Abstract Learning how to generalize the model to unseen domains is an important area of research. In this paper, we propose TripleE, and the main idea is to encourage the network to focus on training on subsets (learning with replay) and enlarge the data space in learning on subsets. Learning with replay contains two core designs, EReplayB and EReplayD, which conduct the replay schema on batch and dataset, respectively. Through this, the network can focus on learning with subsets instead of visiting the global set at a glance, enlarging the model diversity in ensembling. To enlarge the data space in learning on subsets, we verify that an exhaustive and singular augmentation (ESAug) performs surprisingly well on expanding the data space in subsets during replays. Our model dubbed TripleE is frustratingly easy, based on simple augmentation and ensembling. Without bells and whistles, our TripleE method surpasses prior arts on six domain generalization benchmarks, showing that this approach could serve as a stepping stone for future research in domain generalization.

Keywords Domain generalization · Augmentation · Learning with replay

1 Introduction

Deep neural networks have achieved remarkable success on various computer vision tasks [15,36,22,66,34] with an assumption that the training and test datasets consist of i.i.d. samples from the same distribution. However, in real-world scenarios, the test data (target domain) are often outside the training dataset domains (source domains), posing a significant challenge to deep learning algorithms. Domain generalization (DG) assumes that a model is trained from multiple source domains and expected to perform well on unseen domains. In such scenarios, the model inherently cannot capture any distribution shift between the source and target domains. Thus, a robust training method is crucial to domain generalization tasks.

Recent studies on DG have explored several directions, and these methods can be broadly classified into three categories: 1) Learning domain-invariant representation [58,10,3,32], which aims to learn a shared domain-invariant representation for images from multiple source domains. 2) General model regularization [24,49,57], which imposes additional regularization terms upon the model during training, e.g., gradient dropouts [24], informative dropout [49] and superficial information regularization [57]. 3) Augmenting source domains [55,51,64,33,60], whose goal is to enlarge the training data to a broader span of the data space, increasing the possibility of covering the data in the target domain. Although prior works have achieved promising results, most methods are complicated, containing hand-crafted architectures, memory banks, multiple training stages, or self-supervised tasks [3,58,7]. For example, Chen et al. [7] proposed a style and semantic memory mechanism, which requires building multi-
ple memory banks to store style and semantic features. Xu et al. [60] proposed a Fourier transformation for DG based on a teacher-student model.

Unlike prior work, we propose a frustratingly easy and powerful baseline method for domain generalization with simple augmentation and ensembling. We discover a key insight of DG is to encourage the network to focus on training on subsets (learning with replay) and enlarge the data space in performing replays. The subsets should belong to the whole set and can be defined on batch and on dataset level. Therefore, learning with replay has two core designs: 1) Episodic replay on batch (EREplayB): augment each batch multiple times. By augmenting batch multiple times, EReplayB encourages the network to focus on learning with subsets (batch). 2) Episodic replay on dataset (EREplayD): randomly split the dataset into sub-datasets, train models on sub-datasets individually, periodically resplit sub-datasets, and ensemble the predictions of models trained with sub-datasets. To enlarge the data space in learning on subsets, we further introduce 3) Exhaustive, and singular augmentation (ESAug): a cascade of successive compositions can produce images that drift far from the original image and lead to unrealistic images. Unlike prior work, we employ exhaustive and singular augmentation to enhance the generalization.

Overall, EReplayB and ESAug work well because they can effectively decrease gradient variance reduction in each optimization step, could help the model avoid sharp minima, and reach a more robust solution. EReplayD enforces the model to learn with sub-datasets instead of visiting the whole set at a glance, and the model has the chance to visit the whole set because of periodic updates of sub-datasets. Therefore, it can generate more diverse models and is demonstrated to be more effective than the traditional ensembling method.

The main contributions of this paper are listed as follows:

- We reveal a key secret for the performance gains is to encourage the network to train with subsets and enlarge the data space in learning on subsets. This simple but overlooked point should be known in the fast-growing DG area.
- We propose TripleE, which consists of three components: EReplayB, EReplayD, and ESAug. EReplayB and EReplayD perform learning with replay on batch and dataset, respectively. ESAug can effectively enlarge the data space during replays.
- Without bells and whistles, TripleE outperforms other state-of-the-art methods on six DG benchmarks, notably achieving 5.54% and 2.23% improvements on Digits-DG and PACS, respectively, showing that our method could serve as a stepping stone for future research in domain generalization.

2 Related Work

Considerable efforts have been devoted to DG to design models which reduce reliance on domain-specific artifacts. In the following, we review the related DG literature from three perspectives. Furthermore, we discuss some related approaches on batch training techniques and augmentations.

