Abstract

Fine-tuning pretrained models is a common practice in domain generalization (DG) tasks. However, fine-tuning is usually computationally expensive due to the ever-growing size of pretrained models. More importantly, it may cause over-fitting on source domain and compromise their generalization ability as shown in recent works. Generally, pretrained models possess some level of generalization ability and can achieve decent performance regarding specific domains and samples. However, the generalization performance of pretrained models could vary significantly over different test domains even samples, which raises challenges for us to best leverage pretrained models in DG tasks. In this paper, we propose a novel domain generalization paradigm to better leverage various pretrained models, named specialized ensemble learning for domain generalization (SEdge). It first trains a linear label space adapter upon fixed pretrained models, which transforms the outputs of the pretrained model to the label space of the target domain. Then, an ensemble network aware of model specialty is proposed to dynamically dispatch proper pretrained models to predict each test sample. Experimental studies on several benchmarks show that SEDGE achieves significant performance improvements comparing to strong baselines including state-of-the-art method in DG tasks and reduces the trainable parameters by $\sim 99\%$ and the training time by $\sim 99.5\%$.

1 Introduction

Distribution shift is a common problem caused by physical or psychological factors of the real-world applications, which breaks the independent and identically distributional (i.i.d.) assumption of machine learning algorithms. Thus, generalization becomes increasingly important when training and applying machine learning models in practice.

The task of domain generalization and the corresponding benchmark [Gulrajani and Lopez-Paz, 2020] have been proposed for studying and improving model generalization by training on source domains and test on target domains. These methods focus on generalizable model training following a fine-tuning paradigm which often leverages pretrained models like ResNet [He et al., 2016] as an initialization and fine-tunes that with some elaborate training algorithms on the source domains. Then, the trained models would be evaluated on the unseen target domains. One common assumption
behind this commonly used paradigm is that fine-tuning brings better performance. However, fine-tuning is usually computationally expensive due to the ever-growing size of pretrained model, and proven to possibly compromise the generalization ability of pretrained models and under-perform in out-of-distribution scenarios [Kumar et al., 2021, Yu et al., 2021].

Therefore, instead of using pretrained model as an initialization like most existing methods on domain generalization, this paper seeks a better way to leverage the vast amount of the existing pretrained models [He et al., 2016, Krizhevsky et al., 2012, Iandola et al., 2014, Zoph et al., 2018, He et al., 2021, Radford et al., 2021]. Generally, the existing pretrained models have already possessed certain generalization ability over out-of-distribution scenarios. As shown in Figure 1 (B), one simple way to exploit pretrained models’ generalization ability is to train a linear label space adapter over a fixed weight pretrained model, which directly transforms the outputs of the pretrained model to the target label space. Our experiments show this minor adjustment bring enhancement over the fine-tuned one on certain target domains (detailed results in section 5.3).

However, fixed pretrained models do not constantly generalize on all domains, and the generalization performances of different pretrained models vary significantly over different target domains, label classes or even samples, as shown in Figure 3. This is caused by various aspects of the pretraining procedure such as model hypothesis, training algorithms and pretraining datasets.

Due to the significant variance of pretrained models’ generalization ability, it is essential to identify the samples a pretrained model generalize to (i.e. model specialty). Here we propose a novel learning paradigm that dispatches proper pretrained models to each sample based on their generalization ability, named specialized ensemble learning for domain generalization (SEEDGE). As shown in Figure 1 (C), specifically, in addition to the label adapter that projects the pretrained domain to the target domain upon the model with the fixed parameters, we further incorporate a model specialty aware ensemble network that selects a set of proper pretrained models and aggregate together to conduct predictions for each specific sample.

