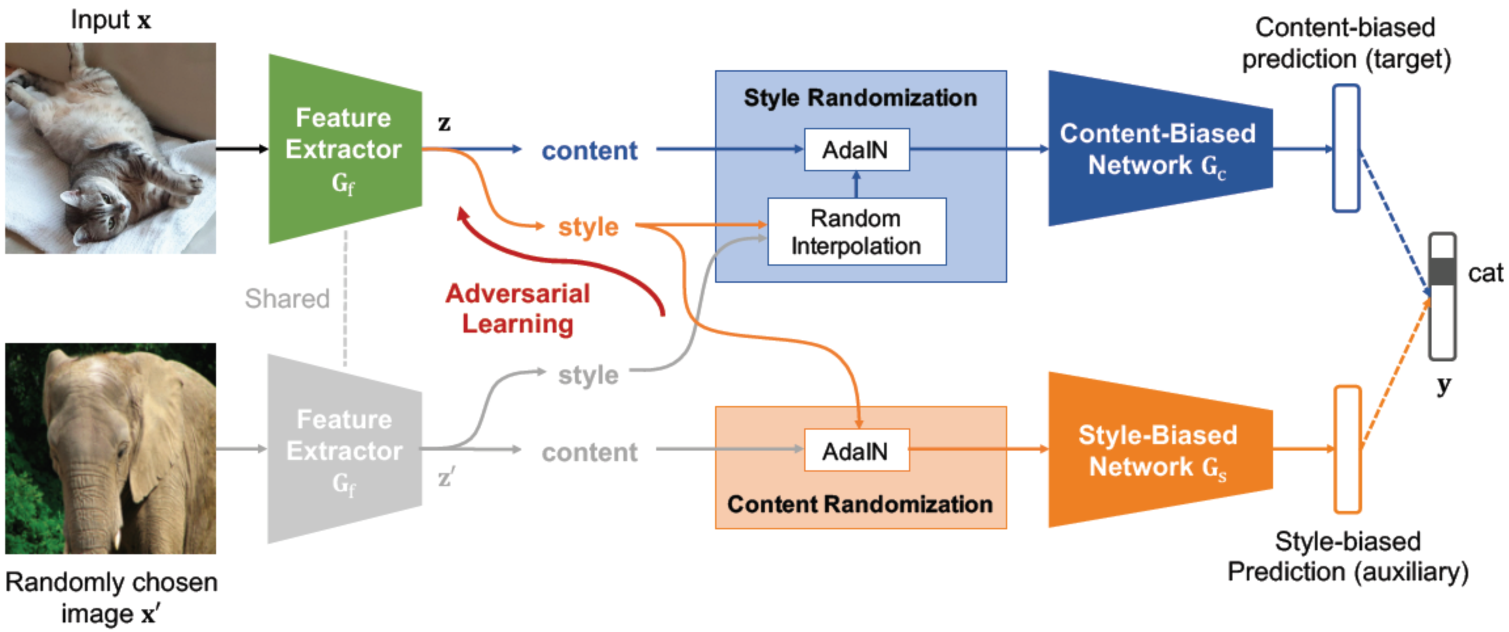
Meta Batch-Instance Normalization for Generalizable Person Re-Identification

Choi et al., CVPR 2021.

Presenter: Yoonki Cho

Recap: Reducing Domain Gap by Reducing Style Bias (CVPR 21, oral)

- Style-Agnostic Network (SagNet)
  - Goal: Content-biased network → Robust under domain shifts.
  - How? → Randomly swap style codes between images.



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Nam et al. Reducing Domain Gap by Reducing Style Bias. In CVPR 2021.

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2. Backgrounds
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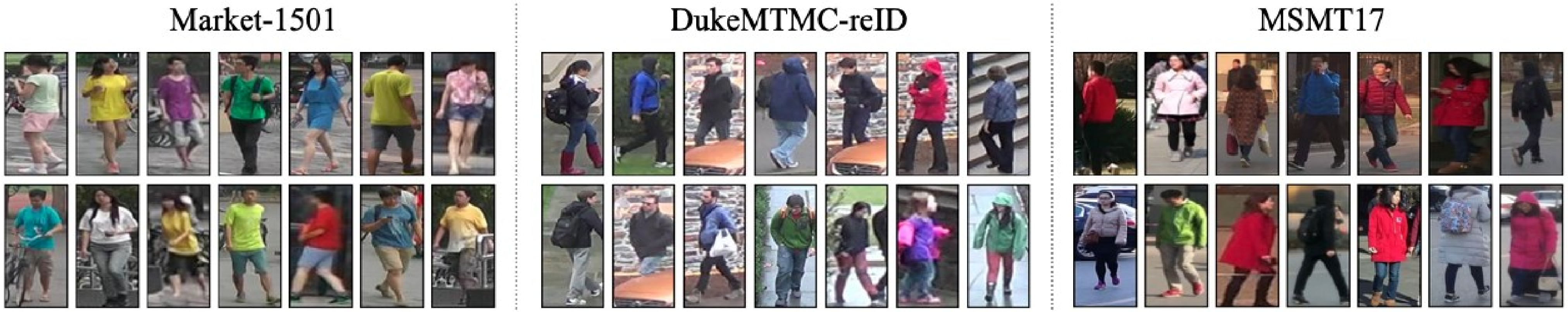
Introduction

Motivation & Research Goal

Generalizable Person Re-identification

- Generalizable person re-ID is a “domain generalization (DG)” problem for person retrieval.
  - Training (Source) domain ≠ Testing (Target) domain.
- Style difference between domains makes a domain gap.
  - Season (Weather), Viewpoint, Clothing, etc.



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Zheng et al. Joint Discriminative and Generative Learning for Person Re-identification. In CVPR 2019.

Generalizable Person Re-identification

- Many works employ an **instance normalization (IN)** to reduce style variations.
  - However, it often loses discriminative information.
  - Also, it requires a lot of trial and error.

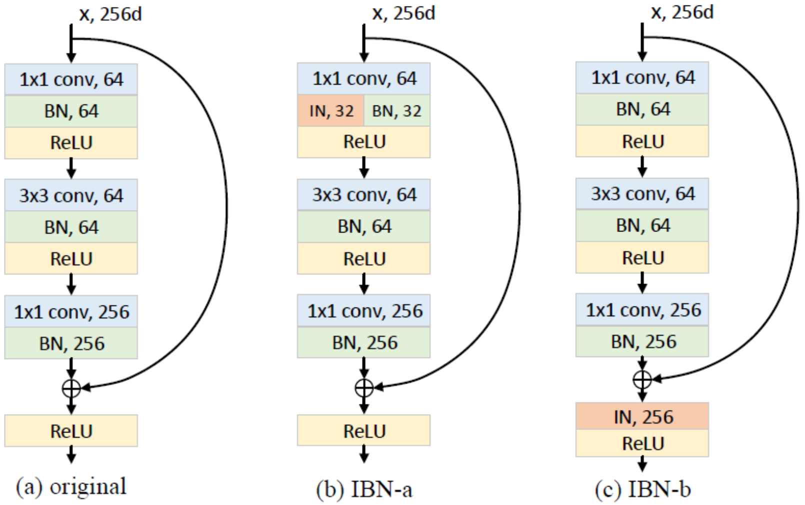
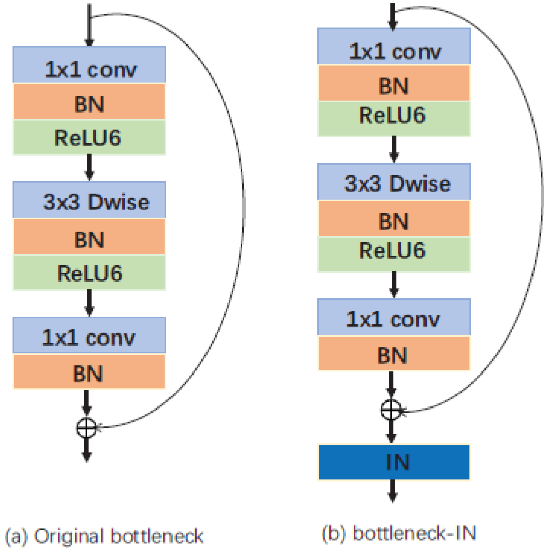


Fig. 3. Instance-batch normalization (IBN) block.

IBN-Net, ECCV 18



DualNorm, BMVC 19

Pan et al. Two at Once: Enhancing Learning and Generalization Capacities via IBN-Net. In ECCV 2018.
Jia et al. Frustratingly Easy Person Re-Identification: Generalizing Person Re-ID in Practice. In BMVC 2019.

Research Goal

- Goal: Solve a generalizable person re-ID using style normalization
  - Preserving discriminative information.
  - Without a trial and error manner.

- To achieve the goal, the proposed method
  - Mimics unsuccessful generalization scenarios in a meta-learning manner.
  - Learn a generalization ability from unsuccessful generalization episodes.

  - Utilizes both IN and BN → learnable batch-instance normalization (BIN).