DG via Learning Domain-invariant Representation. The research in this direction aims to learn domain-invariant representation by minimizing the discrepancy between source domains [16, 41, 29, 30, 31, 10, 32]. The resulting domain-invariant representation can then be used for downstream tasks in the unseen target domain. Along this track, Ghifary [16] designed a multi-task autoencoder, which transfers an image to its related domains and thereby learns robust representation across various domains. Another related work is the maximum mean discrepancy-based adversarial autoencoder (MMD-AAE) [32], which applies MMD distance to align the distributions among different domains via adversarial training [17]. However, these methods require the source domain partitions.

Recent DG methods forgo the requirement of source domain partitions and directly learn with the mixed domains of training data. Some methods designed additional regularizations for learning invariant representation. For example, JiGen [3] developed a self-supervised task, solving jigsaw puzzles, to capture the invariant information within images from multiple source domains. Instead of only capturing invariance within a single image, Wang et al. [58] proposed to learn an extrinsic relationship among images across domains to improve generalization.

DG via General Model Regularization. The research in this line considers improving domain generalization through reducing the factor of superficial information on the model prediction [57, 56, 24, 49]. For example, Wang et al. [57] proposed to reduce the model’s reliance on known superficial information such as irrelevant textures and encourage the model to rely more on.
informative parts. Some Dropout-like algorithms [52] are also introduced to solve the DG problem [49,22]. Shi et al. [49] designed an InfoDrop to improve the model generalization by reducing model bias to texture.

**DG via Augmenting Source Domain.** Since no information from the target domain is available during training, some researchers proposed to generate synthetic images derived from multiple source domains to increase the diversity of the training data [62,61,48,55,64,51,60]. By augmenting the source domain data, the model has a broader range of visible domains and a higher possibility of covering the span of target data. For example, Yue et al. [61] proposed to augment the training data by randomizing the synthetic images with the styles of real images from auxiliary datasets.

Our method belongs to the augmentation-based method. Unlike the above methods, we present a frustratingly easy domain generalization based on simple augmentation and ensembling. We point out an important insight for DG via augmentations, that is, learning with replay on subsets and enlarging the data space when performing replays. However, this simple yet effective point has been overlooked in prior work and should be known given the recent progress in domain generalization.

**Batch Training and Augmentation.** Outside the literature of domain generalization, many recent works studied several general techniques for improved batch training and augmentation, which go beyond augmenting source domain data [21,25,39]. For example, Hoffer et al. [21] proposed adding repetitive data to a batch to improve robustness in a supervised learning setting. Many other researchers developed various automated data augmentation methods [8,37,9,42] to define different augmentation search policies and strategies. In contrast, this paper reveals a key idea to generalization improvements but neglected in prior work: learning with replay and enlarging the data space when performing replays.

### 3 Our Approach

We denote $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^N$ as a mixed training dataset from multiple source domains, consisting of $N$ image-label pairs, where $y_i$ denotes the class label of image $x_i$. Note we do not assume we have access to the domain label, i.e., which source domain a given $x_i$ belongs to. The goal in DG is to learn a domain-generalized network $f_B(\cdot)$ from the source domains and test it on an unseen target domain. Fig. 1 shows an illustration of TripleE.

#### 3.1 EReplayB: Episodically Replay on Batch

The main idea of EReplayB is to episodically replay each training sample in a batch, and it works as follows. Let $\mathcal{B} \subseteq \mathcal{D}$ denote a set of randomly sampled images during training, where the cardinal number of set $\mathcal{B}$ is batch size $b$. We denote a set of augmentations as $\mathcal{A}$, where $\mathcal{A} = \{a_1, a_2, \ldots, a_n\}$. The standard operation in many DG methods [3,60,58] is to sequentially apply each augmentation function with some randomness to an input image and the perturbed image can be described as $(a_n \ldots a_2(a_1(x_i)))$. We introduce EReplayB to episodically replay each sample in a batch. Specifically, each sample in $\mathcal{B}$ is augmented by $r$ different transformations from $\mathcal{A}$. As a result, we can obtain an augmented sample set, denoted as $\mathcal{B}'$ and $|\mathcal{B}'| = r|\mathcal{B}|$.

As each batch contains multi-views for a single image, it is natural to include positive pairs, which motivates us to leverage the supervised contrastive loss [26]. Unlike existing methods designed complicated self-learning loss [3,58], we use a simple weighted combination of a standard cross-entropy loss and a supervised contrastive loss. We denote $\mathcal{P}(i) = \{j \in [0,|\mathcal{B}'|) \mid y_i = y_j, j \neq i\}$ as the set of indices of all positives (with the same label) in the batch $\mathcal{B}'$ distinct from $i$ and $|\mathcal{P}(i)|$ is its cardinality. Note that we guarantee that $\forall i, |\mathcal{P}(i)| \geq r - 1$ since each sample is replayed in the updated batch $\mathcal{B}'$. The positive pairs in the batch include the augmented views of image $x_i$, and may also contain other image samples with the same label with image $x_i$ from the current or different source domains. The negative pairs in the batch are images with different labels.

