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Informatics & Telematics

A Short Tutorial on Domain Generalization

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Outline

Part 1: Introduction to DG

Part 2: Overview of representative DG methods

Part 3: DG datasets and benchmarks

Part 4: DG for biomedical signals: The BioDG benchmark

Part 5: Conclusions

Part 1: Introduction to the Domain Generalization problem

(A) **Cow: 0.99**, Pasture: 0.99, Grass: 0.99, No Person: 0.98, Mammal: 0.98

(B) No Person: 0.99, Water: 0.98, Beach: 0.97, Outdoors: 0.97, Seashore: 0.97

(C) No Person: 0.97, **Mammal: 0.96**, Water: 0.94, Beach: 0.94, Two: 0.94

Beery et al. "Recognition in terra incognita." ECCV 2018


Predicted: wolf
True: wolf
Predicted: husky
True: husky
Predicted: wolf
True: wolf
Predicted: wolf
True: husky
Predicted: husky
True: husky
Predicted: wolf
True: wolf

source

Background (1)

Supervised statistical machine learning methods aim at learning a function

$$\hat{y} = f(x;\, \theta)$$

which provides an estimate/probabilities $\hat{y}$ of the true value of the label(s)/target(s) y, given a previously unseen data sample x

In our previous example, $x =$

$\hat{y} =$ (A) **Cow: 0.99**, Pasture: 0.99, Grass: 0.99, No Person: 0.98, Mammal: 0.98

Background (2)

Let P_{XY} on $\mathcal{X} \times \mathcal{Y}$ be the distribution of the training data. A fundamental assumption of most ML methods is that the unseen (test) data follow the same distribution as the training data (i.i.d. assumption).

However, in our example:

$$P_{XY}^{(1)} \neq P_{XY}^{(2)}$$

(1): Cows + grass

(2): Cows + beach

Domains

Let's call each $P_{XY}^{(i)},\ i = 1, \ldots, K$ a **domain**

Example domains:

- Cows with grass
- Cows with beach
- Wolves with snow
- Wolves with gravel

Domains

Let's call each $P_{XY}^{(i)},\ i = 1, \ldots, K$ a **domain**

Example domains:

- Cows with grass
- Cows with beach
- Wolves with snow
- Wolves with gravel

Problem 1: How can we train a model to correctly classify samples from different domains?

Solution 1: Just train a model with pictures from both domains

Domains

Let's call each $P_{XY}^{(i)},\ i = 1, \ldots, K$ a **domain**

Example domains:

- Cows with grass
- Cows with beach
- Wolves with snow
- Wolves with gravel

- Dataset distribution can be device-specific
  - X-rays of device A
  - X-rays of device B
- Dataset distribution may vary across individuals
  - Blood sample from person 1
  - Blood sample from person 2
- Privacy / legal / technical restrictions

Problem 2: In many real-world scenarios it is difficult to have access to large volumes of data from all domains during training

Transfer learning (for the same labels)

Given a model trained on a **source domain**: $P_{XY}^{(S)}$

Train a model on the **target domain**: $P_{XY}^{(T)}$ by performing a (hopefully small) number of training iterations

Requirements:

- Large numbers of labeled data on source domain
- Availability of labeled data on target domain

Domain adaptation

Train a model on the **source domain(s)**: $P_{XY}^{(S)}$

Use unlabeled data (or very small number of labeled data) to adapt the model to the **target domain**, $P_{XY}^{(T)}$

Requirements:

- Unlabelled data (or small number of labeled data) from the target domain

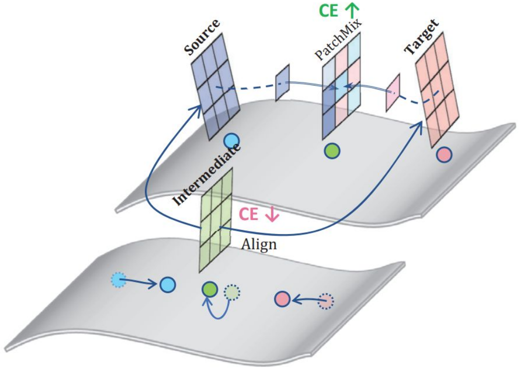


Image from: Zhu, J. et al. "Patch-Mix Transformer for Unsupervised Domain Adaptation: A Game Perspective.", CVPR 2023

Domain Generalization (1)

In this scenario we don't have access to **any** data from the target domain during training.

Our goal is to train a model using data from the source domain(s) that are effective in the unseen target domain(s)

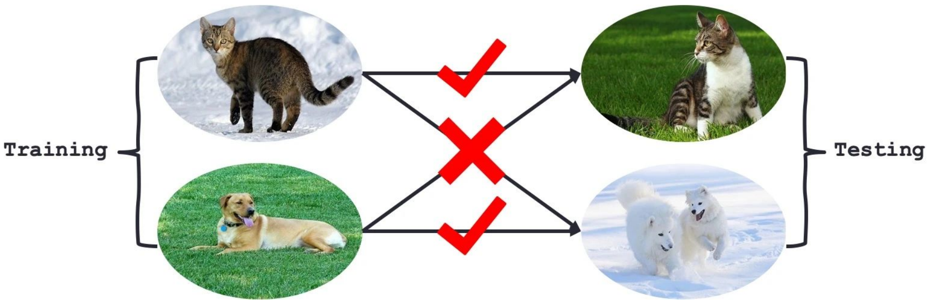
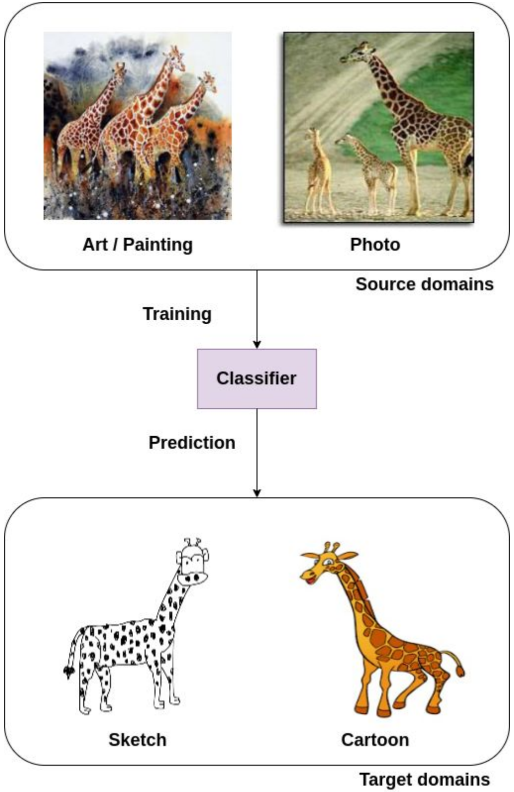


Image: Zhang et al., NICO++: Towards Better Benchmarking for Domain Generalization
https://github.com/xxgege/NICO-plus

Domain Generalization (2)



Sample images from the PACS dataset

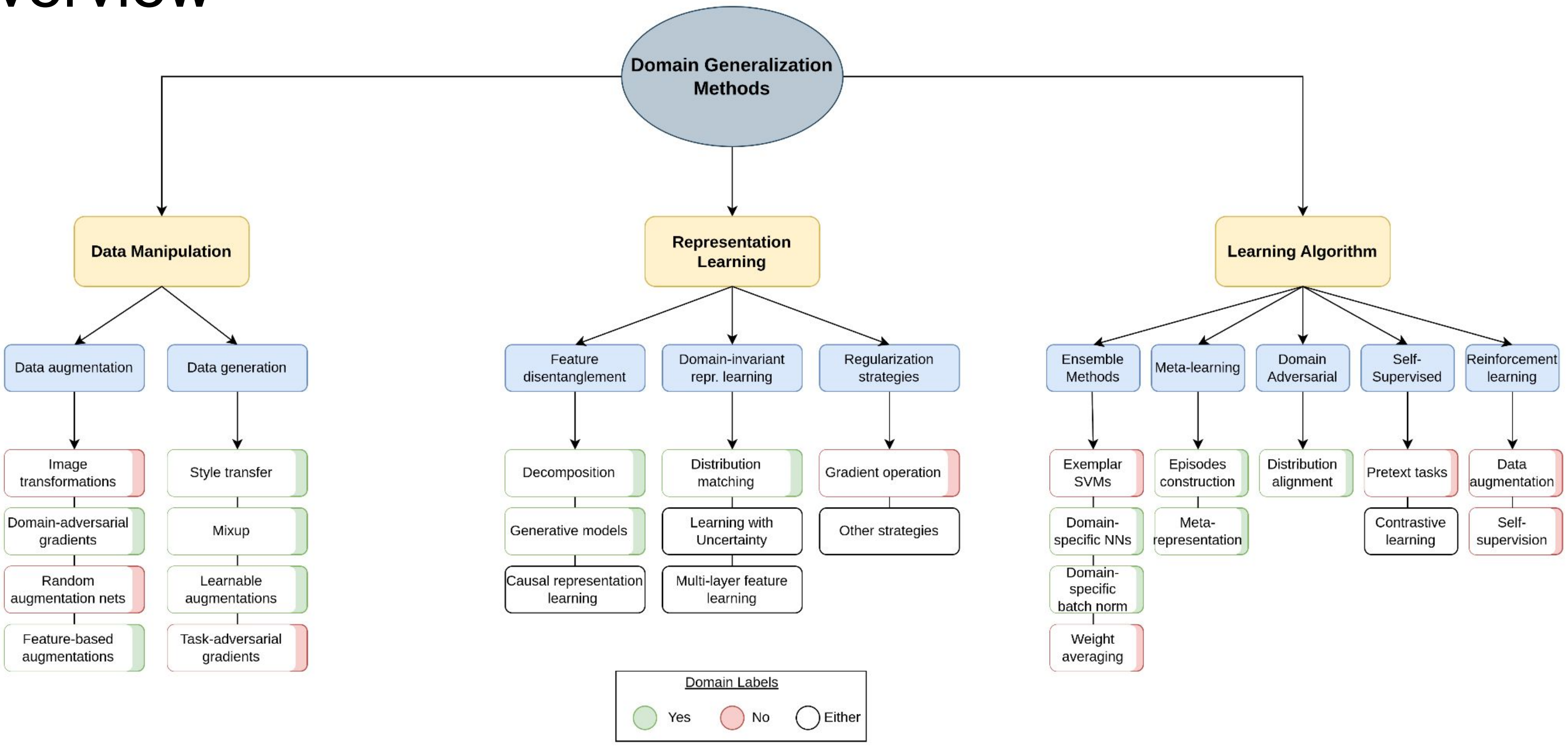
Observation:

