Test-Time Style Shifting: Handling Arbitrary Styles in Domain Generalization

Jungwuk Park [*1] **Dong-Jun Han** [*2] **Soyeong Kim** [1] **Jaekyun Moon** [1]

Abstract

In domain generalization (DG), the target domain is unknown when the model is being trained, and the trained model should successfully work on an arbitrary (and possibly unseen) target domain during inference. This is a difficult problem, and despite active studies in recent years, it remains a great challenge. In this paper, we take a simple yet effective approach to tackle this issue. We propose *test-time style shifting*, which shifts the style of the test sample (that has a large style gap with the source domains) to the nearest source domain that the model is already familiar with, before making the prediction. This strategy enables the model to handle any target domains with arbitrary style statistics, without additional model update at test-time. Additionally, we propose *style balancing*, which provides a great platform for maximizing the advantage of test-time style shifting by handling the DG-specific imbalance issues. The proposed ideas are easy to implement and successfully work in conjunction with various other DG schemes. Experimental results on different datasets show the effectiveness of our methods.

1. Introduction

The huge success of deep convolutional neural networks (CNNs) relies on the assumption that the *domains* of the training data and the test data are the same. However, this assumption does not hold in practice. For example, in self-driving cars, although we may only have train images on sunny days and foggy days during training (source domains), we would have to make predictions for images on snowy days during testing (unseen target domain). Due to the practical significance of this problem setup, domain generalization (DG) is receiving considerable attention nowadays. Given a training set that consists of multiple (or a single) source domains, the goal of DG is to achieve generalization capability to predict well on an arbitrary target domain. Existing works tackle this problem via meta-learning (Li et al., 2019; 2018a; Zhao et al., 2021), data augmentation (Nam et al., 2021; Shankar et al., 2018; Yue et al., 2019; Zhou et al., 2020) or domain alignment (Li et al., 2018b;c;b; Erfani et al., 2016). Recently, motivated by the observations (Huang & Belongie, 2017; Li et al., 2021; Dumoulin et al., 2017) that the domain characteristic of data has a strong correlation with the feature statistics (or style statistics) of the early layers of CNNs, the authors of (Zhou et al., 2021; Li et al., 2022; Zhang et al., 2022; Kang et al., 2022) proposed to generate new style statistics during training via style augmentation.

However, DG is still regarded as a challenging problem since the target domain is unknown during training, and the trained model should be able to handle *arbitrary*, and *possibly unseen* target domains during inference; the target domain could have a significantly large discrepancy with the source domains due to domain shift, limiting the prediction performance. As an example, consider the well-known PACS dataset (Li et al., 2017) in Fig. 1, which shows the t-SNE of feature-level styles statistics of the samples. It can be seen that the Sketch domain has a large style gap with other source domains, which results in limited performance when Sketch domain becomes the target.

Contributions. In this paper, we take a simple yet effective approach to improve the DG performance when there is a significant domain shift between the source and target domains. Specifically, in order to handle arbitrary target domains during inference, we propose *test-time style shifting*, which shifts the style of the test sample (that has a large style gap with the source domains) to the nearest source domain that the model is already familiar with, before making the prediction. Note that our scheme only performs style shifting in the style-space and thus does not require any model updates at test-time. Moreover, our test-time style shifting does not require additional changes in the model architecture or the objective function, making our scheme to be more compatible with any tasks/models.

In order to maximize the effectiveness of test-time style shifting, the model should be well-trained on the styles

[*]Equal contribution [1]School of Electrical Engineering, Korea Advanced Institute of Science and Technology (KAIST), South Korea. [2]Purdue University, USA. Correspondence to: Jaekyun Moon <jmoon@kaist.edu>.

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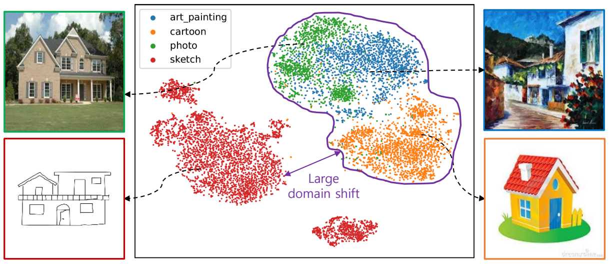


Figure 1. t-SNE of concatenated feature-level style statistics $\Phi = [\mu, \sigma]$ of samples, obtained from the output of second residual block of ResNet-18. Samples are clustered based on domain characteristics. Sketch domain has a large style gap with other domains, resulting in low model accuracy when Sketch is the target domain. Our test-time style shifting tackles this scenario by shifting the style of the test sample to the nearest source domain that the model is already well-trained on.

of the source domains. Motivated by this, we also propose *style balancing*, which provides a great platform to increase the potential of test-time style shifting by handling the DG-specific imbalance issues. Note that in DG scenarios with multiple domains, the imbalance issues have different characteristics compared to the traditional class imbalance problem in a single domain; when a specific domain lacks certain classes, it turns out, as will seen in Section 5.3, that existing methods based on resampling or reweighting fail to handle these DG-specific imbalance issues. Our proposed style balancing handles this issue by choosing the sample that has similar style statistics to other samples (and thus has a similar role compared to others) in the same domain, and converting the style of this sample to another domain; this improves the domain diversity per classes during training by compensating for the missing classes in each domain.

Our test-time style shifting and style balancing work in a highly complementary fashion; style balancing plays a key role in improving the performance of test-time style shifting by exposing the model to various styles per classes during training. Moreover, removing one of these components can degrade the performance in practice having (i) DG-specific imbalance issues and (ii) large domain shift between source and target at the same time. Our solution is compatible with not only the style-augmentation based DG schemes (e.g., MixStyle, DSU, EFDMix) that operate in the style space as ours, but also other DG ideas relying on domain alignment or meta-learning. Extensive experimental results on various DG benchmarks show the improved performance of our scheme over existing methods.

2. Related Works

DG with style augmentation. DG has been actively studied for the past few years using meta-learning (Li et al., 2019; Chen et al., 2022; Du et al., 2020; Li et al., 2018a; Zhao et al., 2021), data augmentation (Nam et al., 2021; Shankar et al., 2018; Yue et al., 2019; Zhou et al., 2020), domain alignment (Li et al., 2018b;c;b; Erfani et al., 2016) and so on. Recently, various style augmentation methods such as MixStyle (Zhou et al., 2021), DSU (Li et al., 2022), Style Neophile (Kang et al., 2022) and EFDMix (Zhang et al., 2022) have been also proposed. As in our solution, style augmentation based DG schemes can be simply applied to any tasks/models and operate in the style space defined with style statistics. However, although these DG approaches explore new styles via style-augmentation, these methods are not able to cover an arbitrary style that has a large style gap with the source domain. Also, the performance of these methods could be potentially limited in practice with DG-specific imbalance issues; even when combined with existing class-imbalanced solutions, the issue on the missing classes in each domain cannot be directly handled, as shown in Section 5. Our test-time shifting and style balancing can successfully work in conjunction with recent style augmentation strategies (and also with other DG methods) to handle these fundamental issues.

Class-imbalanced learning. Targeting class-imbalanced datasets, various over/down-sampling strategies (He et al., 2008; Pouyanfar et al., 2018) and loss function modification (e.g., reweighting) methods (Huang et al., 2016; Shu et al., 2019; Cui et al., 2019) have been proposed. While these works focus on class imbalance within a single domain, in a DG setup with multiple domains, the imbalance issues make the problem more challenging. Especially when a specific domain does not have data samples of certain classes, these missing classes cannot be compensated via over/under-sampling or loss modification strategies. A recent work (Yang et al., 2022) focused on a similar multi-domain setup with imbalanced datasets, by defining a new loss function using the distance between representations. However, the loss function proposed in (Yang et al., 2022) does not capture the classes missing in each domain. Our style balancing module handles this issue by shifting the style statistics of the sample to another domain, compensating for the missing classes in each domain.