The advantages of our proposed learning paradigm lie in three aspects. First, it shows a significant improvement over the existing state-of-the-art (SOTA) result using the model pool pretrained only on ImageNet [Krizhevsky et al., 2012] dataset and gains even larger using the relatively larger model pool pretrained with additional datasets. Second, it exhibits significantly higher training efficiency. The only parameters trained on the source domains contain (1) a linear adapter transforming model outputs to the target label space and (2) a lightweight ensemble network that has largely reduced the training cost on the source domains comparing with that fine-tuning the pretrained models. We visualize the comparison of the performance w.r.t. to training parameter size and cost of training time in Figure 2. Last, this method illustrates a flexible way to utilize pretrained models, making it easier to exploit the abundant resource of pretrained models.
Figure 2: The comparison of the average performance (x-axis, the higher the better) of different algorithms, their training time (y-axis, the smaller the better), and the number of their training parameters (the size of the marker). We also list the corresponding information (number of training parameters, test accuracy, training time) of each algorithm.

2 Related work

2.1 Domain Generalization

Mainstream domain generalization research can be divided into following categories. (1) Domain alignment. In order to find the invariant representation across various domains, Ganin et al. [2016] adversarially train a generator and discriminator to reach the equilibrium of optimal invariant features across domains, hence the classifier trained on multiple source domains would generalize well to target unseen domains. Gong et al. [2019] consider reducing domain discrepancy in a manifold space. Some works resort to explicit feature distribution alignment on maximum mean discrepancy (MMD) [Pan et al., 2010, Tzeng et al., 2014, Wang et al., 2018], second order correlation [Sun et al., 2016, Sun and Saenko, 2016, Peng and Saenko, 2018], moment matching [Peng et al., 2019] and Wasserstein distance [Zhou et al., 2020, Lyu et al., 2021], etc. Besides learning invariant representation, Arjovsky et al. [2019] consider to learn an optimal invariant classifier on top of the representation space, and enforce the learned classifier predicts according with causal mechanism. (2) Data manipulation. Tobin et al. [2017] first introduce this idea, which aims to create diverse training data to simulate unseen target domain. Besides, Peng et al. [2018] and Tremblay et al. [2018] strengthen the generalization capability of the models via domain randomization, while other works consider using self-supervised learning [Carlucci et al., 2019, Kim et al., 2021] to match representation of an image with various augmentations. (3) Meta-learning. Inspired by Finn et al. [2017] and with the expectation to capture the most transferable representations across domains, MLDG [Li et al., 2018a] split the multiple source domains data into meta-train and meta-test set to simulate domain shifts to learn more generalizable representations. Dou et al. [2019] introduce additional losses to explicitly pertain to the semantic structure in representations. Balaji et al. [2018] consider learning a regularization function on classifier to avoid biasing to domain-specific information, while Du et al. [2020] resort to regularize Kullback-Leibler (KL) divergence between distributions of latent representations within samples from different domains.

While above categories more focus on algorithmic improvements, our proposed method SEDGE emphasizes the innovation of a learning paradigm based on a specialized pretrained model ensemble.

2.2 Ensemble Learning

Ensemble learning methods [Hansen and Salamon, 1990, Zhou et al., 2018] exploit multiple models to produce prediction results and combine the results with various techniques, e.g., boosting [Schapire, 1990, Freund, 1995, Moghimi et al., 2016] or mean aggregation [Zhou et al., 2018, Zhang et al., 2020], etc., to achieve better performance than individual model alone. These methods combine base
model learning and ensemble as a whole and focus more on training diverse base models [Zhou et al., 2018].

In DG, specifically, ensemble methods are used to exploit the relationship between source domains and the overall prediction results are composed of the superposition of the multiple networks on each domain. Mancini et al. [2018] proposed to aggregate different predictions from specific trained source models. Segu et al. [2020] proposed domain specific batch-norm statistics for each source domain. Zhou et al. [2021] proposed one shared CNN feature extractor with domain specific classifiers and each classifier is an expert to its own domain but non-expert to other domains. MulDEns [Thopalli et al., 2021] relaxes the requirement for domain-specific models and uses a model-domain relevance matrix to define the relations between models and domains. Besides aggregating different domain expert models, other works consider combining model weights in different runs. SWAD [Cha et al., 2021] avoids overfitting models to local sharp minima by averaging model weights below a validation loss threshold. EoA [Arpit et al., 2021] further lessens the frequent computations on validation set by averaging model weights simply from start to the end.