- Some features are common (invariant) across domains

Goal: Learn the invariant features, not spurious domain features

- **Multi-source DG**: Multiple training domains, access to domain labels (we know the domain of each training sample)
- **Single-source DG**: Single training domain and/or no-access to domain labels

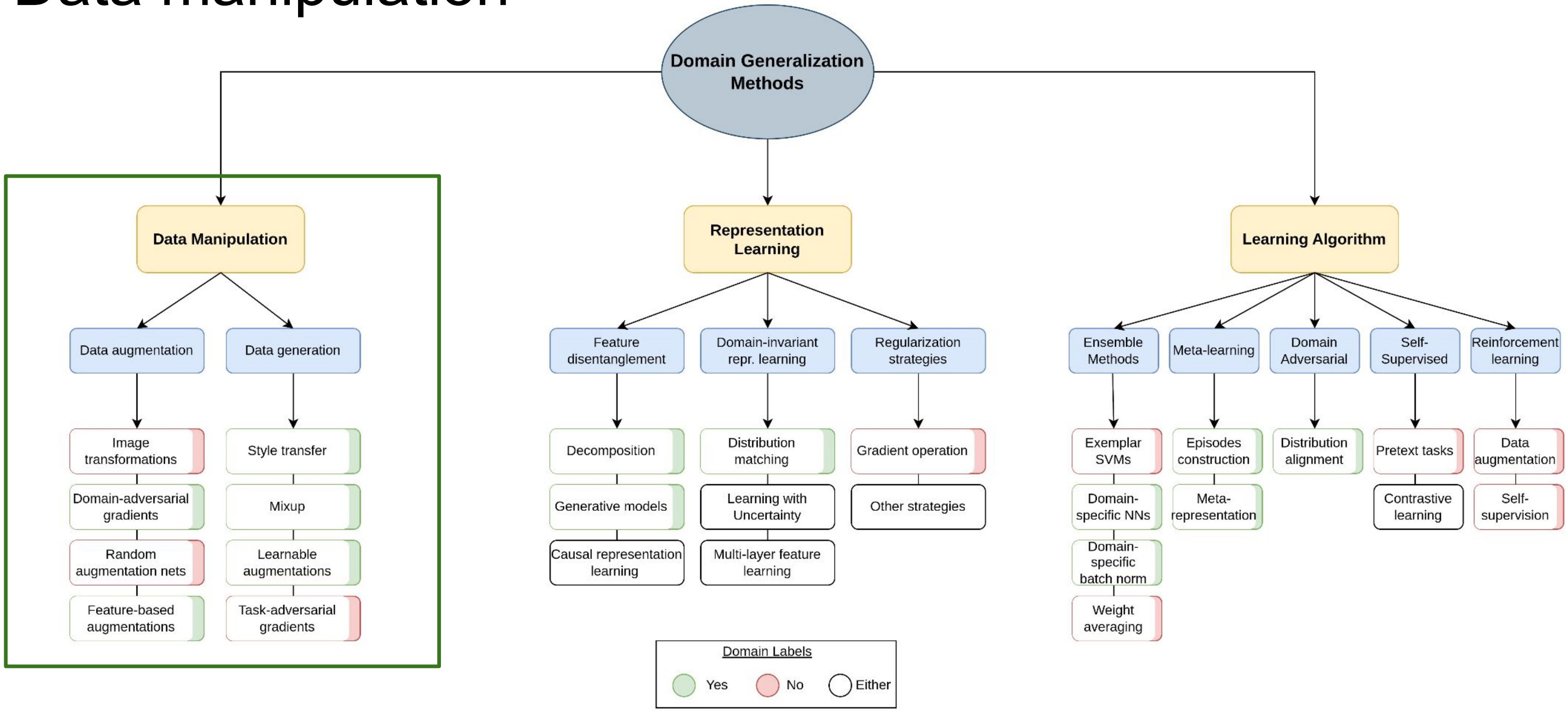
Overview



This taxonomy is a variation / extension of the ones on Wang, J, et al. "Generalizing to unseen domains: A survey on domain generalization." IEEE Transactions on Knowledge and Data Engineering (2022), and Zhou, Kaiyang, et al. "Domain generalization: A survey." IEEE Transactions on Pattern Analysis and Machine Intelligence (2022).

Part 2: Overview of representative DG methods

Data manipulation



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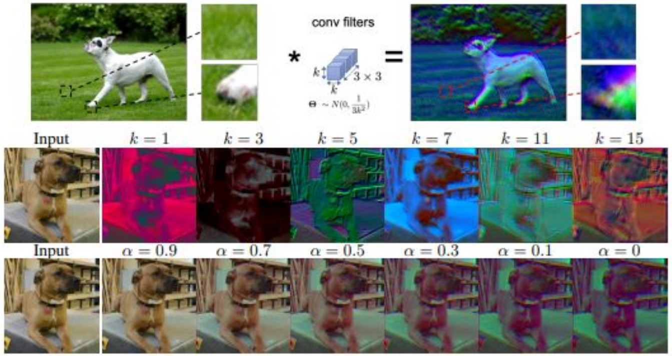
Data Augmentation

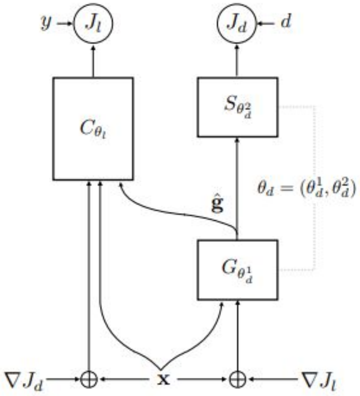
RandConv: Random Convolutions



RandConv uses multi-scale random-convolutions to generate images with random texture while maintaining global shapes

Xu et al. Robust and Generalizable Visual Representation Learning via Random Convolutions. ICLR 2021.

CrossGrad: Cross-Gradient



Adversarially augment data via gradient training to generate data that share the same label y but different domain label d.

Algorithm 1 CROSSGRAD training pseudocode.

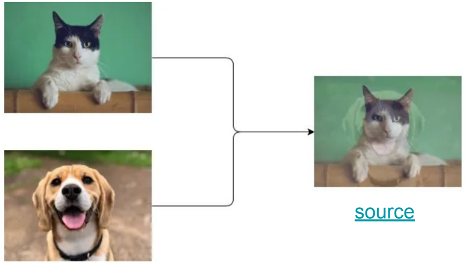
Input: Labeled data $\{(\mathbf{x}_i, y_i, d_i)\}_{i=1}^{M}$, step sizes ϵ_l, ϵ_d, learning rate η, data augmentation weights α_l, α_d, number of training steps n.
Output: Label and domain classifier parameters θ_l, θ_d
Initialize θ_l, θ_d $\{J_l, J_d$ are loss functions for the label and domain classifiers, respectively$\}$
for n training steps **do**
  Sample a labeled batch (X, Y, D)
  $X_d := X + \epsilon_l \cdot \nabla_X J_d(X, D; \theta_d)$
  $X_l := X + \epsilon_d \cdot \nabla_X J_l(X, Y; \theta_l)$
  $\theta_l \leftarrow \theta_l - \eta \nabla_{\theta_l}((1-\alpha_l) J_l(X, Y; \theta_l) + \alpha_l J_l(X_d, Y; \theta_l))$
  $\theta_d \leftarrow \theta_d - \eta \nabla_{\theta_d}((1-\alpha_d) J_d(X, D; \theta_d) + \alpha_d J_d(X_l, D; \theta_d))$
end for

Shankar et al. Generalizing across Domains via Cross-Gradient Training. ICLR 2018.

Data Generation

<u>Mixup</u>: Improve model robustness by training the network on convex combinations of pairs of examples and their labels.

$$\tilde{x} = \lambda x_i + (1 - \lambda) x_j,$$
$$\tilde{y} = \lambda y_i + (1 - \lambda) y_j,$$
$$\text{where } \lambda \in [0, 1]$$



source

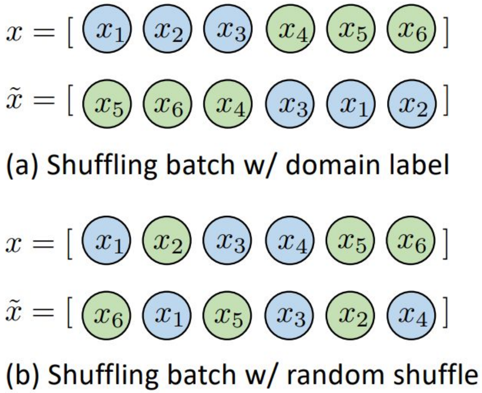
<u>Style transfer</u>: Applying the AdaIN transformation to features can lead decoders to change the style of the input

$$AdaIN(x) = \sigma(y) \frac{x - \mu(x)}{\sigma(x)} + \mu(y)$$

<u>MixStyle</u>: Mix the styles of training instances in each mini-batch to increase the domain diversity of the source domains

