THE UNIVERSITY of EDINBURGH
informatics

Feature-Critic Networks for Heterogeneous Domain Generalisation

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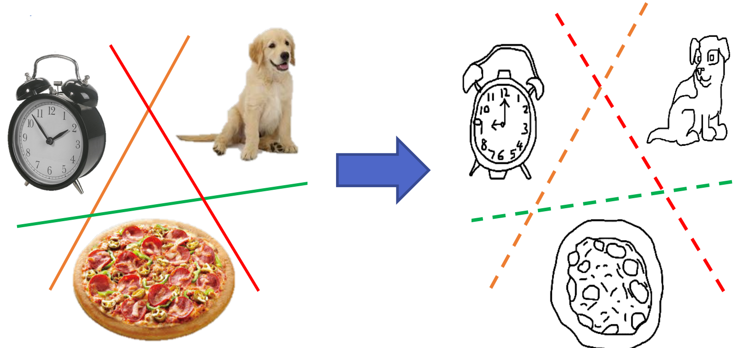
Motivation



Domain Shift:

➢Model performance degrades when deployed to a new target domain with different statistics to training.

To Ameliorate Domain Shift:

➢Domain Adaptation

- $\{X_{\mathcal{T}}\}$ or $\{X_{\mathcal{T}}, Y_{\mathcal{T}}\}$ accessible during training

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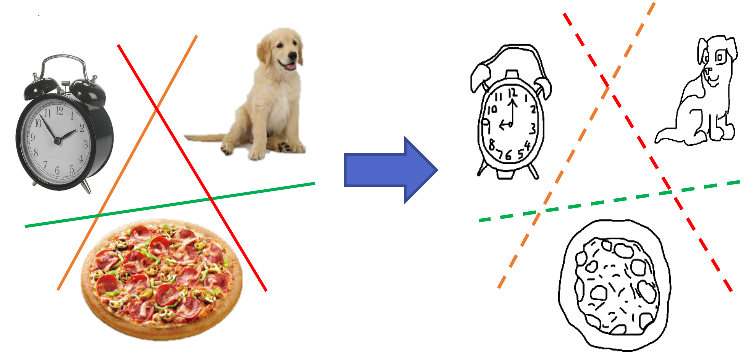

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➢ Domain Generalisation (Harder)

- $\{X_{\mathcal{T}}\}$ ***not*** accessible during training
- Several Methods: Muandet ICML'13, Li ICCV'17, Balaji NeurIPS'18.
- Common assumption: <u>Shared Label Space</u> (Homogeneous DG)

Heterogeneous DG is a Common Workflow

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- Disjoint label space in source + target → Feature generalisation.
- "*ImageNet trained CNN as feature extractor*"

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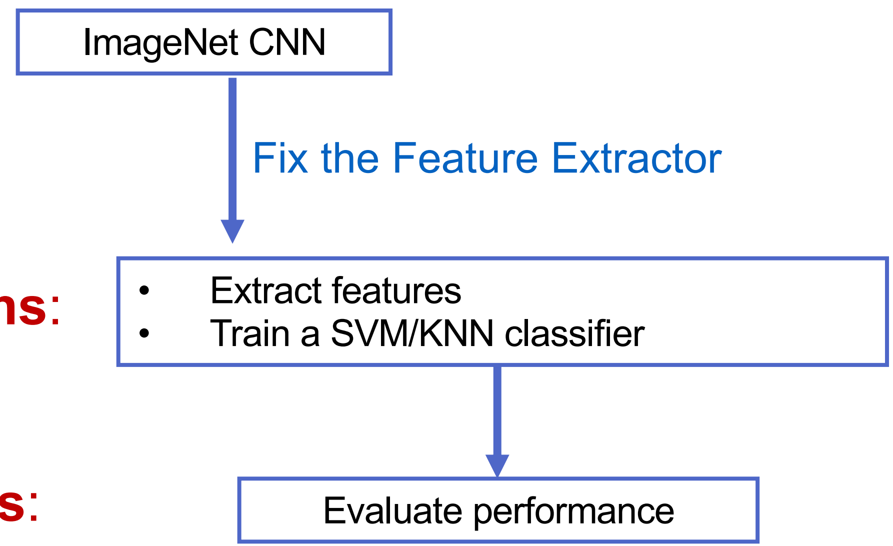
Source domains:

Train split of **target domains**:

Test split of **target domains**:



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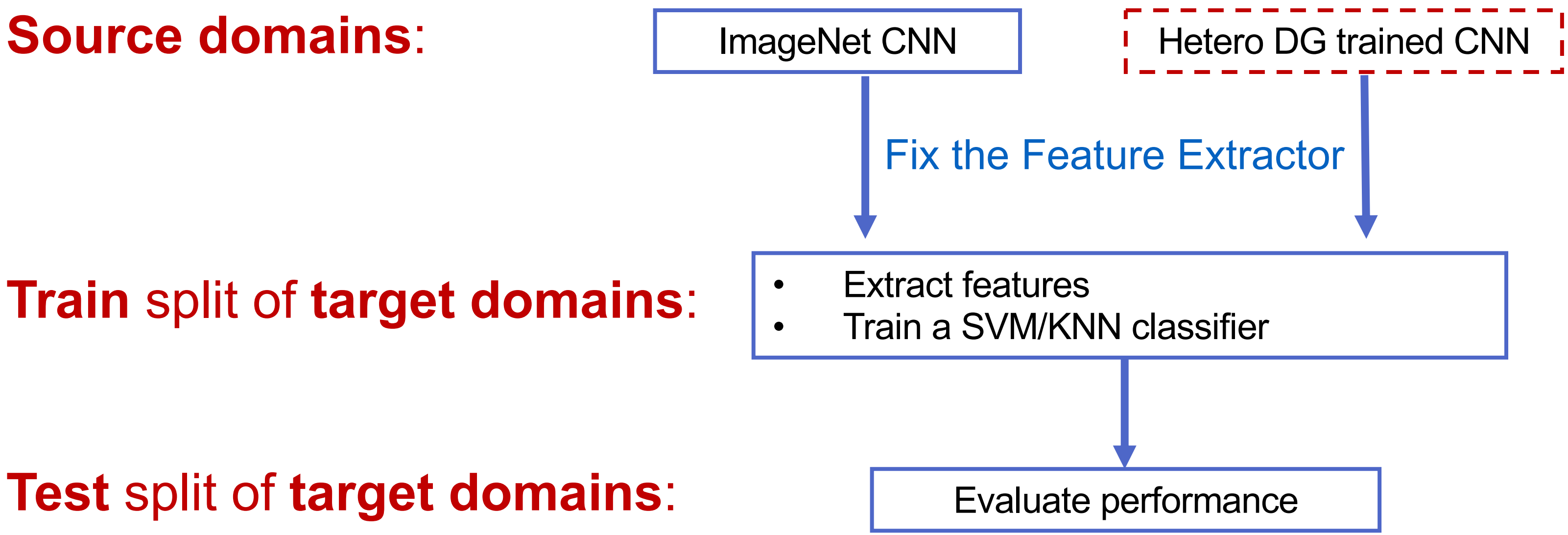
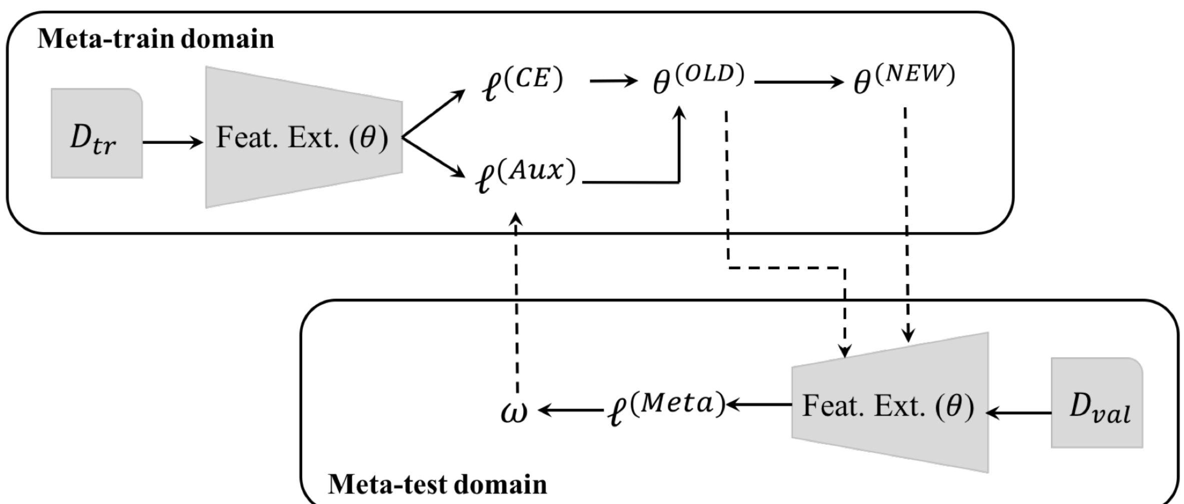


