

# 1. Introduction

- Humans encounter new task conditions all the time
  - Used to develop strategies which are robust to different task contexts
  - We want artificial learning agents to do the same
  - More versatility
  - Better out the box performance

## 2. MLDG Algorithm

High-level pseudocode of the MLDG algorithm can be found in Figure 2. One can intuitively interpret that the parameters ( $\Theta$ ) are corrected by the loss function of the meta-test set ( $G$ ). Therefore, the model will not overfit on a set of domains.

## Explanation:

- line 2** the algorithm starts off by defining the domains  $S$ .
- line 3** the initial model parameters ( $\Theta$ ) and hyperparameters are set.
- line 4** denotes the start of the iterations.
- line 5** the training data are split in a meta-train set and a meta-test set (Figure 3)
- line 6** the gradients for meta-train are calculated using the loss function ( $F$ ).
- line 7** the proposed updated parameters can be calculated for the meta train set.
- line 8** the loss function ( $G$ ) is calculated for the meta-test set as well.
- line 9** the updated parameters ( $\Theta$ ) are calculated based on the meta-train set loss function ( $F$ ) and the meta-test set loss function ( $G$ ) times a constant gamma.

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**Algorithm 1** Meta-Learning Domain Generalization

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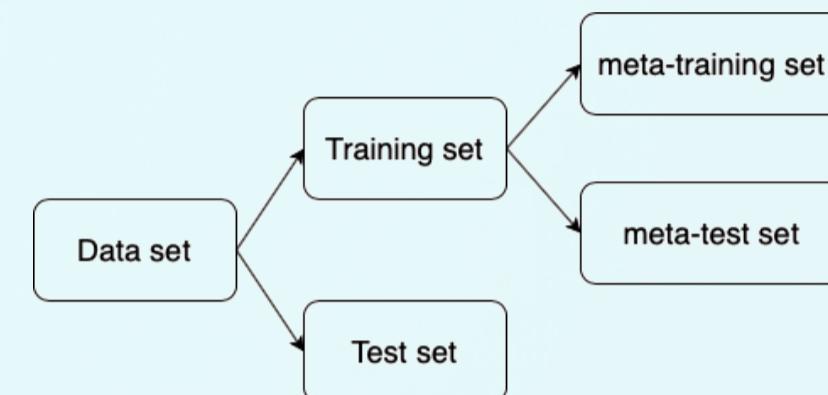
```

1: procedure MLDG
2:   Input: Domains  $\mathcal{S}$ 
3:   Init: Model parameters  $\Theta$ . Hyperparameters  $\alpha, \beta, \gamma$ .
4:   for ite in iterations do
5:     Split:  $\bar{\mathcal{S}}$  and  $\check{\mathcal{S}} \leftarrow \mathcal{S}$ 
6:     Meta-train: Gradients  $\nabla_{\Theta} = \mathcal{F}'_{\Theta}(\bar{\mathcal{S}}; \Theta)$ 
7:     Updated parameters  $\Theta' = \Theta - \alpha \nabla_{\Theta}$ 
8:     Meta-test: Loss is  $\mathcal{G}(\check{\mathcal{S}}; \Theta')$ .
9:     Meta-optimization: Update  $\Theta$ 

```

$$\Theta = \Theta - \gamma \frac{\partial(\mathcal{F}(\bar{\mathcal{S}}; \Theta) + \beta \mathcal{G}(\check{\mathcal{S}}; \Theta - \alpha \nabla_{\Theta}))}{\partial \Theta}$$

