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Dynamical Adapter Fusion: Constructing A Global Adapter for Pre-Trained Model-based Class-Incremental Learning

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➢ Introduction

■ Class-incremental Learning

In class-incremental learning, models must learn new classes without forgetting old ones. Training a separate adapter for each task reduces interference between tasks, but creates two practical challenges.

■ Challenges

- Growing adapter storage
- Costly, error-prone adapter retrieval

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➢ Related work & Challenges

■ Catastrophic Forgetting

- Regularization-based methods constrain the updates to essential parameters of the model, thereby preserving important knowledge across tasks.
- Architecture-based methods introduce task-specific components or allocate new parameters for each new task.
- Rehearsal-based methods continuously replay samples from previous tasks to ensure that knowledge is retained.

■ From Scratch to Pre-Trained Models

- Training from scratch is computationally demanding, which makes it difficult to scale under limited resources. Parameter-efficient fine-tuning reuses visual features from a frozen pre-trained backbone and updates only lightweight adapters, reducing the number of trainable parameters and the cost of learning new classes.

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➢ Related work & Challenges

■ Task-Specific Adapters

A common approach freezes the pre-trained backbone and trains a lightweight adapter for each task to reduce interference between tasks.

- Growing adapter storage. Each new task adds an adapter, so storage grows with the number of tasks.
- Test-time adapter retrieval. Test inputs come without task IDs, so retrieval-based methods must select an adapter for each input. This adds latency, and selecting the wrong adapter can hurt classification accuracy.

■ Can a single adapter learn new classes and retain knowledge of earlier classes?

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➢ Motivation

■ One Global Adapter for All Learned Classes

$$\theta_t^* = \underbrace{\beta_t \theta_p + \beta_t \theta_{t-1}^*}_{\text{Stability}} + \underbrace{(1 - 2\beta_t)\theta_t}_{\text{Plasticity}}$$

DAF fuses each new task adapter into a single global adapter that learns new classes while retaining prior knowledge. The same adapter serves all learned classes, eliminating test-time retrieval and keeping adapter storage constant as tasks accumulate.

