Segmentation Assisted Incremental Test Time Adaptation in an Open World

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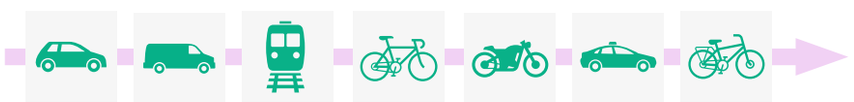
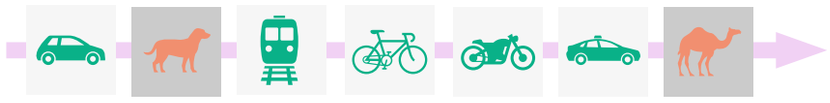
1 Test data streams

Classes of interest : Car, bike, truck, train, bicycle etc.

Closed-set test data stream :



Open-set test data stream :



2 A step towards real-world Test Time Adaptation

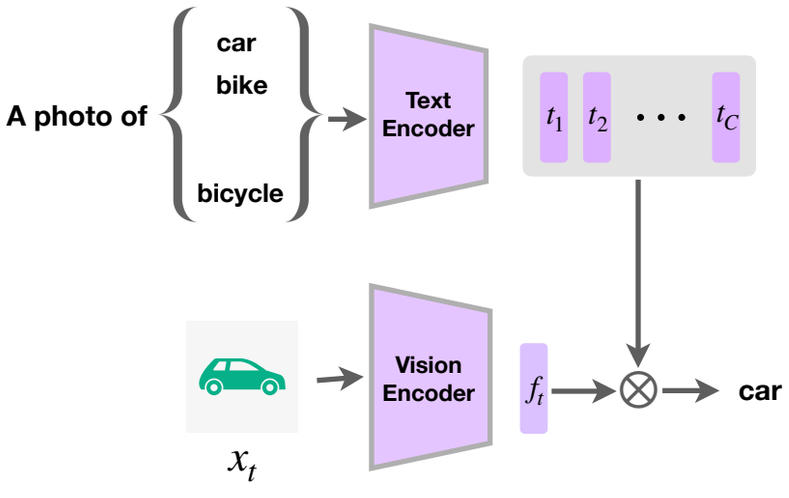
Training	TTA	Covariate shift	Label shift	Single image	Classification task	Problem setting
✓	✓	✓	✗	✗	C_s	Closed-set TTA
✗	✓	✓	✗	✓	C_s	Single-image Closet-set TTA
✗	✓	✓	✓	✗	C_s+1	Open-set TTA
✓	✗	✗	✓	✗	C_s+C_u	Class Incremental Learning
✗	✓	✓	✓	✓	C_s+C_u	Incremental TTA

Comparison of the Incremental Test Time Adaptation (ITTA) protocol with existing research directions

Need for ITTA

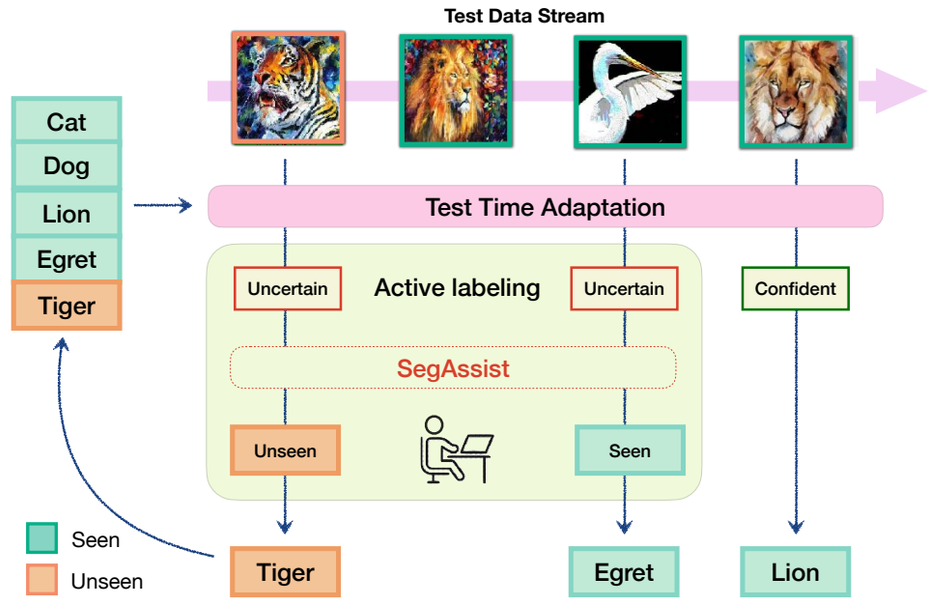
1. Continuously adapt to covariate shifts.
2. Recognize and incorporate new classes as they appear.
3. Operate on a single-image basis without access to batches or any labeled data.
4. Maintain performance across seen classes and a growing set of dynamically incorporated unseen classes

