Towards Robust and Efficient Cloud-Edge Elastic Model Adaptation via Selective Entropy Distillation

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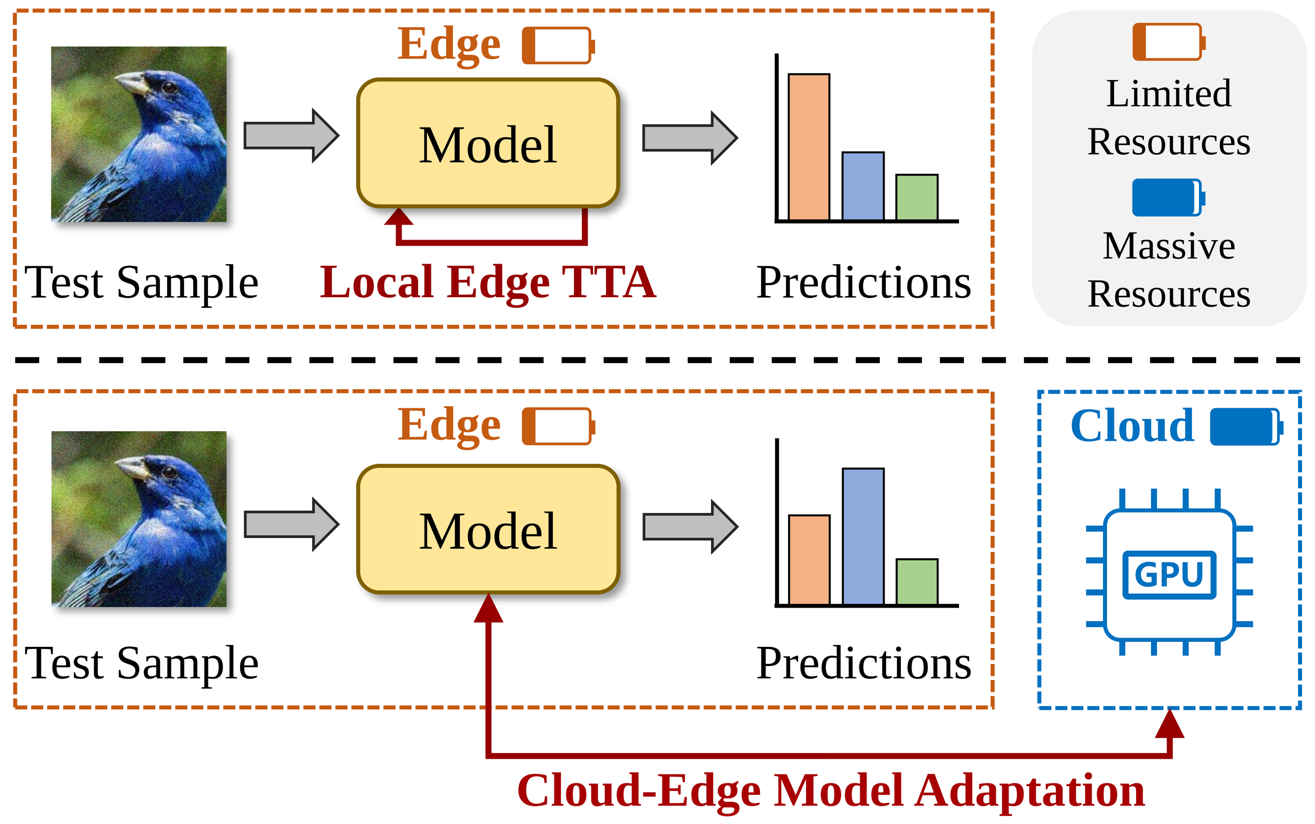
Background

When deploying a cloud-trained model in the edge devices:

- The model **remains fixed** due to the **high cost** of adaptation for **resource-limited edge devices**.
- It is difficult for the **fixed model** to handle **distribution shifted data**.

Model Adaptation in Cloud-Edge Collaborative Style

- **Local Test-time Adapttion** (upper): It locally performs adaptation only in the edge with **limited resources**.
- **Cloud-edge Adaptation** (lower): It conducts model adaptation **more efficiently** in the edge, which **offloads the heavy adaptation workloads to the cloud** with massive resources.



