LORA: LOW-RANK ADAPTATION OF LARGE LANGUAGE MODELS

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Presented by,
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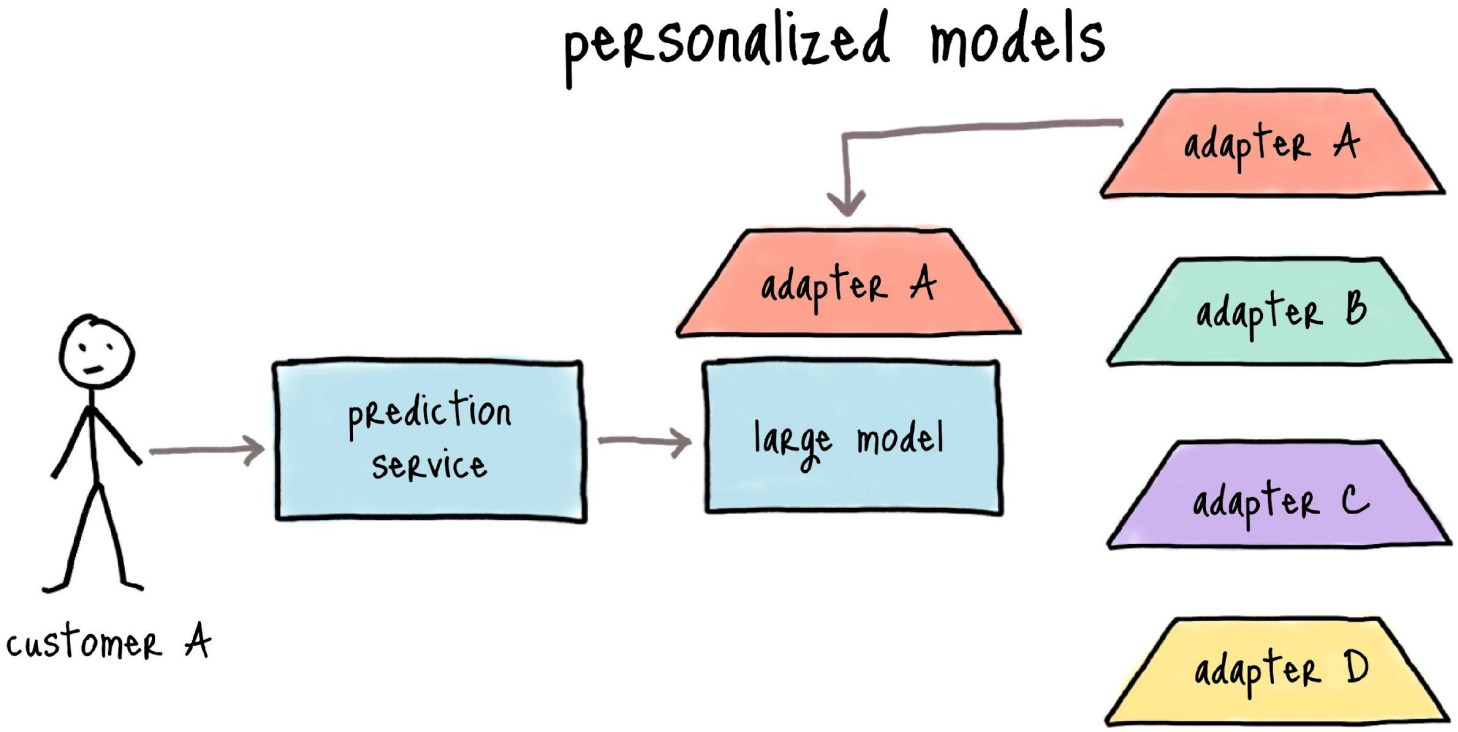

personalized models
adapter A
adapter A
adapter B
prediction service
large model
adapter C
adapter D
customer A

Challenges with Existing Adaptation Methods

Adapter Layers:

Small modules inserted into transformer layers.Their purpose is to modify the model's behavior for specific tasks without fine-tuning the entire network.

Advantages: Parameter-efficient; supports multi-task learning

Problems:

- **Inference Latency:** Additional depth increases sequential computations.
- **Scalability Issues:** Requires GPU synchronization (e.g., AllReduce) in large-scale deployments.

Prompt Tuning:

Modifies **input tokens** with task-specific prefixes.

Example:

Input sequence: "Translate English to French: What is your name?"

With prompt tuning: "[TASK_SPECIFIC] Translate English to French: What is your name?"

Advantages: Keeps model weights frozen; lightweight.

Problems:

- **Optimization Difficulty:** Training prompt embeddings is unstable.
- **Sequence Length Reduction:** Prefix tokens reduce space for task input.

Eckart-Young Theorem

Given a matrix $A \in R^{m \times n}$ and its singular value decomposition:

$$A = U\Sigma V^T$$

where $\Sigma = \text{diag}(\sigma_1, \sigma_2, ..., \sigma_r)$, with $\sigma_1 \geq \sigma_2 \geq ... \geq \sigma_r > 0$ (singular values), the best rank-k approximation of A, in the Frobenius norm, is:

$$A_k = U_k \Sigma_k V_k^T$$

where Σ_k is the diagonal matrix containing the top k singular values, and U_k, V_k are the corresponding singular vectors.

