中国人民大學
RENMIN UNIVERSITY OF CHINA

高瓴人工智能学院
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Paper Sharing

LoRA：Low-Rank Adaptation of Large Language Models

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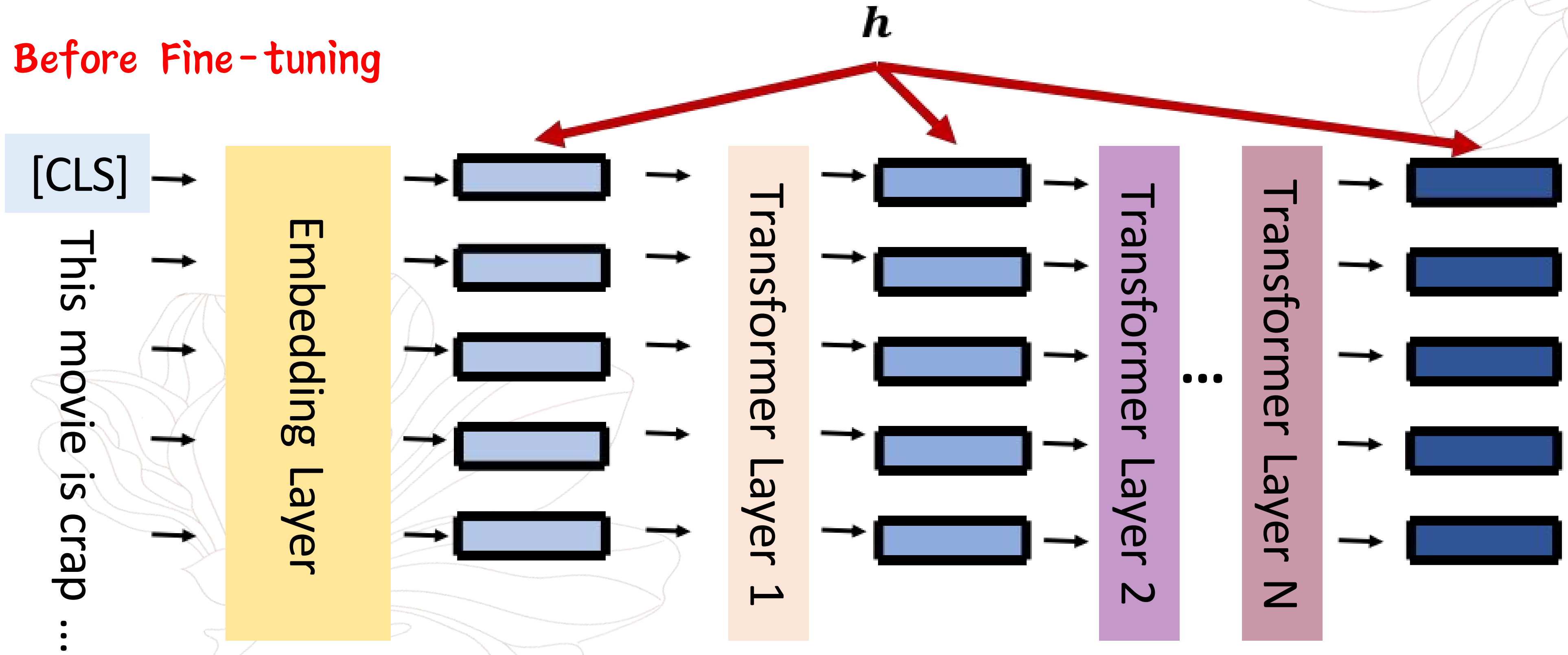
2024.1.18

Fine-tuning

- **What is standard fine-tuning really doing?**
- Modify the hidden representations (*h*) of the PLM such that it can perform well on downstream task

