# Normalization Perturbation: A Simple Domain Generalization Method for Real-World Domain Shifts

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#### **Abstract**

Improving model's generalizability against domain shifts is crucial, especially for safety-critical applications such as autonomous driving. Real-world domain styles can vary substantially due to environment changes and sensor noises, but deep models only know the training domain style. Such domain style gap impedes model generalization on diverse real-world domains. Our proposed Normalization Perturbation (NP) can effectively overcome this domain style overfitting problem. We observe that this problem is mainly caused by the biased distribution of low-level features learned in shallow CNN layers. Thus, we propose to perturb the channel statistics of source domain features to synthesize various latent styles, so that the trained deep model can perceive diverse potential domains and generalizes well even without observations of target domain data in training. We further explore the style-sensitive channels for effective style synthesis. Normalization Perturbation only relies on a single source domain and is surprisingly effective and extremely easy to implement. Extensive experiments verify the effectiveness of our method for generalizing models under real-world domain shifts.

#### 1 Introduction

Deep learning has made great progress on in-domain data [1, 2], but its performance usually degrades under domain shifts [3, 4], where the testing (target) data differ from the training (source) data. Real-world domain shifts are usually brought by environment changes, such as different weather and time conditions, attributed by diverse contrast, brightness, texture, etc. Trained models usually overfit to the source domain style and generalize poorly in other domains, posing serious problems in challenging real-world usage such as autonomous driving. Domain generalization (DG) [5, 6, 7, 8], as well as unsupervised domain adaptation (UDA) methods [9, 10, 11], aims to solve this hard and significant problem.

Deep models do not generalize well to unseen domains because they only know the training domain style. Figure 1(b) shows a large gap of feature channel statistics between two distinct domains: Cityscapes [12] and Foggy Cityscapes [3], especially in shallow CNN layers which preserve more style information. Deep models trained on the source domain cannot generalize well on the target domain, due to the discrepancy in feature channel statistics caused by the domain style overfitting.

Ideally, if a model can perceive a large variety of potential domains during training, it can learn domain-invariant representations and generalizes well. However, it is expensive and even impossible

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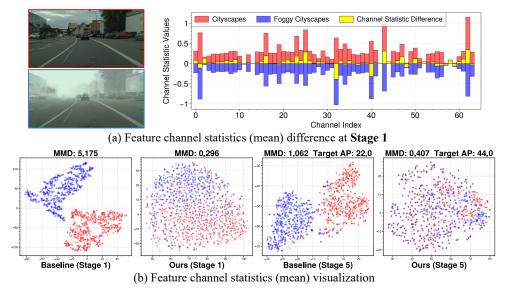


Figure 1: Visualizations for feature channel statistics on Cityscapes (source domain, red) and Foggy Cityscapes (target domain, blue). (a) For two domain images with the same content but different styles, we show their feature channel statistics and differences on the pretrained backbone at stage 1. The statistic values of the Foggy Cityscapes image are converted to negative for better visualization. The feature channel statistics of the target domain image deviate around the source domain statistics. (b) The t-SNE [19] visualization for the feature channel statistics on different stages. The model is trained on the source domain and evaluated on both domains. The distance between two domains is computed by Maximum Mean Discrepancy [20] (MMD). After equipping Normalization Perturbation (NP) in shallow CNN layers, our model can effectively blend distinct domain style distributions. The target domain distribution can be properly covered by the perturbed source domain distribution in the deep CNN layers. Thus our model generalizes much better on the target domain.

to collect data for all possible domains. Synthesizing new domains is a feasible solution. But existing domain synthesis methods still require diverse style sources and can only generalize well to limited domain styles. The image generation based synthesis approach [13, 14, 15] is powerful but inefficient. The feature-level synthesis approach [16, 17, 18] is efficient but relies on multiple source domains and the synthesized styles are limited. In this paper, we propose a novel domain style synthesis approach with high efficiency and effectiveness for real-world DG.

Figure 1(a) shows our motivation: feature channel statistics of the target domain image deviate around the source domain statistics. Thus by perturbing the feature channel statistics of source domain images in the shallow CNN layers, we can effectively synthesize new domains. The perturbed feature statistics correspond to various latent domain styles, so that the trained model perceives diverse potential domains accordingly. Such perturbation enables deep models to learn domain-invariant representations where distinct domains can be effectively blended together in the learned feature space. To further boost the performance, we have also explored the style-sensitive channels for effective domain style synthesis. Figure 1(b)<sup>2</sup> shows the distinct domains can be effectively blended by the perturbed channel statistics in shallow CNN layers. The learned deep CNN representations are thus more robust to the variations of different domain styles and generalize well on the target domain. Note that the model is only trained using a single source domain data without any access to the target domain style or data.

Our method normalizes features into different scales, thus called as Normalization Perturbation (NP). Our NP is surprisingly effective and extremely easy to implement. Our NP generalizes well under various real-world domain shifts and outperforms previous DG and UDA methods on multiple dense prediction tasks. Besides, our method does not change the model architecture, does not require any extra input, learnable parameters or loss. In fact, nothing needs to be changed, except that we

<sup>&</sup>lt;sup>2</sup>For all t-SNE visualizations in this paper, the features from multiple models are mapped jointly into a unified space but are separately visualized for clarity.

perform feature channel statistics perturbation on shallow layers during training for synthesizing diverse potential styles from source domain itself. In summary, our contributions are:

- We investigate the real-world domain shifts and observe that the domain overfitting problem is mainly derived from the biased feature distribution in low-level layers.
- We propose to perturb the channel statistics of source domain features to synthesize various new domain styles, which enables a model to learn domain-variant representations for good domain generalization.
- Our method generalizes surprisingly well under various real-world domain shifts and is extremely easy to implement, without any extra input, learnable parameters or loss. Extensive experiments verify the effectiveness of our method.

#### 2 Related Works

Domain Generalization (DG) [21, 22, 23, 24, 25, 26], which targets at generalizing models to unseen domains, relies on source data typically consisting of multiple distinct domains. DG has been mainly studied in the context of object recognition task [27, 28, 29, 30, 31, 32, 33, 34]. DG of dense prediction tasks [35, 36, 37, 38, 39, 40, 41, 42] has attracted increasing interests because of its wide real-world applications. The closely related unsupervised domain adaptation (UDA) [43, 44, 45, 46, 47, 48, 49] has been widely studied on dense prediction tasks [50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63] for real-world applications, which aims to generalize model to the target domain by accessing its unlabeled images. Both DG and UDA share significant overlap in technicalities, such as domain alignment [64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75], self-supervised learning [76, 77, 78, 79, 80, 81, 82], feature disentanglement [23, 83, 84, 85, 86, 87, 88, 89], and data augmentation [90, 91, 92, 93, 94, 95, 96, 97, 98]. Our method closely relates to the following works.

Normalization-based Methods. The normalization layers are leveraged to improve model generalization ability. Various normalization variants have been proposed, such as domain-specific Batch-Norm [99, 100, 101, 102], AdaBN [103], PreciseBN [104], Instance-Batch Normalization [105, 106], Adversarially Adaptive Normalization [107], Switchable Normalization [108], and Semantic Aware Normalization [109]. The test-time adaptation [110, 111, 112, 113, 114, 115, 115, 116] attempts to estimate accurate normalization statistics for the target domain during testing. These methods fit normalization layers to the specific target domains, while our method normalizes features into different scales to implicitly synthesize arbitrary new domains, and is optimization-free.

