

# Towards Stable Test-Time Adaptation in Dynamic Wild World

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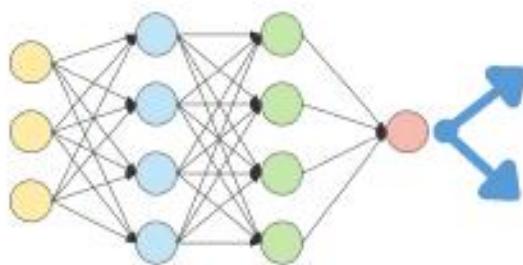
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- 02 Why Unstable Test-Time Adaptation?**
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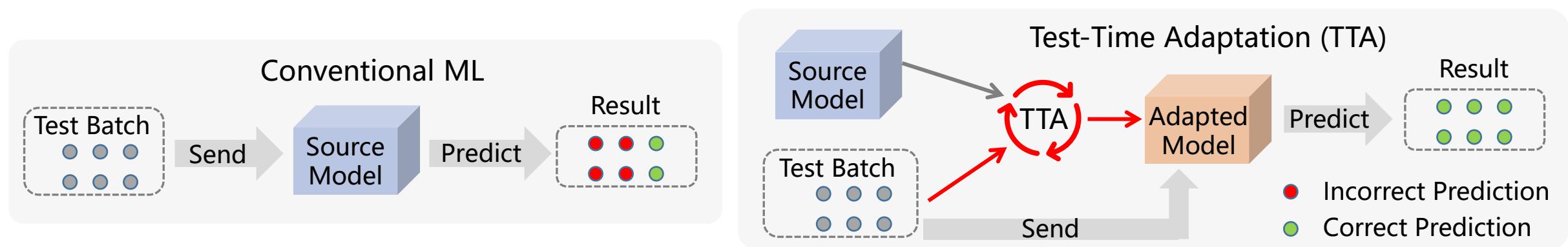
# Background: Test Data Shifts

- Deep models are often very sensitive when test samples encountering **natural variations or corruptions** (*also called distribution shifts*):
  - Weather change
  - Unexpected noises



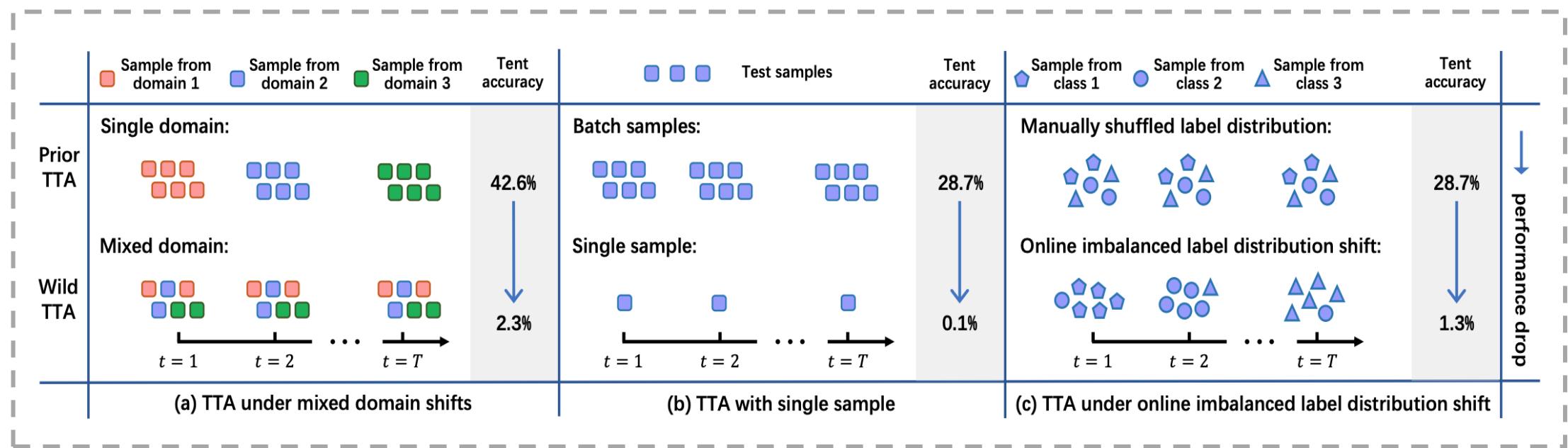
# Test-Time Adaptation for Overcoming Data Shifts

