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Online Continual Learning for Robust Indoor Object Recognition

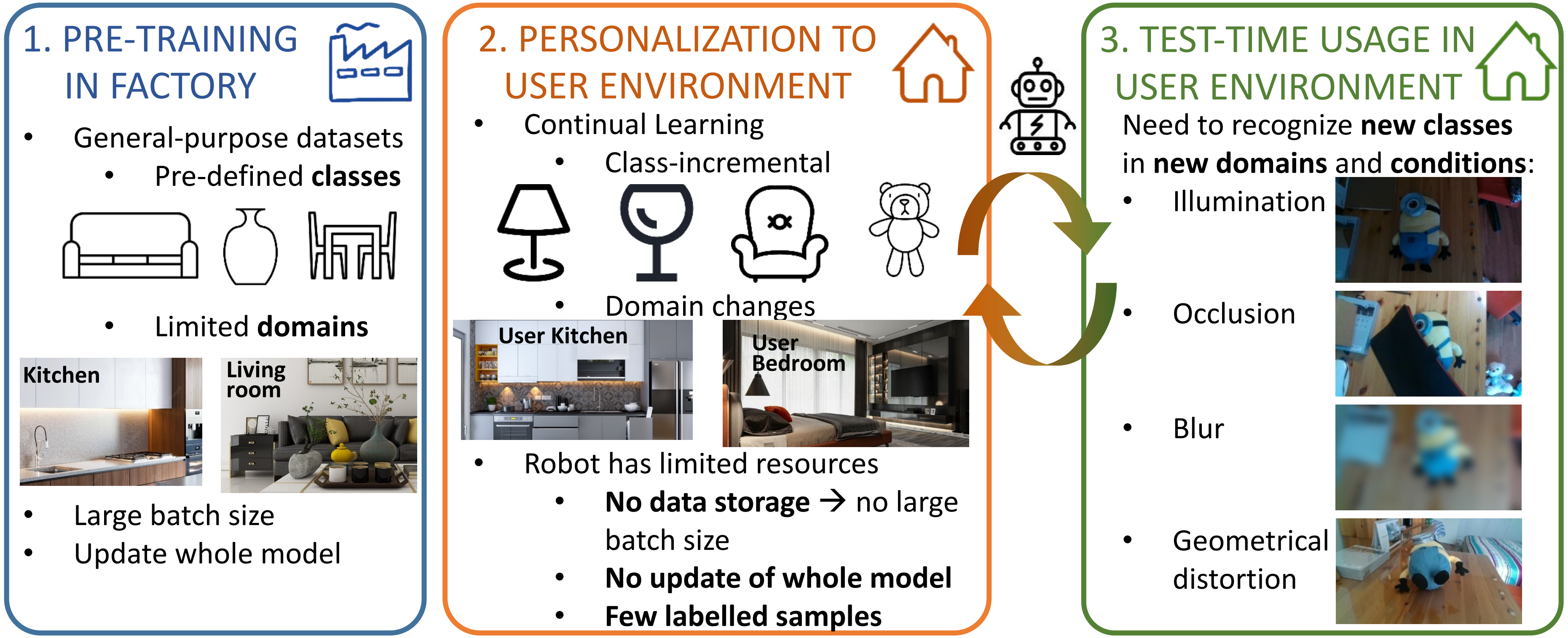
Umberto Michieli, Mete Ozay

Samsung Research UK

SUMMARY

1) Setup
2) Our Method: RobOCLe
3) Main Results
4) Conclusion

1) Setup



TASK: Class-Incremental Online Continual Learning

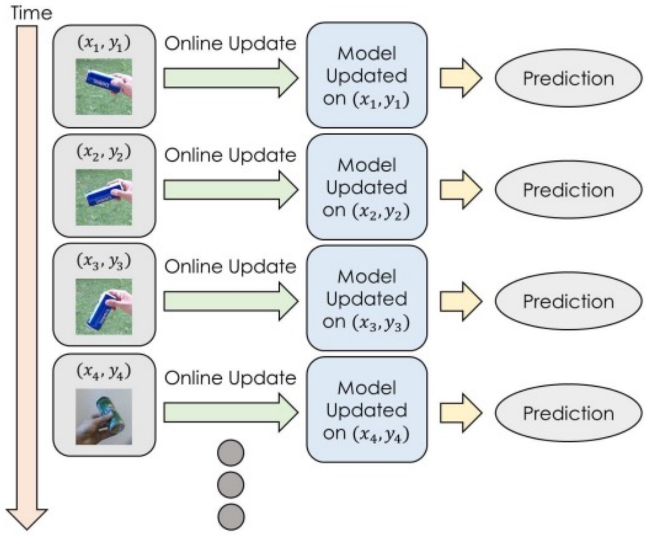
DESIDERATA:

- Robust to Test Time Variations
- Data-Efficient (Few-Shot Training)
- Targeting Limited-Resource Devices

2) Our Method

Three main components:

1. **Feature Extractor →** pre-trained on server on public data and frozen



(b) Streaming Learning

2) Our Method

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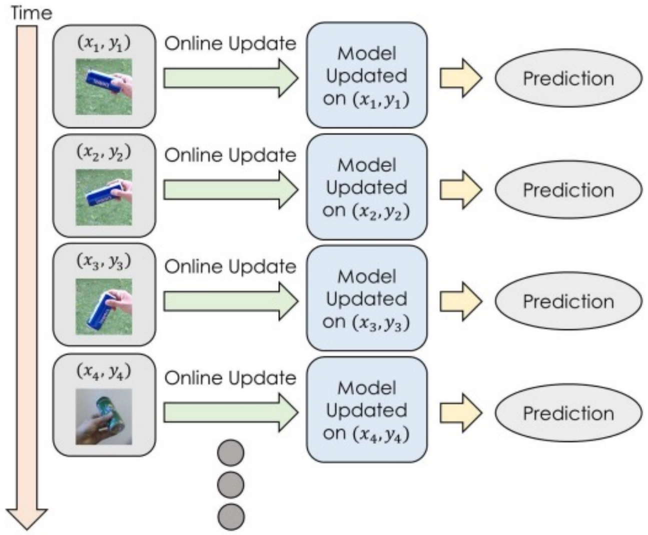
Three main components:

1. **Feature Extractor →** pre-trained on server on public data and frozen

2. **Pooling scheme →** concatenation of first R statistical moments (e.g., R=3)
   - Richer feature space to extract cues from a single-epoch training
   - Increased accuracy
   - Increased robustness

$$P(g) = \Big\|\left(\mu, E_{\mathcal{G}}\left[(g-\mu)^2\right]^{\frac{1}{2}}, \Big\|_{r=3}^{R} E_{\mathcal{G}}\left[\frac{g-\mu}{E_{\mathcal{G}}\left[(g-\mu)^2\right]^{\frac{1}{2}}}\right]^r\right),$$



(b) Streaming Learning

2) Our Method

Three main components:

1. **Feature Extractor →** pre-trained on server on public data and frozen

2. **Pooling scheme →** concatenation of first R statistical moments (e.g., R=3)
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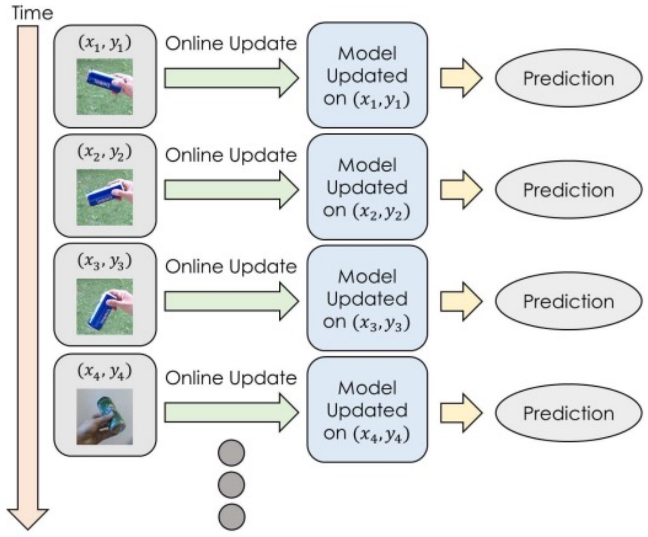
$$P(g) = \Big\Vert \left(\mu, E_{\mathcal{G}}\left[(g-\mu)^2\right]^{\frac{1}{2}}, \mathop{\Big\Vert}_{r=3}^{R} E_{\mathcal{G}}\left[\frac{g-\mu}{E_{\mathcal{G}}\left[(g-\mu)^2\right]^{\frac{1}{2}}}\right]^r \right),$$

3. **Classifier →** lightweight online continual learning method
   → We use SLDA [1] on the enriched feature space

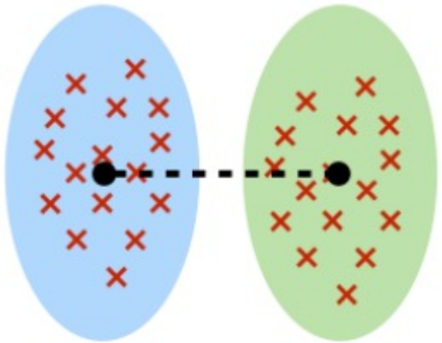
   SLDA estimates a Gaussian model for each class over the feature space with a class-wise mean (prototype) and shared-across-classes covariance