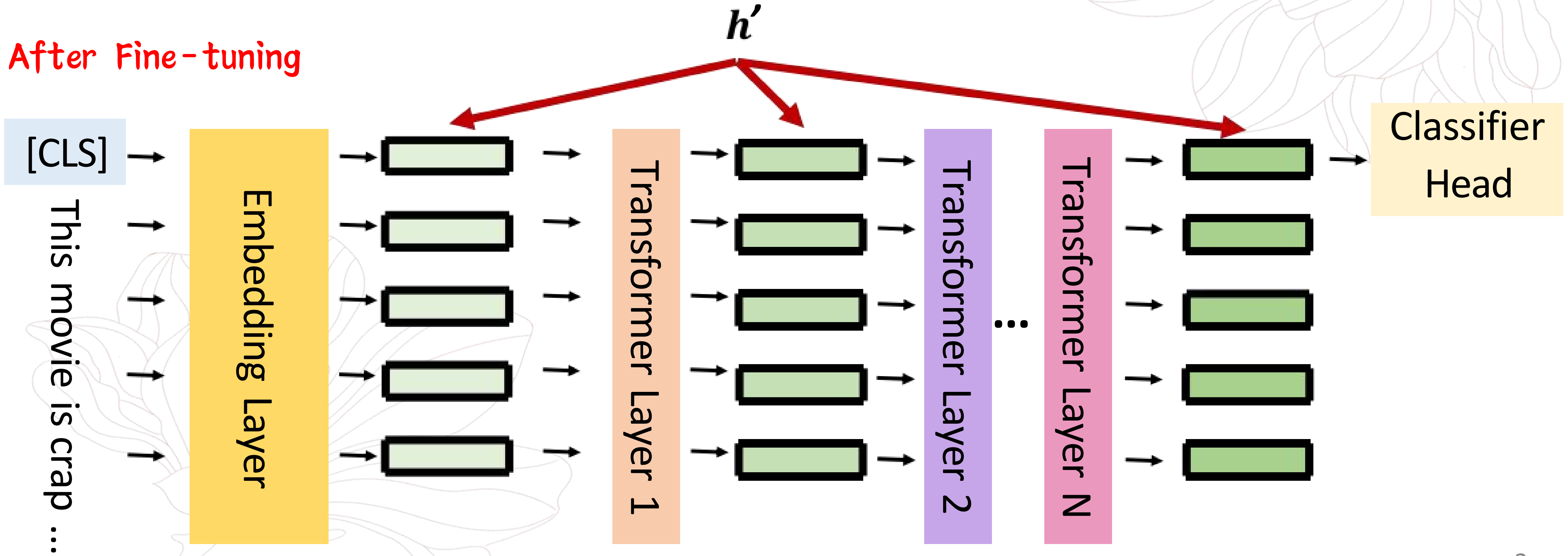
Before Fine-tuning



Fine-tuning

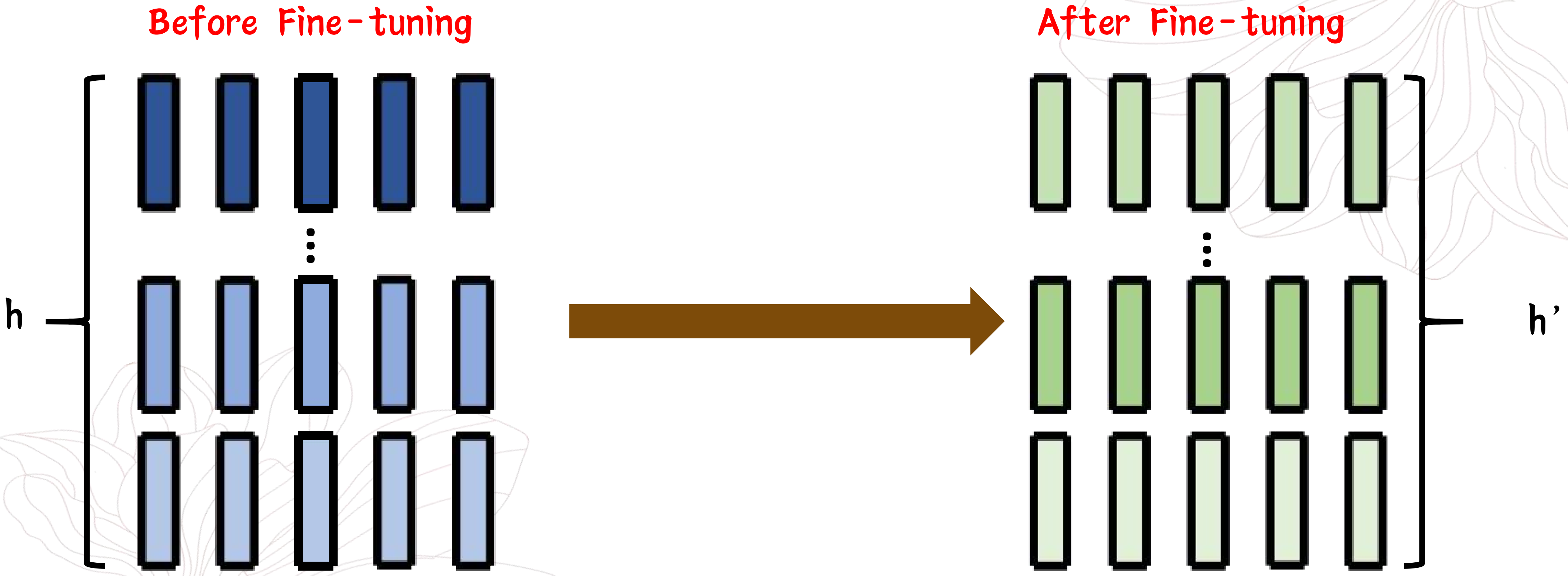
- What is standard fine-tuning really doing?
- Modify the hidden representations (h) of the PLM such that it can perform well on downstream task

After Fine-tuning



Parameter-Efficient Fine-tuning

- Fine-tuning = modifying the hidden representation based on a PLM



h: hidden representation calculated by the original PLM

h' : hidden representation calculated by the pre-trained model

Parameter-Efficient Fine-tuning

- However

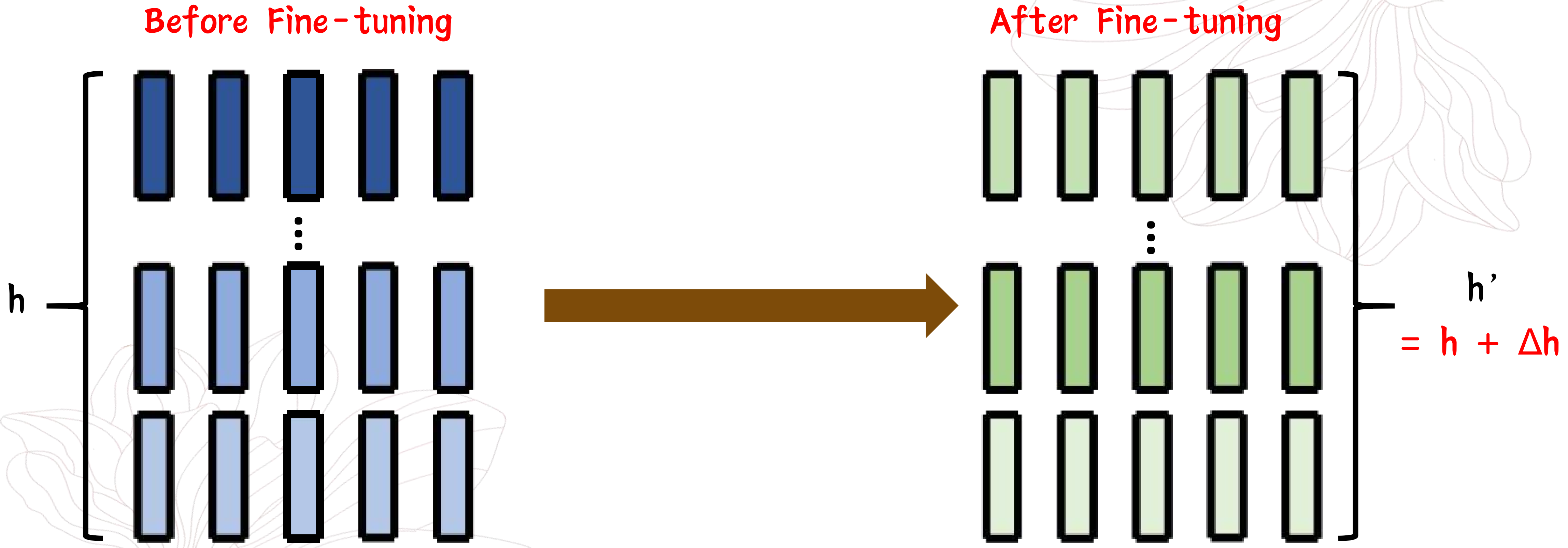
Finetune LLM is quite expensive

A more parameter-efficient approach is needed

$$\max_{\Phi} \sum_{(x,y)\in\mathcal{Z}} \sum_{t=1}^{|y|} \log\left(P_{\Phi}(y_t|x, y_{<t})\right) \quad \Longrightarrow \quad \max_{\Theta} \sum_{(x,y)\in\mathcal{Z}} \sum_{t=1}^{|y|} \log\left(p_{\Phi_0+\Delta\Phi(\Theta)}(y_t|x, y_{<t})\right)$$