$$MixStyle(x) = \gamma_{mix} \frac{x - \mu(x)}{\sigma(x)} + \beta_{mix}$$

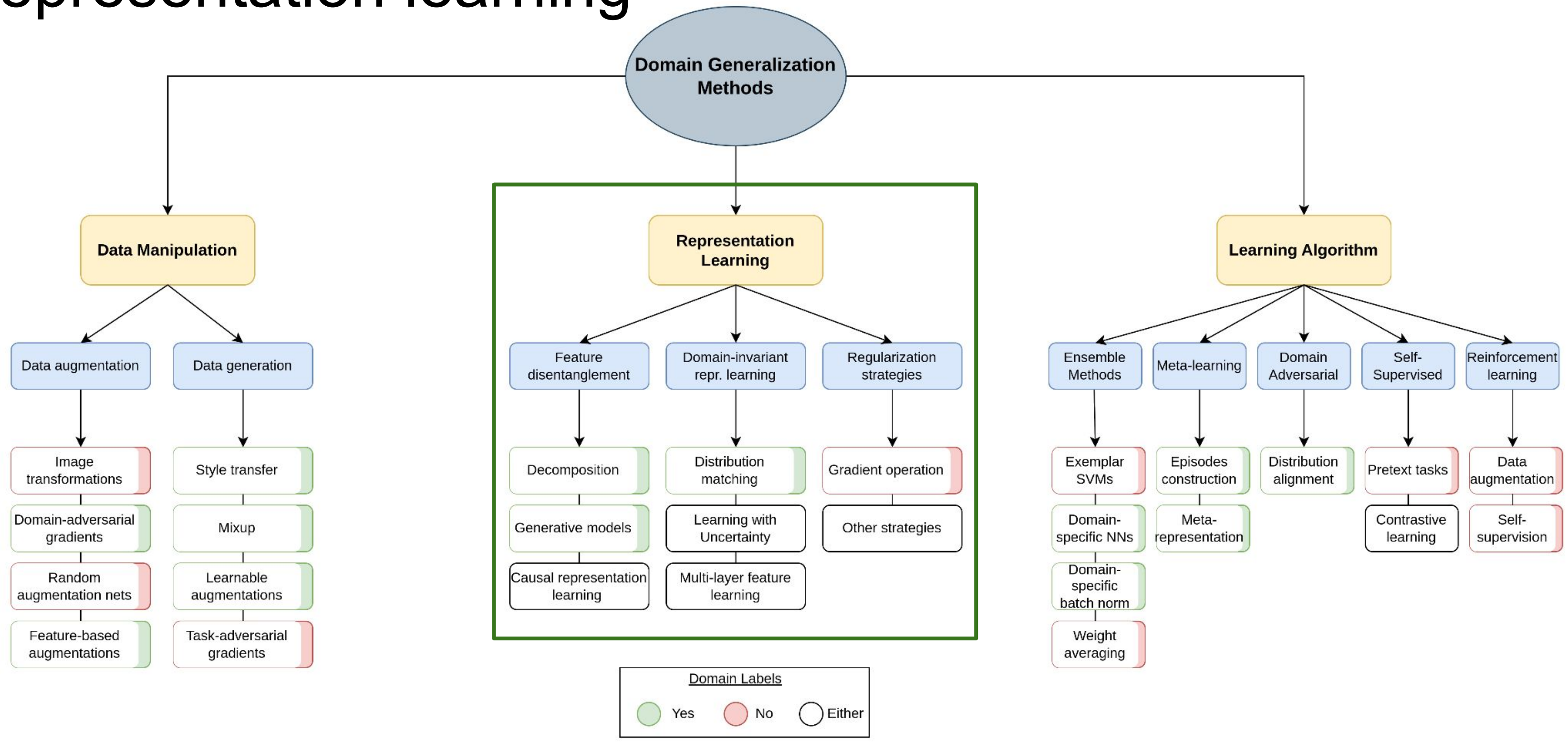
$$\gamma_{mix} = \lambda \sigma(x) + (1 - \lambda) \sigma(\tilde{x}),$$
$$\beta_{mix} = \lambda \mu(x) + (1 - \lambda) \mu(\tilde{x}),$$
$$where\, \lambda \sim Beta(a, a)$$



Zhang et al. "Mixup: Beyond empirical risk minimization". arXiv 2017

Zhou et al. "Domain generalization with mixstyle". ICLR 2021

Representation learning



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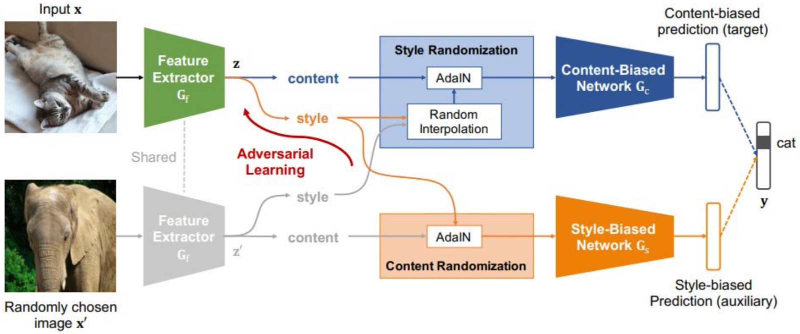
Feature Disentanglement

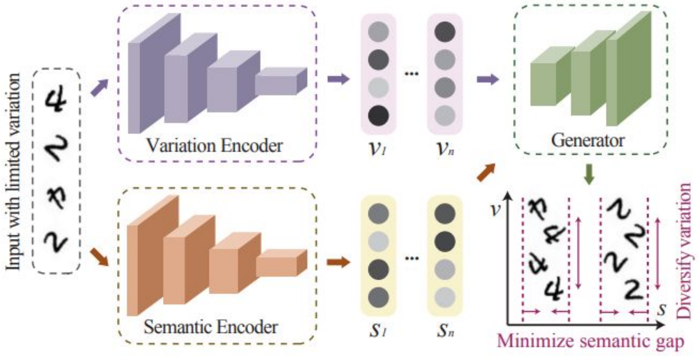
SagNet: Style Agnostic Networks



SagNets disentangle style encodings from class categories to prevent style biased predictions and focus more on the contents.

Nam et al. "Reducing domain gap by reducing style bias". CVPR 2021.

DDG: Disentanglement-constrained DG



Zhang et al. "Towards Principled Disentanglement for Domain Generalization". CVPR 2022

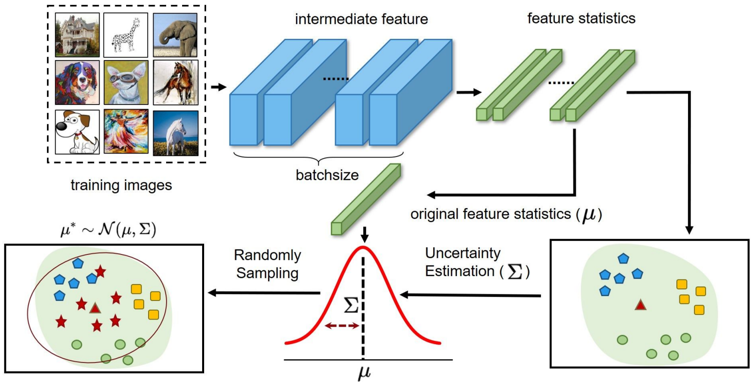
Definition 3 *(Constrained domain generalization problem) Given a fixed margin $\gamma > 0$, with Assumption 3 and enforcing the invariance on the semantic featurizer f_s, we transform the vanilla formulation Eq. (2) to the following inequality-constrained optimization*

$$\mathcal{P}^\star \triangleq \min_{f_s \in \mathcal{F}} \mathcal{L}(f_s) \triangleq \mathbb{E}_{\mathbb{P}(X,Y)} \ell(f_s(X), Y),$$
$$\text{s.t. } d(\mathbf{x}, D(f_s(\mathbf{x};\theta), f_v(\tilde{\mathbf{x}};\phi))) \leq \gamma, \text{ a.e. } \mathbf{x}, \tilde{\mathbf{x}} \sim \mathbb{P}(X). \quad (3)$$

DDG seeks to minimize the semantic difference of the generated samples from the same class while diversifying the variation across source domains.

Domain Invariant Representation Learning

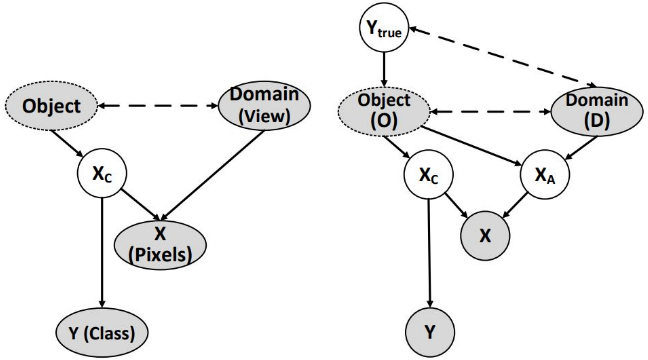
DSU: Domain Shifts with Uncertainty



Under the assumption that the feature statistics of each source data distribution follows a multivariate Gaussian distribution, DSU models the uncertainty of domain shifts with synthesized feature statistics during training.

Li et al. “Uncertainty modeling for Out-of-Distribution Generalization” ICLR 2022

MatchDG: Build Representations via Causal Matching

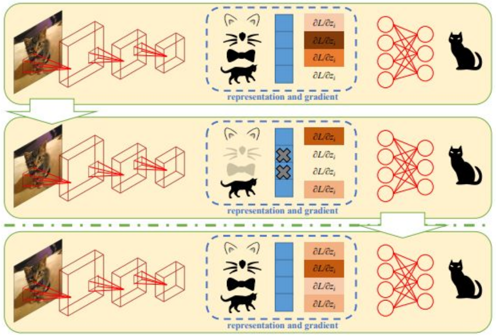


MatchDG utilizes contrastive learning to build a representation such that inputs sharing the same causal features are closer to one another.