Test-time adaptation. Several test-time adaptation methods (Wang et al., 2020; Iwasawa & Matsuo, 2021; Pandey et al., 2021; Sun et al., 2020; Xiao et al., 2022; Zhao et al., 2022) have been recently proposed, where (Pandey et al., 2021; Iwasawa & Matsuo, 2021; Xiao et al., 2022; Zhao et al., 2022) specifically focused on DG. In (Wang et al., 2020; Iwasawa & Matsuo, 2021; Sun et al., 2020), the authors proposed schemes to update model parameters during testing. Compared to these works, our test-time style shifting does not require further model update at test time; we simply utilize adaptive instance-normalization (AdaIN) (Huang & Belongie, 2017) to shift the style of the test sample to the familiar source domain. Recently in (Xiao et al., 2022), the authors proposed a method that does not require fine-tuning on target samples at test-time. However, this work requires additional networks and perform Monte Carlo sampling for variational inference, which increases training costs. Notably, (Pandey et al., 2021) proposed to construct a source manifold and projects the feature of the test samples to this source manifold. Orthogonal to this work focusing on the output of the feature extractor where the data are clustered according to classes (regardless of the domains), we deal with shifting the style statistics at earlier layers where the data are clustered according to the domains (regardless of the classes). Moreover, our test-time style shifting does not require additional changes in the model architecture or the objective function, making our scheme to be more compatible with any task/models. To the best of our knowledge, our approach is the first work that shifts the feature-level *style statistics* of the target sample in the style space at testing.

We stress that our style balancing and test-time style shifting are orthogonal to the aforementioned works in that we only shift the style statistics in the style-space during training/testing. Previous works on DG, class-imbalanced learning and test-time adaptation can work in conjunction with our scheme to improve the prediction performance further.

3. Problem Setup

3.1. Backgrounds: Style Augmentation in DG

Let $x \in \mathbb{R}^{B\times C\times H\times W}$ be a mini-batch of features at a specific layer, where B, C, H, W are the dimensions of mini-batch, channel, height, width, respectively. We also let $\mu(x) \in \mathbb{R}^{B\times C}$ and $\sigma(x) \in \mathbb{R}^{B\times C}$ be the channel-wise mean and standard deviation of each instance within the batch as:

$$\mu(x)_{b,c} = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W} x_{b,c,h,w}, \tag{1}$$

$$\sigma^2(x)_{b,c} = \frac{1}{HW}\sum_{h=1}^{H}\sum_{w=1}^{W} (x_{b,c,h,w} - \mu_{b,c}(x))^2. \tag{2}$$

The values $\mu(x)$ and $\sigma(x)$ denote instance-level feature statistics of x. These values also denote **style statistics** since the instance-level feature statistics carry out style information in CNNs (Huang & Belongie, 2017). Now define new style statistics $\mu(y)$ and $\sigma(y)$ computed by feature y, corresponding to another batch of images. According to AdaIN (Huang & Belongie, 2017), one can generate new features having content x and style y as follows:

$$\text{AdaIN}(x, y) = \sigma(y)\frac{x - \mu(x)}{\sigma(x)} + \mu(y). \tag{3}$$

Based on AdaIN, MixStyle (Zhou et al., 2021) and DSU (Li et al., 2022) focus on constructing new style statistics as $\gamma\frac{x-\mu(x)}{\sigma(x)} + \beta$ to improve generalization, where β and γ are the coefficients that determine the style of the image as in (3). MixStyle specifically mixes the style statistics as $\beta = \lambda\mu(x) + (1-\lambda)\mu(y)$, $\gamma = \lambda\sigma(x) + (1-\lambda)\sigma(y)$ for $0 < \lambda < 1$. On the other hand, DSU generates new styles by sampling β_{mix} and γ_{mix} from Gaussian distributions.

The authors of (Zhang et al., 2022) proposed EFDM to replace AdaIN in (3). By redefining $x \in \mathbb{R}^{HW}$ on a specific sample and a channel, the elements of vector x are reordered in an ascending order as $[x_{\tau_1}, x_{\tau_2}, \ldots, x_{\tau_{HW}}]$, where $x_{\tau_i} \le x_{\tau_j}$ holds for $i < j$ and $\{x_{\tau_i}\}_{i=1}^{HW}$ are the elements of vector x. The elements of y are similarly reordered as $[y_{\kappa_1}, y_{\kappa_2}, \ldots, y_{\kappa_{HW}}]$. Then, arbitrary style transfer can be performed as $\text{EFDM}(x, y)_{\tau_i} = y_{\kappa_i}$ to replace (3), where $\text{EFDM}(x)_{\tau_i}$ is the τ_i-th element of the output. Based on EFDM, the authors of (Zhang et al., 2022) also propose EFDMix, which replaces the concept of AdaIN in MixStyle with EFDM, in a channel-wise manner as follows: $\text{EFDMix}(x)_{\tau_i} = \lambda x_{\tau_i} + (1-\lambda)y_{\kappa_i}$.

3.2. Problem Formulation

Notations. Let N be the number of source domains and S_n be the set of train samples in source domain n, where $S = \cup_{n=1}^{N} S_n$ is the overall train set. Let $S_{n,k}$ be the set of train samples in domain n labeled as class k satisfying $S_n = \cup_{k=1}^{K} S_{n,k}$, where K is the number of classes. Given a sample $s \in S$, let $f(s) \in \mathbb{R}^{C\times H\times W}$ be the encoded features at a specific layer. We define $\mu(f(s)) \in \mathbb{R}^{C}$ and $\sigma(f(s)) \in \mathbb{R}^{C}$ as the channel-wise mean and standard deviation of $f(s)$, similar to (1) and (2). Related to the notations in Section 3.1, we have $x = [f(s_1), f(s_2), \ldots, f(s_B)]$, $\mu(x) = [\mu(f(s_1)), \mu(f(s_2)), \ldots, \mu(f(s_B))]$, $\sigma(x) = [\sigma(f(s_1)), \sigma(f(s_2)), \ldots, \sigma(f(s_B))]$ where B is the batch size. For any set $A \subseteq S$, we also define the mean of style statistics in set A as $\mu_A = \frac{1}{|A|}\sum_{s\in A}\mu(f(s))$, $\sigma_A = \frac{1}{|A|}\sum_{s\in A}\sigma(f(s))$. Given a set A and corresponding μ_A, σ_A, the concatenation of these two are defined as

$$\Phi_A = [\mu_A, \sigma_A]. \tag{4}$$

Similarly, we define $\Phi(f(s)) = [\mu(f(s)), \sigma(f(s))]$ for any sample s. Using these notations, we can formally state the issue and goal of the paper as follows.

Issue and goal. Let t be the test sample in the target domain. In practice, the style gap between source and target domains could be large, i.e., $\|\Phi_{S_n} - \Phi(f(t))\|$ is large for all $n \in \{1, 2, \ldots, N\}$ (see Sketch domain in Fig. 1). This issue can degrade the model performance since the trained model is not familiar with the new target domain that has a large gap with the source domains. In the next section, we describe our test-time style shifting that handles this issue. However, in DG-specific imbalance scenarios with missing classes in each domain (i.e., specific classes missing in S_n), the gain

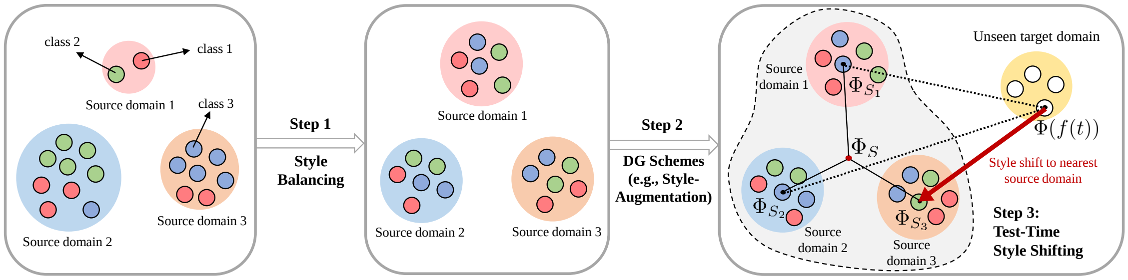


Figure 2. An overview of proposed idea. Given imbalanced feature statistics at a specific layer, style balancing is first performed to balance the style statistics across all domains. Then, a specific DG scheme (e.g., style-augmentation) can be adopted for training. At testing, the style of the test sample (far from the source domains) is shifted to the nearest source domain based on our test-time style shifting. The style balancing module and the test-time style shifting module can be flexibly applied at any layers of the backbone network.

of test-time style shifting could be limited. Therefore, to maximize the potential of test-time style shifting we also propose the style balancing strategy in the next section.

4. Proposed Algorithm

Section 4.1 describes our *style balancing*, which provides a good platform for our test-time style shifting by handling the DG-specific imbalance issues during training. Based on the model obtained by our style balancing, in Section 4.2, we propose *test-time style shifting* to handle the issue on the large style gap between source and target domains. A high-level description of our idea is shown in Fig. 2.