3 Classification using Vision Language Models



Zero-shot image classification using VLM

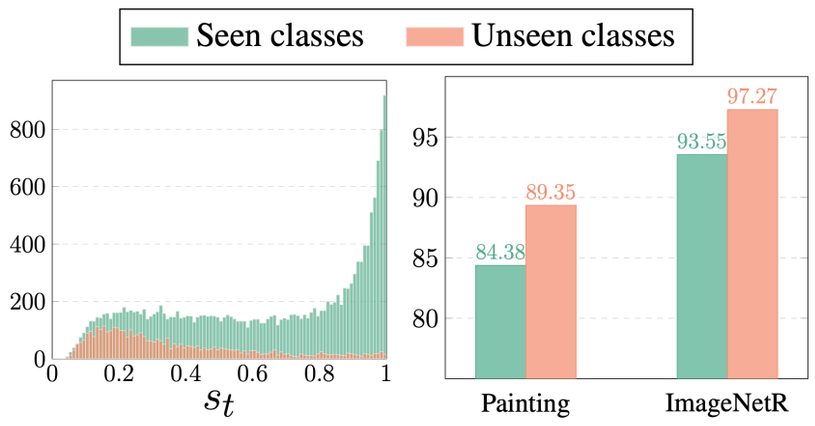
4 Incremental Test Time Adaptation



ITTA enables the model to

1. The goal here is to incorporate new classes during testing.
2. Uncertain samples are actively labeled
3. The set of seen classes is expanded if the oracle identifies a sample as an unseen class.
4. TTA is continued with expanded set of classes.

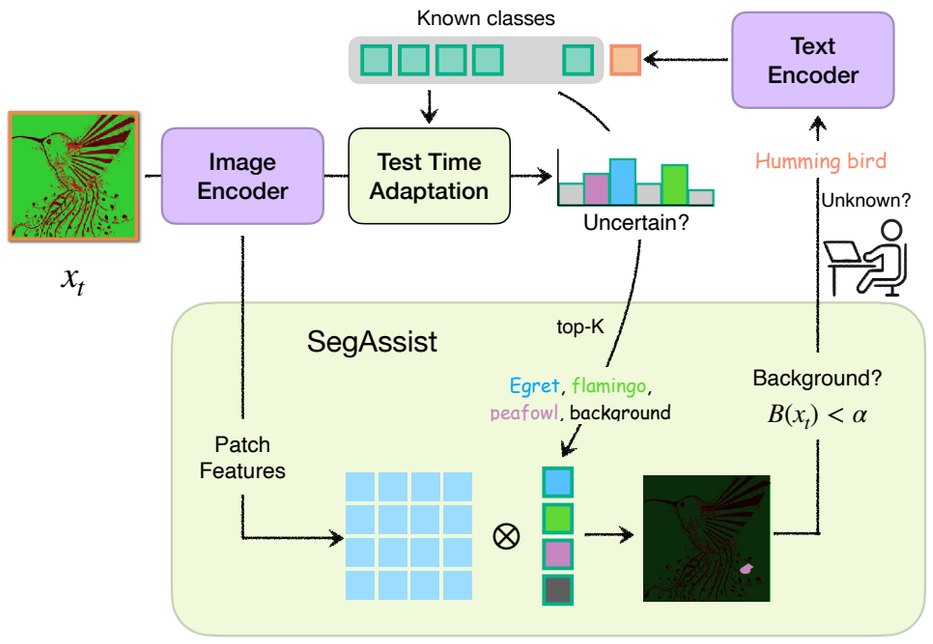
5 CLIP Scores of uncertain samples



(a) MSP scores for Painting (b) % of background images.

- The histogram of MSP scores obtained based on global features overlap significantly.
- Segmentation maps obtained from local features can help distinguish the seen and unseen class samples

6 SegAssist



1. Pixelwise Segmentation

- Select topK classes.
- Add “background” class.
- Perform patch-wise predictions.
- Bilinear interpolation to obtain segmentation map

2. Compute Background ratio

$$B(x_t) = \frac{1}{S(x_t)} \mathbb{I}[S_i(x_t) = \text{"background"}]$$

Selection criteria

$$B(x_t) > \alpha$$

7 Experimental Results

	Method	DN-Clipart			
		$Acc_S \uparrow$	$Acc_U \uparrow$	HM↑	ICDD ↓
TDA	Random	83.25	13.03	22.54	75.30
	Entropy	83.56	45.35	58.79	49.1
	MSP	83.63	45.56	58.99	50.68
	SegAssist	**83.61**	**47.10**	**60.25**	**48.96**
DPE	Random	83.45	13.58	23.36	75.30
	Entropy	83.67	8.54	15.5	80.27
	MSP	83.52	53.67	65.35	49.00
	SegAssist	**83.47**	**53.89**	**65.49**	**49.00**

