ATTA: Anomaly-aware Test-Time Adaptation

for Out-of-Distribution Detection in Segmentation

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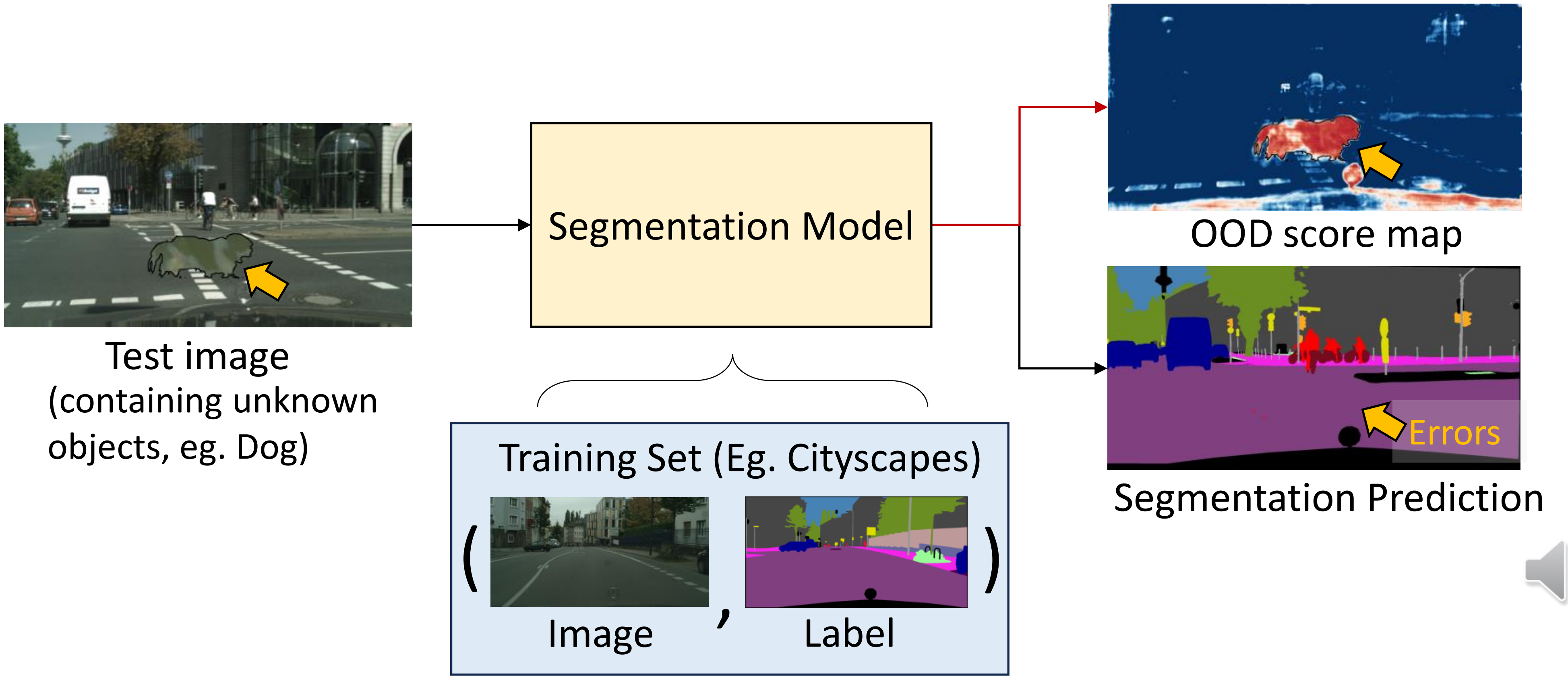
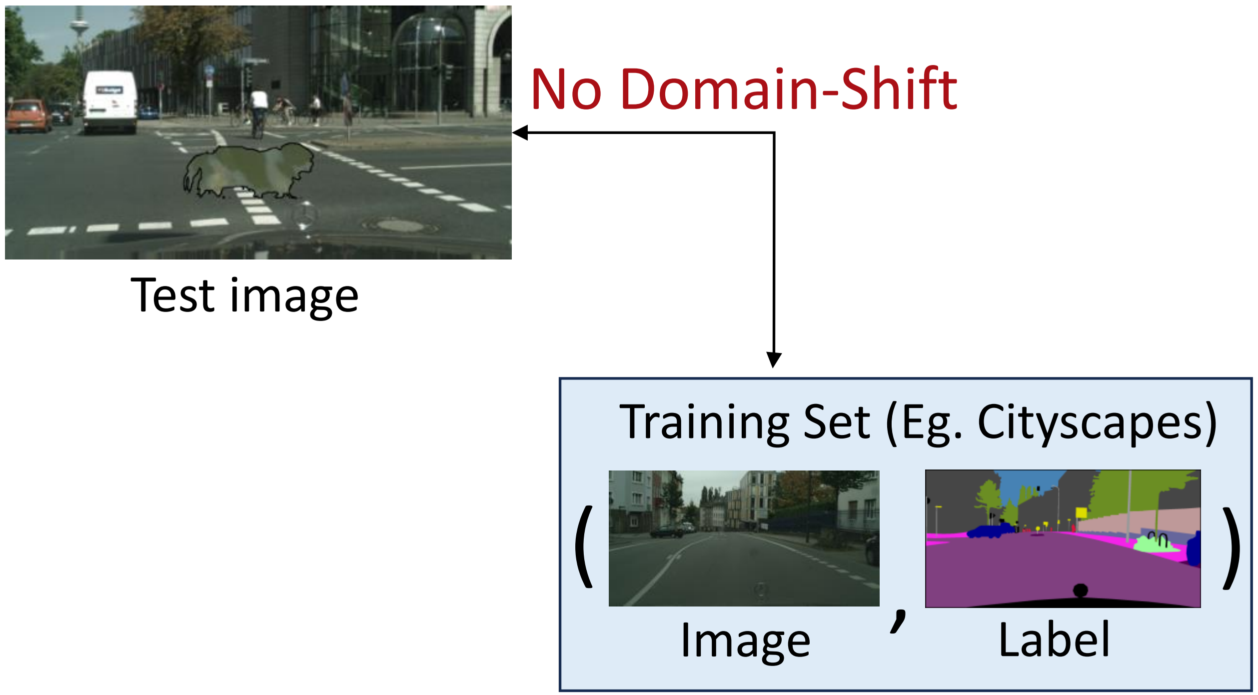
Dense OOD Detection