4.1. Style Balancing

Style balancing strategically shifts the style (i.e., style statistics) of each train sample to another source domain that has an insufficient number of data samples for each class. Given a mini-batch, style balancing is applied to each class $k \in \{1, 2, \dots, K\}$ independently. Hence, we describe our scheme focusing on a specific class k.

Step 1: Determining the number of samples to shift. We define $\tilde{S}_{n,k}$ as the set of samples that belong to source domain n labeled as class k in a specific mini-batch. We would like to balance the number of samples across all source domains $n \in \{1, 2, \dots, N\}$ so that each domain has average number of samples $Q_k := \frac{1}{N}\sum_{n=1}^{N} |\tilde{S}_{n,k}|$ for class k. If $|\tilde{S}_{n,k}| > Q_k$ holds, $|\tilde{S}_{n,k}| - Q_k$ samples in source domain n should shift their styles to other domains that have less than Q_k samples. Otherwise (i.e., $|\tilde{S}_{n,k}| < Q_k$), we similarly shift the styles of samples in other domains (that have more than Q_k samples) to domain n. Based on this, one can easily determine the number of samples to be shifted from domain n to another domain n' for all $n, n' \in \{1, 2, \dots, N\}$, in order to balance class k across all source domains.

Step 2: Sample selection. In this step, for domain n satisfying $|\tilde{S}_{n,k}| > Q_k$, we strategically select $|\tilde{S}_{n,k}| - Q_k$ samples to be shifted from domain n to other source domains. Our key insight is that samples having similar style statistics would provide similar effects on improving domain diversity, when existing DG schemes are applied. Based on this intuition, we propose to move the style of the sample that has very similar style statistics with other samples.

We first define the distance between the style statistics of any two samples $s_i, s_j \in \tilde{S}_{n,k}$ as

$$d_{i,j} = \|\Phi(f(s_i)) - \Phi(f(s_j))\|, \tag{5}$$

where $\|\cdot\|$ is the Euclidean distance. Then we choose two samples s_{i^*} and s_{j^*} from $\tilde{S}_{n,k}$ that satisfy $(i^*, j^*) = \text{argmin}_{(i,j)} d_{i,j}$; these two samples have the closest style statistics so that similar effect can be observed even when one of these samples is removed from source domain n. Among these two samples, we choose the sample that has a smaller minimum distance from other samples, and shift its style to another domain; we choose sample s_{i^*} if $\min\{d_{z,i^*}\}_{z=1,z\neq j^*}^{|\tilde{S}_{n,k}|} < \min\{d_{z,j^*}\}_{z=1,z\neq i^*}^{|\tilde{S}_{n,k}|}$ and choose sample s_{j^*}, otherwise. This process is repeated until $|\tilde{S}_{n,k}| - Q_k$ samples are selected from domain n. We repeat this process for all source domains $n \in \{1, 2, \dots, N\}$.

Step 3: Balancing. Suppose sample s in domain n has to shift its style to domain n', according to Steps 1 and 2 above. We randomly select two samples $s_1', s_2' \in S_{n'}$ from domain n' and shift the style of s to s_1', s_2' via EFDM, and apply EFDMix. Specifically, our style balancing (SB) performs

$$\text{SB}(f(s))_{\tau_i} = \lambda f(s_1')_{\kappa_i} + (1-\lambda) f(s_2')_{\eta_i} + f(s)_{\tau_i} - \langle f(s)_{\tau_i} \rangle, \tag{6}$$

where τ_i, κ_i, η_i are the indices of the i-th smallest elements of vectors $f(s)$, $f(s_1')$, $f(s_2')$, respectively. $\langle\cdot\rangle$ is the stop gradient operation; $\langle f(s)\rangle$ is the copy of $f(s)$ detached from computational graph. The term $f(s) - \langle f(s)\rangle$ is introduced to facilitate backpropagation of sample s as in (Zhang et al., 2022). The process in (6) eventually shifts the style of sample s in source domain n to domain n'. λ is a mixing parameter which is sampled from the Beta distribution.

The above three steps are applied to the samples in each class $k \in \{1, 2, \ldots, K\}$ independently. By balancing the number of samples for each class across all source domains, our style balancing not only handles the DG-specific imbalance issues but also maximizes the advantage of test-time style shifting, as described in the next subsection.

4.2. Test-Time Style Shifting

Our test-time style shifting strategy shifts the styles of the test samples during testing to handle arbitrary target domains. If the test sample has a large style gap with the source domains, then the style of the test sample is shifted to the nearest source domain that the model is already familiar with, before making the prediction. Otherwise, the test sample keeps its original style.

Let $t \in T$ be the test sample from an arbitrary unseen domain in test set T, where $f(t)$ is the encoded features of t at a specific layer. Recall that $\mu(f(t))$ and $\sigma(f(t))$ are the channel-wise mean and standard deviation of $f(t)$. Also recall that the mean of feature statistics in each source domain $n \in \{1, 2, \ldots, N\}$ are written as $\mu_{S_n} = \frac{1}{|S_n|}\sum_{s\in S_n}\mu(f(s))$ and $\sigma_{S_n} = \frac{1}{|S_n|}\sum_{s\in S_n}\sigma(f(s))$. We also define the mean feature statistics averaged over all source domains as $\mu_S = \frac{1}{N}\sum_{n=1}^{N}\mu_{S_n}$ and $\sigma_S = \frac{1}{N}\sum_{n=1}^{N}\sigma_{S_n}$. According to the definition in (4), we have $\Phi_{S_n} = [\mu_{S_n}, \sigma_{S_n}]$, $\Phi_S = [\mu_S, \sigma_S]$.

Based on these notations, at a specific layer, we generate new style statistics of sample t as $\Phi(f(t))_{\text{new}} =$

$$\begin{cases} \Phi_{S_{n'}} & \text{if } \frac{1}{N}\sum_{n=1}^{N}\|\Phi(f(t)) - \Phi_{S_n}\| > \alpha\Big(\frac{1}{N}\sum_{n=1}^{N}\|\Phi_S - \Phi_{S_n}\|\Big) \\ \Phi(f(t)) & \text{otherwise,} \end{cases} \tag{7}$$

where $\Phi(f(t))_{\text{new}} = [\mu(f(t))_{\text{new}}, \sigma(f(t))_{\text{new}}]$, n' is the index of the closest source domain to the test sample t, i.e., $n' = \text{argmin}_n\|\Phi(f(t)) - \Phi_{S_n}\|$, and α is a hyperparameter greater than or equal to 0.

Now based on $\mu(f(t))_{\text{new}}$ and $\sigma(f(t))_{\text{new}}$, following the process of AdaIN in (3), our test-time style shifting (TS) shifts the style of sample t while preserving its content as

$$\text{TS}(f(t)) = \sigma(f(t))_{\text{new}}\frac{f(t) - \mu(f(t))}{\sigma(f(t))} + \mu(f(t))_{\text{new}}. \tag{8}$$

Intuitions. In (7), if there is a large gap between style statistics of source domains and the test sample, we shift the style statistics of the test sample to the *nearest source domain*. This enables predictions on the domain that the model is already familiar with. Otherwise, i.e., when the style gap is acceptable, the model is likely to be well-trained on the style of the test sample. Thus, we let the test sample t keep its current style. This strategy enables the model to handle any target domains with arbitrary styles. Moreover, compared to the existing test-time adaptation ideas, our scheme requires less computational burden at testing since only AdaIN is required without any model update process.

Remark. Consider a DG-specific imbalance scenario where some of the classes are missing in each domain. When test-time style shifting is applied without performing style balancing (of Section 4.1), the model performance could be limited since the trained model does not make reliable predictions even for the samples in the source domains. Hence, it is advantageous to perform style balancing during training to improve the effectiveness of test-time style shifting.

4.3. Overall Procedure and Discussions

The overall procedure of our algorithm is shown in Fig. 2. Given imbalanced style statistics, we first perform style balancing. Then, we can apply any DG methods for training (e.g., style augmentation). When training is finished, we apply our test-time style shifting and make a prediction.

Where to apply SB and TS. Our style balancing (SB) and test-time style shifting (TS) can be flexibly applied at any layer of the backbone. During training, we only have the SB module, which is discarded when training is finished. During testing, the TS module is applied at a predetermined layer. Various ablations and of SB/TS modules are provided in Section 5 and Appendix.