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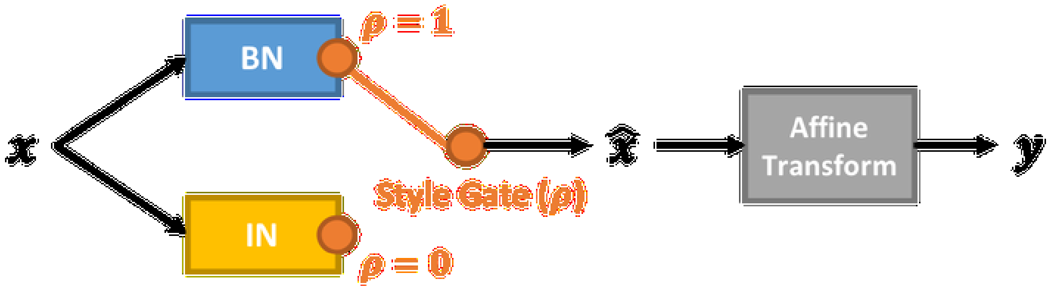
Backgrounds

Batch-Instance Normalization (BIN)

Batch-Instance Normalization (BIN)

- Batch-Instance Normalization for Adaptively Style-Invariant Neural Networks. In NeurIPS 2018.
  - BIN learns to selectively normalize a disturbing style while preserving an useful style.
  - The learnable parameter $\rho \in [0,1]^C$ controls how much to normalize style for each channel



$$\mathbf{y} = \left(\rho \cdot \hat{\mathbf{x}}^{(B)} + (1-\rho) \cdot \hat{\mathbf{x}}^{(I)}\right) \cdot \gamma + \beta$$

Batch-normalized feature map

Style-normalized feature map

Image credit: © Lunit Tech Blog. https://blog.lunit.io/2018/05/25/batch-instance-normalization/

Method

Meta Batch-Instance Normalization (MetaBIN)

Meta Batch-Instance Normalization (MetaBIN)

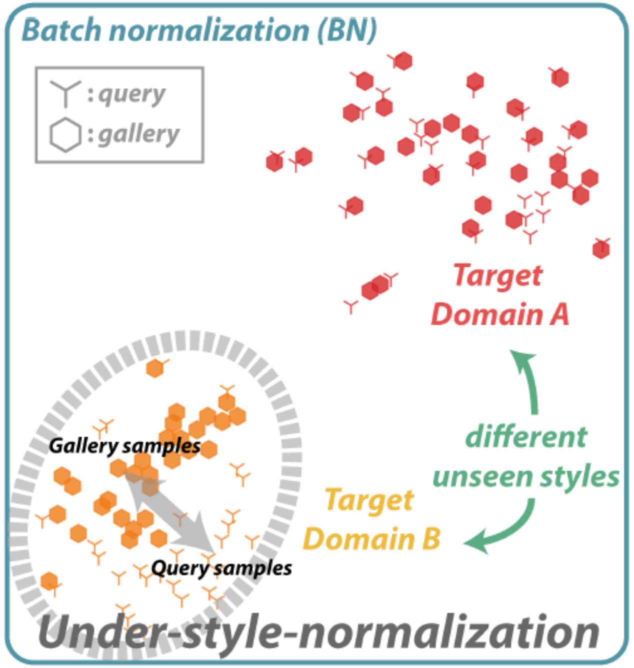
- The paper proposes a novel generalizable re-ID framework called MetaBIN that prevents overfitting to given source domain styles.

- The proposed method selectively normalize disturbing style by **unsuccessful generalization scenarios in a meta-learning manner.**

- To diversify the virtual simulations (i.e., unsuccessful generalization scenarios), the paper proposes **meta-train loss.**

Experimental Observation

- Train a model with only BNs across multiple source domains.
- Under-style-normalization by BN.
  - When unexpected styles are given from unseen target domain, the model often fails to distinguish inputs' IDs.



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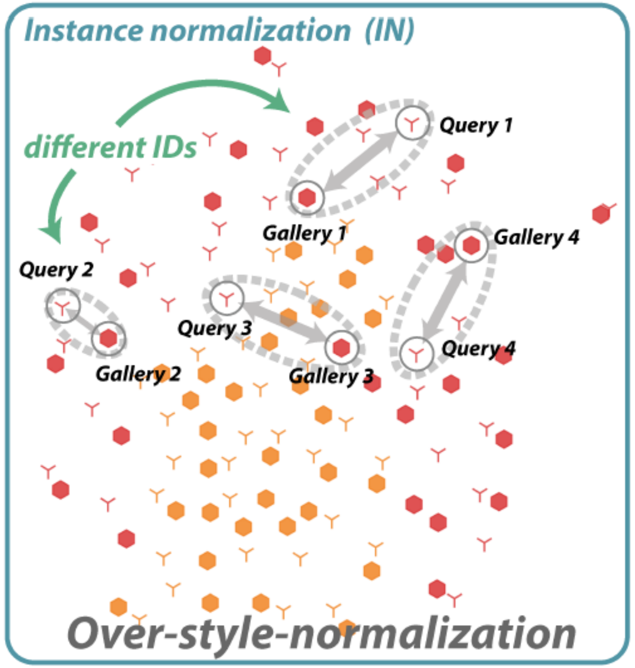
Experimental Observation

- Train a model with only INs across multiple source domains.
- Over-style-normalization by IN.
  - It can remove unseen styles in the target domain.
  - However, it can also removes some discriminative information for re-identifying a person.



Meta Batch-Instance Normalization (MetaBIN)

- To address under- and over-style-normalization problems, the proposed method utilizes a batch-instance normalization (BIN).

$$\mathbf{y} = \rho\left(\gamma_B \cdot \underset{\substack{\uparrow \\ \text{Batch-normalized} \\ \text{feature map}}}{\hat{\mathbf{x}}_B} + \beta_B\right) + (1-\rho)\left(\gamma_I \cdot \underset{\substack{\uparrow \\ \text{Style-normalized} \\ \text{feature map}}}{\hat{\mathbf{x}}_I} + \beta_I\right)$$

- So how can we train a learnable balancing parameter $\rho \in [0,1]^C$?
  - If we directly train ρ with a end-to-end manner, it can easily overfit to the source domain's style.

MetaBIN Framework

- The proposed method trains a learnable balancing parameter ρ using a meta-learning pipeline.

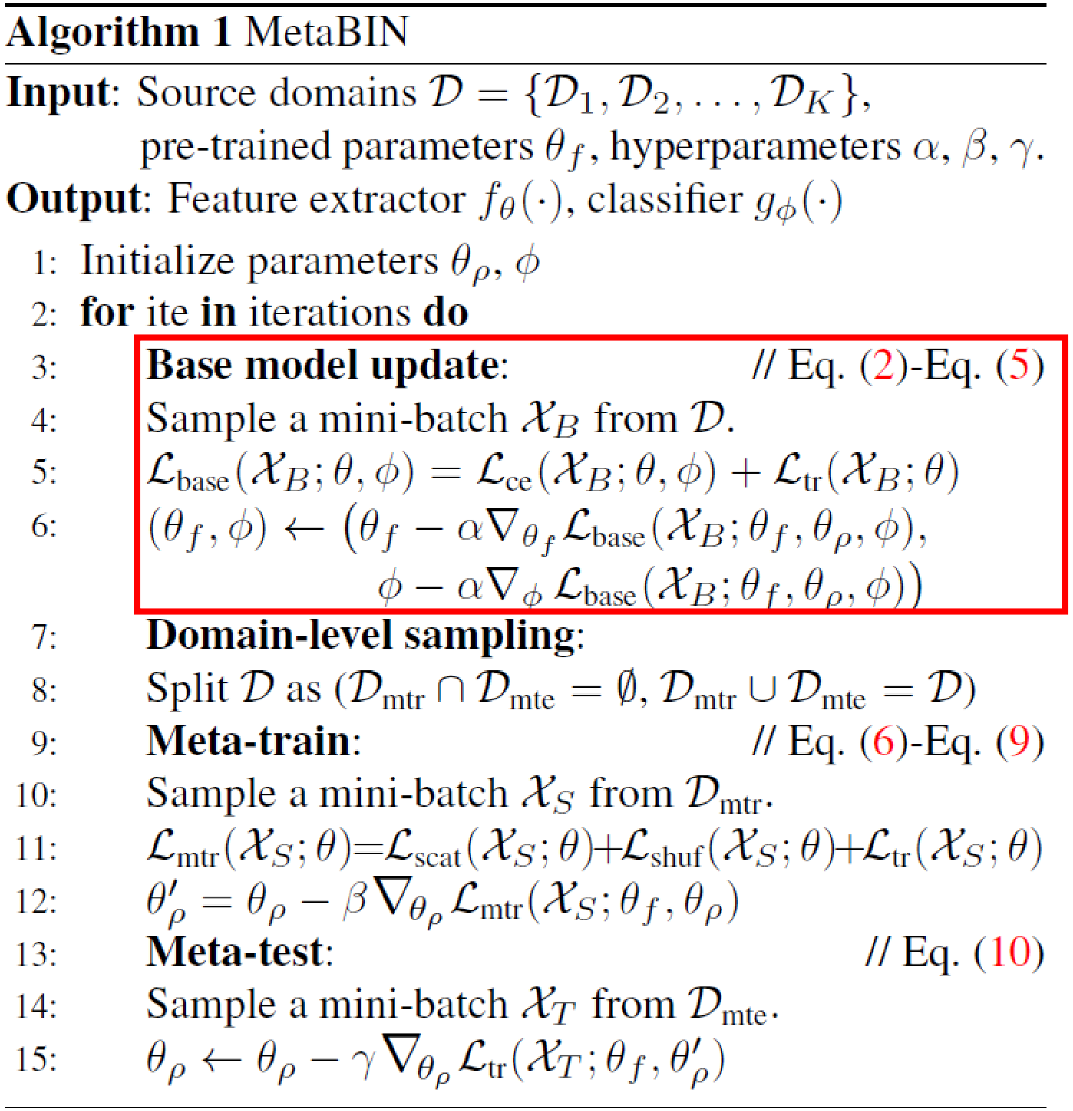
- Separate the training procedure to two episodes, then alternate both episodes.
  - Base model (Feature extractor) training.
  - Balancing parameter training.