- **Goal**: Generate pixel-wise identification of unknown objects.



Dense OOD Detection

- **Goal**: Generate pixel-wise identification of unknown objects.
- **Previous Assumption:** Training and testing data share a similar domain.



Dense OOD Detection

- **Goal:** Generate pixel-wise identification of unknown objects.
- **Previous Assumption:** Training and testing data share a similar domain.
- **Motivation:** Domain shift widely exists in real-world situations.

Test image

No Domain-Shift

Domain-Shift

E.g. various road, weather and lighting conditions.

Training Set (Eg. Cityscapes)

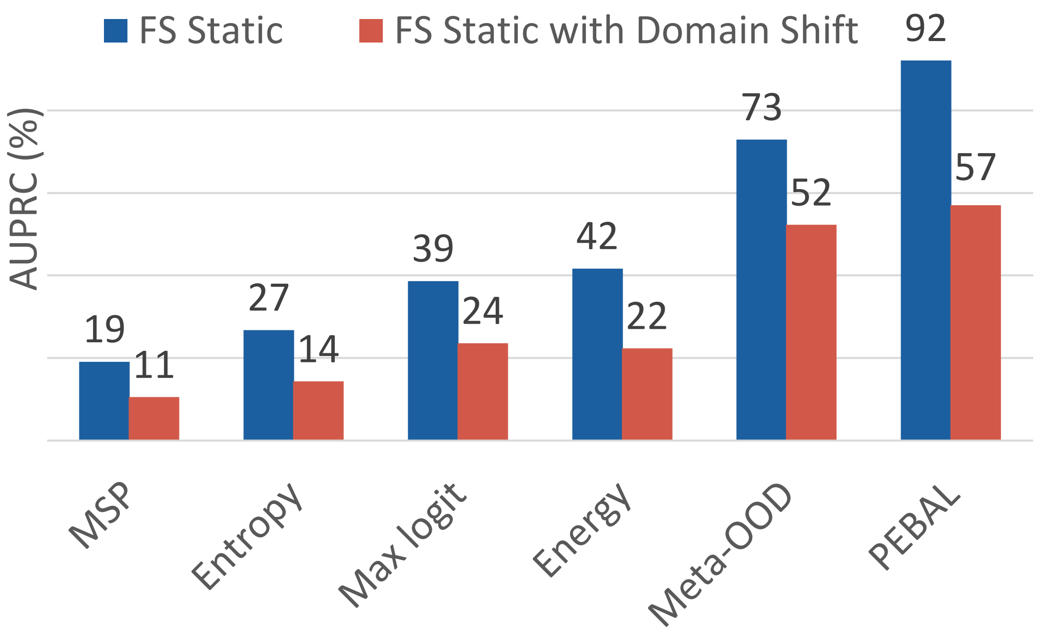
( , )