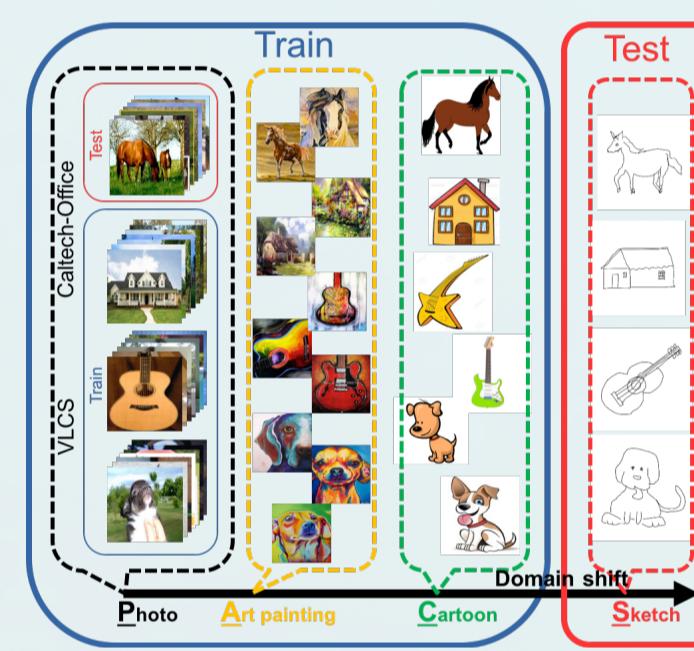
## Figure 1



# 3. Experiment to Reproduce

- Recognize object in one domain, while only training in other domains
  - PACS multi-domain recognition benchmark
  - 9991 images across 7 categories spread over 4 domains (see figure 3)
  - Results to be reproduced are shown in table 1

Categories	Domains
- Dog	- Photo
- Elephant	- Art painting
- Giraffe	- Cartoon
- Guitar	- Sketch
- House	
- Horse	
- Person	



# 4. Reproducability Efforts

# Code changes

- Rewrite existing code to Python 3
  - Rewrite code to utilize PyTorch

# Extra

- Investigate hyperparam robustness
  - Investigate loss over time

Table 1: Cross-domain recognition accuracy (Multi-class accuracy) on the PACS dataset. Best performance in bold.

	D-MTAE (Ghifary et al. 2015)	Deep-all	DSN (Bousmalis et al. 2016)	AlexNet+TF (Li et al. 2017)	MLDG (CNN)
art_painting	60.27	64.91	61.13	62.86	<b>66.23</b>
cartoon	58.65	64.28	66.54	<b>66.97</b>	66.88
photo	<b>91.12</b>	86.67	83.25	89.50	88.00
sketch	47.86	53.08	58.58	57.51	<b>58.96</b>
Ave.	64.48	67.24	67.37	69.21	<b>70.01</b>

# 5. Intermediate Reproducability Results

- Single run with 3 iterations
  - Original paper performed 5 runs with 3 iterations each
  - Reproduced accuracy is expected to converge towards table 1 for more runs

# MLP (Baseline)

```
ite: 0 loss: 5.83397 lr: 0.0005
ite: 5000 loss: 0.7646471 lr: 0.0005
ite: 10000 loss: 0.41197827 lr: 0.0005
ite: 15000 loss: 0.21348761 lr: 5e-06
ite: 20000 loss: 0.23729184 lr: 5e-05
ite: 25000 loss: 0.23310997 lr: 5e-05
ite: 30000 loss: 0.23491922 lr: 5.000000000000002e-07
ite: 35000 loss: 0.20772612 lr: 5.000000000000001e-06
ite: 40000 loss: 0.2116398 lr: 5.000000000000001e-06
ite: 45000 loss: 0.19999795 lr: 5.000000000000001e-06
```

Average accuracy: 69.5%

# MLDG

```
ite: 0 meta_train_loss: 3.9915504 meta_val_loss: 7.7315373 lr: 0.0005  
ite: 5000 meta_train_loss: 0.38368234 meta_val_loss: 0.7135035 lr: 0.0005  
ite: 10000 meta_train_loss: 0.47828954 meta_val_loss: 0.22636156 lr: 0.0005  
ite: 15000 meta_train_loss: 0.3709153 meta_val_loss: 0.018917829 lr: 5e-06  
ite: 20000 meta_train_loss: 0.33163258 meta_val_loss: 0.014834516 lr: 5e-05  
ite: 25000 meta_train_loss: 0.3221491 meta_val_loss: 0.039074518 lr: 5e-05  
ite: 30000 meta_train_loss: 0.34363568 meta_val_loss: 0.03459864 lr: 5.000000000000002e-07  
ite: 35000 meta_train_loss: 0.3272212 meta_val_loss: 0.0419287 lr: 5.000000000000001e-06  
ite: 40000 meta_train_loss: 0.031871844 meta_val_loss: 0.29184628 lr: 5.000000000000001e-06  
ite: 45000 meta_train_loss: 0.2500644 meta_val_loss: 0.00020526 lr: 5.000000000000001e-06
```

Average accuracy: 71.7%