On Generalizing Beyond Domains in Cross-Domain Continual Learning
Supplementary Material

Christian Simon[1,3,5] Masoud Faraki[2] Yi-Hsuan Tsai[6] Xiang Yu[2]
Samuel Schulter[2] Yumin Suh[2] Mehrtash Harandi[3,5] Manmohan Chandraker[2,4]

[1]The Australian National University [2]NEC Labs America [3]Monash University
[4]University of California, San Diego [5]Data61 [6]Phiar Technologies

sen.christiansimon@gmail.com, mfaraki@nec-labs.com, wasidennis@gmail.com
{xiangyu, samuel, yumin}@nec-labs.com, mehrtash.harandi@monash.edu, manu@nec-labs.com

While the main focus of the supervised experiments is evaluation on the unseen data in leave-one-domain-out protocol, in this supplementary material, we provide additional results on the test sets of the seen domains.

A. Additional Results on the Seen Domains

In the main paper, we have shown that our proposed approach is superior to all the competitors when evaluating on the unseen domains in the supervised experiments. Here, we provide additional results on seen domains to demonstrate that our methods achieve improvements on all domains, including the seen ones. As we can observe in Table A1, our MSL and MSL + Mov are also superior to other baselines when seen domains are considered. For example, the best accuracy number of 71.0% on DomainNet-Real is obtained by MSL + Mov (see the last row in Table A1) with the gap of 4.3% compared to the recent method of GeoDL.

Furthermore, Table A2 shows that our methods can achieve the best accuracy numbers on the unseen domains of the PACS and NICO datasets. On the seen domains, we observe that the best accuracy number is sometimes about 1-2% better than ours (*e.g.* on the NICO dataset row-col: water-ground and grass-ground). However, our proposal achieves the best average accuracy over both the test sets of seen and unseen domains.

References

[1] Saihui Hou, Xinyu Pan, Chen Change Loy, Zilei Wang, and Dahua Lin. Learning a unified classifier incrementally via rebalancing. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2019. 2

[2] Zhizhong Li and Derek Hoiem. Learning without forgetting. *IEEE transactions on pattern analysis and machine intelligence*, 40(12):2935–2947, 2017. 2

[3] Christian Simon, Piotr Koniusz, and Mehrtash Harandi. On learning the geodesic path for incremental learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pages 1591–1600, 2021. 2

[4] Vladimir N. Vapnik. *Statistical Learning Theory Wiley*. 1998. 2

[5] Marvin Zhang, Henrik Marklund, Abhishek Gupta, Sergey Levine, and Chelsea Finn. Adaptive risk minimization: A meta-learning approach for tackling group shift. *CoRR*, abs/2007.02931, 2020. 2

[6] Kaiyang Zhou, Yongxin Yang, Yu Qiao, and Tao Xiang. Domain generalization with mixstyle. In *International Conference on Learning Representations*, 2021. 2