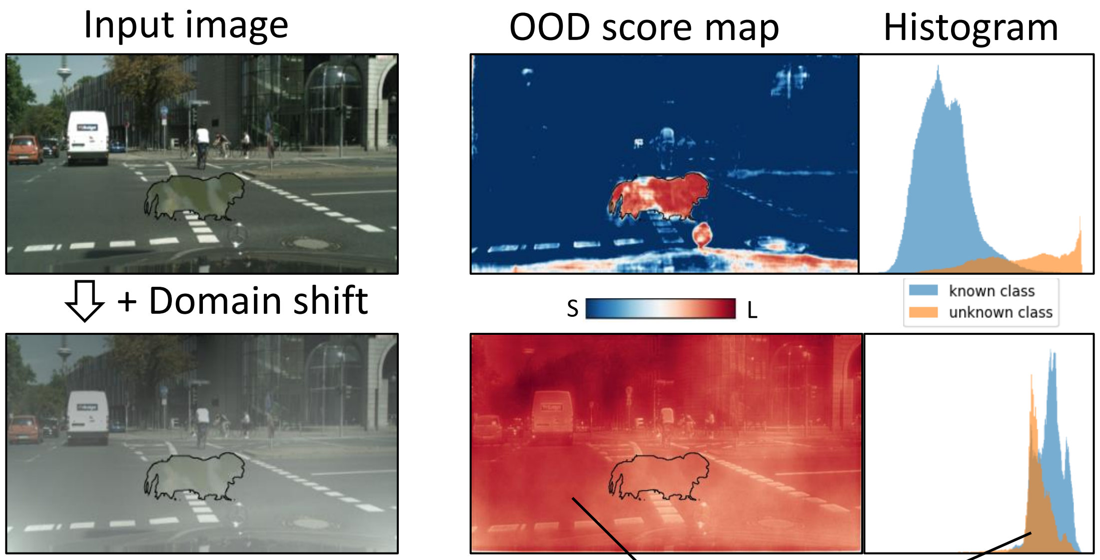
Image, Label

Example images from RoadAnomaly and RoadObstable datasets.

Dense OOD Detection with Domain Shift

- **Existing OOD Detection Methods**: Domain shift highly <u>impacts</u> their performance.





Fail to distinguish two distribution shifts.

Dense OOD Detection with Domain Shift

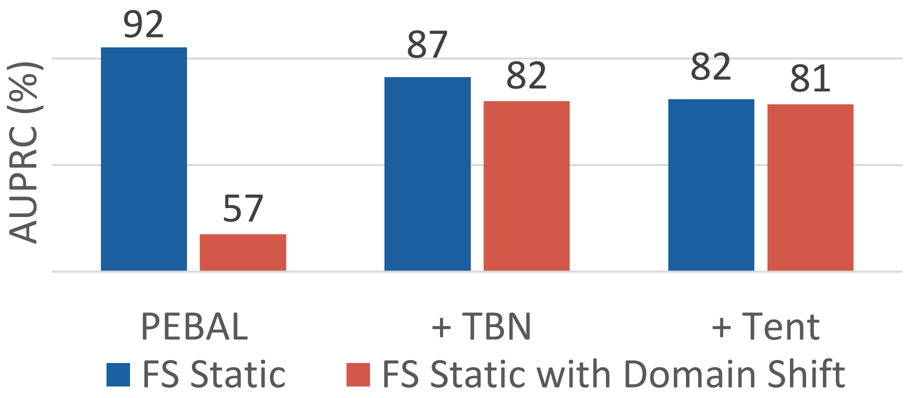
- **Existing OOD Detection Methods**: Domain shift highly impacts their performance.
- **+ Test-Time Adaptation (TTA):** Applying existing techniques faces challenges.

