Robust Domain-Free Domain Generalization With Class-Aware Alignment

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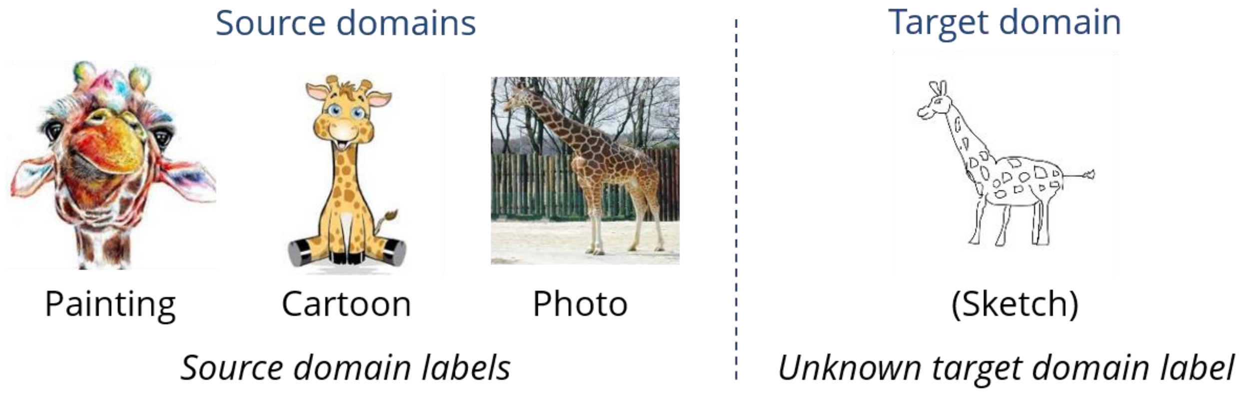
Domain Generalization Problem

Problem of Deep Learning

Deep learning has widely acclaimed performance in various applications. Yet, its success is typically reliant on the assumption that train and test data are sampled from the same distribution. Many real-world environments are highly dynamic, making test samples to be out of distribution.

Domain Generalization

Domain generalization aims to realize more practical and robust models deployable in the wild. Multiple source domains are leveraged to directly generalize to unseen domains with new data distributions. A core strategy is to align the source domains in a common, class-discriminative representation space.



Challenges in Domain Generalization

- Source domain labels may be unavailable in practice for training, and dataset labels cannot replace domain labels when samples of a dataset are drawn from a mixture of domains.
- The domain-invariant representation should be class-discriminative, and ignore domain-specific information which promotes overfitting to train data, e.g. specific illumination, image style, or imaging system.
- Most of existing approaches only align the features distributions and ignore the fine-grained class relationships which can impact performance.

Proposed Approach: Domain-Free Domain Generalization (DFDG)

Main Contributions

- A Domain-Free Domain Generalization (DFDG) method that is model-agnostic, and requires no domain labels and expert-driven feature engineering.
- Class-wise alignment loss to consider the class relationships of samples from different domains.
- Automatically filter out task-irrelevant features by masking superficial observations (i.e. pixels, time step readings) from the training inputs via saliency maps.

Setup

For each domain D, samples $\left(x_i^{(D)}, y_i^{(D)}\right)$ are drawn from a fixed distribution $\left(X^{(D)}, Y^{(D)}\right) \sim P^{(D)}$; y_i is one-hot vector of true class label in C classes. No sample from the target domain is available.

For model f parameterized by θ, $p_i = softmax\left(f(x_i;\theta)\right)$ are soft labels.