**Synthesizing New Domains.** Data augmentation [36, 90, 117, 118, 119] has been widely used to synthesize new domains in DG and UDA. Some methods synthesize new domain images using image-to-image translation models, such as the random [91] or learnable augmentation networks [14, 120, 121, 122], and style transfer models [34, 94, 92, 93]. Other works propose to perform implicit domain synthesis through the feature-level augmentation [16, 17, 18, 123, 124, 15] to mix CNN feature statistics of distinct domains to significantly improve the domain synthesis efficiency.

The above methods rely on image generation or multiple source domains for new domain synthesis, and thus the efficiency or effectiveness is limited. On the other hand, our method only relies on a single source domain to diversify by perturbing the feature channel statistics to produce various latent domain styles.

While SFA [125] performs the activation-wise feature perturbation, which may destroy meaningful image contents, our method performs the channel-wise feature statistics perturbation and keeps the image contents unchanged. Note that A-FAN [126] and FSR [127] also perform feature statistics perturbation. But A-FAN [126] relies on specially designed adversarial loss, with the hyperparameters requiring case-by-case tuning. The FSR [127] needs a learnable network to produce diverse styles. Their effectiveness is also unknown for dense prediction tasks under real-world domain shifts. In contrast, our method is extremely simple while surprisingly effective for the real-world applications.

#### 3 Problem Analysis

We conduct empirical studies to demonstrate the real-world domain shift problem, so as to motivate our Normalization Perturbation method on the robust object detection task. The model is trained on the source domain Cityscapes [12] train set and directly evaluated on Cityscapes and two unseen target domains Foggy Cityscapes [3] and BDD100k [128] validation sets. We use the Faster R-CNN [2]

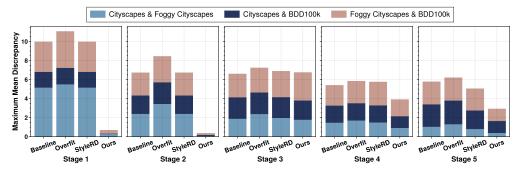


Figure 2: Accumulated Maximum Mean Discrepancy (MMD) for the feature channel statistics of different dataset pairs. Four models are evaluated on different convolutional stages. The smaller MMD means smaller feature-level domain/style gap among datasets.

Table 1: Four Faster R-CNN models with different settings. They are all trained on Cityscapes train set and evaluated on Cityscapes (C), Foggy Cityscapes (F) and BDD100k (B) val sets.

Method	Description	С	F	В
Baseline	The Stage1-2 layers are frozen.	58.1	22.0	21.8
Overfit	The Baseline with no frozen layers.	59.5	16.3	20.5
${ t StyleRD}$	The Baseline trained with the style randomization.	51.9	30.4	26.0
Ours	The Baseline trained with our Normalization Perturbation.	58.7	44.0	30.1

model (with ImageNet [129]-pretrained ResNet-50 [130] backbone) as the baseline. In our analysis experiments, the shallow CNN layers (stage 1 and 2) and all BatchNorm parameters are frozen<sup>3</sup> by default following the common object detection practice. Such setting applies to all object detection experiments. The detection performance is evaluated using the mean average precision (mAP) metric with the threshold of 0.5. Refer to the supplementary material for full experimental details.

Table 1 shows four Faster R-CNN models used for analysis and their performance on three datasets.

**Biased Model Impedes Domain Generalization.** With training data under the same domain style, the learned model performs well in testing for data under the same distribution as the training data, with ability of grouping in-domain features together. But the learned model tends to separate distinct domains and thus hardly generalizes from the source to target domain. Figure 1 shows image feature channel statistics of the same domain are grouped together, while different domains are separated. Figure 2 and Table 1 show that the biased distribution in the Baseline and Overfit models causes large domain feature statistic discrepancy which impedes model generalization to unseen domains.

Shallow CNN Features Matter for Generalization. Figure 1 and Figure 2 show that shallow CNN layers exhibit larger domain feature statistic discrepancy. Such discrepancy is propagated from the shallow to deep layers and finally results in the poor target domain performance. The shallow CNN layers suffer more from severe biased distribution when they are further trained on the source domain. Note in particular Figure 2 shows that the Overfit model has larger domain feature gaps on all layers. Table 1 further shows quantitatively that this overfitting model generalizes worse on unseen target domains, while capable of producing better source domain performance. Thus shallow CNN layers do matter for generalizing model to different domain styles, because they preserve more style information through encoding local structures, such as corner, edge, color and texture, which are closely relevant to styles [131]. While the deep CNN layers encode more semantic information which are more insensitive to the style effect, if the model is trained on the biased shallow CNN features, the deep layers cannot effectively calibrate the style-biased semantic information and thus the entire model overfits to the source domain.

**Reducing Domain Style Overfitting.** Diverse training domains would help deep models to learn domain-invariant representations and thus reduce the domain style overfitting. Our NP efficiently synthesizes diverse latent domain styles and effectively reduces any inherent domain style overfitting. Figure 1 and Figure 2 show our NP significantly reduces the domain feature gap, especially in

<sup>&</sup>lt;sup>3</sup>In this case, the shallow CNN layers are biased towards the domain style of the pretrained ImageNet dataset.

IN 
$$\rightarrow$$
 Stage 1  $\xrightarrow{x_1} \alpha_1 x_1 + (\beta_1 - \alpha_1) \mu_{1,c} \rightarrow$  Stage 2  $\xrightarrow{x_2} \alpha_2 x_2 + (\beta_2 - \alpha_2) \mu_{2,c} \rightarrow$  Stage 3-5  $\rightarrow$  OUT 
$$x_i \in \mathcal{R}^{B \times C \times H_i \times W_i} \qquad \qquad \mu_{i,c} = \frac{1}{H_i W_i} \sum_{H_i} \sum_{W_i} x_i \in \mathcal{R}^{B \times C} \qquad \qquad \alpha_i, \beta_i \sim Gaussian(1, 0.75) \in \mathcal{R}^{B \times C}$$

Figure 3: Our Normalization Perturbation (NP) is applied at shallow CNN layers only during training. NP is enabled with probability p = 0.5.

the shallow and deep CNN layers. Table 1 shows that Ours model with NP generalizes well on unseen target domains while simultaneously keeping the source domain performance. The image-level domain style synthesis method StyeRD also reduces domain style gaps and improves domain generalization. However, as we will show shortly, this method is not as desirable as ours.

#### 4 Method and Analysis

It has been widely studied that feature channel statistics, e.g., mean and standard deviation, tightly relate to image styles. Changing feature channel statistics can be regarded as implicitly changing the input image styles. The Adaptive Instance Normalization (AdaIN) [132] achieves arbitrary style transfer through the feature channel statistics normalization and transformation. Given a mini-batch B of CNN features  $x \in \mathcal{R}^{B \times C \times H \times W}$  with C channels and  $H \times W$  spatial size from the content images. AdaIN can be formulated as:

$$y = \sigma_s \frac{x - \mu_c}{\sigma_c} + \mu_s,\tag{1}$$

where both  $\{\mu_c, \sigma_c\} \in \mathcal{R}^{B \times C}$  and  $\{\mu_s, \sigma_s\} \in \mathcal{R}^{B \times C}$  are feature channel statistics, estimated from the input content images and style images, respectively. The normalized features y can be decoded into the stylized content images. AdaIN provides a feasible and efficient way to implicitly change image styles in the feature space.

