



Parameter-Efficient Orthogonal Finetuning via Butterfly Factorization

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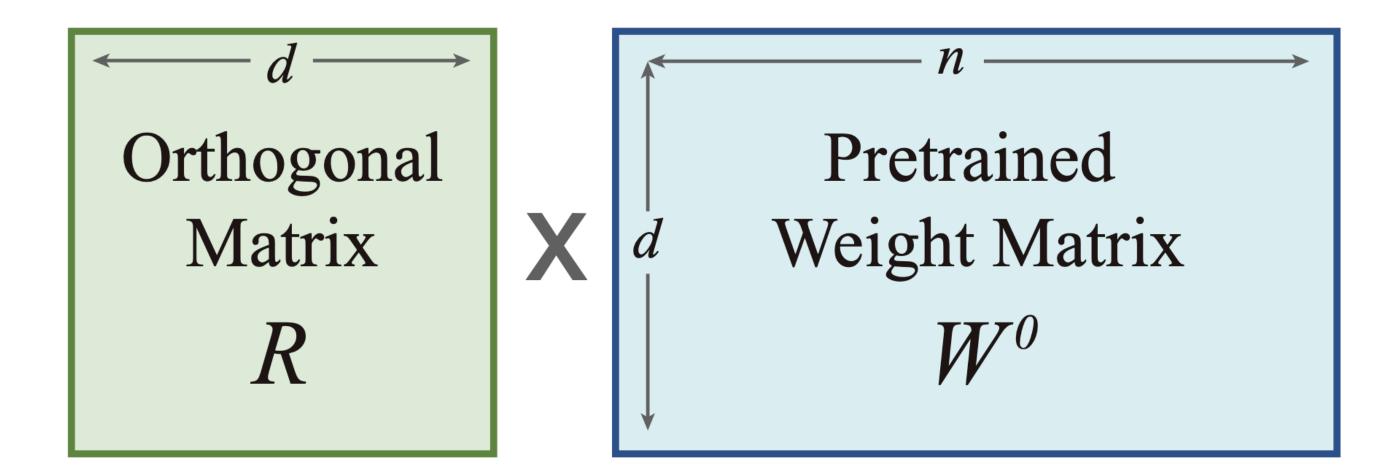






Orthogonal Finetuning

- Key idea: Angular information in neurons preserves semantics, so finetuning should preserve the angles between neurons.
- Method: Learn orthogonal multiplicative weight update



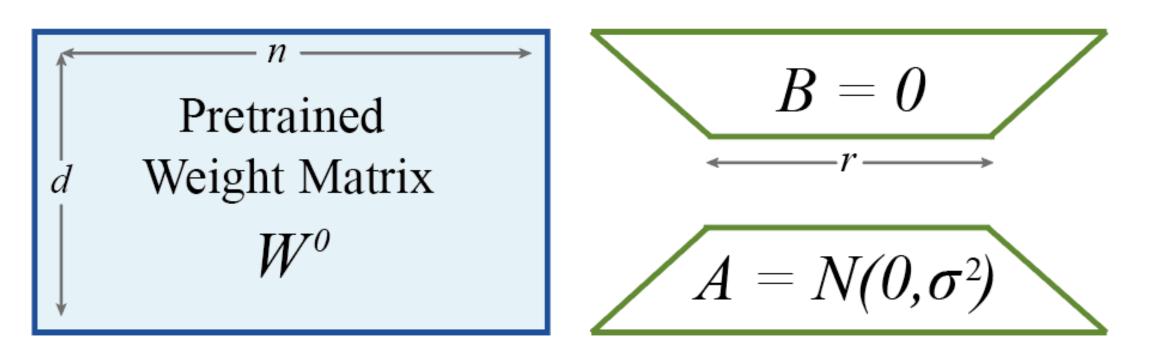
The hyperspherical energy does not change under the orthogonal transformation!

