

APPENDIX

A DETAILS ON RELATED WORKS

Some existing style augmentation approaches can generate novel statistic mean $\hat{\mu}$ and standard deviation $\hat{\sigma}$. For instance, single-domain style exploration method DSU (Li et al., 2021) expands the mean μ and standard deviation σ by sampling perturbs from the estimated Gaussian distribution. AdvStyle (Zhong et al., 2022) expands μ and σ by maximizing the cross-entropy loss of the current model $\mathcal{F}_i \circ \mathcal{C}_i$ to learn the adversarial perturbs. However, these single-domain style exploration approaches only explores the styles based on the current source domain and ignores the other decentralized source domains, which leads to limited diversity of styles. Although some FedDG methods, e.g. CCST (Chen et al., 2023) and StableFDG (Park et al., 2023), share the mean μ and standard deviation σ across multiple decentralized source domains to conduct multi-domain style interpolation, the generated novel styles still come from the style space of existing source domains. Different from the existing approaches, we propose a CSA module to generate out-of-distribution styles of novel statistic mean $\hat{\mu}$ and standard deviation $\hat{\sigma}$ with the collaboration of other source domains.

B DETAILS OF EXPERIMENTAL SETUP

Following previous works (Wu & Gong, 2021; Yuan et al., 2023), we exploit the pre-trained ResNet-18 on ImageNet as the backbone for PACS, Office-Home, and VLCS dataset. The SGD optimizer is used to optimize the network with momentum 0.9 and weight decay $5e-4$. The initial learning rate is 0.001 decayed by the cosine schedule to 0.0001 for the PACS and VLCS datasets. For the Office-Home dataset, the initial learning rate is 0.002 and decayed to 0.0001. The batch size is 16 for PACS and VLCS, and 30 for Office-Home. The adversarial learning rate η is 1.0 for PACS and VLCS dataset, 0.3 for Office-Home datasets. The λ_{SupCon} is 1.0 for PACS and Office-Home dataset, 0.3 for VLCS dataset. λ_{cdrm} is 4.0 for PACS, 0.7 for Office-Home, and 0.3 for VLCS dataset. the τ of \mathcal{L}_{cdrm} is 1.5 for all dataset. The values of hyper-parameters are set according to the performance on validation set of source domains.

We train the local model on each client 1 epoch in Step 1 and then upload the local models to the server side for model aggregation. The total communication rounds between clients and server is 40 for PACS, Office-Home, VLCS. All experiments are conducted three times with different random seeds, and the mean accuracy (%) is reported.

For evaluating the effectiveness of our method, we make a comparison with the state-of-the-art domain generalization approaches. DeepAll indicates training the model by cross-entropy on the centralized source domains. FedAvg (McMahan et al., 2017) indicates collaborative training the decentralized source domains.

C NOVELTY OF FED-MCSAD

The Collaborative Adversarial Style Augmentation method is motivated by AdvStyle (Zhong et al., 2022). AdvStyle explores the style space on the image level, while we conduct style augmentation on the feature level and lead border style space. Moreover, AdvStyle is designed for the single-domain generalization. Different from this method, Fed-MCSAD exploits the classifier heads of other clients as the bridge to solve the federated multi-source domain generalization, which can explore the novel styles out of the existing source domains on local clients without accessing the data of other clients. The ablation study in Table 6 also indicates Fed-MCSAD significantly outperforms AdvStyle (up to 1.8%).

The domain-invariant learning paradigm is combined with the collaborative style augmentation module, which aims to learn the intrinsic semantic information between original and augmented data. The cross-domain feature alignment aligns the original and augmented data on feature space to learn the semantic information within the same category, and the cross-domain relation matching learns the intrinsic relationship between different categories from multiple classifier heads. The main contribution is the cross-domain relation matching, which distills the relationship of diverse classes from multiple classifier heads.

D PRIVACY ANALYSIS OF FED-MCSAD

Under the federated learning setting, either features or models from other devices are shared to bridge the devices/domains gap in existing works (Chen et al., 2023; Park et al., 2023; Feng et al., 2021). However, sharing features directly leads to local data privacy leakage. Furthermore, the original data of other clients can be generated by GAN with the collaboration of fully shared local models. In this paper, different from the existing approaches, we only share partial models, e.g., classifier heads, which makes it hard to generate the original data of other clients. In this way, the risk of privacy leakage of Fed-MCSAD is smaller than sharing features or the full model.

E OUT-OF-DISTRIBUTION STYLE GENERATION

The motivation of Fed-MCSAD is to explore the out-of-distribution styles with the collaboration of other classifier heads. The local model tends to work well for the specific domain. Thus, the generated data, which cannot be classified well by the existing classifier heads, tends to be out of the existing domains. Furthermore, the ablation study demonstrates that Fed-MCSAD significantly outperforms the existing data augmentation methods, which indicates that the generated data have border style space.

F ANALYSIS ON LEARNING ACROSS DIFFERENT CLIENTS/DOMAINS

For domain generalization tasks, the key challenge is to generalize well on the unseen domain, not the existing source domains. Thus, we focus on generating data out of the existing domains. Once the out-of-distribution data are generated on different local clients, we conduct DIL between the original local client data and the generated out-of-distribution data to achieve excellent generalization capability on out-of-distribution data. Aligning data across existing domains/clients leads to overfitting the existing domains and marginal improvement on generalization, so we align original data and out-of-distribution data in each client on the domain-invariant learning stage for better generalization.

G LIMITATIONS

Fed-MCSAD is designed for the federated domain generalization setting, where the label space of different local clients is the same. In real scenarios, the label space of different clients can be different, which cannot be addressed with the proposed approach. Furthermore, Fed-MCSAD focuses on the data heterogeneous scenario, which cannot address the model heterogeneous scenario. In the future, we plan to work on how to solve the federated domain generalization under the open-set setting and the heterogeneous model scenarios.

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