Methodology: Key Idea

Loss Learning:

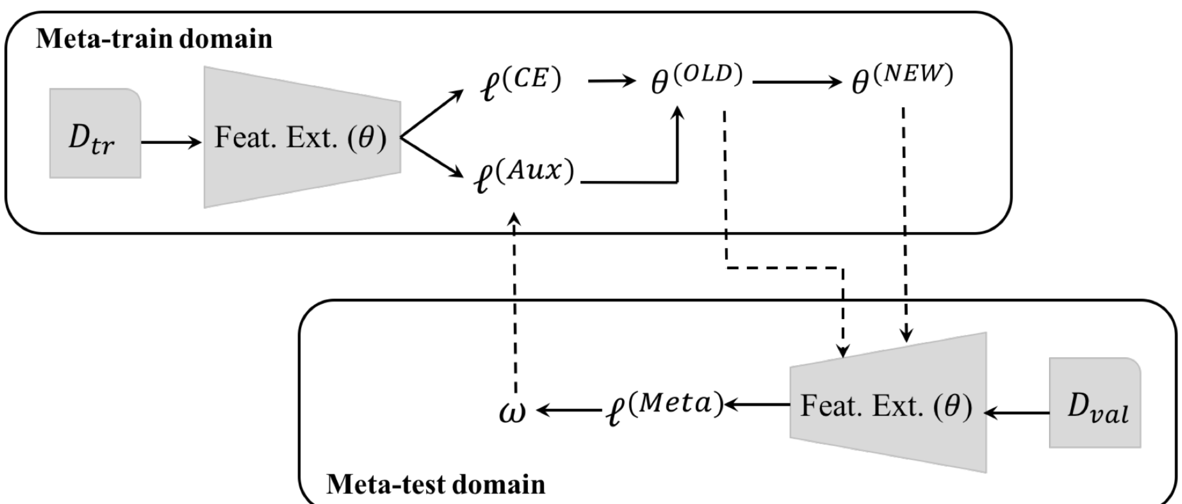
- Simulate domain-shift among a set of source domains.
- Meta-learn a loss function that promotes domain robustness.



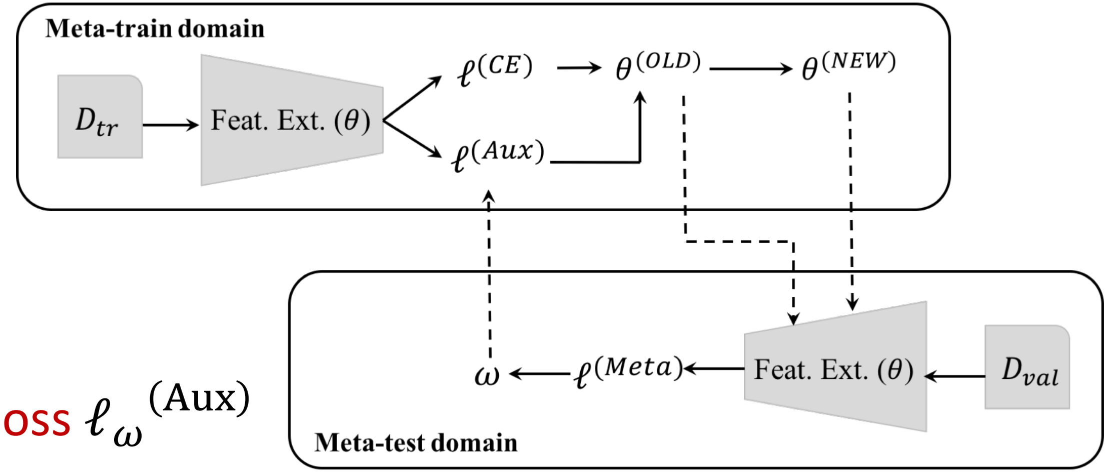
Methodology: Key Idea

Loss Learning:

- Simulate domain-shift among a set of source domains.
- Meta-learn a loss function that promotes domain robustness.
- Loss function is defined on extracted features alone
  - Interpretation: Feature quality critic.



Algorithm



- Introduce a learnable auxiliary loss $\ell_\omega^{(\mathrm{Aux})}$
- Conventional vs feature critic updates:
  - $\theta^{(\mathrm{OLD})} = \theta - \alpha \nabla_\theta \ell^{(\mathrm{CE})}(\mathcal{D}_{\mathrm{meta-train}} | \theta)$
  - $\theta^{(\mathrm{NEW})} = \theta - \alpha \nabla_\theta (\ell^{(\mathrm{CE})}(\mathcal{D}_{\mathrm{meta-train}} | \theta) + \ell_\omega^{(\mathrm{Aux})}(\mathcal{D}_{\mathrm{meta-train}} | \theta))$

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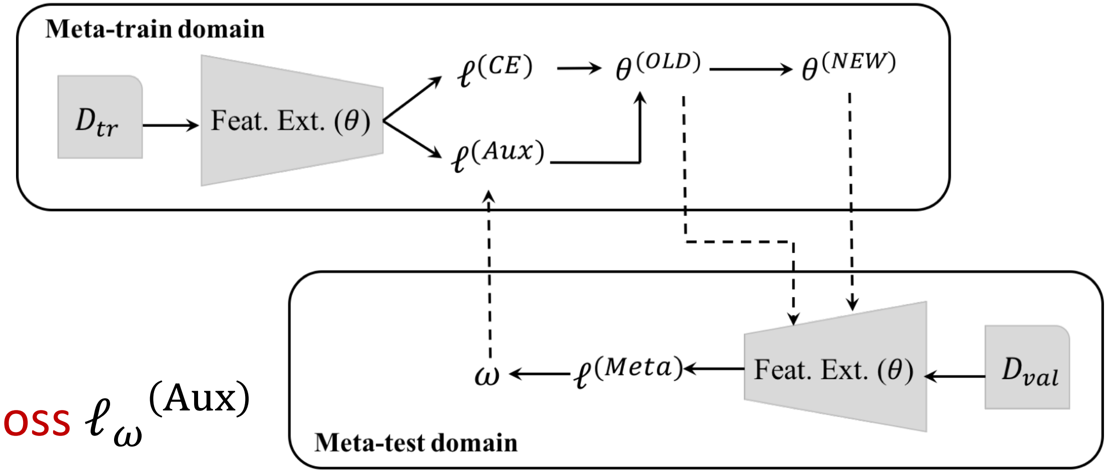

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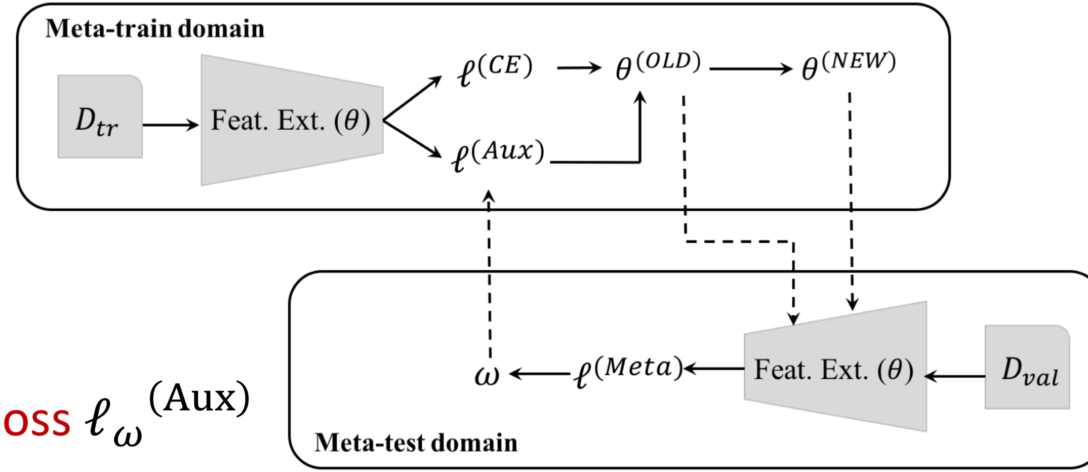
- Meta-loss optimizes the resulting domain invariance