Qiu*, Liu*, et al. Controlling Text-to-Image Diffusion by Orthogonal Finetuning, NeurIPS 2023

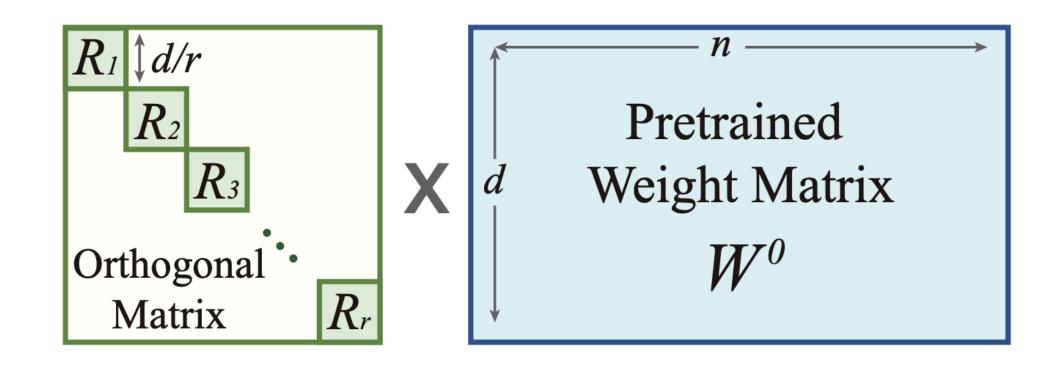


Comparison to Low-Rank Adaptation (LoRA)

• LoRA uses a low-rank additive weight update:



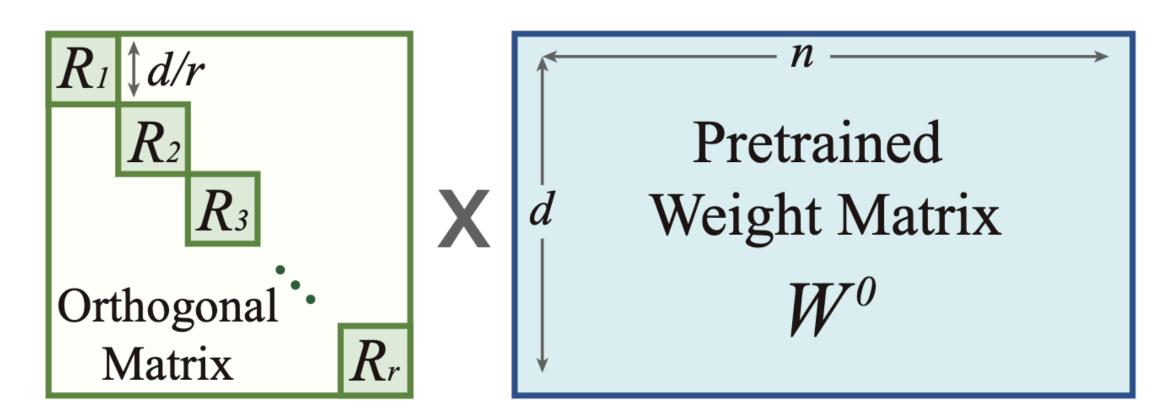
The block diagonal structure in OFT acts like the low-rank structure in LoRA



Hu, et al. LoRA: Low-Rank Adaptation of Large Language Models, ICLR 2022



Revisit OFT's Parameter-efficiency



Sparse orthogonal matrix

We need a dense orthogonal matrix!

Why the block-diagonal structure? What about other sparsity pattern? How to improve the expressiveness?

Parameter-efficiency vs. Dense connectivity





The Problem

- Orthogonal transformation happens separately in different blocks.
 - Makes no sense to group dimensions in advance \bigcirc
 - Less flexible and expressive for finetuning \bigcirc
- To address this problem, we have to produce a dense orthogonal matrix.

Parameter-efficiency vs. Dense connectivity

It seems impossible to have the best of both world.



Can we have a way to parameterize a dense orthogonal matrix while making it parameter-efficient?

Factorize into multiple sparse orthogonal matrices!