Parameter-Efficient Fine-tuning

- Fine-tuning = modifying the hidden representation based on a PLM



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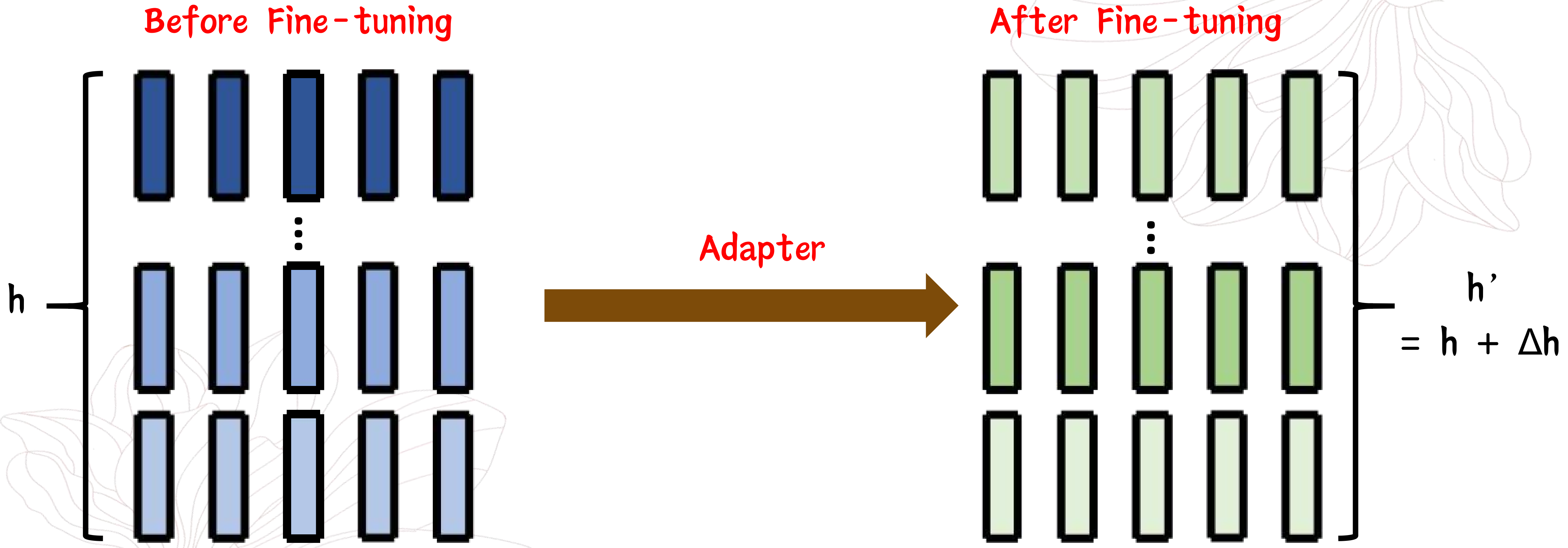
Parameter-Efficient Fine-tuning: Adapter

- Use special submodules to modify hidden representations



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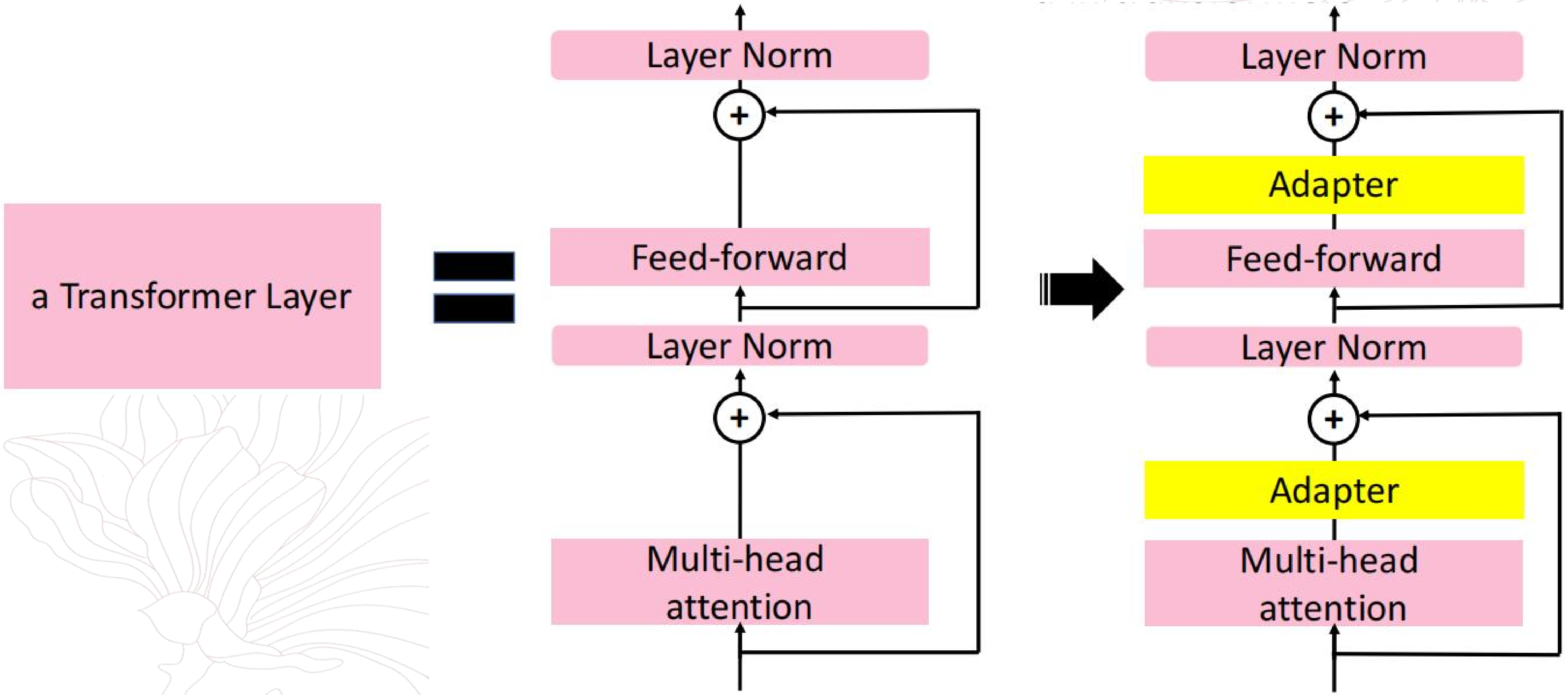
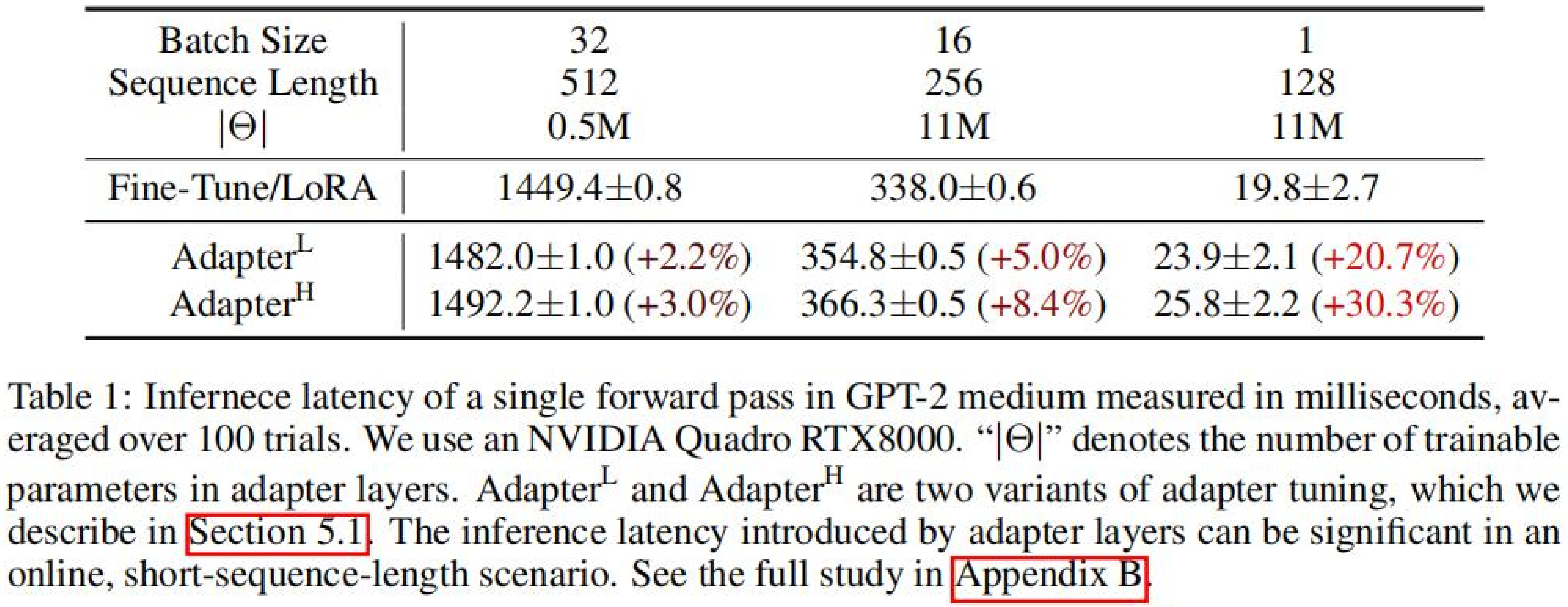
Parameter-Efficient Fine-tuning: Adapter