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➢ Method

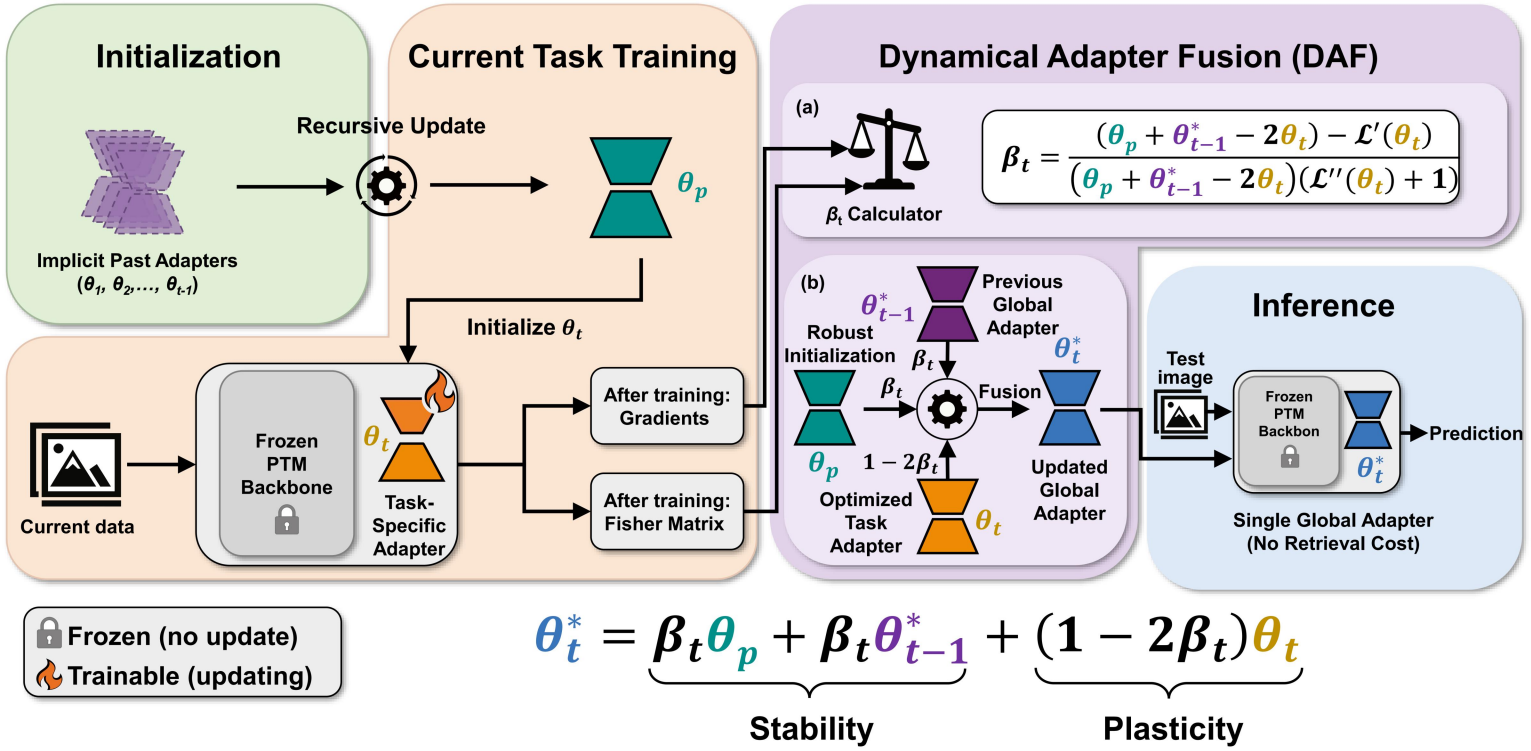
■ Dynamical Adapter Fusion (DAF)

● Robust Initialization

- We initialize each new task adapter with a running average of previously trained adapters, transferring shared knowledge without storing individual past adapters.

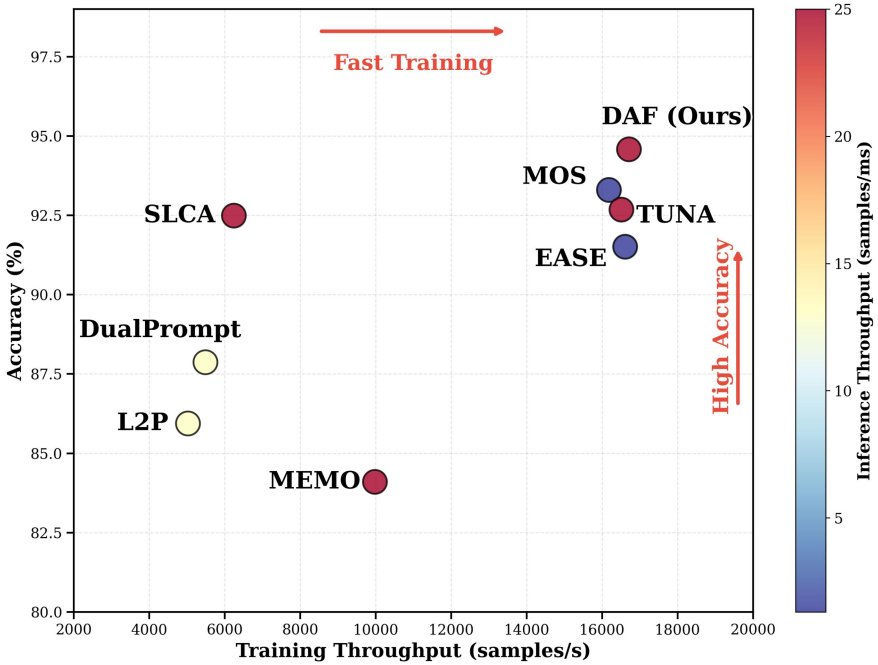
● Dynamical Fusion

- After each task, we use PAC-Bayes–guided, parameter-wise weights to fuse the initialization, previous global adapter, and newly trained task adapter.

