DELTA: Decoupling Long-Tailed Online Continual Learning

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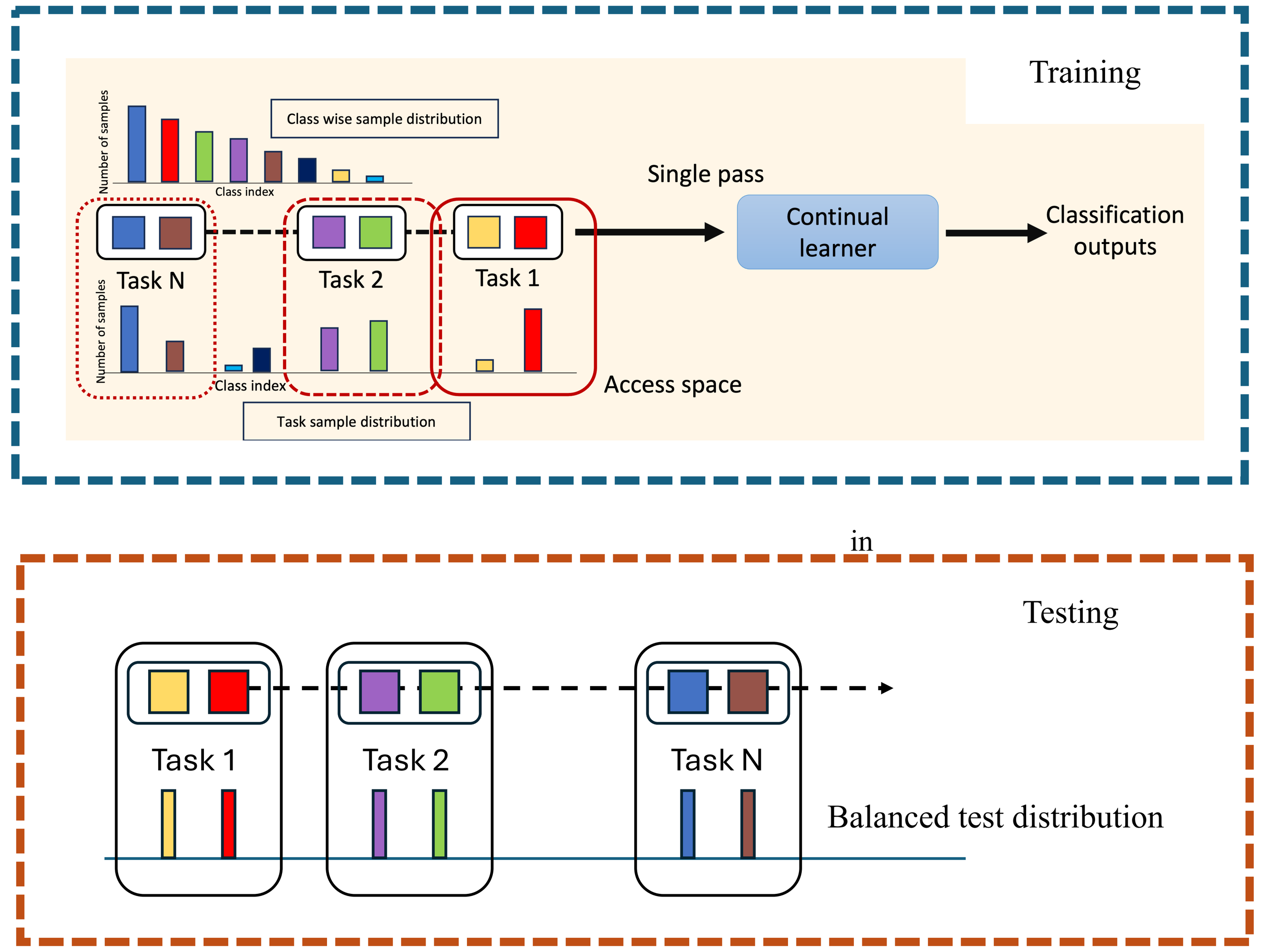
Long-Tailed Online Continual Learning