- Adapters: small trainable submodules inserted in transformers



Parameter-Efficient Fine-tuning: Adapter

- Adapters: Introduce Inference Latency



Batch Size	32	16	1
Sequence Length	512	256	128
$\|\Theta\|$	0.5M	11M	11M
Fine-Tune/LoRA	1449.4±0.8	338.0±0.6	19.8±2.7
Adapter^L	1482.0±1.0 (+2.2%)	354.8±0.5 (+5.0%)	23.9±2.1 (+20.7%)
Adapter^H	1492.2±1.0 (+3.0%)	366.3±0.5 (+8.4%)	25.8±2.2 (+30.3%)

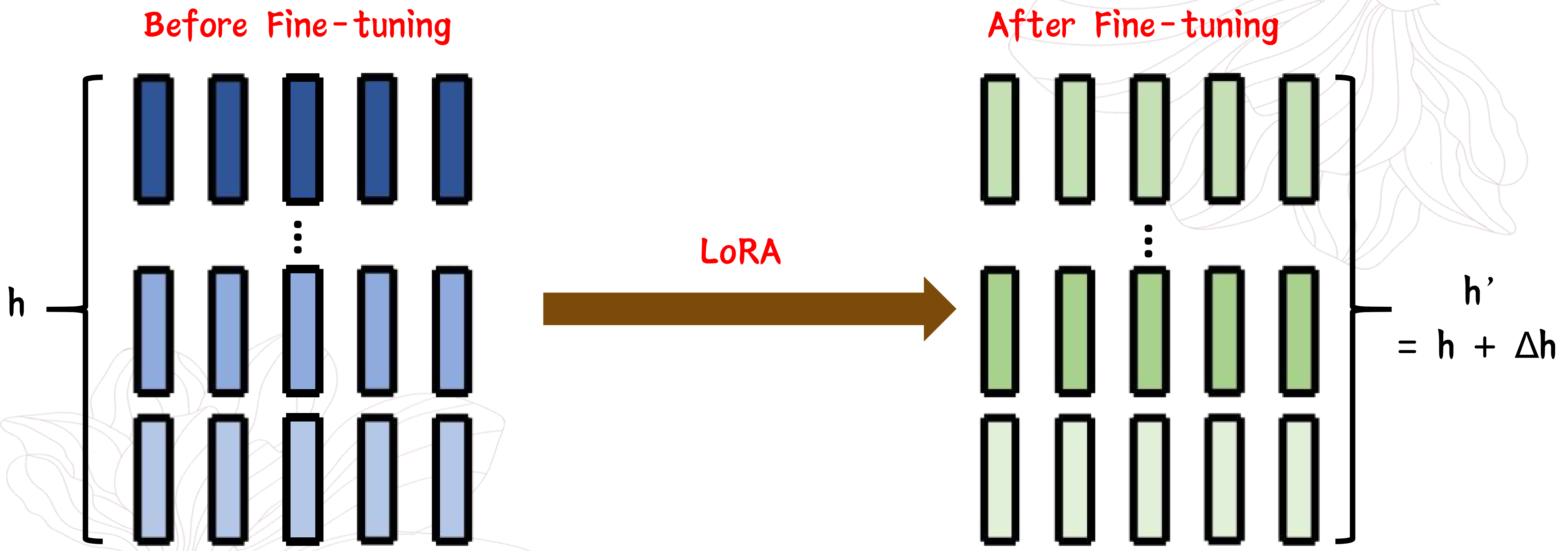
Table 1: Infernece latency of a single forward pass in GPT-2 medium measured in milliseconds, averaged over 100 trials. We use an NVIDIA Quadro RTX8000. "$|\Theta|$" denotes the number of trainable parameters in adapter layers. Adapter^L and Adapter^H are two variants of adapter tuning, which we describe in Section 5.1. The inference latency introduced by adapter layers can be significant in an online, short-sequence-length scenario. See the full study in Appendix B.

Parameter-Efficient Fine-tuning: Prefix

- Prefix
  - difficult to optimize
  - reserving a part of the sequence length for adaptation necessarily reduces the sequence length available to process a downstream task

