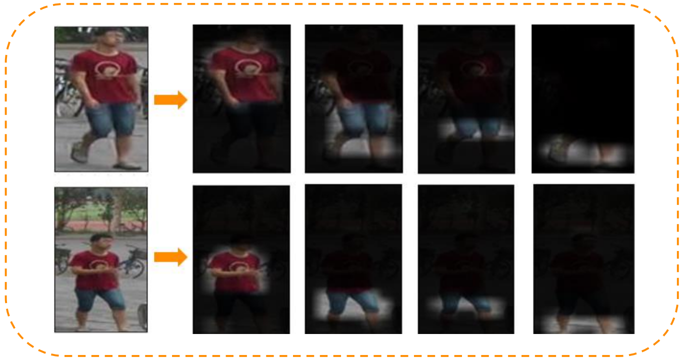
Liang Zheng, Yujia Huang, Huchuan Lu, Yi Yang: Pose Invariant Embedding for Deep Person Re-identification. CoRR abs/1701.07732 (2017)

Yumin Suh, Jingdong Wang, Siyu Tang, Tao Mei, Kyoung Mu Lee: Part-Aligned Bilinear Representations for Person Re-identification. ECCV 2018

Pose-guided Part-Aligned Representation

- Attention
  - Weak-supervision
  - w/o pose
- Pose-guided

Attention maps



Part boxes

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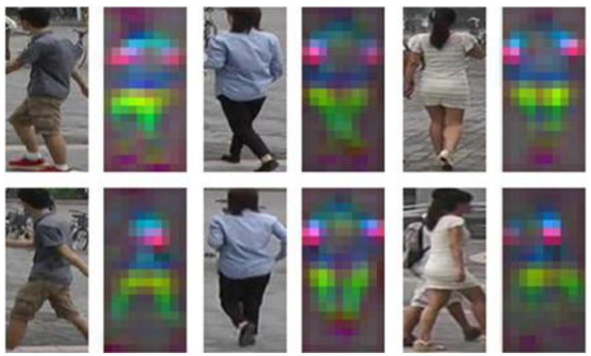
Pose-guided Part-Aligned Representation