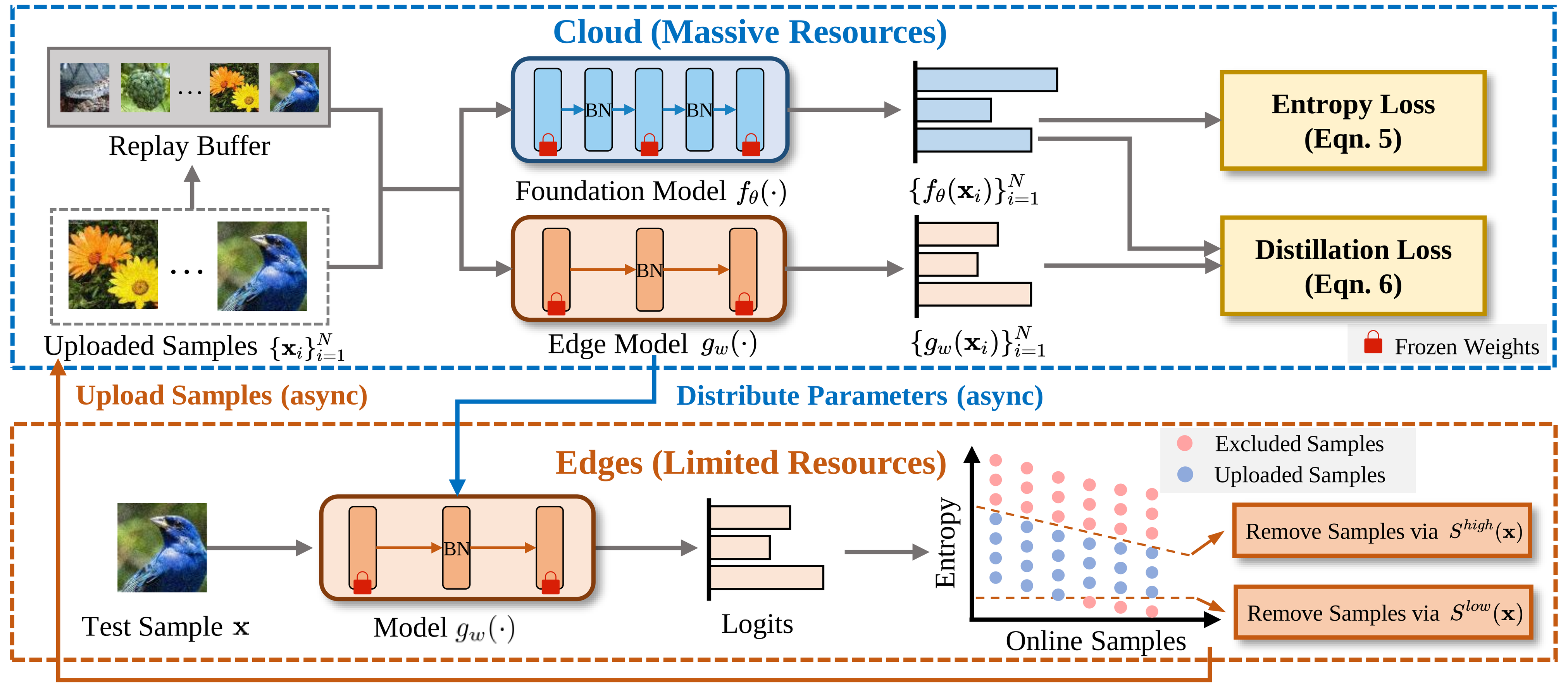
Raised Challenges: 1) The **data communication cost may be heavy** if uploading all samples. 2) It is unclear how to **exploit the massive resource in the cloud** to enhance the performance.

Contributions

- We establish a **Cloud-Edge Elastic Model Adaptation (CEMA)** paradigm designed for **efficient collaborative model adaptation**. Our CEMA is a general paradigm that is applicable to online adapt edge models to new dynamically changing environments.
- We reduce communication costs by devising **entropy-based criteria** for excluding **unreliable** and **low-informative** samples from being uploaded. Experimental results show CEMA **lowers 60% communication cost** than SOTAs on ImageNet-C (**Challenge 1**).
- We improve the adaptation performance of the edge model by performing a **replay-based entropy distillation**, which minimizes **prediction entropy** and the **KL divergence** between the **edge model** and the **foundation model** using a sample replay strategy (**Challenge 2**).