   - Online estimate of covariance
   - Shared covariance across classes



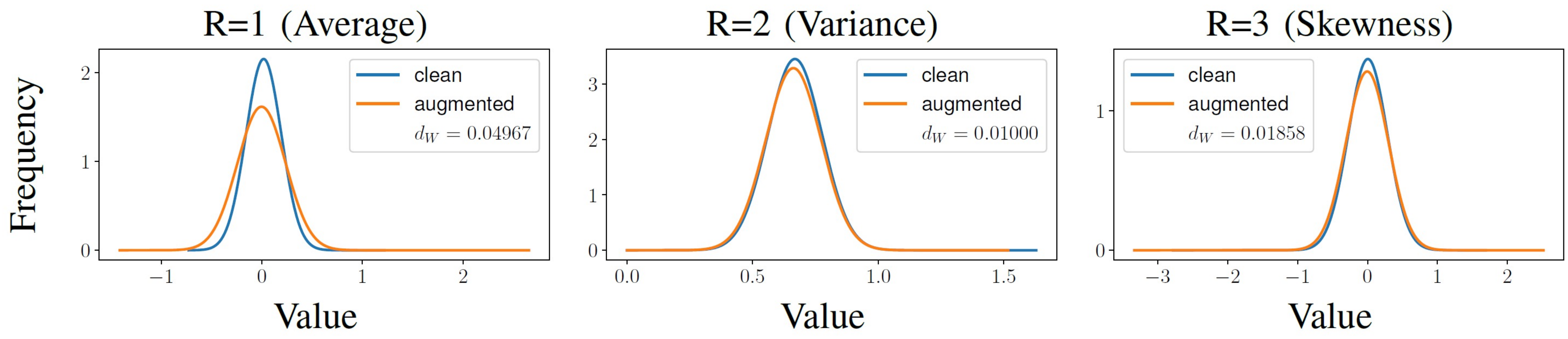
(b) Streaming Learning

[1] Hayes, Tyler L. et al. "Lifelong machine learning with deep streaming linear discriminant analysis." CVPRW 2020.



2) Our Method: Intuition

We plot the distribution of statistical moments of features extracted from **clean** or **augmented** samples and we compute their Wasserstein distance (d_W) :



First statistical moment suffer from more variability than second and third ones

→ Higher order moments improve robustness/resilience and invariance to domain shift.

3) Results: Same-Domain

TABLE I

ACC ON SAME-DOMAIN OPENLORIS DATA ON 16 BACKBONES AND 10 OCL BASELINES. MN: MOBILENET, EN: EFFICIENTNET, RN:RESNET.

	MN-S	MN-L	EN-B0	EN-B1	RN18	RN34	RN50	RN101	RN152	Swin-T	Swin-S	Swin-B	ViT-B16	ViT-B32	ViT-L16	ViT-L32	Avg
FT	84.22	93.38	96.14	97.89	83.35	83.84	94.19	95.43	94.33	95.68	96.07	96.04	59.07	67.27	92.47	62.85	87.01
PRCPT [4]	74.49	89.75	94.02	95.94	80.47	78.58	92.18	91.24	92.35	93.40	94.21	94.46	48.70	58.51	85.62	55.19	82.44
SNB [67]	31.12	37.84	77.96	83.91	1.51	0.84	0.00	0.00	0.00	87.30	86.94	86.14	3.51	4.60	42.90	5.76	34.40
SOvR [4]	37.42	60.17	73.92	80.65	34.65	31.77	71.54	64.57	67.68	80.03	79.01	77.92	4.91	18.83	62.61	22.02	54.23
NCM/CBCL [64], [25]	72.89	81.83	85.94	88.34	79.69	80.47	84.62	83.98	84.12	87.77	87.54	87.94	64.99	63.38	79.47	68.09	80.07
SQDA [66]	77.71	55.84	2.45	6.16	81.59	81.36	5.66	24.24	1.64	83.84	62.53	63.27	8.91	15.74	3.53	7.50	36.37
iCaRL [63]	91.76	95.54	97.60	98.06	92.76	93.21	97.18	97.47	97.63	97.65	97.57	97.98	86.43	89.61	95.52	89.61	94.72
iCaRL (2pc) [63]	89.29	95.09	97.07	96.43	91.21	92.34	96.50	96.99	96.79	97.13	97.13	97.68	79.41	82.49	93.34	81.78	92.54
SLDA [20]	95.57	97.93	98.83	98.98	95.01	95.47	99.00	99.10	99.13	98.25	98.18	98.85	96.74	96.20	98.69	97.04	97.69
RobOCLe$_{\mathrm{SLDA}}$ (ours)	**98.20**	**99.37**	**99.70**	**99.72**	**97.65**	**97.96**	**99.69**	**99.78**	**99.78**	**99.28**	**99.31**	**99.65**	**99.16**	**99.02**	**99.73**	**99.33**	**99.21**
(Δ_R [%])	(+59.5)	(+69.4)	(+74.8)	(+72.3)	(+52.8)	(+54.9)	(+69.1)	(+75.6)	(+75.2)	(+58.6)	(+62.0)	(+69.9)	(+74.2)	(+74.3)	(+79.6)	(+77.4)	(+65.8)

We evaluate on **OpenLORIS dataset** with **16 backbone architectures** against **10** OCL competitors.

→ RobOCLe outperforms all baseline competitors in every scenario.

99.21% accuracy on average, compared to 97.69% of the runner-up method.

3) Results: Other-Domain

TABLE II

ACCURACY ON REAL OTHER-DOMAIN FEW-SHOT DATASETS ON RESNETS AND VITS BACKBONES.