- Attention
  - Weak-supervision
  - w/o pose
- Pose-guided part maps

Attention maps

Part boxes



Ours: Part maps

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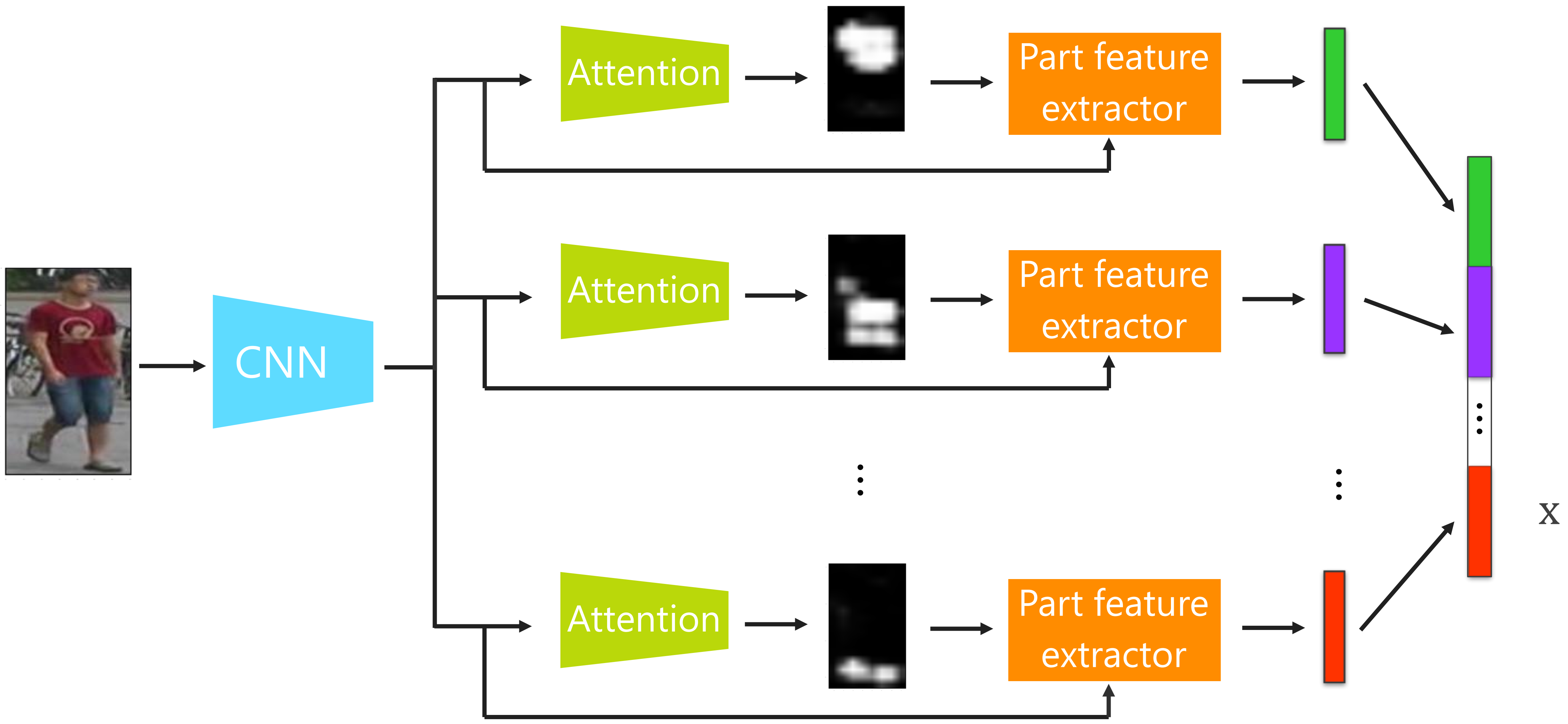
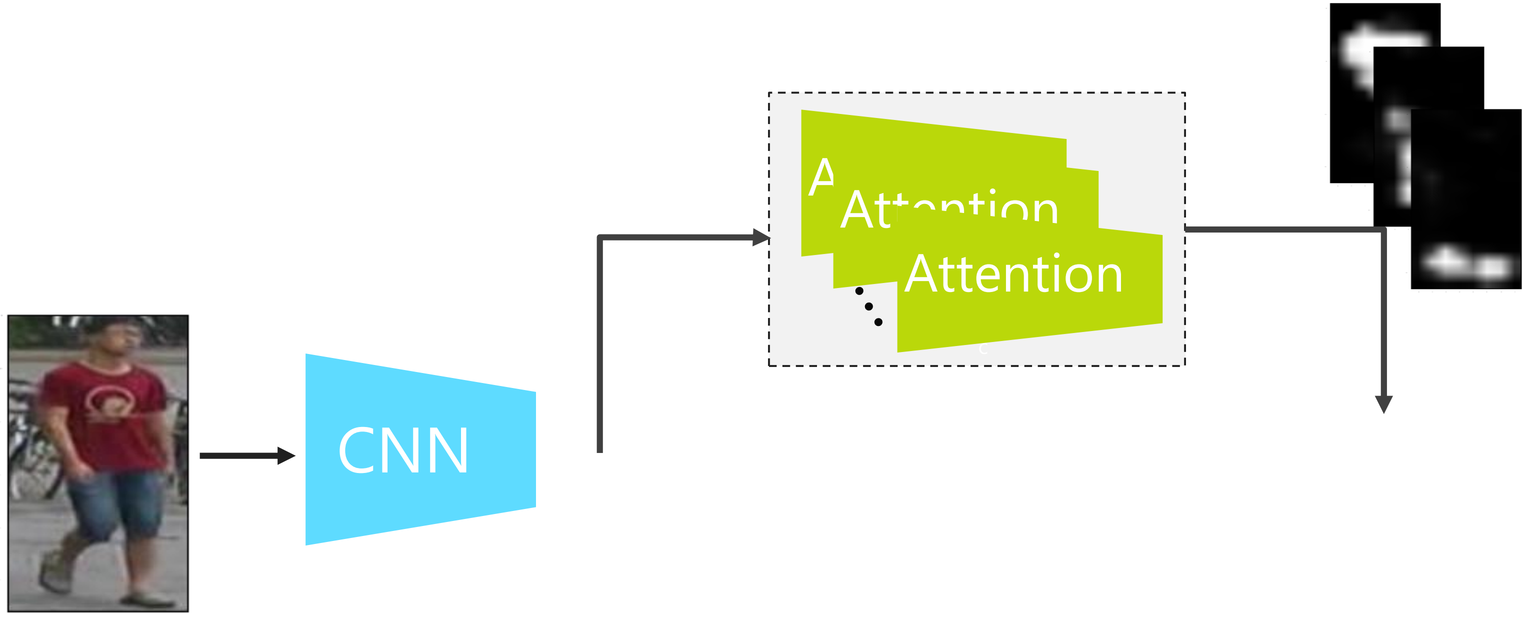
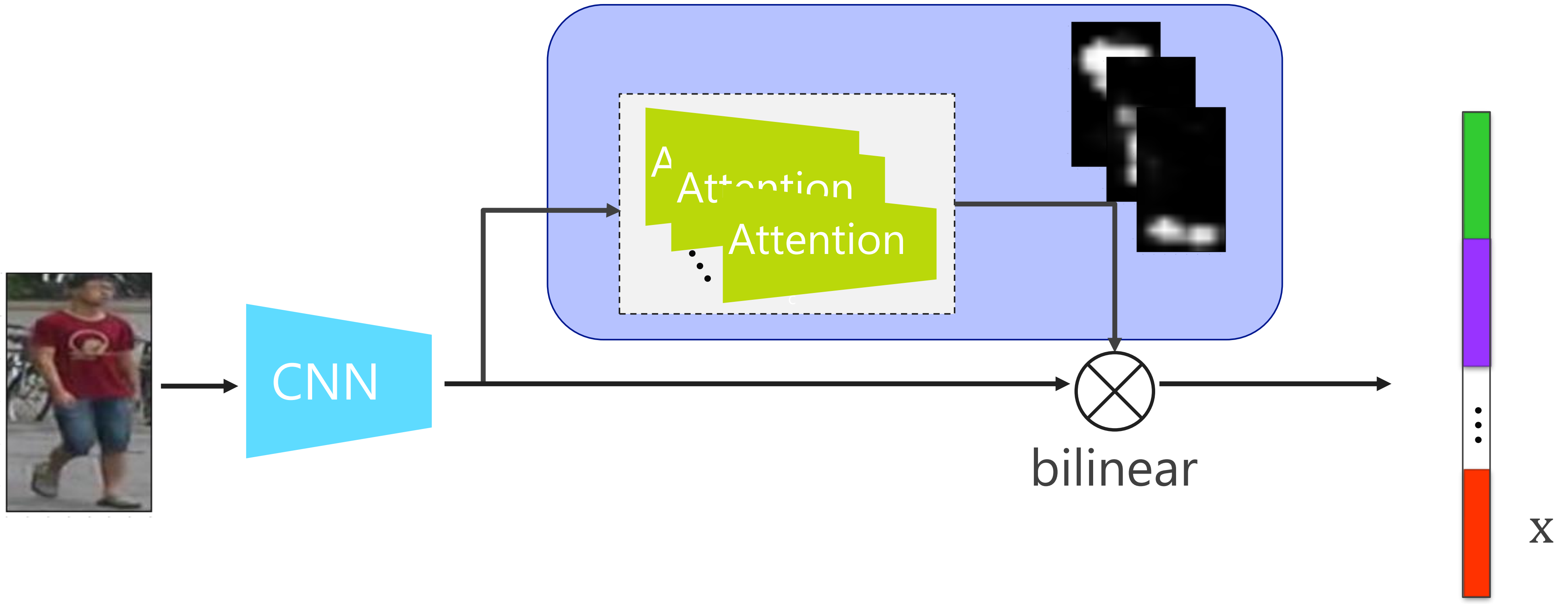
Attention–based Representations as Bilinear Mapping