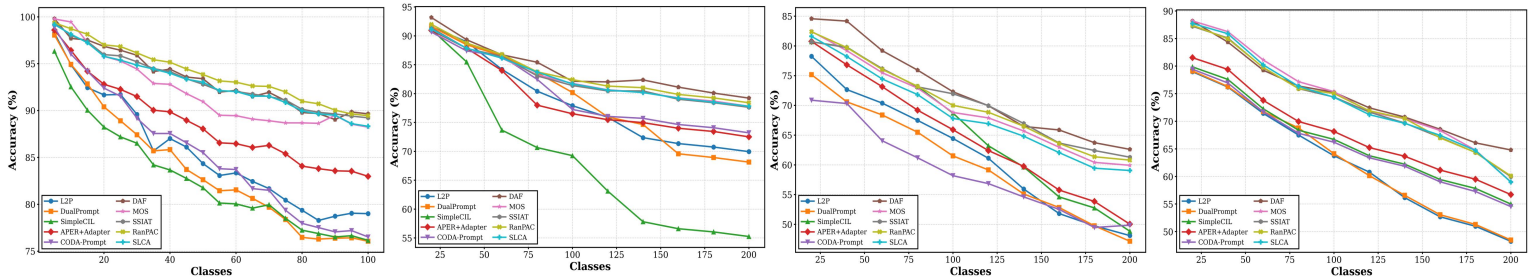


➢ Experiments

DAF achieves the highest average and final accuracy across four benchmarks, with high training and inference throughput.



Method	CIFAR-100		ImageNet-R		ImageNet-A		ObjectNet	
	$\bar{\mathcal{A}}$ (%)	$\mathcal{A}_T$ (%)	$\bar{\mathcal{A}}$ (%)	$\mathcal{A}_T$ (%)	$\bar{\mathcal{A}}$ (%)	$\mathcal{A}_T$ (%)	$\bar{\mathcal{A}}$ (%)	$\mathcal{A}_T$ (%)
Finetune	38.90	20.17	32.32	22.78	24.28	14.51	19.14	8.73
L2P [43]	85.94	79.93	75.46	69.77	49.39	41.71	63.78	52.19
DualPrompt [41]	87.87	81.15	73.10	67.18	53.71	41.67	59.27	49.33
CODA-Prompt [32]	89.11	81.96	77.97	72.27	53.54	42.73	66.07	53.29
SLCA [46]	92.49	88.55	81.17	77.00	68.66	58.74	72.55	61.30
RanPAC [24]	94.00	90.62	82.98	77.94	69.32	61.82	72.76	62.02
SSIAT [36]	93.52	90.07	83.20	78.85	70.83	62.23	73.65	62.45
SimpleCIL [50]	87.57	81.26	61.26	54.55	59.77	48.91	65.45	53.59
APER + Adapter [50]	90.65	85.15	75.82	67.95	60.47	49.37	67.18	55.24
EASE [49]	91.51	85.80	81.74	76.17	65.34	55.04	70.84	57.86
TUNA† [39]	92.68	86.19	81.24	72.92	56.14	28.64	72.61	58.52
MOS [34]	93.30	89.25	82.96	77.93	67.08	56.22	74.69	63.62
DAF (Ours)	**94.58**	**91.15**	**84.01**	**79.63**	**72.06**	**62.54**	**76.11**	**66.37**



