Gradient Reweighting: Towards Imbalanced Class-Incremental Learning



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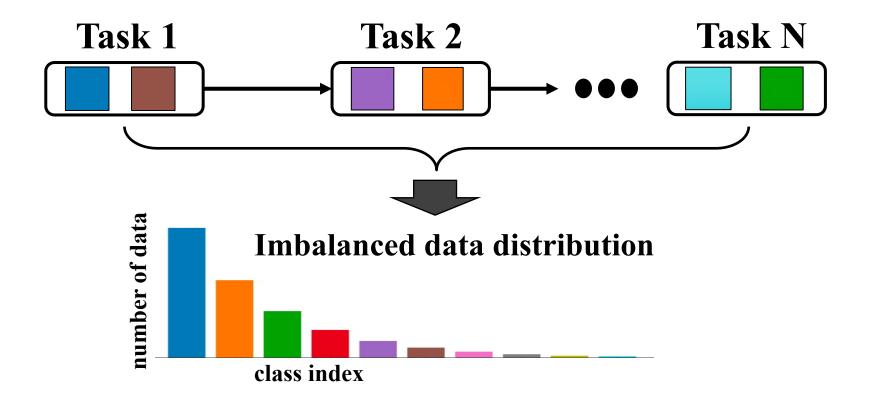


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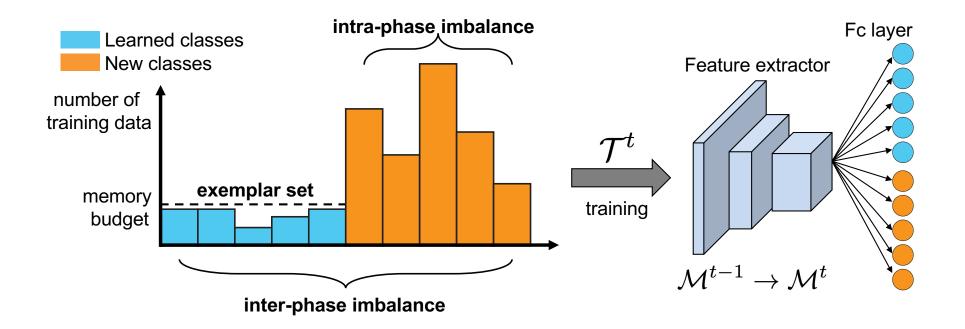
Imbalanced Class-Incremental Learning

Learning classes incrementally from non-uniform data distribution





Challenge - Dual Imbalance

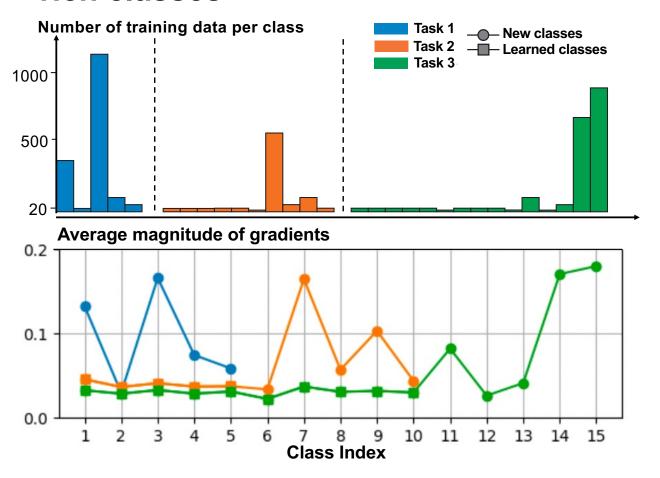


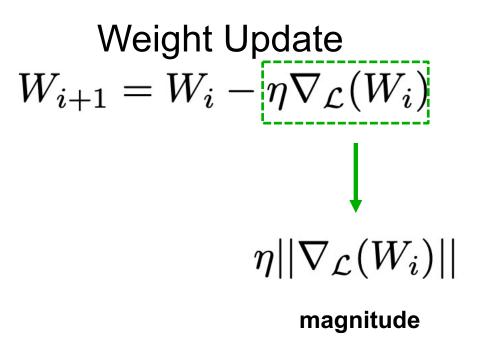
- Inter-phase imbalance: disparities between stored exemplars of old tasks and new class data
- Intra-phase imbalance: severe class imbalances within each individual task

