Supplement Material of "Meta-causal Learning for Single Domain Generalization"

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1. Future work

In this work, the factor set is defined manually, which may not capture all causes of the domain shift. In future work, we are going to discover latent factors so as to analyze the domain shift more flexibly and comprehensively.

2. Ablation Study of Eq.8

We add an ablation study by removing Eq.8 from our method ("Ours w/o Eq.8"). From the results shown in Table 1, "Ours w/o Eq.8" performs worse than "Ours". The reason is that Eq.8 restricts each feature mapping to address a specific domain shift, facilitating the reduction of combined domain shift in Eq.7.

Table 1. Ablation studies (%) of Eq.8 on PACS with ResNet-18.

Method	Artpaint	Cartoon	Sketch	Photo	Avg
Ours w/o Eq.8	74.37	75.65	59.71	55.10	66.21
Ours	**77.13**	**80.14**	**62.55**	**59.60**	**69.86**

3. Network Architecture.

For the Digits dataset, we use ConvNet [9] as the backbone [11, 17]. Each feature mapping is built with two FC layers (512→1024) with ReLU following the first FC layer. For the CIFAR-10 dataset, we use WRN [22] with 16 layers and widen factor 4 as the backbone [11, 17]. Each feature mapping is built with four FC layers (512→512→512→256) with ReLU following the first three FC layer. For the PACS dataset, we use ResNet-18 [7] pretrained on ImageNet as the backbone [6, 20]. Each feature mapping is built with four FC layers (1024→1024→1024→2048) with ReLU following the first three fc layer. For all tasks, the effect-to-weight network is built with two FC layers ($|\mathcal{Y}|\rightarrow 10\times|\mathcal{Y}|\rightarrow 1$) with ReLU after the first FC layer, where $|\mathcal{Y}|$ is the number of categories.

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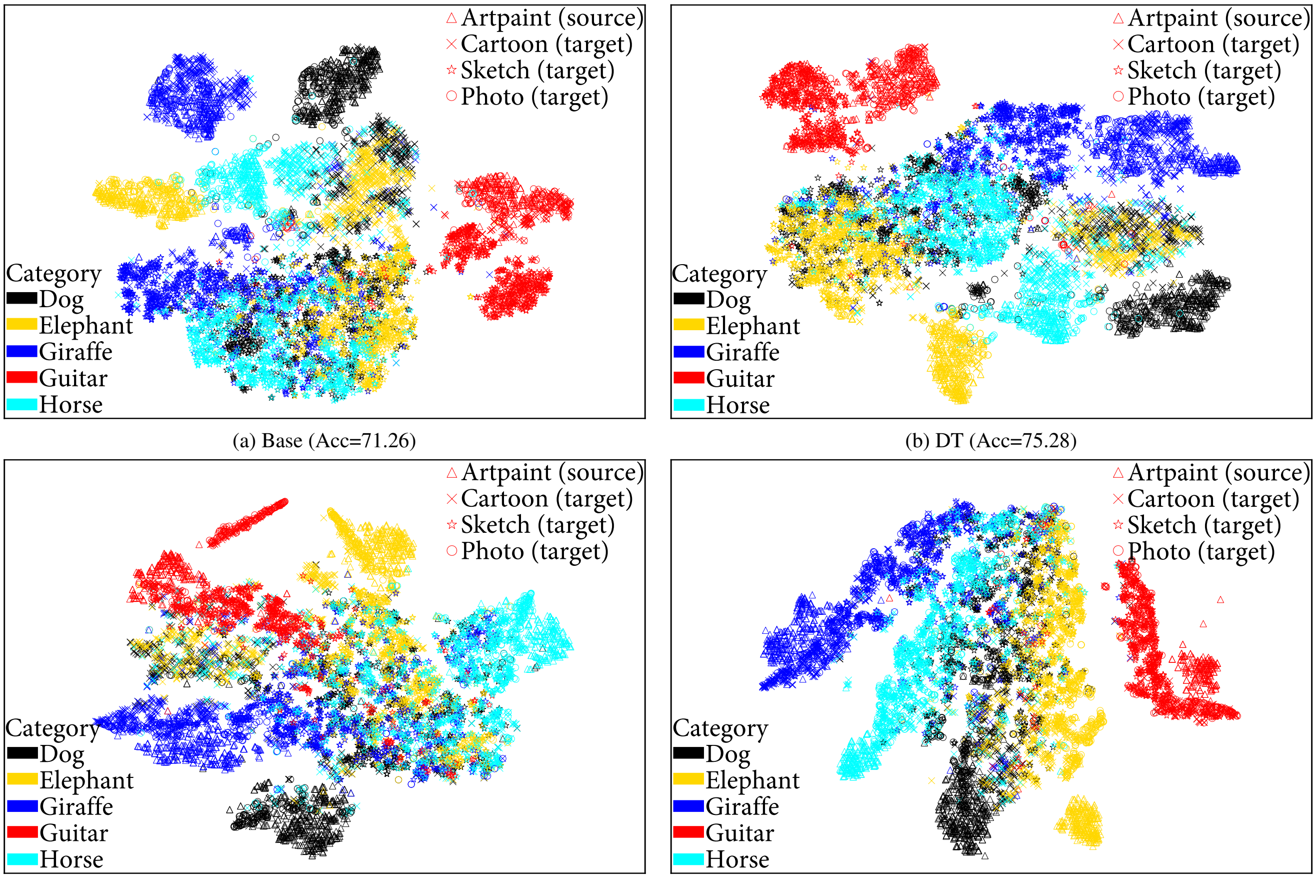
Table 2. Leave-one-domain-out results (%) on PACS with ResNet-50. One domain (name in column) is used as the target domain and the other three domains are used as source domains.