A. Impair OOD detection performance on images from seen domains.

- E.g. Transductive BN.

B. Indiscriminately reduce uncertainty of unknown classes.

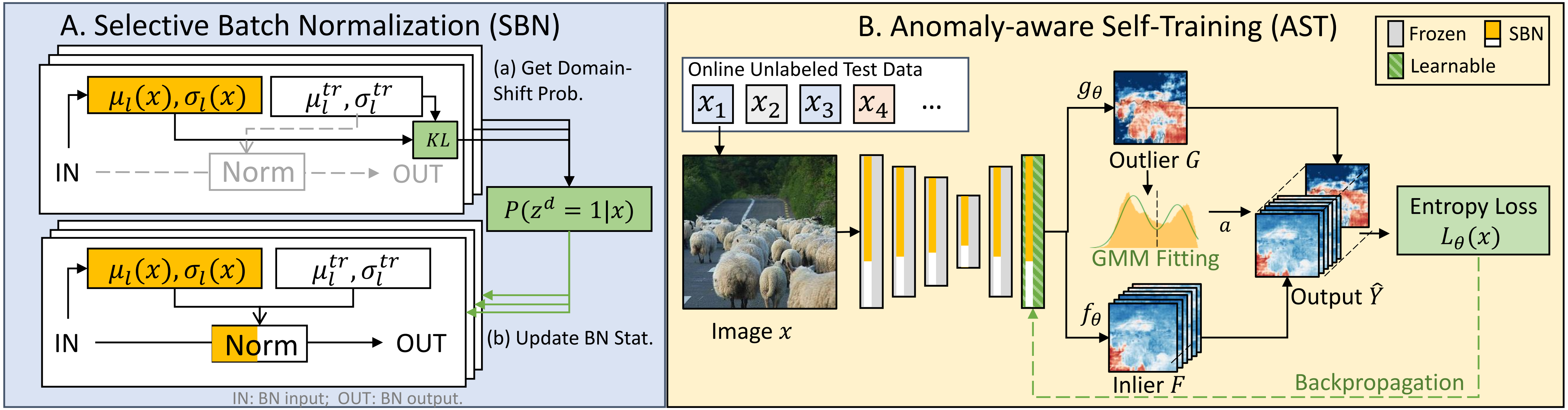
- E.g. Entropy Minimization.



Main Idea

- A dual-level OOD detection framework:
  1. Distinguish whether domain shift exists by leveraging <u>global low-level</u> features;
  2. Identify pixels with semantic shift by utilizing <u>dense high-level</u> feature maps.
- Selectively adapt the model to unseen domains as well as enhance model’s capacity in detecting novel classes.

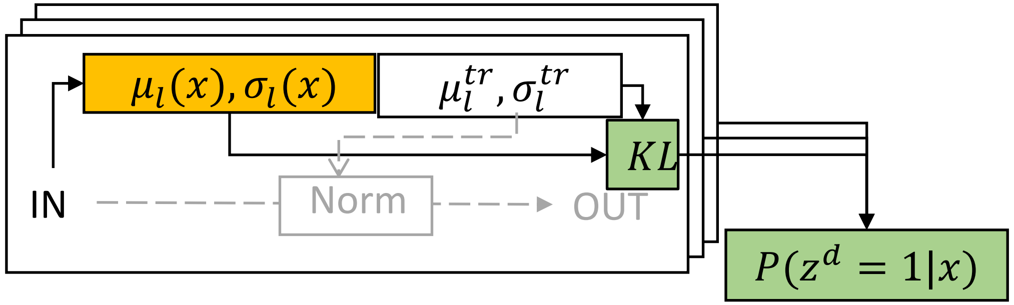
Method Overview



Selective Batch Normalization (SBN)

1. Estimate the **probability of domain-shift** by considering image-level stat.

$$P(z^d = 1|x) = \underbrace{h_{(a,b)}}_{\mathrm{sigmoid}((x+a)/b)}\left(\sum_{l=1}^{L} KL\left(\overbrace{\boxed{N(\mu_l(x), \sigma_l(x))}}^{\text{Test feature Stat.}} \middle\| \underbrace{\boxed{N(\mu_l^{tr}, \sigma_l^{tr})}}_{\text{Training feature Stat.}}\right)\right)$$



IN: BN input; OUT: BN output.