Method

Objective function for batch of samples B: $L = \ell_{ce} + \alpha \ell_{align}$

Classification task loss: $\ell_{ce} = -\frac{1}{|B|}\sum_{i \in B} y_i^T \log(p_i)$

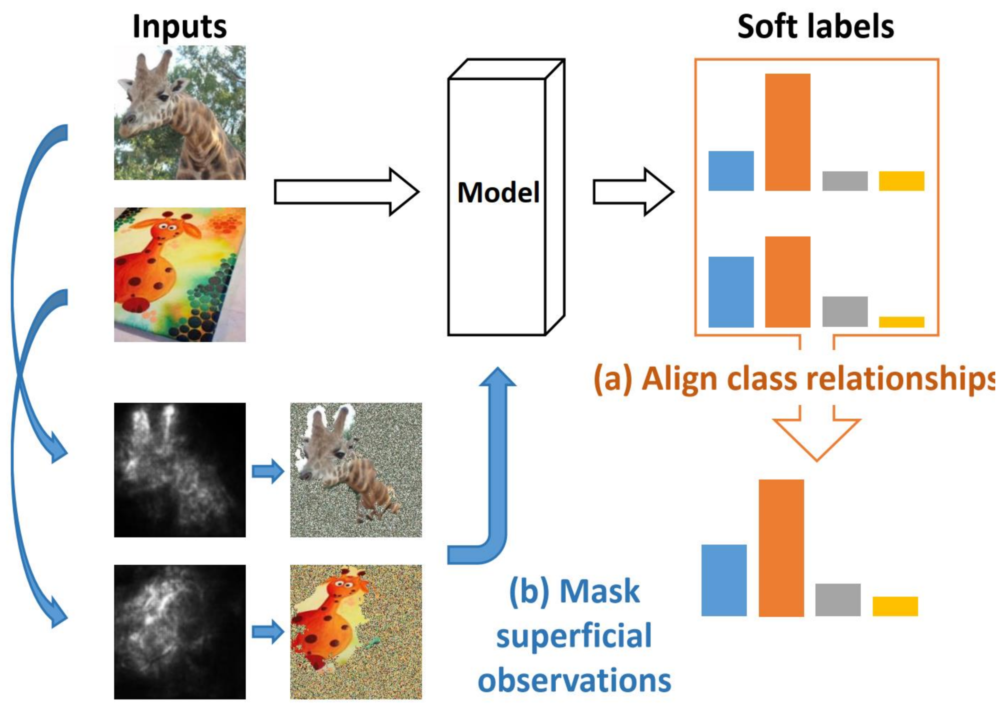
Regularize for class-relationship alignment of samples regardless of their domains.

$$\ell_{align} = \sum_{c=1}^{C} \frac{1}{|B(c)|} \sum_{i \in B(c)} \left\| p^{(i)} - \mu(c) \right\|_2^2$$

where

$$B(c) = \{i | i \in B, [1, \cdots, C] y_i = c\}$$

$$\mu(c) = \frac{1}{|B(c)|} \sum_{i \in B(c)} p^{(i)}$$



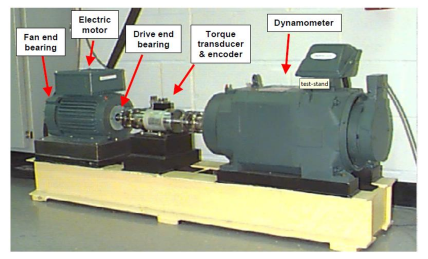
Masking of superficial observations:

1. Rank observations by SmoothGrad [1]
   saliency score: $g(x,c) = \left(\frac{\partial f(x,\theta)[c]}{\partial x}\right)^2$
2. Sample $q \sim Unif(0, qMax)$
3. Observations with saliency score below the q^{th} percentile are shuffled
4. In each batch, augment m% of samples

Datasets for DFDG Evaluation

Bearings [2] (vibration sensor signals)

- 10 classes: 9 faulty classes, 1 healthy class
- 8 operating conditions (domains): 4 loading torques x 2 bearing locations



HHAR [3] (device motion sensor signals)

- 6 human activity classes
- 9 users (domains)

PACS [4] (images)

- 7 classes
- 4 art styles (domains)

Experimental Results

Generalization Performance:

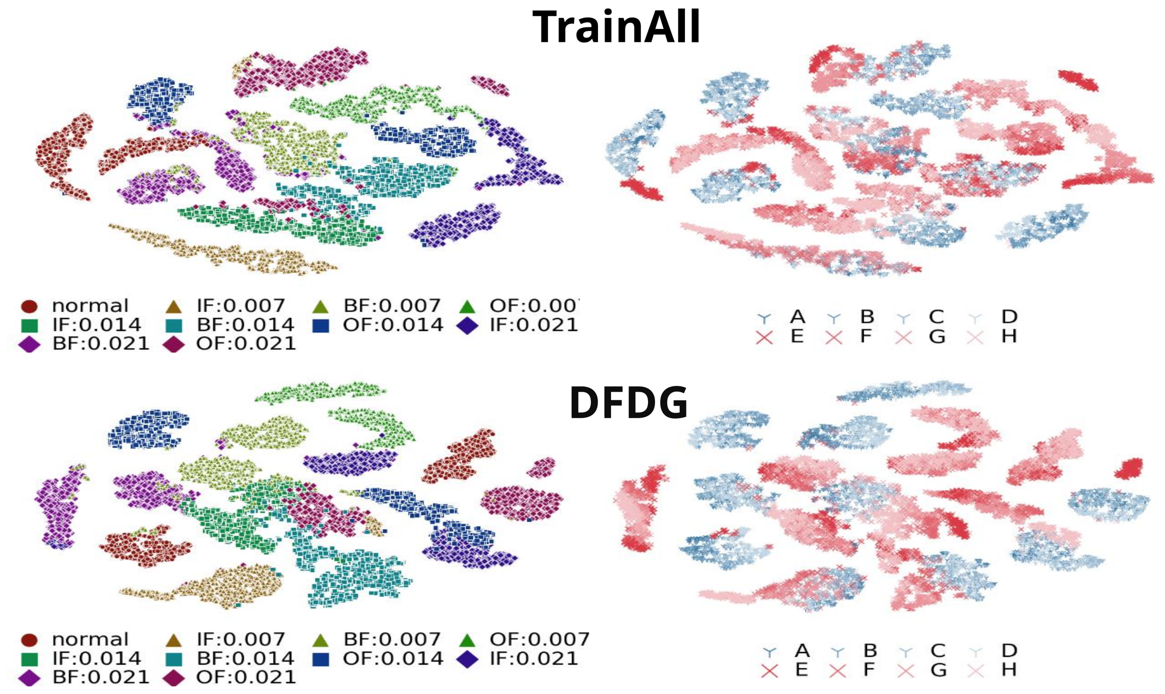
- DFDG hyperparameters: $\alpha = 0.1$, m=50, $qMax = 70$.
- Methods for comparison: TrainAll, MMLD [6], RSC [5].

Bearings

Target	Accuracy (%)				
	TrainAll	RSC	MMLD	DFDG	DFDG+RSC
A	52.33	68.43	65.70	66.60	68.23
B	90.50	91.10	95.37	89.30	90.90
C	92.90	97.60	89.33	89.67	92.47
D	74.97	77.73	65.87	77.73	77.97
E	70.73	70.33	64.20	73.40	74.77
F	88.53	86.40	79.03	91.50	90.23
G	87.20	90.20	86.83	91.40	94.30
H	85.20	90.50	75.53	85.30	88.37
Avg	80.30	84.04	77.73	83.13	**84.65**

HHAR

Target	Accuracy (%)			
	TrainAll	RSC	MMLD	DFDG
A	43.27	41.28	45.82	36.76
B	48.91	44.54	60.43	70.91
C	49.15	47.68	46.73	54.63
D	45.73	52.23	49.93	62.60
E	46.59	44.80	52.88	66.40
F	41.98	43.02	46.95	69.28
G	30.36	29.99	43.90	60.64
H	54.84	57.75	52.38	47.30
I	40.86	40.59	47.19	55.07
Avg	45.15	45.23	49.58	**58.18**



