

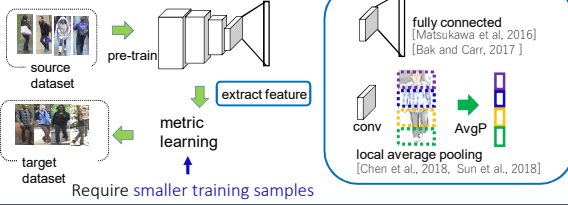
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## Approach

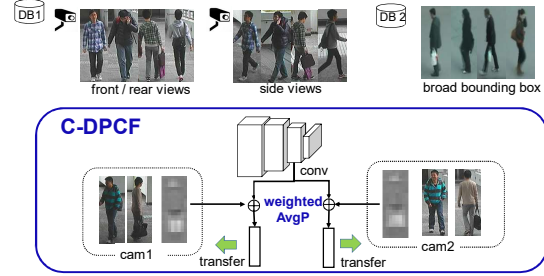
Practical issue

- Lack of training person IDs
- Require GPU for fine-tuning

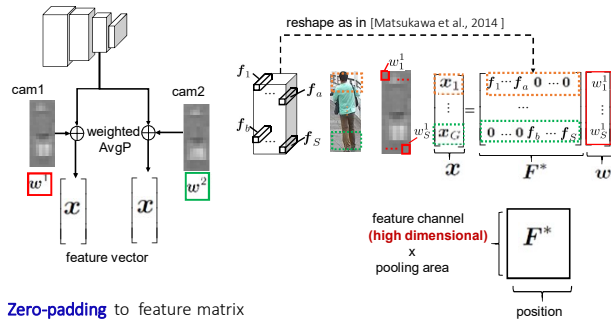
CNN-feature transfer



Conventional features are less transferable to different camera/datasets due to spatial bias



## Camera-specific weight local AvgP



## Weight map learning

- Given a training data  $\{F_i, p_i, c_i\}_{i=1}^N$
- Optimize sum of distances of  $K$ -weight map pairs

➢ Random projection distance

$$\delta_{w_k}^2(i, j) = \|R^T x_{k,i} - R^T x_{k,j}\|_2^2$$

$$= \|R^T F_i w_k - R^T F_j w_k\|_2^2$$

$$= \|Q_i w_k - Q_j w_k\|_2^2$$

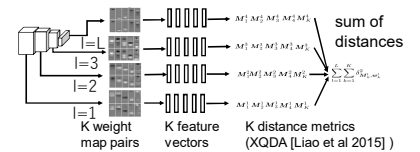
- Optimization problem

$$\max_W J(W) = \text{Tr}[W^T \Sigma_D W] - \text{Tr}[W^T \Sigma_S W] \quad s.t. \quad W^T W = I_K$$

avg. distance of different persons      avg. distances of same person

## Distance for re-id

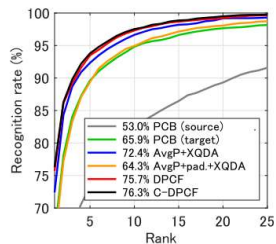
- C-DPCF is applied to  $L$  layers



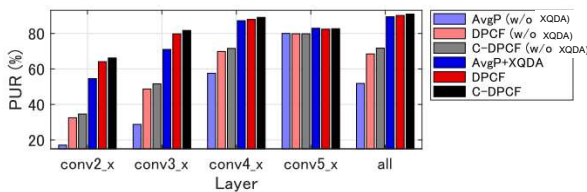
## Experiments

### Comparison with baselines

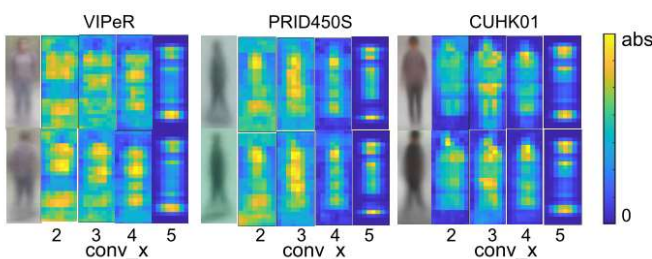
Baseline: PCB [Sun et al., 2018] trained on (source/target) dataset



### Convolutional layers



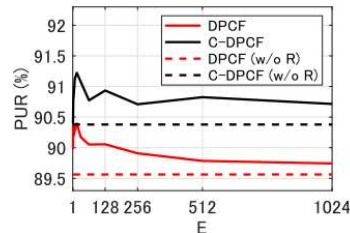
### Weight maps



### Rank-1 rates of SOTA

	Type	VIPeR	GRID	PRID	CUHK01
CNN features	CMDL[PAMI18]	S 66.4	30.9	52.0	78.2
	HGD[PAMI20]	S 52.8	28.2	-	-
	Synthesis[ECCV18]	U 43.0	-	-	54.9
	One-shot [CVPR17]	U+S 34.3	-	-	45.6
	CRAFT [PAMI18]	S 50.3	22.4	-	-
Mobilenet-V2	C-DPCF [ours]	S 76.3	34.8	79.4	89.1
	DIMM [CVPR19]	DG 51.2	29.3	-	-
	DN [BMVC19]	DG 58.8	39.7	73.6	-
	DN + ours	DG+S 73.9	42.3	84.1	-

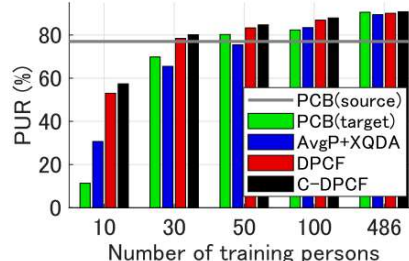
### Random projection dim



Training time (CUHK01)

Method	Training time (E=64)
C-DPCF	1684.4 sec
w/o R	49.0 sec

### Accurate even with a smaller training data



- C-DPCF improves PCB(source) with 30 persons
- Camera-specific weight maps always outperforms common weight maps