

Domain Generlization

- Generalizes the model to correctly classify the data sampled from the unseen domain.
- Tries to learn the domain-invariant representation of the class using data from multiple source domains.



Training set

Why domain generalization?

- No prior information about data
- Data domain-shifts

Major Challenge: Minimizing the domain-dependant features.

Zero Shot Domain Generalization (ZSDG)

- The test data can belong to unseen classes and also unseen domains. Hence, knowledge gap and domain gap are both present.
- Needs attributes for features of unseen but similar classes.
- Learn domain invariant features for generalization.

Major Challenges:

- Learning the domain-independent features.
- Model robust to domains.'
- **H**andling the new unseen classes.

Mitigating the class-imbalance present in the data.

Contributions

- Proposed a novel framework, termed (MAMC-Net) to address the ZSDG task.
- Studied the effectiveness of adaptive margin-based classifier for ZSDG to handle class-imbalance present in the data.
- Mixing techniques along with adaptive margin-based classifier can be used to effectively learn domain-independent features, and class imbalance in the data.
- Ratio-predictor helps in retaining the class information only.
- Extensive experiments on two large benchmark datasets, namely DomainNet, and DomainNet-LS show the effectiveness of proposed approach.









Test set











Model Variants	quick
Base Model	9
$Base model + \mathcal{L}_{\mathit{dar}}$	10
$Base \; model + \mathcal{L}_{\mathit{dar}} + \mathcal{L}_{\mathit{fix}-\mathit{margin}}$	11
MAMC-Net	12



DomainNet: It consists of 6 domains and 345 classes. **DomainNet-LS**: It is a splitwise modification of domainNet where only real and painting domain is used for training. It also consists of 6 domains and 345

Target Domain					Avg
painting	inforgraph	quickdraw	sketch	clipart	
17.6	11.7	6.1	16.7	20.1	14.4
20.2	12.7	6.8	18.5	22.7	16.2
23.8	16.9	8.2	21.8	26.0	19.4
16.4	10.4	7.1	15.1	20.5	13.9
19.7	12.5	7.4	17.9	21.2	15.7
24.1	15.8	8.4	21.3	25.9	19.1
19.3	13.9	7.3	17.2	21.6	15.9
21.4	14.1	7.8	20.9	23.2	17.5
24.6	16.7	9.2	23.2	26.4	20.0
25.5	17.8	9.9	22.6	27.6	20.7
25.2	17.1	9.3	22.1	26.5	20.0
26.6	18.4	11.5	25.2	27.8	21.9
27.3	19.5	12.1	26.0	28.8	22.7

Target Domain					Avg
nting	inforgraph	quickdraw	sketch	clipart	
7.6	16.3	9.7	25.9	27.8	21.5
8.8	17.6	11.5	26.3	29.1	22.7
).2	18.8	12.2	27.4	30.0	23.5

Target Domain					Avg.
	quickdraw	sketch	inforgraph	clipart	
	4.8	17.3	14.1	21.5	14.4
	5.6	18.7	14.9	22.5	15.4
	5.5	19.7	17.1	23.7	16.5
	7.2	20.5	16	24	16.9
	8.2	21.2	17.6	23.6	17.7

. Massimiliano Mancini, Zeynep Akata, Elisa Ricci, and Barbara Caputo. Towards recognizing unseen

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