

## ADAPTIVE LORA MERGING FOR DOMAIN INCREMENTAL LEARNING



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# Introduction

Foundation models fine-tuned with PEFT methods perform well under strong iid assumptions but lose performance in dynamic contexts like DIL scenarios.



#### Our contributions

- Analysis of the performance of state-of-the-art
   LoRA merging algorithms on DIL tasks
- Novel merging method that dynamically computes the importance of each task



### Background

- We focus on merging **LoRA** adapters in DIL scenarios
- LoRA is a PEFT technique, where the model updates are computed as:

$$W = W_0 + BA$$

- We compare **linear merging**, **TIES** and **DARE+TIES** with different weights value
- They heavily rely on manual coefficients selection, which makes it hard to pick the optimal configuration



Our method learns dynamically the relevance of each domain in the merging process:

$$\alpha_i = \sigma(c_i) \cdot b$$
$$b = 1 + (b_{\max} - 1) \cdot \sigma(b_{\max})$$



where **bmax** is a hyperparameter, allowing for adaptive coefficients scaling. We use a small memory buffer to learn the coefficients, with as low as one sample per class.

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### Results

SPC = 1	Fixed Coefficients				Adaptive Coefficients				
Merging Algorithm	<b>W</b> = 1	<b>W</b> = 3	W = 5		$\boldsymbol{b}_{\max} =$	= 1.0 <b>b</b>	max = 3.0	$\boldsymbol{b}_{\max}=5.0$	
Task Arithmetic TIES DARE TIES	$ \begin{vmatrix} 29.19 \pm 9.99 \\ 82.42 \pm 11.76 \\ 20.37 \pm 5.02 \end{vmatrix} $	$\begin{array}{c} 11.38 \pm 4.76 \\ 25.19 \pm 9.86 \\ 42.58 \pm 8.88 \end{array}$	$ \begin{array}{cccccccccccccccccccccccccccccccccccc$	6.57 90 4.10	$76.48 \pm 62.62 \pm 16.42 \pm$	14.65       29         10.10       82         4.93       20	$72 \pm 10.15 \\ 62 \pm 11.39 \\ 0.41 \pm 5.27$	$\begin{array}{c} 17.84 \pm 4.44 \\ 80.44 \pm 12.3 \\ 25.02 \pm 5.69 \end{array}$	
Task Arithmetic TIES DARE TIES		$\begin{array}{c} 1.50 \pm 0.29 \\ 2.17 \pm 0.42 \\ 13.50 \pm 2.32 \end{array}$	$ \begin{array}{r} 1.77 \pm 0 \\ 2.16 \pm 0 \\ 2 & 34.12 \pm 4 \end{array} $	.34 .65 .85	42.09 ± 24.88 ± 1.68 ±	5.95       2.         3.51       62         0.20       2.	$17 \pm 0.58$ $2.95 \pm 5.17$ $72 \pm 0.21$	$\begin{array}{c} 1.58 \pm 0.53 \\ 62.74 \pm 5.83 \\ 3.18 \pm 0.21 \end{array}$	
ExperienceAdapter Weights ( $b_{max} = 3.0$ )Domain Accuracy (%)PhotoCartoonSketchArtPhotoCartoonSketch						Art			
1	1.09	_ 1.09		10	00.00	-	-	_	
23	0.94	1.08 1.05 1.	.01 –	9	6.05	90.30 86.60	85.19	_	
4	0.85	1.07 1.	.02 0.86	9	7.72	80.72	76.23	87.40	

- For *fixed-coefficients* method, picking the merging weights wrongly leads to huge performance loss
- Our *adaptive-coefficients* approach learns the importance of each adapter in the merging, assigning different weights according to the complexity of each task
- By introducing **bmax**, we improve model robustness, with small performance variations



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