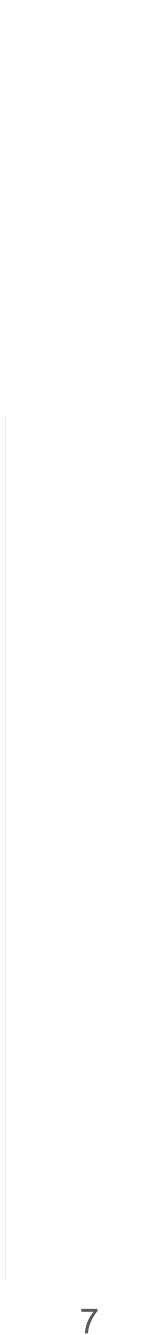


Inspiration

- Consider the fast Fourier transform algorithm:
 - recursive, divide-and-conquer \bigcirc

$$F_N x = \begin{bmatrix} F_{N/2} x_{\text{even}} + \Omega_{N/2} F_{N/2} x_{\text{odd}} \\ F_{N/2} x_{\text{even}} - \Omega_{N/2} F_{N/2} x_{\text{odd}} \end{bmatrix}$$
$$F_N = \begin{bmatrix} I_{N/2} & \Omega_{N/2} \\ I_{N/2} & -\Omega_{N/2} \end{bmatrix} \begin{bmatrix} F_{N/2} & 0 \\ 0 & F_{N/2} \end{bmatrix} \begin{bmatrix} \text{Sort} \\ \text{and odd} \end{bmatrix}$$

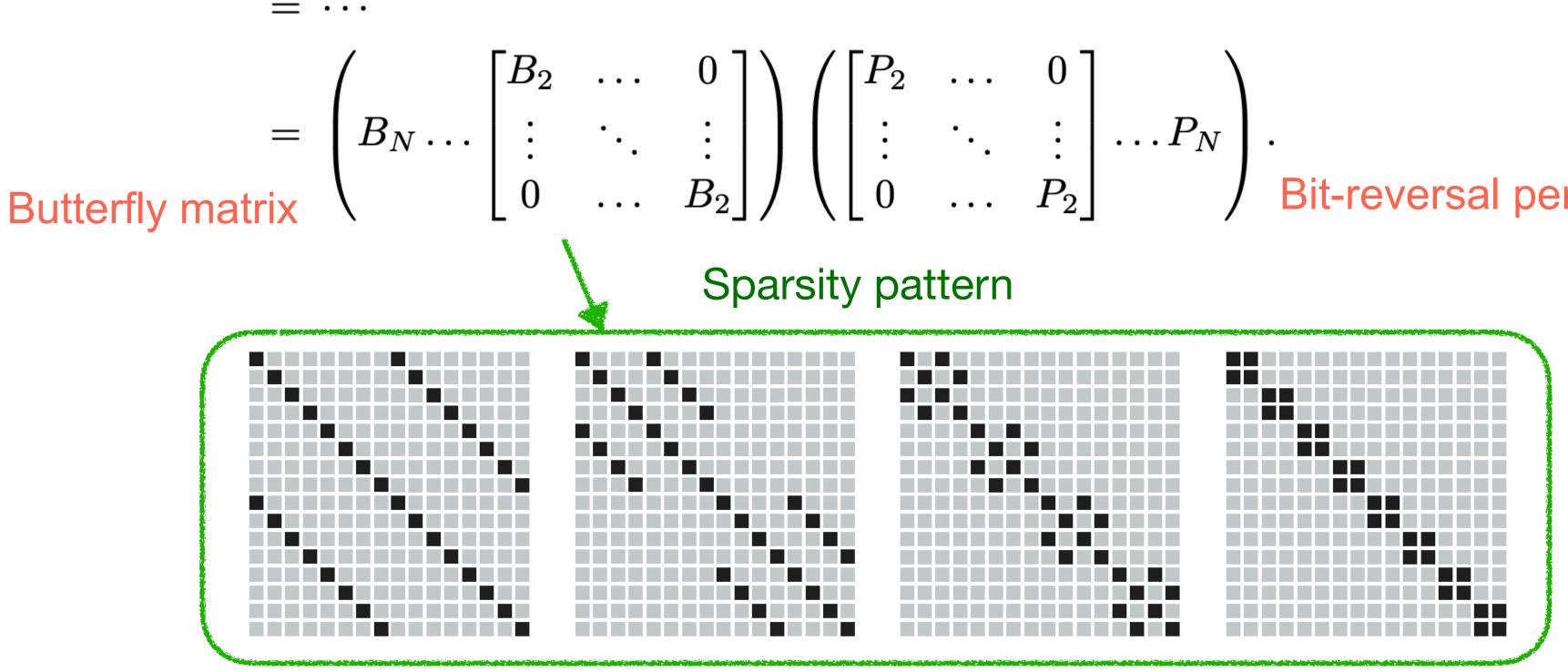
E[0] $\sum_{W_N^0} X[0]$ $x[0] \longrightarrow$ E[1] $x[2] \longrightarrow$ N/2-point E[2] DFT $x[4] \longrightarrow$ E[3] $x[6] \longrightarrow$ $\longrightarrow X[3]$ W_N^3 $\overset{\bullet}{\xrightarrow{}} X[4]$ $x[1] \longrightarrow$ O[0] $\overset{\bullet}{\xrightarrow{}} X[5]$ W^5_N $x[3] \longrightarrow$ the even O[1]N/2-point dd indices DFT $x[5] \sim$ $\overset{\blacktriangleright}{\overset{}}_{W^6_N} X[6]$ O[2] $x[7] \longrightarrow$ $\overset{\blacktriangleright}{\overset{}_{W_N^7}} X[7]$ O[3]



