Advancing Open-Set Domain Generalization Using Evidential Bi-Level Hardest Domain Scheduler

Kunyu Peng[1], Di Wen[1], Kailun Yang[2,*], Ao Luo[3], Yufan Chen[1], Jia Fu[4], M. Saquib Sarfraz[1,5], Alina Roitberg[6], Rainer Stiefelhagen[1]

[1]Karlsruhe Institute of Technology [2]Hunan University [3]Waseda University
[4]KTH Royal Institute of Technology [5]Mercedes-Benz Tech Innovation [6]University of Stuttgart

Open Set Domain Generalization

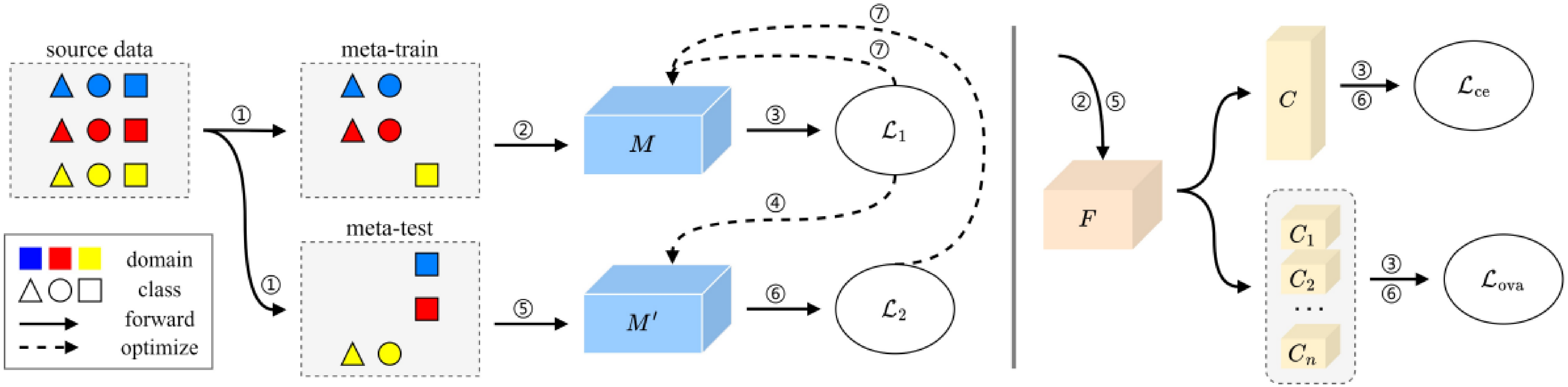
- A joint challenge of the combination of **open set recognition** and **domain generalization**.

- The model is expected to generalize well on unseen domain while delivering low confidence score on the samples from unseen categories.

- Existing literatures have demonstrated that meta learning work well on the open set domain generalization challenge.

Limitation of Existing Meta Learning Approach

- The existing state of the art meta learning approach relies on sequential domain scheduler to achieve the data partition for the meta train and meta test stages. [Wang et al. ICCV2023]



- **Question**: Will an adaptive domain scheduler help to improve open-set domain generalization performance?

How to Achieve Adaptive Domain Scheduler?

- We designed a **follower network** which is jointly trained with the main network in a **bilevel** manner.
- The follower network **shares the same model structure** with the main network.
- The follower network is used to predict the **domain reliability**.
- We conduct the data partition for meta learning according to the domain with less reliability (**hardest domain**).

Max Rebiased Evidential Learning

- Evidential learning is effective to achieve better confidence calibration, however it is easy to get overfitting during the training.