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Motivation

 The magnitude of weight update significantly biased towards instancerich classes

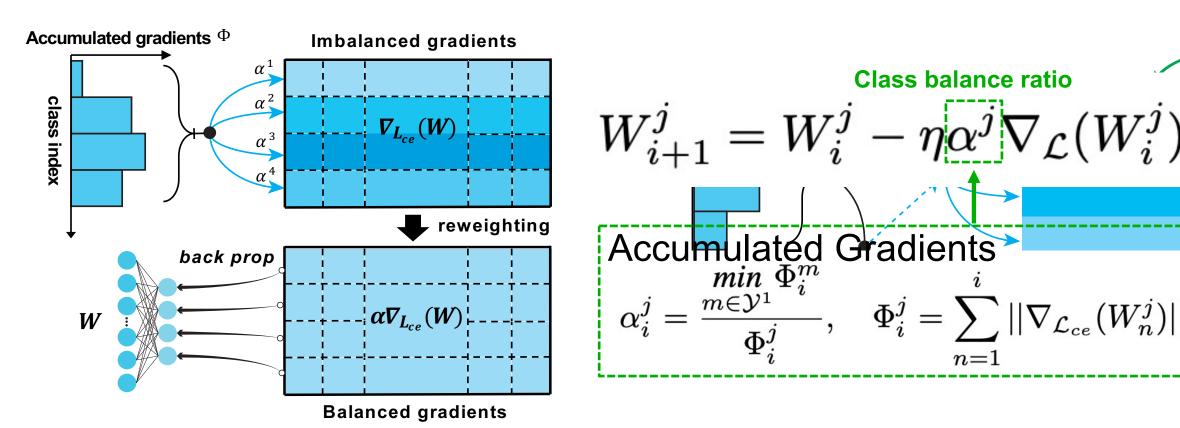






Intra-Phase Gradient Reweighting

Leveraging the per-class balance ratio during training process

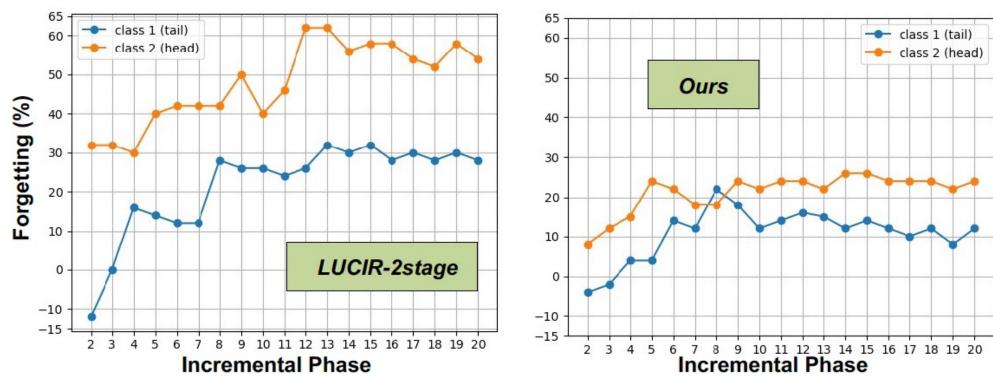




Imbalanced Catastrophic Forgetting

 Head classes suffers more forgetting than tail classes as most the training data becomes unavailable in subsequent incremental phases

ImageNetSubset-LT (*LFS*, N=20 , $n_{arepsilon}=20$)





Distribution-Aware Knowledge Distillation

- The DAKD loss prioritize preserving knowledge for classes with more training data lost during incremental learning
- Decouple the original distillation loss into a weighted sum of two parts
 - $-\sigma = [0,1]$ and $\sigma = 1$ indicates balanced data lost and the DAKD will performs the same as regular knowledge distillation loss

Measure the imbalance

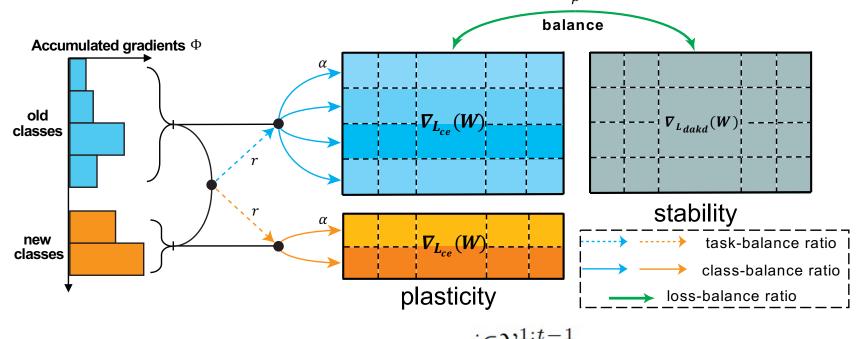
$$\mathcal{L}_{dakd}(z, \hat{z}|\mathbf{s}) = \sigma \mathcal{L}_{kd}(z, \hat{z}) + (1 - \sigma) \mathcal{L}_{kd}^{imb}(\tilde{z}, \hat{z})$$

$$\tilde{z}_{j} = \frac{s_{j}}{\sum_{m}^{|\mathcal{Y}^{1:t-1}|} s_{m}} z_{j} + \left(1 - \frac{s_{j}}{\sum_{m}^{|\mathcal{Y}^{1:t-1}|} s_{m}}\right) \hat{z}_{j}$$