	OpenLORIS-small								F-SIOL-310 (5-shots)								F-SIOL-310 (10-shots)							
	RN50	RN101	RN152	ViT-B16	ViT-B32	ViT-L16	ViT-L32	Avg	RN50	RN101	RN152	ViT-B16	ViT-B32	ViT-L16	ViT-L32	Avg	RN50	RN101	RN152	ViT-B16	ViT-B32	ViT-L16	ViT-L32	Avg
FT	13.64	14.81	16.05	2.08	2.08	2.51	2.08	7.61	40.72	27.65	31.96	8.56	9.87	19.67	8.63	21.01	30.25	26.75	32.83	5.00	7.33	14.42	7.25	17.69
PRCPT [4]	27.45	21.68	21.36	2.08	2.18	6.64	2.08	11.92	32.16	24.12	34.31	4.84	5.42	7.39	4.84	16.15	38.25	24.42	32.75	5.17	5.17	9.75	4.92	17.20
SNB [67]	0.57	0.58	0.25	3.10	4.19	23.52	5.16	5.34	4.90	2.94	6.47	11.31	9.28	24.90	7.84	9.66	6.00	0.83	1.92	6.92	6.42	20.58	15.42	8.30
SOvR [4]	46.72	45.96	43.76	9.33	10.31	29.21	17.24	28.93	80.39	63.01	64.97	18.69	8.17	54.58	14.51	43.47	76.33	63.67	67.50	17.75	7.00	50.08	10.00	41.76
SQDA [66]	37.65	47.08	46.10	37.34	36.20	41.41	36.41	40.31	93.73	94.18	91.70	96.27	94.44	95.03	93.40	94.11	94.67	96.00	95.50	96.00	96.92	96.42	96.42	95.99
iCaRL [63]	51.29	51.04	50.33	33.60	33.57	42.76	32.58	42.17	58.95	66.21	63.53	34.90	40.39	38.50	32.16	47.81	68.83	77.75	76.50	47.08	48.75	51.42	44.08	59.20
iCaRL (2pc) [63]	49.08	47.28	47.93	31.83	28.92	40.89	31.73	39.67	58.04	67.12	64.12	37.25	37.65	38.69	32.88	47.96	69.33	78.33	76.33	46.17	49.83	50.50	45.33	59.40
NCM/CBCL [64], [25]	50.59	48.31	47.68	34.58	32.20	40.57	34.28	41.17	94.90	93.53	93.66	91.96	92.22	94.84	91.70	93.26	93.83	94.42	94.33	93.58	96.17	96.67	94.17	94.74
RobOCLe$_{NCM}$ (ours)	**55.67**	**54.84**	**54.89**	**36.39**	**32.74**	**41.23**	**35.12**	**44.41**	**95.90**	**95.37**	**94.85**	**94.33**	**93.91**	**95.70**	**92.99**	**94.72**	**95.86**	**96.81**	**96.51**	**95.58**	**97.00**	**97.69**	**95.71**	**96.45**
(Δ_R [%])	(+10.3)	(+12.6)	(+13.8)	(+2.8)	(+0.8)	(+1.1)	(+1.3)	(+5.5)	(+19.7)	(+28.5)	(+18.8)	(+29.5)	(+21.6)	(+16.)	(+15.6)	(+21.7)	(+32.9)	(+42.8)	(+38.5)	(+31.2)	(+21.7)	(+30.6)	(+26.4)	(+32.6)
SLDA [20]	50.26	49.91	50.41	43.96	41.50	**45.51**	42.93	46.35	94.38	94.77	93.99	96.34	95.62	94.64	**95.23**	95.00	97.00	97.92	96.25	99.00	98.17	98.33	98.67	97.90
RobOCLe$_{SLDA}$ (ours)	**51.33**	**51.44**	**52.42**	**44.73**	**42.86**	45.22	**43.07**	**47.29**	**96.12**	**96.98**	**95.84**	**96.96**	**95.80**	**95.38**	94.73	**95.97**	**97.42**	**98.33**	**97.47**	**99.18**	**98.31**	**98.40**	**98.78**	**98.27**
(Δ_R [%])	(+2.1)	(+3.1)	(+4.1)	(+1.4)	(+2.3)	(-0.5)	(+0.2)	(+1.8)	(+31.0)	(+42.2)	(+30.8)	(+17.0)	(+4.0)	(+13.7)	(-10.5)	(+19.5)	(+13.9)	(+20.0)	(+32.6)	(+17.9)	(+8.0)	(+4.3)	(+8.4)	(+17.5)

We evaluate on **3 few-shot datasets** with **7 backbone architectures** against **10 OCL competitors**.

→ RobOCLe outperforms all baseline competitors in every scenario.

3) Results: Other-Domain

TABLE III

ACCURACY ON OTHER-DOMAIN DATA GENERATED VIA CONTROLLED AUGMENTATIONS ON THE OPENLORIS WITH RESNET152 AND VIT-L16. RESULTS HIGHLIGHTED IN YELLOW: SAME AUGMENTATIONS BETWEEN TRAIN AND TEST. TR: TRAIN, TE:TEST.