Parameter-Efficient Fine-tuning: LoRA

- Use special submodules to modify hidden representations



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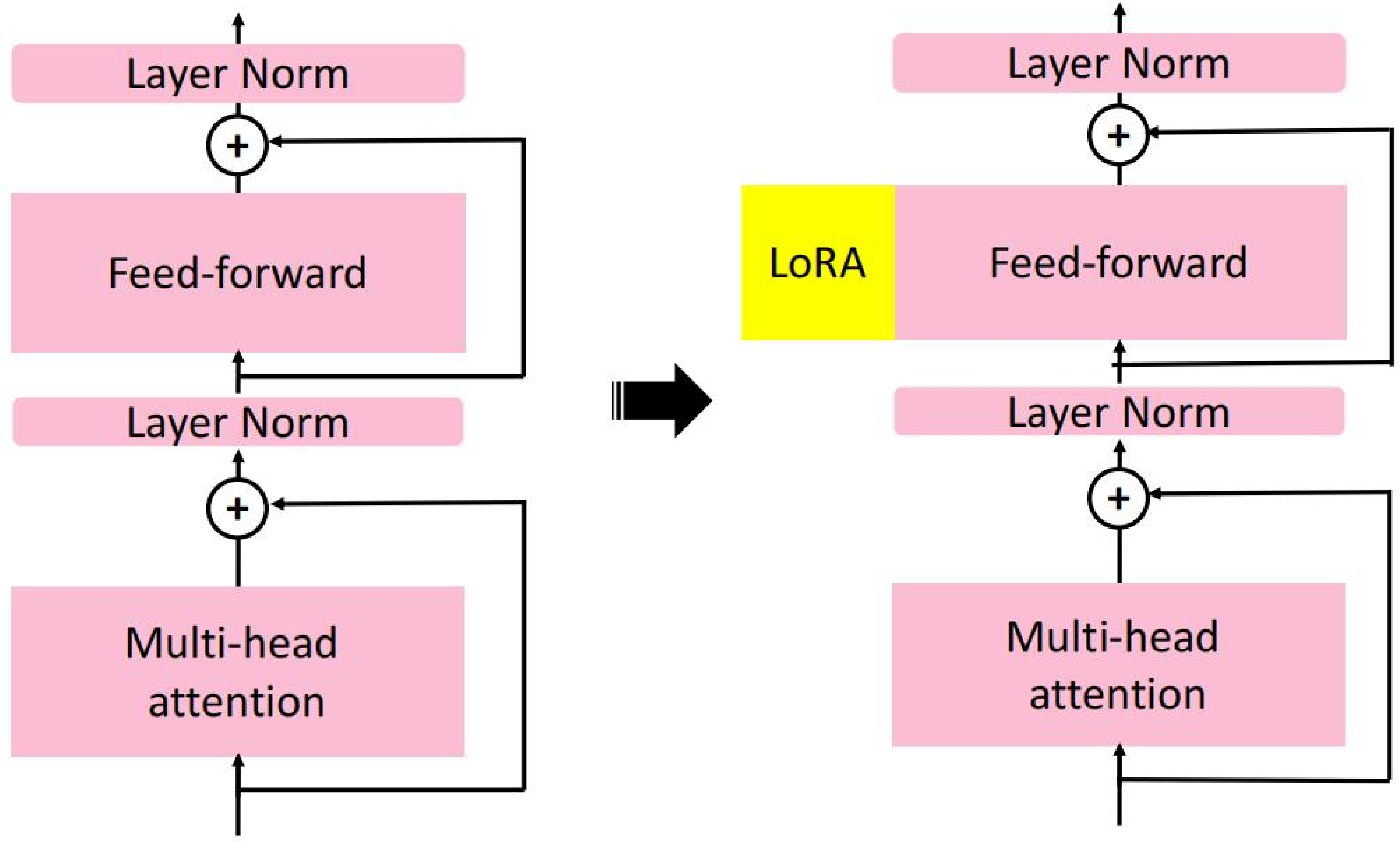
Parameter-Efficient Fine-tuning: LoRA

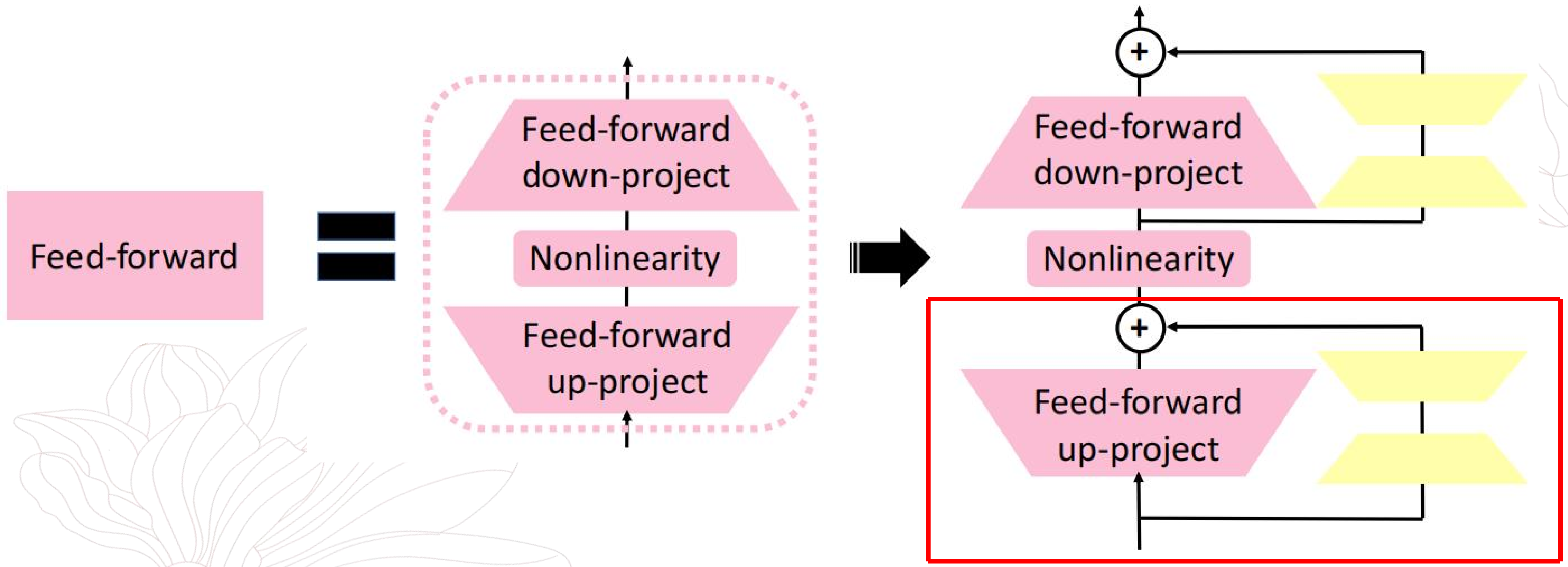
- LoRA: Low-Rank Adaptation of Large Language Models