- Goal: TTA aims to adapt model to test-data domain before prediction
  - Adapt online with only **unlabeled** test data



# Problem: Test-Time Adaptation in Wild World

- **Limitation:** TTA is **unstable** under wild scenarios
  - severe performance degradation, or even **model collapse**



- **GOAL:** we aim to **figure out the reason why TTA is unstable in the wild world, and then boost its stability**

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# I: What Leads to Unstable TTA?

Batch Normalization (BN) is a crucial factor hindering TTA stability under the above wild test settings

$$y^{(k)} = \gamma^{(k)} \hat{x}^{(k)} + \beta^{(k)}, \text{ where } \hat{x}^{(k)} = \frac{x^{(k)} - \mathbb{E}[x^{(k)}]}{\sqrt{\text{Var}[x^{(k)}]}}.$$

BN statistics estimation would be inaccurate when test data stream has:

- Mixed Shifts: ideally each domain should have its own E and Var
- Single Sample: it is hard to estimate E and Var accurately
- Online Imbalanced Label Shifts: will bias to some specific class



Our claim: models with batch-agnostic norm layers are more suitable for TTA

# I: What Leads to Unstable TTA?--Empirical Study

GN and LN models performs more stably than BN models (but still suffer several failure cases)

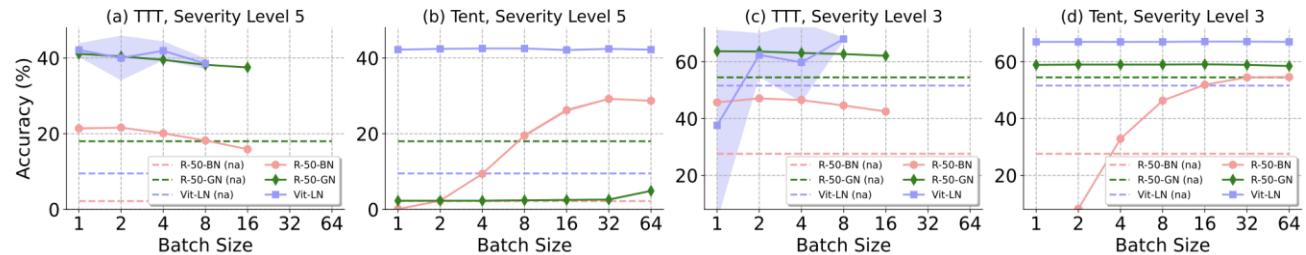
Methods:

- **TTT** (Sun et al., 2020)
- **Tent** (Wang et al., 2021)

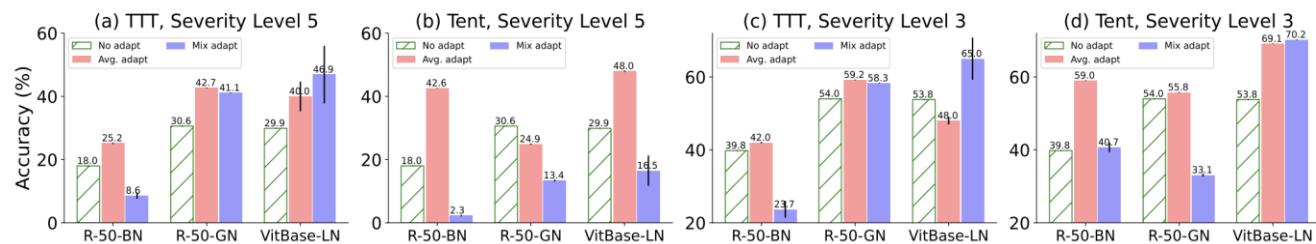
Norms:

- **GN** (group norm)
- **LN** (layer norm)
- **BN** (batch norm)

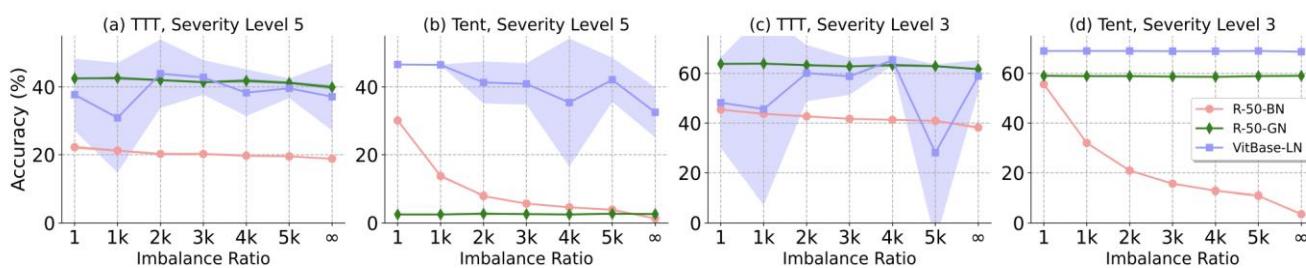
## ① TTA under small batch sizes



## ② TTA under mixed domain shifts

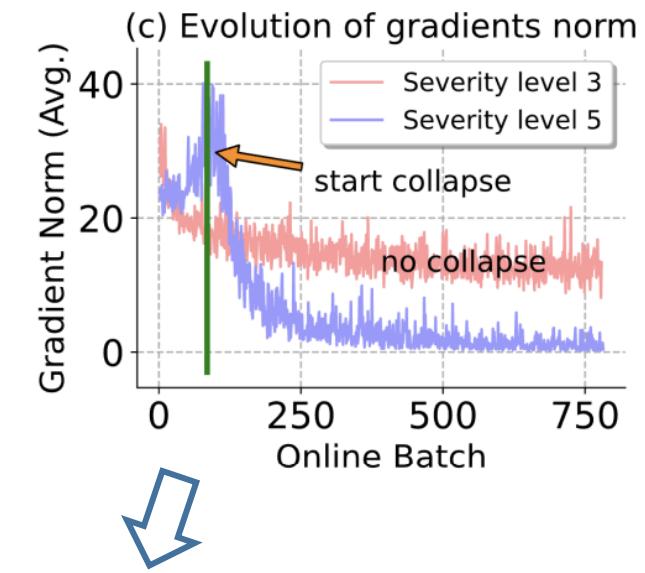
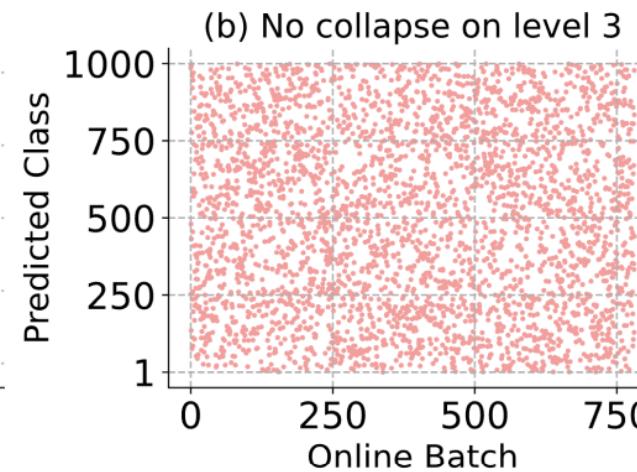
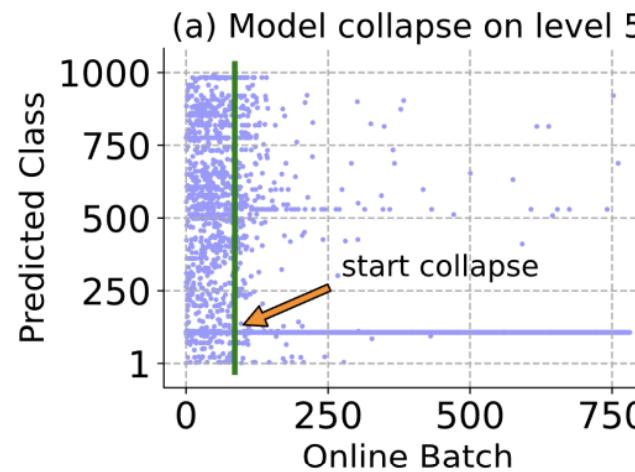