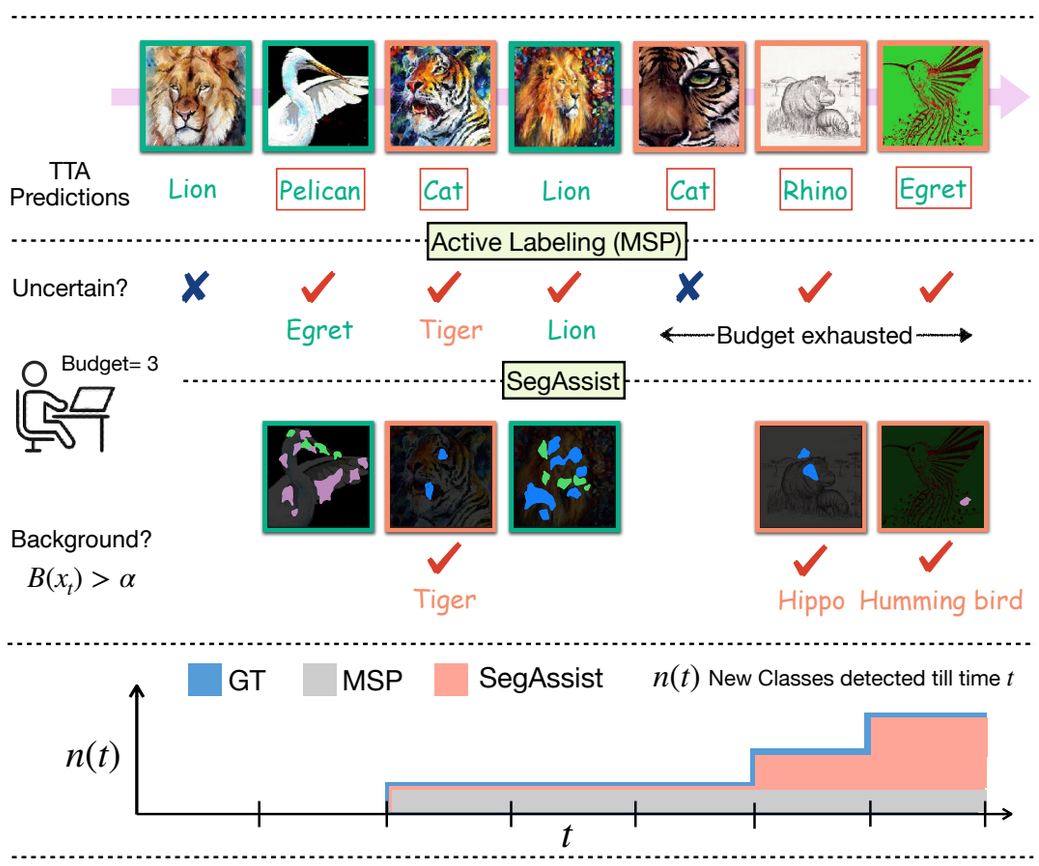
Comparison of SegAssist with different Active Learning methods when integrated with TTA methods

Budget	Method	DN-Painting
0.5%	ZSEval*	62.00 / 50.32
	+SegAssist	**63.13 / 50.28**
1.0%	ZSEval*	70.59 / 39.14
	+SegAssist	**71.21 / 38.56**
1.5%	ZSEval*	73.82 / 32.56
	+SegAssist	**75.98 / 29.93**

Method	0.1	0.5	1.0
ZSEval*	62.30	64.38	60.50
+SegAssist	**70.38**	**65.12**	**61.10**
TDA*	64.34	64.96	60.28
+SegAssist	**64.74**	**66.78**	**62.35**
DPE*	63.32	64.00	60.31
+SegAssist	**66.24**	**64.56**	**61.20**

Performance of SegAssist in different ITTA scenarios

8 Incremental Class Detection Delay (ICDD) Metric



Computation of the ICDD Metric

How do we quantify the effectiveness of active sample selection method?

Proposed metric : ICDD

Cumulative count of classes in ground truth sequence till time t.

Cumulative count of classes discovered using MSP till time t.

Cumulative count of classes discovered using SegAssist till time t.

$$\text{ICDD} = \text{AUC}(n_{gt}(t)) - \text{AUC}(n_{det}(t))$$

ICDD (SegAssist) < ICDD (MSP)