These ensemble learning methods rely on training or fine-tuning from a pretrained model, share the same limitation of training cost and initialization model selection. They did not consider the model specialty in different domains, classes or even samples. We start from a novel perspective that incorporates various pretrained models without fine-tuning and builds a lightweight specialty-aware ensemble network, which illustrates better generalization performance and largely reduces training costs.

3 Preliminaries

3.1 Problem Formulation

Domain generalization aims to tackle the shift of data distribution among different domains by zero-shot transferring knowledge from seen to unseen domains. Specifically, unlike domain adaptation, samples from unseen target domain(s) are inaccessible in domain generalization. For a domain, its input and label space can be denoted as $\mathcal{X} \in \mathbb{R}^d$ and $\mathcal{Y} \in \mathbb{R}^C$, and its samples are observed constructing a dataset $D = \{(x_i, y_i)\}_{i=1}^N$ with $N$ sample points. Consider that we have $S$ source domains $\mathcal{D}_s = \{D_1, \ldots, D_S\}$ and $T$ target domains $\mathcal{D}_t = \{D_1, \ldots, D_T\}$ with different distributions on $\mathcal{X} \times \mathcal{Y}$ and sharing the label space. Given instances drawn from source domains, the task is to learn a predictor parameterized by $\theta$ as $f_{\theta} \in \mathcal{M}: \mathbb{R}^d \longrightarrow \mathbb{R}^C$, where $d$ is the dimension of input and $C$ is the number of classes in $\mathcal{Y}$. We can define a population loss as $\mathcal{L}_D(\theta) = \frac{1}{|D|} \sum_{j=1}^{|D|} \mathbb{E}_{x_j \sim \mathcal{D}_s} [l(f_{\theta}(x_j), y_j)]$ over the given domain $D$. The objective is to minimize the task-specific loss $l$ (e.g., cross-entropy loss for classification) over both source domains $\mathcal{D}_s$ and target domains $\mathcal{D}_t$ by only minimizing the empirical risk $\hat{\mathcal{L}}_{D_s}(\theta)$ w.r.t. model parameter $\theta$. The performance on the target domains, then, measures the generalization ability of the learned model.

3.2 Preliminary Analysis

In this section, we want to investigate the generalization ability of various pretrained models, to gain some insights to motivate our method. As suggested by preliminary work [Kumar et al., 2021], a pretrained model with a linear probing layer (i.e., replacing the last layer of the pretrained model and retraining that) may achieve better accuracy in out-of-distribution scenarios than fine-tuning the whole model. However, linear probing is not feasible due to different pretrained models having different penultimate layer output feature dimensions. Instead, as shown in Figure 1 (B), we only train a label space adapter which learns the mapping function parameterized with $\phi$ as $h_{\phi} \in \mathcal{A}: \mathbb{R}^{C_0} \longrightarrow \mathbb{R}^C$, where $C_0$ is the dimension of the label space of the original pretraining dataset (pretraining domain). Thus, all the pretrained models on the same pretraining dataset (e.g., ImageNet) share the same label space. Given the pretrained model pool $\{f_k\}_{k=1}^K$ with $K$ pretrained models each of which is parameterized as $\theta_k$, we further parameterize the adapted model $h_{\phi}(f_k(\cdot))$ as $\theta'_k = [\phi; \theta_k]$. Then we train this shared adapter $h_{\phi}$ with the empirical loss $\hat{\mathcal{L}}_{D_s}(\phi)$ without fine-tuning the pretrained model parameters $\{\theta_k\}$. With the trained adapter, we use the likelihood of the ground truth label $p(y_i | x_i; \theta'_k)$ on the $i$-th
Figure 3: Performance distribution of the pretrained models over the samples within (a) different domains and (b) different classes. Each column of the left panel displays the relative performance distribution of the pretrained models; the right panel shows the Kullback-Leibler divergence between the performance distribution of different (a) domains and (b) classes. The comparison of the domain-level and class-level specialty shows that the performance of the pretrained models differs more significantly at the finer level.