Mahajan et al. “Domain Generalization Using Causal Matching.” PMLR 2021

Regularization Strategies

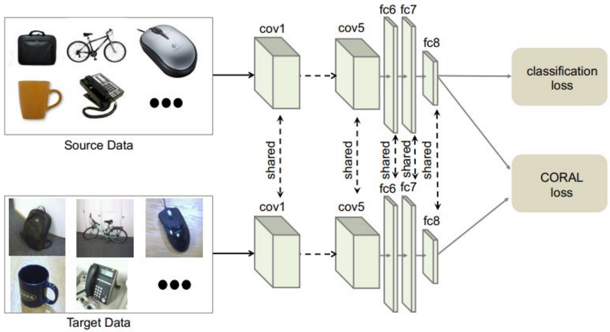
RSC: Representation Self-Challenging



RSC mutes the feature representations associated with the highest gradient, such that the network is forced to predict the labels through other features

Huang et al. "Self-Challenging Improves Cross-Domain Generalization". ECCV 2020

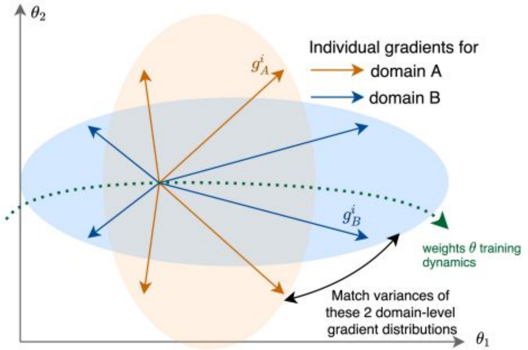
CORAL: Correlation Alignment



CORAL focuses on minimizing the distance between the second-order statistics (covariances) between domains.

Sun et al. "Deep CORAL: Correlation Alignment for Deep Domain Adaptation". ECCV 2016

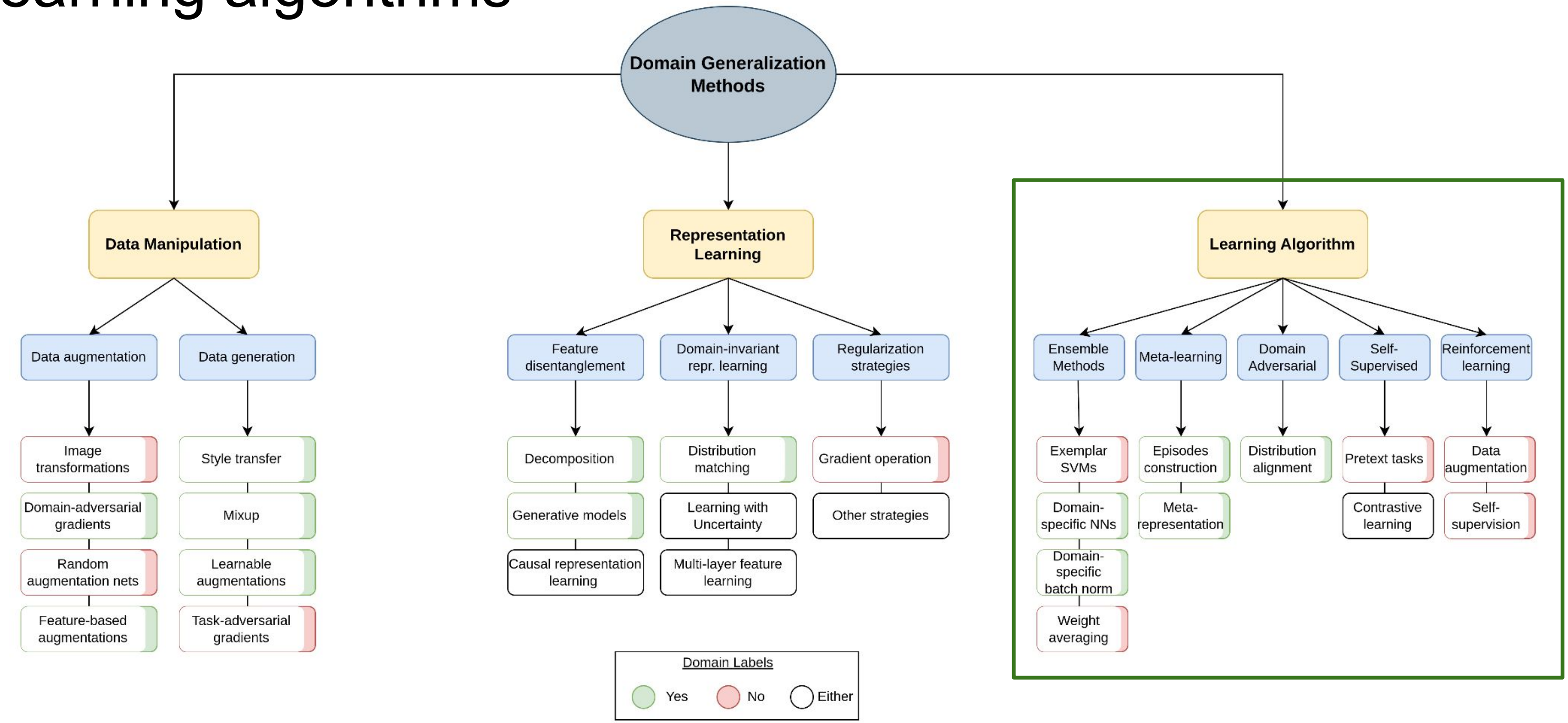
FISHR: Regularization with Fisher Information



FISHR introduces a regularization term that matches the domain-level variances of gradients across training domains

Rame et al. "Fishr: Invariant gradient variances for out-of-distribution generalization." PMLR, 2022.

Learning algorithms



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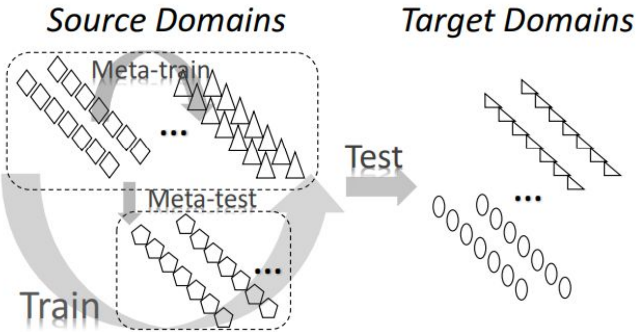
Meta-Learning

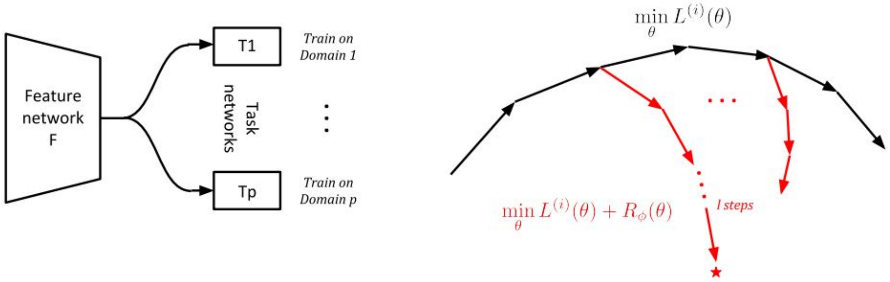
MLDG: Meta-Learning for DG



In each mini-batch a loss is computed based on evaluation on meta-test domains. This meta-test evaluation simulates testing on new domains with different statistics, thus improving robustness.

Li et al. Learning to generalize: Meta-learning for domain generalization. AAAI 2018.

MetaReg: Meta-Learning for regularization



The goal is to learn a regularizer model from multiple domain-specific networks in order to update the parameters of the base classifier.

Balaji et al. "Metareg: Towards domain generalization using meta-regularization". NIPS 2018.

Ensemble Methods

MIRO: Mutual Information Regularization with Oracle

Algorithm 1: Mutual Information Regularization with Oracle (MIRO)

Input: feature extractor f, classifier g, mean encoder μ, variance encoder Σ, regularization coefficient λ, batch size N.
Init: initialize f to pre-trained feature extractor f^0.
Output: learned feature extractor f and learned classifier g.
for sampled mini-batch $(\mathbf{x}, \mathbf{y})$ **do**

$\mathbf{z}_f = f(\mathbf{x})$

$\mathbf{z}_{f^0} = f^0(\mathbf{x})$

$\mathcal{L} =$

$$\frac{1}{N}\sum_i^N \left[\texttt{CrossEntropy}\left(g(z_f^i), y^i\right) + \lambda\left(\log\left|\Sigma(z_f^i)\right| + \|z_{f^0}^i - \mu(z_f^i)\|^2_{\Sigma(z_f^i)^{-1}}\right)\right]$$

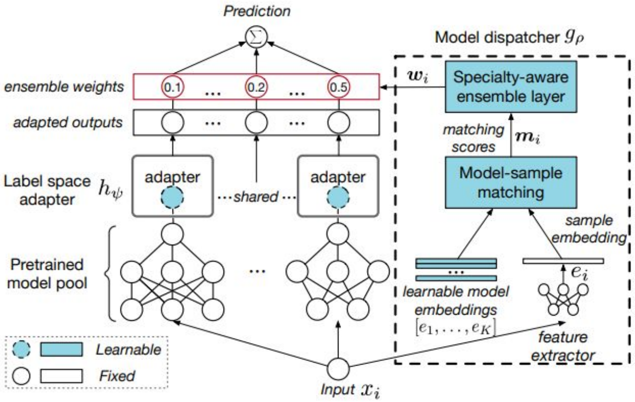
update f, g, μ, Σ to minimize $\mathcal{L}$

end

In MIRO, a large pre-trained model is used as an "Oracle" model and is leveraged to guide a classifier by minimizing the Mutual Information between their representations.

Cha et al. "Domain generalization by mutual-information regularization with pre-trained models." ECCV 2022.