ResNet152

	NCM						RobOCLe$_{NCM}$ (ours)						
tr↓ te→	clean	illum	geom	noise	all	Avg OD	clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	84.12	34.75	77.37	60.82	13.40	46.59	**88.15**	41.26	82.10	66.16	18.16	**51.92**	(+10.0)
illum	56.91	53.91	54.77	45.75	30.29	46.93	62.65	**56.83**	59.92	51.26	31.91	**51.44**	(+8.5)
geom	82.01	40.49	81.07	64.05	19.67	51.55	86.21	45.11	**84.39**	67.92	23.90	**55.79**	(+8.7)
noise	77.27	35.60	71.99	74.31	20.08	51.23	82.78	43.99	78.67	**78.82**	24.84	**57.57**	(+13.0)
all	40.45	43.49	38.22	32.35	35.02	38.63	43.07	44.33	41.64	35.95	**37.33**	**41.25**	(+4.3)

	SLDA						RobOCLe$_{SLDA}$ (ours)						
tr↓ te→	clean	illum	geom	noise	all	Avg OD	clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	99.13	47.19	92.55	77.09	19.74	59.14	**99.78**	48.69	93.31	80.17	20.32	**60.63**	(+3.6)
illum	86.68	79.65	77.76	61.88	39.41	66.43	89.02	**82.21**	79.29	64.58	40.89	**68.45**	(+6.0)
geom	98.05	49.50	97.53	78.08	22.59	62.06	98.81	51.32	**98.40**	78.05	23.12	**62.83**	(+2.0)
noise	97.81	50.14	90.12	96.83	28.12	66.55	98.72	51.82	92.85	**98.12**	28.57	**67.99**	(+4.3)
all	70.16	68.79	70.85	66.35	62.60	69.04	74.78	71.70	74.88	68.73	**65.31**	**72.52**	(+11.3)

ViT-L16

	NCM						RobOCLe$_{NCM}$ (ours)						
tr↓ te→	clean	illum	geom	noise	all	Avg OD	clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	79.47	35.11	73.43	66.57	19.49	48.65	**80.31**	33.13	73.69	68.38	19.74	**48.73**	(+0.2)
illum	30.78	40.58	33.00	29.12	30.00	30.73	30.82	**35.00**	35.17	30.65	31.22	**31.96**	(+1.8)
geom	78.01	36.62	79.19	68.73	23.31	51.67	78.70	37.05	**78.64**	68.87	24.32	**52.24**	(+1.2)
noise	73.67	36.37	66.27	75.64	25.41	50.43	73.84	36.58	68.55	**76.51**	25.56	**51.13**	(+1.4)
all	15.32	32.27	21.58	15.25	31.79	21.11	17.05	32.26	20.98	18.21	**24.77**	**22.13**	(+1.3)

	SLDA						RobOCLe$_{SLDA}$ (ours)						
tr↓ te→	clean	illum	geom	noise	all	Avg OD	clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	98.69	38.30	92.94	90.09	21.49	60.71	**99.73**	40.69	95.04	93.03	22.53	**62.82**	(+5.4)
illum	83.68	77.13	72.86	72.39	50.58	69.88	86.13	**80.65**	77.00	76.19	52.56	**72.97**	(+10.3)
geom	97.72	46.72	96.86	89.44	27.98	65.46	98.74	45.87	**98.10**	92.25	28.08	**66.23**	(+2.2)
noise	97.42	40.08	89.87	97.19	26.21	63.40	98.82	41.90	93.41	**98.68**	26.69	**65.21**	(+4.9)
all	71.27	68.15	66.03	68.67	65.09	68.53	72.81	71.36	71.58	71.59	**68.43**	**71.84**	(+10.5)

TABLE IV

ACCURACY ON OTHER-DOMAIN DATA WITH CONTROLLED AUGMENTATIONS ON RN152 ON THE FEW-SHOT BENCHMARKS.

		NCM						RobOCLe$_{NCM}$ (ours)						
	tr↓ te→	clean	illum	geom	noise	all	Avg$_{OD}$	clean	illum	geom	noise	all	Avg$_{OD}$	Δ_R^{OD}
OLORIS-small	clean	47.68	20.68	43.99	34.50	9.22	27.10	**54.89**	25.64	50.50	41.32	11.43	**32.22**	(+7.0)
	illum	32.92	29.84	31.11	25.77	14.77	26.14	36.62	**31.87**	34.83	29.64	15.30	**29.10**	(+4.0)
	geom	47.15	22.36	46.14	35.27	11.16	28.98	53.61	27.19	**51.60**	40.87	13.51	**33.80**	(+6.8)
	noise	42.00	19.07	38.32	39.62	11.45	27.71	47.44	25.22	45.18	**44.22**	14.56	**33.10**	(+7.5)
	all	21.39	25.70	26.02	23.71	23.25	24.21	27.31	28.23	31.37	26.73	**25.17**	**28.41**	(+5.5)
FSIOL310-5s	clean	93.66	34.44	71.90	55.49	19.35	45.29	**94.58**	42.16	77.78	63.79	23.53	**51.81**	(+11.9)
	illum	48.04	56.01	37.52	36.14	27.06	37.19	51.70	**61.31**	39.74	36.73	30.33	**39.62**	(+3.9)
	geom	76.86	34.97	81.57	35.75	24.05	42.91	77.65	40.92	**82.03**	39.67	29.54	**46.94**	(+7.1)
	noise	53.46	29.08	35.62	68.82	16.67	33.71	58.10	36.41	40.65	**75.16**	18.63	**38.45**	(+7.1)
	all	32.03	30.13	31.96	25.23	40.85	29.84	34.77	36.01	34.84	29.54	**44.64**	**33.79**	(+5.6)
FSIOL310-10s	clean	94.33	38.25	76.58	60.83	17.42	48.27	**96.50**	45.00	79.75	68.08	22.50	**53.83**	(+10.8)
	illum	57.00	63.50	46.67	40.25	32.17	44.02	58.75	**71.58**	52.17	43.58	38.75	**48.31**	(+7.7)
	geom	82.83	39.83	86.58	37.42	23.83	45.98	85.92	46.08	**87.83**	42.17	31.00	**51.29**	(+9.8)
	noise	58.50	32.25	47.33	78.42	17.83	38.98	68.17	37.75	45.25	**85.83**	20.75	**42.98**	(+6.6)
	all	35.58	38.92	36.00	29.33	49.92	34.96	39.42	47.50	43.42	27.50	**53.17**	**39.46**	(+6.9)

