

Maintaining Structural Integrity in Parameter Efficient Fine-Tuning

Chongjie Si¹, Xuehui Wang¹, Xue Yang², Zhengqin Xu¹, Qingyun Li², Jifeng Dai², Yu Qiao², Xiaokang Yang¹, Wei Shen¹ ¹Shanghai Jiao Tong University ²Shanghai AI Laboratory

Observation

Task:

Parameter Efficient Fine-Tuning (PEFT), minimal trainable parameters, comparable or even superior performance.

Problem:

- Almost all of existing methods focus on linear weights, neglecting other higher dimensions spaces like convolution.
- Some methods adapt high-dimensional parameter spaces by compressing changes into a two-dimensional representation and applying low-rank matrix adaptations, yet this compression undermines the inherent structural integrity of the original space.

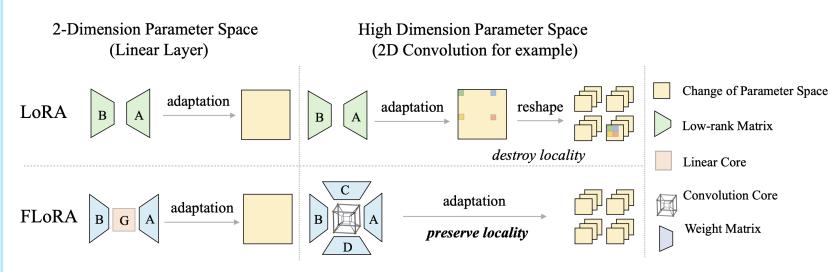
An Ideal Method Should Satisfy:

- Appropriate low-rank representation for the changes in various dimensional parameter spaces, without destructing the structural integrity of the original parameter spaces.
- Maintain a consistent formulation across various dimensional parameter spaces.

Contributions:

- We propose a novel PEFT method, FLoRA. To the best of our knowledge, it is the first time that a PEFT method has been designed for different dimensional parameter spaces, aiming to preserve their topological structure while seeking low-rank representations.
- Extensive experiments on different tasks, include computer vision, natural language processing and multi-modal tasks, demonstrates that FLoRA significantly surpasses other baselines, validating the effectiveness of FLoRA.

Framework:



For N-dimension:

 $\mathcal{W}_0 \to \mathcal{W}_0 + s * \Delta \mathcal{W} = \mathcal{W}_0$

For 4-dimension:

 $\Delta \mathcal{W} = \mathcal{G} \times_1 \mathbf{A} \times_2 \mathbf{B} \times_3 \mathbf{C} \times_4 \mathbf{D}$

For 2-dimension:

 $\Delta \mathbf{W} = \mathcal{G} \times_1 \mathbf{A} \times_2 \mathbf{B} = \mathbf{A}\mathbf{G}\mathbf{B}^{\mathsf{T}}$

Method

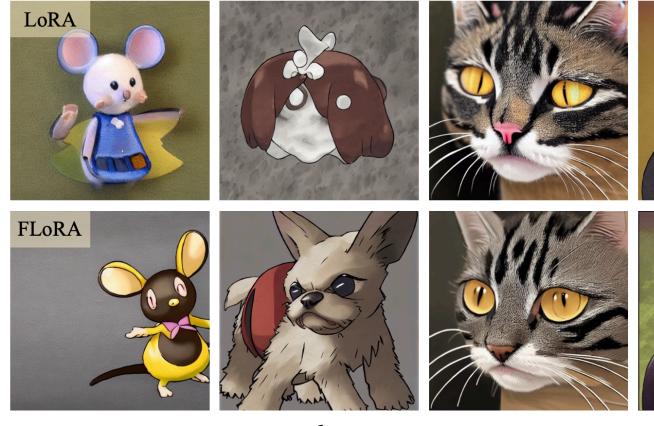
LoRA employs low-rank matrix adaptation for each dimensional parameter space. However, for higher dimensional parameter space, the reshaping operation causes adjacent elements within the kernel to be separated in the matrix, disrupting the spatial locality inherent in the original convolutional space.

 FLoRA asserts that the alternations of each dimensional parameter space has a low-rank core space with the consistent topological structure. This enables FLoRA to effectively preserve the structural integrity of the original parameter space.

$$s + s * \mathcal{G} \times_1 \mathbf{A}^{(1)} \times_2 \mathbf{A}^{(2)} \times \cdots \times_N \mathbf{A}^{(N)}$$

Experiment BitFit HAdapte PAdapter AdaLoRA LoRA DoRA FLoRA DOTA-mAP

Method	# Params	СОСО						ADE20K]
		mAP	AP_{50}	AP_{75}	AP_S	AP_M	AP_L	mAcc	mIoU	mAP
Base	-	37.3	63.3	39.7	27.8	41.0	46.2	59.6	48.5	31.4
Fully FT	196M	52.7	74.3	58.7	38.3	56.9	67.3	64.7	53.1	33.9
BitFit	0.2M	43.1	67.6	47.4	29.5	46.7	55.3	61.2	49.1	34.6
LoRA	12.94M	47.4	70.3	53.0	32.4	51.8	61.2	63.6	51.4	18.3
DoRA	13.07M	47.2	69.8	52.7	32.1	51.5	61.4	63.0	50.9	19.6
FLoRA	12.77M	48.1	71.1	53.6	33.1	52.3	62.3	64.1	51.9	37.3
LoRA	25.89M	48.0	70.4	53.6	33.0	52.3	62.8	63.9	51.4	20.0
DoRA	26.16M	48.1	70.7	53.6	33.1	52.1	62.6	64.0	51.9	21.1
FLoRA	25.65M	49.2	71.7	54.7	34.3	53.3	63.5	65.0	52.6	38.8
LoRA	51.78M	48.2	70.7	53.7	33.4	52.5	62.7	63.9	51.6	20.4
DoRA	51.95M	44.0	68.2	48.9	29.1	48.2	57.5	64.1	51.9	21.7
FLoRA	40.49M	50.4	72.6	56.2	35.4	54.6	64.8	65.1	52.8	39.7

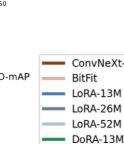


a mouse

a dog

an elephant





FLORA-15M							
FLORA-26M							
	FLOKA	-40M					
DOTA		All					
AP_{50}	AP_{75}	Avg.					
61.8	27.3	44.0					
59.9	34.0	54.0					
64.2	32.9	48.3					
36.2	16.3	45.6					
37.9	17.2	45.8					
65.6	37.7	52.5					
38.3	18.3	46.5					
39.7	19.1	46.9					
68.4	39.5	53.7					
39.4	19.1	46.9					
40.9	20.3	45.0					
69.0	40.9	54.7					

DoRA-26M

DoRA-52M

FLORA-13N