## ③ TTA under online imbalanced label shifts



## II: What Leads to Unstable TTA?

Online entropy minimization tends to result in collapsed trivial solutions,  
i.e., predict all samples to the same class



Some large/noisy gradients cause collapse

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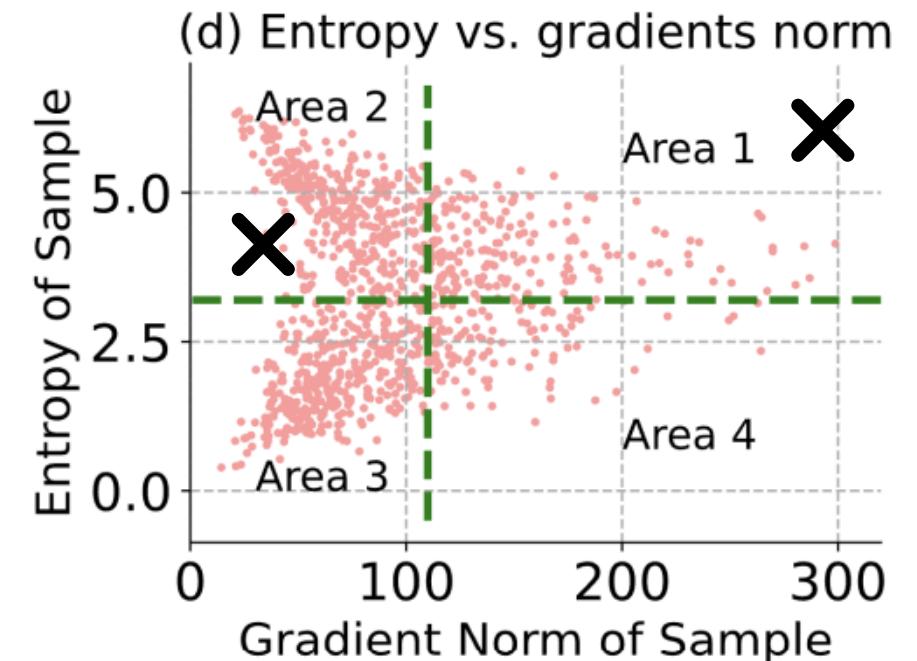
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# SAR: Sharpness-Aware and Reliable Entropy Minimization

Motivation:

- We find that removing noisy gradients via **gradient norm filtering** is **infeasible**, since its threshold is hard to select
- We instead use **entropy for filtering**, which is easier to select threshold