- In the balancing parameter training, it mimics unsuccessful generalization scenarios.
  - Learn a generalization from generalization episodes.

MetaBIN Framework

- Base model update (Train a feature extractor and a classifier).
    - Utilizes cross-entropy loss and triplet loss.
    - Learn to re-identify a person.

$$\mathcal{L}_{\text{base}}(\mathcal{X}_B;\underset{\substack{\uparrow\\ \text{Feature extractor's}\\ \text{params}}}{\theta},\overset{\substack{\text{Classifier's}\\ \text{params}\\ \downarrow}}{\phi}) = \underbrace{\mathcal{L}_{\text{ce}}(\mathcal{X}_B;\theta,\phi)}_{\text{Cross-entropy loss}} + \underbrace{\mathcal{L}_{\text{tr}}(\mathcal{X}_B;\theta)}_{\text{Triplet loss}}.$$



Algorithm 1 MetaBIN

Input: Source domains $\mathcal{D}=\{\mathcal{D}_1,\mathcal{D}_2,\dots,\mathcal{D}_K\}$,
pre-trained parameters θ_f, hyperparameters α, β, γ.

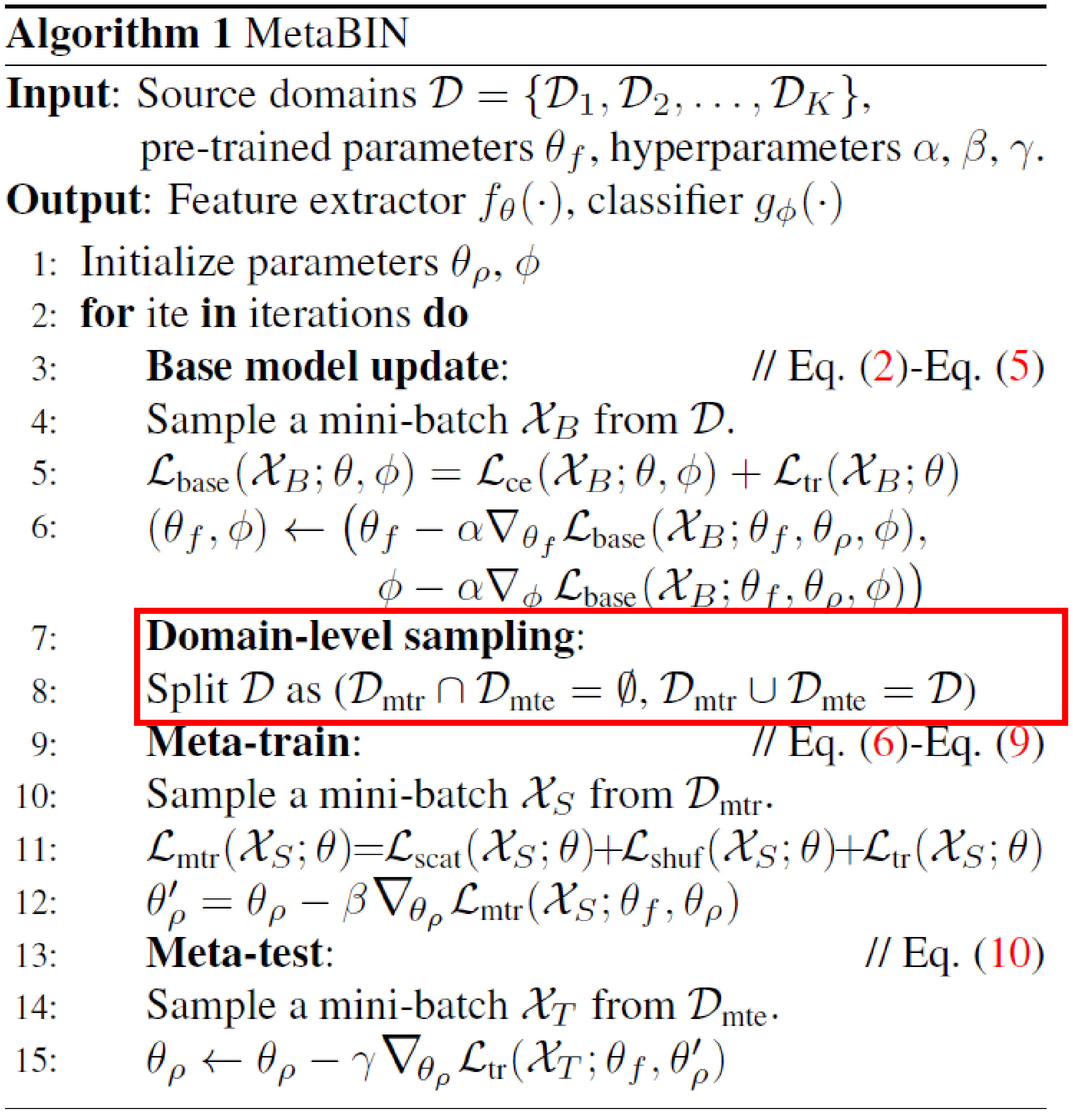
Output: Feature extractor $f_\theta(\cdot)$, classifier $g_\phi(\cdot)$

```
Initialize parameters $\theta_\rho$, $\phi$
for ite in iterations do
    Base model update:                                   // Eq. (2)-Eq. (5)
    Sample a mini-batch $\mathcal{X}_B$ from $\mathcal{D}$.
    $\mathcal{L}_{\text{base}}(\mathcal{X}_B;\theta,\phi) = \mathcal{L}_{\text{ce}}(\mathcal{X}_B;\theta,\phi) + \mathcal{L}_{\text{tr}}(\mathcal{X}_B;\theta)$
    $(\theta_f,\phi) \leftarrow (\theta_f - \alpha\nabla_{\theta_f}\mathcal{L}_{\text{base}}(\mathcal{X}_B;\theta_f,\theta_\rho,\phi),$
        $\phi - \alpha\nabla_\phi\mathcal{L}_{\text{base}}(\mathcal{X}_B;\theta_f,\theta_\rho,\phi))$
    Domain-level sampling:
    Split $\mathcal{D}$ as $(\mathcal{D}_{\text{mtr}} \cap \mathcal{D}_{\text{mte}} = \emptyset, \mathcal{D}_{\text{mtr}} \cup \mathcal{D}_{\text{mte}} = \mathcal{D})$
    Meta-train:                                          // Eq. (6)-Eq. (9)
    Sample a mini-batch $\mathcal{X}_S$ from $\mathcal{D}_{\text{mtr}}$.
    $\mathcal{L}_{\text{mtr}}(\mathcal{X}_S;\theta)=\mathcal{L}_{\text{scat}}(\mathcal{X}_S;\theta)+\mathcal{L}_{\text{shuf}}(\mathcal{X}_S;\theta)+\mathcal{L}_{\text{tr}}(\mathcal{X}_S;\theta)$
    $\theta'_\rho = \theta_\rho - \beta\nabla_{\theta_\rho}\mathcal{L}_{\text{mtr}}(\mathcal{X}_S;\theta_f,\theta_\rho)$
    Meta-test:                                           // Eq. (10)
    Sample a mini-batch $\mathcal{X}_T$ from $\mathcal{D}_{\text{mte}}$.
    $\theta_\rho \leftarrow \theta_\rho - \gamma\nabla_{\theta_\rho}\mathcal{L}_{\text{tr}}(\mathcal{X}_T;\theta_f,\theta'_\rho)$
```

MetaBIN Framework

- Domain-level sampling
- Split the given domains to
  - meta-train domains $\mathcal{D}_{mtr}$.
  - meta-test domains $\mathcal{D}_{mte}$.

- Now, we can mimic a domain generalization scenario!
  - Train on $\mathcal{D}_{mtr}$, then generalize to $\mathcal{D}_{mte}$.