#### 4.1 Normalization Perturbation Method

Our proposed method, Normalization Perturbation (NP), perturbs the feature channel statistics of training images by inserting random noises. Formally, NP can be formulated as:

$$y = \sigma_s^* \frac{x - \mu_c}{\sigma_c} + \mu_s^*, \qquad \sigma_s^* = \alpha \sigma_c, \qquad \mu_s^* = \beta \mu_c$$
 (2)

where  $\{\mu_c, \sigma_c\} \in \mathcal{R}^{B \times C}$  are the channel statistics, mean and variance, estimated on the input features. The  $\{\alpha, \beta\} \in \mathcal{R}^{B \times C}$  are random noises drawn from the Gaussian distribution. This equation can be further simplified as:

$$y = \alpha x + (\beta - \alpha)\mu_c. \tag{3}$$

As shown in Figure 3, NP is applied at shallow CNN layers (following the backbone stage 1 and stage 2). NP is enabled with probability p only in the training stage.

Our NP method is fundamentally different from conventional normalization methods [132, 133, 134, 135], whose affine parameters  $\{\mu_s, \sigma_s\}$  are learned from the training set or estimated from extra input style images. While NP affine parameters  $\{\mu_s^\star, \sigma_s^\star\}$  are obtained by perturbing the input feature channel statistics, they are obtained without relying on extra style inputs and are optimization-free. The perturbed affine parameters can be regarded as the channel statistics corresponding to diverse latent domain styles, enabling models to learn domain-invariant representations and preventing them from style overfitting.

In NP, all channel statistics are randomly perturbed with the same noise distribution. We further propose Normalization Perturbation Plus (NP+) to adaptively control the noise magnitude in different channels, based on the feature statistic variance across different images. Such adaptive perturbation is motivated by the observation that some channels significantly vary as the domain style changes. We thus apply more noise on these style-sensitive channels. Specifically, we use the mini-batch of B feature channel statistics  $\mu_c = \{\mu_c^1, ..., \mu_c^b, ..., \mu_c^B\}$  to compute the statistic variance  $\Delta \in \mathcal{R}^{1 \times C}$ :

$$\Delta = \frac{1}{B} \sum_{b=1}^{B} (\mu_c^b - \bar{\mu}_c)^2, \qquad \bar{\mu}_c = \frac{1}{B} \sum_{b=1}^{B} (\mu_c^b). \tag{4}$$

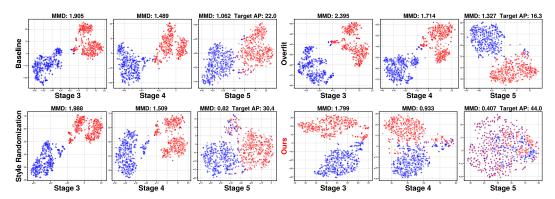


Figure 4: The t-SNE visualization for the feature channel statistics of different methods on Cityscapes (source domain) and Foggy Cityscapes (target domain). The target domain performance is presented.

Table 2: Ablation studies on Normalization Perturbation (NP). SR denotes style randomization.

Method	С	F	В		С	F	В			С	F	В
Baseline	58.0	22.0	21.8	B(0.75, 0.75)	59.0	43.0	29.5		Stage 1	59.3	40.7	29.6
Image-level SR	51.9	30.4	26.0	U(0, 2.0)	58.4	42.0	28.9		Stage 2	58.4	41.5	29.5
Feat-level SR	58.2	42.0	29.0	G(1, 0.50)	58.3	40.1	29.6		Stage 3	59.7	27.7	24.2
Ours	58.7	44.0	30.1	G(1, 0.75)	58.7	44.0	30.1		Stage 12	58.7	44.0	30.1
(a) Effect of feature-level latent styles.				G(1, 1.00)	57.4	44.3	30.2		Stage 123	58.3	43.8	29.9
(b) Effect of noise types.							(c) Effect	of NP	positi	ions.		

Then we use the normalized statistic variance  $\delta = \Delta/\max(\Delta) \in \mathcal{R}^{1 \times C}$  to control the injected noise magnitude for each channel:

$$y = \alpha x + \delta(\beta - \alpha)\mu_c,\tag{5}$$

where max is the maximum operation. When applying NP+, we use the photometric data augmentation (Color Jittering, GrayScale, Gaussian Blur and Solarize, only for NP+ by default) to generate pseudo domain styles to facilitate the exploration on style-sensitive channels.

#### 4.2 Normalization Perturbation Advantages

Our Normalization Perturbation can be implemented as a plug-and-play component in modern CNN models to effectively solve the domain style overfitting problem. NP has multiple advantages.

**Effective Domain Blending.** Our NP can effectively blend feature channel statistics of different domains, corresponding to learning better domain-invariant representations. Figure 4 shows that the Ours model trained with NP can effectively reduce the learned distribution distance between source and target domains, especially on deep CNN layers. Compared to other methods, NP results in smaller cross-domain distribution distance and better generalization performance on target domains.

**High Content Fidelity.** Our NP processes feature channel statistics while keeping image and feature spatial structures unchanged. Note that image-level domain synthesis methods may destroy the content structures of the original images in the image generation procedure. Besides, NP trains deep models with numerous content-style combinations in the high-dimensional feature space, which is much more efficient and effective than the image-level methods, whose styles are deterministic and limited and the style augmentation is only performed on the low-dimensional image space.

Table 2(a) shows the comparisons between image- and feature-level domain synthesis methods. Image-level style randomization [13] sacrifices the source domain performance due to its potential destruction on image contents, although this method effectively improves the detection performance on unseen target domains. We further compare this method with feature-level style randomization, which is similar to our NP method except that its affine parameters are obtained from extra input style images. The feature-level style randomization performs well on both source and target domains, while our method performs best on all datasets due to our diverse latent styles, even without extra style information.

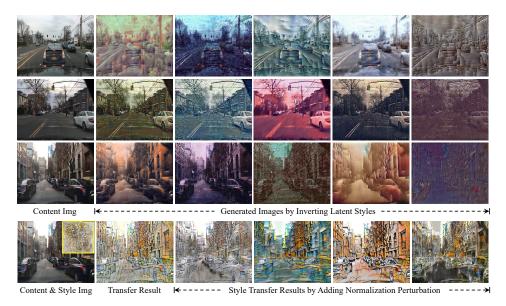


Figure 5: Latent style visualization. Top: the perturbed channel statistics of the training image features are inverted back to the image space. Bottom: style transfer results of adding our perturbation.

Table 3: Ablation studies on Normalization Perturbation (NP). DA denotes data augmentation.

	C	F	В		С	F	В		C	F	В
Baseline	58.1	22.0	21.8	DA	57.2	35.5	30.5	NP	58.7	44.0	30.1
Spatial	59.6	24.9	22.6	SN & CN [123]	58.1	31.7	26.6	NP w/ DA	57.6	45.2	32.6
Activation	58.1	25.3	26.4	MixStyle [16]	57.7	30.1	26.5	NP+ w/o DA	58.8	43.2	29.9
Channel	58.7	44.0	30.1	Ours	58.7	44.0	30.1	NP+ w/ DA	58.3	46.3	32.8

(a) Comparison to other noise types. (b) Comparison to other methods.

(c) Ablation on NP+.

Diverse Latent Styles. Our NP effectively diversify the latent styles. For better understanding, we map the NP perturbed feature channel statistics back into the image space using the feature inverting technique [136, 131]. Figure 5 shows that the generated latent styles are diverse to effectively enlarge the style scopes, covering various potential unseen domain styles in real-world environments, e.g., dawn, dusk, night times and foggy, rainy, snowy weathers.

#### 4.3 Normalization Perturbation Ablation Studies

**Noise types.** Our NP is insensitive to the noise types and hyperparameters. Table 2(b) shows our method works well with Beta, Uniform and Gaussian noises. The only requirement is that the noise should be generated around one to enable the perturbed affine parameters be around the input feature channel statistics.