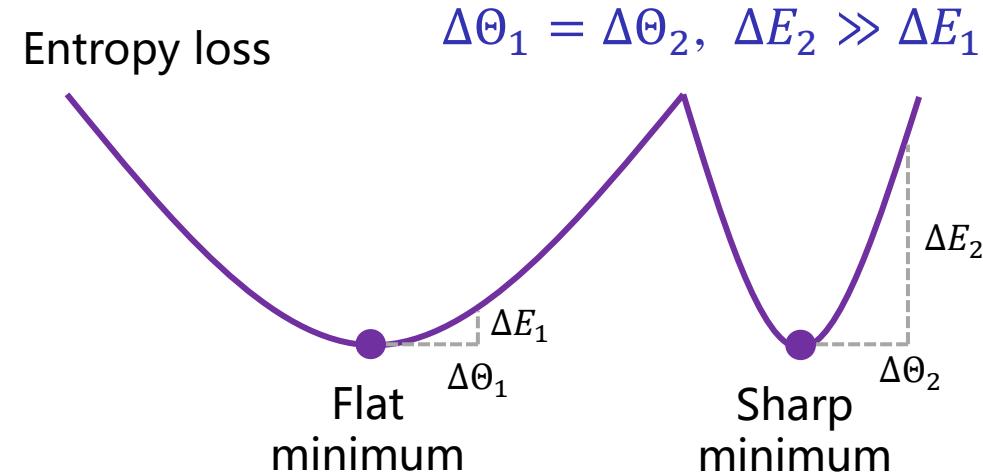
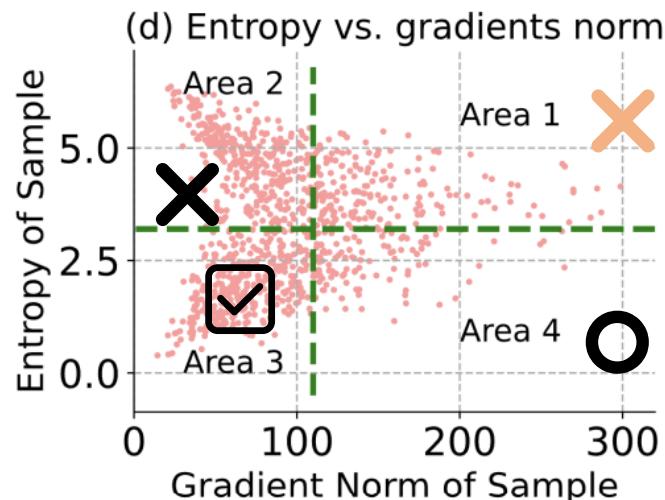
- **Reliable Entropy:**

- Remove samples in Areas 1 (large gradients) and Area 2 (unconfident):

$$\min_{\Theta} S(\mathbf{x})E(\mathbf{x}; \Theta), \text{ where } S(\mathbf{x}) \triangleq \mathbb{I}_{\{E(\mathbf{x}; \Theta) < E_0\}}(\mathbf{x}).$$

where the threshold  $E_0 \in (0, \ln C]$ , and  $C$  is the class number

# SAR: Sharpness-Aware and Reliable Entropy Minimization



- **Sharpness-Aware:** make the model more robust to large/noisy gradients in Area 4
$$\min_{\Theta} E^{SA}(\mathbf{x}; \Theta), \text{ where } E^{SA}(\mathbf{x}; \Theta) \triangleq \max_{\|\epsilon\|_2 \leq \rho} E(\mathbf{x}; \Theta + \epsilon).$$
- We use SAM (Foret et al. 2021) to address the optimization, leading to the final objective:

$$\min_{\tilde{\Theta}} S(\mathbf{x}) E^{SA}(\mathbf{x}; \Theta)$$



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# Results under Online Imbalanced Label Distribution Shifts

- SAR achieves the best performance over ResNet50-GN and VitBase-LN
  - Compare to Tent, SAR leads to 15.2% gains on R-50-GN and 10.7% gain on Vit-B-LN