An efficient way to parameterize orthogonal matrices

$$F_N = B_N \begin{bmatrix} F_{N/2} & 0 \\ 0 & F_{N/2} \end{bmatrix} P_N$$

$$= B_N \begin{bmatrix} B_{N/2} & 0 \\ 0 & B_{N/2} \end{bmatrix} \begin{bmatrix} F_{N/4} & 0 \\ 0 & 0 \\ 0 \end{bmatrix}$$

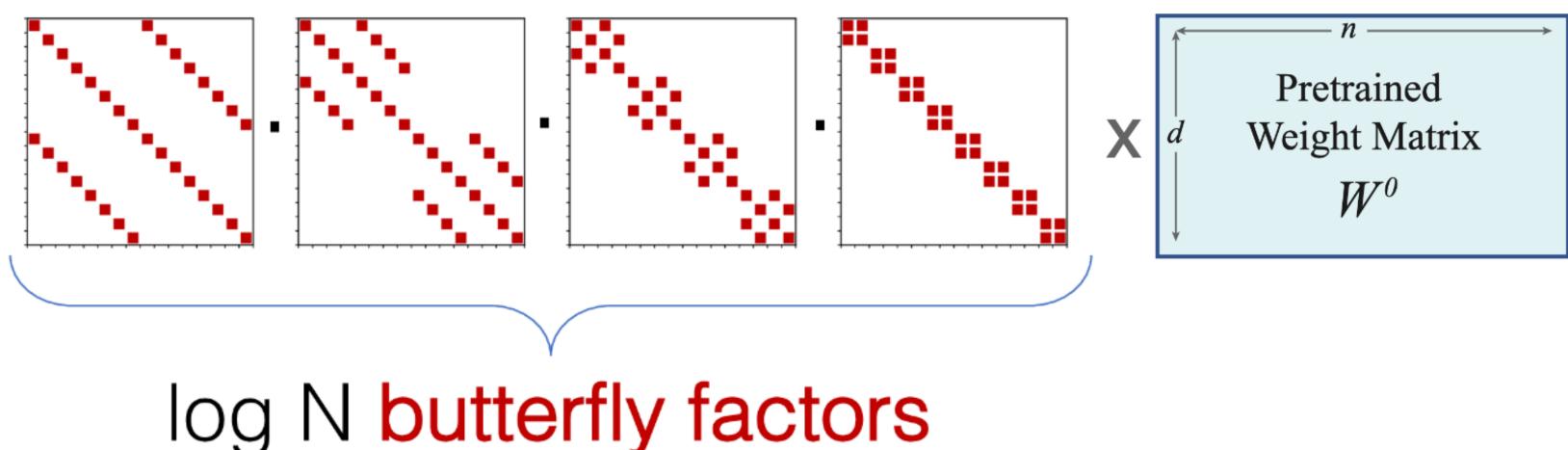


$$\begin{bmatrix} 0 & 0 & 0 \\ F_{N/4} & 0 & 0 \\ 0 & F_{N/4} & 0 \\ 0 & 0 & F_{N/4} \end{bmatrix} \begin{bmatrix} P_{N/2} & 0 \\ 0 & P_{N/2} \end{bmatrix} P_N$$

$$\left(\begin{bmatrix} P_2 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & P_2 \end{bmatrix} \dots P_N \right).$$
Bit-reversal permutation