**NP positions.** Table 2(c) shows our NP performs best when applied in shallow CNN layers. This is because shallow CNN layers are more style sensitive, which fundamentally affect the entire model training as discussed before.

**NP probability.** Figure 6 shows how NP probability p affects the model performance. When the NP probability is higher, the generalization performance on target domains tends to be better, but the source domain performance will suffer when the probability is too large. Interestingly, when NP probability is lower than 0.5, NP helps model to perform better on the source domain, probably because NP provides desirable regularization and feature augmentation effect. We set the probability p as 0.5 in our experiments to achieve the best balance, improving model generalization performance on unseen target domains and simultaneously keeping the source domain performance.

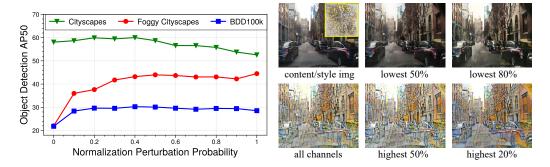


Figure 6: Effect of NP probability.

Figure 7: The style transfer results with style-insensitive/sensitive channels.

Table 4: Rob	oust object	detection	results.
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		Day → AP50										
Faster R-CNN [2]	17.84	31.35	17.68	19.14	33.04	19.16	10.07	19.62	9.05	8.65	17.26	7.49
+ Rotation + Jigsaw + CycConsist [42] + CycConf [42]	17.47 18.35		16.81 18.07	19.22 18.89	33.87 33.50	18.71 18.31	9.86 11.55	19.93 23.44	8.40 10.00	8.34 9.11	16.58 17.92	7.26 7.98
+ NP (Ours) + NP+ (Ours)		36.22 <b>36.76</b>										

**Perturbation types.** NP perturbs feature channel statistics, which is much better than the spatial-level and activation-level [125] perturbation as shown in Table 3(a). This is because our channel-level perturbation fittingly solves the style overfitting problem, without affecting spatial content structures.

Comparison to related methods. As shown in Table 3(b), our method performs better than other methods. While photometric data augmentation (DA) improves model generalization, its performance depends on the augmentation and dataset matching degree. Other feature-level domain synthesis methods [123, 16] also work, but are inferior to our method thanks to our diverse latent styles generated by the perturbation operation.

**NP+.** NP+ adaptively applies heavier perturbation on style-sensitive channels containing larger channel statistic variance. This is motivated by the observation that style information is mainly preserved at the style-sensitive channels. As shown in Figure 7, we choose the style-sensitive/insensitive channels to perform style transfer, based on the channel statistic variance between the content and style features. The style can be effectively transferred into the content image with only the 20% highest style-sensitive channels, while the remaining 80% channels with low channel statistic variance are style-insensitive and are hardly used to transfer styles.

Table 3(c) shows the NP+ performs slightly worse than the NP method without data augmentation because the in-domain images have minor style difference. But when equipped with photometric data augmentation, the pseudo domain images enable NP+ to effectively find style-relevant channels and thus performs better than NP.

#### 5 Comparison Experiments

We apply our NP method on two representative real-world dense prediction tasks: object detection and semantic segmentation. Existing DG and UDA methods mainly focus on one specific task, segmentation or detection. While our method works on both tasks.

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Table 6: Semantic	segmentation dome	ain generaliz	ation recilife	Train datasets a	ire iinderlined

Method	С	В	M	S	<u>G</u>	mean	G	В	M	S	<u>C</u>	mean
Baseline SW [146]						36.39 37.64	1					
IBN-Net [106]	33.85	32.30	37.75	27.90	72.90	40.94	45.06	48.56	57.04	26.14	76.55	50.67
IterNorm [147] ISW [37]						39.73 42.50						
NP (Ours)						42.95	ı					
NP+ (Ours)						43.38						

#### 5.1 Robust Object Detection

We follow CycConf [42] to train and evaluate models on the robust object detection benchmark. Specifically, there are two evaluation settings: Domain Shift by Time of Day, where the model is trained on BDD100k [128] daytime/night train set and evaluated on BDD100k night/daytime val set, and Cross-Camera Domain Shift, where the model is trained on Waymo [137] Front Left/Right train set and evaluated on BDD100k night val set. Table 4 shows our NP outperforms previous SOTA CycConf [42] on all domain shift settings, especially on the Waymo Front Left/Right to BDD100k Night setting. Our NP+ further boosts the performance to a new SOTA.

# 5.2 Unsupervised Domain Adaptive Object Detection Table 5: UDA object detection AP50

Unsupervised domain adaptive object detection models are trained on labeled source domain and unlabeled target domain. We consider two popular adaptation settings: Sim10k [141] to Cityscapes (S  $\rightarrow$  C) and Cityscapes [12] to Foggy Cityscapes [3] (C  $\rightarrow$  F) adaptations. Table 5 shows that our method significantly outperforms other methods by a large margin even without accessing the target domain data. Our training setting is more practical for real-world applications and surprisingly has much better performance. Our good performance is properly derived from our improved shallow CNN layers, while other UDA methods attempt to improve deep layers unfortunately based on the biased shallow CNN features.

## NP (Ours) NP+ (Ours)

DivMatch [55] 43.9 34.9 SW-DA [56] 44.6 35.3 SC-DA [57] 45.1 35.9 MTOR [138] 46.6 35.1 GPA [139] 47.6 39.5 ViSGA [51] 49.3 43.3 EPM [140]<sup>†</sup> 51.2 40.2 CvcConf [42] 52.4 41.5 22.0 Our Baseline 32.8

X

performance on ResNet-50 backbone ex-

Target  $S \to C$   $C \to F$ 

31.9

41.9

54.1

58.7

22.8

32.0

44.0

46.3

cept † which are ResNet-101.

Method

FR-CNN [2]

DA-Faster [53]

### 5.3 Semantic Segmentation Domain Generalization

We follow the previous semantic segmentation domain generalization SOTA method RobustNet [37] to train and evaluate our method. The model is trained on GTAV/Cityscapes datasets, and evaluated on various datasets, i.e., GTAV (G) [143], Cityscapes (C) [12], BDD100k (B) [128], Mapillary Vistas (M) [144], and Synthia (S) [145]. Table 6 shows that our method performs the best.

#### Conclusion

We find that biased shallow CNN layers are one of the main causes of the domain style overfitting problem under real-world domain shifts. To address the problem, we propose Normalization Perturbation (NP) to perturb the channel statistics of source domain features to synthesize various latent styles. The trained deep model can perceive diverse potential domains and thus generalizes well on unseen domains thanks to the learned domain-invariant representations. Our NP method only relies on a single source domain to generalize on diverse real-world domains. Our NP method is surprisingly effective and extremely simple, operates without any extra input, learnable parameters or loss. Extensive analysis and experiments verify the effectiveness of our Normalization Perturbation.