Method	DomainNet									OfficeHome								
	Unseen Domain	10-Task Acc. (% ↑)				5-Tasks Acc. (% ↑)				Unseen Domain	10-Task Acc. (% ↑)				5-Tasks Acc. (% ↑)			
		Clip	Paint	Real	Sketch	Clip	Paint	Real	Sketch		Art	Product	Clipart	Real	Art	Product	Clipart	Real
ERM [4]	Clip	60.0	56.7	65.4	58.7	59.7	52.7	62.0	54.0	Art	48.8	55.8	69.1	67.1	49.7	56.1	70.2	67.9
	Paint	64.4	51.4	65.3	55.7	63.6	50.2	61.7	55.2	Product	52.7	52.3	68.9	67.0	54.9	51.6	64.9	61.9
	Real	64.6	53.8	60.3	55.9	61.3	50.2	57.7	54.4	Clipart	52.3	57.0	64.7	66.1	53.8	55.6	64.9	67.2
	Sketch	65.2	56.0	65.4	53.1	61.5	52.9	63.0	51.7	Real	52.3	54.8	66.4	62.4	51.9	55.4	66.6	61.9
LwF [2]	Clip	61.3	57.0	67.4	58.0	62.2	56.8	67.6	60.3	Art	49.4	57.5	69.2	67.1	49.9	57.8	70.8	68.2
	Paint	64.7	51.9	65.4	56.4	65.2	52.1	67.0	60.4	Product	53.7	53.8	70.5	68.1	54.8	51.3	70.7	68.6
	Real	65.0	54.7	60.0	56.1	64.89	52.2	62.6	59.2	Clipart	52.6	57.4	65.2	66.4	54.2	56.4	67.5	68.5
	Sketch	65.8	56.2	66.7	53.5	65.0	54.8	66.3	54.9	Real	53.1	55.7	66.1	63.2	53.1	55.7	66.1	63.1
LUCIR [1]	Clip	61.1	57.1	65.7	57.9	61.3	56.5	67.1	60.3	Art	49.3	56.2	69.0	67.2	49.7	57.7	70.9	68.5
	Paint	65.0	52.1	65.5	55.7	65.1	52.7	66.3	59.3	Product	53.4	53.6	71.0	67.9	55.0	51.6	70.3	68.3
	Real	64.9	54.7	59.7	56.8	64.0	52.7	61.1	59.2	Clipart	52.8	56.4	65.7	66.3	54.3	56.5	67.5	68.6
	Sketch	66.1	56.0	65.4	53.0	64.9	55.2	66.4	55.4	Real	52.8	55.0	66.4	62.3	53.7	56.4	67.2	64.9
GeoDL [3]	Clip	61.0	55.6	64.9	58.2	62.1	56.7	67.3	60.1	Art	50.6	56.7	69.6	68.0	50.5	57.6	71.0	68.9
	Paint	65.6	50.5	64.4	56.2	64.9	52.8	66.8	59.6	Product	51.9	53.0	69.7	67.2	54.6	52.4	70.4	68.4
	Real	64.7	53.1	58.5	57.5	63.8	53.0	61.1	59.1	Clipart	54.5	58.4	67.1	68.3	54.4	56.5	67.4	68.7
	Sketch	65.8	56.0	66.7	54.1	65.1	55.1	66.2	55.5	Real	52.5	55.9	67.0	63.1	53.6	55.7	66.8	64.2
ARM [5]	Clip	57.0	50.9	65.0	50.5	55.4	52.2	64.5	49.9	Art	39.8	56.2	58.2	51.7	43.6	58.4	61.7	57.0
	Paint	61.1	49.3	64.0	52.9	62.7	51.8	66.3	54.4	Product	46.4	55.0	60.3	54.8	50.0	56.3	62.8	58.3
	Real	60.4	51.7	62.3	52.9	59.2	51.6	60.2	53.0	Clipart	45.3	55.4	54.3	53.0	48.7	56.9	54.5	54.8
	Sketch	61.9	52.5	65.8	51.2	60.2	53.0	64.6	47.7	Real	43.6	54.7	56.6	51.7	48.7	56.8	60.4	55.4
MixStyle [6]	Clip	58.0	53.4	65.7	52.7	59.6	56.1	69.8	55.5	Art	47.3	60.7	65.1	60.5	48.9	60.9	65.8	61.3
	Paint	60.7	51.4	65.6	52.3	65.5	48.5	69.4	57.0	Product	48.6	54.9	65.1	61.0	51.2	56.9	68.1	65.2
	Real	60.8	53.4	59.5	54.6	63.6	57.3	56.0	57.2	Clipart	48.5	58.9	56.3	57.3	50.0	61.6	57.7	58.7
	Sketch	62.3	53.7	66.8	52.5	63.8	57.6	69.2	53.5	Real	48.2	56.7	62.5	56.0	49.4	59.3	65.3	59.8
MSL (ours)	Clip	63.2	56.6	68.1	59.1	63.3	58.3	70.4	61.5	Art	**61.6**	64.1	75.5	74.5	54.3	64.9	72.6	68.0
	Paint	67.1	51.3	67.2	58.3	65.8	**55.4**	69.1	60.9	Product	61.5	61.4	77.7	74.6	59.1	**63.6**	73.1	69.9
	Real	67.2	55.5	61.8	57.5	64.7	54.2	63.6	60.0	Clipart	60.4	63.0	71.7	73.1	60.3	64.6	68.0	67.5
	Sketch	67.8	57.7	67.9	55.6	65.4	57.1	68.6	57.4	Real	61.5	64.4	74.9	72.7	58.8	63.6	70.6	67.3
MSL + Mov. (ours)	Clip	**63.7**	58.2	71.0	60.9	**63.8**	58.9	71.1	62.6	Art	61.2	65.7	76.8	75.1	**57.9**	63.4	75.3	74.0
	Paint	68.0	**55.0**	69.5	58.7	66.4	55.3	69.7	61.3	Product	63.3	**63.0**	76.4	75.2	60.3	60.2	75.1	74.9
	Real	67.7	57.7	**63.1**	59.8	65.7	55.2	**64.6**	61.4	Clipart	63.7	64.3	**75.3**	73.7	60.3	61.8	**71.4**	73.2
	Sketch	68.1	60.6	71.0	**56.4**	66.6	58.0	69.3	**58.3**	Real	61.3	64.9	73.7	**73.1**	56.6	62.5	73.0	**70.9**

Table A1. Cross-domain continual learning average accuracy with 10-tasks and 5-tasks protocols, and 10 exemplar size and 5 exemplar size in the memory on DomainNet and OfficeHome datasets, respectively. Within each block that corresponds to a method, the domain shown in the beginning of each row is excluded from training, while each column shows the achieved accuracy when a test set of a domain is used. Therefore, the grey cells show the accuracy on unseen domains in leave-one-domain-out protocol while the off-diagonal cells are the accuracy numbers on the test set of seen domains.