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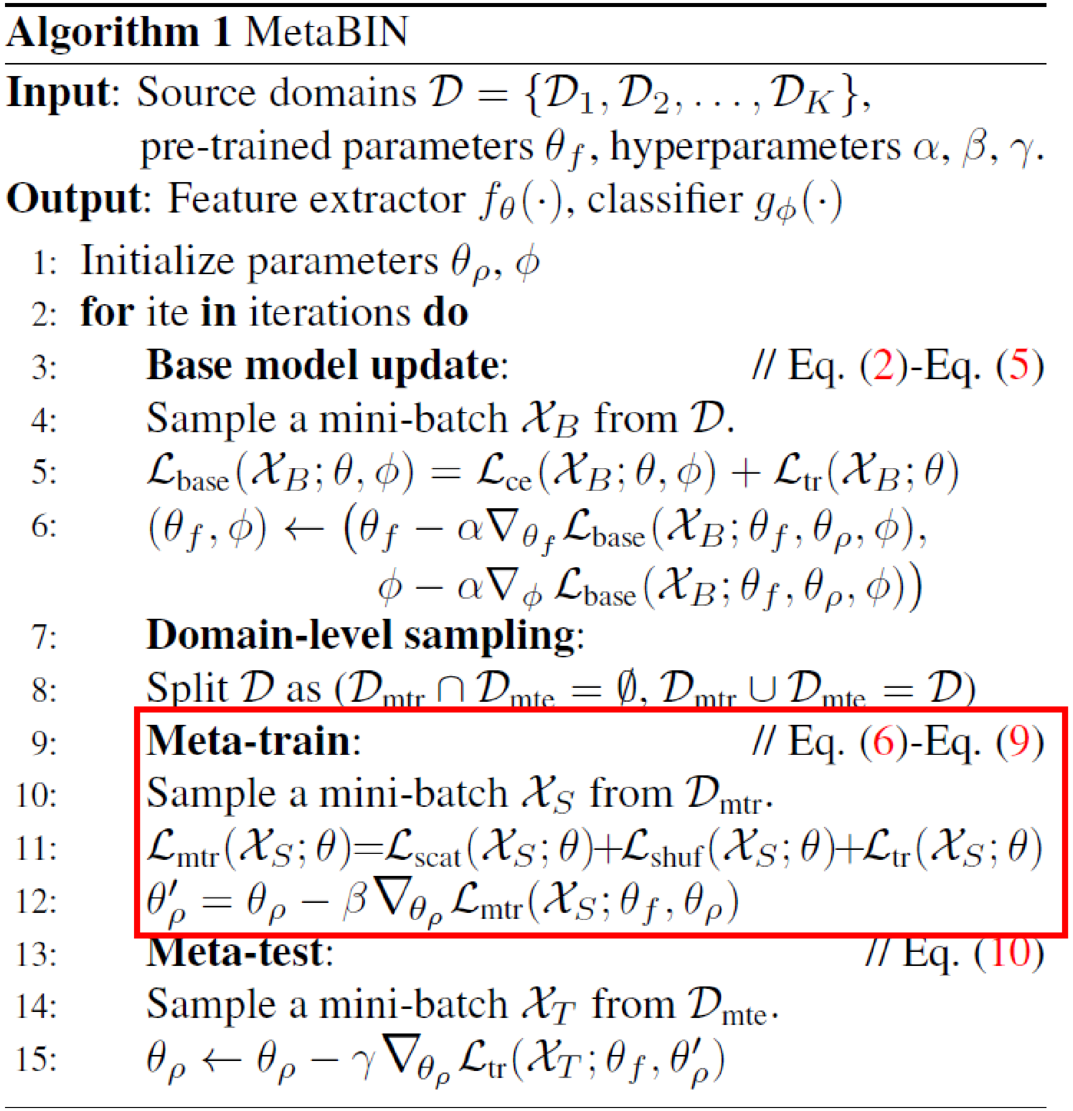

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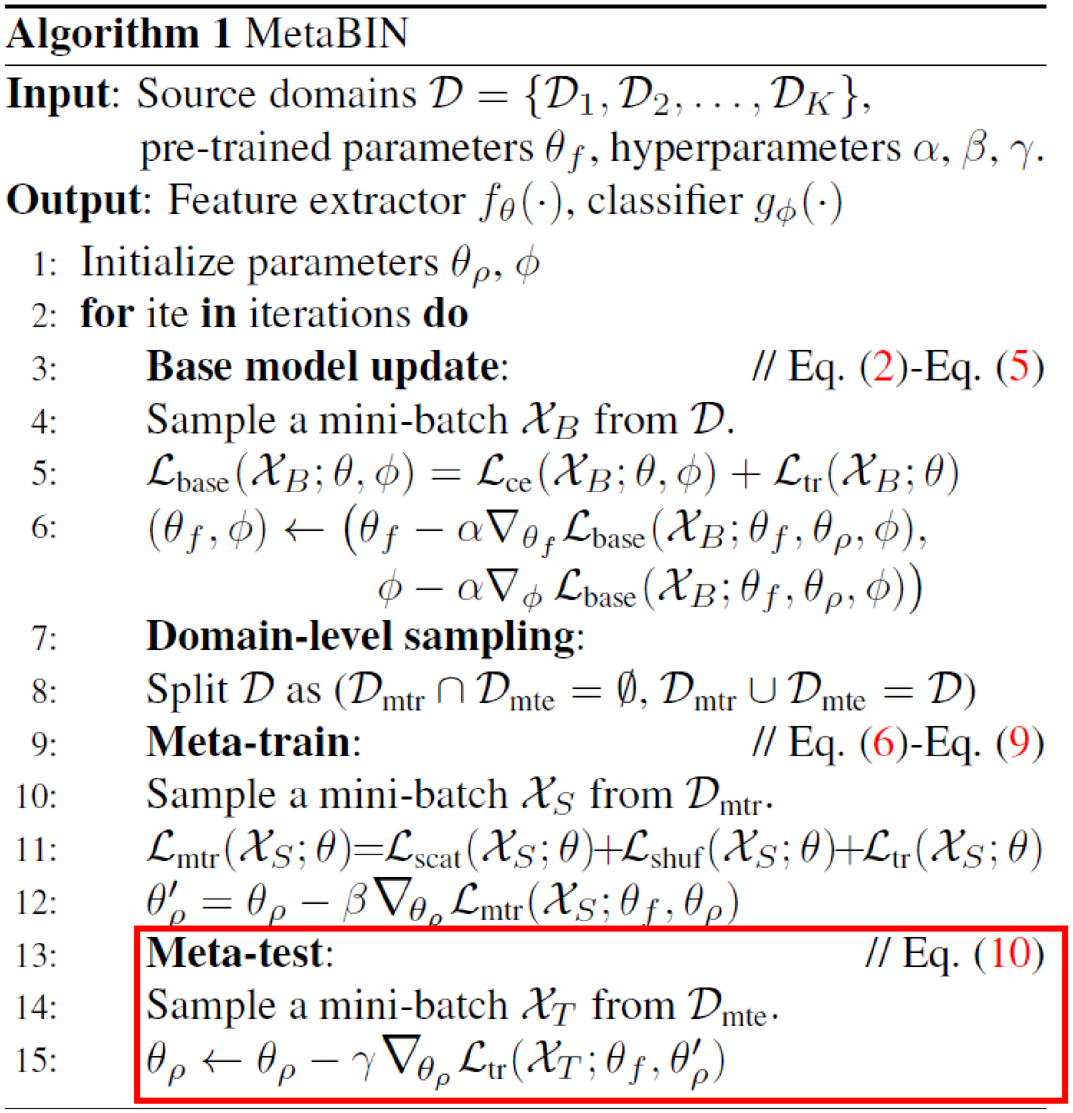

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```

Meta-train stage

- In this stage, MetaBIN **trains the balancing parameter ρ to mimic unsuccessful generalization scenarios.**
- Unsuccessful generalization scenarios = under- or over-style-normalization

- To make under-&over-style-normalization, the paper proposes the meta-train loss.

$$\mathcal{L}_{\mathrm{mtr}}(\mathcal{X}_S;\theta) = \underbrace{\mathcal{L}_{\mathrm{scat}}(\mathcal{X}_S;\theta)+\mathcal{L}_{\mathrm{shuf}}(\mathcal{X}_S;\theta)}_{\text{for over-style-normalization}}+\underbrace{\mathcal{L}_{\mathrm{tr}}(\mathcal{X}_S;\theta)}_{\text{for under-style-normalization}}.$$

K_S : number of domains in a mini-batch
N_S^k : number of samples in domain k
N_S : number of samples in a mini-batch

Meta-train stage (over-style-normalization)

- Intra-domain scatter loss: ***Each feature should be far from its own domain's centroid feature.***

$$\mathcal{L}_{\text{scat}}(\mathcal{X}_S;\theta) = \frac{1}{N_S}\sum_{k=1}^{K_S}\sum_{i=1}^{N_S^k} cos(\boldsymbol{f}_i^k, \bar{\boldsymbol{f}}^k)$$

mean feature vector
(centroid)