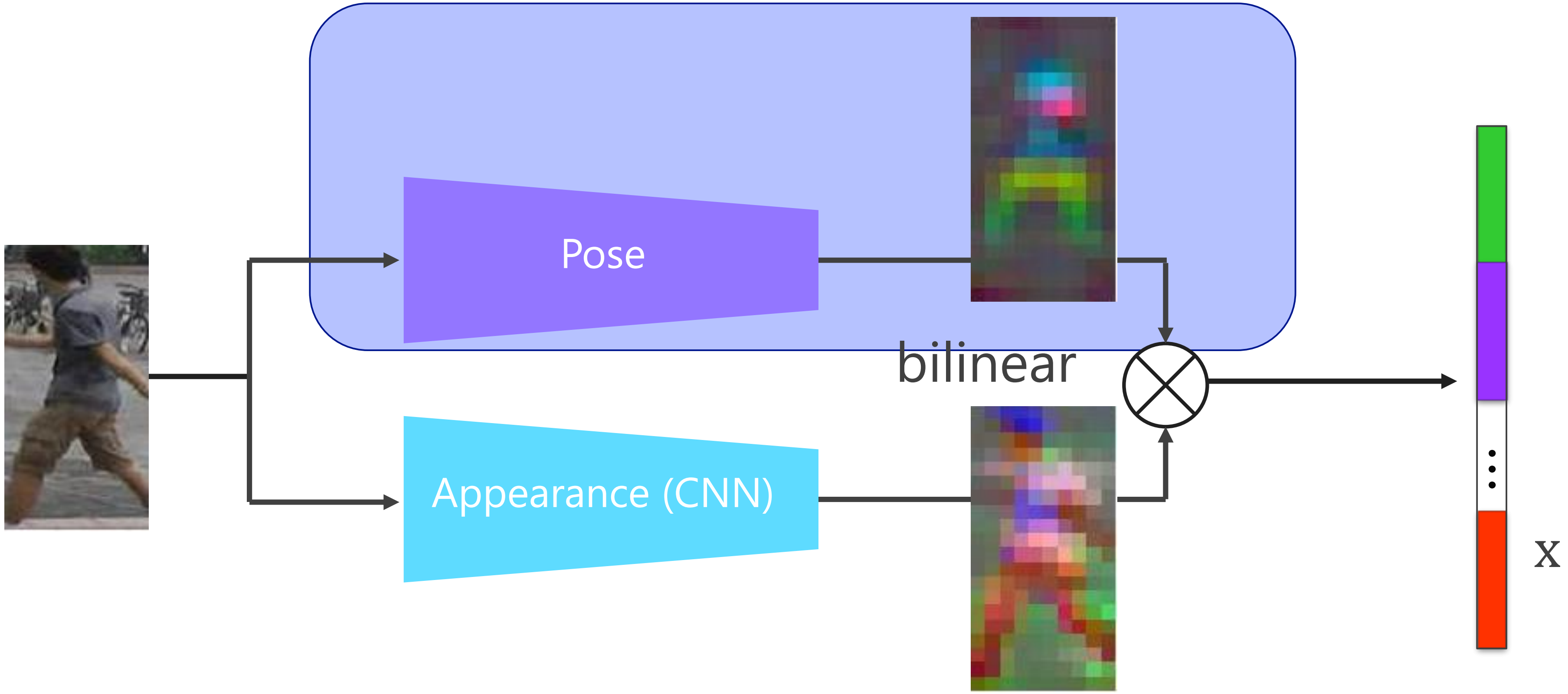
Attention–based Representations as Bilinear Mapping