- **Solution:** Max Rebiased Regularization.

$$\mathcal{L}_{RBE}(\mathbf{y}, \mathbf{x}; \Theta) = \sum_{i \in \{1,2\}} \left[\sum_{c=1}^{\mathcal{C}} [\mathbf{y}_c (\log S_i - \log(R_{\theta_i}(M_\alpha(\mathbf{x}))_c + 1))] \right] - \boxed{\mathcal{R}_{RB}(\mathbf{x}; \Theta)}$$

$$\boxed{\mathcal{R}_{RB}(\mathbf{x}; \Theta) = \sum_{i \in \{1,2\}} \mathbb{E}\left[\mathcal{K}(R_{\theta_i}(M_\alpha(\mathbf{x})), R_{\theta_i}(M_\alpha(\mathbf{x})))\right] - 2 * \mathbb{E}[\mathcal{K}(R_{\theta_1}(M_\alpha(\mathbf{x})), R_{\theta_2}(M_\alpha(\mathbf{x})))].}$$

$$S_i = \sum_{c=1}^{C} (Dir(p|R_{\theta_i}(M_\alpha(\mathbf{x}))_c + 1)$$

Bilevel Optimization

- We jointly updated the parameters of the follower network and the main network using the following equation.

$$\Theta^* = \arg\min_{\Theta} \mathcal{L}_m(M_\Theta(\mathbf{x}), \omega^* \leftarrow M_{\beta^*}(\mathbf{x})) \quad \textbf{subject to} \quad \beta^* = \arg\min_{\beta} L_f(M_\Theta(\mathbf{x}), M_\beta(\mathbf{x}))$$

$$\beta^*(\Theta) = \arg\min_\beta L_f(M_\Theta(\mathbf{x}), M_\beta(\mathbf{x}))$$

$$\Theta^* = \arg\min_{\Theta} L_m(\Theta, \beta^*(\Theta))$$

Hardest Domain Scheduler

- We thereby achieve the hardest domain scheduler using the following equation.

$$d^* = \arg\min_d(\{\omega_d | d \in \mathcal{D}\}), \; \omega_d = \min_{c \in \mathcal{C}^*} \left[\exp\left[1 + \sum_{i=1}^{N_c^*} \frac{(M_\beta(\mathbf{x}_i^{(c,d)}))}{N_c^*} \right] * (0.1 + \sigma * \gamma_d) \right]$$

How to Use Data Partition in Meta Learning?

Algorithm 1 Training with Evidential Bi-Level Hardest Domain Scheduler.

Require: Known domains $\mathcal{D}$; Known classes $\mathcal{C}$; backbone M_α; two rebiased layers R_{θ_1} and R_{θ_2}; two heads H_{ϕ_1} and H_{ϕ_2}; follower scheduling network M_β; weighted cross entropy WCE; mean squared error MSE.

while not converged **do**
 Randomly select two known classes $c_i, c_j \leftarrow \mathcal{C}$;
 Get the hardest domain d^* using M_β by Eq. 5; Select two domains from $d_i, d_j \leftarrow \mathcal{D}/\{d^*\}$;
 Sample data $\Omega_a, \Omega_b = \{\mathbf{x}^{[c_k,d_k]} | k \in [i,j]\}, \{\mathbf{x}^{[c_k,d_k]} | c_k \in \{\mathcal{C}/\{c_i,c_j\}, d_k \in \{d^*\}\}$;
 Construct meta-train set by $\Omega_{m-train} = \Omega_a \cup \Omega_b$;
 Meta-train:
 for $\mathbf{x}$ in $\Omega_{m-train}$ **do**;
  Extract rebiased embeddings $\mathbf{f}_1 = R_{\theta_1}(M_\alpha(\mathbf{x}))$ and $\mathbf{f}_2 = R_{\theta_2}(M_\alpha(\mathbf{x}))$;
  Obtain the max rebiased discrepancy evidential learning loss $L_{RBE}(\mathbf{x})$ using $\mathbf{f}_1$ and $\mathbf{f}_2$;
  Follower learning $L_{REG}(\mathbf{x}) = MSE(M_\beta(\mathbf{x}), \frac{1}{2}\sum_{k\in\{1,2\}} Conf(H_{\Phi_k}(\mathbf{f}_k)))$;
  Obtain classification loss $L_{CLS}(\mathbf{x}) = \sum_{k\in\{1,2\}}(WCE(H_{\Phi_k}(M_\alpha(\mathbf{x}))), \mathbf{y}, \omega))$, $\omega \leftarrow M_\beta(\mathbf{x})$, where $\mathbf{y}$ indicates the classification annotation;
 end for
 $L_{m-train} \leftarrow \sum_{\mathbf{x}\in\Omega_{m-train}}(L_{CLS}(\mathbf{x}) + L_{REG}(\mathbf{x}) + L_{RBE}(\mathbf{x}))$. Backpropagation and parameter update for the whole network;
 Meta-test:
 Sample data $\Omega_a^*, \Omega_b^* = \{\mathbf{x}^{[c_k,d_k]} | c_k \in \{c_i,c_j\}, d_k \in \{d^*\}\}, \{\mathbf{x}^{[c_k,d_k]} | c_k \in \mathcal{C}/\{c_i,c_j\}, d_k \in \{d_i,d_j\}\}$. Construct meta-test set $\Omega_{m-test} = \Omega_a^* \cup \Omega_b^*$;
 Obtain loss for meta-test $L_{m-test} \leftarrow \sum_{\mathbf{x}\in\{\Omega_{m-test}\}}(L_{CLS}(\mathbf{x}) + L_{REG}(\mathbf{x}) + L_{RBE}(\mathbf{x}))$;
 Back propagation and parameter update using $L_{all} = L_{m-test} + L_{m-train}$.
end while