SIMPLE: Specialized Model-Sample Matching

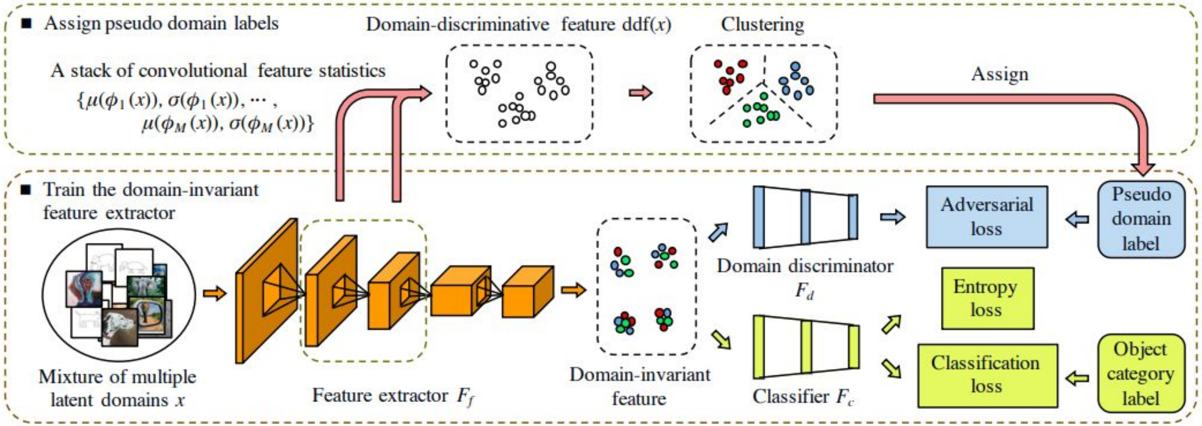


SIMPLE utilizes a pool of fixed pretrained models and selects the best subset for each downstream task/dataset.

Li et al. "SIMPLE: Specialized Model-Sample Matching for Domain Generalization." ICLR 2023.

Domain Adversarial Learning

MMLD: Mixture of Multiple Latent Domains

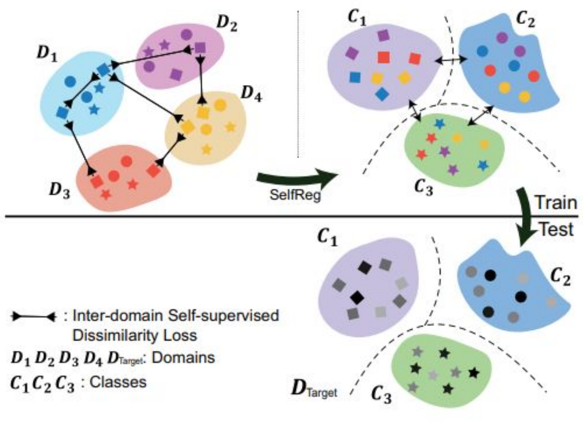


MMLD iteratively assigns pseudo domain labels by clustering domain discriminative features extracted from lower layers of the feature extractor, and trains the domain-invariant feature extractor via adversarial learning.

Matsuura et al. "Domain generalization using a mixture of multiple latent domains." AAAI 2020.

Self-Supervised Learning

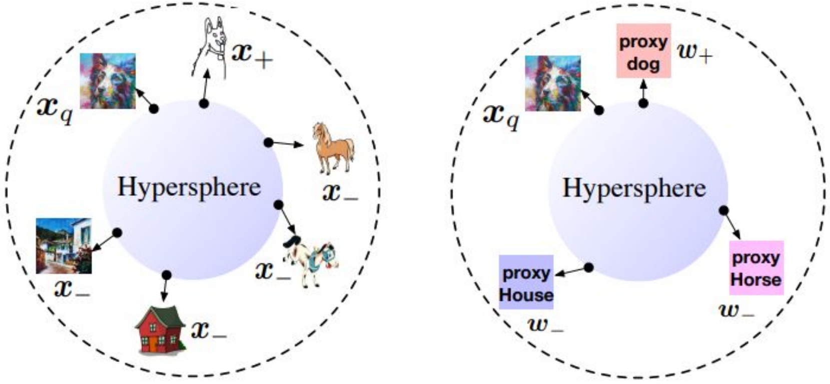
SelfReg: Self-Supervised Contrastive Regularization



SelfReg maps the latent representations of same-class samples close together to learn domain-invariant properties.

Kim et al. "Selfreg: Self-supervised contrastive regularization for domain generalization". ICCV 2021.

PCL: Proxy-Based Contrastive Learning



The PCL paper indicates that aligning positive sample-to-sample pairs hinders the model generalization and proposes aligning proxy-to-sample representations.

Yao et al. "Pcl: Proxy-based contrastive learning for domain generalization". CVPR 2022.

Part 3: Datasets and Benchmarks

DG Applications & Datasets

There are several applications and datasets which can be used for evaluating DG algorithms. To name a few:

<u>Object Recognition</u>
- PACS
- VLCS
- OfficeHome
- DomainNet
- WILDS
- TerraInc
- NICO++

<u>Action Recognition</u>
- IXMAS
- UCF-HMDB

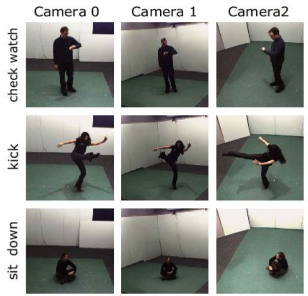
<u>Sentiment Classification</u>
- Amazon Reviews

<u>Medical Imaging</u>
- Multi-site Prostate MRI Seg
- Chest X-rays

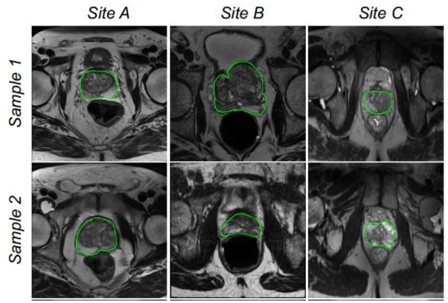
<u>Reinforcement Learning</u>
- Coinrun
- OpenAI Procgen

PACS

IXMAS



MRI Seg



DG Benchmarks & Codebases (1)

Lately, the **DomainBed** benchmark for domain generalization image classification has been generally recognized and used by researchers.

The currently available datasets are:

- RotatedMNIST
- ColoredMNIST
- VLCS
- PACS
- Office-Home
- TerraIncognita
- DomainNet
- A SVIRO
- WILDS FMoW
- WILDS Camelyon17
- Spawrious

Algorithm	**CMNIST**	**RMNIST**	**VLCS**	**PACS**	**Office-Home**	**TerraInc**	**DomainNet**	**Avg**
ERM	34.2 ± 1.2	98.0 ± 0.0	76.8 ± 1.0	83.3 ± 0.6	67.3 ± 0.3	46.2 ± 0.2	40.8 ± 0.2	63.8
IRM	36.3 ± 0.4	97.7 ± 0.1	77.2 ± 0.3	82.9 ± 0.6	66.7 ± 0.7	44.0 ± 0.7	35.3 ± 1.5	62.9
DRO	32.2 ± 3.7	97.9 ± 0.1	77.5 ± 0.1	83.1 ± 0.6	67.1 ± 0.3	42.5 ± 0.2	32.8 ± 0.2	61.8
Mixup	31.2 ± 2.1	98.1 ± 0.1	78.6 ± 0.2	83.7 ± 0.9	68.2 ± 0.3	46.1 ± 1.6	39.4 ± 0.3	63.6
MLDG	36.9 ± 0.2	98.0 ± 0.1	77.1 ± 0.6	82.4 ± 0.7	67.6 ± 0.3	45.8 ± 1.2	42.1 ± 0.1	64.2
CORAL	29.9 ± 2.5	98.1 ± 0.1	77.0 ± 0.5	83.6 ± 0.6	68.6 ± 0.2	48.1 ± 1.3	41.9 ± 0.2	63.9
MMD	42.6 ± 3.0	98.1 ± 0.1	76.7 ± 0.9	82.8 ± 0.3	67.1 ± 0.5	46.3 ± 0.5	39.3 ± 0.9	64.7
DANN	29.0 ± 7.7	89.1 ± 5.5	77.7 ± 0.3	84.0 ± 0.5	65.5 ± 0.1	45.7 ± 0.8	37.5 ± 0.2	61.2
C-DANN	31.1 ± 8.5	96.3 ± 1.0	74.0 ± 1.0	81.7 ± 1.4	64.7 ± 0.4	40.6 ± 1.8	38.7 ± 0.2	61.1

Gulrajani et al. "In search of lost domain generalization." arXiv 2020.
Code: https://github.com/facebookresearch/DomainBed

