Sparse Fusion Mixture-of-Experts are Domain Generalizable Learners

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Abstract

Domain generalization (DG) aims at learning generalizable models under distribution shifts to avoid redundantly overfitting massive training data. Previous works with complex loss design and gradient constraint have not yet led to empirical success on large-scale benchmarks. In this work, we reveal the mixture-of-experts (MoE) model’s generalizability on DG by leveraging to distributively handle multiple aspects of the predictive features across domains. To this end, we propose Sparse Fusion Mixture-of-Experts (SF-MoE), which incorporates sparsity and fusion mechanisms into the MoE framework to keep the model both sparse and predictive. SF-MoE has two dedicated modules: 1) sparse block and 2) fusion block, which disentangle and aggregate the diverse learned signals of an object, respectively. Extensive experiments demonstrate that SF-MoE is a domain-generalizable learner on large-scale benchmarks. It outperforms state-of-the-art counterparts by more than 2% across 5 large-scale DG datasets (e.g., DomainNet), with the same or even lower computational costs. We further reveal the internal mechanism of SF-MoE from distributed representation perspective (e.g., visual attributes). We hope this framework could facilitate future research to push generalizable object recognition to the real world. Our code and models will be released at SF-MoE.

1 Introduction

Generalizing to out-of-distribution (OOD) data is an innate ability for humans, but challenging for machine learning models [54, 64, 78]. To address this problem, domain generalization (DG) research encourages models to be resilient in the face of various distribution shifts such as lighting, textures, backgrounds, and geographic/demographic factors [83, 96].

To achieve model generalizability, learning domain-invariant representations [3, 20] for DG has been extensively explored as they are theoretically grounded. However, their performance has been challenged on large-scale DG benchmarks [23]. On the one hand, strong evidence has revealed the insufficiency of only learning domain-invariant representations in domain adaptation problems [89, 44]. Zhao et al. [89] proved that, if the marginal label distributions differ across training domains, domain-invariant methods can harm generalization performance on target domains. On the other hand, the utilization of domain-specific information has also been considered in recent works, which proposes multiple networks to capture and align domain-specific information individually [15], or utilize domain-invariant and domain-specific networks simultaneously [8].

Meanwhile, another line of studies [23, 9] has observed that when backbone architectures and datasets get larger, simple baselines can match and even outperform existing DG methods with complex designs. For example, Li et al. [46] trained a linear probing MLP to dynamically routing samples to several pretrained networks with diverse architectures. Cha et al. [11] proposed training a network which approximates to oracle representations from an optimal model that is generalizable to
sparse/fusion block. A sparse block consists of a multi-head attention (MHA) layer and a mixture-of-experts (MoE) layer. MHA layer focuses on sparse signals and build self-attentions between patches (a subset of features). Then MoE layer further disentangles the learned attentions by distributing patches to different experts. The sparse block works in a grid-wise manner as shown in Figure 2.

However, adding sparsity would also bring training difficulty [42]. Therefore, we introduce a fusion block, which consists of a MHA layer and a dense feed-forward-network (FFN) layer. The dense FFN learns to integrate positional information across patches and transform sparse signals from MHA layer.

To further save computational cost and improve performance, we propose an efficient variant: Hybrid SF-MoE, which consists of a ResNet backbone to compress and extract features from raw images into smaller patches (compared with vanilla patch embedding). Overall, SF-MoE, with its efficient variant Hybrid SF-MoE, outperforms other state-of-the-art counterparts by large margins with similar or even lower training cost. The figurative comparison is shown in Figure 1-(b).

In general, we summarize our main contributions as follows:
A Novel DG Model: SF-MoE: To pursue a good structure that is both sparse and predictive, we propose Sparse Fusion Mixture-of-Experts, or SF-MoE, a unified architecture that sparsely handles multiple aspects of the discriminative features.

