



TEA: Test-time Energy Adaptation

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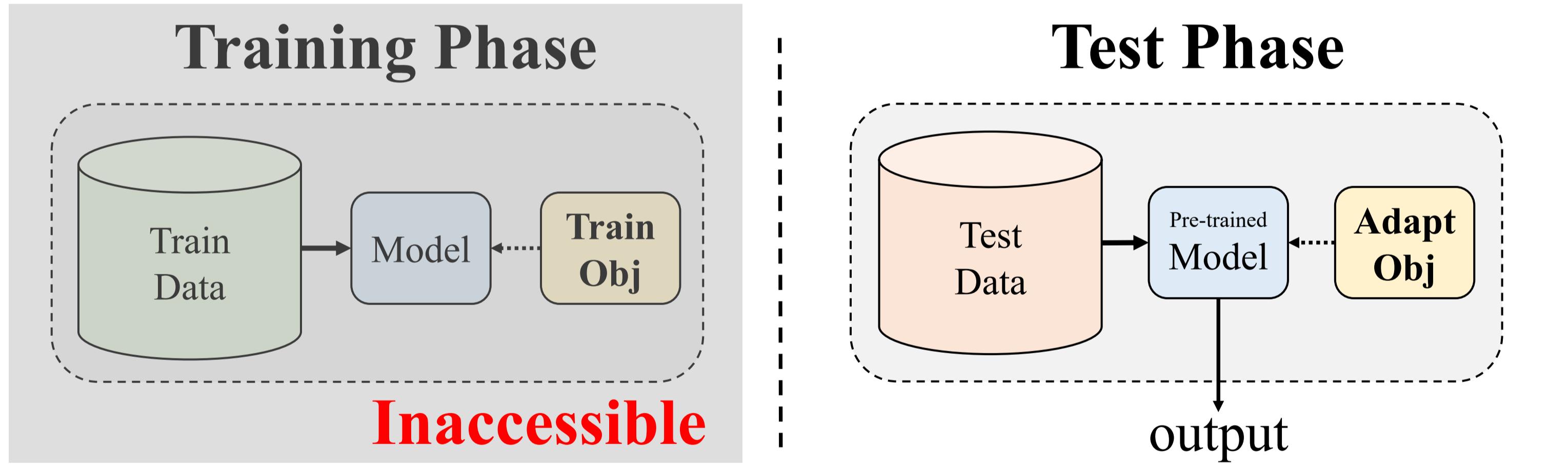
INTRODUCTION

Objective: Improving model generalizability when test data diverges from training distribution, without requiring access to training data and processes.

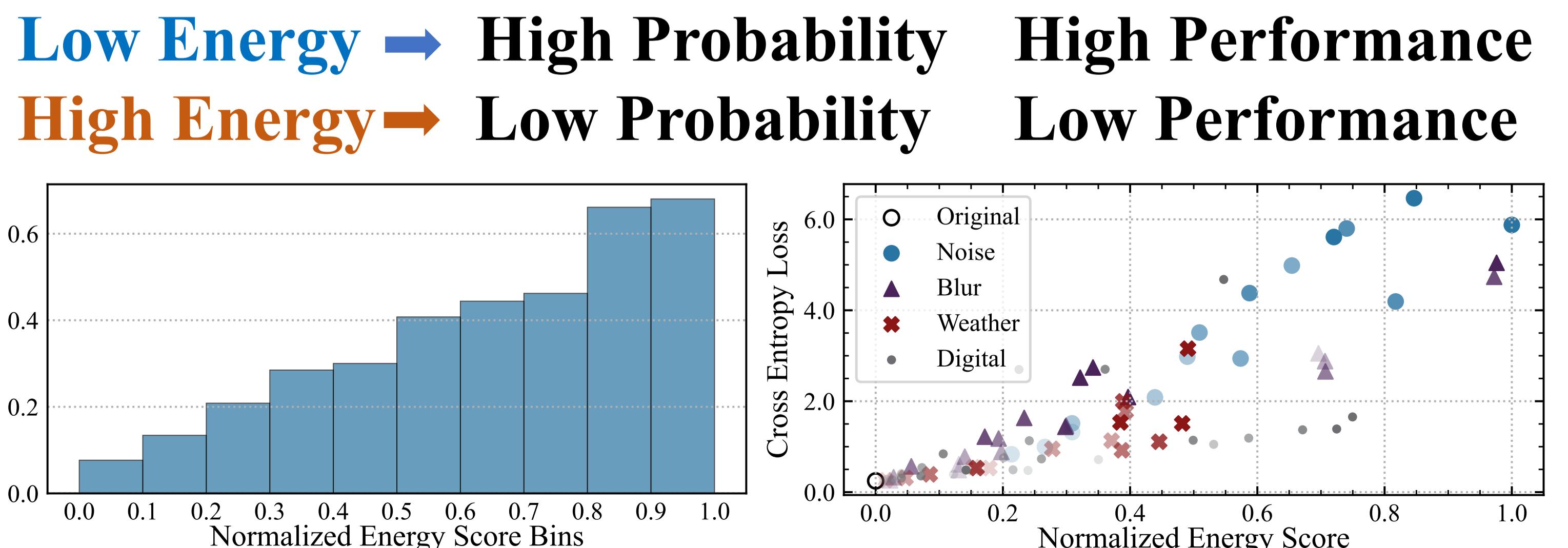
Weakness of existing methods: Current TTA methods fail to address the fundamental issue: covariate shift, i.e., the decreased generalizability can be attributed to the model's reliance on the marginal distribution of the training data, which may impair model calibration and introduce confirmation bias.