Sidenote: Example of method outpeforming ERM on average

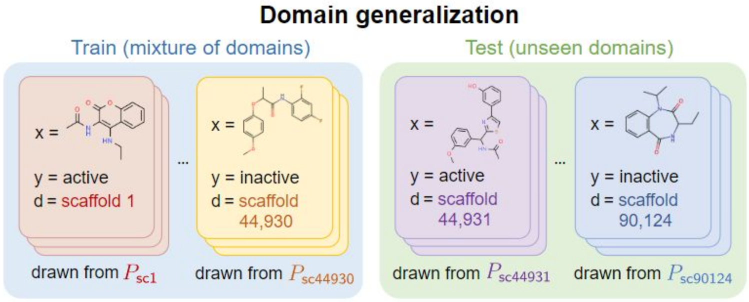
Algorithm	Accuracy (↑)								Ranking (↓)		
	CMNIST	RMNIST	VLCS	PACS	OfficeHome	TerraInc	DomainNet	Avg	Arith. mean	Geom. mean	Median
ERM	57.8 ± 0.2	97.8 ± 0.1	77.6 ± 0.3	86.7 ± 0.3	66.4 ± 0.5	53.0 ± 0.3	41.3 ± 0.1	68.7	9.1	8.1	8
IRM	67.7 ± 1.2	97.5 ± 0.2	76.9 ± 0.6	84.5 ± 1.1	63.0 ± 2.7	50.5 ± 0.7	28.0 ± 5.1	66.9	14.7	12.4	16
GroupDRO	61.1 ± 0.9	97.9 ± 0.1	77.4 ± 0.5	87.1 ± 0.1	66.2 ± 0.6	52.4 ± 0.1	33.4 ± 0.3	67.9	8.6	7.5	8
Mixup	58.4 ± 0.2	98.0 ± 0.1	78.1 ± 0.3	86.8 ± 0.3	68.0 ± 0.2	**54.4** ± 0.3	39.6 ± 0.1	69.0	5.3	3.9	4
MLDG	58.2 ± 0.4	97.8 ± 0.1	77.5 ± 0.1	86.8 ± 0.4	66.6 ± 0.3	52.0 ± 0.1	41.6 ± 0.1	68.7	9.1	8.2	9
CORAL	58.6 ± 0.5	98.0 ± 0.0	77.7 ± 0.2	87.1 ± 0.5	**68.4** ± 0.2	52.8 ± 0.2	41.8 ± 0.1	69.2	4.6	3.4	3
MMD	63.3 ± 1.3	98.0 ± 0.1	77.9 ± 0.1	**87.2** ± 0.1	66.2 ± 0.3	52.0 ± 0.4	23.5 ± 9.4	66.9	7.0	4.9	6
DANN	57.0 ± 1.0	97.9 ± 0.1	79.7 ± 0.5	85.2 ± 0.2	65.3 ± 0.8	50.6 ± 0.4	38.3 ± 0.1	67.7	11.9	9.6	15
CDANN	59.5 ± 2.0	97.9 ± 0.0	**79.9** ± 0.2	85.8 ± 0.8	65.3 ± 0.5	50.8 ± 0.6	38.5 ± 0.2	68.2	9.6	7.4	10
MTL	57.6 ± 0.3	97.9 ± 0.1	77.7 ± 0.5	86.7 ± 0.2	66.5 ± 0.4	52.2 ± 0.4	40.8 ± 0.1	68.5	8.4	7.8	7
SagNet	58.2 ± 0.3	97.9 ± 0.0	77.6 ± 0.1	86.4 ± 0.4	67.5 ± 0.2	52.5 ± 0.4	40.8 ± 0.2	68.7	8.0	7.2	6
ARM	63.2 ± 0.7	**98.1** ± 0.1	77.8 ± 0.3	85.8 ± 0.2	64.8 ± 0.4	51.2 ± 0.5	36.0 ± 0.2	68.1	9.9	7.5	12
V-REx	67.0 ± 1.3	97.9 ± 0.1	78.1 ± 0.2	**87.2** ± 0.6	65.7 ± 0.3	51.4 ± 0.5	30.1 ± 3.7	68.2	7.7	5.5	5
RSC	58.5 ± 0.5	97.6 ± 0.1	77.8 ± 0.6	86.2 ± 0.5	66.5 ± 0.6	52.1 ± 0.2	38.9 ± 0.6	68.2	9.9	9.4	9
AND-mask	58.6 ± 0.4	97.5 ± 0.0	76.4 ± 0.4	86.4 ± 0.4	66.1 ± 0.2	49.8 ± 0.4	37.9 ± 0.6	67.5	13.4	13.1	12
SAND-mask	62.3 ± 1.0	97.4 ± 0.1	76.2 ± 0.5	85.9 ± 0.4	65.9 ± 0.5	50.2 ± 0.1	32.2 ± 0.6	67.2	14.3	13.5	15
Fish	61.8 ± 0.8	97.9 ± 0.1	77.8 ± 0.6	85.8 ± 0.6	66.0 ± 2.9	50.8 ± 0.4	**43.4** ± 0.3	69.1	8.4	6.6	7
Fishr	**68.8** ± 1.4	97.8 ± 0.1	78.2 ± 0.2	86.9 ± 0.2	68.2 ± 0.2	53.6 ± 0.4	41.8 ± 0.2	**70.8**	**3.9**	**2.8**	**2**

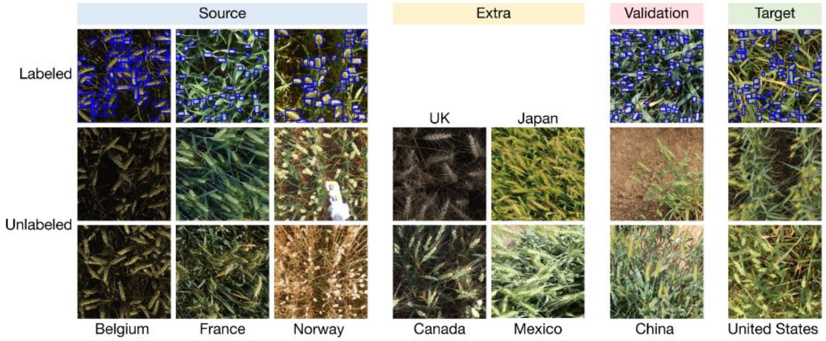
DG Benchmarks & Codebases (2)

WILDS is a collection of benchmark datasets that represent distribution shifts faced in the wild.

WILDS provides the following datasets:

- iWildCAM
- Camelyon17
- VLCS
- RxRx1
- OGB-MolPCBA
- GlobalWheat
- DomainNet
- CivilComments
- FMoW
- PovertyMap
- Amazon
- Py150





Koh et al. "Wilds: A benchmark of in-the-wild distribution shifts." PMLR 2021.
Code: https://github.com/p-lambda/wilds/

DG Benchmarks & Codebases (3)

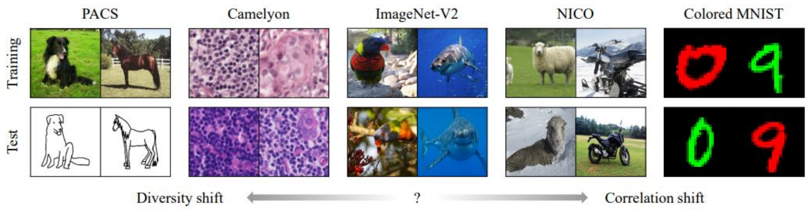
NICO++ is specifically designed for OOD (Out-of-Distribution) image classification. It simulates a real world setting that the testing distribution may induce arbitrary shifting from the training distribution

Zhang et al. "NICO++: Towards better benchmarking for domain generalization." CVPR 2023.
Code: https://github.com/xxgege/NICO-plus

DG Benchmarks & Codebases (4)

Building on DomainBed, additional benchmarks have been proposed.

OoD-Bench adopts similar datasets to DomainBed and splits the benchmark into two dimensions, focusing on data suffering from either *diversity* or *correlation* shift.



Ye et al. "Ood-bench: Quantifying and understanding two dimensions of out-of-distribution generalization." CVPR 2022.
Code: https://github.com/xxgege/NICO-plus

DeepDG is proposed as a simplified version of DomainBed with additional features.

Specifically it:

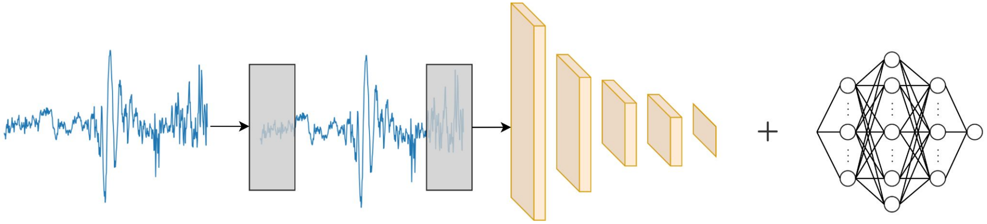
- Avoids huge hyperparameter tuning
- Provides a more friendly interface and
- Has better customization

J. Wang et al., "Generalizing to Unseen Domains: A Survey on Domain Generalization". IEEE TKDE 2022
Code: https://github.com/jindongwang/transferlearning

Part 4: Application to biomedical signals and the BioDG benchmark

Domain Generalization in Biosignal Classification

Up until now, we have presented an abundance of methods / datasets / benchmarks for the DG problem regarding images.



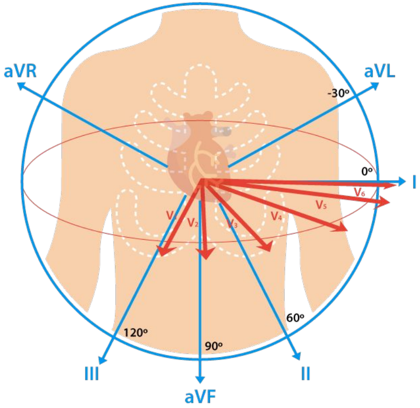
*The DG problem is somewhat under-researched in other settings such as **Biosignal Classification**.*

Distributional shifts can occur due to:

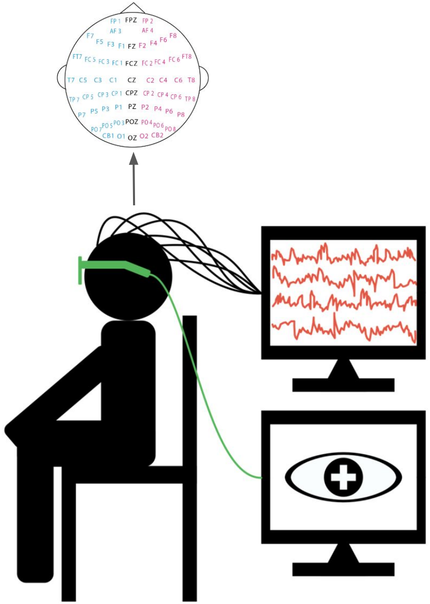
- Different hospital equipment
- Different or evolving hospital procedures
- Different testing environments
- Different physiology of patients

Biosignal Classification in General

We consider domain generalization for the **12-lead ECG** and **62-channel EEG** classification task and aim to improve the ability of a model $M_\theta : X \to Y$ to detect domain-invariant features of a class.