Orthogonal Butterfly (BOFT)



- Ensure each butterfly factor to be orthogonal
 - We simply need to ensure each 2x2 block is orthogonal! \bigcirc
- A more efficient parameterization
 - From $O(d^2)$ to $O(d\log d)$

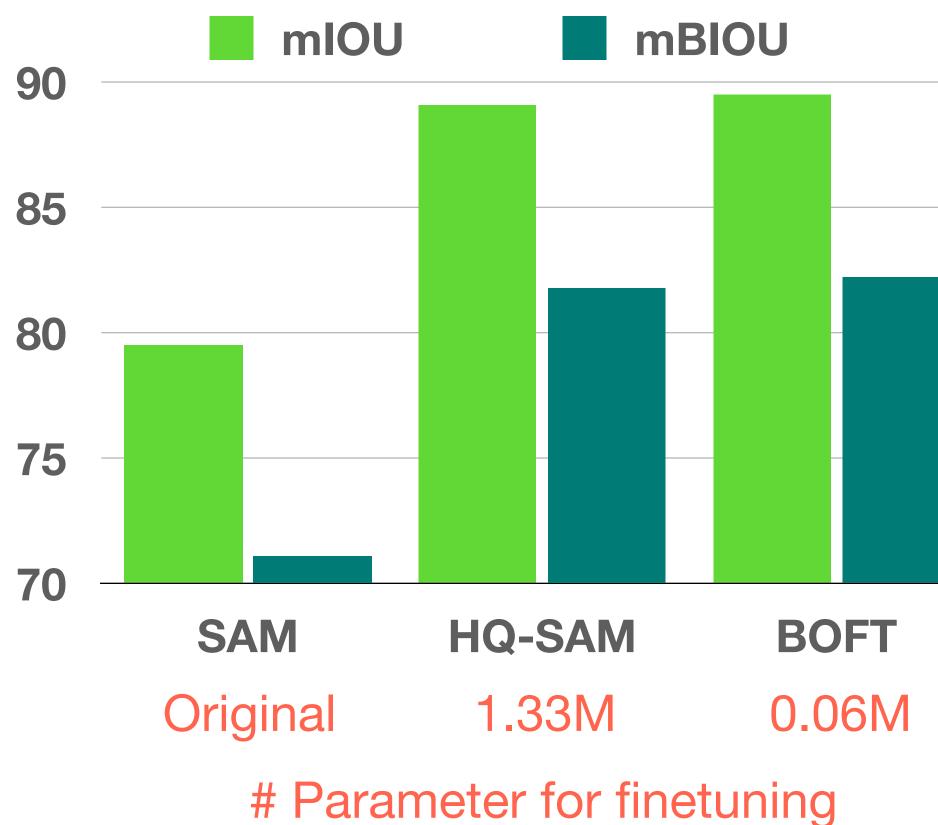
Liu*, et al. Parameter-Efficient Orthogonal Finetuning via Butterfly Factorization, ICLR 2024



Orthogonal Butterfly for Vision Tasks

Finetuning Segment Anything (SAM):









Orthogonal Butterfly for NLP Tasks

Finetuning Llama-2-7B on the Alpaca dataset and test on MMLU

			MMLU (5-shot)			MMLU (0-shot)						
	Method	# Param	Hums.	STEM	Social	Other	Avg.	Hums.	STEM	Social	Other	Avg.
	Llama-2-7B	-	43.0	36.9	51.6	52.1	45.7	38.8	33.3	46.8	45.0	40.8
	$LoRA_{r=16}$	0.125%	42.9	38.5	54.5	53.8	47.0	42.5	37.1	51.5	52.3	45.5
	$LoRA_{r=32}$	0.25%	42.9	38.7	54.6	54.7	47.3	42.5	36.7	52.8	52.7	45.9
	OFT $_{b=16}$	0.13%	44.0	38.9	54.2	54.3	47.5	44.0	36.7	52.9	52.0	46.2
	BOFT $_{b=8}^{m=2}$	0.12%	44.5	39.0	54.4	55.1	47.9	44.3	37.4	53.1	52.8	46.7

