ICCV23 PARIS

Residual Pattern Learning for Pixel-wise Out-of-Distribution Detection in Semantic Segmentation

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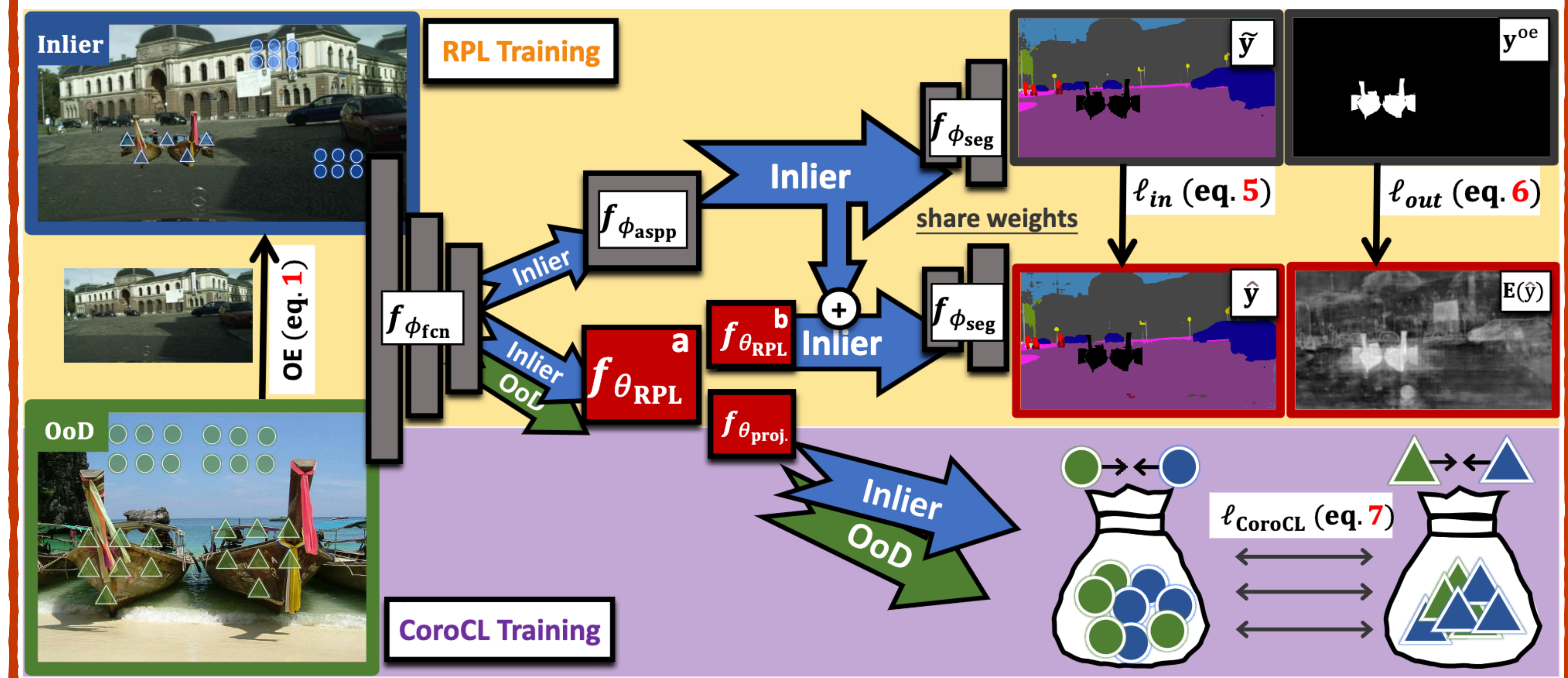
Motivation

AIM: OoD detector shouldn't affect inlier model & robust for various contexts.

- The re-training methods worsen the in-distribution segmentation accuracy.
- The training-free methods fail to distinguish the hard inliers & outliers.
- Previous methods struggle to generalise well across various environments, which is a common issue in practice.