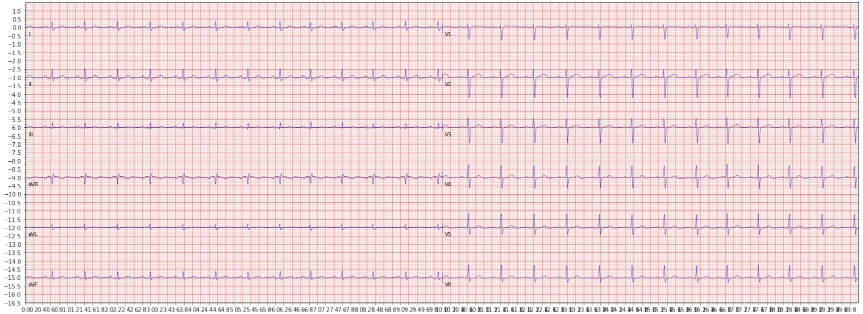


12-Lead ECG. source



62-channel EEG. source

Visualizations of 12-lead ECG and 62-channel EEG signals.



Typical 12-lead electrocardiogram.

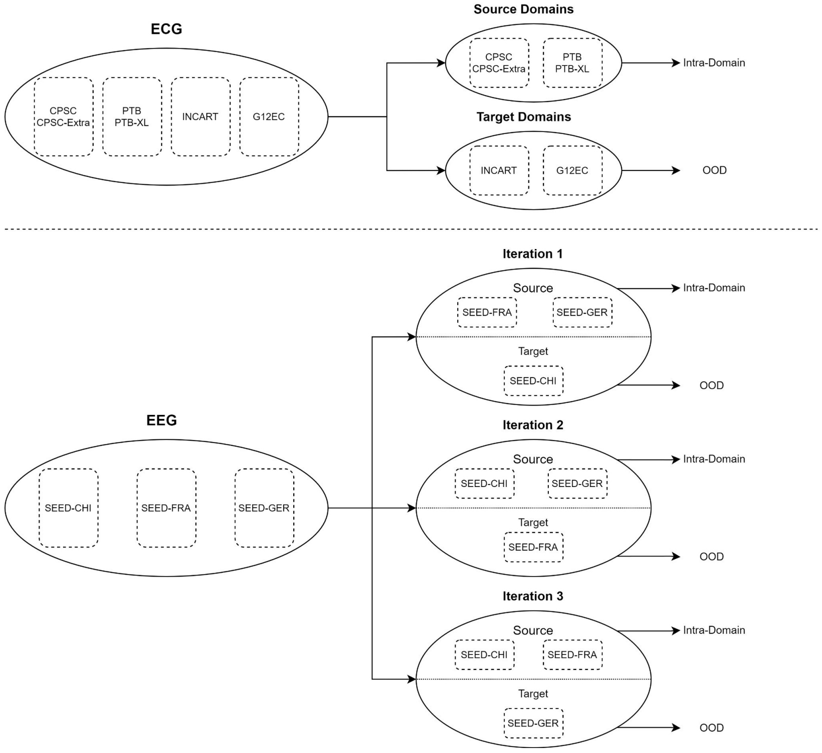
Spike and wave discharges monitored EEG

The BioDG Benchmark (1)

We introduce a novel DG open-source evaluation benchmark, namely **BioDG** for the biosignal classification setting.

Specifically, BioDG:

- Proposes a DG setup for ECG and EEG classification, using datasets from PhysioNet and SEED
- Adapts state-of-the-art image DG algorithms to 1D signal classification and
- Provides researchers with the means to pour further research in biomedical DG.

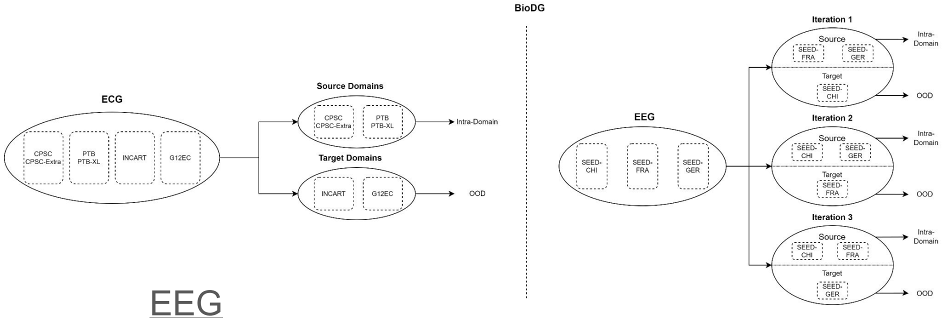


The BioDG benchmark

Ballas and Diou. "Towards Domain Generalization for ECG and EEG Classification: Algorithms and Benchmarks.", IEEE TETCI 2023
Code: https://github.com/aristotelisballas/biodg

The BioDG Benchmark (2)

For the DG setup, we used publicly available datasets from the PhysioNet (ECG) and SEED (EEG) repositories.



<u>ECG</u>

We used datasets from 4 different sources:

- CPSC, CPSC Extra
- G12EC
- INCART
- PTB, PTB-XL

The ECG signals are multi-class and multi-label (24 labels).

Task: Disease prediction

Alday et al. "Classification of 12-lead ecgs: the physionet/computing in cardiology challenge 2020." Physiological measurement 2020.

<u>EEG</u>

We used the datasets from 3 different populations:

- SEED-CHI
- SEED-FRA
- SEED-GER

The EEG signals are multi-class (3 labels) problem.

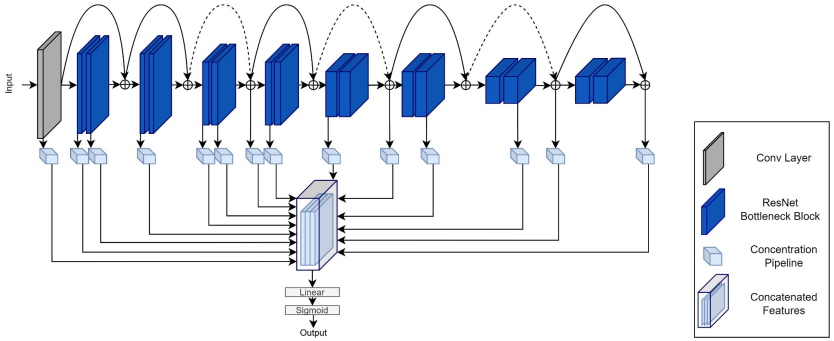
Task: Emotion classification

Zheng et al, "Investigating Critical Frequency Bands and Channels for EEG-Based Emotion Recognition with Deep Neural Networks". IEEE TAE 2015.

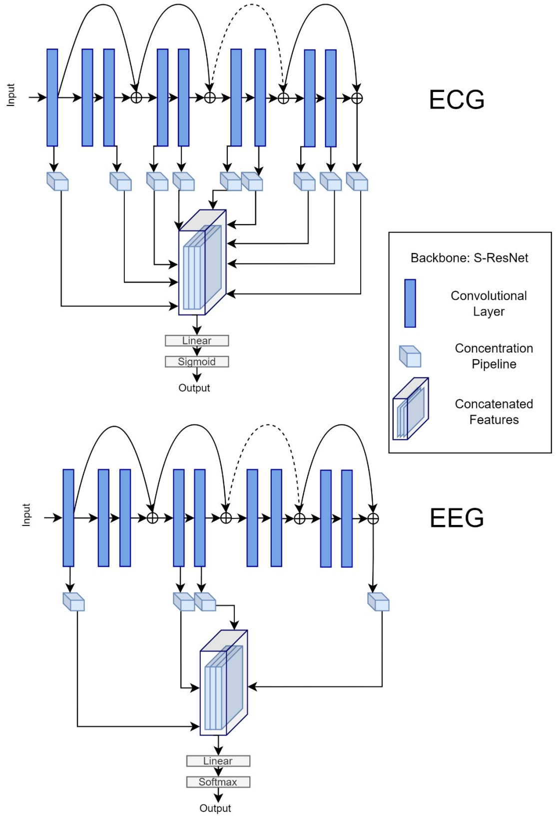
The BioDG Benchmark (3)

We also propose an alternative architecture to tackle DG in 1D biosignal classification, which utilizes representations from multiple intermediate layers of a backbone ResNet model.

ECG - ResNet18



Ballas and Diou. “Towards Domain Generalization for ECG and EEG Classification: Algorithms and Benchmarks.”, IEEE TETCI 2023
Code: https://github.com/aristotelisballas/biodg



The BioDG baseline models

The BioDG Benchmark (4)

BioDG provides evaluation metrics for both
Intra-Distribution and Out-of-Distribution data splits.

Clearly, we have a long way to go.