Overview of Cloud-Edge Elastic Model Adaptation

- **Edge Side**: To reduce the communication cost, the edge asynchronously uploads samples to the cloud by **excluding unreliable and low-informative ones**.
- **Cloud Side**: We first adapt the foundation model via entropy minimization and meanwhile **stores uploaded samples into a replay buffer**. Then, with samples from **the edge and the replay buffer**, we adapt the edge model $g_w(\cdot)$ by **distillating** from the foundation model $f_\theta(\cdot)$.



Entropy-based Sample Filtration

Challenge: Uploading all test samples to the cloud introduces a **heavy communication burden**.

Solution: We exclude the **unreliable** (**high-entropy**) samples via a **dynamically adjudsted** threshold $E^t_{\max}$ and **low-informative** (**low-entropy**) samples via a fixed threshold $E_{\min}$

$$S^{high}(\mathbf{x}) = \mathbb{1}_{\{E(\mathbf{x};w)<E^t_{\max}\}}(\mathbf{x}), \quad S^{low}(\mathbf{x}) = \mathbb{1}_{\{E(\mathbf{x};\theta)>E_{\min}\}}(\mathbf{x}). \tag{1}$$

where the threshold would be changed dynamically according the entropy of current batch samples $E^t_{\max} \leftarrow \lambda \times E^{t-1}_{\max} \times \frac{E^t_{avg}}{E^{t-1}_{avg}}$, t denote the batch index.

Replay-based Knowledge Distillation

Challenge: Vanilla distillation needs **a large number of samples** but we have only **limited** ones.

Solution: Upon receiving uploaded samples $\hat{\mathcal{X}}=\{\mathbf{x}_i\}_{i=1}^N$, we put them into a **replay buffer** $\mathcal{B}=\mathcal{B}\cup\hat{\mathcal{X}}$. Then, based on **newly uploaded samples and samples from the replay buffer**, we optimize the edge model $g_w(\cdot)$ by distilling from adapted foundation model $f_\theta(\cdot)$

$$\min_{\tilde{w}} H(\mathbf{x})[\alpha\mathcal{L}_{\mathrm{KL}}(g_w(\mathbf{x}), f_\theta(\mathbf{x})) + \beta\mathcal{L}_{\mathrm{CE}}(g_w(\mathbf{x}), \hat{y}) + \mathcal{L}_{\mathrm{ENT}}(g_w(\mathbf{x}))]. \tag{2}$$

Comparisons with SoTA Methods

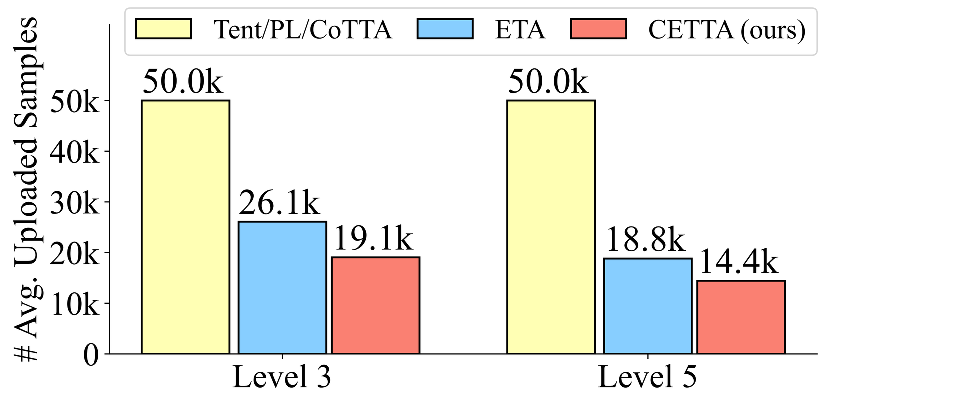
- **Comparisons with CNN-based models on ImageNet-C**