$$\min_{\omega} \tanh\left(\ell^{(\text{CE})}(\mathcal{D}_{\text{meta-test}} | \theta^{(\text{NEW})}) - \ell^{(\text{CE})}(\mathcal{D}_{\text{meta-test}} | \theta^{(\text{OLD})})\right)$$

Algorithm



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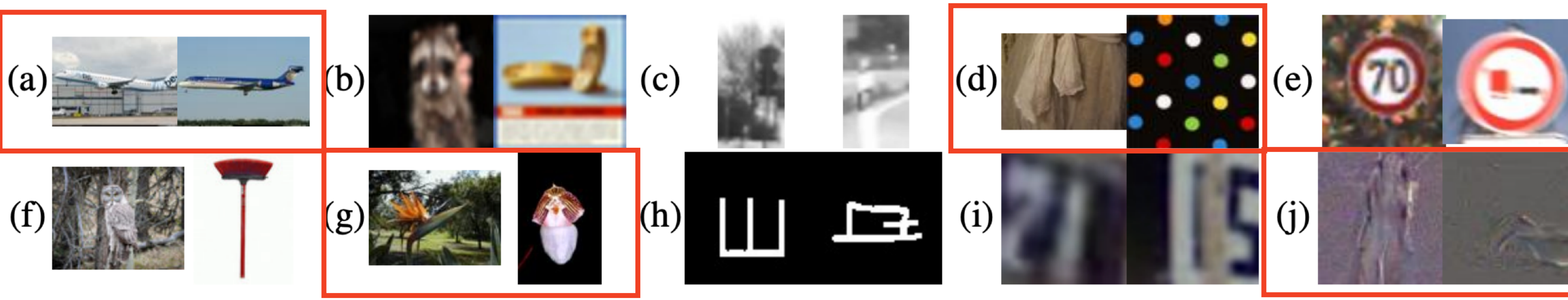
- Auxiliary loss design:

$$\ell_{\omega}{}^{(\mathrm{Aux})} := \mathrm{mean}(\mathrm{softplus}(h_{\omega}(f_{\theta}(x_i))))$$

Results

Heterogeneous DG: Visual Decathlon - ResNet18



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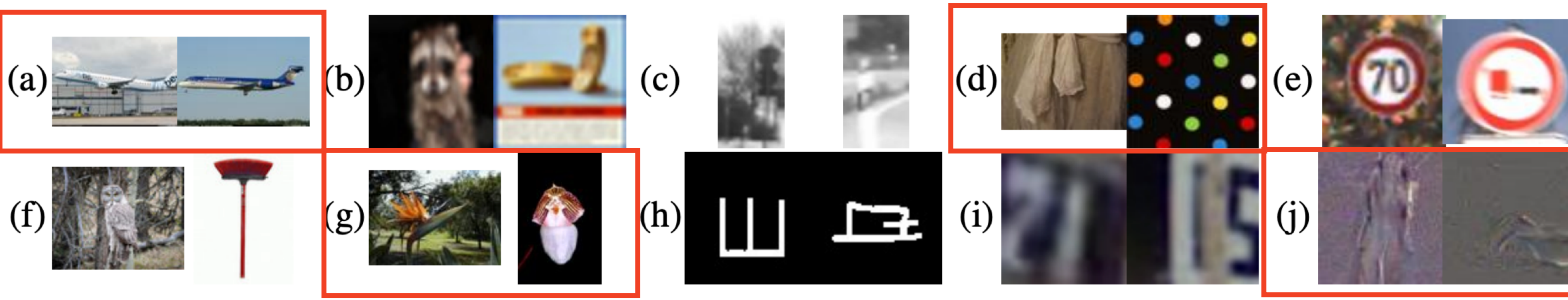


Table 1. Recognition accuracy (%) and VD scores on four held out target datasets in Visual Decathlon using ResNet-18 extractor.