- Inter-domain shuffle loss: ***Inter-domain features should be closer than intra-domain features.***

$$\mathcal{L}_{\text{shuf}}(\mathcal{X}_S;\theta) = \frac{1}{N_S}\sum_{i=1}^{N_S} l_s\big(d(\boldsymbol{f}_i^a, \boldsymbol{f}_i^{n-}) - d(\boldsymbol{f}_i^a, \boldsymbol{f}_i^{n+})\big)$$

negative sample
from the inter-domain

negative sample
from the intra-domain

K_S : number of domains in a mini-batch
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Meta-train stage (over-style-normalization)

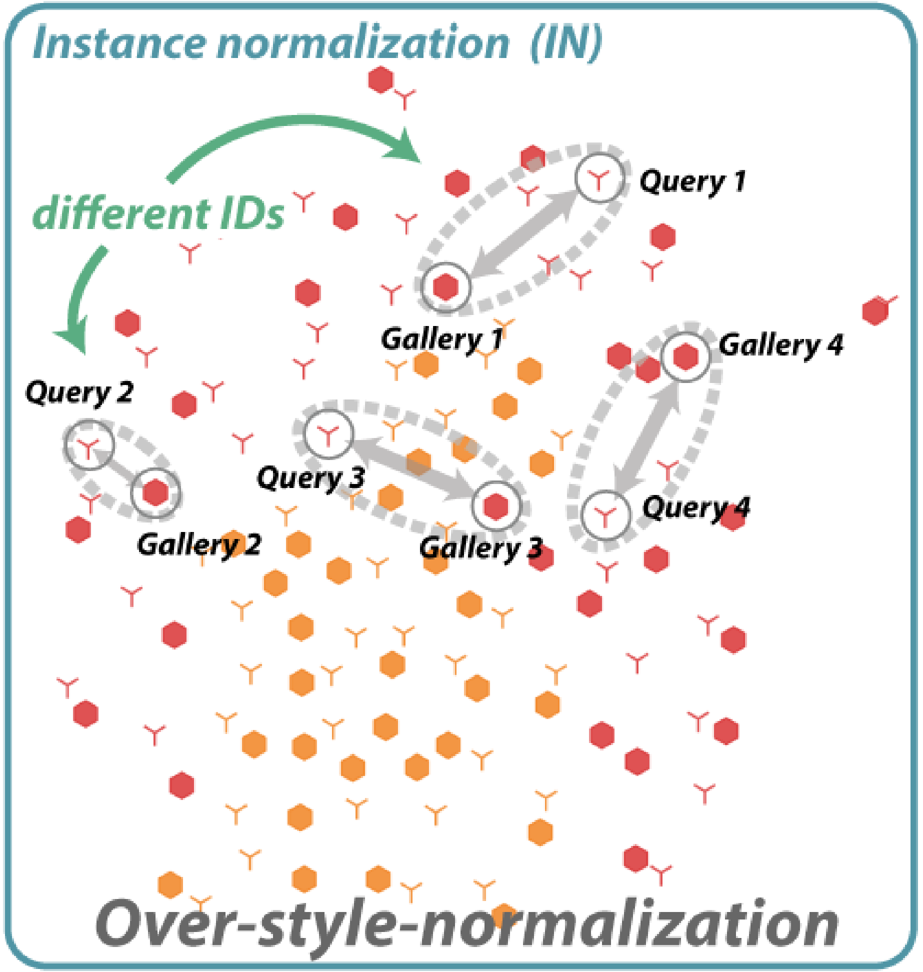
- Intra-domain scatter los *wn domain's centroid* ***feature.***

$\mathcal{L}_{\mathrm{sc}}$

ctor

- Inter-domain shuffle los ***er than intra-domain features.***

$\mathcal{L}_{\mathrm{shuf}}(\mathcal{X}_S$ $f_i^{n+}))$



negative sample
om the intra-domain

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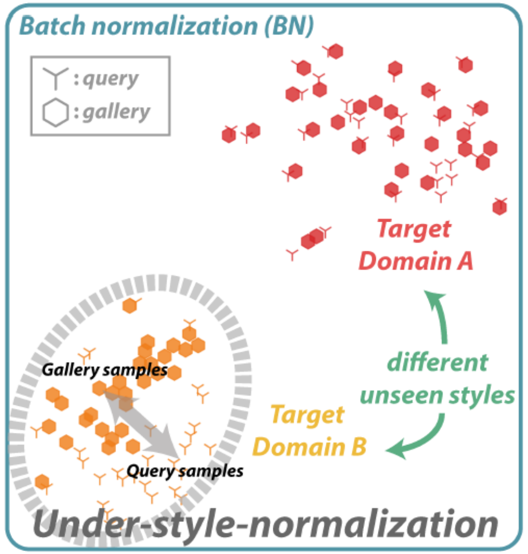
Meta-train stage (under-style-normalization)

- Triplet loss for under-style-normalization
  - It leads to overfitting to the styles of the meta-train domains $\mathcal{D}_{mtr}$.



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$$\theta'_\rho = \theta_\rho - \beta \nabla_{\theta_\rho} \mathcal{L}_{\text{mtr}}(\mathcal{X}_S;\theta_f,\theta_\rho)$$ Update the balancing parameter!

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Meta-test stage

- In this stage, MetaBIN mimics a domain generalization scenario.
    - Evaluate the model with updated balancing parameter on meta-test domains $\mathcal{D}_{mte}$.
    - Employ the triplet loss on a mini-batch X_T from meta-test domains $\mathcal{D}_{mte}$.

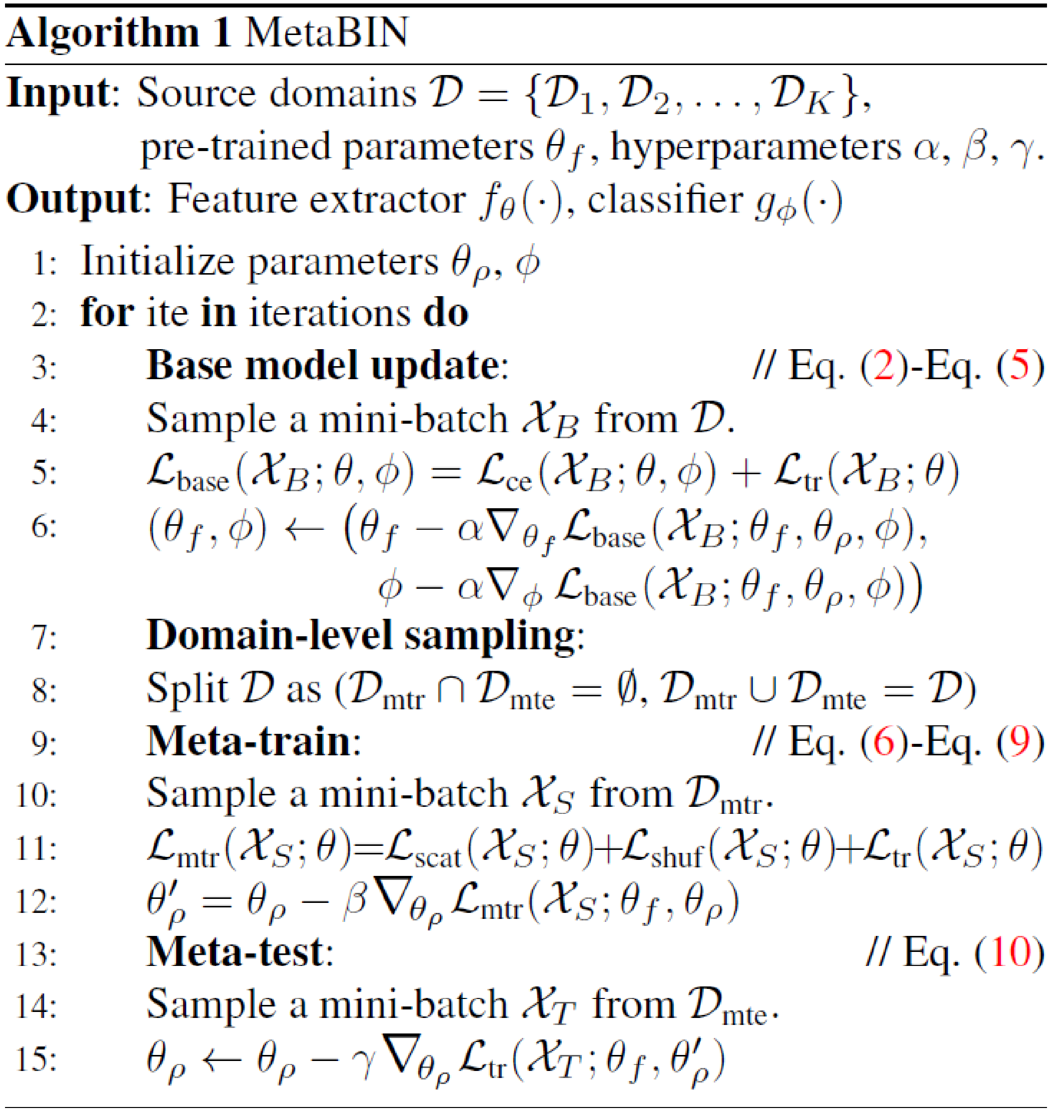
$$\theta_\rho \leftarrow \theta_\rho - \gamma \nabla_{\theta_\rho} \mathcal{L}_{\mathrm{tr}}(\mathcal{X}_T; \theta_f, \underset{\uparrow}{\theta'_\rho})$$

Updated parameter by meta-train stage

- Meta-update the balancing parameter to overcome the virtual simulations.
    - Learn a generalization from unsuccessful generalization scenarios!