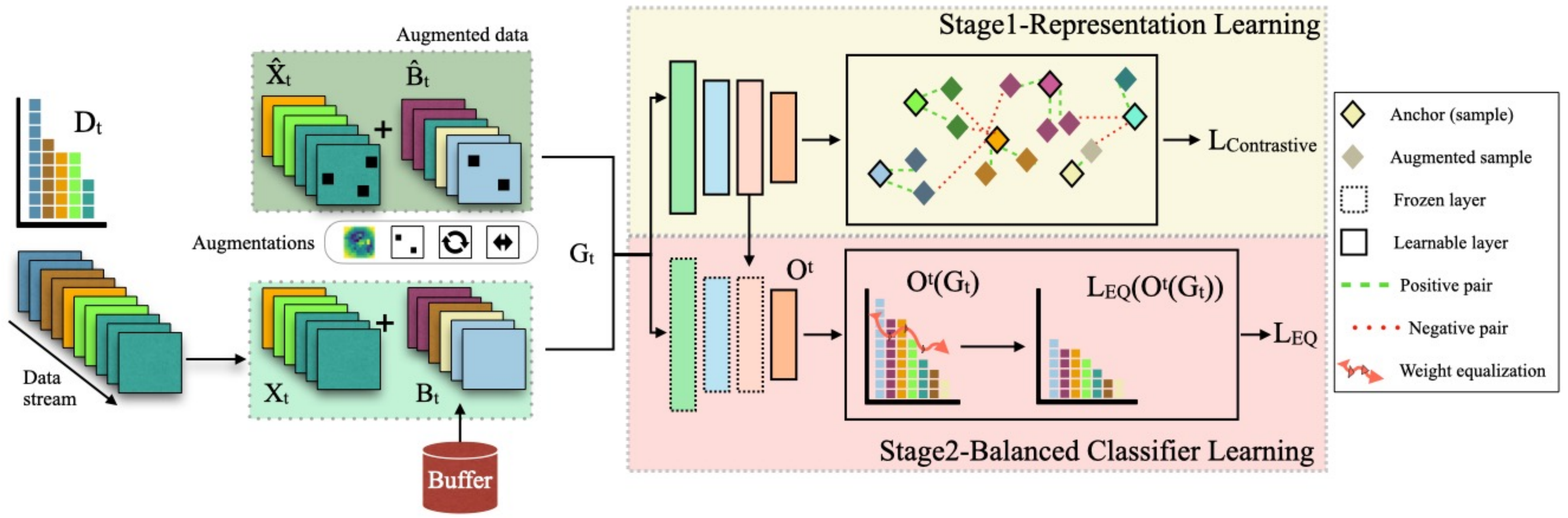
Challenge

- **Imbalanced class representation** - Dealing with real-world scenarios where the data follows long-tailed distributions where each class may not be equally represented.
- **Catastrophic forgetting and model bias** - Limited set of exemplars can be biased towards the frequently appearing classes.
- **Exemplar Management and Data Efficiency**: Utilizing existing continual learning models can introduce distribution challenges and biases, making it difficult to adapt to evolving data distributions while maintaining balanced performance across all classes.

Outcome

- Develop a **two-stage decoupling strategy** that effectively handles real-world distribution scenarios, ensuring freedom from biases and enhancing performance outcomes.
- We propose a **multi-exemplar pairing strategy** to demonstrate the potential performance enhancement in Long-Tail Online Continual Learning

Methodology



Decoupling learning through two stage training.