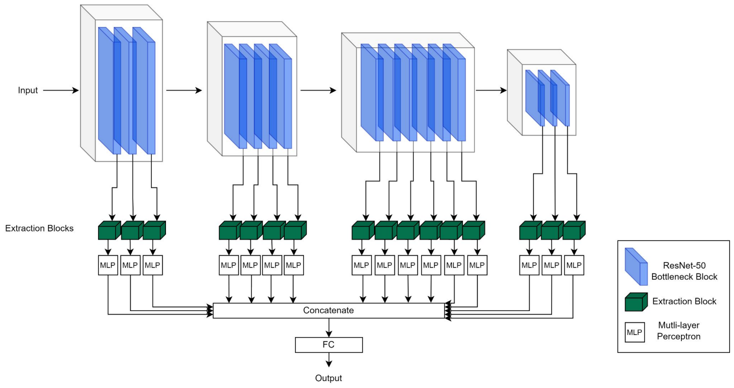
ECG Classification Results

Backbone: S-ResNet	Intra-Distribution						OOD					
Diagnosis	ERM	IRM	MMD	RSC	CORAL	BioDG	ERM	IRM	MMD	RSC	CORAL	BioDG
1st degree AV block	16.14	0	7.69	15.00	10.67	**61.88**	7.30	0	5.84	0.51	7.38	62.24
Atrial fibrillation	55.84	18.18	23.98	36.99	24.81	**87.05**	32.58	12.16	13.28	12.16	13.22	62.51
Atrial flutter	19.05	0	0	13.33	0	**50.00**	0	0	0	0	0	10.70
Bradycardia	0	0	0	**5.26**	7.69	0	0	0	0	0	0	0
Complete right bundle branch block	73.38	16.16	60.41	72.58	64.19	**82.46**	60.15	11.50	50.90	47.75	52.64	64.55
Incomplete right bundle branch block	11.01	0	13.05	4.86	22.19	**43.03**	14.56	0	20.09	10.85	25.65	30.27
Left anterior fascicular block	54.67	0	50.83	52.8	53.37	**70.29**	31.03	0	21.01	17.16	20.84	33.29
Left axis deviation	58.10	31.15	58.34	56.26	60.56	**66.87**	44.98	17.79	37.75	36.09	39.16	50.42
Left bundle branch block	80.49	0	0	78.33	45.49	**85.48**	62.44	0	0	0	40	74.04
Low QRS voltages	0	0	0	0	0	0	0	0	0	0	0	0
Non-specific intraventricular conduction disorder	0	0	0	**4.55**	0	2.34	0	0	0	0	0	0
Pacing rhythm	58.62	0	37.84	43.90	48.15	**78.46**	0	0	0	0	0	0
Premature ventricular contractions	0	0	0	0	0	0	0	0	0	0	0	0
Prolonged PR interval	0	0	0	0	0	**15.00**	0	0	0	0	0	0
Prolonged QT interval	0	0	0	0	0	0	0	0	0	0	0	0
Q wave abnormal	0	0	0	0	0	**11.11**	0	0	0	0	0	0
Right axis deviation	5.48	0	23.27	9.52	**27.92**	24.53	0	0	18.58	21.54	17.35	2.84
Sinus arrhythmia	**2.17**	0	0	0	0	0	1.94	0	0	0	0	10.85
Sinus bradycardia	4.49	0	0	9.03	0	**36.70**	31.56	31.56	31.56	31.56	31.56	47.33
Sinus rhythm	84.60	80.94	80.94	82.56	80.94	**91.44**	38.89	0	12.54	0.62	15.17	82.68
Sinus tachycardia	27.86	0	10.37	20	15.54	**79.82**	1.35	0	9.98	0	8.07	1.92
Supraventricular premature beats	9.27	0	10.07	**11.28**	8.17	3.68	0	0	10.02	0	6.26	5.84
T wave abnormal	18.57	15.68	28.62	13.31	26.14	**33.89**	8.11	38.40	37.22	0	30.35	4.53
T wave inversion	0	0	0	0	0	0	0	0	0	0	0	0
# of Predicted Classes	16	5	12	17	15	**18**	12	5	12	9	13	15
Macro-F1 (Predicted)	41.46	9.01	38.00	17.03	37.82	**53.91**	31.15	7.43	32.43	14.92	31.70	36.44
Macro-F1 (All)	31.10	6.75	28.50	12.77	28.37	**40.44**	19.47	4.64	20.27	9.33	19.81	22.77

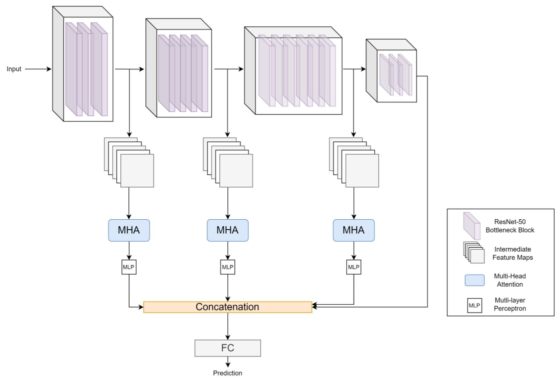
EEG Classification Results

	Intra		
Method	FRA-GER	CHI-GER	CHI-FRA
ERM	70.94 ± 2.51	73.63 ± 2.08	76.10 ± 2.27
IRM	70.75 ± 2.81	71.42 ± 2.98	73.90 ± 3.15
CORAL	71.42 ± 1.67	73.72 ± 1.91	74.96 ± 2.59
MMD	71.23 ± 2.23	74.34 ± 1.87	76.26 ± 1.95
RSC	70.15 ± 2.43	72.01 ± 2.37	**76.15** ± 2.08
BioDG	**77.59** ± 2.23	**76.11** ± 1.25	75.61 ± 1.15
	OOD		
Method	CHI	FRA	GER
ERM	54.60 ± 3.44	45.83 ± 3.53	63.75 ± 4.01
IRM	53.70 ± 1.42	43.82 ± 0.75	66.87 ± 3.49
CORAL	53.18 ± 3.29	45.00 ± 2.51	67.04 ± 3.27
MMD	54.17 ± 2.68	45.80 ± 3.46	66.04 ± 3.39
RSC	53.86 ± 2.55	44.37 ± 2.99	58.79 ± 3.93
BioDG	**57.09** ± 0.44	**51.74** ± 0.35	**68.04** ± 0.24

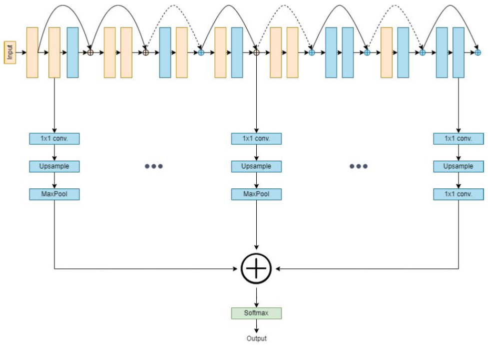
Some of our other works



Ballas, Aristotelis, and Christos Diou. "Multi-Scale and Multi-Layer Contrastive Learning for Domain Generalization" *Under Review* at IEEE TAI, 2023.



Ballas, Aristotelis, and Christos Diou. "CNNs with Multi-Level Attention for Domain Generalization." ICMR 2023.



Ballas, Aristotelis, and Christos Diou. "Multi-layer Representation Learning for Robust OOD Image Classification." SETN 2022.

?

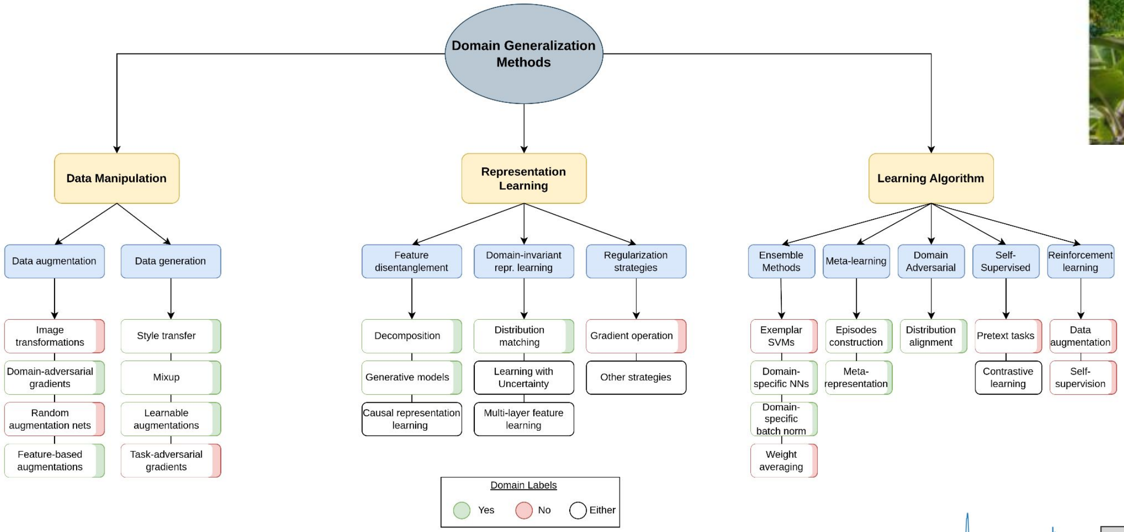
Ballas, Aristotelis, and Christos Diou. "CNN Feature Map Augmentation for Single-Source Domain Generalization." BDS 2023.

Presented at Wednesday.

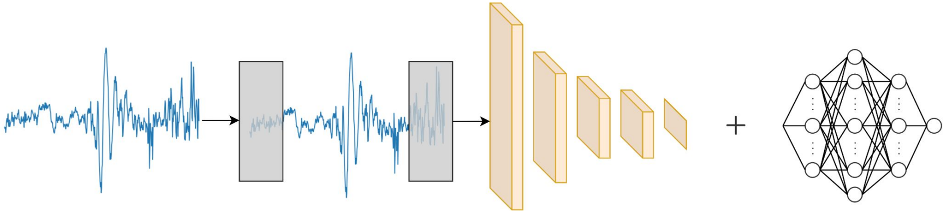
Conclusions

Recap


Machine Learning Algorithms
Different distributions / non-i.i.d.
Domain Adaptation
No data (not even unlabeled)
Domain Generalization


Domain Generalization Methods
Data Manipulation
Representation Learning
Learning Algorithm
Data augmentation
Data generation
Feature disentanglement
Domain-invariant repr. learning
Regularization strategies
Ensemble Methods
Meta-learning
Domain Adversarial
Self-Supervised
Reinforcement learning
Image transformations
Domain-adversarial gradients
Random augmentation nets
Feature-based augmentations
Style transfer
Mixup
Learnable augmentations
Task-adversarial gradients
Decomposition
Generative models
Causal representation learning
Distribution matching
Learning with Uncertainty
Multi-layer feature learning
Gradient operation
Other strategies
Exemplar SVMs
Domain-specific NNs
Domain-specific batch norm
Weight averaging
Episodes construction
Meta-representation
Distribution alignment
Pretext tasks
Contrastive learning
Data augmentation
Self-supervision
Domain Labels
Yes
No
Either


Grass
Water
Autumn
Rock



Future directions

- DG remains an open problem
  - Effectiveness of methods remains low compared to training with i.i.d. data
- Applies to several application areas
  - Many of them still unexplored
- Several subproblems emerge
  - Federated DG
- Several links to model explainability, model testing / assessment of robustness and bias

Thank you!

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