Inter-Phase Decoupled Gradient Reweighting

- Reweight the gradient for new tasks and learned tasks separately
- Tune the balance between stability and plasticity



$$W_{i+1}^{j} = W_{i}^{j} - \underbrace{\eta(\alpha_{i}^{j}r_{i}^{j}\nabla_{\mathcal{L}_{ce}}(W_{i}^{j}) + \beta_{i}\nabla_{\mathcal{L}_{dakd}}(W_{i}^{j}))}_{j \in \mathcal{Y}^{t}}$$

$$\underbrace{\eta(\alpha_{i}^{j}r_{i}^{j}\nabla_{\mathcal{L}_{ce}}(W_{i}^{j}) + \beta_{i}\nabla_{\mathcal{L}_{dakd}}(W_{i}^{j}))}_{j \in \mathcal{Y}^{t}}$$



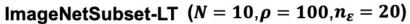
Experiments

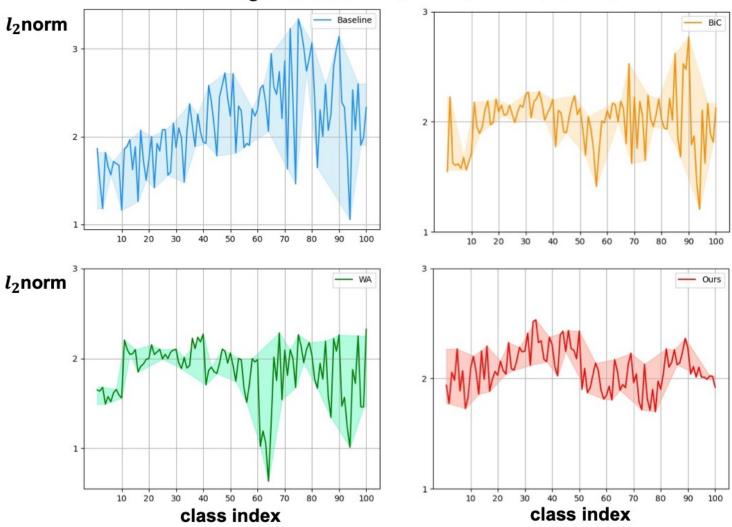
Datasets	CIFAR100-LT				ImageNetSubset-LT				Food101-LT			
Evaluation protocol	LFS		LFH		LFS		LFH		LFS		LFH	
Total tasks N	10	$-\frac{1}{20}$	5	10	10	20		10	10	$-\frac{1}{20}$	5	
iCaRL [37]	21.83	24.28	28.68	28.33	33.75	29.71	41.82	40.21	18.13	12.50	21.83	21.31
IL2M [5]	31.37	29.99	34.90	33.42	31.70	25.20	40.75	39.08	16.11	16.27	23.93	22.48
BiC [46]	28.89	20.10	25.68	25.95	33.31	30.86	33.18	29.23	16.94	16.81	22.80	20.75
WA [53]	27.63	23.48	32.07	26.85	32.58	29.03	32.62	28.10	16.58	15.99	18.45	19.45
SSIL [1]	26.07	26.15	30.72	29.21	30.38	25.99	38.97	35.18	16.86	15.65	21.65	19.03
FOSTER [44]	30.43	29.96	37.25	37.91	34.38	29.75	46.51	43.88	24.27	20.45	32.39	31.46
MAFDRC [11]	32.67	31.95	37.94	38.51	40.01	34.48	48.23	44.12	26.93	19.21	34.22	30.91
EEIL-2stage [10, 26]	33.64	32.25	36.40	34.91	36.84	30.39	43.62	41.49	19.75	20.02	22.65	22.83
LUCIR-2stage [21, 26]	31.09	31.03	38.47	37.86	39.87	34.79	48.97	47.39	27.65	24.68	36.05	35.06
PODNet-2stage [14, 26]	30.41	30.37	38.38	38.45	35.47	31.71	48.02	47.74	23.78	21.13	35.42	35.22
FOSTER-2stage [26, 44]	31.27	30.68	40.26	39.43	36.47	33.95	48.89	46.93	25.82	22.28	35.69	33.48
Ours	35.66	34.35	40.18	39.11	45.12	40.79	50.57	49.13	29.05	26.42	36.84	36.19



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Weight Bias Correction Effects





The L2 norm of learned weight vectors



Source Code

https://github.com/JiangpengHe/imbalanced_cil



Contact

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