An Overview of the Performances

- Our approach achieve SOTA performances on three benchmarks for OSDG, i.e., PACS, DigitsDG, and OfficeHome.

PACS

Method	Photo (P) Acc	Photo (P) H-score	Photo (P) OSCR	Art (A) Acc	Art (A) H-score	Art (A) OSCR	Cartoon (C) Acc	Cartoon (C) H-score	Cartoon (C) OSCR	Sketch (S) Acc	Sketch (S) H-score	Sketch (S) OSCR	Avg Acc	Avg H-score	Avg OSCR
OpenMax [3]	95.56	92.48	-			-	78.61	64.36	-	70.89	50.67	-	82.19	69.28	-
ERM [50]	**96.04**	93.40	**95.11**	84.18	70.54	71.89	77.63	62.80	62.57	70.44	55.81	51.75	82.07	70.64	70.33
ARPL [8]	94.83	**95.06**													
MMLD [39]	94.83	88.80													
RSC [23]	94.43	88.37													
DAML [46]	91.44	80.87													
MixStyle [65]	95.23	82.02													
SelfReg [28]	95.72	89.34													
MLDG [30]	94.99	91.48													
MVDG [30]	94.43	74.07													

DigitsDG

Method	MNIST Acc	MNIST H-score	MNIST OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR
OpenMax [3]	97.33	52.03													
MixStyle [65]	97.86	73.25													
ERM [50]	97.47	80.90													
ARPL [8]	97.75	85.74													
MLDG [30]	97.83	80.36													
SWAD [6]	97.71	84.44													
ODG-Net [4]	96.86	71.34													
MEDIC-cls [54]	97.89	67.37													
MEDIC-bcls [54]	97.89	83.20	95.81	71.14	**60.98**	58.28	76.00	58.77	57.60	88.11	62.24	72.91	83.28	66.30	71.15
EBiL-HaDS-cls	**99.50**	87.40	97.49	74.28	56.58	**60.86**	**80.33**	61.27	62.84	**93.97**	**73.95**	78.14	**87.02**	70.27	75.83
EBiL-HaDS-bcls	**99.50**	**91.63**	**97.58**	74.28	60.72	59.39	**80.33**	**62.23**	**63.88**	**93.97**	69.92	**79.28**	**87.02**	**71.13**	**75.87**