Method	Artpaint	Cartoon	Photo	Sketch	Avg
MetaReg [1]	87.20	79.20	97.60	70.30	83.60
MASF [5]	82.89	80.49	95.01	72.29	82.67
EISNet [19]	86.64	81.53	97.11	78.07	85.84
RSC [8]	87.89	82.16	97.92	83.35	87.83
FACT [21]	89.63	81.77	96.75	84.46	88.15
MatchDG [14]	85.61	82.12	**97.94**	78.76	86.11
CSG-ind [12]	88.60	84.60	97.80	81.10	88.03
CIRL [13]	**90.67**	84.30	97.84	87.68	90.12
Ours	90.58	**85.11**	97.60	**88.62**	**90.48**

4. Results on Multiple Domain Generalization

To further evaluate the effectiveness of our method, we also conduct experiments of multi-source domain generalization with ResNet50 as backbone on PACS. We employ the leave-one-domain-out protocol following existing multi-source domain generalization [13, 21]. We compare our method with most related methods that introduces causal inference into generalization (MatchDG [14], CSG-ind [12], CIRL [13]), and existing popular domain generalization methods (MetaReg [1], GUD [18], Epi-FCR [10], MASF [5], JiGen [2], DMG [3], DDAIG [24], CSD [16], L2A-OT [25], EISNet [19], RSC [8], ME-ADA [23], MMLD [15], L2D [20], FACT [21]).

Table 2 shows the leave-one-domain-out results on the PACS dataset with ResNet-50 as backbone. From the re-



(a) Base (Acc=71.26)

(b) DT (Acc=75.28)

(c) DTA (Acc=71.64)

(d) Ours (Acc=77.13)

Figure 1. Feature visualization on the PACS dataset with ResNet-18 as backbone. "△", " × ", "☆", and " ○ " denote the features of the source domain (Artpaint) and three target domains (Cartoon, Sketch, Photo), respectively. Different colors denote different categories as shown in the legend.

sults, it is noteworthy that our method achieves the state-of-the-art results in terms of the overall metric "Avg" although we not utilize the domain labels during training. In particular, when Cartoon or Sketch are used as the target domain, the domain shift is larger than other tasks due to the totally different styles of Cartoon and the highly abstracted shapes of Sketch. In these challenging tasks, our method not only beats all popular domain generalization methods but also surpasses the methods of introducing causal inference (MatchDG [14], CSG-ind [12], CIRL [13]), clearly showing the advantages of analyzing the causes of the domain shift by causal inference.

5. Feature Visualization

In Figure 1, we visualize the data distributions of the learned features by "Base", "DT", "DTA" and our method on the PACS dataset with Artpaint as the source domain, where ResNet-18 is used as backbone. For clarity, we only show the first five categories from both the source and unseen target domains using t-SNE embeddings [4]. It is noteworthy to observe that comparing with this three variants of our method, our method aligns the source features with the target features of unseen target domains well, further verifying the superiority of the new *simulate-analyze-reduce* paradigm.

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