Parameter-efficient fine-tuning

CS 5624: Natural Language Processing

Spring 2025

https://tuvllms.github.io/nlp-spring-2025

Tu Vu

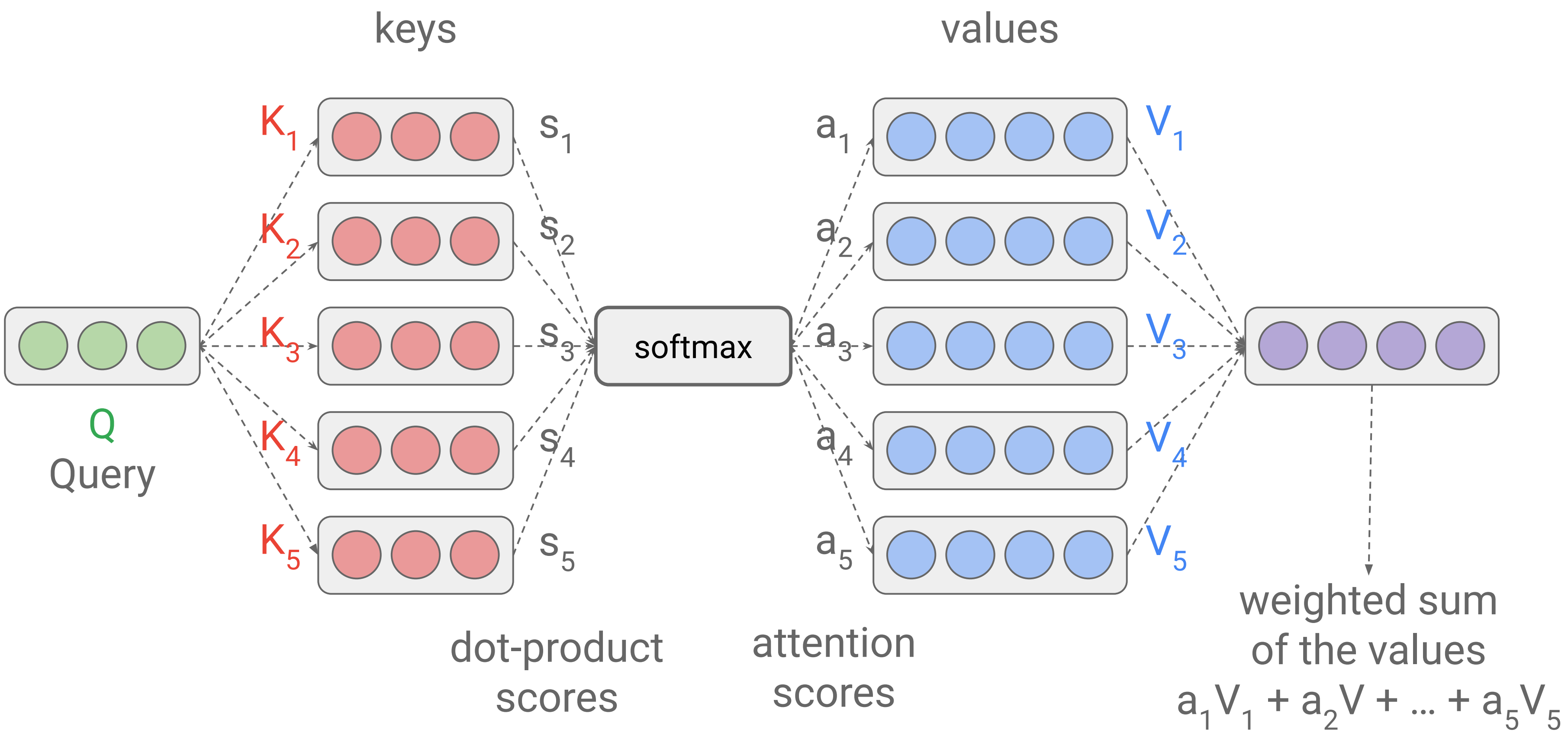
VIRGINIA TECH.