4 SEDGE: A New Paradigm for Domain Generalization

In this section, we introduce our proposed learning paradigm, namely specialized ensemble learning for domain generalization (SEDGE), with the motivation and specific details of the whole method. We first present the whole framework in Section 4.1 and then discuss the gathered pretrained models in Section 4.2. After that, we introduce the model dispatcher with ensemble learning in Section 4.3 and the corresponding learning algorithm in Section 4.4.
4.1 Framework: Pretrained Model without Fine-tuning

Recall that the focus of the paper is on leveraging pretrained models without fine-tuning to cope with domain generalization. As motivated in Section 3.2, each model has its own specialty and each sample may require to choose a specific set of models to give a good prediction. As a result, we learn the matching of pretrained models and samples from the source domains’ training data.

Based on this idea, as illustrated in Figure 4, we propose a novel specialty-aware domain generalization framework to dispatch an ensemble of specialized models for each sample. Specifically, a label space adapter described in Section 3.2 is trained to transform the prediction of the pretrained models. And then, an ensemble network is learned to dispatch the models in a model pool to each sample according to their estimated specialty at sample level, and aggregate their outputs as an ensemble to output the final prediction for each sample.

4.2 Pretrained Model Pool

This section presents the pretrained models used in SEDGE. With more and more pretrained models being published, it is straightforward to build a pretrained model pool consisting of several public pretrained models for direct adapting to novel domains.

On one hand, utilizing a ConvNet backbone [LeCun et al., 2015] pretrained on ImageNet is a common practice of DG algorithms [Kim et al., 2021]. Based on that, we first build Model Pool-A which only contains 15 models pretrained on ImageNet for fair comparison with the existing algorithms. In Model Pool-A, we incorporate the architectures including AlexNet (1) [Krizhevsky et al., 2012], DenseNet-121/169/201 (3) [Iandola et al., 2014], Dual-Path-Network-68 (1) [Chen et al., 2017], NASNetMobile (1) [Zoph et al., 2018], ResNet-18/34/50 (3) [He et al., 2016], SE-ResNet-50 (1) [Hu et al., 2018], SqueezeNet-1.0/1.1 (2) [Iandola et al., 2016], and MAE-ViT-Base/Large/Huge (3) [He et al., 2021] with pretrained weights.

On the other hand, several DG algorithms also use models pretrained on other datasets, such as 1G-1B [Arpit et al., 2021] and ILSVRC12 [Thomas et al., 2021]. Therefore, we build Model Pool-B which contains two more CLIP models [Radford et al., 2021], ViT-B/16 and ViT-B/32, which are trained on a subset of the YFCC100M dataset of roughly the same size as ImageNet. We denote SEDGE using Model Pool-B as SEDGE+ to distinguish it from the one using Model Pool-A.

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Figure 4: SEDGE framework. Based on a pool of several fixed pretrained models, an ensemble network learns the matching of models and samples for model dispatching with the help of a label space adapter for prediction transformation.

https://github.com/Cadene/pretrained-models.pytorch
Note that, the models pretrained on the same dataset, i.e., ImageNet, will share the same label adapter transforming the vanilla model outputs to the target label space.

4.3 Ensemble Network

As demonstrated by the findings in Section 3.2 for generalizing to unseen domains, we need to take advantage of each of the pretrained models with consideration of their specialties. Additionally, rather than using one model to predict each sample, we propose to use an ensemble of multiple pretrained models, which is known to bring less generalization error [Ueda and Nakano, 1996]. Moreover, our method incorporates sample-level model specialty into consideration and conducts fine-grained specialty-aware ensemble learning, which is novel comparing to the existing ensemble learning methods as discussed in Section 2. This section will elaborate on the process of obtaining the most specialized pretrained models for a given sample and aggregating the outputs of selected models based on their specialty. The process can be divided into three steps as shown in Figure 4.