Compatibility with various DG methods. The simplest way to combine our work with others is to apply SB before style augmentation (e.g., MixStyle), which also work in the style space as our scheme. Due to the high flexibility of SB and TS modules, our method can also work in conjunction with other DG strategies. For example, the SB module can be applied at the inner optimization process of meta-learning DG approach (Li et al., 2018a) to handle the imbalance issues in the meta-train source domains. As another example, our SB can be applied at the feature learning network of conditional invariant deep DG method (Li et al., 2018c). For all methods, TS can be applied at a specific layer of the network during testing. In Section 5, we show that SB and TS are compatible not only with style augmentation based schemes but also with other DG methods relying on meta-learning or domain alignment.

Hyperparameters. In our SB, the mixing parameter λ in (6) is sampled from Beta distribution as $\lambda \sim Beta(\tau, \tau)$. This parameter also appears in MixStyle (Zhou et al., 2021) and EFDMix (Zhang et al., 2022), and we set $\tau = 0.1$ for all experiments as in these prior works. Compared to existing style augmentation methods, our scheme requires an additional hyperparameter α that appears in (7) of our

TS module, which is set to 3 for all classification results. A detailed discussion regarding α is provided in Appendix.

Complexity. Once the style statistics of train samples are obtained, only the style gaps between the test sample and the center of N source domains are required for test-time style shifting; this makes the additional complexity negligible compared with existing test-time adaptation methods that require additional model updates. Our strategy only require AdaIN during testing. Regarding style balancing, suppose that there are $\frac{B}{NK}$ samples in a mini-batch corresponding to each domain n with class label k. Then, the additional complexity required for our style balancing (during training) becomes $\mathcal{O}((\frac{B}{NK})^2 \times N \times K) = \mathcal{O}(\frac{B^2}{NK})$, which is the additional cost for achieving an improved domain diversity.

5. Experimental Results

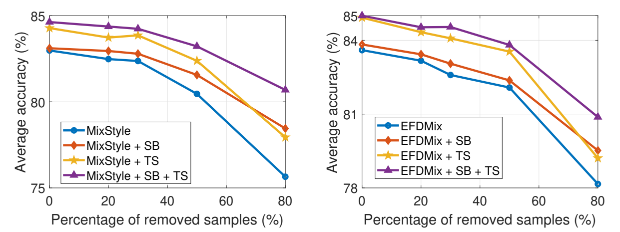
5.1. Generalization on Multi-Domain Classification

Experimental setup. Targeting multi-domain classification, we perform experiments using PACS (Li et al., 2017) with 4 domains (Art, Cartoon, Photo, Sketch) and VLCS (Fang et al., 2013) with 4 domains (Caltech, LabelMe, Pascal, Sun), which are the commonly adopted benchmarks for DG. We also considered Office-Home (Venkateswara et al., 2017) dataset in Appendix. We focus on the leave-one-domain-out setting where the model is trained on three domains and tested on the remaining one domain. The case with single-domain generalization is considered in Section 5.3. Following the setups in (Zhou et al., 2021; Li et al., 2022; Zhang et al., 2022), we adopt ResNet-18 pre-trained on ImageNet as a backbone, where the results with ResNet-50 are reported in Appendix. For PACS, the proposed SB module is probabilistically operated once at first or second or third residual blocks during training, while the TS module is operated at the second residual block during testing. Other implementation details and ablations on SB/TS locations are provided in Appendix. We utilize the term "TSB" for the scheme that uses TS and SB simultaneously.

We consider not only the original PACS and VLCS but also the imbalanced version of each dataset. We consider two different imbalance scenarios: cross-domain data imbalance and cross-domain class imbalance scenarios. To model the first scenario, we keep the training data of the largest source domain while removing a specific portion of training data of the remaining two source domains, which will be clarified soon. When constructing the cross-domain class-imbalanced dataset, among 7 classes in PACS, we select 3 classes from the first source domain, other 2 classes from the second source domain, and the remaining 2 classes from the last source domain. In VLCS, among 5 classes, we select 2, 2, 1 classes from each source domain to construct the imbalanced dataset. This effectively models the missing

Table 1. Results on **original PACS**. We reproduced the results of MixStyle, DSU, EFDMix while other values are from original papers (denoted with *). TS plays a key role in improving the model accuracy on original PACS, especially on the Sketch domain that has a large style gap with other domains (as shown in Fig. 1).

Methods	Art	Cartoon	Photo	Sketch	Avg.
L2A-OT* (Zhou et al., 2020)	83.3	78.2	96.2	73.6	82.8
pAdaIN* (Nuriel et al., 2021)	81.74	76.91	96.29	75.13	82.51
SagNet* (Nam et al., 2021)	83.58	77.66	95.47	76.3	83.25
Tent* (Wang et al., 2020)	81.55	77.67	95.49	77.64	83.09
T3A* (Iwasawa & Matsuo, 2021)	80.4	75.2	94.7	76.5	81.7
SSG* (Xiao et al., 2022)	82.02	79.73	95.87	78.96	84.15
Baseline - ResNet18	73.97	74.71	96.07	65.71	77.62
SB (Baseline)	80.55	77.16	96.39	71.68	81.44
TS (Baseline)	73.89	75.14	95.87	72.00	79.23
TSB (Baseline)	80.60	77.58	96.35	74.37	**82.22**
MixStyle (Zhou et al., 2021)	82.54	79.42	95.88	74.06	82.98
SB (+ MixStyle)	83.48	79.07	96.15	73.74	83.11
TS (+ MixStyle)	82.59	79.99	95.88	78.66	84.28
TSB (+ MixStyle)	83.62	80.07	96.15	78.66	**84.63**
DSU (Li et al., 2022)	81.78	78.66	95.91	76.75	83.27
SB (+ DSU)	80.98	79.61	95.95	78.66	83.80
TS (+ DSU)	81.12	80.31	95.82	79.19	84.11
TSB (+ DSU)	80.73	80.69	95.83	79.47	**84.18**
EFDMix (Zhang et al., 2022)	83.12	79.76	96.43	75.08	83.60
SB (+ EFDMix)	83.98	79.75	96.47	75.12	83.83
TS (+ EFDMix)	83.05	81.31	96.40	78.93	84.92
TSB (+ EFDMix)	84.00	80.72	96.46	78.85	**85.00**



(a) Effect of SB/TS on MixStyle (b) Effect of SB/TS on EFDMix

Figure 3. Results on **domain-imbalanced PACS**. We remove the samples of each source domains except the largest one. Both SB and TS are effective in improving the model performance.

classes in each domain. The class imbalanced dataset could be also constructed in different settings, e.g., in a long-tailed imbalance setting (Cao et al., 2019). The corresponding results are reported in Appendix. The performance is obtained by averaging the results over 5 independent trials. More details on our experimental setup are provided in Appendix.

Baselines. First, we consider the state-of-the-art style augmentation schemes, MixStyle (Zhou et al., 2021), DSU (Li et al., 2022), EFDMix (Zhang et al., 2022), that also work in the style space as ours. We apply our SB and TS to these schemes to validate the effectiveness of the proposed ideas. To confirm the compatibility with other DG methods, we also apply our SB/TS to MLDG (Li et al., 2018a) and CDANN (Li et al., 2018c) in Section 5.3. For a fair comparison, all hyperparemters are set to be same as in the original setup of each baseline. We also apply our methods to the pure baseline without any DG algorithm. The following other recent works are also considered: L2A-OT (Zhou et al., 2020), pAdaIN (Nuriel et al., 2021), SagNet (Nam

Table 2. Results on **imbalanced PACS**. Compared to Table 1, the role of SB becomes more significant in severely imbalanced scenarios; SB not only improves the model performance by itself but also provides a good platform for maximizing the advantage of TS.