Selective Batch Normalization (SBN)

1. Estimate the **probability of domain-shift** by considering image-level stat.
2. Update **BN statistics** according to the probability.

Test feature Stat.

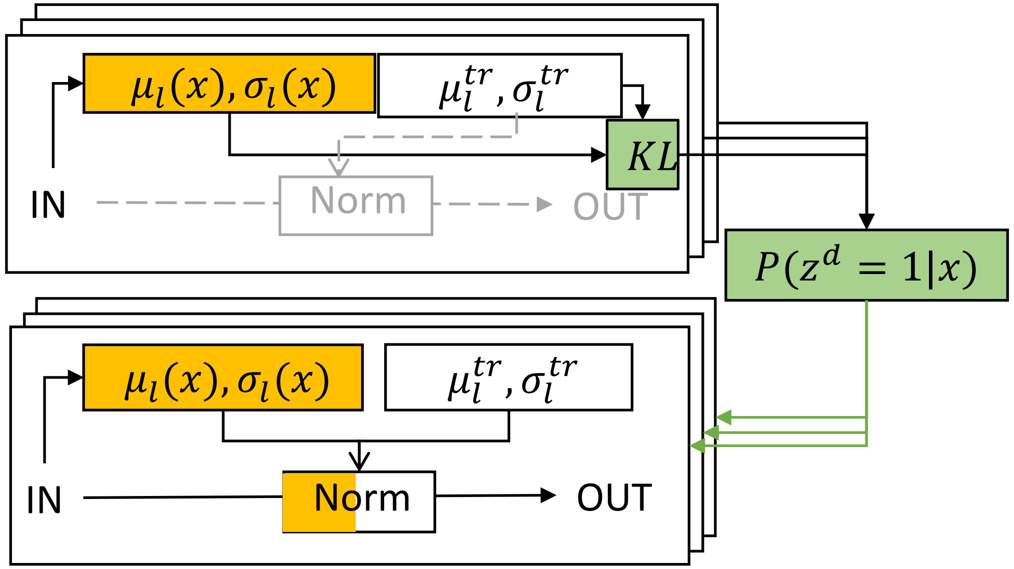
$$P(z^d = 1|x) = h_{(a,b)}\left(\sum_{l=1}^{L} KL\left(\boxed{N(\mu_l(x), \sigma_l(x))} \,||\, \boxed{N(\mu_l^{tr}, \sigma_l^{tr})}\right)\right)$$

sigmoid((x + a)/b)

Training feature Stat.

$$\hat{\mu}_l = P(z^d = 1|x) * \boxed{\mu_l(x)} + P(z^d = 0|x) * \boxed{\mu_l^{tr}}$$