$$
\ell_{sup} = - \sum_i \frac{1}{|\mathcal{P}(i)|} \sum_{j \in \mathcal{P}(i)} \log \left( \frac{\exp(s_{i,j}/\tau)}{\sum_{k=1}^{r|\mathcal{B}'|} \mathbb{1}_{[k \neq j]} \exp(s_{i,k}/\tau)} \right)
$$

(1)

where $\tau > 0$ is the temperature; $s_{i,j}, s_{i,k}$ denote the feature similarities among positive pairs and negative pairs, respectively; $r : |\mathcal{B}|$ is the size of the sample set $\mathcal{B}'$. The total objective is

$$
\ell = \ell_{ce} + \ell_{sup},
$$

(2)

where $\ell_{ce}$ refers to a standard cross-entropy loss. It is worth mentioning that the performance gains of EReplayB are mainly from episodically replaying of the image sample (+4.78% Acc.), instead of the contrastive loss (+0.74% Acc.); see results in Table 5.
3.2 ESAug: Exhaustive and Singular Augmentation

ESAug enlarges the data space when performing EReplayB and EReplayD. It highlights two core questions: (1) what should be included in the transformation list when performing replays and (2) how to perform augmentation?

First, we empirically demonstrated that the augmentation should consist of exhaustive transformation functions when learning with replays. We let the augmentation set $\mathcal{A}$ to include transformations defined in [9], each of which can generate a set of distortions to an image. However, these augmentations only perform transformations within a single image. To improve model generalization, we enlarge $\mathcal{A}$ to $\mathcal{A}'$ by introducing two cross-image augmentations (Fourier-based augmentation and Style-based augmentation) to encourage the network to learn high-level semantics by exchanging the low-level statistics among images in the source domains.

**Fourier-based augmentation.** Considering that the Fourier phase component contains some semantic-preserving (high-level) information, augmenting the training data by distorting the amplitude information while keeping the phase information unchanged is a good way for the model to learn robust features. Through a Fourier-based augmentation, our model can avoid overfitting to low-level statistics carried in the amplitude information, thus paying more attention to the phase information when making decisions. Specifically, we employ a Fourier-based augmentation by linearly interpolating between the amplitude spectrums of two images from arbitrary source domains:

$$\hat{T}(x_i) = (1 - \lambda)T(x_i) + \lambda T(x_j),$$

where $T(x_i)$ refers to amplitude component of image $x_i$ calculated by FFT [45] algorithm. $\lambda \sim U(0, \xi)$ and hyperparameter $\xi$ controls the strength of the augmentation. The mixed amplitude spectrum is then combined with the original phase spectrum to form a new Fourier representation:

$$\mathcal{F}(\hat{x}_i)(u,v) = \mathcal{F}(x_i)(u,v) * e^{-i\xi \mathcal{P}(x_i)(u,v)},$$

where $\mathcal{P}(x_i)$ refers to phase component. Then, the augmented image can be described as

$$\hat{x}_i = \mathcal{F}^{-1}[\mathcal{F}(\hat{x}_i)(u,v)].$$

We denote the set $\mathcal{A}'$ to represent the transformation from $x_i$ to $\hat{x}_i$. The final augmentation set can be defined as $\mathcal{A}'$ and $\mathcal{A}' = \mathcal{A} \cup \mathcal{A}'$.

**Style-based augmentation.** The core idea of style-based augmentation is motivated by the fact that different domains contain different style information. To learn domain-invariant features, a good model should be invariant to style changes among domains. To achieve it, we include a random stylization as an augmentation to enhance the network. Specifically, we use...
Algorithm 1 TripleE for Domain Generalization

Require: Source domains $D$, batch size $b$, replay times $r$, sub-sampling times $m$
Require: $m$ neural networks that share a same structure $f_1(\theta),...,f_m(\theta)$
Require: A set of exhaustive augmentations $\mathcal{A}'$

1: while not converged do
2: Initialize model parameters for $f_1(\theta),...,f_m(\theta)$
3: for epochs = 1 to $N$ do
4: Randomly split $D$ into $D^1, D^2, ..., D^m$ # EReplayD
5: for each sub-dataset $D^i$ in $D$ do
6: for each step do
7: Sample $B$ from $D^i$ # ESAug
8: Sample an augmentation $a$ from $\mathcal{A}'$ # ESAug
9: Sample a strength $s$ from $\{0, ..., 30\}$ # EReplayB
10: Obtain $B'$ by augmenting $B$ with $r$ different transformations from $\mathcal{A}'$, where each augmentation is $a(x, s)$ # EReplayB
11: Optimize $f_i(\theta)$ using Eq. 2.
12: end for
13: end for
14: end while
15: end for
16: return $\theta_1, ..., \theta_m$