First, we embed the input sample and the available models to a hidden space. For an image sample \( x_i \), we use a fixed pretrained model (i.e., ResNet-34 in our implementation) to embed \( x_i \) to \( e_i \in \mathbb{R}^{d_e} \). Meanwhile, we introduce a learnable latent variable \( E_m \in \mathbb{R}^{K \times d_m} \) as model embedding dictionary corresponding to the \( K \) models \( \{f_k\}_{k=1}^K \), which is randomly initialized and optimized during training. Furthermore, we map \( e_i \) and \( E_m \) to a joint latent space as

\[
c_i = \sigma(e_i W_i), \quad C_m = \sigma(E_m W_m),
\]

where \( W_i \in \mathbb{R}^{d_e \times d_w}, \quad W_m \in \mathbb{R}^{d_m \times d_w} \), and \( \sigma(\cdot) = \max\{\cdot, 0\} \). We then perform matrix multiplication of \( c_i \) and \( C_m \) to calculate the matching score \( s = c_i C_m^T \in \mathbb{R}^K \) between the sample and each model. To dispatch each model output to the final prediction on the sample, we use one layer multi-layer perceptron and perform softmax operation to output the ensemble weights \( w = [w_1, \ldots, w_K] \in \mathbb{R}^K \) with \( w_k \) equals to

\[
w_k = \frac{e^{\zeta(W(s))_k}}{\sum_{j=1}^{K} e^{\zeta(W(s))_j}},
\]

where \( W \in \mathbb{R}^{K \times K} \) and \( \zeta(\cdot) = \log(1 + \exp(\cdot)) \). Finally, the prediction for \( x_i \) based on an ensemble of \( K \) model outputs is written as

\[
\hat{y}_i = \sum_{k=1}^{K} w_k h_\phi(f_k(x_i)), \quad \text{s.t.} \quad \sum_{k=1}^{K} w_k = 1.
\]

4.4 Learning Algorithm

As discussed above, the ensemble network acts as a model dispatcher through generating ensemble weights to aggregate multiple model predictions for each sample. Section 3.2 shows that model performance varies significantly over samples. Thus, we expect to assign more weights to the models with higher sample-level specialty to achieve the best utilization of the pretrained models. That is, we try to minimize the estimation risk of the estimated model specialty on the ground truth, i.e., \( w_k \) and \( p(y_i | x_i; \theta_k^c) \), as

\[
\mathcal{L}_c = -\sum_{k=1}^{K} \left[ p(y_i | x_i; \theta_k^c) \cdot \ln(w_k) + (1 - p(y_i | x_i; \theta_k^c)) \cdot \ln(1 - w_k) \right].
\]

\( \mathcal{L}_c \) is used to optimize the ensemble network to be a specialty-aware model dispatcher.

To train the general label space adapter \( h_\phi \) for all pretrained models, we incorporate the classification losses of adapted predictions of pretrained models

\[
\mathcal{L}_b = \sum_{k=1}^{K} w_k \cdot l \left( h_\phi(f_k(x_i)), y_i \right),
\]

where \( l(\cdot) \) is the classification loss.

\[
\mathcal{L}_c = l \left( \hat{y}_i, y_i \right)
\]
to optimize the likelihood of final ensemble output. $L_e$ is used to update both ensemble network and adapter.

It is worth noting that the only parameters to update is the label space adapter and ensemble network, each of which is lightweight compared to the pretrained models which remain fixed in our method yet have been fine-tuned in the previous works.

**Relation to weight ensemble.** Previous methods, such as SWAD [Cha et al., 2021] and EoA [Arpit et al., 2021], show that averaging model weights during training can avoid overfitting and achieve better generalization performance. Their experimental results show superior performance compared with methods without weight averaging. While in SEDGE, all pretrained model weights are not involved in training. Accordingly, we perform weight averaging for adapter and ensemble network starting from a certain iteration, which is served as a hyper-parameter.

**Top-k model selection in inference.** To save the inference time, we further select models with the highest $k$ ensemble weights and perform softmax on their ensemble weights for aggregation. In this paper, we set $k$ as 6.

5 Experiments

5.1 Evaluation Protocol

We conduct experiments on DomainBed suite [Gulrajani and Lopez-Paz, 2020], which provides like-for-like comparisons between algorithms and has a standard evaluation protocol to follow.

**Datasets.** We experiment on 5 real-world benchmark datasets including PACS (4 domains, 9,991 samples, 7 classes) [Li et al., 2017], VLCS (4 domains, 10,729 samples, 5 classes) [Fang et al., 2013], OfficeHome (4 domains, 15,588 samples, 65 classes) [Venkateswara et al., 2017], TerraIncognita (4 domains, 24,778 samples, 10 classes) [Beery et al., 2018], and DomainNet (6 domains, 586,575 samples, 345 classes) [Peng et al., 2019].