#### References

- [1] Liang-Chieh Chen, Yukun Zhu, George Papandreou, Florian Schroff, and Hartwig Adam. Encoder-decoder with atrous separable convolution for semantic image segmentation. In *ECCV*, 2018. 1
- [2] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *NeurIPS*, 2015. 1, 3, 8, 9
- [3] Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Semantic foggy scene understanding with synthetic data. *IJCV*, 2018. 1, 3, 9
- [4] Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Acdc: The adverse conditions dataset with correspondences for semantic driving scene understanding. In *ICCV*, 2021. 1
- [5] Krikamol Muandet, David Balduzzi, and Bernhard Schölkopf. Domain generalization via invariant feature representation. In *ICML*, 2013. 1
- [6] Muhammad Ghifary, David Balduzzi, W Bastiaan Kleijn, and Mengjie Zhang. Scatter component analysis: A unified framework for domain adaptation and domain generalization. TPAMI, 2016.
- [7] Divyat Mahajan, Shruti Tople, and Amit Sharma. Domain generalization using causal matching. In *ICML*, 2021. 1
- [8] Haoliang Li, YuFei Wang, Renjie Wan, Shiqi Wang, Tie-Qiang Li, and Alex Kot. Domain generalization for medical imaging classification with linear-dependency regularization. *NeurIPS*, 2020.
- [9] Steffen Schneider, Evgenia Rusak, Luisa Eck, Oliver Bringmann, Wieland Brendel, and Matthias Bethge. Improving robustness against common corruptions by covariate shift adaptation. In *NeurIPS*, 2020.
- [10] Zachary Nado, Shreyas Padhy, D Sculley, Alexander D'Amour, Balaji Lakshminarayanan, and Jasper Snoek. Evaluating prediction-time batch normalization for robustness under covariate shift. arXiv preprint arXiv:2006.10963, 2020. 1
- [11] Lukas Hoyer, Dengxin Dai, and Luc Van Gool. Daformer: Improving network architectures and training strategies for domain-adaptive semantic segmentation. In *CVPR*, 2022. 1
- [12] Marius Cordts, Mohamed Omran, Sebastian Ramos, Timo Rehfeld, Markus Enzweiler, Rodrigo Benenson, Uwe Franke, Stefan Roth, and Bernt Schiele. The cityscapes dataset for semantic urban scene understanding. In *CVPR*, 2016. 1, 3, 9
- [13] Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A Wichmann, and Wieland Brendel. Imagenet-trained cnns are biased towards texture; increasing shape bias improves accuracy and robustness. In *ICLR*, 2018. 2, 6
- [14] Fabio Maria Carlucci, Paolo Russo, Tatiana Tommasi, and Barbara Caputo. Hallucinating agnostic images to generalize across domains. In *ICCV Workshop*, 2019. 2, 3
- [15] Rui Gong, Wen Li, Yuhua Chen, and Luc Van Gool. Dlow: Domain flow for adaptation and generalization. In *CVPR*, 2019. 2, 3
- [16] Kaiyang Zhou, Yongxin Yang, Yu Qiao, and Tao Xiang. Domain generalization with mixstyle. In ICLR, 2020. 2, 3, 7, 8
- [17] Xin Jin, Cuiling Lan, Wenjun Zeng, and Zhibo Chen. Style normalization and restitution for domain generalization and adaptation. *TMM*, 2021. 2, 3
- [18] Massimiliano Mancini, Zeynep Akata, Elisa Ricci, and Barbara Caputo. Towards recognizing unseen categories in unseen domains. In ECCV, 2020. 2, 3
- [19] Laurens Van der Maaten and Geoffrey Hinton. Visualizing data using t-sne. *Journal of machine learning research*, 2008. 2
- [20] Karsten M Borgwardt, Arthur Gretton, Malte J Rasch, Hans-Peter Kriegel, Bernhard Schölkopf, and Alex J Smola. Integrating structured biological data by kernel maximum mean discrepancy. *Bioinformatics*, 2006. 2
- [21] Dan Hendrycks and Thomas Dietterich. Benchmarking neural network robustness to common corruptions and perturbations. In *ICLR*, 2018. 3

- [22] Kate Saenko, Brian Kulis, Mario Fritz, and Trevor Darrell. Adapting visual category models to new domains. In ECCV, 2010. 3
- [23] Da Li, Yongxin Yang, Yi-Zhe Song, and Timothy M Hospedales. Deeper, broader and artier domain generalization. In *ICCV*, 2017. 3
- [24] Haohan Wang, Zexue He, Zachary C Lipton, and Eric P Xing. Learning robust representations by projecting superficial statistics out. In *ICLR*, 2018. 3
- [25] Chen Fang, Ye Xu, and Daniel N Rockmore. Unbiased metric learning: On the utilization of multiple datasets and web images for softening bias. In ICCV, 2013. 3
- [26] Hemanth Venkateswara, Jose Eusebio, Shayok Chakraborty, and Sethuraman Panchanathan. Deep hashing network for unsupervised domain adaptation. In *CVPR*, 2017. 3
- [27] Saeid Motiian, Marco Piccirilli, Donald A Adjeroh, and Gianfranco Doretto. Unified deep supervised domain adaptation and generalization. In *ICCV*, 2017. 3
- [28] Yogesh Balaji, Swami Sankaranarayanan, and Rama Chellappa. Metareg: Towards domain generalization using meta-regularization. In *NeurIPS*, 2018. 3
- [29] Yiying Li, Yongxin Yang, Wei Zhou, and Timothy Hospedales. Feature-critic networks for heterogeneous domain generalization. In *ICML*, 2019. 3
- [30] Da Li, Jianshu Zhang, Yongxin Yang, Cong Liu, Yi-Zhe Song, and Timothy M Hospedales. Episodic training for domain generalization. In *ICCV*, 2019. 3
- [31] Yuyang Zhao, Zhun Zhong, Fengxiang Yang, Zhiming Luo, Yaojin Lin, Shaozi Li, and Nicu Sebe. Learning to generalize unseen domains via memory-based multi-source meta-learning for person re-identification. In *CVPR*, 2021. 3
- [32] Yingjun Du, Jun Xu, Huan Xiong, Qiang Qiu, Xiantong Zhen, Cees GM Snoek, and Ling Shao. Learning to learn with variational information bottleneck for domain generalization. In ECCV, 2020. 3
- [33] Yingjun Du, Xiantong Zhen, Ling Shao, and Cees GM Snoek. Metanorm: Learning to normalize few-shot batches across domains. In *ICLR*, 2020. 3
- [34] Xiangyu Yue, Yang Zhang, Sicheng Zhao, Alberto Sangiovanni-Vincentelli, Kurt Keutzer, and Boqing Gong. Domain randomization and pyramid consistency: Simulation-to-real generalization without accessing target domain data. In *ICCV*, 2019. 3
- [35] Fengchun Qiao, Long Zhao, and Xi Peng. Learning to learn single domain generalization. In CVPR, 2020. 3
- [36] Riccardo Volpi and Vittorio Murino. Addressing model vulnerability to distributional shifts over image transformation sets. In *ICCV*, 2019. 3
- [37] Sungha Choi, Sanghun Jung, Huiwon Yun, Joanne T Kim, Seungryong Kim, and Jaegul Choo. Robustnet: Improving domain generalization in urban-scene segmentation via instance selective whitening. In *CVPR*, 2021. 3, 9
- [38] Karthik Seemakurthy, Charles Fox, Erchan Aptoula, and Petra Bosilj. Domain generalisation for object detection. *arXiv preprint arXiv:2203.05294*, 2022. 3
- [39] Chuang Lin, Zehuan Yuan, Sicheng Zhao, Peize Sun, Changhu Wang, and Jianfei Cai. Domain-invariant disentangled network for generalizable object detection. In *ICCV*, 2021. 3
- [40] Xingxuan Zhang, Zekai Xu, Renzhe Xu, Jiashuo Liu, Peng Cui, Weitao Wan, Chong Sun, and Chen Li. Towards domain generalization in object detection. arXiv preprint arXiv:2203.14387, 2022. 3
- [41] Claudio Michaelis, Benjamin Mitzkus, Robert Geirhos, Evgenia Rusak, Oliver Bringmann, Alexander S Ecker, Matthias Bethge, and Wieland Brendel. Benchmarking robustness in object detection: Autonomous driving when winter is coming. *arXiv preprint arXiv:1907.07484*, 2019. 3
- [42] Xin Wang, Thomas E Huang, Benlin Liu, Fisher Yu, Xiaolong Wang, Joseph E Gonzalez, and Trevor Darrell. Robust object detection via instance-level temporal cycle confusion. In *ICCV*, 2021. 3, 8, 9
- [43] Yaroslav Ganin and Victor Lempitsky. Unsupervised domain adaptation by backpropagation. In ICML, 2015. 3