4 Experiments

4.1 Datasets and Settings

Datasets. We evaluate our method on six widely-used datasets in domain generalization, i.e.,Digits-DG, PACS and Office-Home, VLCS, TerraInc and DomainNet. Digits-DG [64] contains four different digit datasets, i.e., MNIST [28], MNIST-M [13], SVHN [43], and SYN [13]. PACS [29] contains 9,991 images of four domains (Artpaint, Cartoon, Sketches, and Photo) and 7 classes. Office-Home [54] contains 15,558 images of 65 classes, distributed across 4 domains (Artistic, Clipart, Product, and Real world). VLCS [12] includes photographic domains (Caltech101, LabelMe, SUN09, VOC2007) with 10,729 images and 5 classes. TerraInc dataset [2] contains 24,788 images with 10 classes over 4 domains. DomainNet dataset [47] has 586,575 images with 345 classes over 6 domains.

Evaluation protocol. Following prior works [60, 3], we train our model on the training splits and select the best model on the validation splits of all source domains. For testing, we evaluate the selected model on all images of the held-out target domain. For performance evaluation, we report top-1 classification accuracy on each test domain and average accuracy accordingly.

4.2 Implementation Details

Here we briefly introduce the main details for training our method.

Basic details: All experiments were implemented in PyTorch [46] and run on a machine with an NVIDIA RTX 3090 GPU. We trained all the models with the

a pre-trained AdaIN [23] which can achieve fast stylization to arbitrary styles. We randomly sample an image $x_j$ from source domains and $y_j = y_i$. Then, we randomly style an image $x_i$ with the style of $x_j$ and obtain $\hat{x}_i$. We denote the set $\mathcal{A}'$ to represent the transformation from $x_i$ to $\hat{x}_i$. The final augmentation set can be defined as $\mathcal{A}'$ and $\mathcal{A}' = \mathcal{A} \cup \mathcal{A}'$.

Singlar Augmentation. Second, we verified that the learning with replay should be performed with a randomly selected transformation from the augmentation list with some randomness instead of sequentially applying several transformation functions. Prior work also observed that a cascade of successive compositions could produce images that drift far from the original image and lead to unrealistic images [20]. Therefore, we randomly select a singular augmentation from the augmentation list. Due to the design of singular augmentation, we randomly set parameter $\xi$ in Fourier-based augmentation to increase some randomness to the augmentation strength, which is different from the fixed $\xi$ and a sequential augmentation in [60]. For style-based augmentation, we increase the augmentation randomness by randomly choosing an image from the dataset as the target to stylize image $x_i$. Fig. 2 shows Python code for ESAug based on numpy.

3.3 EReplayD: Episodically Replay on Dataset

The idea of learning with replay is further performed on a sub-dataset, namely EReplayD. The key motivation of EReplayD is that learning with periodic updates of sub-datasets can achieve more diverse models, leading to an improved model ensemble. Specifically, instead of training a model on a whole training dataset $D$, EReplayD randomly splits the training dataset $D$ into $m$ sub-datasets $D^1, D^2, ..., D^m$ and trains $m$ models on each sub-dataset. Note that the dataset will be randomly split into $m$ sub-datasets every epoch such that each model can focus on learning each sub-dataset while keeping a chance to visit the overall dataset. The final prediction will be an ensemble of predictions from $m$ models. Fig. 1(b) shows the comparison of the traditional model ensemble and our EReplayD. Algorithm 1 shows the overall training pipeline of TripleE.
Table 1: Domain generalization results on the Digits-DG dataset ( Backbone: 4 conv layer, which is used in [64]). “DL” refers to using domain label or not.

| Method                      | DL | SYN | SVHN | MNIST-M | MNIST | Avg  |
|-----------------------------|----|-----|------|---------|-------|------|
| Vanilla [63]                | ✓  | 78.6| 61.7 | 58.8    | 56.8  | 71.7 |
| MMD-AAE [32]                | ✓  | 78.4| 65.0 | 58.4    | 56.5  | 71.6 |
| CrossGrad [44]              |   | 80.2| 63.1 | 61.1    | 56.7  | 75.8 |
| DDAIC [63]                  | ✓  | 81.0| 68.6 | 64.1    | 59.6  | 77.6 |
| L2A-OT [64]                 |   | 83.2| 68.6 | 63.9    | 59.7  | 78.1 |
| STEAM [7]                   | ✓  | 92.2| 76.0 | 67.5    | 59.6  | 83.1 |

| Method                      | DL | SYN | SVHN | MNIST-M | MNIST | Avg  |
|-----------------------------|----|-----|------|---------|-------|------|
| JMix [9]                    |    | 74.8| 63.7 | 61.4    | 56.5  | 71.9 |
| SFA [33]                    |    | 85.0| 70.3 | 66.5    | 56.5  | 79.6 |
| FACT [60]                   | ✓  | 90.3| 72.4 | 65.6    | 57.9  | 81.5 |
| TripleE-Style (ours)        | ✓  | 95.48| 81.76| 72.52   | 58.28 | 89.39|
| TripleE-Fourier (ours)      | ✓  | 95.48| 81.22| 73.15   | 58.33 | 87.04|

