Learning to Optimize Domain Specific Normalization for Domain Generalization

Supplementary Document

1 Domain Diversification via Augmentation

As domain generalization aims at working robustly over arbitrary domains, having diverse source domains in the training set is crucial for generalization ability. Based on this intuition, we propose to diversify source domains by domain augmentation. Our key idea is that a mixed set of samples from multiple domains can be interpreted as a new domain with deviated statistics from the original ones. We employ a simple generation strategy; a new domain is constructed by making a union of multiple existing domains. It generates $\binom{S}{1}+\binom{S}{2}+\cdots+\binom{S}{S-1}$ different domains from the original S source domains. For example, suppose that there exist three original domains denoted by $\mathcal{U}$, $\mathcal{V}$, and $\mathcal{W}$ and each domain contains the instances in the corresponding domain. We construct a new domain as a union of all the elements in two or more original domains, *i.e.,* $\mathcal{U}\cup\mathcal{V}, \mathcal{V}\cup\mathcal{W}, \mathcal{W}\cup\mathcal{U}$. Although these are trivial augmentations, we argue that this strategy is useful since an interpolated domain can be considered indirectly. With the new domains, we construct new datasets, $\mathcal{D}_1 = \{\mathcal{U}, \mathcal{V}, \mathcal{W}\}$, $\mathcal{D}_2 = \{\mathcal{U}\cup\mathcal{V}, \mathcal{V}\cup\mathcal{W}, \mathcal{W}\cup\mathcal{U}\}$, and $\mathcal{D}_3 = \{\mathcal{U}\cup\mathcal{V}\cup\mathcal{W}\}$. Then, we run DSON on each of the datasets and make an ensemble of the learned models to obtain the final results.

In Table 1, we compare three variations of the proposed network, DSON-$\mathcal{D}_1$, DSON-$\mathcal{D}_2$, and DSON-$\mathcal{D}_3$, which are trained using three different training datasets, $\mathcal{D}_1$, $\mathcal{D}_2$ and $\mathcal{D}_3$, respectively. Finally, ensembling the three models (DSON-Ensemble-$\mathcal{D}_{all}$) further improves the accuracy, and shows much stronger performance as compared to an ensemble of 3 independently trained BN models, which is denoted by BN-Ensemble(3).

Table 1: Effects of domain augmentation in terms of domain generalization accuracy (%) on Office-Home dataset. We compare DSON (ours) with different augmented domains, as well as the baseline model.

	Art	Clipart	Product	Real World	Avg.
BN	58.71	44.20	71.75	73.19	61.96
BN-Ensemble(3)	59.70	43.85	72.47	73.67	62.42
DSON-$\mathcal{D}_1$	59.37	45.70	71.84	74.68	62.90
DSON-$\mathcal{D}_2$	59.58	**46.80**	70.53	73.65	62.64
DSON-$\mathcal{D}_3$	58.72	44.61	72.04	73.65	62.25
DSON-Ensemble-$\mathcal{D}_{all}$	**60.28**	46.19	**72.94**	**75.28**	**63.67**