Method	# Param	GSM8K	MATH	
Llama-2-7B	-	14.6	2.5	
$LoRA_{r=32}$	0.25%	50.2	7.8	
OFT $_{b=16}$	0.13%	50.1	8.4	
BOFT $_{b=8}^{m=2}$	0.12%	50.6	8.6	

Finetuning Llama-2-7B on MetaMathQA-40K and test on math questions



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Orthogonal Butterfly for NLP Tasks

Finetuning Llama-2-7B on MetaMathQA-40K and test on math questions

Method	# Param	GSM8K	MATH
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$LoRA_{r=32}$	0.25%	50.2	7.8
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Example E.1: Case Study 1

Question: James much did he pay? Llama-2 Answer So he paid 5 * 4 * BOFT Answer: J pounds of beef. T

Example E.2: Case Study 2

Question: James meters does he ru Llama-2 Answer is 180. BOFT Answer: Each sprint is 60 r total of 540 meter

Question: James buys 5 packs of beef that are 4 pounds each. The price of beef is \$5.50 per pound. How much did he pay? (Ground-truth answer is 110)

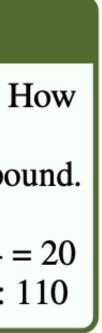
Llama-2 Answer: James bought 5 packs of beef that are 4 pounds each. The price of beef is 5.50 per pound. So he paid 5 * 4 * 5.50 = 137.50 dollars. The answer is 137.50.

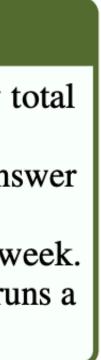
BOFT Answer: James bought 5 packs of beef, and each pack is 4 pounds, so he bought a total of 5 * 4 = 20 pounds of beef. The price of beef is \$5.50 per pound, so James paid 20 * \$5.50 = \$110. The answer is: 110

Question: James decides to run 3 sprints 3 times a week. He runs 60 meters each sprint. How many total meters does he run a week? (Ground-truth answer is 540)

Llama-2 Answer: James runs 60 meters each sprint. So he runs 60 * 3 = 180 meters each week. The answer

BOFT Answer: James runs 3 sprints 3 times a week, so he runs 3 sprints x 3 times = 9 sprints in a week. Each sprint is 60 meters, so James runs 9 sprints x 60 meters = 540 meters in a week. Therefore, James runs a total of 540 meters in a week. The answer is: 540







Orthogonal Butterfly for Text-to-image Tasks

• Qualitative results (controllable generation)

Text prompt: a man with blonde hair



Control signal



LoRA



OFT

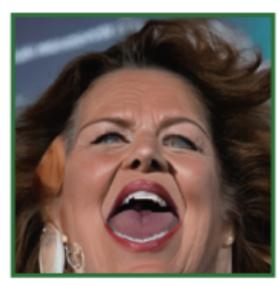


BOFT

Text prompt: a woman with her mouth open



Control signal



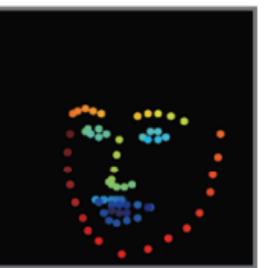




OFT



BOFT



Control signal

Text prompt: a man wearing a hat



LoRA







BOFT

Text prompt: a woman with long black hair



Control signal



LoRA







BOFT





Orthogonal Butterfly for Text-to-image Tasks

Qualitative results (subject-driven generation)