Table 2: Domain generalization results on the PACS dataset. “S,C,A,P” refer to “Sketch, Cartoon, Art painting, and Photo”, respectively. Each reported result of our method is averaged over three runs. “use test-domain-validation-set, where some target images are used to select the best model. “DL” refers to using domain label or not.

| Method                      | DL | S    | C    | A    | P    | Avg  |
|-----------------------------|----|------|------|------|------|------|
| Vanilla                     | ✓  | 99.04| 75.65| 71.58| 94.25| 79.25|
| MMD-AAE [32]                | ✓  | 64.2 | 72.7 | 71.2 | 96.0 | 77.0 |
| CCSA [44]                   | ✓  | 66.8 | 76.9 | 80.5 | 93.6 | 79.4 |
| D-SAM [11]                  | ✓  | 77.83| 72.43| 77.33| 95.30| 80.72|
| MASF [60]                   | ✓  | 71.69| 77.17| 80.29| 94.99| 81.04|
| DMG [6]                     | ✓  | 75.21| 80.38| 76.90| 93.35| 81.46|
| Epi-FCR [31]                | ✓  | 73.0 | 77.0 | 82.1 | 93.9 | 81.5 |
| CalMix [58]                 | ✓  | 72.6 | 76.5 | 82.3 | 95.1 | 81.6 |
| MetaReg [5]                 | ✓  | 70.3 | 77.2 | 81.7 | 95.5 | 81.7 |
| L2A-OT [64]                 | ✓  | 73.6 | 78.2 | 83.3 | 96.2 | 82.8 |
| Scallo [27]                 | ✓  | 77.47| 78.43| 82.34| 96.22| 83.62|
| STEAM [7]                   | ✓  | 82.9 | 80.6 | 85.5 | 97.5 | 86.6 |

| Method                      | DL | S    | C    | A    | P    | Avg  |
|-----------------------------|----|------|------|------|------|------|
| Vanilla                     | ✓  | 99.04| 75.65| 71.58| 94.25| 79.25|
| MMD-AAE [32]                | ✓  | 64.2 | 72.7 | 71.2 | 96.0 | 77.0 |
| CCSA [44]                   | ✓  | 66.8 | 76.9 | 80.5 | 93.6 | 79.4 |
| D-SAM [11]                  | ✓  | 77.83| 72.43| 77.33| 95.30| 80.72|
| MASF [60]                   | ✓  | 71.69| 77.17| 80.29| 94.99| 81.04|
| DMG [6]                     | ✓  | 75.21| 80.38| 76.90| 93.35| 81.46|
| Epi-FCR [31]                | ✓  | 73.0 | 77.0 | 82.1 | 93.9 | 81.5 |
| CalMix [58]                 | ✓  | 72.6 | 76.5 | 82.3 | 95.1 | 81.6 |
| MetaReg [5]                 | ✓  | 70.3 | 77.2 | 81.7 | 95.5 | 81.7 |
| L2A-OT [64]                 | ✓  | 73.6 | 78.2 | 83.3 | 96.2 | 82.8 |
| Scallo [27]                 | ✓  | 77.47| 78.43| 82.34| 96.22| 83.62|
| STEAM [7]                   | ✓  | 82.9 | 80.6 | 85.5 | 97.5 | 86.6 |

4.3 Evaluation on six DAG benchmarks

**Digits-DG dataset.** Table 1 shows the results on the Digits-DG dataset. It is clear that our TripleE method outperforms the prior state-of-the-art DG methods STEAM [7] and FACT [60] by an average of 3.9% and 5.5% on top-1 classification accuracy, respectively. Please note that STEAM [7] not only requires domain label information but also requires carefully designing a teacher-student model and multiple memory banks to store the style features for each source domain. In contrast, our TripleE method does not require a domain label and does not need any particular architecture design. Using simple data augmentation and sub-sampling cross-entropy loss and an InfoNCE loss function [26]. For Digits-DG, we use the same backbone network as [64, 43]. We train the network from scratch using SGD and the initial learning rate is set to 0.01. For PACS and Office-Home, we use ImageNet pretrained ResNet [19] as our backbone. The initial learning rate of PACS is 0.0001 and decayed by 0.5 every 30 epochs. The initial learning rate of Office-Home is 0.01 and decayed by 0.5 every 40 epochs. We trained 100 epochs for this dataset. For DomainNet, we also use the ImageNet pretrained ResNet-50 [19] as our backbone. The initial learning rate is 0.001 and decayed by 0.5 every 16 epochs. We trained 40 epochs for this dataset.