Motivation: Transforming the trained classifier into an energy-based model and aligning the model's distribution with the test data's, enhancing its ability to perceive test distributions and thus improving overall generalizability.

BACKGROUND



MOTIVATION

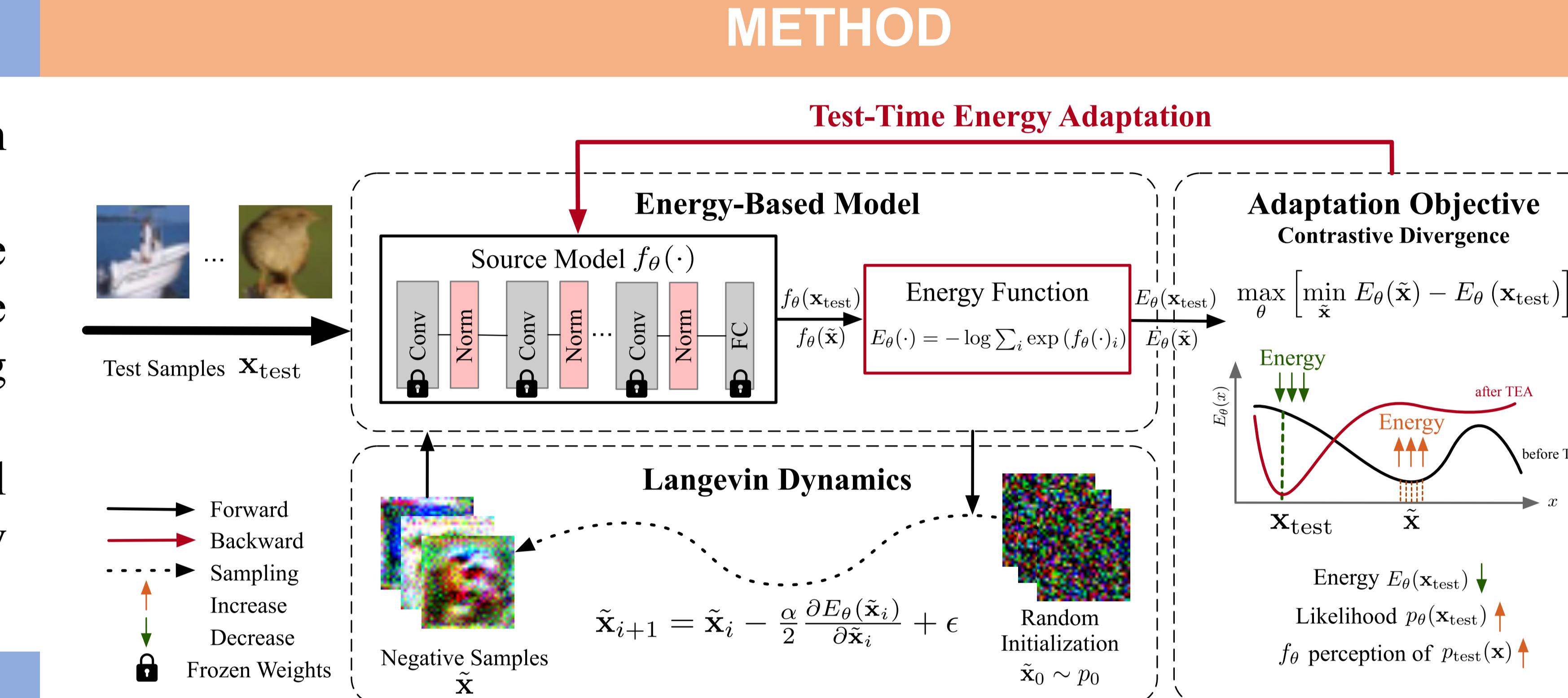


Treating Classifier As EBM

$$\begin{aligned} \text{Pretrained Classifier} & \rightarrow p_{\theta}(y | \mathbf{x}) = \frac{\exp(f_{\theta}(\mathbf{x})[y])}{\sum_{y'} \exp(f_{\theta}(\mathbf{x})[y'])} \\ & \rightarrow \text{introduce unknown normalizing constant } Z_{\theta} \\ & \rightarrow p_{\theta}(\mathbf{x}, y) = \frac{\exp(f_{\theta}(\mathbf{x})[y])}{Z_{\theta}} \\ & \rightarrow \text{marginalize out } y \\ & \rightarrow p_{\theta}(\mathbf{x}) = \sum_y p_{\theta}(\mathbf{x}, y) = \sum_y \exp(f_{\theta}(\mathbf{x})[y]) / Z_{\theta} \\ & \rightarrow \text{substitute } E_{\theta} \\ & \rightarrow E_{\theta}(\mathbf{x}) = -\log \sum_y \exp(f_{\theta}(\mathbf{x})[y]) \end{aligned}$$