Excellent Performance and Efficiency: To demonstrate the efficacy of our proposed sparse architecture SF-MoE, we provide extensive experimental results on 8 large-scale DG datasets in Sec. 3. SF-MoE and Hybrid SF-MoE outperform other state-of-the-art counterparts by more than 2% across 5 datasets with similar or even lower cost.

Model Analysis on SF-MoE: To understand SF-MoE’s working mechanisms internally, we propose a diagnostic dataset CUB-DG to study 1) generalization performance across domains with different image styles, and 2) correlation between expert’s decision and the visual attributes in images. We also examine learned attentions in different attention head and router’s impact on generalization performance in sparse blocks.

2 Sparse Fusion Mixture-of-Experts

In this section, we introduce the working mechanism and the key component of SF-MoE architecture. We start with the ViT model (in Sec. 2.1) and highlight a drawback that standard multi-head attention usually produce redundant attention heads. Therefore, we propose SF-MoE, where sparse blocks (in Sec. 2.2) encourage attention heads to focus on more diverse features within layers, and fusion blocks (in Sec. 2.3) encourage the integration of diverse attentions among heads. SF-MoE can further utilize convolutional features for enhanced performance (in Sec. 2.4).

2.1 Preliminary: ViT and Multi-Head Attention

SF-MoE is built on Vision Transformer, which contains two essential components, the multi-head attention (MHA) layer and the feed-forward-network (FFN) layer. Each layer is constructed with the shortcut connection and the layer normalization. Recent study shows that sub-layers in multi-head attention and FFN layers have the inherent ensemble sub-structure [48, 53]. The sub-structure in each layer can be viewed as an ensemble of smaller sparse models. In detail, we regard the projection weight matrix $W_o$ into $h$ parts by rows, hence $W_o = [W_{o_1}^T; \ldots; W_{o_h}^T]^T$. Given a sequence of patches $x = [x_1, \ldots, x_n] \in \mathbb{R}^d$ processed by patch-embedding layer, and a query vector $q \in \mathbb{R}^d$. One multi-head attention layer is parameterized by weight matrices $W_Q, W_K, W_V \in \mathbb{R}^{d \times d}$, the $h$ independently heads could be computed in parallel to obtain the final results:

$$f_{MHA}(x, q) = \sum_{i=1}^{h} W_{o_i} \sum_{j=1}^{n} \text{SoftMax}(\frac{q^T W_k^T W_v}{\sqrt{d}} x_i) W_{v_i} x_i.$$

(1)
In this case, the multi-head attention mechanism can be viewed as jointly attending to multiple places by ensembling multiple attention heads, with each attention head focusing on its specific attention relationship between all patches. This also reveals the inherent collaboration mechanism of multi-head attentions.

However, recent studies [13] demonstrate that multiple-head attention layers could learn redundant key/query projections, i.e. some heads might attend to similar features in input space. To illustrate this issue, we consider the case that two heads $head_i$ and $head_j$ are computing the same key/query representations up to a unitary matrix $I \in \mathbb{R}^{d \times d}$ such that $W_{Q_i} = W_{Q_j}I$ and $W_{K_i} = W_{K_j}I$. In this case, even though the two heads are computing identical attention scores, i.e. $W_{Q_i}II^T W_{K_i}$, the concatenation $[W_{Q_i}, W_{Q_j}] \in \mathbb{R}^{d \times 2d}$ can also be full rank, which indicates that some attention heads would focus on the same content but are agnostic to each other.

2.2 Sparse Blocks: Disentangling Attentions

To avoid head redundancy and improve network sparsity, we introduce a mixture-of-experts (MoE) layer after the multi-head attention (MHA) layer and name it the sparse block. Next, we study the innate disentanglement and sparsity mechanism in a sparse block. In Figure 2, presented in a grid fashion, the MHA layer focuses on different signals (features) in different heads while MoE layer disentangles the information by handling each patch to different experts. This mechanism extends the network sparsity and hence is able to improve the model generalizability. In sum, the sparse block is designed to leverage different experts to model the relations between distinct image signals instead of explicitly capturing domain-invariant/-specific information.