Stage 1

$$\mathcal{L}_{stage1}(O^t(G_t)) = \mathcal{L}_{contrastive}(O^t(G_t))$$

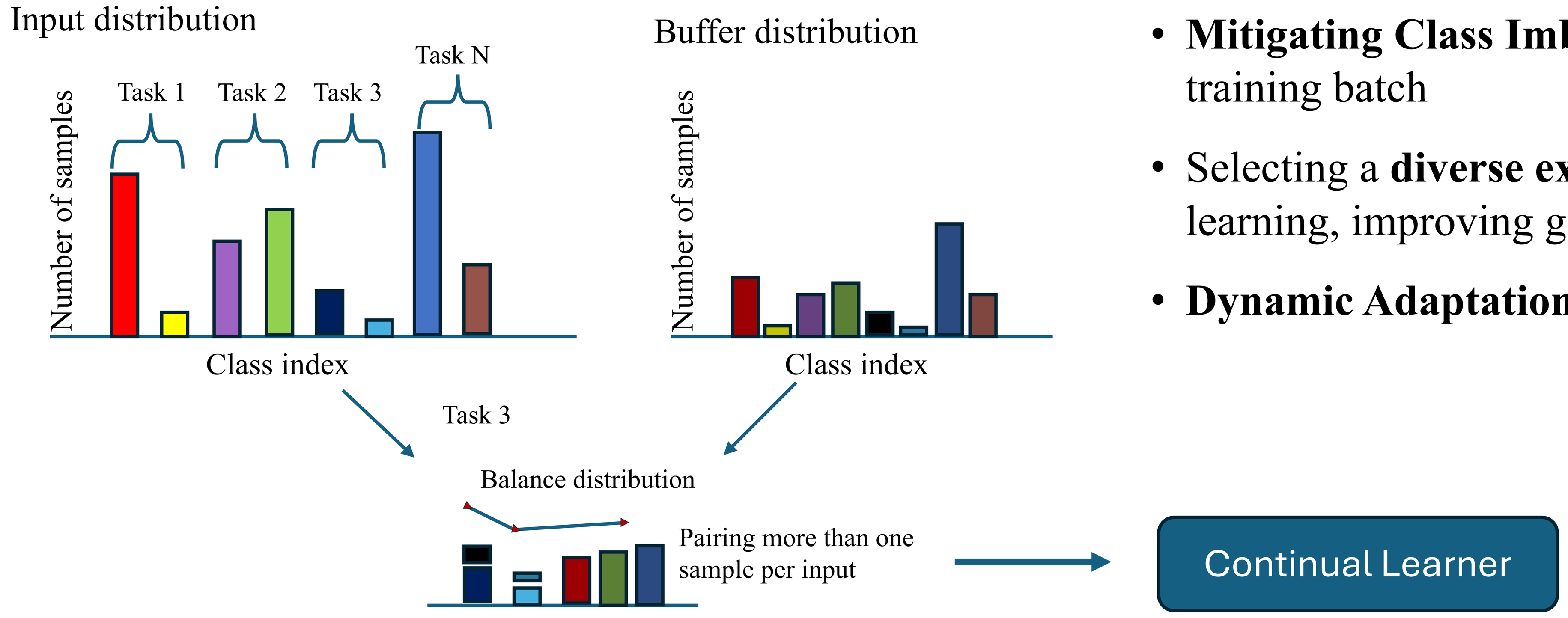
$$\mathcal{L}_{contrastive}(Z_T) = \sum_{j \in T} \frac{-1}{|P(j)|} \sum_{p \in P(j)} \frac{exp(v_j \cdot v_p/\tau)}{\sum_{k \in A(j)} exp(v_j \cdot v_p/\tau)}$$

Stage 2

$$\mathcal{L}_{stage2}(O^t(G_t)) = \mathcal{L}_{EQ}(O^t(G_t))$$

$$\mathcal{L}_{EQ}(O^t(I_x)) = \sum_{i=1}^{k^{1:t}} -I_{y_{(i)}} \sigma([\log[(P(k^t)] + O^t(I_x))])$$

Multi-exemplar pairing



Motivation

- **Mitigating Class Imbalance** and balance the input training batch
- Selecting a **diverse exemplar** set ensures better learning, improving generalization and performance.
- **Dynamic Adaptation** to varying data distribution.