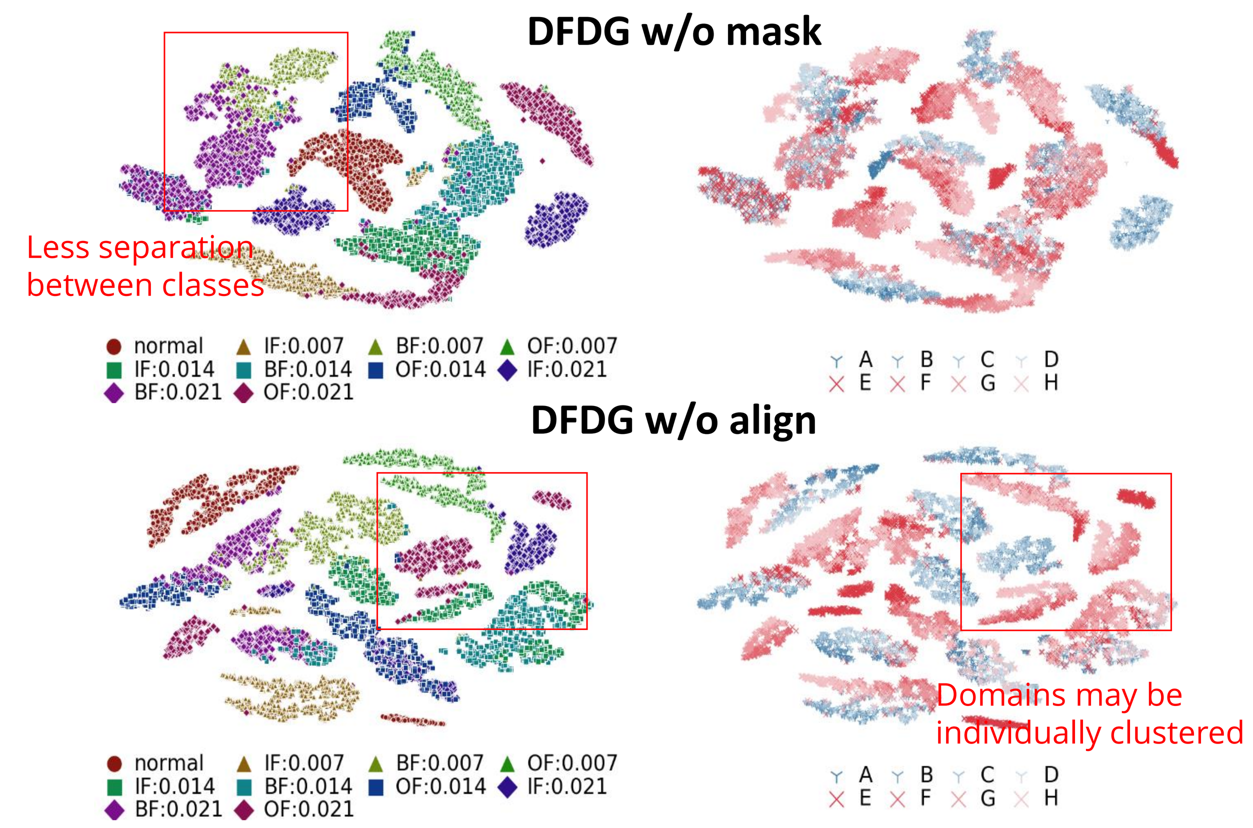
PACS

Target	Accuracy (%)			
	TrainAll	RSC	MMLD	DFDG
Art	78.73	80.37	78.99	79.23
Cartoon	74.30	76.84	77.06	75.84
Photo	94.55	94.99	95.41	95.45
Sketch	76.19	74.40	62.56	77.87
Avg	80.94	81.65	78.51	**82.10**

Ablation Studies (on Bearings):

Saliency Map	Avg Accuracy (%)
Vanilla gradient	80.77
SmoothGrad	83.42

Regularization	Masking		Avg Accuracy (%)
α	m	qMax	
-	-	-	79.75
0.01	-	-	80.21
0.1	-	-	79.97
-	33	30	83.21
-	50	70	83.42



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