Methodology



Experiments

a. validation results

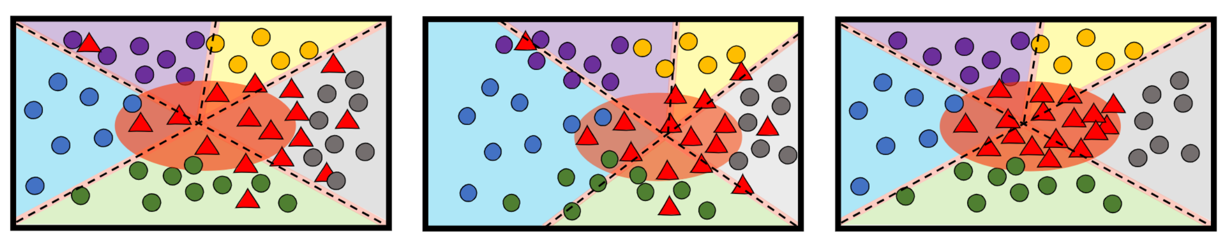
Methods	Fishyscapes (validation set)						SMIYC (validation set)					
	Static			L&F			Anomaly			Obstacle		
	FPR ↓	AuPRC ↑	AUROC ↑	FPR ↓	AuPRC ↑	AUROC ↑	FPR ↓	AuPRC ↑	$F1^*$ ↑	FPR ↓	AuPRC ↑	$F1^*$ ↑
Maximum softmax [16] [baseline]	23.31	26.77	93.14	10.36	40.34	90.82	60.2	40.4	42.6	3.8	43.4	53.7
Mahalanobis [23] [baseline]	11.7	27.37	96.76	11.24	56.57	96.75	86.4	22.5	31.7	26.1	25.9	27.7
SML [19] [ICCV'21]	12.14	66.72	97.25	33.49	22.74	94.97	84.13	21.68	28.00	91.31	18.60	28.39
Synboost [9] [CVPR'21]	25.59	66.44	95.87	31.02	60.58	96.21	30.9	68.8	65.6	2.8	81.4	73.2
Meta-OoD [4] [ICCV'21]	13.57	72.91	97.56	37.69	41.31	93.06	17.43	80.13	74.3	0.41	94.14	88.4
DenseHybrid [11] [ECCV'22]	4.17	76.23	99.07	5.09	69.79	99.01	52.65	61.08	53.72	0.71	89.49	81.05
PEBAL [37] [ECCV'22]	1.52	92.08	99.61	4.76	58.81	98.96	36.74	53.10	57.99	7.92	10.45	22.10
RPL+CoroCL [Ours]	**0.85**	**92.46**	**99.73**	**2.52**	**70.61**	**99.39**	**7.18**	**88.55**	**82.90**	**0.09**	**96.91**	**91.75**

b. test results

Methods	Fishyscapes (test)				SMIYC (test)				**Overall**	
	Static		L&F		Anomaly		Obstacle			
	FPR ↓	AuPRC ↑	FPR ↓	AuPRC ↑	FPR ↓	AuPRC ↑	FPR ↓	AuPRC ↑	$\overline{\text{FPR}}$ ↓	$\overline{\text{AuPRC}}$ ↑
Resynthesis [28][ICCV'19]	27.13	29.6	48.05	5.70	25.93	52.28	4.70	37.71	26.45	31.32
Embedding [2][IJCV'19]	20.25	44.03	30.02	3.55	70.76	37.52	46.38	0.82	41.85	21.48
Synboost [9][CVPR'19]	18.75	72.59	15.79	43.22	61.86	56.44	3.15	71.34	24.89	60.90
Meta-OoD [4][ICCV'21]	8.55	86.55	35.14	29.96	15.00	**85.47**	0.75	85.07	14.86	71.76
DenseHybrid [11][ECCV'22]	5.51	72.27	6.18	43.90	62.25	42.05	6.02	80.79	19.99	59.75
GMMSeg [25]* [NIPs'22]	15.96	76.02	6.61	**55.63**	-	-	-	-	-	-
PEBAL [37][ECCV'22]	1.73	92.38	7.58	44.17	40.82	49.14	12.68	4.98	15.70	47.67
RPL+CoroCL [Ours]	**0.52**	**95.96**	**2.27**	53.99	**11.68**	83.49	**0.58**	**85.93**	**3.76**	**79.84**

Contribution

- We introduce Residual Pattern Learning to detect anomalies, without impacting closed-set segmentation results.
- On top of RPL, we propose Context-robust Contrastive Learning to detect OoD pixels in various environments.
- Our approach achieves SOTA results in FS, SMIYC, RoadAnomaly benchmarks.