a [V] bowl with a wheat field in the background



a [V] bowl with a city in the background

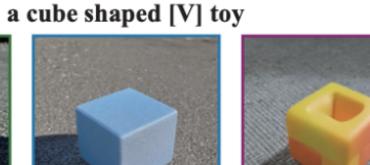


LoRA





BOFT





a [V] toy with a tree and autumn leaves in the background

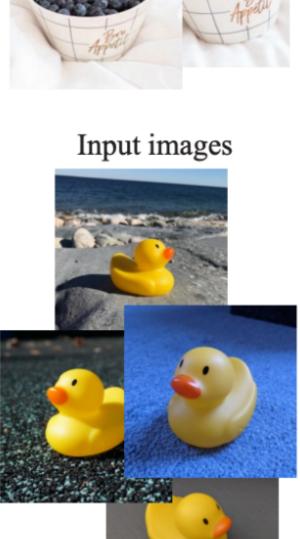


LoRA





BOFT



Input images



Input images



a shiny [V] backpack







a [V] backpack in the snow









BOFT





a [V] sneaker with the Eiffel Tower in the background















BOFT



BOFT comes with free weight interpolation

BOFT with 6 butterfly components

B₆ **B**₅ **B**₄ **B**₃ **B**₂ **B**₁



4 matrices

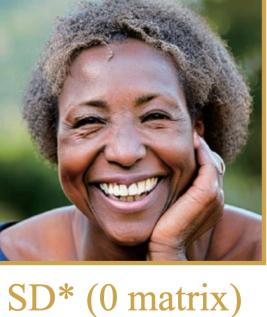
5 matrices



2 matrices

1 matrix





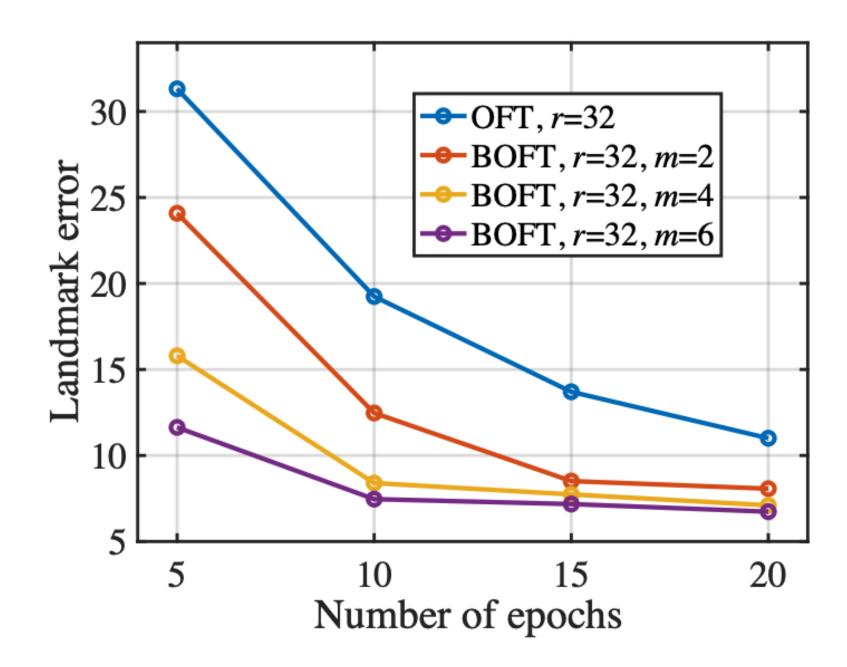




Orthogonal Butterfly for Text-to-image Tasks

• Quantitative results

Method	# Param	Error	
$LoRA_{r=128}$	20.17M	8.038	
$LoRA_{r=16}$	2.52M	8.878	
OFT $_{r=16}$	2.71M	8.876	
OFT $_{r=4}$	10.50M	6.537	
BOFT $m=2$ r=32	2.66M	8.070	
BOFT $_{r=16}^{m=5}$	12.93M	6.387	
BOFT $_{r=8}^{m=4}$	20.76M	5.667	





Thanks!

- Our project page: <u>https://boft.wyliu.com/</u>
- BOFT is integrated into the Hugging Face PEFT library.
 - https://huggingface.co/docs/peft/main/en/conceptual_guides/oft



Project page



Hugging Face PEFT