Inject Test Distribution Into Classifier

$$\begin{aligned} \text{Contrastive Divergence} & \quad \frac{\partial \log p_{\theta}(\mathbf{x}_{\text{test}})}{\partial \theta} = \mathbb{E}_{\tilde{\mathbf{x}} \sim p_{\theta}} \left[\frac{\partial E_{\theta}(\tilde{\mathbf{x}})}{\partial \theta} \right] - \frac{\partial E_{\theta}(\mathbf{x}_{\text{test}})}{\partial \theta} \\ \text{Stochastic Gradient Langevin Dynamics} & \quad \tilde{\mathbf{x}}_{t+1} = \mathbf{x}_t - \frac{\alpha}{2} \frac{\partial E_{\theta}(\tilde{\mathbf{x}}_t)}{\partial \tilde{\mathbf{x}}_t} + \sqrt{\alpha} \epsilon, \quad \epsilon \sim \mathcal{N}(\mathbf{0}, \mathbf{I}), \\ \text{Overall Objective} & \quad \max_{\theta} p_{\theta}(\mathbf{x}_{\text{test}}) = \max_{\theta} [\min_{\tilde{\mathbf{x}}} E_{\theta}(\tilde{\mathbf{x}}) - E_{\theta}(\mathbf{x}_{\text{test}})] \end{aligned}$$