Methods	Reference	**Cross-domain data imbalance**					**Cross-domain class imbalance**				
		Art	Cartoon	Photo	Sketch	Avg.	Art	Cartoon	Photo	Sketch	Avg.
MixStyle	ICLR'21	71.73	73.80	90.60	66.48	75.65	39.91	54.08	56.45	44.82	48.82
SB (+ MixStyle)	Ours	76.53	75.61	93.33	68.34	78.45	44.49	55.57	56.28	44.93	50.32
TS (+ MixStyle)	Ours	72.04	74.01	90.60	75.12	77.94	39.98	54.01	56.45	44.44	48.74
TSB (+ MixStyle)	Ours	76.97	76.62	93.29	75.88	**80.69**	44.50	55.84	56.28	46.68	**50.83**
DSU	ICLR'22	75.76	75.26	91.90	72.45	78.84	29.61	45.24	46.90	39.37	40.28
SB (+ DSU)	Ours	76.04	76.15	92.87	73.47	79.64	45.09	53.93	60.25	47.74	51.75
TS (+ DSU)	Ours	75.49	76.69	91.92	76.36	80.12	29.78	44.54	46.90	36.65	39.47
TSB (+ DSU)	Ours	75.93	77.39	92.85	75.90	**80.52**	45.03	54.42	60.24	49.20	**52.22**
EFDMix	CVPR'22	75.33	75.67	90.59	71.07	78.16	44.68	54.87	58.15	44.64	50.59
SB (+ EFDMix)	Ours	77.91	76.38	92.79	70.99	79.52	46.63	54.84	57.89	44.47	50.96
TS (+ EFDMix)	Ours	75.39	75.92	90.56	74.97	79.21	44.56	55.05	58.15	45.96	50.93
TSB (+ EFDMix)	Ours	77.90	76.54	92.71	76.37	**80.88**	46.03	55.29	57.87	49.99	**52.30**

Table 3. Results on **imbalanced VLCS**.

Methods	Caltech	LabelMe	Pascal	Sun	Avg.
MixStyle	68.87	53.32	55.12	39.09	54.10
SB (+ MixStyle)	69.97	53.87	55.51	38.51	54.47
TS (+ MixStyle)	73.51	53.20	55.15	38.98	**55.21**
TSB (+ MixStyle)	73.27	53.78	55.02	38.58	55.16
DSU	63.07	54.13	56.01	39.90	53.28
SB (+ DSU)	74.02	53.40	55.91	40.22	55.89
TS (+ DSU)	65.99	53.90	55.93	40.02	53.96
TSB (+ DSU)	75.99	53.50	55.46	40.28	**56.31**

et al., 2021). We also compare our scheme with the recent test-time adaptation works: Single sample generalization (SSG) (Xiao et al., 2022), T3A (Iwasawa & Matsuo, 2021) and Tent (Wang et al., 2020). A more detailed comparison with the test-time adaptation works is reported in Appendix. Finally, in Appendix, we compare our SB module with the recent work BoDA (Yang et al., 2022) that tackles the imbalance issues in a multi-domain setup.

Result 1: Original dataset. We first observe Table 1, which shows the results on original PACS. Both SB and TS play important roles in all baselines. The performance gain of SB is noticeable since PACS is already slightly imbalanced across domains. The performance gain of TS is especially large in Sketch, since the Sketch domain has a large style gap with other source domains (see Fig. 1). The overall results show that our scheme significantly boosts up the performance of recent style-augmentation methods. Our scheme also outperforms other recent methods for DG.

Result 2: Cross-domain data imbalanced dataset. In Fig. 3, we plot the average accuracy on the imbalanced version of PACS. We removed a certain portion of all source domains except the largest one. It can be observed that the gain of SB becomes larger as the portion of removed samples increases, i.e., as the dataset becomes more severely imbalanced. The TS module is effective for all cases. The left part of Table 2 shows the full result for the case of 80%. The advantage of SB is significant compared to the case in Table 1; the major performance gains of Art, Cartoon, Photo come from SB, showing the effectiveness of SB to improve the domain diversity in imbalanced datasets. On the other hand, the main performance gain of Sketch comes from TS as in Table 1; again, this is because Sketch has a significant style gap with other source domains as shown in Fig. 1. The overall results confirm the advantage of both SB and TS.

Result 3: Cross-domain class imbalanced dataset. In cross-domain class imbalance scenario (right part of Table 2), different from the trends in original dataset and cross-domain data imbalanced dataset, directly applying TS (without SB) does not improve the performance in general (even in Sketch). This is because the model trained without SB lack generalization capability in this scenario, indicating that SB also plays a key role for maximizing the advantage of TS. The performance gain of SB is especially large when combined with DSU; compared to MixStyle or EFDMix, in DSU, each class tends to get exposed to only the styles that are close to the original source domain without SB. Table 3 shows the performance on cross-domain class imbalanced VLCS. Although the performance gain is smaller compared to PACS due to the small style gaps of source and target domains, the trend is consistent with the results in PACS.

5.2. Generalization on Instance Retrieval

We also consider a different task, known as multi-domain instance retrieval. We consider person re-identification (re-ID), where the goal is to match the same person using various camera views. This setup can be viewed as a multi-domain image matching problem by regarding different camera views as distinct domains. As in the setup of (Zhang et al., 2022), we adopt Market1501 (Zheng et al., 2015) and GRID (Loy et al., 2009) datasets, and train the model in one dataset and test on the other one. We train OSNet (Zhou et al., 2019) which was specifically designed for per-

Table 4. Results on **person re-ID task**, using Market1501 and GRID datasets.

Methods	Reference	Market → GRID mAP	R1	R5	R10	GRID → Market mAP	R1	R5	R10
MixStyle (Zhou et al., 2021)	ICLR'21	35.30	26.67	**44.53**	53.07	5.25	16.40	30.05	37.05
TSB (+ MixStyle)	Ours	**36.30**	**28.27**	42.93	**55.47**	**5.70**	**17.75**	**31.90**	**39.65**
DSU (Li et al., 2022)	ICLR'22	38.57	30.40	46.40	53.07	4.45	14.90	27.65	34.60
TSB (+ DSU)	Ours	**40.10**	**30.67**	**48.00**	**58.13**	**5.25**	**16.70**	**31.60**	**38.85**
EFDMix (Zhang et al., 2022)	CVPR'22	36.33	**27.47**	45.87	52.27	6.07	19.27	33.70	41.30
TSB (+ EFDMix)	Ours	**36.67**	26.93	**46.67**	**55.57**	**6.53**	**20.23**	**35.37**	**43.13**

Table 5. Compatibility with other DG strategies.

Methods	Art	Cartoon	Photo	Sketch	Avg.
MLDG	31.18	46.70	44.76	38.39	40.26
SB (+ MLDG)	42.89	60.66	58.68	50.89	53.28
TSB (+ MLDG)	42.95	61.67	58.68	50.86	**53.54**
CDANN	17.69	24.36	27.25	33.14	25.61
SB (+ CDANN)	40.94	52.61	50.15	41.16	46.21
TSB (+ CDANN)	40.94	52.61	50.15	41.16	**46.22**

Table 7. Results in a single-domain generalization setup.

Methods	Art	Cartoon	Photo	Sketch	Avg.
MixStyle	64.32	71.77	42.98	32.18	52.81
TS (+ MixStyle)	72.19	77.25	48.50	43.62	**60.39**
DSU	64.85	74.53	39.48	36.20	53.77
TS (+ DSU)	70.99	73.95	51.18	49.03	**61.28**
EFDMix	66.56	73.93	44.74	36.36	55.40
TS (+ EFDMix)	73.87	76.79	53.04	49.41	**63.28**

Table 6. Comparing SB with existing class imbalanced methods.

Methods	Avg. accuracy
DSU (Li et al., 2022)	40.28
SB (+ DSU)	**51.75**
DSU + Undersampling	40.37
SB (+ DSU) + Undersampling	**47.74**
DSU + Oversampling	43.91
SB (+ DSU) + Oversampling	**54.01**
DSU + Reweighting	41.57
SB (+ DSU) + Reweighting	**52.57**

son re-ID. Other details are provided in Appendix. Table 4 shows the corresponding results, indicating that our idea is powerful even in multi-domain image matching problem.

5.3. Further Experiments and Discussions

Compatibility with other DG methods. Due to the flexibility of our SB and TS modules, our scheme can also work effectively with other DG strategies based on meta-learning and domain alignment. Table 5 shows the results of MLDG (Li et al., 2018a) (meta-learning based method) and CDANN (Li et al., 2018c) (domain alignment based method) combined with our scheme on cross-domain class imbalanced PACS. We consider the DomainBed setup for experiments. It can be seen that our scheme improves the model performance of both methods, confirming that both SB and TS can work in conjunction with various DG methods to mitigate the cross-domain imbalance issue and the style gap issue concurrently.

Comparing SB with existing class imbalanced methods. In Table 6, we compare SB with existing class imbalanced learning methods in a cross-domain class imbalance scenario, under the same setup in Table 2. We consider the following baselines: undersampling majority classes, oversampling minority classes, reweighting the objective function based on the *effective number* (Cui et al., 2019). It can be seen that existing methods generally fail to handle the issue since the missing classes in each domain cannot be compensated via over/under-sampling or reweighting in this DG-specific imbalance setup. Our SB effectively alleviates this issue, significantly improving the model performance.