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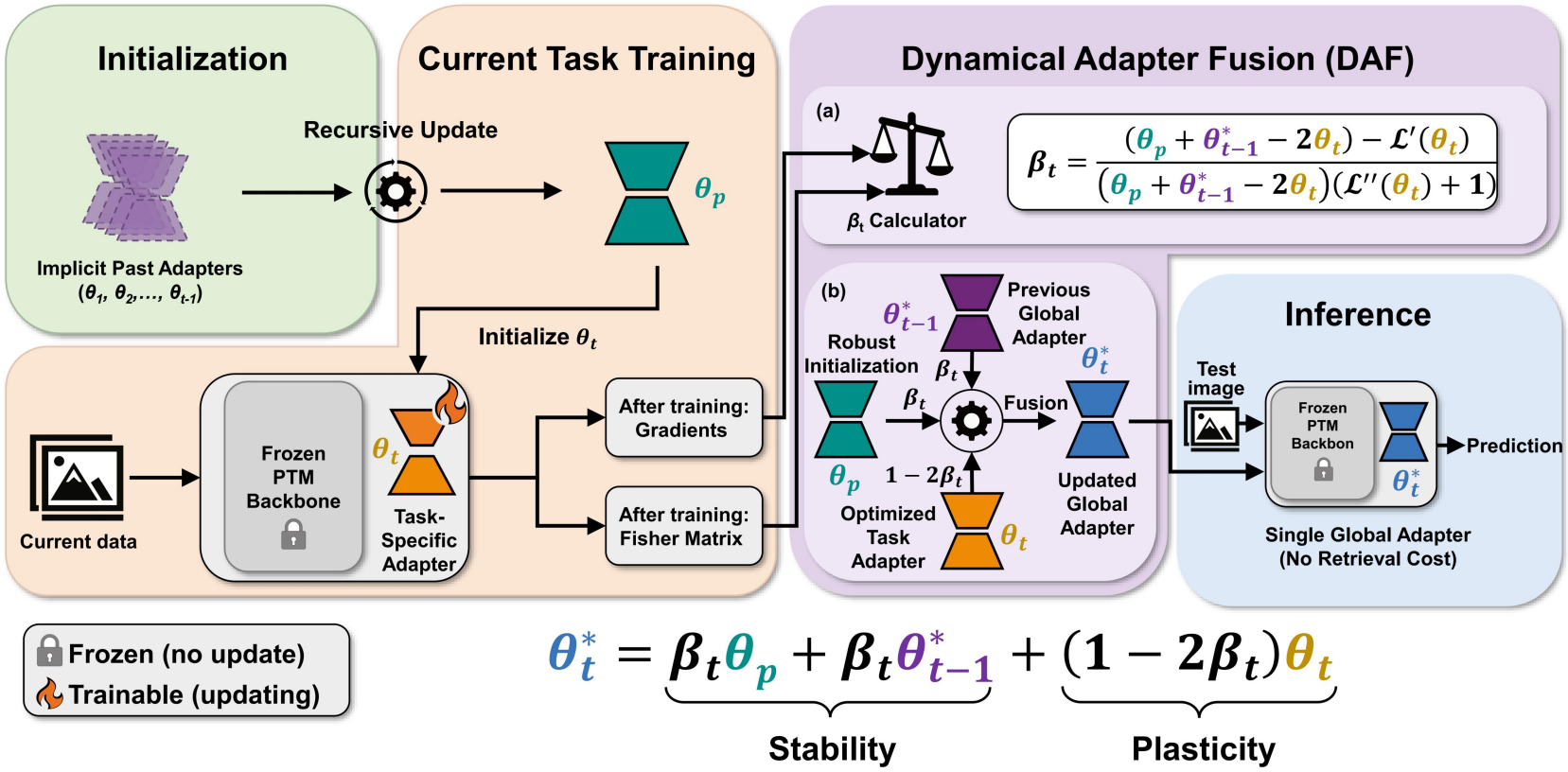
➢ Conclusion

■ Dynamical Adapter Fusion

- Dynamical Adapter Fusion uses robust initialization and PAC-Bayes–guided fusion to learn new classes while retaining prior knowledge in a single global adapter. DAF achieves the highest average and final accuracy across four benchmarks while keeping adapter storage constant and eliminating test-time adapter retrieval.



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Thank You!

For further details, feel free to get in touch with us

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https://github.com/EMLS-ICTCAS/DAF

https://arxiv.org/abs/2601.21341