transformer layer



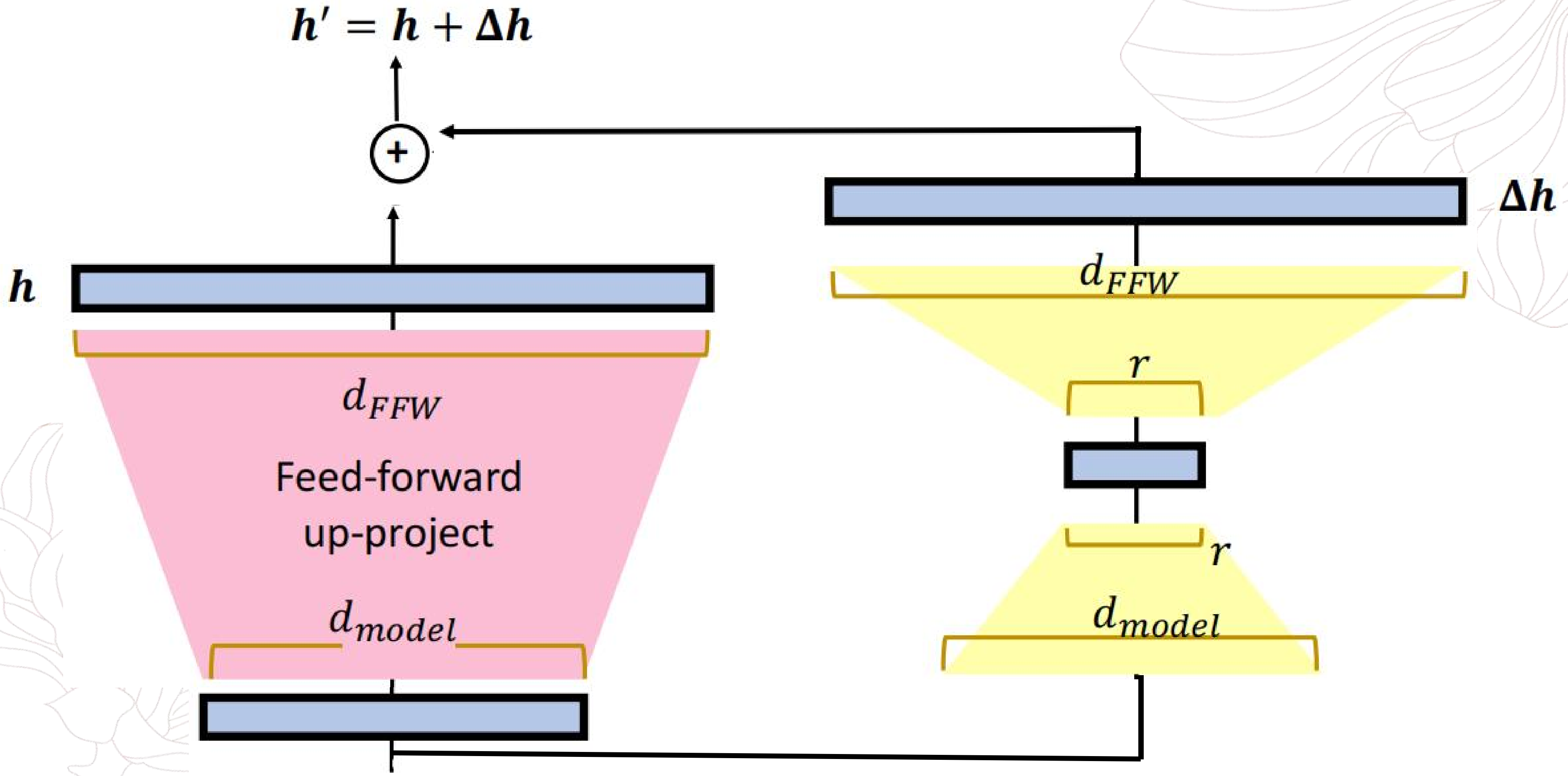
Parameter-Efficient Fine-tuning: LoRA

- LoRA: Low-Rank Adaptation of Large Language Models



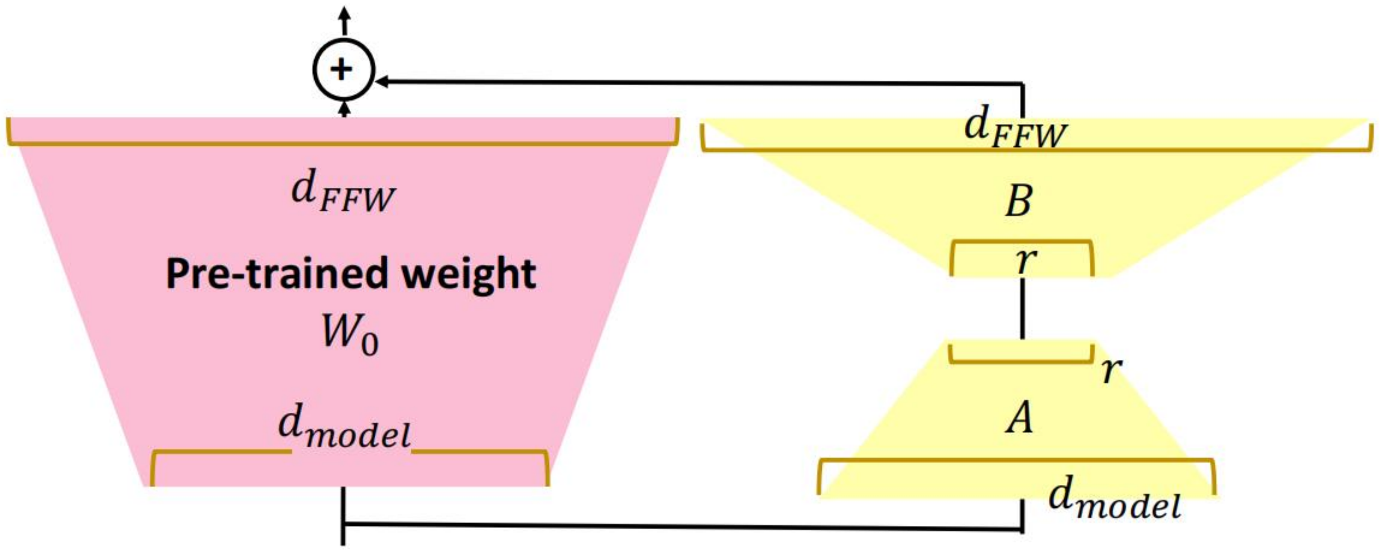
Parameter-Efficient Fine-tuning: LoRA

- LoRA



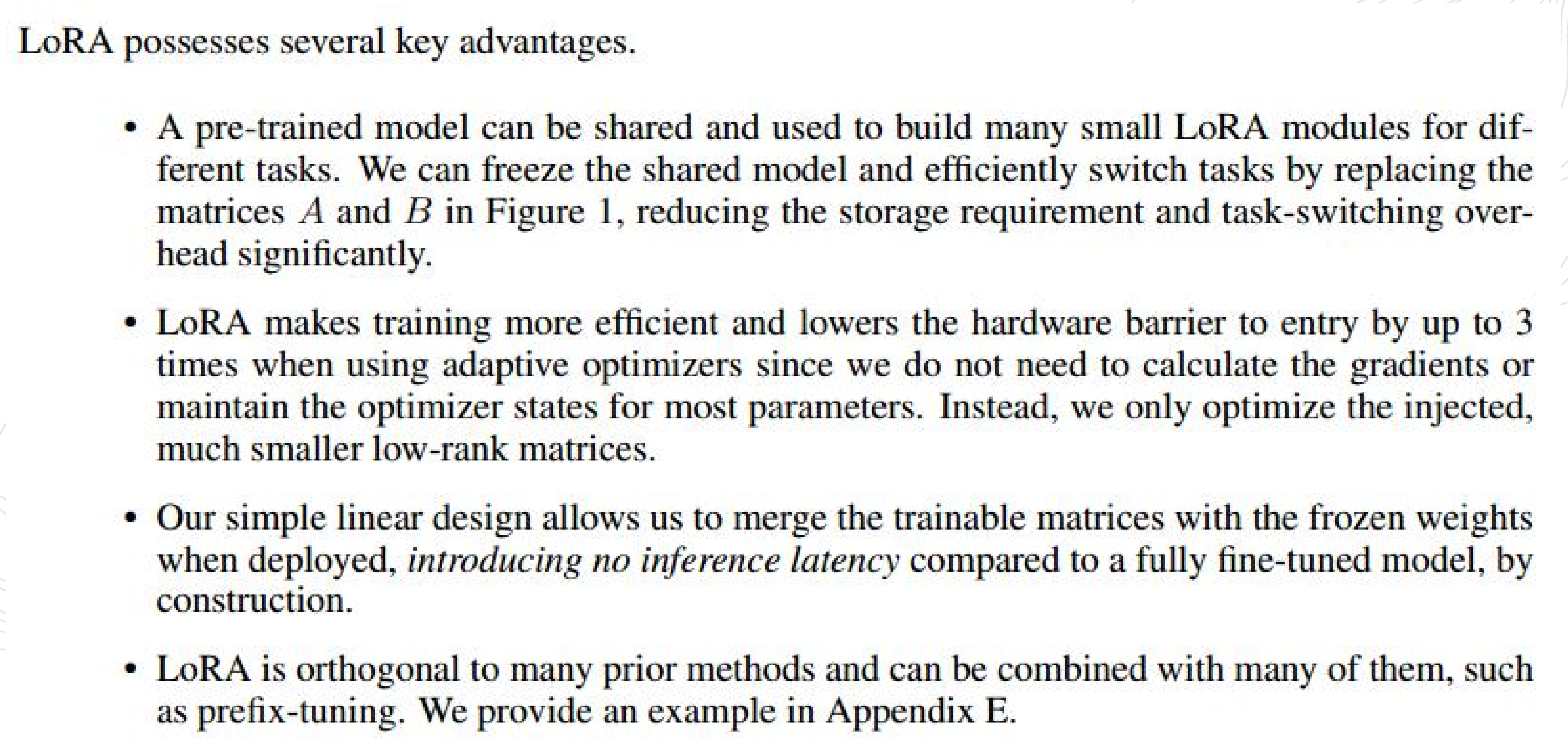
Parameter-Efficient Fine-tuning: LoRA

- LoRA
  - Low-Rank Adaptation of Large Language Models
  - Motivation: Downstream fine-tunings have low intrinsic dimension
  - Weight after fine-tuning = w_o (pre-trained weight) $+\Delta w$ (updates to the weight)
  - Hypothesis: The updates to the weight (Δw) also gives a low intrinsic rank
  - Fine-tuned weight = $w_o + \Delta w = w_o + BA$, rank $r \ll \min(d_{FFW}, d_{model})$



Parameter-Efficient Fine-tuning: LoRA

- LoRA

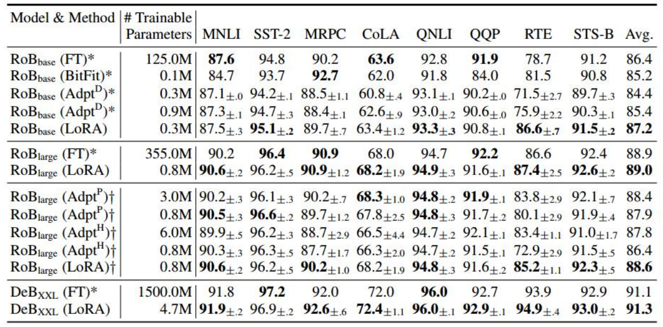


LoRA possesses several key advantages.

- A pre-trained model can be shared and used to build many small LoRA modules for different tasks. We can freeze the shared model and efficiently switch tasks by replacing the matrices A and B in Figure 1, reducing the storage requirement and task-switching overhead significantly.
- LoRA makes training more efficient and lowers the hardware barrier to entry by up to 3 times when using adaptive optimizers since we do not need to calculate the gradients or maintain the optimizer states for most parameters. Instead, we only optimize the injected, much smaller low-rank matrices.
- Our simple linear design allows us to merge the trainable matrices with the frozen weights when deployed, *introducing no inference latency* compared to a fully fine-tuned model, by construction.
- LoRA is orthogonal to many prior methods and can be combined with many of them, such as prefix-tuning. We provide an example in Appendix E.