Single-domain generalization. In Table 7, we also show the results in a single-domain generalization setup using the original PACS dataset: the model is trained with one source domain, and tested on the remaining three domains to measure the model accuracy. We do not apply SB since only one source domain exists during training. At testing, we shift the style statistics of all test samples to the source domain. It can be seen that our TS significantly boosts up the performance of existing methods in a single domain setup by simply shifting the style statistics of the test samples.

Additional experimental results. Other results including results in a DomainBed setup, detailed comparison with test-time adaptation works, results without domain labels, results on long-tailed imbalance settings, and results on the Office-Home dataset are shown in Appendix. We also perform additional studies on our SB/TS modules, in Appendix.

6. Conclusion

In this paper, we proposed test-time style shifting, a simple yet effective strategy that can handle the domain shift issue in DG. By shifting the styles of specific test samples to the nearest the source domain before making predictions, our scheme is able to handle any target domains with arbitrary style statistics. We also proposed style balancing, to increase the potential of test-time style shifting while handling the DG-specific imbalance issues. Experimental results on various datasets and data distribution scenarios confirmed the effectiveness of the proposed ideas, providing new guidelines for DG in practice with imbalance and domain shift issues.

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A. Comparison with other State-of-the-Arts in DomainBed Setup

Following the DomainBed setup (Gulrajani & Lopez-Paz, 2021), in Table 8, we compare our approach with other state-of-the-arts using ResNet-50. Training-domain validation strategy is used for selecting the model in DomainBed setup. It can be seen that the proposed scheme combined with MixStyle achieves the best performance with average accuracy of 86.6%. We also combine our scheme with one of the state-of-the-art benchmarks, termed SWAD (Cha et al., 2021). It is shown that our scheme can further improve the performance of the existing method. The overall results in Table 8 show that our style balancing (SB) and test-time style shifting (TS) can be easily combined with other state-of-the-arts to achieve the best performance.

Table 8. Performance in DomainBed setup.

Methods	Art	Cartoon	Photo	Sketch	Average
ERM (Vapnik, 1999)	84.7	80.8	97.2	79.3	85.5
IRM (Arjovsky et al., 2019)	84.8	76.4	96.7	76.1	83.5
GroupDRO (Sagawa et al., 2019)	83.5	79.1	96.7	78.3	84.4
Mixup (Zhang et al., 2017)	86.1	78.9	97.6	75.8	84.6
MLDG (Li et al., 2018a)	85.5	80.1	97.4	76.6	84.9
CORAL (Sun & Saenko, 2016)	88.3	80.0	97.5	78.8	86.2
MMD (Li et al., 2018c)	86.1	79.4	96.6	76.5	84.6
DANN (Ganin et al., 2016)	86.4	77.4	97.3	73.5	83.6
CDANN (Li et al., 2018c)	84.6	75.5	96.8	73.5	82.6
MTL (Blanchard et al., 2017)	87.5	77.1	96.4	77.3	84.6
SagNet (Nam et al., 2021)	87.4	80.7	97.1	80.0	86.3
ARM (Zhang et al., 2020)	86.8	76.8	97.4	79.3	85.1
VREx (Krueger et al., 2021)	86.0	79.1	96.9	77.7	84.9
RSC (Huang et al., 2020)	85.4	79.7	97.6	78.2	85.2
EFDMix (Zhang et al., 2022),	86.7	80.3	96.3	80.8	86.0
MixStyle (Zhou et al., 2021)	85.6	80.6	95.5	81.6	85.8
SB (ours) (+MixStyle)	87.8	82.1	95.6	81.0	**86.6**
Combination with SWAD					
SWAD (Cha et al., 2021)	89.3	83.4	**97.3**	82.5	88.1
SWAD + MixStyle	90.3	84.4	97.2	85.0	89.2
TSB (ours) (+ SWAD + MixStyle)	**90.8**	**84.5**	97.1	**85.4**	**89.4**

B. Ablation Studies on Style Balancing

We first provide ablations studies on our style balancing (SB) module. In Step 2 of our style balancing procedure, we proposed to move the style of the sample that has very similar statistics with other samples. To validate the effectiveness of this idea, here we provide results with random sample selection; for domain n satisfying $|\tilde{S}_{n,k}| > Q_k$, we randomly select $|\tilde{S}_{n,k}| - Q_k$ samples to shift their styles to other domains. Table 9 shows the results in a cross-domain class imbalance scenario. The setup is exactly the same as in the main manuscript. The results of both Table 9 confirm the effectiveness of our sample selection strategy in SB compared to the random sampling strategy.

Table 9. Effect of the proposed sample selection method in style balancing (SB) in **cross-domain class imbalanced PACS**.

Methods	Art	Cartoon	Photo	Sketch	Average
SB (+ Random sampling + MixStyle)	43.37	54.02	54.91	45.74	49.51
SB (+ Proposed sampling + MixStyle)	44.49	55.57	56.28	44.93	**50.32**
TSB (+ Random sampling + MixStyle)	43.43	54.32	54.91	44.60	49.32
TSB (+ Proposed sampling + MixStyle)	44.50	55.84	56.28	46.68	**50.83**

C. Ablation Studies on Test-Time Style Shifting

In this section, we provide ablation studies on our test-time style shifting (TS) module.

Variants of test-time style shifting. We investigate the performance of other possible variants of TS. We consider two additional strategies for TS: first, instead of only shifting the style of the test samples that have large style gaps with the source domains (as in the main manuscript), we consider a scheme that *shifts the styles of all samples* to the nearest source domain (TS variant 1). We also consider a scheme that shifts the style of the sample to the nearest sample among randomly selected 100 samples, based on the condition in equation (8) of the main manuscript (TS variant 2). Table 10 compares the results of variants of TS. It can be first seen that TS variant 2 has lower performance compared to others, indicating that shifting the style to the nearest sample is less effective compared to the scheme that shifts the style to the nearest center of the source domain. Shifting all the samples (TS variant 1) can improve the performance on Cartoon or Sketch domains, but suffers from performance degradation on Art or Photo; this indicates that it is better to keep the sample's original style when the gap with the source domain is small. In general, TS variant 1 achieves similar or lower performance compared to our TS strategy.

Table 10. Comparison with other test-time style shifting (TS) variants in original PACS.

Methods	Art	Cartoon	Photo	Sketch	Average
TSB variant 1 (shift all samples) (+ MixStyle)	82.71	81.66	95.55	78.81	<u>**84.68**</u>
TSB variant 2 (shift to the nearest sample) (+ MixStyle)	83.60	79.57	96.15	77.25	84.14
TSB proposed (+ MixStyle)	83.62	80.07	96.15	78.66	84.63
TSB variant 1 (shift all samples) (+ DSU)	79.75	80.18	94.80	79.49	83.55
TSB variant 2 (shift to the nearest sample) (+ DSU)	80.58	80.14	95.83	77.92	83.62
TSB proposed (+ DSU)	80.73	80.69	95.83	79.47	<u>**84.18**</u>

Location of TS module. In the main manuscript, our TS module is applied at the output of the 2$^{\text{nd}}$ residual block of ResNet-18, when training with PACS dataset. In Table 11, we applied the proposed TS module at different residual blocks. It is observed that applying TS module after the 1$^{\text{st}}$ block or the 2$^{\text{nd}}$ block or the 3$^{\text{rd}}$ block improves the performance. However, operating our TS module after the 4$^{\text{th}}$ residual block significantly degrades the performance, which is straightforward since data are clustered according to the classes (regardless of the domains) at later layers.

Table 11. Effect of location of test-time style shifting (TS) module in original PACS.

Methods	Art	Cartoon	Photo	Sketch	Average
SB (+ MixStyle)	83.48	79.07	96.15	73.74	83.11
TSB (+ MixStyle) (output of 1$^{\text{st}}$ residual block)	83.50	79.11	96.15	75.67	83.61
TSB (+ MixStyle) (output of 2$^{\text{nd}}$ residual block)	83.62	80.07	96.15	78.66	84.63
TSB (+ MixStyle) (output of 3$^{\text{rd}}$ residual block)	83.66	79.80	96.09	77.85	84.35
TSB (+ MixStyle) (output of 4$^{\text{th}}$ residual block)	18.51	25.60	18.84	17.89	20.21

D. Detailed comparison with test-time adaptation baselines.

This section provides a detailed comparison between our TSB and existing test-time adaptation works to clarify the difference. Different from the prior works, the unique contribution of our test-time style shifting is the effectiveness of handling arbitrary domains in the style-space, using feature-level style statistics, where the advantages are also confirmed via experiments. In Table 12, we compare the accuracy and inference time of our scheme with the recent test-time adaptation works, T3A (Iwasawa & Matsuo, 2021) and Tent (Wang et al., 2020) using PACS dataset. We reimplemented them in our experimental setup, where the "Baseline" indicates training with ResNet-18 backbone without style augmentation.