Attention–based Representations as Bilinear Mapping



Part-Aligned Bilinear Representations



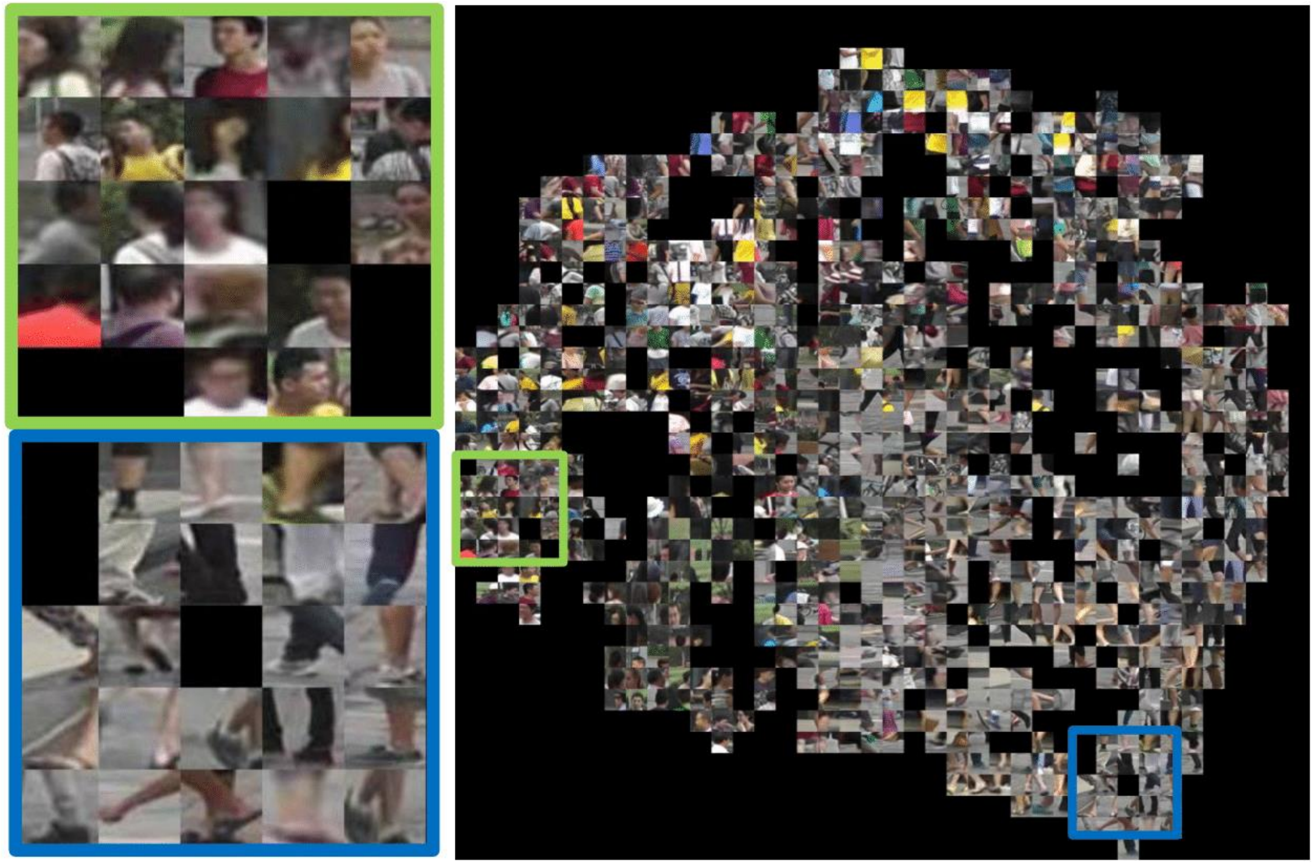
Each subvector in $\mathbf{x}$ corresponds to a key point:

$$\mathrm{vec}(\mathbf{a} \otimes \mathbf{p}) = [(p_1\mathbf{a})^\top \; (p_2\mathbf{a})^\top \; \dots (p_{c_P}\mathbf{a})^\top]^\top$$

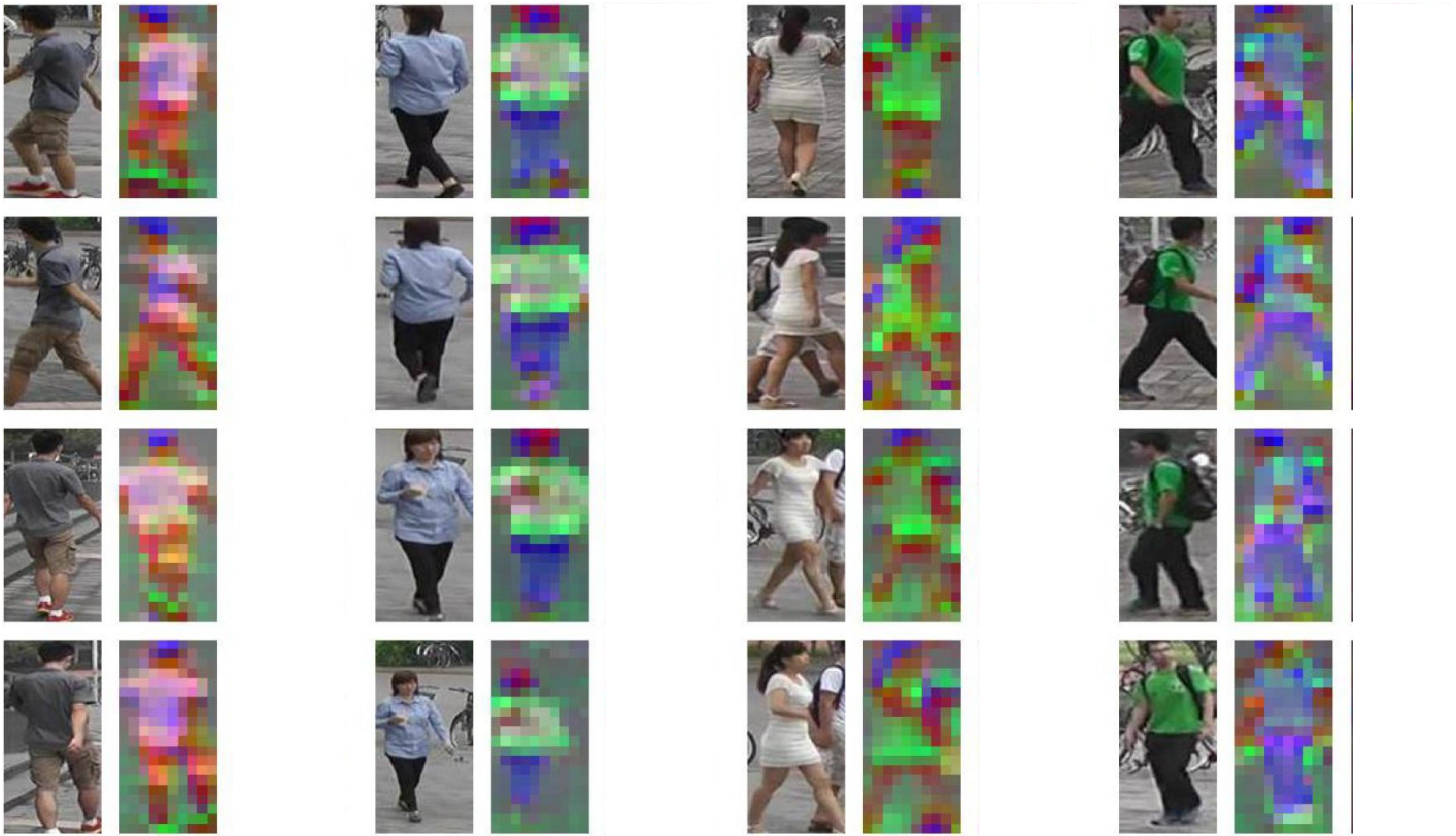
Pose estimator *pretrained on COCO*, and re-trained *only with the re-id loss*