Method-specific details: For Digits-DG and PACS, both batch size $b$ and repeat time $r$ are set to 4. For Office-Home, both $b$ and $r$ are set to 32. For VLCS, TerraInc, and DomainNet, the batch size $b$ is 16, and the repeat time $r$ is 4. For all experiments, we set the sampling times $m$ to 3.

**PACS dataset.** Table 2 shows the results on the PACS dataset. We can see that our TripleE can clearly outperform the prior best DG method under the same setting by 2.2% and 2.4% using ResNet-18 and ResNet-50, respectively. Notably, TripleE-Style and TripleE-Fourier can reach comparable performance on both PACS and Digits-DG, showing that these two kinds of augmentation can encourage the network to learn high-level semantics by exchanging low-level statistics among images. Note that FACT [60] built a dual-model (teacher-student models) and encourages high-level semantic exchanges among domains to improve generalization. Under-
Table 3: Domain generalization results on the Office-Home dataset. “DL” refers to using domain label or not (Backbone: resnet-18).

| Method          | PACS     | VLCS     | Office-Home | TerraInc | DomainNet |
|-----------------|----------|----------|-------------|----------|-----------|
| Vanilla [3,63]  | 63.9     | 78.9     | 68.6        | 67.5     | 84.0      |
| MMD-MIN-C [16]  | ✓ 67.5   | ✓ 78.1   | ✓ 68.5      | ✓ 67.6   | ✓ 84.0    |
| Cross[48]       | ✓ 65.8   | ✓ 74.9   | ✓ 67.8      | ✓ 66.4   | ✓ 83.4    |
| CCSA [41]       | ✓ 59.9   | ✓ 74.1   | ✓ 65.7      | ✓ 64.9   | ✓ 82.9    |
| DDAG [41]       | ✓ 59.2   | ✓ 73.6   | ✓ 65.0      | ✓ 65.5   | ✓ 82.5    |
| L2A-OT [43]     | ✓ 60.6   | ✓ 70.1   | ✓ 70.0      | ✓ 65.6   | ✓ 81.6    |
| STEAM [7]       | ✓ 62.1   | ✓ 75.3   | ✓ 77.5      | ✓ 66.8   | ✓ 82.8    |
| JGEN [34]       | ✓ 54.9   | ✓ 67.5   | ✓ 72.8      | ✓ 61.2   | ✓ 80.1    |
| RSC [43]        | ✓ 74.5   | ✓ 71.6   | ✓ 70.8      | ✓ 63.2   | ✓ 81.9    |
| FACT [60]       | ✓ 60.3   | ✓ 56.8   | ✓ 68.5      | ✓ 66.5   | ✓ 81.8    |
| TripleE-Style (ours) | ✓ 83.10 | ✓ 76.47 | ✓ 76.10     | ✓ 76.4   | ✓ 80.04   |
| TripleE-Feature (ours) | ✓ 82.59 | ✓ 75.55 | ✓ 73.69     | ✓ 77.48  | ✓ 88.33   |

Table 4: Comparisons of results on PACS, VLCS, Office-Home, TerraInc, and DomainNet. Except for our method, other results are adopted from [4].

| Method          | PACS     | VLCS     | Office-Home | TerraInc | DomainNet |
|-----------------|----------|----------|-------------|----------|-----------|
| Mixstyle [65]   | 60.8     | 85.4     | 76.6        | 70.6     | 94.4      |
| C-DANN [55]     | 62.6     | 82.8     | 78.2        | 65.4     | 47.6      |
| DANN [14]       | 63.1     | 84.6     | 78.7        | 65.4     | 48.4      |
| ERM [35]        | 63.8     | 85.7     | 77.1        | 67.7     | 47.2      |
| Fish [56]       | 61.9     | 85.5     | 77.8        | 68.6     | 45.1      |
| CORAL [55]      | 64.1     | 86.0     | 77.7        | 68.6     | 46.4      |
| MIR [7]         | 65.9     | 85.4     | 79.0        | 70.5     | 50.4      |
| SWAD [5]        | 66.9     | 88.1     | 79.1        | 70.6     | 50.0      |
| TripleE (ours)  | ✓ 69.1   | ✓ 90.5   | ✓ 80.1      | ✓ 74.0   | ✓ 52.7    |

Table 5: Effectiveness of different components on Digits-DG, PACS, and Office-Home datasets (Backbone: ResNet-18). Vanilla refers to baseline used in early DG methods [63,3]. Compared to Vanilla, recent DG methods [58,60] use Baseline† that additionally employs color jittering as the basic data augmentation. Baseline(ours) keeps consistent with Baseline† except for an additional contrastive loss [26].

Like this method, our TripleE is a simple augmentation and ensemble method. It is worth mentioning that SFA [33] is also an augmentation-based method that augments feature embeddings to improve domain generalization. However, in terms of accuracy, our method can excel other DG methods and reach a comparable performance with STEAM [7], which uses domain labels and builds a complex network with at least three memory banks.