To corroborate this, we conduct experiments on vanilla ViT and SF-MoE trained on DomainNet (all domains) and capture their multi-head attention outputs using validation images from the Real domain. The example of a bird image in Figure 3 indicates that the attention regions of ViT’s heads overlap to a large extent, while our proposed SF-MoE has two heads (head #1, 2) focus on the image’s background, three heads (head #3, 5, 6) attend to bird’s claw, and one head (head #4) attend to the bird’s beak. More visualizations are in the appendix.

In detail, we denote the multiple independent $N$ experts as $E_i, i = 1, \ldots, N$, each with specific learnable weights and not shared within the layer. Following the architecture in [67], we use multiple FFNs as experts, denoted as $E_i(x) = f_{FFN_i}(x) = \phi(xW^{1}W^{2})$, where $W^{1,2}$ are parameters of two layers MLP in each expert, and $\phi(\cdot)$ is the non-linear activation function. We use a gating network to route each token from the previous block’s output to different experts. The MoE layer is denoted as

$$f_{MoE}(x) = \sum_{i}^{N} G(x)_i f_{FFN_i}(x), \quad (2)$$

where $x \in \mathbb{R}^d$ is the input to the FFN layer $f_{FFN_i} : \mathbb{R}^d \to \mathbb{R}^d$, and $G : \mathbb{R}^d \to \mathbb{R}^N$ is the routing function, which prescribes the input-conditioned weight for the experts, e.g., $G(x)_i$ denotes the probability of selecting experts $E_i$ for $x$. 

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{image.png}
\caption{Comparison between multi-head attention visualization on the last block of vanilla ViT and SF-MoE. Images are selected from Real domain in DomainNet.}
\end{figure}
Routing function is specifically defined as $G(x_i) = \text{TOP}_k(\text{SoftMax}(Wx_i + \epsilon))$, where $\text{TOP}_k$ operation is a one-hot embedding that sets all other elements in the output vector to zero except for the elements with the largest $k$ values (we choose $k = 2$ in our scenario), and $\epsilon$ is sampled from $\epsilon \sim \mathcal{N}(0, 1/N^2)$. Due to space limit, we leave more details in appendix.

2.3 Fusion Blocks: Aggregating Attentions

In sparse block, the MoE layer leverages a routing network to learn patch-to-expert affinity. In theory, the learned routing network should allocate identical or related patches to the same expert. Ideally, when all patches are invariant to the routing network, a suboptimal strategy would result in a few experts adapting most of the patches, while the remaining experts are under-parameterized. Under-parametrization may induce a large auxiliary loss for load balancing, but less effective routing. This will make training more challenging, since more experts in different layers would require more training data that is properly balanced to each expert [42].

Empirically, in Figure 4, we find that keep adding sparse blocks (e.g., $[S] \times 12$) would result in performance drop. We opine that increasing sparsity also results in retaining more spurious information. More spurious information will falsify the network to capture spurious correlation in training data, and also weaken the generalization performance.

Due to the aforementioned difficulties, we cannot directly apply V-MoE [67] structure with a full sparse blocks pattern. To alleviate this issue, we propose a fusion block with a MHA layer and a dense FFN layer $f_{\text{dense}}(x) = \phi(xW^1)W^2$, $W^1 \in \mathbb{R}^{d \times k}$, $W^2 \in \mathbb{R}^{k \times d}$. Empirically, we set $k = 4d$. The dense FFN layer integrates and transforms diverse attentions among different heads. Accordingly, our empirical investigation in Figure 4 indicates that balancing the number of sparse/fusion blocks (e.g., 6 sparse blocks, 6 fusion blocks in 12-block ViT) would improve out-of-domain generalization performance in three datasets.