Key Ideas of LoRA

- Instead of updating all model parameters, LoRA injects trainable low-rank matrices into the pretrained weights.
- Pretrained weights remain frozen, reducing computational overhead.
- Parameter updates are represented as the product of two low-rank matrices.
- Gradients scaled by α/r

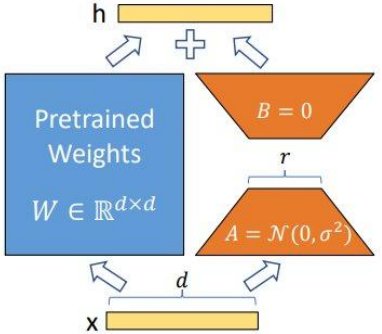


Figure 1: Our reparametrization. We only train A and B.

$$h = W_0 x + \Delta W x = W_0 x + BAx$$

LoRA Memory Efficiency

- The low-rank structure significantly reduces memory overhead and computational complexity during training.

  Storage: $d \times k \rightarrow r(d+k)$
  - Example: For d=512, k=512, r=8
  - Original: 262,144 parameters
  - LoRA: 8,192 parameters (96.9% reduction)

- Maintains expressiveness of full-rank updates with far fewer trainable parameters.

https://colab.research.google.com/drive/1DzArDRxgcPiu32fwWd3BgREy9SKRcOJ_

https://colab.research.google.com/drive/142Wy4B5cVUWnzS2JaSt9jPsyVcYTtB3O

Applications of LoRA

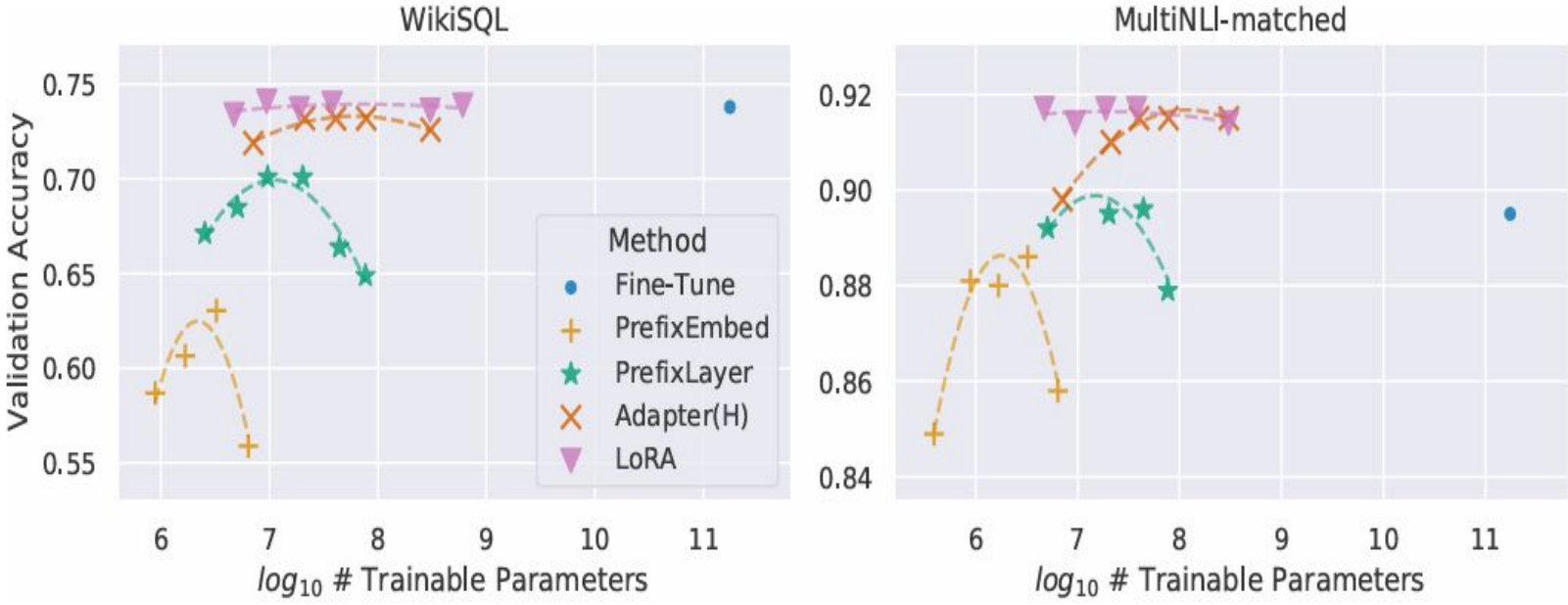
1. Natural Language Processing (NLP)
    a. **Text Classification**: Fine-tuning LLMs like RoBERTa, BERT, or GPT for sentiment analysis, spam detection, or topic classification with minimal parameter updates.
    b. **Question Answering (QA)**: Tuning models like RoBERTa or GPT for domain-specific Q&A applications, such as customer support or medical FAQs.
2. Personalized AI and Chatbots
3. Generative AI

EMPIRICAL EXPERIMENTS

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

EMPIRICAL EXPERIMENTS

GPT-3 175 B



CONCLUSION

Fine-tuning enormous language models is expensive in terms of the hardware required and the storage/switching cost for hosting independent instances for different tasks.

LoRA, an efficient adaptation strategy that neither introduces inference latency nor reduces input sequence length while retaining high model quality.

References

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Thank you!