Office-Home dataset. The results are shown in Table 3. Notably, a simple vanilla model shows strong results on this benchmark. Most baselines provide only marginal improvements to the vanilla model with less than 1.0% improvements. One reason is that Office-Home is a relatively large composition of data, compared with PACS and Digits-DG, thus offering inherently bigger domain diversity in training data already [64]. Overall, our TripleE can surpass the best DG method FACT [60] and STEAM [7] by 1.77% and 1.53%, respectively. The state-of-the-art result on Office-Home dataset further validates the effectiveness of our proposed EReplayB, ESAug, and EReplayD.

VLCS, TerraInc and DomainNet datasets. Table 4 shows the comparison with existing state-of-the-arts on multiple DG benchmarks. SWAD [4] is one of the existing DG methods. In all experiments, our TripleE achieves significant performance gain against the previous best method SWAD [4]. The comparison shows that our TripleE could serve as a stepping stone for future research in domain generalization.

4.4 Ablation Studies

Ablation of our baseline model. We first point out that there are several inconsistent baselines in DG that share the same network structures but employ different augmentations. As shown in Table 5, early DG methods [63,3] use random crop, and random horizontal flip as the augmentation denoted as Vanilla. Whereas, recent DG methods [58,60] use a stronger Baseline† that additionally employs color jittering as the basic data augmentation, which can enhance the performance from 73.7% to 77.1%. Baseline(ours) keeps consistent with Baseline† except for an additional contrastive loss [26]. To use the contrastive loss, we add a projection head, which sequentially consists of a fully connected layer, a batch normalization layer, a ReLU, and a fully connected layer to map the feature dimension to 128. Although with a slightly stronger baseline, we verify that the performance improvements are from our proposed TripleE instead of the baseline.

Impact of different components. Table 5 shows the effectiveness of our proposed TripleE (EReplayB, ESAug, and EReplayD). Note that all experiments used Baseline(ours) as the backbone model. From experiments on Digits-DG, we can see that EReplayB,
ESAug, and EReplayD can enhance our baseline by 4.0%, 4.3%, 2.74%, respectively. From Model d and Model e, we can see that combining ESAug with EReplayB or EReplayD can largely improve the performance to 85.43% and 85.26%. With all these three components, our TripleE can achieve 86.97%. The result verifies our idea that ESAug can improve generalization performance by enlarging the data space in replays. Note that except for Model c, all other combinations of our method can exceed the current best DG method FACT [60] (81.5%). For experiments on PACS and Office-Home, we can see that training with EReplayB can outperform our baseline by 2.3% and 1.7% on PACS and Office-Home, respectively. Note that compared to our baseline, EReplayB only changes the batch size $b$ and repeat times $r$, showing that training with subsets can effectively improve the model generalization. By comparing Model a and Model b, we can see that using ESAug can increase the performance by 0.7% and 1.4% on PACS and Office-Home, respectively. These results demonstrated the effectiveness of enlarging data space when training with replays. Finally, we can see that using all three components can achieve the best performance on three datasets.

Ablation of EReplayB: a small batch with sufficient replay can enhance the generalization. Fig. 3 shows ablation study on parameter $b$ and $r$. Here, we empirically let $b$ equal to $r$ and show their effects to the performance. From Fig. 3 we can see that when $b = r = 4$ in Digits-DG and PACS, our method can achieve the best performance. The result verified the effectiveness of training a small batch (sub-set) with replay (augment for multiple times). Whereas when $b = r = 32$, our method can achieve the best result on Office-Home. As $b$ and $r$ increase, our performance may be higher, but this experiment has a high computational cost and is left as our future work.

Ablation of ESAug: exhaustive and singular augmentation can boost the generalization. Table 6 shows the effectiveness of our ESAug in terms of augmentation type and list. Compared with StandardAug, TrivialAug uses singular augmentation, which improves the performance from 82.52% to 86.33%. Therefore, we verified that a singular augmentation type effectively improves the performance. By comparing StandardAug and our method, we demonstrated that including a context-based image augmentation, Fourier or style, can further enhance the performance to 86.9% and 87.0%, respectively.

Ablation of $m$ in EReplayD: episodically replay sub-datasets can help the generalization. Table 7 shows the results with different sub-sample times in EReplayD. We tried $m$ from 1 to 5 and we found that setting $m = 3$ can achieve the best performance. In particular, our method can achieve 1.5% improvement over the model without EReplayD ($m = 1$).