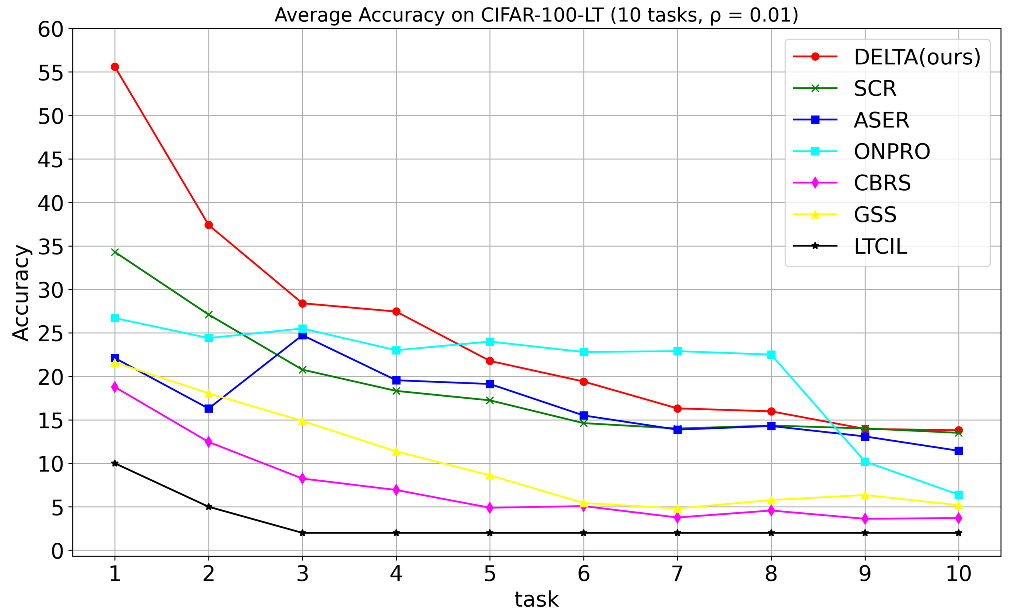
Experiments

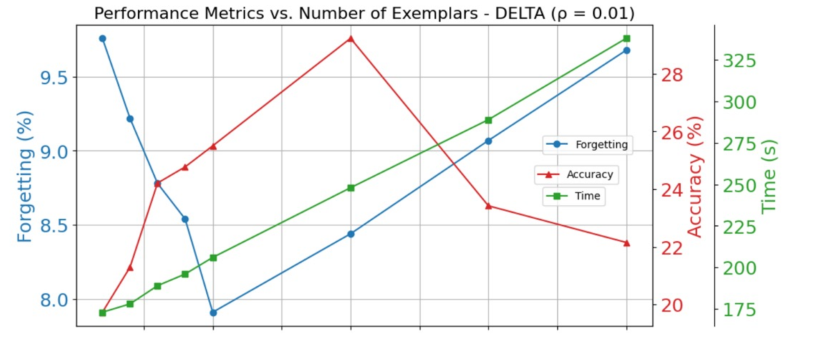
Methods	CIFAR100-LT						VFN-LT					
	20 tasks	20 tasks	20 tasks	10 tasks	10 tasks	10 tasks	15 tasks	15 tasks	15 tasks	7 tasks	7 tasks	7 tasks
	M=0.5K	M=1K	M=2K	M=0.5K	M=1K	M=2K	M=0.5K	M=1K	M=2K	M=0.5K	M=1K	M=2K
OnPRO[ICCV '23]	14.02 ± 0.44	16.28 ± 0.81	18.01 ± 0.22	16.53 ± 0.55	16.92 ± 0.08	18.85 ± 0.32	11.93 ± 0.04	12.77 ± 0.07	13.50 ± 0.05	**8.02 ± 0.60**	9.38 ± 0.21	11.84 ± 0.49
SCR[CVPRW '21]	12.22 ± 0.72	13.48 ± 0.90	15.88 ± 0.79	16.65 ± 0.90	17.02 ± 0.77	17.58 ± 0.66	11.55 ± 0.17	11.82 ± 0.10	12.39 ± 0.73	7.71 ± 0.49	9.19 ± 0.46	9.48 ± 0.47
ASER[AAAI '21]	8.86 ± 0.30	7.86 ± 0.61	8.18 ± 0.31	12.68 ± 0.70	13.76 ± 0.01	15.90 ± 0.91	6.85 ± 0.34	7.61 ± 0.38	7.22 ± 0.36	7.46 ± 1.18	7.52 ± 1.09	6.35 ± 0.19
PRS[ECCV '20]	7.61 ± 0.09	7.54 ± 0.21	7.03 ± 0.13	7.34 ± 0.92	8.95 ± 0.33	9.01 ± 0.39	7.17 ± 0.83	8.72 ± 0.15	8.39 ± 0.19	7.85 ± 0.50	8.66 ± 0.22	9.21 ± 0.30