- [44] Muhammad Ghifary, W Bastiaan Kleijn, Mengjie Zhang, David Balduzzi, and Wen Li. Deep reconstruction-classification networks for unsupervised domain adaptation. In ECCV, 2016. 3
- [45] Konstantinos Bousmalis, George Trigeorgis, Nathan Silberman, Dilip Krishnan, and Dumitru Erhan. Domain separation networks. In *NeurIPS*, 2016. 3
- [46] Konstantinos Bousmalis, Nathan Silberman, David Dohan, Dumitru Erhan, and Dilip Krishnan. Unsupervised pixel-level domain adaptation with generative adversarial networks. In CVPR, 2017. 3
- [47] Yaroslav Ganin, Evgeniya Ustinova, Hana Ajakan, Pascal Germain, Hugo Larochelle, François Laviolette, Mario Marchand, and Victor Lempitsky. Domain-adversarial training of neural networks. *The journal of machine learning research*, 2016. 3
- [48] Mingsheng Long, Han Zhu, Jianmin Wang, and Michael I Jordan. Unsupervised domain adaptation with residual transfer networks. In *NeurIPS*, 2016. 3
- [49] Bharath Bhushan Damodaran, Benjamin Kellenberger, Rémi Flamary, Devis Tuia, and Nicolas Courty. Deepjdot: Deep joint distribution optimal transport for unsupervised domain adaptation. In ECCV, 2018. 3
- [50] Vibashan VS, Vikram Gupta, Poojan Oza, Vishwanath A Sindagi, and Vishal M Patel. Megacda: Memory guided attention for category-aware unsupervised domain adaptive object detection. In *CVPR*, 2021. 3
- [51] Farzaneh Rezaeianaran, Rakshith Shetty, Rahaf Aljundi, Daniel Olmeda Reino, Shanshan Zhang, and Bernt Schiele. Seeking similarities over differences: Similarity-based domain alignment for adaptive object detection. In *ICCV*, 2021. 3, 9
- [52] Antonio D'Innocente, Francesco Cappio Borlino, Silvia Bucci, Barbara Caputo, and Tatiana Tommasi. One-shot unsupervised cross-domain detection. In ECCV, 2020. 3
- [53] Yuhua Chen, Wen Li, Christos Sakaridis, Dengxin Dai, and Luc Van Gool. Domain adaptive faster r-cnn for object detection in the wild. In *CVPR*, 2018. 3, 9
- [54] Naoto Inoue, Ryosuke Furuta, Toshihiko Yamasaki, and Kiyoharu Aizawa. Cross-domain weakly-supervised object detection through progressive domain adaptation. In *CVPR*, 2018. 3
- [55] Taekyung Kim, Minki Jeong, Seunghyeon Kim, Seokeon Choi, and Changick Kim. Diversify and match: A domain adaptive representation learning paradigm for object detection. In *CVPR*, 2019. 3, 9
- [56] Kuniaki Saito, Yoshitaka Ushiku, Tatsuya Harada, and Kate Saenko. Strong-weak distribution alignment for adaptive object detection. In *CVPR*, 2019. 3, 9
- [57] Xinge Zhu, Jiangmiao Pang, Ceyuan Yang, Jianping Shi, and Dahua Lin. Adapting object detectors via selective cross-domain alignment. In *CVPR*, 2019. 3, 9
- [58] Yi-Hsin Chen, Wei-Yu Chen, Yu-Ting Chen, Bo-Cheng Tsai, Yu-Chiang Frank Wang, and Min Sun. No more discrimination: Cross city adaptation of road scene segmenters. In *ICCV*, 2017. 3
- [59] Yang Zhang, Philip David, and Boqing Gong. Curriculum domain adaptation for semantic segmentation of urban scenes. In *ICCV*, 2017. 3
- [60] Swami Sankaranarayanan, Yogesh Balaji, Arpit Jain, Ser Nam Lim, and Rama Chellappa. Learning from synthetic data: Addressing domain shift for semantic segmentation. In *CVPR*, 2018. 3
- [61] Yiheng Zhang, Zhaofan Qiu, Ting Yao, Dong Liu, and Tao Mei. Fully convolutional adaptation networks for semantic segmentation. In *CVPR*, 2018. 3
- [62] Zuxuan Wu, Xintong Han, Yen-Liang Lin, Mustafa Gokhan Uzunbas, Tom Goldstein, Ser Nam Lim, and Larry S Davis. Dcan: Dual channel-wise alignment networks for unsupervised scene adaptation. In *ECCV*, 2018. 3
- [63] Yang Zou, Zhiding Yu, BVK Kumar, and Jinsong Wang. Unsupervised domain adaptation for semantic segmentation via class-balanced self-training. In *ECCV*, 2018. 3
- [64] Haoliang Li, Sinno Jialin Pan, Shiqi Wang, and Alex C Kot. Domain generalization with adversarial feature learning. In *CVPR*, 2018. 3