Comparison with Tent (Wang et al., 2020): Although only the BN layers are perturbed in Tent, it still requires both the forward propagation for computing the entropy and the backpropagation for updating the BN layers. On the other hand, in our scheme, only one forward propagation is required along with the simple AdaIN process in the style space (without any backpropagation), further reducing the inference time compared to Tent. It is also worth mentioning that Tent requires a batch of test samples to compute the entropy, while our scheme can be operated sample-by-sample, which is another advantage of our test-time style shifting compared to Tent.

Comparison with T3A (Iwasawa & Matsuo, 2021): T3A does not require additional parameter updates during testing, which results in small inference time. However, it can be seen that our scheme achieves better generalization, especially for the Sketch domain that has a large style gap with other domains. This is the advantage of our test-time style shifting that is able to handle arbitrary styles. Moreover, T3A requires multiple test samples to continuously update the support set during testing, while our scheme can directly make a reliable prediction given only a single test sample.

Table 12. Detailed comparison with test-time adaptation baselines in original PACS.

Methods	Art	Cartoon	Photo	Sketch	Average	Inference time
Tent (Baseline) (Wang et al., 2020)	77.78	78.03	94.07	66.27	79.04	40.08 ms
T3A (Baseline) (Iwasawa & Matsuo, 2021)	73.83	77.65	95.81	69.58	79.22	28.99 ms
TSB (Baseline)	80.60	77.58	96.35	74.37	**80.22**	32.43 ms
Tent (+Mixstyle) (Wang et al., 2020)	81.20	80.12	94.43	74.80	82.64	40.08 ms
T3A (+Mixstyle) (Iwasawa & Matsuo, 2021)	83.20	80.38	96.17	72.19	83.17	28.99 ms
TSB (+Mixstyle)	83.62	80.07	96.15	78.66	**84.63**	32.43 ms

E. Comparison with BoDA (Yang et al., 2022).

We also compare our method with the recent work (Yang et al., 2022) focusing on a multi-domain setup with imbalanced datasets, in Table 13. The results on original PACS and cross-domain class imbalanced PACS again confirm the advantages of the proposed SB module over the recent work, BoDA (Yang et al., 2022). By strategically handling the imbalance issue in DG (e.g., missing classes in each domain in class-imbalanced scenario), our style balancing can perform better than this baseline on both original and imbalanced PACS dataset.

Table 13. Comparison with BoDA (Yang et al., 2022).

(a) Results on original PACS.

Methods	Art	Cartoon	Photo	Sketch	Average
BoDA	74.46	76.54	95.27	67.72	78.50
SB (Baseline)	80.55	77.16	96.39	71.68	81.44
SB (+ MixStyle)	83.48	79.07	96.15	73.74	**83.11**

(b) Results on cross-domain class imbalanced PACS.

Methods	Art	Cartoon	Photo	Sketch	Average
BoDA	53.56	63.27	94.97	60.92	68.18
SB (Baseline)	65.04	64.63	95.63	67.85	73.29
SB (+ MixStyle)	66.26	64.46	94.97	71.44	**74.28**

F. Results without Domain Labels

Throughout the main manuscript, we described our algorithm using domain labels. In Table 14, we show the performance of our scheme without any domain labels. Here, we provide pseudo domain labels using k-means clustering, where k is set to be 3. We apply our SB and TS by utilizing the clustered domains with pseudo labels. We let $\alpha = 2$ throughout all experiments in Table 14. Experimental results show that both SB and TS are effective even without any domain labels. The performance of TS *without* domain labels is sometimes even better compared to the case *with* domain labels. This indicates that it is more important to consider how the train samples are clustered in the style space, rather than the original domain label, during the TS process.

G. Effect of α

Recall that α is a hyperparameter that appears in equation (8) of the main manuscript. In the main manuscript, we set $\alpha = 3$ for all experiments for PACS and VLCS. However, this value may not be the optimal value for each domain/setup. In Table 15, we provide results on various α values. When α is large ($\alpha = 5$), most of the test samples do not shift their styles; this reduces to the scheme with only SB. When $\alpha = 0$, all the test samples move their styles to the nearest source domain, which can degrade the performance of specific domains (Art and Photo) but improves the performance of Cartoon and Sketch. One can also select the α value by considering the extended validation set at feature-level; one can additionally generate

Table 14. Performance without domain label on original PACS.

Methods	Reference	Art	Cartoon	Photo	Sketch	Average
MixStyle (Zhou et al., 2021)	ICLR'21	82.65	78.84	96.09	72.23	82.45
SB (+ MixStyle)	Ours	83.72	79.34	96.43	73.22	83.18
TS (+ MixStyle)	Ours	83.10	80.99	96.15	78.11	84.59
TSB (+ MixStyle)	Ours	83.61	81.79	96.31	79.03	**85.19**
DSU (Li et al., 2022)	ICLR'22	81.78	78.66	95.91	76.75	83.27
SB (+ DSU)	Ours	81.92	79.14	95.95	78.54	83.89
TS (+ DSU)	Ours	80.16	79.37	94.91	78.97	83.35
TSB (+ DSU)	Ours	81.59	80.01	95.19	79.16	**83.99**
EFDMix (Zhang et al., 2022)	CVPR'22	83.35	79.91	96.67	74.52	83.61
SB (+ EFDMix)	Ours	83.38	80.22	96.81	75.13	83.89
TS (+ EFDMix)	Ours	83.43	81.25	96.26	78.92	84.96
TSB (+ EFDMix)	Ours	83.80	81.57	96.49	79.05	**85.23**

new styles that have large style gaps with the current source domains, so that the extended set contains both samples that have small/large style gaps with the source domains. Nevertheless, whatever α we choose, we have additional performance improvement (or at least the same performance) compared to the case with no TS, confirming the advantage of our TS module.

Table 15. Performance with varying α on original PACS: *whatever α we choose, an additional performance gain can be obtained compared to no TS*.

Methods	Reference	Art	Cartoon	Photo	Sketch	Average
MixStyle (Zhou et al., 2021)	ICLR'21	82.54	79.42	95.88	74.06	82.98
SB (+ MixStyle)	Ours	83.48	79.07	**96.15**	73.74	83.11
TSB (+ MixStyle) ($\alpha = 0$)	Ours	82.71	81.66	95.55	**78.81**	84.68
TSB (+ MixStyle)($\alpha = 2$)	Ours	83.31	**81.81**	96.01	**78.81**	**84.99**
TSB (+ MixStyle) ($\alpha = 3$)	Ours	**83.62**	80.07	**96.15**	78.66	84.63
TSB (+ MixStyle) ($\alpha = 4$)	Ours	83.48	79.10	**96.15**	73.81	83.13
TSB (+ MixStyle) ($\alpha = 5$)	Ours	83.48	79.07	**96.15**	73.74	83.11

H. Experiments on Office-Home Dataset

In addition to the results on PACS, VLCS, Market1501 and GRID in the main manuscript, in Table 16, we provide additional results on Office-Home dataset (Venkateswara et al., 2017) with 4 domains and 65 classes. We can observe a performance gain via SB even in the original Office-Home dataset. The performance gain of TS is marginal since the style gaps between domains are relatively small in Office-Home. Nevertheless, existing schemes can still benefit from the proposed SB and TS modules.

Table 16. Performance on original Office-Home dataset.

Methods	Reference	Art	Clipart	Product	Real world	Average
MixStyle (Zhou et al., 2021)	ICLR'21	57.99	53.04	73.64	74.98	64.91
SB (+ MixStyle)	Ours	58.29	53.20	74.01	75.29	65.20
TSB (+ MixStyle)	Ours	58.27	53.41	74.05	75.33	**65.27**

I. Experiments on DomainNet Dataset

We performed additional experiments on DomainNet (Peng et al., 2019) with 6 domains and 345 classes using ResNet-50. In Table 17, we compare our scheme with BoDA (Yang et al., 2022) on DomainNet dataset. The *Baseline* indicates training with ResNet-50 backbone without style augmentation. The results show that our proposed TSB consistently outperforms Baseline and the recent work, BoDA, demonstrating the advantage of the proposed algorithm in a larger dataset.