For fair comparison, we follow the training and evaluation protocol of DomainBed [Gulrajani and Lopez-Paz, 2020]. We use the *training-domain validation set* protocol for model selection. Specifically, one domain in a dataset is selected as the target domain and the rest as source domains, from which 20% of samples are used as the validation set. All runs are repeated 3 times using different random seeds, thus, with different train-validation splits. The out-of-domain test performance averaged over all domains will be reported for each dataset. In addition, we use the standard number of iterations of 5,000 for all datasets, with early-stop based on validated accuracy to reduce unnecessary computational costs.

**Baselines.** We compare SEDGE with some strong DG baselines including state-of-the-art. As discussed in Section 2, some of the compared methods incorporate elaborate learning algorithms including ERM [Vapnik, 1998], CORAL [Sun and Saenko, 2016], MLDG [Li et al., 2018a], MMD [Li et al., 2018b], DANN [Gann et al., 2016], C-DANN [Li et al., 2018c], and Fish [Shi et al., 2021].

Some other works compared in our evaluation incorporate ensemble learning as listed as below.

- **Stochastic Weight Averaging Densely (SWAD)** [Cha et al., 2021]: SWAD performs weight ensemble during model training.
- **Ensemble of Average (EoA)** [Arpit et al., 2021]: EoA combines both model ensemble and weight ensemble by taking an ensemble of moving average models from 6 runs. They experiment with two different pretrained models as initialization. One is pretrained on ImageNet with ResNet-50 and the other is pretrained on both ImageNet and a much larger additional dataset, IG-1B, with a more advanced backbone, ResNeXt-50 [Xie et al., 2017]. We denote the latter one as EoA$^+$ to indicate it uses the additional dataset.
- **Random ensemble**: In contrast to SEDGE of learning to select models for ensemble, we also compare it with average ensemble of $k$ models chosen randomly for each sample.

In addition, LP-FT [Kumar et al., 2021] reveals the generalization of pretrained models and proposes an elaborated fine-tuning strategy. However, it does not follow the protocol of DomainBed and does not provide implementation details for replication. Our runs for LP-FT show it performs worse than...
As shown in Table 1, SEDGE achieves an average performance of 69.4%, exceeding SW AD by 2.5%.

SEDGE only utilizes fixed pretrained models and learns to dispatch them.

This section presents experimental results on the DomainBed suite, with performance comparison shown in Table 1 and training/inference time comparison in Table 2.

**Comparison with fine-tuning paradigm.** The main difference between previous algorithms and SEDGE lies in fine-tuning or no fine-tuning on top of pretrained models. To verify whether the dispatcher of fixed pretrained models can outperform fine-tuning paradigm, we conduct a comparison of the algorithms that use models only pretrained on ImageNet, e.g., SEDGE using Model Pool-A. As shown in Table 1, SEDGE achieves an average performance of 69.4%, exceeding SW AD by 2.5%. Results show evidence that our novel paradigm is more effective than the traditional paradigm.

**Performance benefits from adding more pretrained models.** SEDGE provides a feasible way to incorporate the ever-emerging publicly available pretrained models. Although Model Pool-A pretrained on ImageNet is in common use, [Kumar et al., 2021] finds that model pretrained on ImageNet may not be good for datasets such as DomainNet. By using Model Pool-B that includes models that have been pretrained on the CLIP dataset [Radford et al., 2021], SEDGE+ further improves the average performance by 4.7% over SEDGE and ranks first on all datasets. This confirms that SEDGE paradigm is expected to generalize better on unseen domains by including models pretrained on more diverse datasets in the model pool.

**Training cost comparison.** SEDGE only utilizes fixed pretrained models and learns to dispatch them through a lightweight ensemble network with the help of a linear label space adapter. Therefore, the number of learnable parameters of SEDGE (up to 0.6M) is minor compared with the normal image backbone network (25.6M for ResNet-50). For fair training cost comparison, we run experiments of ERM, SWAD, SEDGE on a single Nvidia Tesla V100 and compare their overall back-propagation time from the start of training to the end (or early-stop). As shown in Table 2, training SEDGE paradigm uses noticeably less time. SEDGE+ takes only 0.6% of the time of ERM on DomainNet. The significant training time advantage of the method and its surpassing performance suggest that SEDGE is an effective and efficient paradigm for domain generalization.