Model+Method	Noise			Blur				Weather				Digital				Avg.
	Gauss.	Shot	Impul.	Defoc.	Glass	Motion	Zoom	Snow	Frost	Fog	Brit.	Contr.	Elastic	Pixel	JPEG	
ResNet50 (BN)	2.2	2.9	1.8	17.8	9.8	14.5	22.5	16.8	23.4	24.6	59.0	5.5	17.1	20.7	31.6	18.0
• MEMO	7.4	8.6	8.9	19.8	13.2	20.8	27.5	25.6	28.6	32.3	60.8	11.0	23.8	33.2	37.7	24.0
• DDA	32.2	33.1	32.0	14.6	16.4	16.6	24.4	20.0	25.5	17.2	52.2	3.2	35.7	41.8	45.4	27.2
• Tent	1.2	1.4	1.4	1.0	0.9	1.2	2.6	1.7	1.8	3.6	5.0	0.5	2.6	3.2	3.1	2.1
• EATA	0.3	0.3	0.3	0.2	0.2	0.5	0.9	0.8	0.9	1.8	3.5	0.2	0.8	1.2	0.9	0.9
ResNet50 (GN)	17.9	19.9	17.9	<b>19.7</b>	11.3	21.3	24.9	40.4	<b>47.4</b>	33.6	69.2	36.3	18.7	28.4	52.2	30.6
• MEMO	18.4	20.6	18.4	17.1	12.7	21.8	26.9	<b>40.7</b>	46.9	34.8	69.6	36.4	19.2	32.2	53.4	31.3
• DDA	<b>42.5</b>	<b>43.4</b>	<b>42.3</b>	16.5	19.4	21.9	26.1	35.8	40.2	13.7	61.3	25.2	<b>37.3</b>	46.9	54.3	35.1
• Tent	2.6	3.3	2.7	13.9	7.9	19.5	17.0	16.5	21.9	1.8	70.5	42.2	6.6	49.4	53.7	22.0
• EATA	27.0	28.3	28.1	14.9	17.1	24.4	25.3	32.2	32.0	39.8	66.7	33.6	24.5	41.9	38.4	31.6
• SAR (ours)	$33.1 \pm 1.0$	$36.5 \pm 0.4$	$35.5 \pm 1.1$	$19.2 \pm 0.4$	$19.5 \pm 1.2$	$33.3 \pm 0.5$	$27.7 \pm 4.0$	$23.9 \pm 5.1$	$45.3 \pm 0.4$	$50.1 \pm 1.0$	$71.9 \pm 0.1$	$46.7 \pm 0.2$	$7.1 \pm 1.8$	$52.1 \pm 0.5$	$56.3 \pm 0.1$	$37.2 \pm 0.6$
VitBase (LN)	9.4	6.7	8.3	29.1	23.4	34.0	27.0	15.8	26.3	47.4	54.7	43.9	30.5	44.5	47.6	29.9
• MEMO	21.6	17.4	20.6	37.1	29.6	40.6	34.4	25.0	34.8	55.2	65.0	54.9	37.4	55.5	57.7	39.1
• DDA	41.3	41.3	40.6	24.6	27.4	30.7	26.9	18.2	27.7	34.8	50.0	32.3	42.2	52.5	52.7	36.2
• Tent	32.7	1.4	34.6	54.4	52.3	58.2	52.2	7.7	12.0	69.3	76.1	66.1	56.7	69.4	66.4	47.3
• EATA	35.9	34.6	36.7	45.3	47.2	49.3	47.7	<b>56.5</b>	<b>55.4</b>	62.2	72.2	21.7	56.2	64.7	63.7	49.9
• SAR (ours)	$46.5 \pm 3.0$	$43.1 \pm 7.4$	$48.9 \pm 0.4$	$55.3 \pm 0.1$	$54.3 \pm 0.2$	$58.9 \pm 0.1$	$54.8 \pm 0.2$	$53.6 \pm 7.1$	$46.2 \pm 3.5$	$69.7 \pm 0.3$	$76.2 \pm 0.1$	$66.2 \pm 0.3$	$60.9 \pm 0.3$	$69.6 \pm 0.1$	$66.6 \pm 0.1$	$58.0 \pm 0.5$