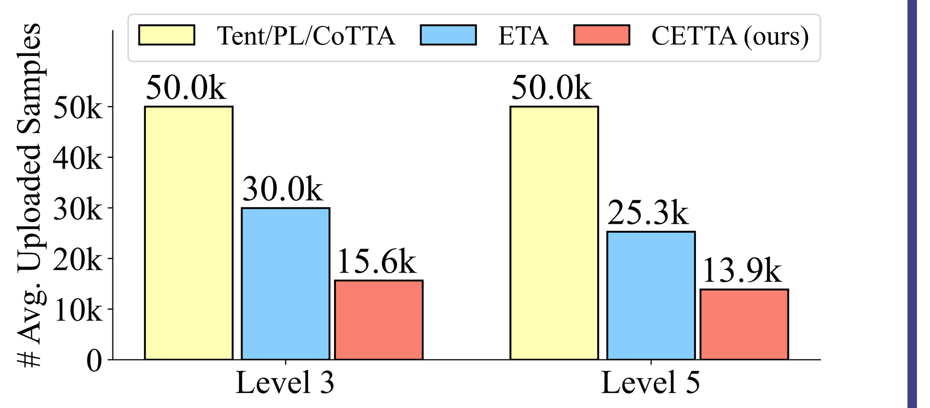
	Noise			Blur				Weather				Digital				
Severity Level=3	Gauss.	Shot	Impul.	Defoc.	Glass	Motion	Zoom	Snow	Frost	Fog	Brit.	Contr.	Elastic	Pixel	JPEG	Avg.
ResNet18 (baseline)	21.6	19.9	18.7	29.9	15.8	28.7	27.6	27.6	23.8	35.5	62.7	38.1	51.8	41.6	53.0	33.1
• BN Adaptation†	42.3	39.8	40.0	37.5	31.4	45.1	44.3	40.8	36.2	53.9	65.0	58.2	60.2	58.0	57.7	47.4
• ONDA†	40.0	38.9	37.5	29.5	27.5	43.8	43.9	40.2	35.2	54.6	65.1	56.1	59.7	58.6	57.6	45.9
• LAME†	20.6	18.9	17.2	29.5	14.7	28.3	26.9	26.8	23.2	34.9	62.4	37.5	51.3	41.1	52.5	32.4
• PL	48.1	48.0	46.1	41.1	39.7	51.3	49.9	47.3	39.8	58.6	64.9	59.2	62.5	60.8	59.4	51.8
• Tent	47.2	47.1	45.1	40.0	38.2	50.4	49.4	46.7	40.1	58.1	64.9	59.0	62.5	60.5	59.2	51.2
• CoTTA	42.0	40.7	39.8	30.3	30.1	46.3	46.1	41.9	36.5	56.2	64.9	58.0	60.2	59.3	58.1	47.4
• ETA	50.1	50.2	48.6	44.0	42.7	52.9	51.4	49.9	43.5	59.5	**65.2**	60.9	**62.9**	**61.6**	**59.9**	53.5
• CEMA (Ours)	**51.1**	**51.2**	**49.8**	**45.2**	**44.1**	**53.7**	**52.0**	**50.8**	**44.2**	**60.1**	65.0	**61.1**	**62.9**	**61.6**	59.8	**54.2**
Severity Level=5	Gauss.	Shot	Impul.	Defoc.	Glass	Motion	Zoom	Snow	Frost	Fog	Brit.	Contr.	Elastic	Pixel	JPEG	Avg.
ResNet18 (baseline)	1.5	2.3	1.5	11.4	8.7	11.1	17.6	10.6	16.2	14.0	51.5	3.4	16.5	23.3	30.7	14.7
• BN Adaptation†	16.6	16.2	17.3	18.6	18.2	25.9	34.7	28.4	29.8	41.2	58.5	22.2	40.1	45.3	38.0	30.1
• ONDA†	13.7	15.0	14.1	12.3	13.2	23.7	34.2	29.4	28.6	40.9	58.5	12.3	39.3	44.6	37.5	27.8
• LAME†	0.9	1.1	0.6	11.2	8.2	10.8	17.0	8.7	15.6	12.4	51.1	3.3	14.9	22.5	30.1	13.9
• PL	24.8	26.8	24.6	20.3	21.3	33.6	41.8	39.0	32.4	49.9	59.5	11.4	47.9	51.5	47.0	35.4
• Tent	22.8	25.0	23.2	20.1	21.1	32.4	41.0	37.8	33.5	48.9	59.3	18.0	46.9	50.6	45.9	35.1
• CoTTA	15.2	16.2	15.7	11.8	14.9	26.9	36.9	31.2	29.9	43.6	59.2	17.0	40.9	47.2	39.3	29.7
• ETA	26.8	29.7	27.6	22.6	22.7	37.1	44.0	42.4	37.6	51.6	60.1	26.1	49.8	53.3	48.5	38.7
• CEMA (Ours)	**29.8**	**32.2**	**30.3**	**25.3**	**26.8**	**39.3**	**45.3**	**43.7**	**38.7**	**52.8**	**60.1**	**32.9**	**50.8**	**54.0**	**49.3**	**40.8**