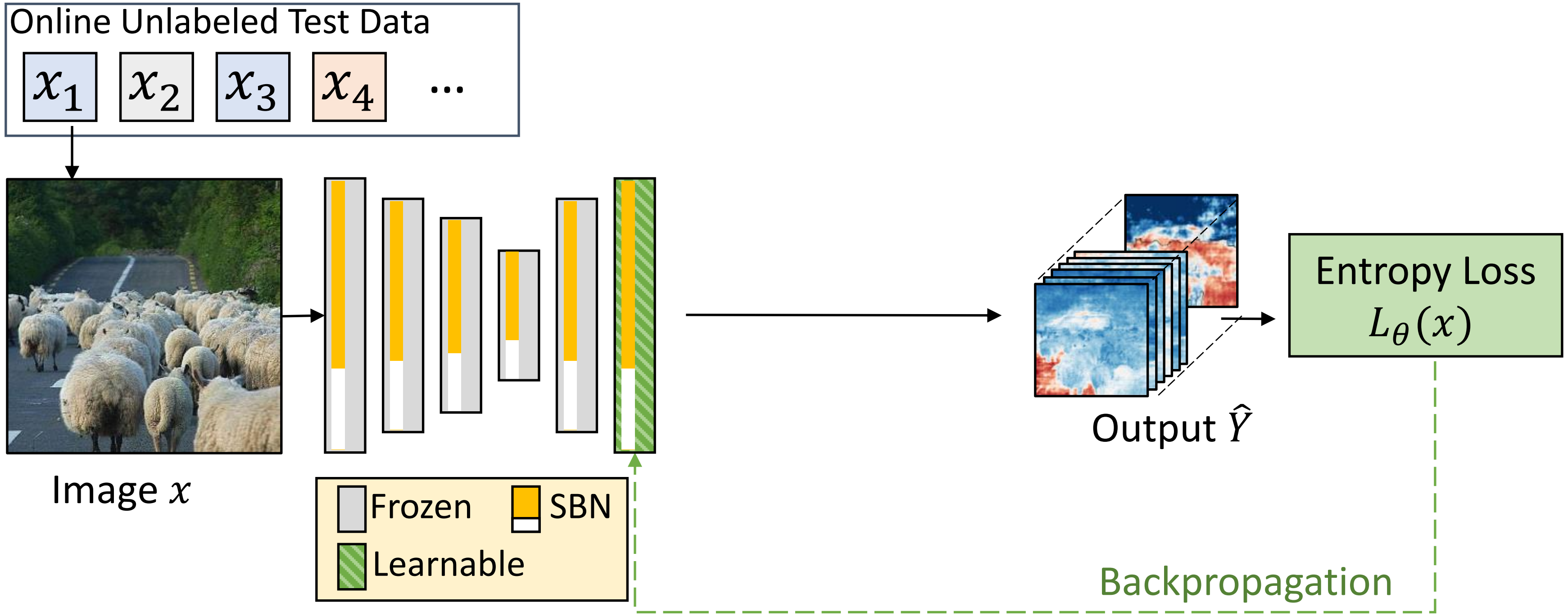
$$\hat{\sigma}_l^{\,2} = P(z^d = 1|x) * \boxed{\sigma_l^2(x)} + P(z^d = 0|x) * \boxed{(\sigma_l^{tr})^2}$$



IN: BN input; OUT: BN output.

Anomaly-aware Self-Training (AST)

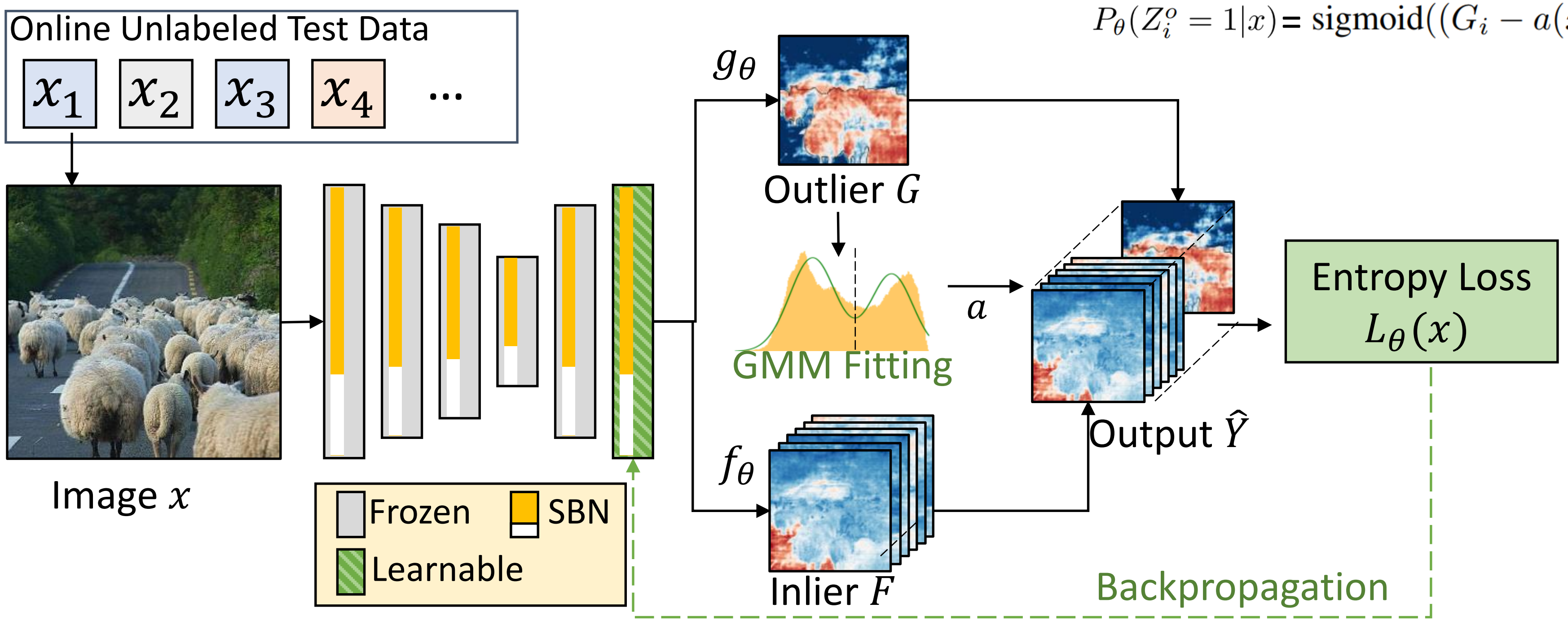
- Overall Loss Function: $\mathcal{L}_\theta(x) = -\sum_i \sum_{c=1}^{C+1} w_c \hat{Y}_{c,i} \log(\hat{Y}_{c,i})$