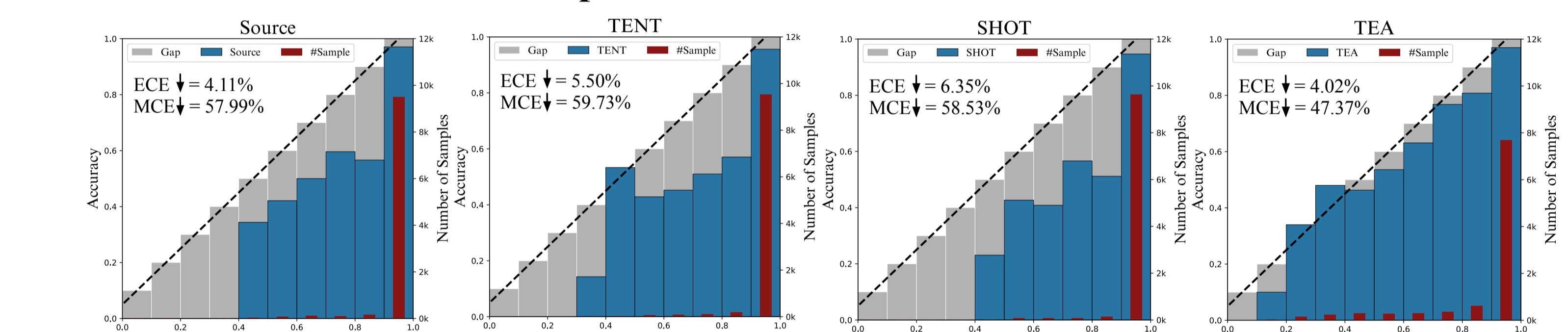
METHOD

EXPERIMENTS

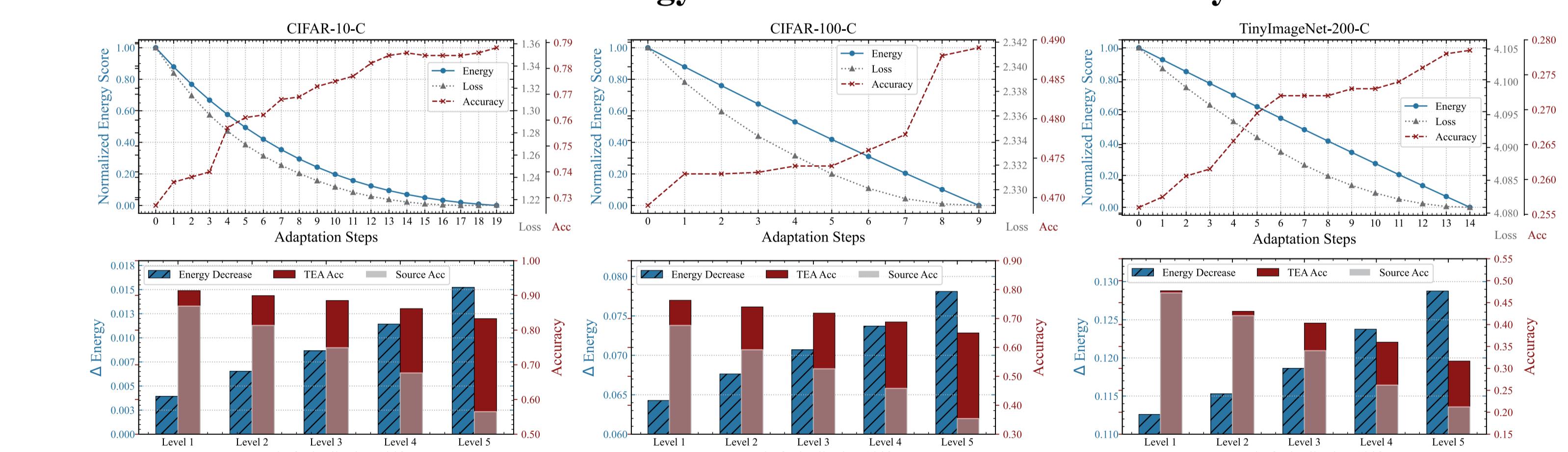
TEA's Adaptation Performance

	CIFAR-10(C)			CIFAR-100(C)			Tiny-ImageNet(C)		
	Clean	Corr Severity 5	Corr Severity 1-5	Clean	Corr Severity 5	Corr Severity 1-5	Clean	Corr Severity 5	Corr Severity 1-5
WRN-28-10	94.77	56.47	100.00	80.83	81.79	35.39	100.00	63.19	21.21
BatchNorm	93.97	79.56	52.65	85.63	60.00	66.06	63.54	68.11	69.42
Source	-	80.10	50.78	-	-	-	-	-	-
BN [52]	93.75	51.42	106.98	72.62	99.37	80.52	53.40	72.12	46.53
DUA* [41]	-	80.10	50.78	-	-	-	-	-	-
Pseudo	93.25	74.77	63.19	82.35	72.61	80.52	56.33	68.01	66.00
SHOT [36]	93.25	74.77	63.19	82.35	72.61	80.52	56.33	68.01	66.00
TENT [60]	93.66	81.41	48.13	86.75	56.17	80.14	63.09	59.42	69.47
ETA [45]	93.96	79.58	52.64	85.63	59.99	80.65	59.82	64.52	72.40
EATA [45]	93.96	79.59	52.62	85.64	59.98	80.68	60.24	67.48	71.66
SAR [46]	93.97	79.77	51.94	85.83	58.97	80.84	62.95	59.37	70.01
Energy	TEA	94.09	83.34	43.69	87.88	52.00	80.88	65.10	56.07
								71.22	63.72
								51.65	31.67
								87.99	39.96
									92.12

TEA's Improvements in Confidence Calibration



Relation between TEA's Energy Reduction and Generalizability Enhancement



TEA's Distribution Perception and Generation