OfficeHome

Method	Art Acc	Art H-score	Art OSCR	Clipart Acc	Clipart H-score	Clipart OSCR	Real World Acc	Real World H-score	Real World OSCR	Product Acc	Product H-score	Product OSCR	Avg Acc	Avg H-score	Avg OSCR
OpenMax [3]	65.59	56.00	-	60.02	47.34	-	83.56	70.48	-	80.50	68.45	-	72.92	60.57	-
MixStyle [65]	62.81	53.93	50.71	52.46	44.53	42.27	81.16	67.70	67.95	76.29	63.46	62.51	68.18	57.41	55.86
ERM [50]	66.30	57.39	54.86	59.60	46.81	47.84	84.50	69.99	74.03	80.81	67.40	67.44	72.80	60.40	61.04
ARPL [8]	60.06	50.34	45.68	54.82	45.72	43.21	76.24	62.04	61.73	75.30	62.47	60.19	66.61	55.14	52.70
MLDG [30]	66.56	52.45	55.10	58.85	53.09	47.69	80.10	70.66	70.02	75.02	66.16	63.49	70.13	60.59	59.08
SWAD [6]	59.12	53.05	47.87	57.37	45.78	47.28	78.38	66.43	65.48	76.50	64.29	63.28	67.84	57.39	58.95
ODG-Net [4]	64.10	54.97	50.64	61.06	52.26	48.33	83.93	70.04	71.34	79.07	65.47	65.49	72.04	60.69	58.95
MEDIC-cls [54]	66.81	55.78	55.85	61.14	54.21	48.51	85.03	71.16	73.15	80.69	67.72	68.09	73.42	62.22	61.40
MEDIC-bcls [54]	66.81	51.76	56.21	61.14	53.28	48.97	85.03	70.61	74.08	80.69	67.70	67.17	73.42	60.82	61.61
EBiL-HaDS-cls	**68.18**	**59.66**	56.83	**63.48**	**57.01**	52.26	85.48	72.88	74.45	81.61	71.03	70.25	**74.69**	**65.15**	63.45
EBiL-HaDS-bcls	**68.18**	53.57	**57.49**	**63.48**	52.12	**53.14**	**85.48**	**74.20**	**75.64**	**81.61**	**72.20**	**71.62**	**74.69**	62.97	**64.47**

An Overview of the Performances

- Our approach shows good generalizability across different backbones on PACS dataset.

ResNet50

Method	Photo (P)			Art (A)			Cartoon (C)			Sketch (S)			Avg		
	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR
OpenMax [3]	97.58	93.09	-	88.37	73.91	-	84.38	68.23	-	80.07	68.06	-	87.60	75.82	-
ARPL [8]	97.09	**96.81**	96.86	88.24	77.48	80.32	82.68	67.19	68.31	78.08	70.04	69.47	86.52	77.88	78.74
MIRO [7]	94.85	92.32	93.27	88.51	65.02	79.01	82.98	63.05	73.72	82.22	69.47	70.61	87.14	72.47	79.15
MLDG [30]	96.77	95.85	96.33	87.99	77.16	79.93	83.45	68.74	71.32	82.25	73.16	72.27	87.61	78.73	79.96
ERM [50]	97.09	96.58	96.68	89.99	76.05	82.44	85.10	65.79	70.59	80.31	70.29	70.16	88.12	77.18	79.97
CIRL [38]	96.53	87.75	95.40	92.06	70.75	77.44	85.71	68.82	73.71	84.35	66.73	77.24	89.66	73.51	80.95
MixStyle [65]	96.53	93.57	95.30	90.87	79.15	83.27	86.80	68.08	74.68	84.88	71.57	73.41	89.77	78.09	81.66
CrossMatch [67]	96.53	96.34	96.12	91.37	75.67	82.32	83.92	67.02	74.55	81.61	72.03	73.99	88.37	77.76	81.75
SWAD [6]	96.37	84.56	93.24	93.75	68.41	85.00	85.57	58.57	75.90	81.90	74.66	74.65	89.40	71.55	82.20
MVDG [60]	97.17	95.02	96.63	**92.50**	79.47	85.02	86.02	71.05	76.03	83.44	75.24	75.18	89.78	80.20	83.21
ODG-Net [4]	96.53	94.93	95.58	89.24	65.22	74.60	83.86	64.32	71.20	84.80	77.58	77.38	88.61	75.51	79.69
MEDIC-cls [54]	96.37	93.80	95.37	91.62	80.80	84.67	86.65	75.85	77.48	84.61	75.80	76.79	89.81	81.56	83.58
MEDIC-bcls [54]	96.37	94.75	95.79	91.62	81.61	85.81	86.65	77.39	78.30	84.61	78.35	79.50	89.81	83.03	84.85
EBiL-HaDS-cls (ours)	**97.82**	93.58	95.69	92.31	80.95	84.35	**87.52**	75.68	78.68	**85.91**	76.05	78.57	**90.89**	81.57	84.32
EBiL-HaDS-bcls (ours)	**97.82**	96.04	**97.14**	92.31	**82.80**	**86.17**	**87.52**	**78.34**	**79.85**	**85.91**	**78.68**	**81.32**	**90.89**	**83.97**	**86.12**