# Efficiency Comparison and Ablations

- While improving adaptation stability, SAR maintains high efficiency

Method	Need source data?	Online update?	#Forward	#Backward	Other computation	GPU time (50,000 images)
MEMO (Zhang et al., 2021)	✗	✗	50,000×65	50,000×64	AugMix (Hendrycks et al., 2020)	933 minutes
DDA (Gao et al., 2022)	✓	✗	50,000×2	0	50,000 diffusion	2,435 minutes
TTT (Sun et al., 2020)	✓	✓	50,000×21	50,000×20	rotation augmentation	61 minutes
Tent (Wang et al., 2021)	✗	✓	50,000	50,000	n/a	110 seconds
EATA (Niu et al., 2022)	✓	✓	50,000 + 26,196	26,196	regularizer	114 seconds
SAR (ours)	✗	✓	50,000 + 12,710×2	12,710×2	Eqn. (5)	115 seconds

- Visualization of entropy loss surface
  - SAR is flatter, and more insensitive to noisy gradients

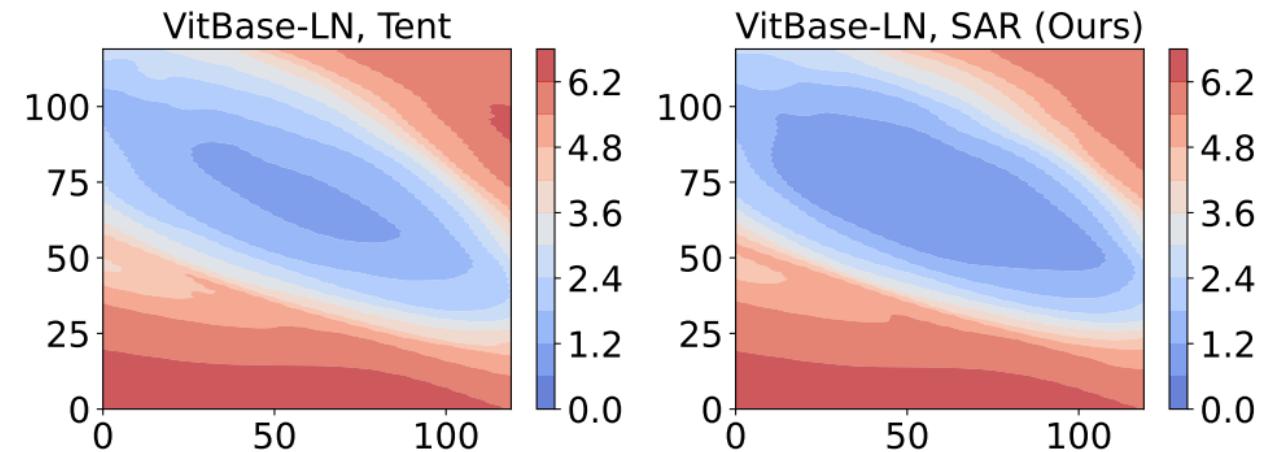


Figure. Loss (entropy) surface.

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# Conclusion

- We find that batch-agnostic norm layers (i.e., GN and LN) are more effective than BN for stable TTA under wild test settings
- We propose to use GN/LN models for stable TTA in the wild
- We further enhance the stability of online TTA for **GN/LN models via a simple yet effective SAR method**



# Please use our github repository: <https://github.com/mr-eggplant/SAR>

**ICLR | Towards Stable Test-Time Adaptation in Dynamic Wild World**

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Tencent AI Lab

**BACKGROUND: DATA SHIFTS**

Distribution shift when using a pre-trained model, the test samples may encounter natural variations or corruptions that were not present in training data:

- **Lighting changes** due to weather change
- **Noises** due to sensor degradation, etc.

These shifts can significantly impact the performance of the model and cause it to degrade.