Summary

- MetaBIN learns the balancing parameter of BIN in a meta-learning manner.
- It mimics unsuccessful generalization scenarios in a meta-learning manner.
- It proposes a meta-train loss to induce over-/under- style-normalization.
  - Meta-train loss collapses the balancing parameter.



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    $\theta'_\rho = \theta_\rho - \beta \nabla_{\theta_\rho} \mathcal{L}_{\text{mtr}}(\mathcal{X}_S; \theta_f, \theta_\rho)$
    Meta-test:                                                  // Eq. (10)
    Sample a mini-batch $\mathcal{X}_T$ from $\mathcal{D}_{\text{mte}}$.
    $\theta_\rho \leftarrow \theta_\rho - \gamma \nabla_{\theta_\rho} \mathcal{L}_{\text{tr}}(\mathcal{X}_T; \theta_f, \theta'_\rho)$
```
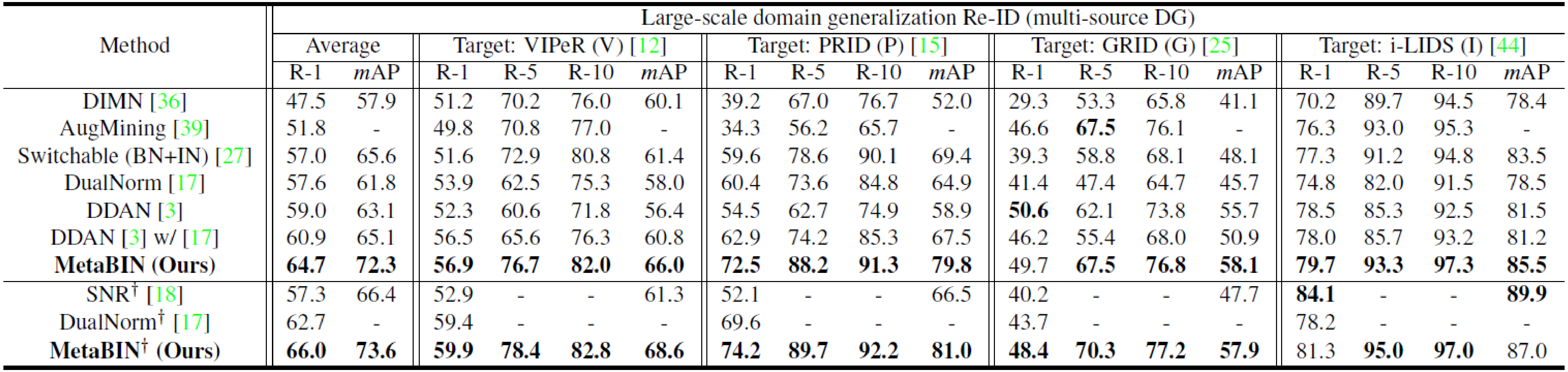

Experiments

Comparison with SOTAs

- Multi-source domain generalization
  - Learn from multiple domains, then generalize to the other single domain.

Table 1. Performance (%) comparison with the state-of-the-arts on the large-scale DG Re-ID benchmark, where '†' is based on ResNet-50.



Method	Large-scale domain generalization Re-ID (multi-source DG)																	
	Average		Target: VIPeR (V) [12]				Target: PRID (P) [15]				Target: GRID (G) [25]				Target: i-LIDS (I) [44]			
	R-1	*m*AP	R-1	R-5	R-10	*m*AP	R-1	R-5	R-10	*m*AP	R-1	R-5	R-10	*m*AP	R-1	R-5	R-10	*m*AP
DIMN [36]	47.5	57.9	51.2	70.2	76.0	60.1	39.2	67.0	76.7	52.0	29.3	53.3	65.8	41.1	70.2	89.7	94.5	78.4
AugMining [39]	51.8	-	49.8	70.8	77.0	-	34.3	56.2	65.7	-	46.6	**67.5**	76.1	-	76.3	93.0	95.3	-
Switchable (BN+IN) [27]	57.0	65.6	51.6	72.9	80.8	61.4	59.6	78.6	90.1	69.4	39.3	58.8	68.1	48.1	77.3	91.2	94.8	83.5
DualNorm [17]	57.6	61.8	53.9	62.5	75.3	58.0	60.4	73.6	84.8	64.9	41.4	47.4	64.7	45.7	74.8	82.0	91.5	78.5
DDAN [3]	59.0	63.1	52.3	60.6	71.8	56.4	54.5	62.7	74.9	58.9	**50.6**	62.1	73.8	55.7	78.5	85.3	92.5	81.5
DDAN [3] w/ [17]	60.9	65.1	56.5	65.6	76.3	60.8	62.9	74.2	85.3	67.5	46.2	55.4	68.0	50.9	78.0	85.7	93.2	81.2
MetaBIN (Ours)	**64.7**	**72.3**	**56.9**	**76.7**	**82.0**	**66.0**	**72.5**	**88.2**	**91.3**	**79.8**	49.7	**67.5**	**76.8**	**58.1**	**79.7**	**93.3**	**97.3**	**85.5**
SNR† [18]	57.3	66.4	52.9	-	-	61.3	52.1	-	-	66.5	40.2	-	-	47.7	**84.1**	-	-	**89.9**