ResNet18

Method	Photo (P)			Art (A)			
	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc
OpenMax [3]	95.56	92.48	-	83.68	69.61	-	78.61
ERM [50]	**96.04**	93.40	**95.11**	84.18	70.54	71.89	77.63
ARPL [8]	94.83	**95.06**	94.63	83.93	67.88	68.82	78.56
MMLD [39]	94.83	88.80	92.94	84.43	64.83	69.43	77.11
RSC [23]	94.43	88.37	91.38	83.36	70.27	73.55	78.09
DAML [46]	91.44	80.87	82.83	83.11	72.05	71.75	79.11
MixStyle [65]	95.23	82.02	88.99	86.18	70.62	72.57	78.92
SelfReg [28]	95.72	89.34	92.26	86.24	72.45	73.77	80.77
MLDG [30]	94.99	91.48	93.70	84.12	69.52	72.15	78.45
MVDG [60]	94.43	74.07	88.07	**87.62**	71.98	75.05	81.18
ODG-Net [4]	93.54	89.39	89.76	85.74	72.36	73.41	81.59
MEDIC-cls [54]	94.83	83.68	90.30	86.20	69.35	74.16	81.94
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

ResNet152

Method	Photo (P)			Art (A)			Cartoon (C)			Sketch (S)			Avg		
	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR
ARPL	94.35	85.45	86.74	89.81	71.27	78.53	83.91	69.75	72.08	77.53	52.70	66.68	77.53	69.81	76.01
MLDG	96.20	91.07	94.64	89.81	77.65	82.19	83.86	73.66	74.03	82.89	64.30	72.98	88.19	76.67	80.96
SWAD	95.64	84.82	89.74	86.30	73.86	75.91	78.49	70.18	68.41	76.92	75.33	63.35	84.34	76.05	74.35
ODG-Net	95.88	89.11	91.85	89.62	80.65	82.48	85.15	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]
MEDIC-cls	94.67	49.54	76.98	89.37	73.26	77.79	86.59								
MEDIC-bcls	94.67	72.88	81.30	89.37	74.92	78.70	86.59								
EBiL-HaDS-cls (ours)	**97.90**	91.66	96.62	**92.06**	81.52	85.43	**87.21**								
EBiL-HaDS-bcls (ours)	**97.90**	**94.34**	**97.39**	**92.06**	**82.00**	**85.94**	**87.21**								

ViT Base

Method	Photo (P)			Art (A)			Cartoon (C)			Sketch (S)			Avg		
	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR	Acc	H-score	OSCR
ARPL	99.19	95.31	98.61	90.49	85.46	88.59	81.88	72.17	73.34	63.01	29.33	50.59	83.64	70.57	77.78
MLDG	99.19	95.40	98.88	91.87	82.46	89.47	80.56	69.62	74.19	61.66	40.79	43.88	83.32	72.07	76.61
SWAD	98.55	93.19	97.62	90.81	81.34	88.52	83.24	73.03	76.59	57.89	35.83	41.68	82.62	70.85	76.10
ODG-Net	97.58	96.24	95.23	90.49	83.32	87.90	82.36	68.66	75.80	62.59	43.59	50.22	83.26	72.95	77.29
MEDIC-cls	99.03	95.33	98.22	92.06	83.27	87.46	85.62	69.79	75.37	68.40	41.95	56.56	86.28	72.59	79.40
MEDIC-bcls	99.03	96.04	97.55	92.06	82.68	87.73	85.62	69.15	76.80	68.40	39.60	55.92	86.28	71.87	79.50
EBiL-HaDS-cls (ours)	**99.52**	**97.30**	99.11	**94.68**	86.10	92.10	**89.22**	**74.31**	77.76	**69.49**	44.34	55.37	**88.23**	75.53	81.09
EBiL-HaDS-bcls (ours)	**99.52**	96.91	**99.18**	**94.68**	**88.31**	**92.28**	**89.22**	73.91	**77.95**	**69.49**	**48.09**	**56.78**	**88.23**	**76.81**	**81.55**

Thank you for your interests!