- [65] Yunpei Jia, Jie Zhang, Shiguang Shan, and Xilin Chen. Single-side domain generalization for face anti-spoofing. In *CVPR*, 2020. 3
- [66] Shanshan Zhao, Mingming Gong, Tongliang Liu, Huan Fu, and Dacheng Tao. Domain generalization via entropy regularization. In *NeurIPS*, 2020. 3
- [67] Xingchao Peng, Qinxun Bai, Xide Xia, Zijun Huang, Kate Saenko, and Bo Wang. Moment matching for multi-source domain adaptation. In *ICCV*, 2019. 3
- [68] Kaiyang Zhou, Yongxin Yang, Yu Qiao, and Tao Xiang. Domain adaptive ensemble learning. TIP, 2021. 3
- [69] Guoqiang Wei, Cuiling Lan, Wenjun Zeng, Zhizheng Zhang, and Zhibo Chen. Toalign: Task-oriented alignment for unsupervised domain adaptation. In *NeurIPS*, 2021. 3
- [70] Guoqiang Wei, Cuiling Lan, Wenjun Zeng, and Zhibo Chen. Metaalign: Coordinating domain alignment and classification for unsupervised domain adaptation. In *CVPR*, 2021. 3
- [71] Chaoqi Chen, Weiping Xie, Wenbing Huang, Yu Rong, Xinghao Ding, Yue Huang, Tingyang Xu, and Junzhou Huang. Progressive feature alignment for unsupervised domain adaptation. In CVPR, 2019. 3
- [72] Guoliang Kang, Liang Zheng, Yan Yan, and Yi Yang. Deep adversarial attention alignment for unsupervised domain adaptation: the benefit of target expectation maximization. In ECCV, 2018. 3
- [73] Baochen Sun and Kate Saenko. Deep coral: Correlation alignment for deep domain adaptation. In ECCV, 2016. 3
- [74] Abhishek Kumar, Prasanna Sattigeri, Kahini Wadhawan, Leonid Karlinsky, Rogerio Feris, Bill Freeman, and Gregory Wornell. Co-regularized alignment for unsupervised domain adaptation. In *NeurIPS*, 2018. 3
- [75] Pietro Morerio, Jacopo Cavazza, and Vittorio Murino. Minimal-entropy correlation alignment for unsupervised deep domain adaptation. In *ICLR*, 2018. 3
- [76] Fabio M Carlucci, Antonio D'Innocente, Silvia Bucci, Barbara Caputo, and Tatiana Tommasi. Domain generalization by solving jigsaw puzzles. In *CVPR*, 2019. 3
- [77] Silvia Bucci, Antonio D'Innocente, Yujun Liao, Fabio Maria Carlucci, Barbara Caputo, and Tatiana Tommasi. Self-supervised learning across domains. *TPAMI*, 2021. 3
- [78] Muhammad Ghifary, W Bastiaan Kleijn, Mengjie Zhang, and David Balduzzi. Domain generalization for object recognition with multi-task autoencoders. In *ICCV*, 2015. 3
- [79] Shujun Wang, Lequan Yu, Caizi Li, Chi-Wing Fu, and Pheng-Ann Heng. Learning from extrinsic and intrinsic supervisions for domain generalization. In *ECCV*, 2020. 3
- [80] Xinpeng Xie, Jiawei Chen, Yuexiang Li, Linlin Shen, Kai Ma, and Yefeng Zheng. Self-supervised cyclegan for object-preserving image-to-image domain adaptation. In ECCV, 2020.
- [81] Xiangyu Yue, Zangwei Zheng, Shanghang Zhang, Yang Gao, Trevor Darrell, Kurt Keutzer, and Alberto Sangiovanni Vincentelli. Prototypical cross-domain self-supervised learning for few-shot unsupervised domain adaptation. In *CVPR*, 2021. 3
- [82] Javed Iqbal and Mohsen Ali. Mlsl: Multi-level self-supervised learning for domain adaptation with spatially independent and semantically consistent labeling. In WACV, 2020. 3
- [83] Aditya Khosla, Tinghui Zhou, Tomasz Malisiewicz, Alexei A Efros, and Antonio Torralba. Undoing the damage of dataset bias. In ECCV, 2012.
- [84] Prithvijit Chattopadhyay, Yogesh Balaji, and Judy Hoffman. Learning to balance specificity and invariance for in and out of domain generalization. In *ECCV*, 2020. 3
- [85] Vihari Piratla, Praneeth Netrapalli, and Sunita Sarawagi. Efficient domain generalization via common-specific low-rank decomposition. In *ICML*, 2020. 3
- [86] Guoqing Wang, Hu Han, Shiguang Shan, and Xilin Chen. Cross-domain face presentation attack detection via multi-domain disentangled representation learning. In *CVPR*, 2020. 3
- [87] Ruichu Cai, Zijian Li, Pengfei Wei, Jie Qiao, Kun Zhang, and Zhifeng Hao. Learning disentangled semantic representation for domain adaptation. In *IJCAI*, 2019. 3

- [88] Yen-Cheng Liu, Yu-Ying Yeh, Tzu-Chien Fu, Sheng-De Wang, Wei-Chen Chiu, and Yu-Chiang Frank Wang. Detach and adapt: Learning cross-domain disentangled deep representation. In CVPR, 2018. 3
- [89] Junlin Yang, Nicha C Dvornek, Fan Zhang, Julius Chapiro, MingDe Lin, and James S Duncan. Unsupervised domain adaptation via disentangled representations: Application to cross-modality liver segmentation. In *MICCI*, 2019. 3
- [90] Yichun Shi, Xiang Yu, Kihyuk Sohn, Manmohan Chandraker, and Anil K Jain. Towards universal representation learning for deep face recognition. In CVPR, 2020. 3
- [91] Zhenlin Xu, Deyi Liu, Junlin Yang, Colin Raffel, and Marc Niethammer. Robust and generalizable visual representation learning via random convolutions. In *ICLR*, 2020. 3
- [92] Nathan Somavarapu, Chih-Yao Ma, and Zsolt Kira. Frustratingly simple domain generalization via image stylization. *arXiv preprint arXiv:2006.11207*, 2020. 3
- [93] Francesco Cappio Borlino, Antonio D'Innocente, and Tatiana Tommasi. Rethinking domain generalization baselines. In *ICPR*, 2021. 3
- [94] Kaiyang Zhou, Chen Change Loy, and Ziwei Liu. Semi-supervised domain generalization with stochastic stylematch. *arXiv preprint arXiv:2106.00592*, 2021. 3
- [95] Jaehoon Choi, Taekyung Kim, and Changick Kim. Self-ensembling with gan-based data augmentation for domain adaptation in semantic segmentation. In *ICCV*, 2019. 3
- [96] Kaihong Wang, Chenhongyi Yang, and Margrit Betke. Consistency regularization with high-dimensional nonadversarial source-guided perturbation for unsupervised domain adaptation in segmentation. In *AAAI*, 2021. 3
- [97] Christian S Perone, Pedro Ballester, Rodrigo C Barros, and Julien Cohen-Adad. Unsupervised domain adaptation for medical imaging segmentation with self-ensembling. *NeuroImage*, 2019. 3
- [98] Qin Wang, Olga Fink, Luc Van Gool, and Dengxin Dai. Continual test-time domain adaptation. In CVPR, 2022.
- [99] Quande Liu, Qi Dou, Lequan Yu, and Pheng Ann Heng. Ms-net: multi-site network for improving prostate segmentation with heterogeneous mri data. *TMI*, 2020. 3
- [100] Seonguk Seo, Yumin Suh, Dongwan Kim, Geeho Kim, Jongwoo Han, and Bohyung Han. Learning to optimize domain specific normalization for domain generalization. In ECCV, 2020. 3
- [101] Massimiliano Mancini, Samuel Rota Bulo, Barbara Caputo, and Elisa Ricci. Robust place categorization with deep domain generalization. *RAL*, 2018. 3
- [102] Woong-Gi Chang, Tackgeun You, Seonguk Seo, Suha Kwak, and Bohyung Han. Domain-specific batch normalization for unsupervised domain adaptation. In *CVPR*, 2019. 3
- [103] Yanghao Li, Naiyan Wang, Jianping Shi, Jiaying Liu, and Xiaodi Hou. Revisiting batch normalization for practical domain adaptation. *arXiv preprint arXiv:1603.04779*, 2016. 3
- [104] Yuxin Wu and Justin Johnson. Rethinking" batch" in batchnorm. *arXiv preprint* arXiv:2105.07576, 2021. 3
- [105] Seokeon Choi, Taekyung Kim, Minki Jeong, Hyoungseob Park, and Changick Kim. Meta batch-instance normalization for generalizable person re-identification. In CVPR, 2021. 3
- [106] Xingang Pan, Ping Luo, Jianping Shi, and Xiaoou Tang. Two at once: Enhancing learning and generalization capacities via ibn-net. In *ECCV*, 2018. 3, 9
- [107] Xinjie Fan, Qifei Wang, Junjie Ke, Feng Yang, Boqing Gong, and Mingyuan Zhou. Adversarially adaptive normalization for single domain generalization. In *CVPR*, 2021. 3
- [108] Ping Luo, Ruimao Zhang, Jiamin Ren, Zhanglin Peng, and Jingyu Li. Switchable normalization for learning-to-normalize deep representation. *TPAMI*, 2019. 3
- [109] Duo Peng, Yinjie Lei, Munawar Hayat, Yulan Guo, and Wen Li. Semantic-aware domain generalized segmentation. In *CVPR*, 2022. 3
- [110] Dequan Wang, Evan Shelhamer, Shaoteng Liu, Bruno Olshausen, and Trevor Darrell. Tent: Fully test-time adaptation by entropy minimization. In *ICLR*, 2020. 3