2.4 Hybrid SF-MoE: Integrating Convolutional Features

The primary elements of multi-head attention and sparse/fusion blocks are MLPs, which could improve the utilization of information while also increase the computational cost. A natural variation [16] is proposed to combine CNN [40] into Transformer architecture. We adopt this design and introduce ResNet [26] backbone for patch embedding. ResNet patch embedding layer would extract a feature map which is much smaller than original $16 \times 16$ patch embedding, and still preserves local information [32]. This property brings a positive impact on DG task since images contain redundant information between pixels in natural images.

We adopt the HybridViT pretrained on ImageNet-21k and fine-tuned on ImageNet-1k, then replace basic blocks of HybridViT with sparse/fusion blocks. To make fair comparison, we compare Hybrid SF-MoE with other counterparts that also pretrained on ImageNet-21k dataset. Hybrid SF-MoE, as
Table 1: Overall out-of-domain accuracies (%) with train-validation selection criterion. To make fair comparison, we divide algorithms into two groups, the best result for each split is highlighted in **bold**.

| Algorithm       | PACS   | VLCS   | OfficeHome | TerraInc | DomainNet |
|-----------------|--------|--------|------------|----------|-----------|
| Pretrained       |        |        |            |          |           |
| ERM (ResNet50)  | 85.7 ± 0.5 | 77.4 ± 0.3 | 67.5 ± 0.5 | 47.2 ± 0.4 | 41.2 ± 0.2 |
| IRM [ArXiv 20]  | 83.5 ± 0.8 | 78.5 ± 0.5 | 64.3 ± 2.2 | 47.6 ± 0.8 | 33.9 ± 2.8 |
| DANN [JMLR 16]  | 84.6 ± 1.1 | 78.7 ± 0.3 | 68.6 ± 0.4 | 46.4 ± 0.8 | 41.8 ± 0.2 |
| CORAL [ECCV 16] | 86.0 ± 0.2 | 77.7 ± 0.5 | 68.6 ± 0.4 | 46.4 ± 0.8 | 41.8 ± 0.2 |
| MMD [CVPR 18]   | 85.0 ± 0.2 | 76.7 ± 0.9 | 67.1 ± 0.1 | 49.3 ± 1.4 | 39.4 ± 0.8 |
| FISH [JCLR 22]  | 85.5 ± 0.3 | 77.8 ± 0.3 | 68.6 ± 0.4 | 45.1 ± 1.3 | 42.7 ± 0.2 |
| SWAD [NeurIPS 21] | **88.1 ± 0.1** | 79.1 ± 0.1 | 70.6 ± 0.2 | 50.0 ± 0.3 | 46.5 ± 0.1 |
| Fishr [ICML 22] | 85.5 ± 0.2 | 77.8 ± 0.2 | 68.6 ± 0.2 | 47.4 ± 1.6 | 41.7 ± 0.0 |
| MIRO [ArXiv 22] | 85.4 ± 0.4 | 79.0 ± 0.0 | 70.5 ± 0.4 | **50.4 ± 1.1** | 44.3 ± 0.2 |
| ViT-S/16 [ICLR 21] | 86.6 ± 0.1 | 77.9 ± 0.0 | 72.3 ± 0.7 | 42.6 ± 0.8 | 46.4 ± 0.2 |
| SF-MoE (Ours)   | 87.3 ± 0.1 | **80.2 ± 0.3** | **73.0 ± 0.2** | 46.3 ± 0.2 | **48.3 ± 0.2** |

| Hybrid ViT-R26-S/16 [16] | 89.3 ± 0.2 | 79.1 ± 0.1 | 79.1 ± 0.3 | 48.0 ± 0.2 | 51.0 ± 0.6 |
| Hybrid SF-MoE (Ours)     | 89.0 ± 0.2 | **80.5 ± 0.6** | **79.3 ± 0.2** | **48.9 ± 0.3** | **51.8 ± 0.2** |

Table 2: Overall out-of-domain accuracy (%) with train-validation selection criterion on SVIRO, Wilds-Camelyon and Wilds-FMoW datasets. The best result for each split is highlighted in **bold**.

| Algorithm       | SVIRO   | Wilds-Camelyon | Wilds-FMoW |
|-----------------|---------|----------------|------------|
| Pretrained       |         |                |            |
| ERM (ResNet50)  | 85.7     | 93.7           | 40.6       |
| ViT-S/16 [16]   | 89.6     | 91.1           | 44.8       |
| SF-MoE (Ours)   | 90.3     | 93.7           | 46.6       |
| Hybrid SF-MoE (IN21k, Ours) | **96.6** | 91.9           | **46.9**   |

an efficient variant of SF-MoE, could improve performance on large-scale datasets with the lowest run-time memory and throughput time.