Appearance Descriptors Clustered by Colors

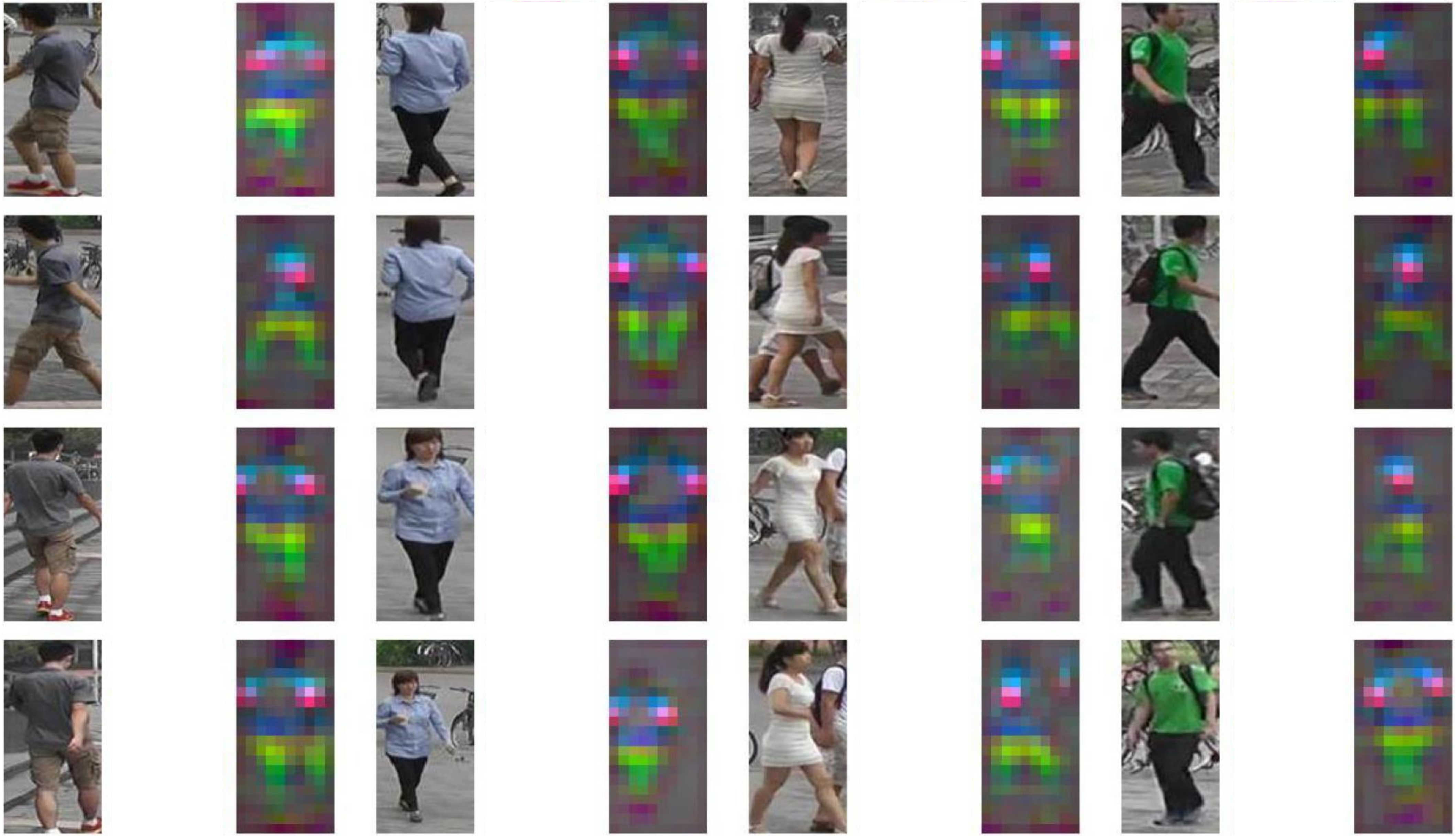
Part Descriptors Clustered by Body Parts