DualNorm† [17]	62.7	-	59.4	-	-	-	69.6	-	-	-	43.7	-	-	-	78.2	-	-	-
MetaBIN† (Ours)	**66.0**	**73.6**	**59.9**	**78.4**	**82.8**	**68.6**	**74.2**	**89.7**	**92.2**	**81.0**	**48.4**	**70.3**	**77.2**	**57.9**	81.3	**95.0**	**97.0**	87.0

Comparison with SOTAs

- Cross-domain generalization
  - Learn from single domains, then generalize to the other single domain.

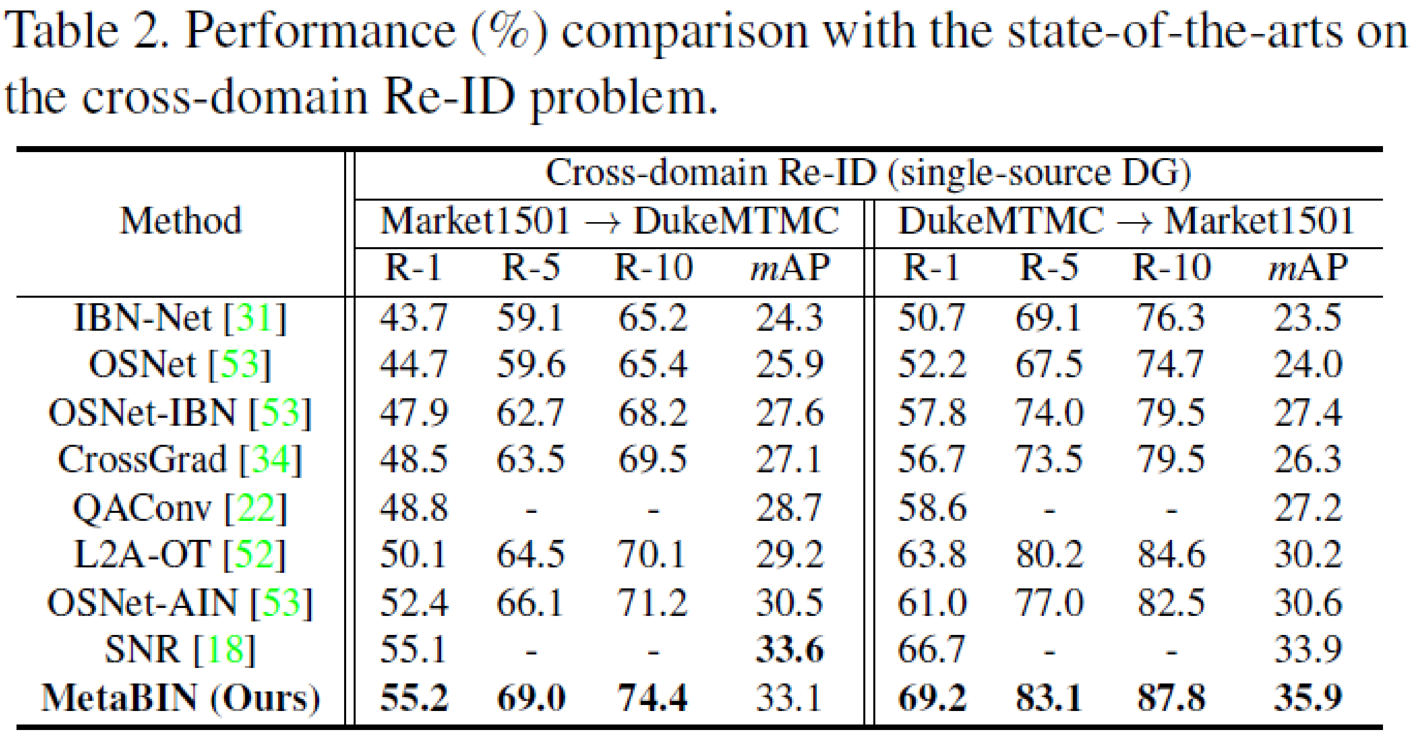


Table 2. Performance (%) comparison with the state-of-the-arts on the cross-domain Re-ID problem.

Method	Cross-domain Re-ID (single-source DG)							
	Market1501 → DukeMTMC				DukeMTMC → Market1501			
	R-1	R-5	R-10	*m*AP	R-1	R-5	R-10	*m*AP
IBN-Net [31]	43.7	59.1	65.2	24.3	50.7	69.1	76.3	23.5
OSNet [53]	44.7	59.6	65.4	25.9	52.2	67.5	74.7	24.0
OSNet-IBN [53]	47.9	62.7	68.2	27.6	57.8	74.0	79.5	27.4
CrossGrad [34]	48.5	63.5	69.5	27.1	56.7	73.5	79.5	26.3
QAConv [22]	48.8	-	-	28.7	58.6	-	-	27.2
L2A-OT [52]	50.1	64.5	70.1	29.2	63.8	80.2	84.6	30.2
OSNet-AIN [53]	52.4	66.1	71.2	30.5	61.0	77.0	82.5	30.6
SNR [18]	55.1	-	-	**33.6**	66.7	-	-	33.9
MetaBIN (Ours)	**55.2**	**69.0**	**74.4**	33.1	**69.2**	**83.1**	**87.8**	**35.9**

Ablation Study

- Meta-learning pipeline is matter.

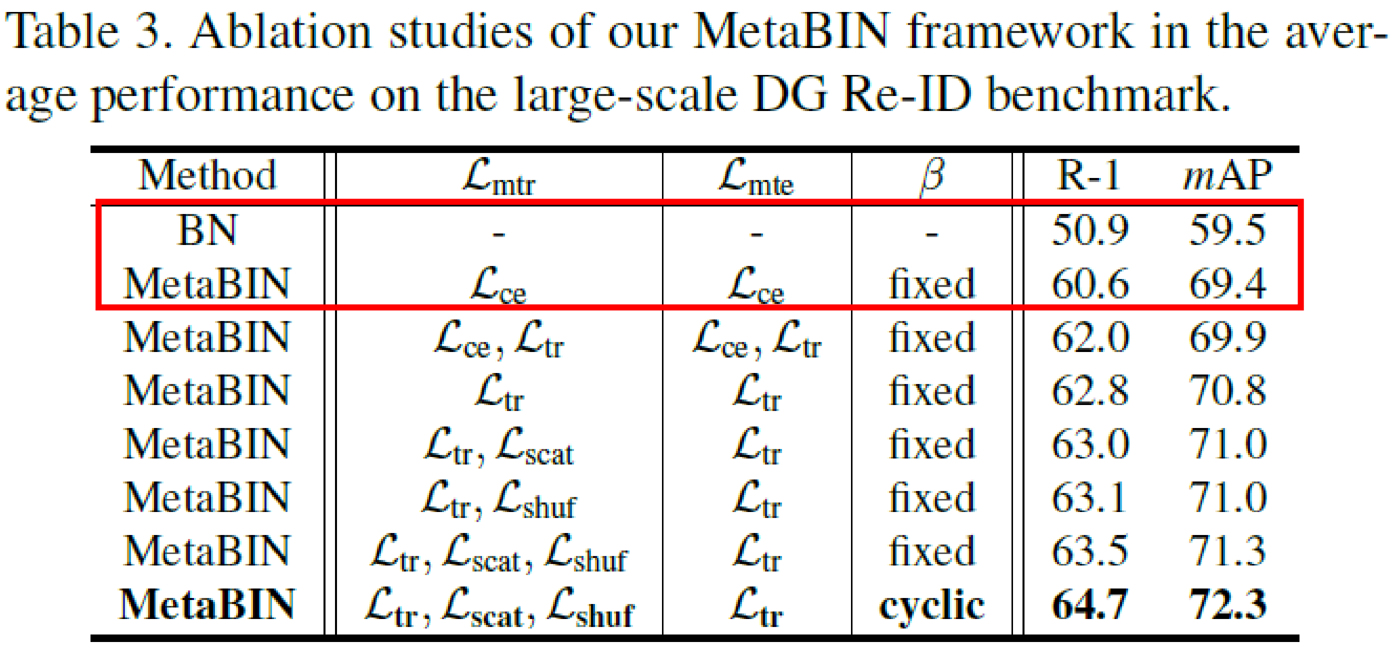
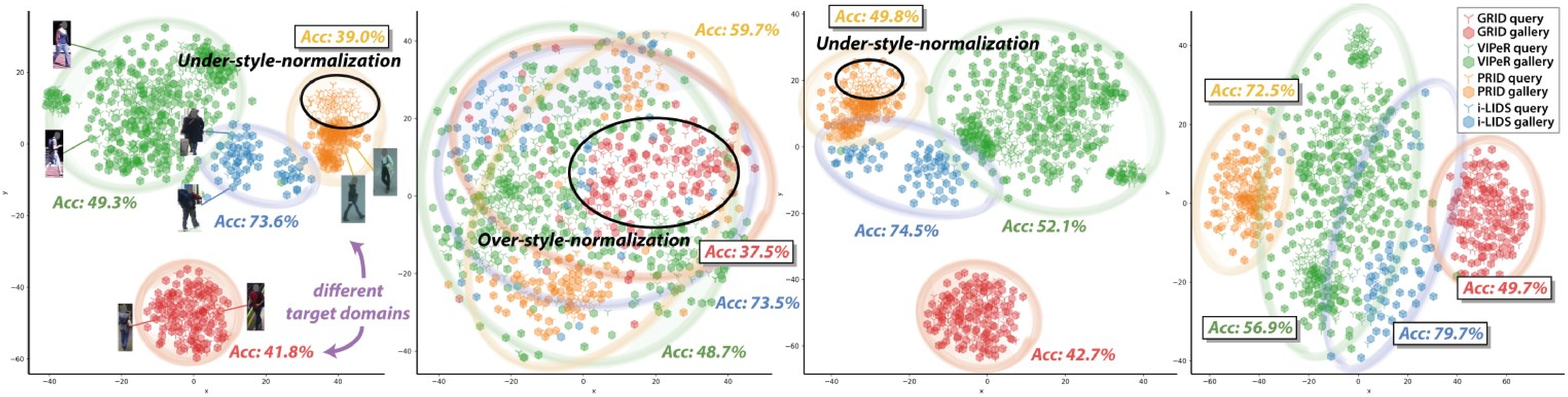


Table 3. Ablation studies of our MetaBIN framework in the average performance on the large-scale DG Re-ID benchmark.

Method	$\mathcal{L}_{\text{mtr}}$	$\mathcal{L}_{\text{mte}}$	β	R-1	mAP
BN	-	-	-	50.9	59.5
MetaBIN	$\mathcal{L}_{\text{ce}}$	$\mathcal{L}_{\text{ce}}$	fixed	60.6	69.4
MetaBIN	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	fixed	62.0	69.9
MetaBIN	$\mathcal{L}_{\text{tr}}$	$\mathcal{L}_{\text{tr}}$	fixed	62.8	70.8
MetaBIN	$\mathcal{L}_{\text{tr}}, \mathcal{L}_{\text{scat}}$	$\mathcal{L}_{\text{tr}}$	fixed	63.0	71.0
MetaBIN	$\mathcal{L}_{\text{tr}}, \mathcal{L}_{\text{shuf}}$	$\mathcal{L}_{\text{tr}}$	fixed	63.1	71.0
MetaBIN	$\mathcal{L}_{\text{tr}}, \mathcal{L}_{\text{scat}}, \mathcal{L}_{\text{shuf}}$	$\mathcal{L}_{\text{tr}}$	fixed	63.5	71.3
MetaBIN	$\mathcal{L}_{\text{tr}}, \mathcal{L}_{\text{scat}}, \mathcal{L}_{\text{shuf}}$	$\mathcal{L}_{\text{tr}}$	**cyclic**	**64.7**	**72.3**