Anomaly-aware Self-Training (AST)

- Overall Loss Function: $\mathcal{L}_\theta(x) = -\sum_i \sum_{c=1}^{C+1} w_c \hat{Y}_{c,i} \log(\hat{Y}_{c,i})$
- Anomaly-aware output representation: $\hat{Y}_{c,i} = F_{c,i}(1 - P_\theta(Z_i^o = 1|x))[\![c \in \mathcal{Y}]\!] + P_\theta(Z_i^o = 1|x)[\![c = C+1]\!]$

$P_\theta(Z_i^o = 1|x) = \mathrm{sigmoid}((G_i - a(x))/b(x))$



Experiments on simulated FS Static -C Dataset

- Constructed by randomly adding smog, color shifting, and Gaussian blur.

	MSP [17]	Entropy [24]	Max logit [15]	Energy [30]	Meta-OOD [4]	PEBAL [44]	+ Ours	+ TBN [36]	+ Tent [46]
AUC ↑	92.36	93.14	95.66	95.90	97.56	99.61	**99.66**	99.25	99.04
	70.85	71.23	74.13	74.02	78.34	67.63	**99.21**	98.96	98.93
AP ↑	19.09	26.77	38.64	41.68	72.91	92.08	**93.61**	86.51	82.38
	10.52	14.32	23.60	22.36	52.31	57.02	**87.14**	81.97	81.42
FPR_{95} ↓	23.99	23.31	18.26	17.78	13.57	1.52	**1.15**	2.33	4.09
	100.0	100.00	89.94	89.94	100.0	97.17	**2.94**	4.26	4.43

FS Static -C dataset (gray rows)

Original FS Static dataset (white rows)

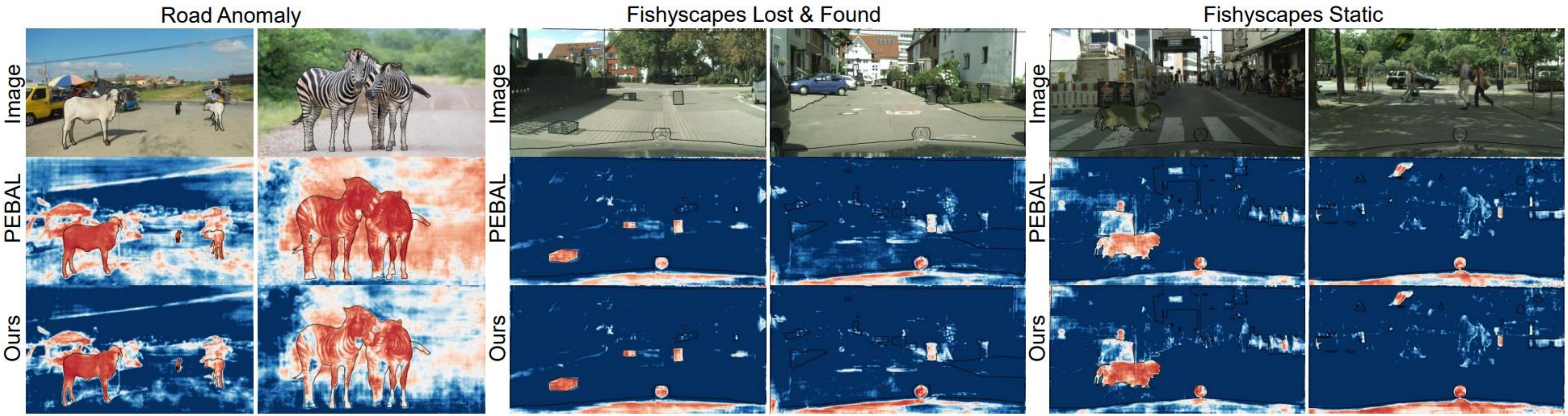
Our method remains more stable in the face of domain shifts.