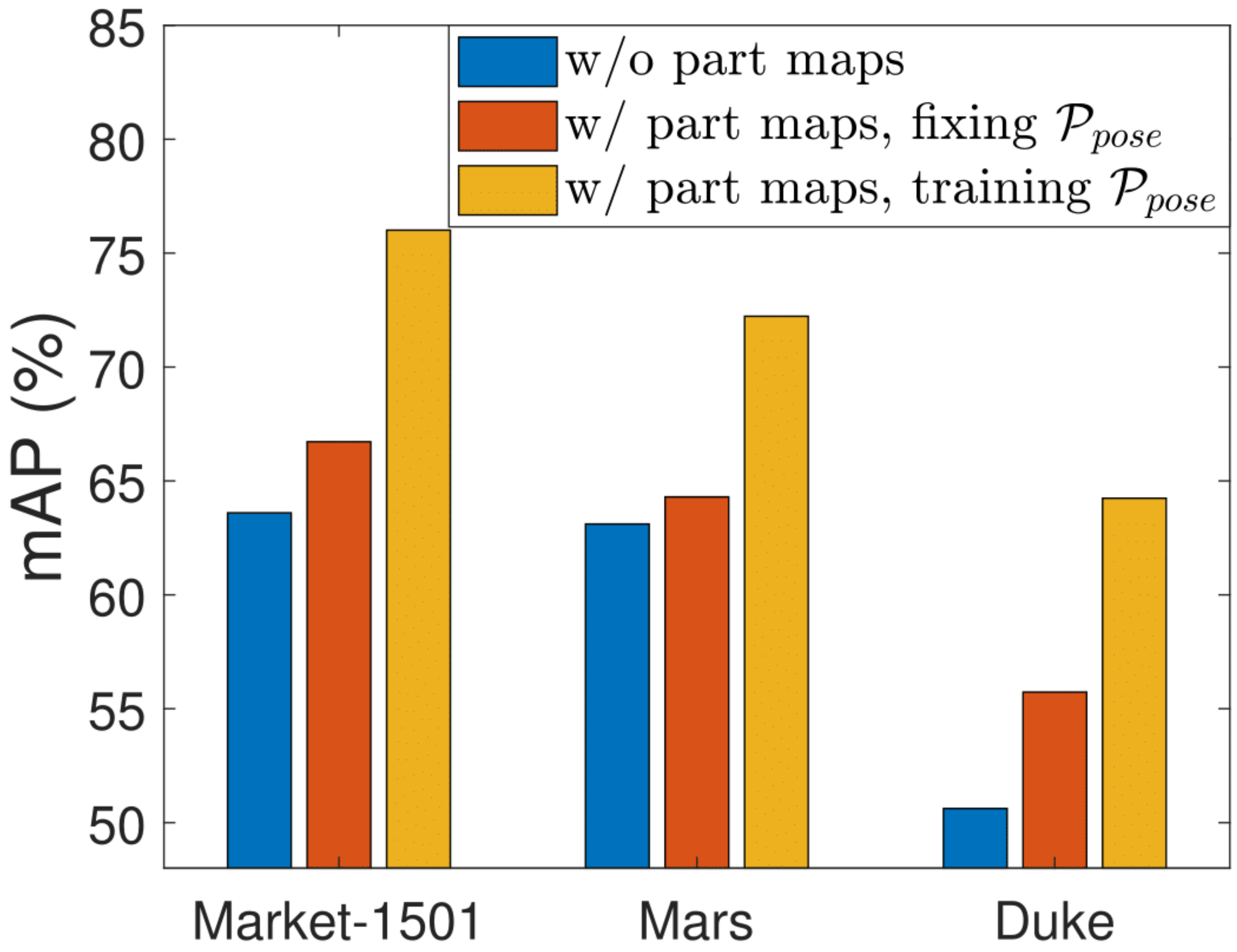
Appearance & Part Descriptors are Informative



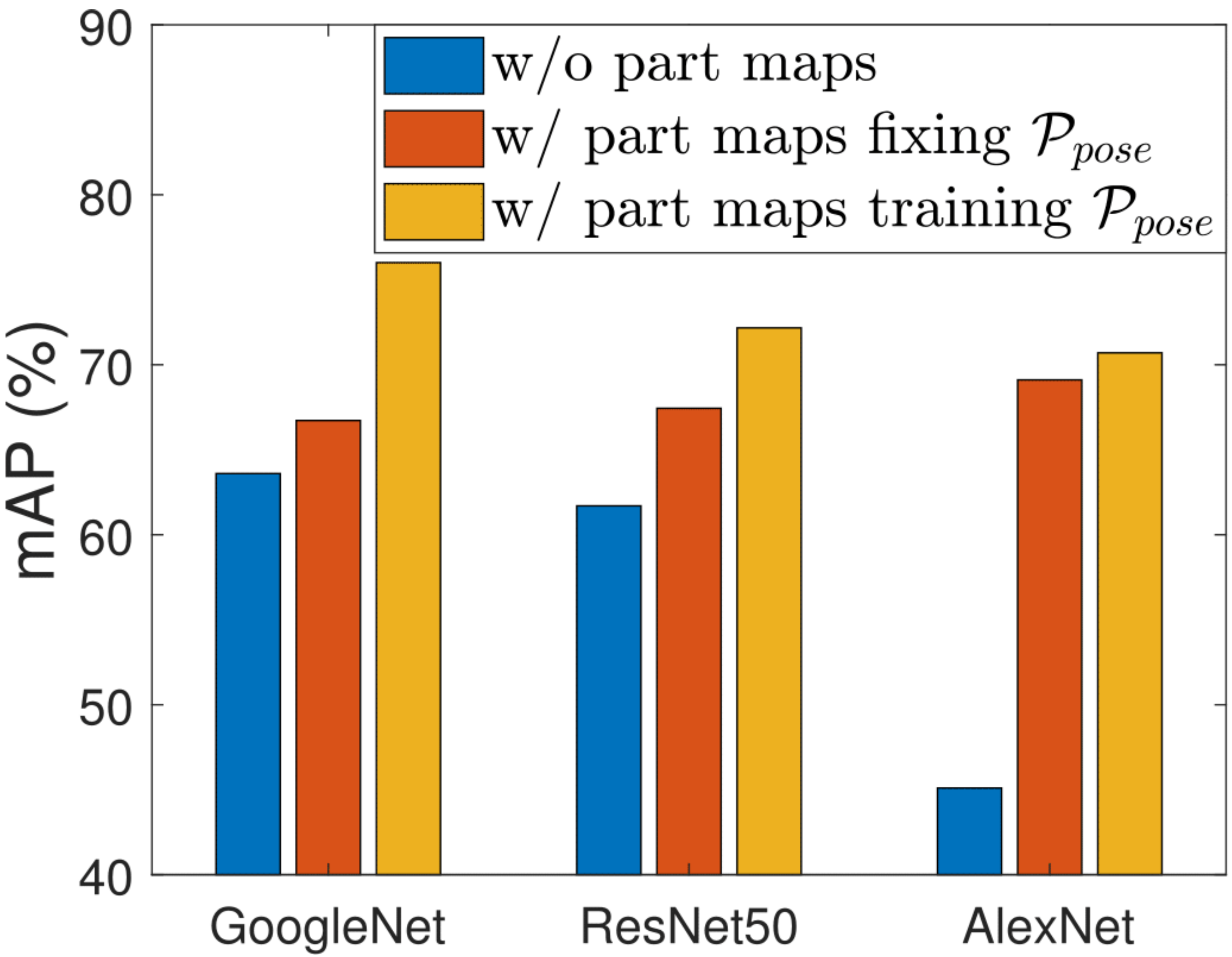
Appearance & Part Descriptors are Informative