- [111] Jogendra Nath Kundu, Naveen Venkat, R Venkatesh Babu, et al. Universal source-free domain adaptation. In CVPR, 2020. 3
- [112] Marvin Mengxin Zhang, Sergey Levine, and Chelsea Finn. Memo: Test time robustness via adaptation and augmentation. In *NeurIPS Workshop*, 2021. 3
- [113] Yusuke Iwasawa and Yutaka Matsuo. Test-time classifier adjustment module for model-agnostic domain generalization. In *NeurIPS*, 2021. 3
- [114] Yu Sun, Xiaolong Wang, Zhuang Liu, John Miller, Alexei Efros, and Moritz Hardt. Test-time training with self-supervision for generalization under distribution shifts. In *ICML*, 2020. 3
- [115] Baochen Sun, Jiashi Feng, and Kate Saenko. Correlation alignment for unsupervised domain adaptation. *Domain Adaptation in Computer Vision Applications*, 2017. 3
- [116] Arthur Gretton, Alex Smola, Jiayuan Huang, Marcel Schmittfull, Karsten Borgwardt, and Bernhard Schölkopf. Covariate shift by kernel mean matching. *Dataset shift in machine learning*, 2009. 3
- [117] Sebastian Otálora, Manfredo Atzori, Vincent Andrearczyk, Amjad Khan, and Henning Müller. Staining invariant features for improving generalization of deep convolutional neural networks in computational pathology. Frontiers in bioengineering and biotechnology, 2019.
- [118] Chen Chen, Wenjia Bai, Rhodri H Davies, Anish N Bhuva, Charlotte H Manisty, Joao B Augusto, James C Moon, Nay Aung, Aaron M Lee, Mihir M Sanghvi, et al. Improving the generalizability of convolutional neural network-based segmentation on cmr images. *Frontiers in cardiovascular medicine*, 2020. 3
- [119] Ling Zhang, Xiaosong Wang, Dong Yang, Thomas Sanford, Stephanie Harmon, Baris Turkbey, Bradford J Wood, Holger Roth, Andriy Myronenko, Daguang Xu, et al. Generalizing deep learning for medical image segmentation to unseen domains via deep stacked transformation. TMI, 2020. 3
- [120] Kaiyang Zhou, Yongxin Yang, Timothy Hospedales, and Tao Xiang. Learning to generate novel domains for domain generalization. In *ECCV*, 2020. 3
- [121] Kaiyang Zhou, Yongxin Yang, Timothy Hospedales, and Tao Xiang. Deep domain-adversarial image generation for domain generalisation. In *AAAI*, 2020. 3
- [122] Zijian Wang, Yadan Luo, Ruihong Qiu, Zi Huang, and Mahsa Baktashmotlagh. Learning to diversify for single domain generalization. In *ICCV*, 2021. 3
- [123] Zhiqiang Tang, Yunhe Gao, Yi Zhu, Zhi Zhang, Mu Li, and Dimitris N Metaxas. Crossnorm and selfnorm for generalization under distribution shifts. In *ICCV*, 2021. 3, 7, 8
- [124] Oren Nuriel, Sagie Benaim, and Lior Wolf. Permuted adain: reducing the bias towards global statistics in image classification. In *CVPR*, 2021. 3
- [125] Pan Li, Da Li, Wei Li, Shaogang Gong, Yanwei Fu, and Timothy M Hospedales. A simple feature augmentation for domain generalization. In *ICCV*, 2021. 3, 8
- [126] Tianlong Chen, Yu Cheng, Zhe Gan, Jianfeng Wang, Lijuan Wang, Zhangyang Wang, and Jingjing Liu. Adversarial feature augmentation and normalization for visual recognition. arXiv preprint arXiv:2103.12171, 2021. 3
- [127] Yue Wang, Lei Qi, Yinghuan Shi, and Yang Gao. Feature-based style randomization for domain generalization. *TCSVT*, 2022. 3
- [128] Fisher Yu, Haofeng Chen, Xin Wang, Wenqi Xian, Yingying Chen, Fangchen Liu, Vashisht Madhavan, and Trevor Darrell. Bdd100k: A diverse driving dataset for heterogeneous multitask learning. In *CVPR*, 2020. 3, 9
- [129] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In *CVPR*, 2009. 4
- [130] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 4
- [131] Matthew D Zeiler and Rob Fergus. Visualizing and understanding convolutional networks. In *ECCV*, 2014. 4, 7
- [132] Xun Huang and Serge Belongie. Arbitrary style transfer in real-time with adaptive instance normalization. In *ICCV*, 2017. 5

- [133] Sergey Ioffe and Christian Szegedy. Batch normalization: Accelerating deep network training by reducing internal covariate shift. In *ICML*, 2015. 5
- [134] Dmitry Ulyanov, Andrea Vedaldi, and Victor Lempitsky. Instance normalization: The missing ingredient for fast stylization. *arXiv preprint arXiv:1607.08022*, 2016. 5
- [135] Yuxin Wu and Kaiming He. Group normalization. In ECCV, 2018. 5
- [136] Pei Wang, Yijun Li, and Nuno Vasconcelos. Rethinking and improving the robustness of image style transfer. In CVPR, 2021. 7
- [137] Pei Sun, Henrik Kretzschmar, Xerxes Dotiwalla, Aurelien Chouard, Vijaysai Patnaik, Paul Tsui, James Guo, Yin Zhou, Yuning Chai, Benjamin Caine, et al. Scalability in perception for autonomous driving: Waymo open dataset. In CVPR, 2020. 9
- [138] Qi Cai, Yingwei Pan, Chong-Wah Ngo, Xinmei Tian, Lingyu Duan, and Ting Yao. Exploring object relation in mean teacher for cross-domain detection. In *CVPR*, 2019. 9
- [139] Minghao Xu, Hang Wang, Bingbing Ni, Qi Tian, and Wenjun Zhang. Cross-domain detection via graph-induced prototype alignment. In *CVPR*, 2020. 9
- [140] Cheng-Chun Hsu, Yi-Hsuan Tsai, Yen-Yu Lin, and Ming-Hsuan Yang. Every pixel matters: Center-aware feature alignment for domain adaptive object detector. In *ECCV*, 2020. 9
- [141] Matthew Johnson-Roberson, Charles Barto, Rounak Mehta, Sharath Nittur Sridhar, Karl Rosaen, and Ram Vasudevan. Driving in the matrix: Can virtual worlds replace humangenerated annotations for real world tasks? In *ICRA*, 2017. 9
- [142] Kai Chen, Jiaqi Wang, Jiangmiao Pang, Yuhang Cao, Yu Xiong, Xiaoxiao Li, Shuyang Sun, Wansen Feng, Ziwei Liu, Jiarui Xu, et al. Mmdetection: Open mmlab detection toolbox and benchmark. *arXiv preprint arXiv:1906.07155*, 2019.
- [143] Stephan R Richter, Vibhav Vineet, Stefan Roth, and Vladlen Koltun. Playing for data: Ground truth from computer games. In ECCV, 2016.
- [144] Gerhard Neuhold, Tobias Ollmann, Samuel Rota Bulo, and Peter Kontschieder. The mapillary vistas dataset for semantic understanding of street scenes. In *ICCV*, 2017. 9
- [145] German Ros, Laura Sellart, Joanna Materzynska, David Vazquez, and Antonio M Lopez. The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes. In CVPR, 2016. 9
- [146] Xingang Pan, Xiaohang Zhan, Jianping Shi, Xiaoou Tang, and Ping Luo. Switchable whitening for deep representation learning. In *ICCV*, 2019. 9
- [147] Lei Huang, Yi Zhou, Fan Zhu, Li Liu, and Ling Shao. Iterative normalization: Beyond standardization towards efficient whitening. In *CVPR*, 2019. 9