3) Results: Other-Domain

TABLE III

ACCURACY ON OTHER-DOMAIN DATA GENERATED VIA CONTROLLED AUGMENTATIONS ON THE OPENLORIS WITH RESNET152 AND VIT-L16. RESULTS HIGHLIGHTED IN YELLOW: SAME AUGMENTATIONS BETWEEN TRAIN AND TEST. TR: TRAIN, TE:TEST.

ResNet152	NCM						RobOCLe$_{NCM}$ (ours)						
tr↓ te→	clean	illum	geom	noise	all	Avg OD	clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	84.12	34.75	77.37	60.82	13.40	46.59	**88.15**	41.26	82.10	66.16	18.16	**51.92**	(+10.0)
illum	56.91	53.91	54.77	45.75	30.29	46.93	62.65	**56.83**	59.92	51.26	31.91	**51.44**	(+8.5)
geom	82.01	40.49	81.07	64.05	19.67	51.55	86.21	45.11	**84.39**	67.92	23.90	**55.79**	(+8.7)
noise	77.27	35.60	71.99	74.31	20.08	51.23	82.78	43.99	78.67	**78.82**	24.84	**57.57**	(+13.0)
all	40.45	43.49	38.22	32.35	35.02	38.63	43.07	44.33	41.64	35.95	**37.33**	**41.25**	(+4.3)
	SLDA						RobOCLe$_{SLDA}$ (ours)						
clean	99.13	47.19	92.55	77.09	19.74	59.14	**99.78**	48.69	93.31	80.17	20.32	**60.63**	(+3.6)
illum	86.68	79.65	77.76	61.88	39.41	66.43	89.02	**82.21**	79.29	64.58	40.89	**68.45**	(+6.0)
geom	98.05	49.50	97.53	78.08	22.59	62.06	98.81	51.32	**98.40**	78.05	23.12	**62.83**	(+2.0)
noise	97.81	50.14	90.12	96.83	28.12	66.55	98.72	51.82	92.85	**98.12**	28.57	**67.99**	(+4.3)
all	70.16	68.79	70.85	66.35	62.60	69.04	74.78	71.70	74.88	68.73	**65.31**	**72.52**	(+11.3)

ViT-L16	NCM						RobOCLe$_{NCM}$ (ours)						
tr↓ te→	clean	illum	geom	noise	all	Avg OD	clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	79.47	35.11	73.43	66.57	19.49	48.65	**80.31**	33.13	73.69	68.38	19.74	**48.73**	(+0.2)
illum	30.78	40.58	33.00	29.12	30.00	30.73	30.82	**35.00**	35.17	30.65	31.22	**31.96**	(+1.8)
geom	78.01	36.62	79.19	68.73	23.31	51.67	78.70	37.05	**78.64**	68.87	24.32	**52.24**	(+1.2)
noise	73.67	36.37	66.27	75.64	25.41	50.43	73.84	36.58	68.55	**76.51**	25.56	**51.13**	(+1.4)
all	15.32	32.27	21.58	15.25	31.79	21.11	17.05	32.26	20.98	18.21	**24.77**	**22.13**	(+1.3)
	SLDA						RobOCLe$_{SLDA}$ (ours)						
clean	98.69	38.30	92.94	90.09	21.49	60.71	**99.73**	40.69	95.04	93.03	22.53	**62.82**	(+5.4)
illum	83.68	77.13	72.86	72.39	50.58	69.88	86.13	**80.65**	77.00	76.19	52.56	**72.97**	(+10.3)
geom	97.72	46.72	96.86	89.44	27.98	65.46	98.74	45.87	**98.10**	92.25	28.08	**66.23**	(+2.2)
noise	97.42	40.08	89.87	97.19	26.21	63.40	98.82	41.90	93.41	**98.68**	26.69	**65.21**	(+4.9)
all	71.27	68.15	66.03	68.67	65.09	68.53	72.81	71.36	71.58	71.59	**68.43**	**71.84**	(+10.5)

TABLE IV

ACCURACY ON OTHER-DOMAIN DATA WITH CONTROLLED AUGMENTATIONS ON RN152 ON THE FEW-SHOT BENCHMARKS.