3 Experimental Results

In this section, we first introduce the DomainBed benchmark datasets and evaluation protocols (in Sec 3.1). Then we report DG performance of SF-MoE with other counterparts on DomainBed (in Sec 3.2). To analyze the internal mechanism, we conduct ablation study on SF-MoE in Sec 3.3.

3.1 Benchmark Datasets

Following previous DG studies, we evaluate our proposed method on DomainBed [23] with 8 benchmark datasets, PACS, VLCS, OfficeHome, TerraIncognita, DomainNet, SVIRO, Wilds-Camelyon and Wilds-FMoW. The detailed information is provided in appendix.

Evaluation protocols. We evaluate our proposed method with two protocols on DomainBed [23] benchmark.

For **train-validation selection**, we split each training domain into training and validation subsets. Then, we pool the validation subsets of each training domain to create an overall validation set. Finally, we choose the model maximizing the accuracy on the overall validation set, and report the final accuracy on one leave out test domain.

For **leave-one-domain-out validation selection**, we train the model on all training domains and one domain out as validation set. We choose the model maximizing the accuracy on the leave-out validation domain, and report accuracy on another leave-out test domain. We should emphasize that leave-one-domain-out validation setting means we choose two domains as leave-out domains.
Table 3: **Left**: Visualization of images from different domains in CUB-DG. **Right**: Out-of-domain accuracy (%) in each domain on CUB-DG dataset. The best is in bold.

| Algorithm          | Candy | Mosaic | Natural | Udnie |
|--------------------|-------|--------|---------|-------|
| ERM (ResNet50)     | 62.9  | 17.3   | 82.1    | 75.3  |
| ERM (ViT-S/16)     | 82.0  | 38.2   | 89.6    | 81.0  |
| DANN [JMLR 16]     | 56.3  | 20.5   | 74.0    | 67.6  |
| FISH [ICLR 22]     | 64.9  | 23.5   | 80.6    | 73.9  |
| SF-MoE             | 83.1  | 40.5   | 90.2    | 82.7  |

This term is used with little misalignment in literature [11, 9] but is recommended in DomainBed’s original paper.

**Standard error bars.** We train the model three times with random choices on hyperparameters, weight initializations. The mean and standard error of these repetitions are reported.

### 3.2 DomainBed Results

The results on DomainBed are presented in Table 1, which include baseline methods and recent state-of-the-art methods. From the results on **training-domain validation selection**, SF-MoE strongly outperforms other counterparts on most of the datasets. We solely present Hybrid SF-MoE and other counterparts that also pretrained on ImageNet-21k [65]. We could observe Hybrid SF-MoE has strong performance on large-scale datasets with almost lowest runtime memory and training step time. SF-MoE also has excellent performance in **leave-one-domain-out criterion**, we leave the results in appendix due to space limit.

We also experiment our methods on another three large-scale datasets: SVIRO, Wilds-Camelyon, Wilds-FMOW. They are in similar scale and captures real-world distribution shifts across a diverse range of domains. We adopt the data preprocessing and domain split in DomainBed. Since we don’t find previous studies experiment their methods with the same criterion, we only report results on our methods and baselines. The results in Table 2 reveal SF-MoE strongly surpass baselines in SVIRO and Wilds-FMOW.

As suggested in Figure 4, we empirically find the optimal configurations in different datasets are slightly different (e.g., 8 experts per Sparse block is best for TerraInc but not for VLCS). More discussions and configuration details are included in appendix.