Effectiveness of Part Descriptors on Various datasets



Effectiveness of Part Descriptors on Various Networks



Market-1501

	Sinlge Query					Multi Query				
Rank	1	5	10	20	mAP	1	5	10	20	mAP
Varior et al. 2016 [58]	61.6	-	-	-	35.3	-	-	-	-	-
Zhong et al. 2017 [86]	77.1	-	-	-	63.6	-	-	-	-	-
Zhao et al. 2017 [76]	80.9	91.7	94.7	96.6	63.4	-	-	-	-	-
Sun et al. 2017 [53]	82.3	92.3	95.2	-	62.1	-	-	-	-	-
Geng et al. 2016 [16]	83.7	-	-	-	65.5	89.6	-	-	-	73.8
Lin et al. 2017 [31]	84.3	93.2	95.2	97.0	64.7	-	-	-	-	-
Bai et al. 2017 [2]	82.2	-	-	-	68.8	88.2	-	-	-	76.2
Chen et al. 2017 [9]	72.3	88.2	91.9	95.0	-	-	-	-	-	
Hermans et al. 2017 [19]	84.9	94.2	-	-	69.1	90.5	96.3	-	-	76.4
+ re-ranking	86.7	93.4	-	-	81.1	91.8	95.8	-	-	87.2
Zhang et al. 2017 [74]	87.7	-	-	-	68.8	91.7	-	-	-	77.1
Zhong et al. 2017 [87]	87.1	-	-	-	71.3	-	-	-	-	-
+ re-ranking	89.1	-	-	-	83.9	-	-	-	-	-
Chen et al. 2017 [8] (MobileNet)	90.0	-	-	-	70.6	-	-	-	-	-
Chen et al. 2017 [8] (Inception-V3)	88.6	-	-	-	72.6	-	-	-	-	-
Ustinova et al. 2017 [57] (Bilinear)	66.4	85.0	90.2	-	41.2	-	-	-	-	-
Zheng et al. 2017 [79] (Pose)	79.3	90.8	94.4	96.5	56.0	-	-	-	-	-
Zhao et al. 2017 [75] (Pose)	76.9	91.5	94.6	96.7	-	-	-	-	-	-
Su et al. 2017 [50] (Pose)	84.1	92.7	94.9	96.8	65.4	-	-	-	-	-
Proposed (Inception-V1, R-CPM)	88.8	95.6	97.3	98.6	74.5	92.9	97.3	98.4	99.1	81.7
Proposed (Inception-V1, OpenPose)	**90.2**	**96.1**	**97.4**	**98.4**	**76.0**	93.2	97.5	98.4	99.1	82.7
+ dilation	**91.7**	**96.9**	**98.1**	**98.9**	**79.6**	**94.0**	**98.0**	**98.8**	**99.3**	**85.2**
+ re-ranking	**93.4**	**96.4**	**97.4**	**98.2**	**89.9**	**95.4**	**97.5**	**98.2**	**98.9**	**93.1**

Market-1501 + 500K

	Gallery size				
	metric	19732	119732	219732	519732
Zheng et al. 2017 [84]	rank-1	79.5	73.8	71.5	68.3
	mAP	59.9	52.3	49.1	45.2
Linet al. 2017 [31]	rank-1	84.0	79.9	78.2	75.4
	mAP	62.8	56.5	53.6	49.8
Hermans et al. 2017 [19]	rank-1	84.9	79.7	77.9	74.7
	mAP	69.1	61.9	58.7	53.6
Proposed (Inception V1, OpenPose)	rank-1	**91.7**	**88.3**	**86.6**	**84.1**
	mAP	**79.6**	**74.2**	**71.5**	**67.2**

CUHK

	CUHK03								CUHK01							
	Detected				Manual				100 test IDs				486 test IDs			
Rank	1	5	10	20	1	5	10	20	1	5	10	20	1	5	10	20
Shi et al. [70]	52.1	84.0	92.0	96.8	61.3	88.5	96.0	99.0	69.4	90.8	96.0	-	-	-	-	-
SIR-CIR [60]	52.2	-	-	-	-	-	-	-	71.8	91.6	96.0	98.0	-	-	-	-
Varior et al. [58]	68.1	88.1	94.6	98.8	-	-	-	-	-	-	-	-	-	-	-	-
Bai et al. [2]	72.7	92.4	96.1	-	76.6	94.6	98.0	-	-	-	-	-	-	-	-	-
Zhang et al. [72]	-	-	-	-	80.2	97.7	99.2	99.8	89.6	97.8	98.9	99.7	76.5	94.2	**97.5**	-
Sun et al. [53]	81.8	95.2	97.2	-	-	-	-	-	-	-	-	-	-	-	-	-
Zhao et al. [76]	81.6	97.3	98.4	**99.5**	85.4	97.6	99.4	**99.9**	88.5	**98.4**	**99.6**	**99.9**	74.7	92.6	96.2	98.4
Geng et al. [16]	84.1	-	-	-	85.4	-	-	-	**93.2**	-	-	-	77.0	-	-	-
Chen et al. [9]	87.5	97.4	98.7	**99.5**	-	-	-	-	-	-	-	-	74.5	91.2	94.8	97.1
Ustinova et al. [57] (Bilinear)	63.7	89.2	94.7	97.5	69.7	93.4	98.9	99.4	-	-	-	-	52.9	78.1	86.3	92.6
Zheng et al. [79] (Pose)	67.1	92.2	96.6	98.1	-	-	-	-	-	-	-	-	-	-	-	-
Zhao et al. [75] (Pose)	-	-	-	-	88.5	97.8	98.6	99.2	-	-	-	-	79.9	**94.4**	97.1	98.6
Su et al. [50] (Pose)	78.3	94.8	97.2	98.4	88.7	98.6	99.2	99.7	-	-	-	-	-	-	-	-
Proposed	**88.0**	**97.6**	**98.6**	**99.0**	**91.5**	**99.0**	**99.5**	**99.9**	90.4	97.1	98.1	98.9	**80.7**	**94.4**	**97.3**	**98.6**