		NCM						RobOCLe$_{NCM}$ (ours)						
	tr↓ te→	clean	illum	geom	noise	all	Avg$_{OD}$	clean	illum	geom	noise	all	Avg$_{OD}$	Δ_R^{OD}
OLORIS-small	**clean**	47.68	20.68	43.99	34.50	9.22	27.10	**54.89**	25.64	50.50	41.32	11.43	**32.22**	(+7.0)
	illum	32.92	29.84	31.11	25.77	14.77	26.14	36.62	**31.87**	34.83	29.64	15.30	**29.10**	(+4.0)
	geom	47.15	22.36	46.14	35.27	11.16	28.98	53.61	27.19	**51.60**	40.87	13.51	**33.80**	(+6.8)
	noise	42.00	19.07	38.32	39.62	11.45	27.71	47.44	25.22	45.18	**44.22**	14.56	**33.10**	(+7.5)
	all	21.39	25.70	26.02	23.71	23.25	24.21	27.31	28.23	31.37	26.73	**25.17**	**28.41**	(+5.5)
FSIOL310-5s	**clean**	93.66	34.44	71.90	55.49	19.35	45.29	**94.58**	42.16	77.78	63.79	23.53	**51.81**	(+11.9)
	illum	48.04	56.01	37.52	36.14	27.06	37.19	51.70	**61.31**	39.74	36.73	30.33	**39.62**	(+3.9)
	geom	76.86	34.97	81.57	35.75	24.05	42.91	77.65	40.92	**82.03**	39.67	29.54	**46.94**	(+7.1)
	noise	53.46	29.08	35.62	68.82	16.67	33.71	58.10	36.41	40.65	**75.16**	18.63	**38.45**	(+7.1)
	all	32.03	30.13	31.96	25.23	40.85	29.84	34.77	36.01	34.84	29.54	**44.64**	**33.79**	(+5.6)
FSIOL310-10s	**clean**	94.33	38.25	76.58	60.83	17.42	48.27	**96.50**	45.00	79.75	68.08	22.50	**53.83**	(+10.8)
	illum	57.00	63.50	46.67	40.25	32.17	44.02	58.75	**71.58**	52.17	43.58	38.75	**48.31**	(+7.7)
	geom	82.83	39.83	86.58	37.42	23.83	45.98	85.92	46.08	**87.83**	42.17	31.00	**51.29**	(+9.8)
	noise	58.50	32.25	47.33	78.42	17.83	38.98	68.17	37.75	45.25	**85.83**	20.75	**42.98**	(+6.6)
	all	35.58	38.92	36.00	29.33	49.92	34.96	39.42	47.50	43.42	27.50	**53.17**	**39.46**	(+6.9)

RoOCLe (ours) outperforms baseline on both:

- In-domain case (same augmentation in train/test sets)

3) Results: Other-Domain

TABLE III

ACCURACY ON OTHER-DOMAIN DATA GENERATED VIA CONTROLLED AUGMENTATIONS ON THE OPENLORIS WITH RESNET152 AND VIT-L16. RESULTS HIGHLIGHTED IN YELLOW: SAME AUGMENTATIONS BETWEEN TRAIN AND TEST. TR: TRAIN, TE:TEST.

ResNet152

tr↓ te→	NCM clean	NCM illum	NCM geom	NCM noise	NCM all	NCM Avg OD	RobOCLe$_{NCM}$ (ours) clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	84.12	34.75	77.37	60.82	13.40	46.59	**88.15**	41.26	82.10	66.16	18.16	**51.92**	(+10.0)
illum	56.91	53.91	54.77	45.75	30.29	46.93	62.65	**56.83**	59.92	51.26	31.91	**51.44**	(+8.5)
geom	82.01	40.49	81.07	64.05	19.67	51.55	86.21	45.11	**84.39**	67.92	23.90	**55.79**	(+8.7)
noise	77.27	35.60	71.99	74.31	20.08	51.23	82.78	43.99	78.67	**78.82**	24.84	**57.57**	(+13.0)
all	40.45	43.49	38.22	32.35	35.02	38.63	43.07	44.33	41.64	35.95	**37.33**	**41.25**	(+4.3)
	SLDA						**RobOCLe$_{SLDA}$ (ours)**						
clean	99.13	47.19	92.55	77.09	19.74	59.14	**99.78**	48.69	93.31	80.17	20.32	**60.63**	(+3.6)
illum	86.68	79.65	77.76	61.88	39.41	66.43	89.02	**82.21**	79.29	64.58	40.89	**68.45**	(+6.0)
geom	98.05	49.50	97.53	78.08	22.59	62.06	98.81	51.32	**98.40**	78.05	23.12	**62.83**	(+2.0)
noise	97.81	50.14	90.12	96.83	28.12	66.55	98.72	51.82	92.85	**98.12**	28.57	**67.99**	(+4.3)
all	70.16	68.79	70.85	66.35	62.60	69.04	74.78	71.70	74.88	68.73	**65.31**	**72.52**	(+11.3)