![Figure 5: The visual attribute & expert correlation in an SF-MoE model trained on CUB-DG in sparse block-5/-11 with 6 experts. The y-axis corresponds to 312 attributes and are divided into 27 categories as shown in y-axis label. The x-axis corresponds to the selected expert label.](image-url)
Table 4: Comparison of training iteration time and run-time memory.

| Algorithm   | ERM | DANN | IRM | VIT | Fish | Fishr | SWAD | EoA | SF MoE | Hybrid SF MoE |
|-------------|-----|------|-----|-----|------|-------|------|-----|--------|---------------|
| Step Time (s) ↓ | 0.59 | 0.61 | 0.68 | 0.59 | 1.56 | 0.62 | 0.67 | 0.68 | 0.60 | 0.57 |
| Run-time Memory (GB) ↓ | 13.13 | 13.14 | 13.40 | 12.83 | 3.48 | 15.25 | 13.23 | 13.41 | 13.64 | 12.76 |

### 3.3 Model Analysis

**CUB-DG: A diagnostic dataset** To understand how SF-MoE internally works, we create CUB-DG from the original Caltech-UCSD Birds (CUB) dataset [81], which is a widely studied fine-grained image classification dataset. In CUB-DG, we first stylize the original images into three domains, Candy, Mosaic and Udnie. The image examples are shown in the left of Table 3. CUB-DG dataset provides visual attributes (e.g., beak’s color) for each bird image. Then we could measure the correlation between visual attributes and experts selection in MoE layer.

**Generalization across image stylization** Since stylization does not modify object shape and outline, different domains would have a strong prior knowledge of invariance. In this way, we could evaluate the SF-MoE’s generalization performance across image stylization with many other methods that address domain-invariant representation learning. The results on the right of Table 3 demonstrate SF-MoE outperforms other state-of-the-art methods by a large margin.

**Correlation between visual attributes and experts** We choose SF-MoE with 6 sparse blocks, each block with 6 experts. After training the model on CUB-DG, we did forward passing with training images and save the top-1 index of router’s decision in block-5 and block-11. For an image that corresponds to a set of attributes, we multiply the expert selections with each attribute as a cumulative amount of this image. In Figure 5, we show the 2D histogram correlation between selected experts and the attributes. From the darker area in 2D histogram, we can see that in both block-5 and block-11, images with attributes **upperparts color** are cumulatively routed to expert #4 and expert #2, respectively. And in block-11, images with attributes **belly pattern, color and bill color** are cumulatively routed to expert #2.

**Computational cost comparison** Since algorithms developed from DomainBed mainly adopt the same architectures (e.g., ResNet50, Linear Classifier), traditional model complexity measures such as flops and model parameters can not truly reflect the difference in efficiency. To evaluate SF-MoE and its efficient variant, Hybrid SF-MoE, we conduct efficiency analysis with respect to training step time, and run-time memory. In this way, different algorithms with more complex loss design or gradient constraints will cause larger changes in these two metrics. From the results in Table 4, we observe that SF-MoE and Hybrid SF-MoE have almost the lowest run-time memory and training step time among all competitors.

### 4 Related Works

#### 4.1 Domain Generalization

Domain Generalization (DG) aims to keep the high performance of the machine learning models even on the domains that are different from the training (source) domain. The following are the main categories of mainstream domain generalization research.

**1) Domain Alignment** Aligning domain distributions and finding invariance between domains has been often studied with empirical results and theoretical proofs [20, 28]. Specifically, researchers seek explicitly aligning feature distributions based on the maximum mean discrepancy (MMD) [56, 79, 82], or second order correlation [75, 76, 59], moment matching [58] and Wasserstein distance [95, 50], etc. Besides aligning distributions in feature space, Arjovsky et al. [3] propose IRM to learn an ideal invariant classifier on top of the representation space. However, Rosenfeld et al. [68] claims that IRM need at least \( d_s \) environments to learn optimal invariant predictors where \( d_s \) is the dimension of spurious features. Similar effect has also been discussed in other recent works [35, 38] and many improvements [68, 1, 43] have been studied.
(2) **Data Manipulation:** Diverse training data are intuitively helpful for improving generalization, researchers proposed manipulation/augmentation techniques [55, 66], domain randomization [7, 86, 87]. Furthermore, some methods [66, 60, 47, 90, 92, 93, 91] exploit generated data samples to enhance the model generalization ability.