Target	SVM Classifier							KNN Classifier						
	Im.N. PT	CrossGrad	MR	MR-FL	Reptile	AGG	FC	Im.N. PT	CrossGrad	MR	MR-FL	Reptile	AGG	FC
Aircraft	16.62	19.92	20.91	18.18	19.62	19.56	**20.94**	11.46	15.93	12.03	11.46	13.27	14.03	**16.01**
D. Textures	**41.70**	36.54	32.34	35.69	37.39	36.49	38.88	39.52	31.98	27.93	**39.41**	32.80	32.02	34.92
VGG-Flowers	51.57	57.84	35.49	53.04	58.26	58.04	**58.53**	41.08	**48.00**	23.63	39.51	45.80	45.98	47.04
UCF101	44.93	45.80	47.34	48.10	49.85	46.98	**50.82**	35.25	37.95	34.43	35.25	39.06	38.04	**41.87**
Ave.	38.71	40.03	34.02	38.75	41.28	40.27	**42.29**	31.83	33.47	24.51	31.41	32.73	32.52	**34.96**
VD-Score	308	280	269	296	324	290	**344**	215	188	144	215	201	189	**236**

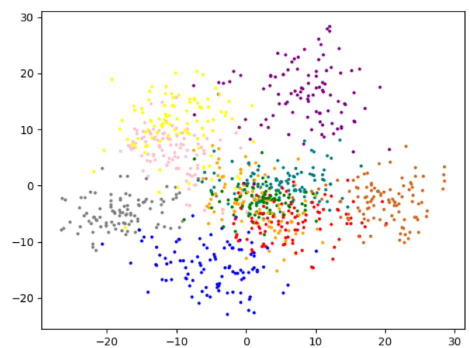
ImageNet 38.7% → Combined Domains 40.3% → Feature Critic 42.3%.

Results

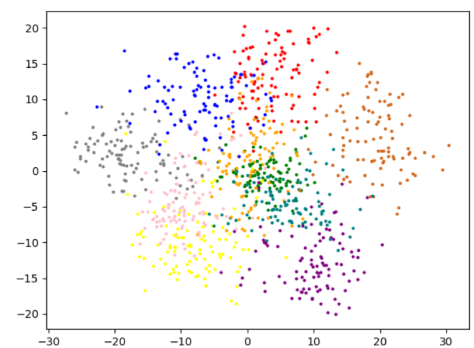
Table 4. Recognition accuracy (%) averaged over 10 train+test runs on Rotated MNIST.

Target	CrossGrad	MetaReg	Reptile	AGG	Feature-Critic-MLP	Feature-Critic-Flatten
M0	86.03 ± 0.69	85.70 ± 0.31	87.78 ± 0.30	86.42 ± 0.24	**89.23** ± 0.25	87.04 ± 0.31
M15	98.92 ± 0.53	98.87 ± 0.41	99.44 ± 0.22	98.61 ± 0.27	**99.68** ± 0.24	99.53 ± 0.27
M30	98.60 ± 0.51	98.32 ± 0.44	98.42 ± 0.24	99.19 ± 0.19	99.20 ± 0.20	**99.41** ± 0.18
M45	98.39 ± 0.29	98.58 ± 0.28	98.80 ± 0.20	98.22 ± 0.24	99.24 ± 0.18	**99.52** ± 0.24
M60	98.68 ± 0.28	98.93 ± 0.32	99.03 ± 0.28	99.48 ± 0.19	**99.53** ± 0.23	99.23 ± 0.16
M75	88.94 ± 0.47	89.44 ± 0.37	87.42 ± 0.33	88.92 ± 0.43	91.44 ± 0.34	**91.52** ± 0.26
Ave.	94.93	94.97	95.15	95.14	**96.39**	96.04

Cross-domain feature encoding quality (PCA):



Baseline



Feature-Critic

Thanks for Listening!

- Please see our poster: Pacific Ballroom #77
- Code: https://github.com/liyiying/Feature_Critic