ViT-L16

tr↓ te→	NCM clean	NCM illum	NCM geom	NCM noise	NCM all	NCM Avg OD	RobOCLe$_{NCM}$ (ours) clean	illum	geom	noise	all	Avg OD	Δ_R^{OD}
clean	79.47	35.11	73.43	66.57	19.49	48.65	**80.31**	33.13	73.69	68.38	19.74	**48.73**	(+0.2)
illum	30.78	40.58	33.00	29.12	30.00	30.73	30.82	**35.00**	35.17	30.65	31.22	**31.96**	(+1.8)
geom	78.01	36.62	79.19	68.73	23.31	51.67	78.70	37.05	**78.64**	68.87	24.32	**52.24**	(+1.2)
noise	73.67	36.37	66.27	75.64	25.41	50.43	73.84	36.58	68.55	**76.51**	25.56	**51.13**	(+1.4)
all	15.32	32.27	21.58	15.25	31.79	21.11	17.05	32.26	20.98	18.21	**24.77**	**22.13**	(+1.3)
	SLDA						**RobOCLe$_{SLDA}$ (ours)**						
clean	98.69	38.30	92.94	90.09	21.49	60.71	**99.73**	40.69	95.04	93.03	22.53	**62.82**	(+5.4)
illum	83.68	77.13	72.86	72.39	50.58	69.88	86.13	**80.65**	77.00	76.19	52.56	**72.97**	(+10.3)
geom	97.72	46.72	96.86	89.44	27.98	65.46	98.74	45.87	**98.10**	92.25	28.08	**66.23**	(+2.2)
noise	97.42	40.08	89.87	97.19	26.21	63.40	98.82	41.90	93.41	**98.68**	26.69	**65.21**	(+4.9)
all	71.27	68.15	66.03	68.67	65.09	68.53	72.81	71.36	71.58	71.59	**68.43**	**71.84**	(+10.5)

TABLE IV

ACCURACY ON OTHER-DOMAIN DATA WITH CONTROLLED AUGMENTATIONS ON RN152 ON THE FEW-SHOT BENCHMARKS.

	tr↓ te→	NCM clean	NCM illum	NCM geom	NCM noise	NCM all	NCM Avg$_{OD}$	RobOCLe$_{NCM}$ (ours) clean	illum	geom	noise	all	Avg$_{OD}$	Δ_R^{OD}
OLORIS-small	clean	47.68	20.68	43.99	34.50	9.22	27.10	**54.89**	25.64	50.50	41.32	11.4	**32.22**	(+7.0)
	illum	32.92	29.84	31.11	25.77	14.77	26.14	36.62	**31.87**	34.83	29.64	15.3	**29.10**	(+4.0)
	geom	47.15	22.36	46.14	35.27	11.16	28.98	53.61	27.19	**51.60**	40.87	13.5	**33.80**	(+6.8)
	noise	42.00	19.07	38.32	39.62	11.45	27.71	47.44	25.22	45.18	**44.22**	14.5	**33.10**	(+7.5)
	all	21.39	25.70	26.02	23.71	23.25	24.21	27.31	28.23	31.37	26.73	**25.1**	**28.41**	(+5.5)
FSIOL310-5s	clean	93.66	34.44	71.90	55.49	19.35	45.29	**94.58**	42.16	77.78	63.79	23.5	**51.81**	(+11.9)
	illum	48.04	56.01	37.52	36.14	27.06	37.19	51.70	**61.31**	39.74	36.73	30.3	**39.62**	(+3.9)
	geom	76.86	34.97	81.57	35.75	24.05	42.91	77.65	40.92	**82.03**	39.67	29.5	**46.94**	(+7.1)
	noise	53.46	29.08	35.62	68.82	16.67	33.71	58.10	36.41	40.65	**75.16**	18.6	**38.45**	(+7.1)
	all	32.03	30.13	31.96	25.23	40.85	29.84	34.77	36.01	34.84	29.54	**44.6**	**33.79**	(+5.6)
FSIOL310-10s	clean	94.33	38.25	76.58	60.83	17.42	48.27	**96.50**	45.00	79.75	68.08	22.5	**53.83**	(+10.8)
	illum	57.00	63.50	46.67	40.25	32.17	44.02	58.75	**71.58**	52.17	43.58	38.7	**48.31**	(+7.7)
	geom	82.83	39.83	86.58	37.42	23.83	45.98	85.92	46.08	**87.83**	42.17	31.0	**51.29**	(+9.8)
	noise	58.50	32.25	47.33	78.42	17.83	38.98	68.17	37.75	45.25	**85.83**	20.7	**42.98**	(+6.6)
	all	35.58	38.92	36.00	29.33	49.92	34.96	39.42	47.50	43.42	27.50	**53.1**	**39.46**	(+6.9)

RoOCLe (ours) outperforms baseline on both:

- In-domain case (same augmentation in train/test sets)
- Other-domain (different augmentations in train/test sets)

4) Conclusion

New task: few-shot online continual learning targeting robust test-time object recognition for low-resource robots with limited labelled data and computational/storage capability.

New method: RobOCLe, a data- and parameter-efficient online continual learning method with robust performance under test-time corruptions.

4) Conclusion

New task: few-shot online continual learning targeting robust test-time object recognition for low-resource robots with limited labelled data and computational/storage capability.

New method: RobOCLe, a data- and parameter-efficient online continual learning method with robust performance under test-time corruptions.

RobOCLe features:

- **Lightweight** solution: frozen feature extractor + class-conditional Gaussian modelling of feature space
- Extraction of **high-order statistical moments** of the embedded features of input samples
- **Robust** recognition in a variety of scenarios, using several backbones, low-shot setups, per-step accuracy, and controlled train/test augmentation on both same-domain and other-domain data

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Online Continual Learning for Robust Indoor Object Recognition

Michieli U., Ozay M.

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