- **Comparisons with Transformer-based models on ImageNet-C**

	Noise			Blur				Weather				Digital				
Severity Level=3	Gauss.	Shot	Impul.	Defoc.	Glass	Motion	Zoom	Snow	Frost	Fog	Brit.	Contr.	Elastic	Pixel	JPEG	Avg.
DeiT-tiny (baseline)	49.1	48.0	48.6	38.1	20.5	43.8	31.6	44.9	44.2	47.0	66.7	60.6	55.5	47.6	56.8	46.9
• LAME†	48.9	47.7	48.3	37.5	19.2	43.5	30.8	44.3	43.8	46.2	66.4	60.3	55.1	47.0	56.4	46.3
• PL	52.7	52.8	53.1	46.1	35.6	53.3	42.4	49.8	46.9	58.4	67.9	63.7	62.3	58.4	59.6	53.5
• Tent	53.1	53.1	53.4	47.9	41.0	54.7	46.3	51.5	48.2	60.0	68.1	64.1	63.8	60.1	60.7	55.1
• CoTTA	49.8	48.8	49.4	39.0	20.9	45.1	32.1	46.0	45.4	49.0	67.0	61.6	56.5	49.0	57.5	47.8
• ETA	54.1	54.2	54.2	49.4	47.0	56.1	51.7	53.7	51.0	**61.5**	68.1	**64.6**	64.7	62.4	62.0	57.0
• CEMA (Ours)	**55.0**	**55.1**	**55.1**	**50.5**	**48.5**	**57.1**	**52.9**	**55.4**	**51.8**	60.2	**68.4**	64.3	**65.5**	**63.4**	**63.0**	**57.7**
Severity Level=5	Gauss.	Shot	Impul.	Defoc.	Glass	Motion	Zoom	Snow	Frost	Fog	Brit.	Contr.	Elastic	Pixel	JPEG	Avg.
DeiT-tiny (baseline)	17.0	18.2	17.4	19.2	12.6	22.9	20.9	32.6	37.6	32.9	59.6	23.9	23.5	10.3	38.5	25.8
• LAME†	16.5	17.9	17.0	18.6	11.4	22.4	19.9	31.4	37.1	29.6	59.3	23.4	21.3	10.1	38.1	24.9
• PL	1.0	2.3	1.1	17.8	2.4	35.9	3.6	9.4	15.2	0.8	62.8	38.6	3.9	35.9	46.2	18.5
• Tent	4.1	13.3	13.6	27.1	1.6	38.7	3.4	11.7	14.6	0.8	63.2	**41.3**	2.4	44.1	47.8	21.8
• CoTTA	17.6	18.8	18.1	19.7	12.7	23.9	21.0	33.7	38.7	34.8	60.4	24.4	24.1	10.6	39.3	26.5
• ETA	32.1	33.7	33.4	33.8	**35.0**	42.9	**43.4**	45.9	46.0	53.2	63.9	33.9	**50.2**	**50.6**	51.0	43.1
• CEMA (Ours)	**34.4**	**36.7**	**36.2**	**35.8**	34.4	**44.8**	43.0	**48.0**	**46.8**	**54.6**	**64.0**	37.0	49.9	50.1	**52.8**	**44.5**

- **Comparions of # uploading samples on CNN- (left) and Transformer-based (right) models**





Contact Information and Code

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- Code: https://github.com/chenyaofo/CEMA

Code

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