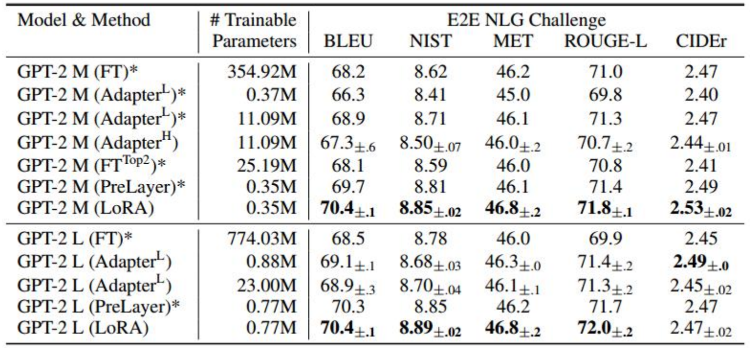
Experiments

- LoRA



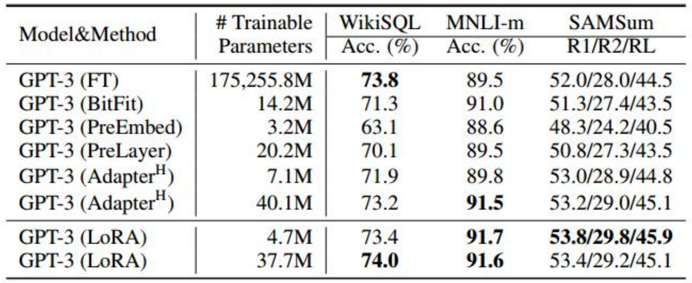
Model & Method	# Trainable Parameters	MNLI	SST-2	MRPC	CoLA	QNLI	QQP	RTE	STS-B	Avg.
RoB$_{\text{base}}$ (FT)*	125.0M	**87.6**	94.8	90.2	**63.6**	92.8	**91.9**	78.7	91.2	86.4
RoB$_{\text{base}}$ (BitFit)*	0.1M	84.7	93.7	**92.7**	62.0	91.8	84.0	81.5	90.8	85.2
RoB$_{\text{base}}$ (Adpt$^{\text{D}}$)*	0.3M	$87.1_{\pm.0}$	$94.2_{\pm.1}$	$88.5_{\pm1.1}$	$60.8_{\pm.4}$	$93.1_{\pm.1}$	$90.2_{\pm.0}$	$71.5_{\pm2.7}$	$89.7_{\pm.3}$	84.4
RoB$_{\text{base}}$ (Adpt$^{\text{D}}$)*	0.9M	$87.3_{\pm.1}$	$94.7_{\pm.3}$	$88.4_{\pm.1}$	$62.6_{\pm.9}$	$93.0_{\pm.2}$	$90.6_{\pm.0}$	$75.9_{\pm2.2}$	$90.3_{\pm.1}$	85.4
RoB$_{\text{base}}$ (LoRA)	0.3M	$87.5_{\pm.3}$	**95.1**$_{\pm.2}$	$89.7_{\pm.7}$	$63.4_{\pm1.2}$	**93.3**$_{\pm.3}$	$90.8_{\pm.1}$	**86.6**$_{\pm.7}$	**91.5**$_{\pm.2}$	**87.2**
RoB$_{\text{large}}$ (FT)*	355.0M	90.2	**96.4**	**90.9**	68.0	94.7	**92.2**	86.6	92.4	88.9
RoB$_{\text{large}}$ (LoRA)	0.8M	**90.6**$_{\pm.2}$	$96.2_{\pm.5}$	**90.9**$_{\pm1.2}$	**68.2**$_{\pm1.9}$	**94.9**$_{\pm.3}$	$91.6_{\pm.1}$	**87.4**$_{\pm2.5}$	**92.6**$_{\pm.2}$	**89.0**
RoB$_{\text{large}}$ (Adpt$^{\text{P}}$)†	3.0M	$90.2_{\pm.3}$	$96.1_{\pm.3}$	$90.2_{\pm.7}$	**68.3**$_{\pm1.0}$	**94.8**$_{\pm.2}$	**91.9**$_{\pm.1}$	$83.8_{\pm2.9}$	$92.1_{\pm.7}$	88.4
RoB$_{\text{large}}$ (Adpt$^{\text{P}}$)†	0.8M	**90.5**$_{\pm.3}$	**96.6**$_{\pm.2}$	$89.7_{\pm1.2}$	$67.8_{\pm2.5}$	**94.8**$_{\pm.3}$	$91.7_{\pm.2}$	$80.1_{\pm2.9}$	$91.9_{\pm.4}$	87.9
RoB$_{\text{large}}$ (Adpt$^{\text{H}}$)†	6.0M	$89.9_{\pm.5}$	$96.2_{\pm.3}$	$88.7_{\pm2.9}$	$66.5_{\pm4.4}$	$94.7_{\pm.2}$	$92.1_{\pm.1}$	$83.4_{\pm1.1}$	$91.0_{\pm1.7}$	87.8
RoB$_{\text{large}}$ (Adpt$^{\text{H}}$)†	0.8M	$90.3_{\pm.3}$	$96.3_{\pm.5}$	$87.7_{\pm1.7}$	$66.3_{\pm2.0}$	$94.7_{\pm.2}$	$91.5_{\pm.1}$	$72.9_{\pm2.9}$	$91.5_{\pm.5}$	86.4
RoB$_{\text{large}}$ (LoRA)†	0.8M	**90.6**$_{\pm.2}$	$96.2_{\pm.5}$	**90.2**$_{\pm1.0}$	$68.2_{\pm1.9}$	**94.8**$_{\pm.3}$	$91.6_{\pm.2}$	**85.2**$_{\pm1.1}$	**92.3**$_{\pm.5}$	**88.6**
DeB$_{\text{XXL}}$ (FT)*	1500.0M	91.8	**97.2**	92.0	72.0	**96.0**	92.7	93.9	92.9	91.1
DeB$_{\text{XXL}}$ (LoRA)	4.7M	**91.9**$_{\pm.2}$	$96.9_{\pm.2}$	**92.6**$_{\pm.6}$	**72.4**$_{\pm1.1}$	**96.0**$_{\pm.1}$	**92.9**$_{\pm.1}$	**94.9**$_{\pm.4}$	**93.0**$_{\pm.2}$	**91.3**

Table 2: RoBERTa$_{\text{base}}$, RoBERTa$_{\text{large}}$, and DeBERTa$_{\text{XXL}}$ with different adaptation methods on the GLUE benchmark. We report the overall (matched and mismatched) accuracy for MNLI, Matthew's correlation for CoLA, Pearson correlation for STS-B, and accuracy for other tasks. Higher is better for all metrics. * indicates numbers published in prior works. † indicates runs configured in a setup similar to Houlsby et al. (2019) for a fair comparison.



Model & Method	# Trainable Parameters	E2E NLG Challenge				
		BLEU	NIST	MET	ROUGE-L	CIDEr
GPT-2 M (FT)*	354.92M	68.2	8.62	46.2	71.0	2.47
GPT-2 M (Adapter$^{\text{L}}$)*	0.37M	66.3	8.41	45.0	69.8	2.40
GPT-2 M (Adapter$^{\text{L}}$)*	11.09M	68.9	8.71	46.1	71.3	2.47
GPT-2 M (Adapter$^{\text{H}}$)	11.09M	$67.3_{\pm.6}$	$8.50_{\pm.07}$	$46.0_{\pm.2}$	$70.7_{\pm.2}$	$2.44_{\pm.01}$
GPT-2 M (FT$^{\text{Top2}}$)*	25.19M	68.1	8.59	46.0	70.8	2.41
GPT-2 M (PreLayer)*	0.35M	69.7	8.81	46.1	71.4	2.49
GPT-2 M (LoRA)	0.35M	**70.4**$_{\pm.1}$	**8.85**$_{\pm.02}$	**46.8**$_{\pm.2}$	**71.8**$_{\pm.1}$	**2.53**$_{\pm.02}$
GPT-2 L (FT)*	774.03M	68.5	8.78	46.0	69.9	2.45
GPT-2 L (Adapter$^{\text{L}}$)	0.88M	$69.1_{\pm.1}$	$8.68_{\pm.03}$	$46.3_{\pm.0}$	$71.4_{\pm.2}$	**2.49**$_{\pm.0}$
GPT-2 L (Adapter$^{\text{L}}$)	23.00M	$68.9_{\pm.3}$	$8.70_{\pm.04}$	$46.1_{\pm.1}$	$71.3_{\pm.2}$	$2.45_{\pm.02}$
GPT-2 L (PreLayer)*	0.77M	70.3	8.85	46.2	71.7	2.47
GPT-2 L (LoRA)	0.77M	**70.4**$_{\pm.1}$	**8.89**$_{\pm.02}$	**46.8**$_{\pm.2}$	**72.0**$_{\pm.2}$	$2.47_{\pm.02}$

Table 3: GPT-2 medium (M) and large (L) with different adaptation methods on the E2E NLG Challenge. For all metrics, higher is better. LoRA outperforms several baselines with comparable or fewer trainable parameters. Confidence intervals are shown for experiments we ran. * indicates numbers published in prior works.



Model&Method	# Trainable Parameters	WikiSQL Acc. (%)	MNLI-m Acc. (%)	SAMSum R1/R2/RL
GPT-3 (FT)	175,255.8M	**73.8**	89.5	52.0/28.0/44.5
GPT-3 (BitFit)	14.2M	71.3	91.0	51.3/27.4/43.5
GPT-3 (PreEmbed)	3.2M	63.1	88.6	48.3/24.2/40.5
GPT-3 (PreLayer)	20.2M	70.1	89.5	50.8/27.3/43.5
GPT-3 (Adapter$^{\text{H}}$)	7.1M	71.9	89.8	53.0/28.9/44.8
GPT-3 (Adapter$^{\text{H}}$)	40.1M	73.2	**91.5**	53.2/29.0/45.1
GPT-3 (LoRA)	4.7M	73.4	**91.7**	**53.8/29.8/45.9**
GPT-3 (LoRA)	37.7M	**74.0**	**91.6**	53.4/29.2/45.1

Table 4: Performance of different adaptation methods on GPT-3 175B. We report the logical form validation accuracy on WikiSQL, validation accuracy on MultiNLI-matched, and Rouge-1/2/L on SAMSum. LoRA performs better than prior approaches, including full fine-tuning. The results on WikiSQL have a fluctuation around $\pm0.5\%$, MNLI-m around $\pm0.1\%$, and SAMSum around $\pm0.2/\pm0.2/\pm0.1$ for the three metrics.

Thank you for listening

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