DukeMTMC

Rank	1	5	10	20	mAP
Zheng et al. [85]	67.7	-	-	-	47.1
Tong et al. [67]	68.1	-	-	-	-
Lin et al. [31]	70.7	-	-	-	51.9
Schumann et al. [47]	72.6	-	-	-	52.0
Sun et al. [53]	76.7	86.4	89.9	-	56.8
Chen et al. [8] (MobileNet)	77.6	-	-	-	58.6
Chen et al. [8] (Inception-V3)	79.2	-	-	-	60.6
Zhun et al. [87]	79.3	-	-	-	62.4
+ re-ranking	84.0	-	-	-	78.3
Proposed (Inception V1, OpenPose)	82.1	90.2	92.7	95.0	64.2
+ dilation	**84.4**	**92.2**	**93.8**	**95.7**	**69.3**
+ re-ranking	**88.3**	**93.1**	**95.0**	**96.1**	**83.9**

Video: Mars

Rank	1	5	10	20	mAP
Xu et al. [68] (Video)	44	70	74	81	-
McLaughlin et al. [40] (Video)	45	65	71	78	27.9
Zheng et al. [78] (Video)	68.3	82.6	-	89.4	49.3
Liu et al. [33] (Video)	68.3	81.4	-	90.6	52.9
Zhou et al. [88]	70.6	90.0	-	97.6	50.7
Li et al. [23]	71.8	86.6	-	93.1	56.1
+ re-ranking	83.0	93.7	-	97.6	66.4
Liu et al. [35]	73.7	84.9	-	91.6	51.7
Hermans et al. [19]	79.8	91.4	-	-	67.7
+ re-ranking	81.2	90.8	-	-	77.4
Proposed (Inception V1, OpenPose)	83.0	92.8	95	96.8	72.2
+ dilation	**84.7**	**94.4**	**96.3**	**97.5**	**75.9**
+ re-ranking	**85.1**	**94.2**	**96.1**	**97.4**	**83.9**

Summary

Large image dataset
Market-1501
ICCV 2015

Large video dataset
MARS
ECCV 2016

Deeply-Learned Part-Aligned Representations. w/o pose
ICCV 2017

Part-Aligned Bilinear Representations. w/ pose
ECCV 2018

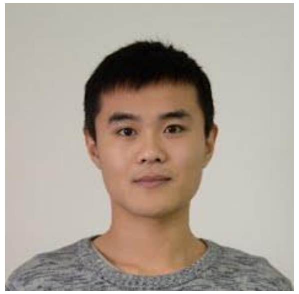
Scan QR codes to download datasets and codes

Collaborators


Jingdong Wang


Qi Tian


Liang Zheng


Liming Zhao


Yumin Suh


Tao Mei


Siyu Tang


Xi Li


Kyoung Mu Lee


Yueting Zhuang

Zhi Bie

Liyue Sheng

Lu Tian

Yifan Sun

Shengjin Wang

Full Publications

[1] Learning Correspondence Structures for Person Re-identification. Weiyao Lin, Yang Shen, Junchi Yan, Mingliang Xu, Jianxin Wu, Jingdong Wang, and Ke Lu. IEEE Transactions on Image Processing (TIP).

[2] Exemplar-Guided Similarity Learning on Polynomial Feature Map for Person Re-Identification. Dapeng Chen, Zejian Yuan, Jingdong Wang, Gang Hua, and Nanning Zheng. International Journal of Computer Vision (IJCV).

[3] Part-Aligned Bilinear Representations for Person Re-identification. Yumin Suh, Jingdong Wang, Siyu Tang, Tao Mei, and Kyoung Mu Lee. ECCV 2018.

[4] Group Re-Identification: Leveraging and Integrating Multi-Grain Information. Hao Xiao, Weiyao Lin, Bin Sheng, Ke Lu, Junchi Yan, Jingdong Wang, Errui Ding, Yihao Zhang, and Hongkai Xiong. ACM MM 2018.

[5] Deeply-Learned Part-Aligned Representations for Person Re-Identification. Liming Zhao, Xi Li, Yueting Zhuang, and Jingdong Wang. ICCV 2017.

[6] MARS: A Video Benchmark for Large-Scale Person Re-identification. Liang Zheng, Zhi Bie, Yifan Sun, Jingdong Wang, Chi Su, Shengjin Wang, and Qi Tian. ECCV 2016.

[7] Scalable Person Re-identification: A Benchmark. Liang Zheng, Liyue Sheng, Lu Tian, Shengjin Wang, Jingdong Wang, and Qi Tian. ICCV 2015.

[8] Person Re-identification with Correspondence Structure Learning. Yang Shen, Weiyao Lin, Junchi Yan, Mingliang Xu, Jianxin Wu, and Jingdong Wang. The Fourteenth IEEE International Conference on Computer Vision ICCV 2015.

[9] Similarity Learning on an Explicit Polynomial Kernel Feature Map for Person Re-Identification. Dapeng Chen, Zejian Yuan, Gang Hua, Nanning Zheng, and Jingdong Wang. IEEE Conference on Computer Vision and Pattern Recognition CVPR15.

Thanks!

QA