Results on offline OOD detection benchmarks

Methods	OoD Data	Road Anomaly AUC ↑	Road Anomaly AP ↑	Road Anomaly FPR_{95} ↓	FS LostAndFound AUC ↑	FS LostAndFound AP ↑	FS LostAndFound FPR_{95} ↓	FS Static AUC ↑	FS Static AP ↑	FS Static FPR_{95} ↓
MSP [17]	✗	67.53	15.72	71.38	89.29	4.59	40.59	92.36	19.09	23.99
Entropy [24]	✗	68.80	16.97	71.10	90.82	10.36	40.34	93.14	26.77	23.31
Mahalanobis [26]	✗	62.85	14.37	81.09	96.75	56.57	11.24	96.76	27.37	11.7
Meta-OoD [4]	✓	-	-	-	93.06	41.31	37.69	97.56	72.91	13.57
Synboost [10]	✓	81.91	38.21	64.75	96.21	60.58	31.02	95.87	66.44	25.59
DenseHybrid [14]	✓	-	-	-	99.01	69.79	5.09	99.07	76.23	4.17
Max Logit [15]	✗	72.78	18.98	70.48	93.41	14.59	42.21	95.66	38.64	18.26
+ ATTA (Ours)	-	**76.60**	**23.96**	**63.49**	**93.53**	**17.39**	**40.69**	95.48	**41.23**	20.89
Energy [30]	✗	73.35	19.54	70.17	93.72	16.05	41.78	95.90	41.68	17.78
+ ATTA (Ours)	-	**77.41**	**25.27**	**62.57**	93.30	**17.47**	43.32	**96.0**	**41.84**	**17.63**
PEBAL [44]	✓	87.63	45.10	44.58	98.96	58.81	4.76	99.61	92.08	1.52
+ ATTA (Ours)	-	**92.11**	**59.05**	**33.59**	**99.05**	**65.58**	**4.48**	**99.66**	**93.61**	**1.15**

Our method consistently improve upon previous models, especially within high-domain-shift dataset.

Results on offline OOD detection benchmarks



Our method effectively mitigates the impact of domain-shift and encourage the confidence of the model predictions.

Results on online OOD detection benchmarks

- SMIYC Benchmark

RoadAnomaly21	AP↑	FPR_{95} ↓	sIoU↑	PPV↑	F1↑
PEBAL [44]	49.1	40.8	38.9	27.2	14.5
+ ATTA (Ours)	**67.0**	**31.6**	**44.6**	**29.6**	**20.6**
RoadObstacle21	AP↑	FPR_{95} ↓	sIoU↑	PPV↑	F1↑
PEBAL [44]	5.0	12.7	29.9	7.6	5.5
+ ATTA (Ours)	**76.5**	**2.8**	**43.9**	**37.7**	**36.6**

- Fishyscapes online Benchmark

Online FS Lost & Found	AP↑	FPR_{95} ↓
PEBAL [44]	44.17	7.58
+ ATTA (Ours)	**55.94**	**4.66**
Online FS Static	AP↑	FPR_{95} ↓
PEBAL [44]	92.38	1.73
+ ATTA (Ours)	**94.68**	**0.68**

Our method achieves consistent performance improvements.

Thanks for listening !

For more information please refer to our paper and code.

Paper

Code