Method	PACS					NICO				
	Unseen Domain	Art	Cartoon	Photo	Sketch	Unseen Domain	Eating	Ground	Water	Grass
ERM [4]	Art	88.0	86.4	84.0	83.8	Eating	76.3	85.1	89.1	69.8
	Cartoon	89.5	86.7	86.2	85.3	Ground	76.6	82.9	85.3	68.0
	Photo	87.3	86.1	82.3	85.1	Water	74.1	81.2	84.7	70.6
	Sketch	88.6	86.5	83.6	84.3	Grass	76.7	81.3	85.9	61.9
LwF [2]	Art	88.2	86.8	83.7	83.8	Eating	76.4	84.7	89.3	69.6
	Cartoon	89.4	86.2	85.8	84.7	Ground	76.6	82.4	84.8	67.3
	Photo	86.9	86.9	83.3	85.7	Water	74.3	81.7	85.5	70.7
	Sketch	88.3	86.6	83.4	84.3	Grass	76.9	81.1	85.6	62.4
LUCIR [1]	Art	88.1	87.1	83.8	84.4	Eating	76.5	84.9	89.5	69.4
	Cartoon	89.6	86.6	85.6	85.3	Ground	76.8	82.1	85.5	67.4
	Photo	87.0	87.1	83.5	85.1	Water	73.5	82.2	84.2	69.5
	Sketch	88.5	86.8	83.3	83.8	Grass	77.2	81.0	85.9	62.1
GeoDL [3]	Art	87.0	86.7	83.2	85.6	Eating	72.8	86.8	86.5	67.5
	Cartoon	88.3	85.0	84.8	85.4	Ground	76.2	83.6	87.3	64.1
	Photo	87.6	87.5	82.0	86.5	Water	73.0	86.4	85.4	68.4
	Sketch	88.4	87.4	84.0	84.3	Grass	77.6	85.9	87.2	60.5
ARM [5]	Art	86.2	85.6	82.6	86.5	Eating	65.1	83.8	80.1	66.0
	Cartoon	86.2	83.5	84.2	83.4	Ground	73.5	83.3	85.4	63.7
	Photo	88.1	85.6	80.8	84.4	Water	72.5	87.6	84.9	69.8
	Sketch	85.0	87.3	81.9	83.5	Grass	72.3	83.4	83.6	64.9
MixStyle [6]	Art	86.1	85.1	83.8	81.6	Eating	73.3	85.8	86.6	68.6
	Cartoon	89.4	84.0	84.5	84.0	Ground	75.1	82.6	86.1	61.3
	Photo	86.8	86.1	81.0	84.1	Water	70.5	85.6	81.1	68.5
	Sketch	88.6	86.6	82.8	83.4	Grass	76.9	82.1	87.3	63.6
MSL (ours)	Art	89.9	88.9	84.9	85.8	Eating	**77.3**	85.9	90.0	69.2
	Cartoon	89.6	86.2	85.7	84.3	Ground	81.6	82.1	91.2	69.3
	photo	90.0	87.0	84.4	84.5	Water	77.8	84.8	87.0	75.0
	Sketch	88.6	88.3	84.4	85.1	Grass	80.5	84.1	90.2	62.8
MSL + Mov (ours)	Art	**91.3**	89.8	86.3	88.2	Eating	77.2	85.4	90.3	68.6
	Cartoon	91.4	**87.9**	86.3	86.7	Ground	76.4	**84.1**	88.0	65.5
	Photo	91.0	90.2	**85.0**	86.5	Water	76.7	85.6	**89.0**	66.9
	Sketch	89.9	89.8	86.5	**87.2**	Grass	77.2	84.7	89.5	**64.9**

Table A2. Cross-domain continual learning average accuracy with the 2-tasks protocol, and 5 exemplar size in the memory on PACS and NICO datasets. Within each block that corresponds to a method, the domain shown in the beginning of each row is excluded from training, while each column shows the achieved accuracy when a test set of a domain is used. Therefore, the grey cells show the accuracy on unseen domains in leave-one-domain-out protocol while the off-diagonal cells are the accuracy numbers on the test set of seen domains.