Table 17. Performance on original DomainNet dataset.

Methods	Clipart	Infograph	Painting	Quickdraw	Real	Sketch	Average
Baseline	60.77	25.63	50.31	12.46	62.33	48.80	43.38
BoDA (Baseline) (Yang et al., 2022)	61.39	25.73	50.01	12.50	62.20	48.72	43.43
TSB (Baseline)	61.40	25.70	51.46	12.52	62.14	50.22	**43.91**

J. Additional Experiments using ResNet-50

In Table 18, we show the results using ResNet-50. Other setups are exactly the same as in the main manuscript with ResNet-18. The results are consistent with all previous results, confirming the strong advantages of our SB and TS modules.

Table 18. Performance comparison using ResNet-50 on original PACS.

Methods	Reference	Art	Cartoon	Photo	Sketch	Average
MixStyle (Zhou et al., 2021)	ICLR'21	89.42	81.94	97.82	76.04	86.31
SB (+ MixStyle)	Ours	89.782	81.71	97.80	75.93	86.31
TSB (+ MixStyle)	Ours	89.92	81.77	97.80	80.20	**87.42**
DSU (Li et al., 2022)	ICLR'22	88.52	82.32	97.17	76.42	86.11
SB (+ DSU)	Ours	88.05	82.90	97.62	80.08	87.16
TSB (+ DSU)	Ours	88.11	82.94	97.59	82.04	**87.67**
EFDMix (Zhang et al., 2022)	CVPR'22	89.68	82.10	97.84	78.37	87.00
SB (+ EFDMix)	Ours	90.08	81.75	97.72	78.17	86.93
TSB (+ EFDMix)	Ours	90.1 4	81.80	97.66	81.16	**87.69**

K. Additional Experiments for Instance Retrieval

In this section, we provide the full version of Table 4 in the main manuscript. Table 19 shows the corresponding result, confirming the effectiveness of the proposed style balancing and test-time style shifting strategies for instance retrieval, especially when they are used together.

Table 19. Performance on person re-ID task, using Market1501 and GRID datasets.

Methods	Reference	Market → GRID				GRID → Market			
		mAP	R1	R5	R10	mAP	R1	R5	R10
MixStyle	ICLR'21	35.30	26.67	**44.53**	53.07	5.25	16.40	30.05	37.05
SB (+ MixStyle)	Ours	35.73	27.73	42.93	52.00	**5.70**	17.70	**31.90**	**39.65**
TS (+ MixStyle)	Ours	34.83	25.60	43.73	50.67	5.25	16.40	30.05	37.10
TSB (+ MixStyle)	Ours	**36.30**	**28.27**	42.93	**55.47**	**5.70**	**17.75**	**31.90**	**39.65**
DSU	ICLR'22	38.57	30.40	46.40	53.07	4.45	14.90	27.65	34.60
SB (+ DSU)	Ours	**41.47**	**33.33**	**48.80**	54.93	**5.25**	**16.75**	**31.65**	**38.85**
TS (+ DSU)	Ours	37.27	28.00	46.13	55.73	4.40	14.75	27.35	34.60
TSB (+ DSU)	Ours	40.10	30.67	48.00	**58.13**	**5.25**	16.70	31.60	**38.85**

L. Additional Experiments in Long-Tailed Imbalance Setting

We have performed additional experiments on the long-tailed imbalance setting where the results are provided in Table 20. The imbalance ratio, which represents the ratio between sample sizes of the most frequent and least frequent class, is set to 64. The results are consistent with the ones in the main manuscript.

The results are consistent with the ones in our original manuscript, confirming the effectiveness of our algorithm in various imbalance scenarios including the setup in (Cao et al., 2019). These results are also provided in Table 2 of Appendix.

Table 20. Experimental results on long-tailed imbalance setting.

Methods	Reference	Art	Cartoon	Photo	Sketch	Average
MixStyle	ICLR'21	73.49	76.75	86.17	62.73	74.79
SB (+ MixStyle)	Ours	76.46	75.30	88.20	61.81	75.44
TS (+ MixStyle)	Ours	73.68	76.75	86.17	69.04	77.53
TSB (+ MixStyle)	Ours	77.25	75.64	88.20	69.04	**77.53**
DSU	ICLR'22	75.47	76.01	89.31	60.81	75.40
SB (+ DSU)	Ours	73.66	76.17	90.93	67.51	77.07
TS (+ DSU)	Ours	74.54	76.43	89.16	66.55	76.67
TSB (+ DSU)	Ours	73.27	76.09	90.78	68.92	**77.26**

M. Algorithm in Pseudo Code

Algorithm 1 shows the sample selection process in style balancing. The process for test-time style shifting is provided in Algorithm 2.

Algorithm 1 Sample Selection Process in Style Balancing (SB)

Input: $\tilde{S}_{n,k}$ (samples in domain n with class k, in a mini-batch) satisfying $|\tilde{S}_{n,k}| > Q_k$

Output: $Z_{n,k}$, which contains $|\tilde{S}_{n,k}| - Q_k$ samples (with class k) to be shifted from domain n to other source domains

$Z_{n,k} = \emptyset$, $E = 0$
while $E < |\tilde{S}_{n,k}| - Q_k$ **do**
  for all $s_i, s_j \in \tilde{S}_{n,k}$ $(i \neq j)$ **do**
    Compute $d_{i,j} = \|\Phi(f(s_i)) - \Phi(f(s_j))\|$
  end for
  Choose two samples $(i^*, j^*) = \text{argmin}_{(i,j)} d_{i,j}$.
  if $\min\{d_{z,i^*}\}_{z=1, z\neq j^*}^{|\tilde{S}_{n,k}|} < \min\{d_{z,j^*}\}_{z=1, z\neq i^*}^{|\tilde{S}_{n,k}|}$ **then**
    $Z_{n,k} \leftarrow Z_{n,k} \cup \{s_{i^*}\}$
  else
    $Z_{n,k} \leftarrow Z_{n,k} \cup \{s_{j^*}\}$
  end if
  $E \leftarrow E + 1$
end while

N. Other Implementation Details

Our work is built upon the official setup of EFDMix (Zhang et al., 2022). Different from the original setting of EFDMix, for image classification tasks, we trained the model for 150 epochs with a mini-batch size of 128. We also randomly sampled the data from all source domains in each mini-batch. Other setups are exactly the same as in MixStyle (Zhou et al., 2021), DSU (Li et al., 2022) and EFDMix (Zhang et al., 2022) when implementing each module; each module is activated with probability 0.5. Following the original setups, Mixstyle and EFDM are inserted after the 1st, 2nd and 3rd residual blocks for PACS. For other datasets, Mixstyle and EFDM are inserted after the 1st and 2nd residual blocks. DSU is inserted after 1st convolutional layer, max pooling, 1,2,3,4-th residual blocks. Here, our SB module is operated at the moment where MixStyle, DSU, EFDMix are first activated. The TS module is operated at first residual blocks during testing for VLCS, Office-Home and person re-ID task. We set $\alpha = 3$ for all experiments on image classification tasks, while $\alpha = 5$ is utilized for person re-ID task.

Algorithm 2 Test-Time Style Shifting (TS)

Input: Test sample t and the corresponding feature $f(t)$ at a specific layer (where TS module is operated), Φ_S and Φ_{S_n} for all source domains $n \in \{1, 2, \ldots, N\}$, and α.
Output: New feature TS$(f(t))$.

for each test sample t **do**
  Compute $\frac{1}{N}\sum_{n=1}^{N} \|\Phi(f(t)) - \Phi_{S_n}\|$
  if $\frac{1}{N}\sum_{n=1}^{N} \|\Phi(f(t)) - \Phi_{S_n}\| > \alpha\Big(\frac{1}{N}\sum_{n=1}^{N} \|\Phi_S - \Phi_{S_n}\|\Big)$ **then**
    $\Phi(f(t))_{\text{new}} = \Phi_{S_{n'}}$, where $n' = \text{argmin}_n \|\Phi(f(t)) - \Phi_{S_n}\|$ // style shift to the nearest source domain
  else
    $\Phi(f(t))_{\text{new}} = \Phi(f(t))$ // keep the original style
  end if
  From $\Phi(f(t))_{\text{new}} = [\mu(f(t))_{\text{new}}, \sigma(f(t))_{\text{new}}]$,
  compute TS$(f(t)) = \sigma(f(t))_{\text{new}} \frac{f(t) - \mu(f(t))}{\sigma(f(t))} + \mu(f(t))_{\text{new}}$
end for