(A) Freeze (B) Retraining (C) RPL

Ablation Studies

Tab). **PE** denotes the positive energy loss, **DS** denotes the dis-similarity regularisation and **CoroCL** is for the context-robust contrastive learning.

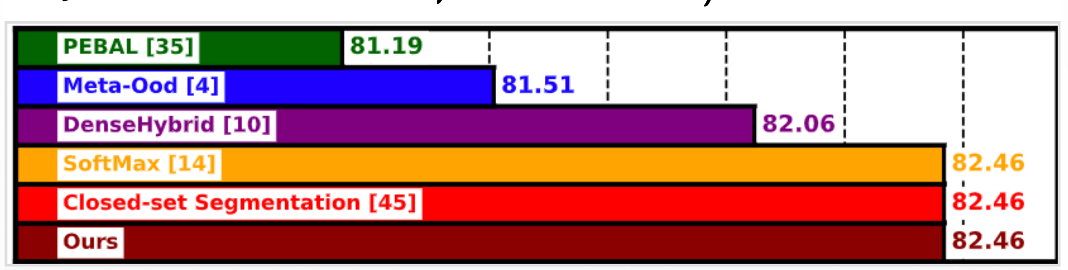
Entropy [4]	Energy [37]	PE	DS	CoroCL	Static		L&F		Anomaly		Obstacle		RoadAnomaly	
					FPR	AuPRC	FPR	AuPRC	FPR	AuPRC	FPR	AuPRC	FPR	AuPRC
✓					1.78	86.88	5.04	52.10	27.59	60.76	2.50	80.85	28.63	49.22
	✓				1.65	89.08	6.64	51.47	28.23	70.18	1.57	71.40	34.39	52.66
		✓			1.55	88.05	4.52	56.85	26.58	73.66	0.51	92.36	31.96	57.28
		✓	✓		1.30	91.16	3.79	63.72	25.65	76.43	0.42	93.25	30.66	63.02
		✓	✓	✓	**0.85**	**92.46**	**2.52**	**70.61**	**7.18**	**88.55**	**0.09**	**96.91**	**17.74**	**71.61**
		✓			6.92	54.31	17.18	32.57	29.69	68.99	0.95	83.08	33.72	57.99

★ Our loss (PE+DS) achieves SOTA in urban context, but perform poorly in country context.

★ With CoroCL, our model generalises well across all the benchmarks (under various contexts).

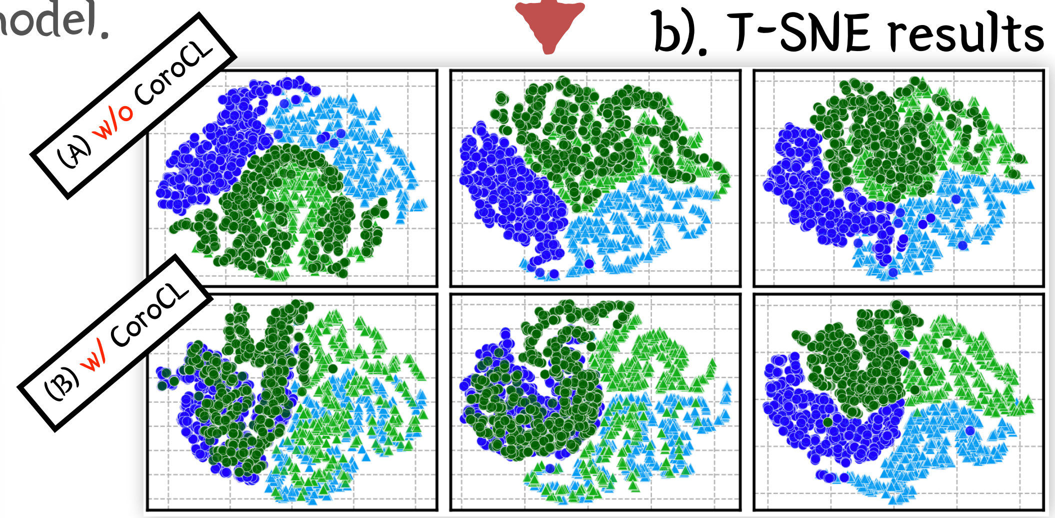
★ RPL is superior to a binary classifier; while the former predict the anomalies directly, RPL learns to induce the inlier model.

a). Closed-set Performance (by mIoU)



★ RPL doesn't impact the original segmentation results.

b). T-SNE results



Visualisation