**TEST-TIME ADAPTATION (TTA)**

- TTA aims to address data shifts by adapting the trained model on test data before prediction.
- Fully TTA adapts models online with only  $x_{\text{test}}$

**PROBLEM: TTA IN THE WILD**

**Limitation:** online TTA is unstable under wild test scenarios (such as mixed domain shifts, single data, and imbalance), leading to severe model collapse.

Goal: we aim to figure out the reason why TTA is unstable in the wild world, and then boost its stability.

**MAIN CONTRIBUTIONS**

- We find that batch-agnostic norm layers (i.e., GN and LN) are more beneficial to stable TTA than BN under wild test settings
- We propose a simple yet effective SAR, which addresses the model collapse of online TTA and makes it more stable under wild test settings

**I: WHAT LEADS TO UNSTABLE TTA?**

- Batch Normalization (BN) is a crucial factor hindering TTA stability under the wild test settings
- Most TTA methods are built upon test-time BN statistics adaptation:  $y^{(k)} \rightarrow \bar{y}^{(k)}\bar{x}^{(k)} + \beta^{(k)}\bar{x}^{(k)}$  –  $(\bar{x}^{(k)} - \mathbb{E}[\bar{x}^{(k)}])/\sqrt{\text{Var}[\bar{x}^{(k)}]}$
- However, the **E** and **Var** estimation under wild settings would be **inaccurate**
  - **Mixed domain shifts**: ideally each domain should have its own statistics
  - **Single sample**: hard to estimate E&Var accurately
  - **Imbalanced label shifts**: biased to specific classes
- **Observation**: models with batch-agnostic norm layer (e.g., layer norm) are more suitable for TTA

**II: WHAT LEADS TO UNSTABLE TTA?**

- TTA on models with GN/LN layers do not always succeed, and still suffer from failure cases
- **Online entropy minimization** tends to result in **collapsed trivial solutions**, i.e., predicting all samples to the same class, as shown in (a) vs. (b)

• Some large/noisy gradients cause collapse, as in (c)

• We address this collapse issue by proposing a SAR approach, as illustrated below

**SAR: SHARPNESS-AWARE AND RELIABLE ENTROPY MINIMIZATION**

- Directly filtering out noisy gradients via gradients norm is infeasible, since the threshold is hard to set
- We seek to filter samples via an alternative metric, and investigate the relation of entropy & gradients norm
- **Reliability**: discard partial large/noisy gradients via entropy
- Remove samples in Areas 1 and 2:
  - $\min_{\theta} S(x|\theta)$ , where  $S(x) \triangleq \mathbb{I}_{\{E(x|\theta) < K_1\}}(x)$
  - Samples in Area 1 have large gradients
  - Samples in Area 2 are unconfident (Niu et al., 2022)
- **Sharpness-Aware**: make the update robust to remaining large/noisy gradients
  - Alleviate the effects of samples in Area 4
  - Constrain the entropy surface to be flat:
 
$$\min_{\theta} E^{\text{SA}}(x; \theta), \text{ where } E^{\text{SA}}(x; \theta) \triangleq \max_{\|x\|_2 \leq r} E(x; \theta + e)$$
  - Following SAM (Fornet et al., 2020) to solve this optimization problem

**RESULTS UNDER ONLINE IMBALANCED LABEL DISTRIBUTION SHIFTS**

Model	Method	Area 1 or Imbalance Class (mostly level 2 regarding Corruption Accuracy %)													
		BN	BN+LN	GN	LN	GN+LN	BN	BN+LN	GN	LN	GN+LN	BN	BN+LN		
ResNet-18	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
ResNet-50	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
ViT-B/16	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
ViT-L/16	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
BERT	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
RoBERTa	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CiT	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
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CoT+LN+GN+BN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
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CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
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CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+LN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN	0.22	2.2	1.8	21.8	9.3	34.7	22.1	14.8	24.8	34.9	32.1	30.1	30.2	21.6	34.4
CoT+LN+GN+BN+LN+GN+BN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+GN+BN	0.22	2.2	1.8	21.8	9.3										