CBRS[ICML '20]	8.51 ± 0.19	8.66 ± 0.61	8.91 ± 0.33	9.50 ± 0.48	7.22 ± 0.43	7.31 ± 0.08	8.12 ± 0.94	8.35 ± 0.33	8.18 ± 0.44	7.52 ± 0.11	7.64 ± 0.08	7.92 ± 0.34
GSS[NeurIPS '19]	5.16 ± 0.10	5.22 ± 0.22	5.09 ± 0.21	8.97 ± 0.65	10.12 ± 0.02	9.96 ± 0.47	5.86 ± 0.30	6.01 ± 0.91	5.86 ± 0.06	5.92 ± 0.54	4.30 ± 0.22	4.66 ± 0.60
LT-CIL(offline)	3.01 ± 0.77	2.67 ± 0.04	2.43 ± 0.02	1.76 ± 0.11	2.36 ± 0.25	3.76 ± 0.22	1.82 ± 0.45	2.02 ± 0.44	2.38 ± 0.08	3.08 ± 0.71	2.92 ± 0.04	1.99 ± 0.31
DELTA (ours)	**16.53 ± 0.01**	**17.71 ± 0.11**	**19.93 ± 0.07**	**20.25 ± 0.71**	**21.06 ± 0.23**	**22.47 ± 0.51**	**12.5 ± 0.01**	**13.45 ± 0.02**	**13.84 ± 0.01**	8.00 ± 0.39	**10.41 ± 0.52**	**12.84 ± 0.54**

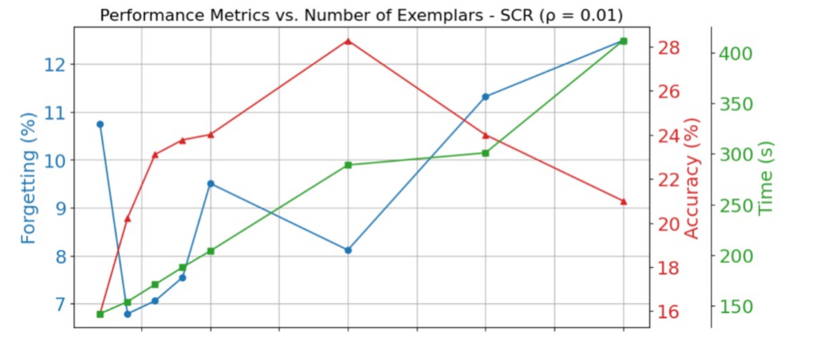
Average Accuracy ± standard deviation (↑) in the long-tailed scenario on Split CIFAR-100-LT, VFN-LT with single exemplar pairing. The highest accuracy is highlighted in red, while the second highest is in blue.