**Inference cost comparison.** As shown in Table 2, although ensemble methods like EoA and SEDGE achieve better generalization performance at the cost of higher inference FLOPs, SEDGE still manages to save a large amount of inference cost compared to the previous best ensemble model (half of the inference FLOPs compared to EoA). This is because SEDGE only selects models with the highest $k(<K)$ ensemble weights. Therefore, only $k$ of $K$ models are activated for inference per sample, which reduces the inference cost to a large extent.

### Table 1: All baseline results are taken from their papers. Our experiments are repeated 3 times using different random seeds.

| Algorithm                  | PACS   | VLCS   | OfficeHome | TerraIncognita | DomainNet | avg.  |
|----------------------------|--------|--------|------------|----------------|-----------|-------|
| ERM (ICLR’21) [Gulrajani and Lopez-Paz, 2020] | 85.7 ± 0.1 | 79.1 ± 0.1 | 70.6 ± 0.2 | 50.0 ± 0.3 | 46.5 ± 0.1 | 65.9 ± 0.1 |
| EoA (arxiv) [Arpit et al., 2021] | 88.6 ± 0.6 | 79.3 ± 0.3 | 72.5 ± 0.2 | 57.3 ± 0.2 | 47.4 ± 0.2 | 68.0 ± 0.2 |
| random ensemble | 58.1 ± 0.13 | 58.5 ± 0.26 | 59.6 ± 0.36 | 31.5 ± 0.40 | 15.8 ± 0.40 | 44.5 ± 0.40 |
| SEDGE | 84.1 ± 0.46 | 79.8 ± 0.12 | 79.9 ± 0.12 | 56.8 ± 0.24 | 46.3 ± 0.10 | 69.4 ± 0.10 |
| EoA+ (arxiv) [Arpit et al., 2021] | 91.2 ± 0.04 | 80.8 ± 0.04 | 80.2 ± 0.2 | 55.2 ± 0.2 | 54.6 ± 0.2 | 72.7 ± 0.2 |
| random ensemble | 59.3 ± 0.06 | 61.1 ± 0.12 | 59.5 ± 0.07 | 30.8 ± 0.37 | 18.7 ± 0.62 | 45.0 ± 0.62 |
| SEDGE+ | 96.1 ± 0.04 | 82.2 ± 0.03 | 80.7 ± 0.21 | 56.8 ± 0.25 | 54.7 ± 0.10 | 74.1 ± 0.10 |

ERM, whose results are shown in Appendix. Note that, all the compared methods mentioned above incorporate a fine-tuning paradigm upon a pretrained model, which is essentially different to our method.

### 5.2 DomainBed Benchmarking

This section presents experimental results on the DomainBed suite, with performance comparison shown in Table 1 and training/inference time comparison in Table 2.

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Table 2: The comparison of training and inference cost. The run for SWAD on DomainNet failed due to out-of-memory. Here, “# parameters” means the number of learnable parameters.

| Algorithm       | PACS     | VLCS     | OfficeHome | Terralognita | DomainNet | avg. |
|-----------------|----------|----------|------------|--------------|-----------|------|
| Training        | GFLOPs   | # parameters | GFLOPs   | # parameters | GFLOPs   | # parameters |
| SWAD (NIPS’21)  | 88.1 ±0.1 | 79.1 ±0.1 | 70.5 ±0.2 | 50.0 ±0.3 | 46.5 ±0.1 | 66.9 |
| best single model + adapter | 79.7 | 73.6 | 78.3 | 49.2 | 32.5 | 62.7 |
| random ensemble | 58.1 ±0.13 | 58.5 ±0.17 | 59.0 ±0.38 | 31.5 ±0.40 | 15.8 ±1.40 | 44.5 |
| SEDGE           | 84.1 ±0.45 | 79.8 ±0.0 | 79.9 ±0.12 | 46.0 ±0.21 | 46.3 ±0.39 | 69.4 |