Compare EReplayD with traditional ensemble. Table 8 shows the effectiveness of EReplayD. A traditional ensemble refers to train $m$ networks on a whole dataset and ensemble the predictions from $m$ networks as the final result. From Table 8 we can see that our proposed EReplayD, i.e., ensemble by periodically sub-sampling, outperforms the traditional model ensemble method by 1.33%. The result verified the effectiveness of our main assumption, that is, to focus more on learning subsets (sub-datasets).
Table 8: Compare EReplayD with the traditional ensemble on Digits-DG. Note that each experiment ensembles three models.

| Ensemble Type       | SYN | SVHN | MNIST-M | MNIST | Avg. |
|---------------------|-----|------|---------|-------|------|
| Traditional Ensemble| 94.93 | 77.88 | 71.83 | 97.95 | 85.64 |
| EReplayD (ours)     | 95.33 | 81.75 | 72.52 | 98.28 | **86.97** |

4.5 Visualization results

t-SNE visualization. Fig. 4 shows the visualization results of our baseline, FACT [60] and ours. The models are trained on art, painting, photo, sketch and tested on cartoon. We can see that our method can better separate the classes on the unseen target domain than the other two methods.

![Fig. 4: The t-SNE visualization on Cartoon on PACS dataset. Each color represents a class. Bested viewed in color.](image)

5 nearest neighbors for the images from unseen domain (art, painting). For each test image, the leftmost image is the closest image from the training dataset (sketch, photo and cartoon).

![Fig. 5: 5-nearest neighbors for the images from unseen domain (art, painting). For each test image, the leftmost image is the closest image from the training dataset (sketch, photo and cartoon).](image)

Table 9: Effects of different \( b \) and \( r \) in EReplayB on Digits-DG.

| \( b \) and \( r \) | SYN | SVHN | MNIST-M | MNIST | Avg. |
|---------------------|-----|------|---------|-------|------|
| \( b = 4, r = 32 \) | 96.2 | 79.57 | 70.12 | 98.30 | 86.05 |
| \( b = 4, r = 16 \) | 96.45 | 80.02 | 70.38 | 98.42 | 86.32 |
| \( b = 4, r = 8 \)  | 95.83 | 78.60 | 71.47 | 98.37 | 86.07 |
| \( b = 4, r = 4 \)  | 95.48 | 81.22 | 72.15 | 98.33 | 87.04 |
| \( b = 4, r = 4 \) (ours) | 95.48 | 81.22 | 73.15 | 98.33 | 87.04 |

5.1 Analysis on different \( b \) and \( r \) in EReplayB.

Table 9 shows the results with different \( b \) and \( r \) on Digits-DG. We can see that with a fixed batch size \( b \), the performance improvement is limited when repeat times \( r \) increase. The result shows that a high repeat time may not be necessary, and the result reaches the best performance when \( r = 4 \). On the other hand, when \( r = 4 \), as \( b \) increases, the performance worsens, and the best result is achieved at \( b = 4 \) and \( r = 4 \).

5.2 Effects of combining Fourier and stylization in ESAug.

Table 10 shows the results of combining Fourier and stylization in ESAug. We can see that adding both Fourier and Stylized transform achieves 86.76% performance, indicating that these two context-based augmentations have similar effects for model generalization. Therefore, in this paper, we present the results generated by Fourier-based and stylized augmentation individually.

Table 10: Effects of combining Fourier and Stylization in ESAug on Digits-DG.

| Combine Fourier and Stylized | SYN | SVHN | MNIST-M | MNIST | Avg. |
|------------------------------|-----|------|---------|-------|------|
| TripleE-Fourier              | 95.33 | 85.75 | 72.52 | 98.28 | 86.97 |
| TripleE-Stylized             | 95.48 | 81.22 | 73.15 | 98.33 | 87.04 |
5.3 Effects of different augmentation probabilities in ESAug

We include Fourier-based augmentation/ stylized augmentation into the standard augmentation list, consisting of 14 transformation functions. We studied different probabilities to include these context-exchange augmentations. Table 11 shows that concatenating the context-exchange augmentation (Fourier/Stylized) with the standard augmentation list achieves the best overall performance.

| Aug prob. | SYN | SVHN | MNIST-M | MNIST | Avg. |
|-----------|-----|------|---------|-------|------|
| Fourier   | 1/2 | 95.41| 76.97   | 69.37 | 98.03| 84.96|
| Fourier(ours) | 1/15 | 95.33| 81.75   | 72.52 | 98.28| 86.76|

Table 11: Effects of different augmentation probabilities in EAug on Digits-DG.

6 Conclusion

This paper presents a frustratingly easy yet should-know method for domain generalization. Unlike prior work that relies on a particular module, loss function, or structure design, our method is based on simple augmentations and ensembling. We reveal the key secret for model improvement is to encourage the network to train on subsets and enlarge the data space in learning on subsets. Our TripleE achieves this goal through three components: EReplayB, EReplayD, and ESAug. Experiments demonstrated that TripleE is outperforming or comparable to the state of the art, showing it could serve as a stepping stone for future research in domain generalization.

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