T-SNE Visualization

- BN, BIN: under-style-normalization.
- IN: over-style-normalization.



(a) Batch Normalization (BN) (b) Instance Normalization (IN) (c) Batch-Instance Normalization (BIN) (d) MetaBIN (Ours)

Conclusion

- The paper proposes MetaBIN that improve the model generalization ability by unsuccessful generalization scenarios in a meta-learning manner.

- Pros
    - Nice observation (over-/under-style-normalization) to motivates the proposed method.
    - Intuitive method to overcome their observation.
    - Extensive experimental results (e.g., visualization, a lot of ablation study) & analysis.
- Cons
    - The proposed method is quite complex.
    - Too many hyperparameters (e.g., there are three learning rate).

Thank you for listening!

Appendix

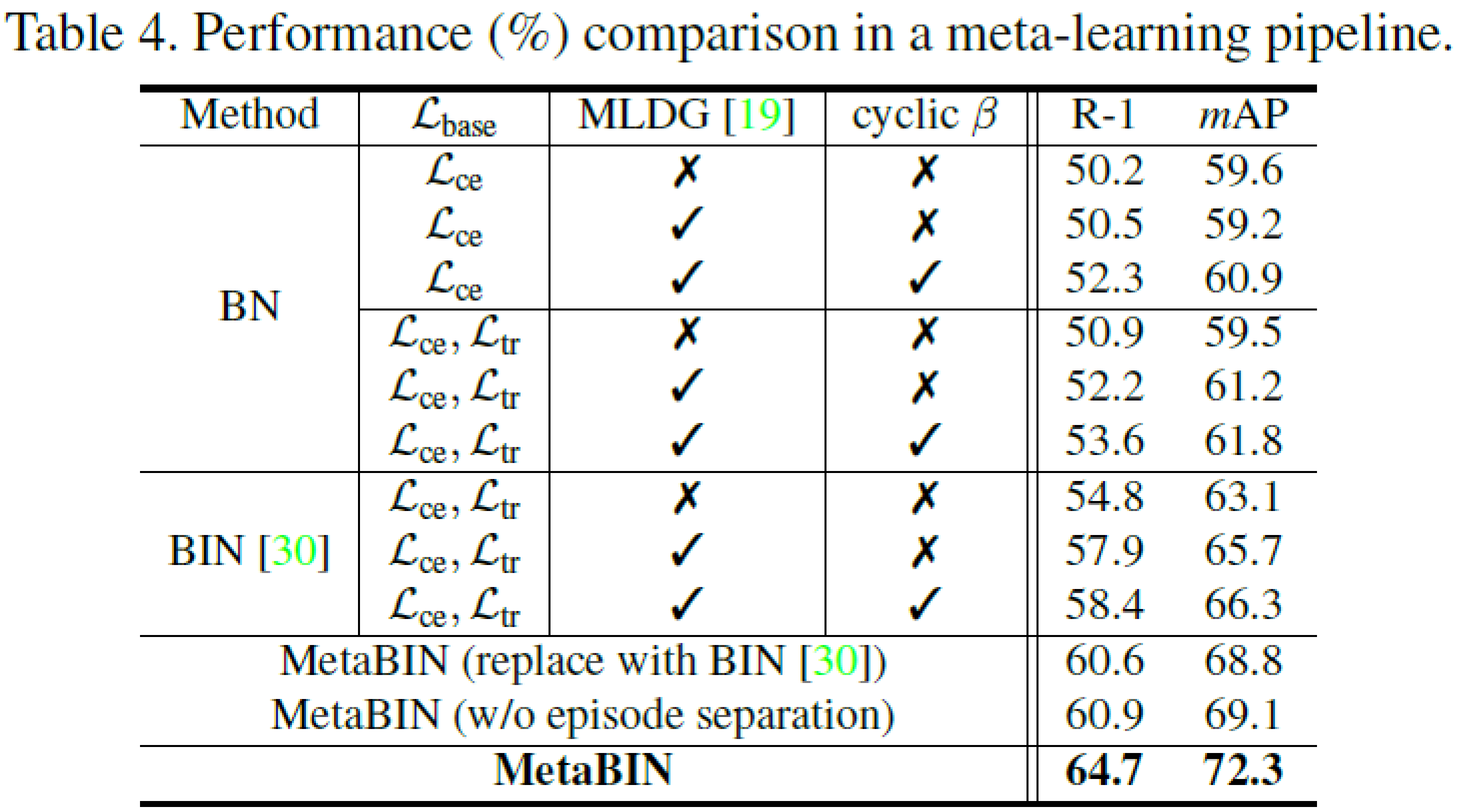


Table 4. Performance (%) comparison in a meta-learning pipeline.

Method	$\mathcal{L}_{\text{base}}$	MLDG [19]	cyclic β	R-1	*m*AP
BN	$\mathcal{L}_{\text{ce}}$	✗	✗	50.2	59.6
	$\mathcal{L}_{\text{ce}}$	✓	✗	50.5	59.2
	$\mathcal{L}_{\text{ce}}$	✓	✓	52.3	60.9
	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	✗	✗	50.9	59.5
	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	✓	✗	52.2	61.2
	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	✓	✓	53.6	61.8
BIN [30]	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	✗	✗	54.8	63.1
	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	✓	✗	57.9	65.7
	$\mathcal{L}_{\text{ce}}, \mathcal{L}_{\text{tr}}$	✓	✓	58.4	66.3
MetaBIN (replace with BIN [30])				60.6	68.8
MetaBIN (w/o episode separation)				60.9	69.1
MetaBIN				**64.7**	**72.3**

Appendix

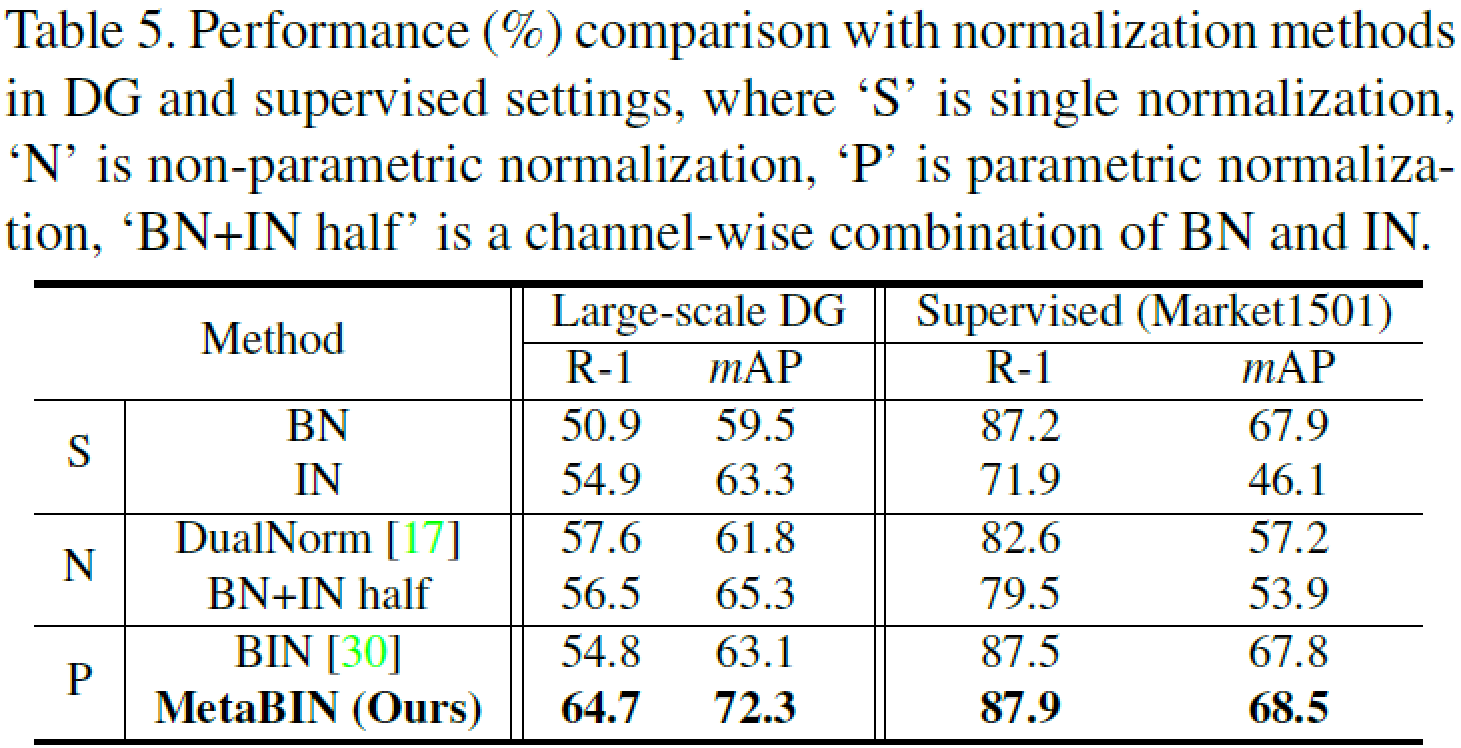


Table 5. Performance (%) comparison with normalization methods in DG and supervised settings, where 'S' is single normalization, 'N' is non-parametric normalization, 'P' is parametric normalization, 'BN+IN half' is a channel-wise combination of BN and IN.

Method		Large-scale DG		Supervised (Market1501)	
		R-1	*m*AP	R-1	*m*AP
S	BN	50.9	59.5	87.2	67.9
	IN	54.9	63.3	71.9	46.1
N	DualNorm [17]	57.6	61.8	82.6	57.2
	BN+IN half	56.5	65.3	79.5	53.9
P	BIN [30]	54.8	63.1	87.5	67.8
	MetaBIN (Ours)	**64.7**	**72.3**	**87.9**	**68.5**