| Algorithm       | PACS     | VLCS     | OfficeHome | Terralognita | DomainNet | avg. |
|-----------------|----------|----------|------------|--------------|-----------|------|
| Inference       | GFLOPs   | # parameters | GFLOPs   | # parameters | GFLOPs   | # parameters |
| SWAD (NIPS’21)  | 95.4 | 82.0 | 78.3 | 49.2 | 52.6 | 71.5 |
| best single model + adapter | 59.5 ±0.05 | 61.1 ±0.12 | 59.5 ±0.07 | 30.8 ±0.37 | 18.7 ±0.62 | 46.0 |
| SEDGE           | 96.1 ±0.04 | 82.2 ±0.03 | 80.7 ±0.21 | 56.8 ±0.29 | 54.7 ±0.10 | 74.1 |

5.3 Ablation Study

We want to verify the effectiveness of SEDGE design by answering two research questions: (Q1) Is grafting a label space adapter on top of model outputs sufficient, for utilizing pretrained models to generalize to novel domains? (Q2) Is specialty-aware ensemble necessary, compared to an average ensemble method?

To verify whether a single model with an adapter can perform well, we train an individual adapter on source domains for each pretrained model in the model pool and compare their performance on target domain with state-of-the-art DG algorithm. To show the “cheating” upper bound of performance under this ablation study, we report the best single model performance on test set as best single model + adapter. As shown in Table 3, the best single model + adapter among Model Pool-A can outperform SWAD only on OfficeHome. It first indicates that the generalization ability of the fixed pretrained models may be more promising than model with fine-tuning on specific domains. However, in other four datasets, it lags behind SWAD by a large margin. This demonstrates a single pretrained model with a label space adapter is not sufficient to generalize to unseen domains, which motivates the main contribution of our method of introducing ensemble learning.

DG algorithms that combine ensemble learning, such as SWAD and EoA, demonstrate promising performance. A natural question is whether using an ensemble of pretrained models rather than a single model can improve performance. Following the ensemble approaches [Lakshminarayanan et al., 2017] using mean average, we experiment a random ensemble over the fixed pretrained models, i.e., randomly sampling k models for each sample and averaging their outputs for final prediction. The results are shown in Table 3. As can be seen, random ensemble results in worse performance than the single model, while SEDGE with specialty-aware ensemble boosts the final performance significantly, albeit with strong or weak individual model performance, which verifies the necessity to select and ensemble the pretrained models based on their specialty over samples as mentioned in Section 3.2 (Q2).

5.4 Further Analysis

As shown in Figure 3, model performance varies across domains, while SEDGE is designed to dispatch specialized models for samples. To analyze whether SEDGE is handling as expected, we present its domain-level model assignment on different domains of Terralognita. Specifically, we calculate the sum of ensemble weights assigned to a model as an evaluation of its importance. In Figure 5, we show the rankings of model importance on different domains. By comparing ranking between different domains, it can be seen that SEDGE dispatches models quite differently over unseen target domains. For example, while CLIP-ViT-B/32 model is used frequently on L38/43/46
Figure 5: Ranking models using the sum of ensemble weights on the sample in four domains of TerraIncognita. Each color block corresponds to a model. The higher rank indicates that this model is given a higher weight in predicting the samples in this domain.

datasets, it lags behind other models on L100. It suggests that SEDGE is making rational model selection as Figure 3 shows CLIP-ViT-B/32 is not a powerful model on this domain. Since the target domain is not known prior to making predictions, SEDGE learns to find suitable models for each sample by learning on source domains only.

## 6 Conclusions

Domain generalization algorithms use the pretrained model as initialization for fine-tuning, while a few works have found that fine-tuning may lead to out-of-distribution performance degradation. Different from the previous fine-tuning paradigm, this paper proposes a novel paradigm for domain generalization, specialized ensemble learning which learns to dispatch an ensemble of fixed pretrained models for each sample based on the model specialty on it. Experiments on five benchmark datasets show that our proposed method has achieved state-of-the-art performance with significant training cost reduction.

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