(3) **Ensemble Learning** methods [52, 69] assume the overall prediction should be inferred by a combination of the different models. Zhou et al. [97] proposed a shared CNN feature extractor as backbone with domain-specific classifiers, each of which is an expert in its own domain but a non-expert in others. SWAD [9] inhibits models from being overfit to local sharp minima by averaging model weights below a validation loss threshold. By averaging the model weights from beginning to end, EoA [4] further reduces the amount of computations on the validation set. SEDGE [46] leverages multiple pretrained models and selects best fit combination weights per sample to reach better accuracy with less trainable parameters and training time.

### 4.2 Vision Transformer

Originated from the machine translation tasks, Transformer [80] has received great attention from broader research communities beyond natural language processing [24, 30, 31, 74, 85]. ViT [16] is marked as the first successful attempt on implementing transformer model into computer vision tasks, which simply splits the whole image into patches and feeds them into Transformer encoders with multi-head attention mechanisms. Since then, many Transformer variants, such as Swin Transformer [49], MViT [17], PVT [84], and PiT [27], have been presented by introducing hierarchical [39] and shift-invariant [36] priors that are proved being useful to vision tasks by classic CNNs [26, 37]. Despite all these great improvement on vision transformer structures, in this paper, we develop our SF-MoE model based on the most classic and extensible ViT model. Besides, some existing works explore and conclude the robustness of the attention-based ViTs over CNNs [57, 6], and attempting to improve the ViT robustness via techniques such as patch-based negative augmentation [61] and extra fully attentional design [94]. To further enhance their robustness, in this paper, we explore the design of Sparse MoEs for ViT models on the domain generalization platform.

### 4.3 Sparse Mixture-of-Experts

Mixture-of-Experts models, or MoEs, make use of the outputs from several sub-models (experts) through an input-dependent routing mechanism for stronger model performance [33, 34]. This training paradigm has led to the development of a plethora of methods for a wide ranges of applications [29, 77], especially in natural language processing [70, 72] and computer vision [21, 22] However, multiple sub-models will inevitably introduce larger model size and longer inference time. To address this problem, Sparse MoEs [72, 67, 41, 18] are proposed with their routers to select only a few of experts, so that the inference time is on-par with the standalone counterpart. The sparsity mechanism finally helped the successful deployment of recently scaled language models reaching trillions of parameters [12, 18]. Some following works attempt to dive deep to explore the merits of Sparse MoEs. As analyzed in [2], Sparse MoE can be seen as a dynamic ensemble of subnetworks. This mechanism explicitly disentangles information within structures and prevents the model from absorbing easy spurious correlations [5]. In this work, we, for the first time, introduce Sparse MoEs into the DG community and provide several valuable insights based on the specific setting.

### 5 Conclusion and Discussion

Previous works in domain generalization with complex loss design and gradient constraint have not yet led to empirical success on large-scale benchmarks. In this paper, we propose **Sparse Fusion Mixture-of-Experts (SF-MoE)**, which incorporates sparsity and fusion mechanisms into the MoE framework to keep the model both sparse and predictive. Our proposed method outperforms other state-of-the-art methods. We also perform extensive experiments to reveal the working mechanisms.

**Weakness** The weakness of our work might be a lack of thorough theoretical analysis, which we anticipate to be rectified in forthcoming work.

**Social Impact** By developing generalizable models, we reduce the expense of mindlessly overfitting redundant large-scale data, which has a favorable societal impact on reducing computational cost and saving energy.
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