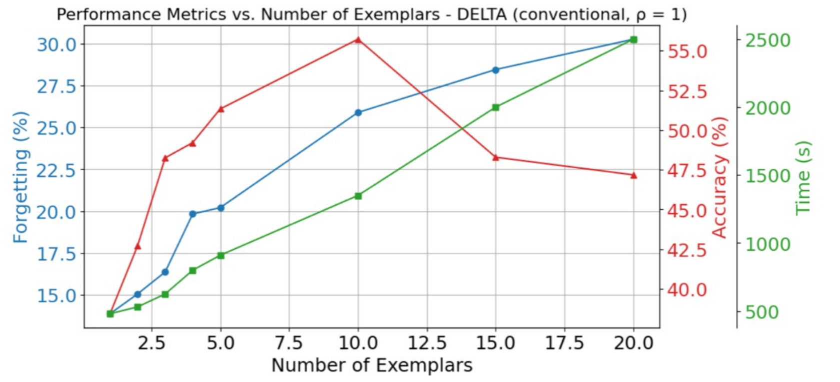
Imbalance ratio (ρ)	SCR	CBRS	DELTA *(ours)*
0.005	3.59 ± 0.64	7.60 ± 0.06	**18.02 ± 0.79**
0.03	4.11 ± 0.42	8.88 ± 0.47	**20.21 ± 0.22**
0.07	8.34 ± 0.04	9.47 ± 0.61	**23.60 ± 0.09**
0.1	6.12 ± 0.35	10.26± 0.38	**24.28 ± 0.60**
1.0 (Conventional)	20.74 ± 0.40	15.79 ± 0.33	**33.23 ± 0.97**

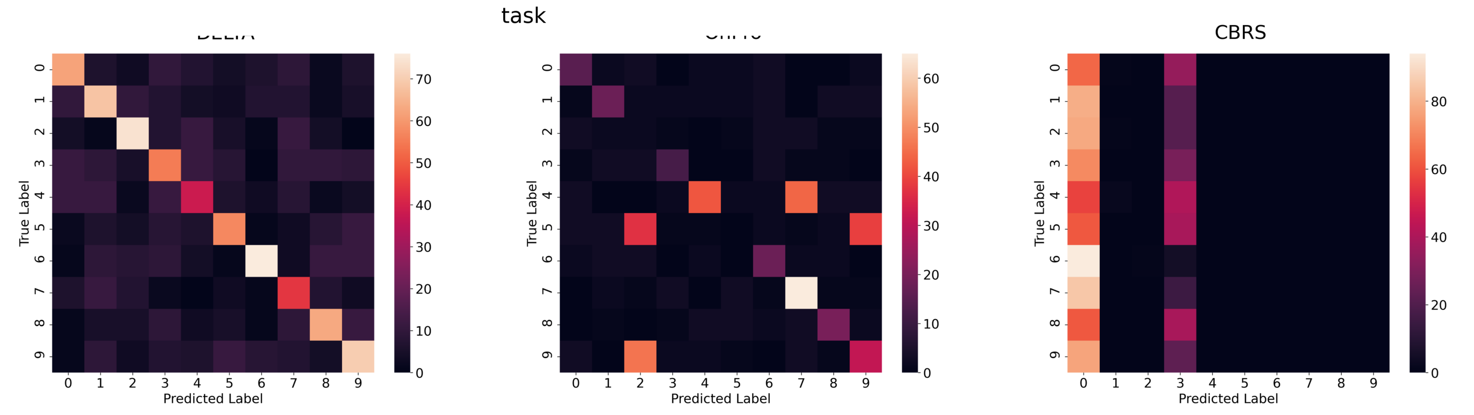
Average Accuracy ± standard deviation (↑) the long-tailed scenario on Split CIFAR-100-LT with varying imbalance factors. Best results in **bold**











Paper

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