Logistics

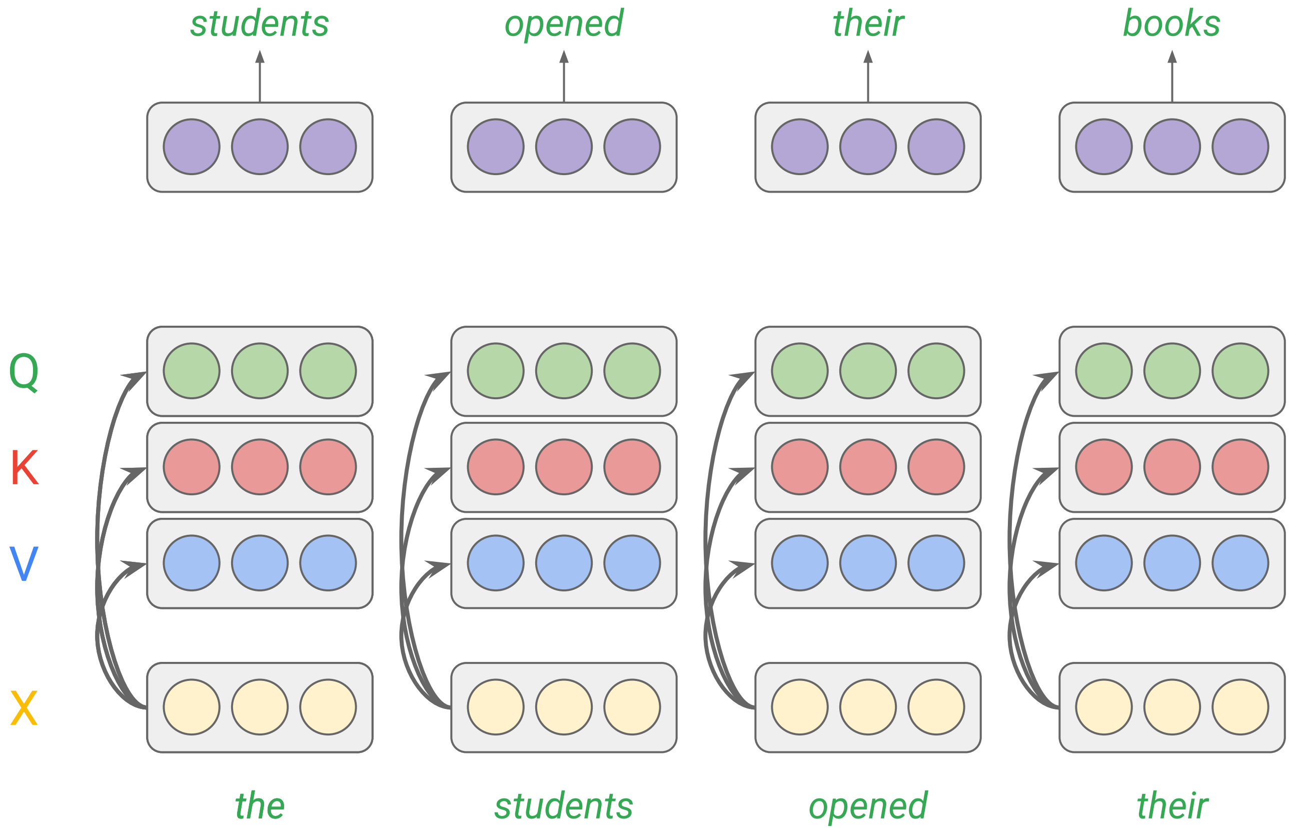
- Quiz 2 will be released tomorrow
- Homework 2 will be released sometime next week
- We are sending out feedback on final project proposals
- Please email us at cs5624instructors@gmail.com

Transformer recap

Attention mechanism



Self-attention



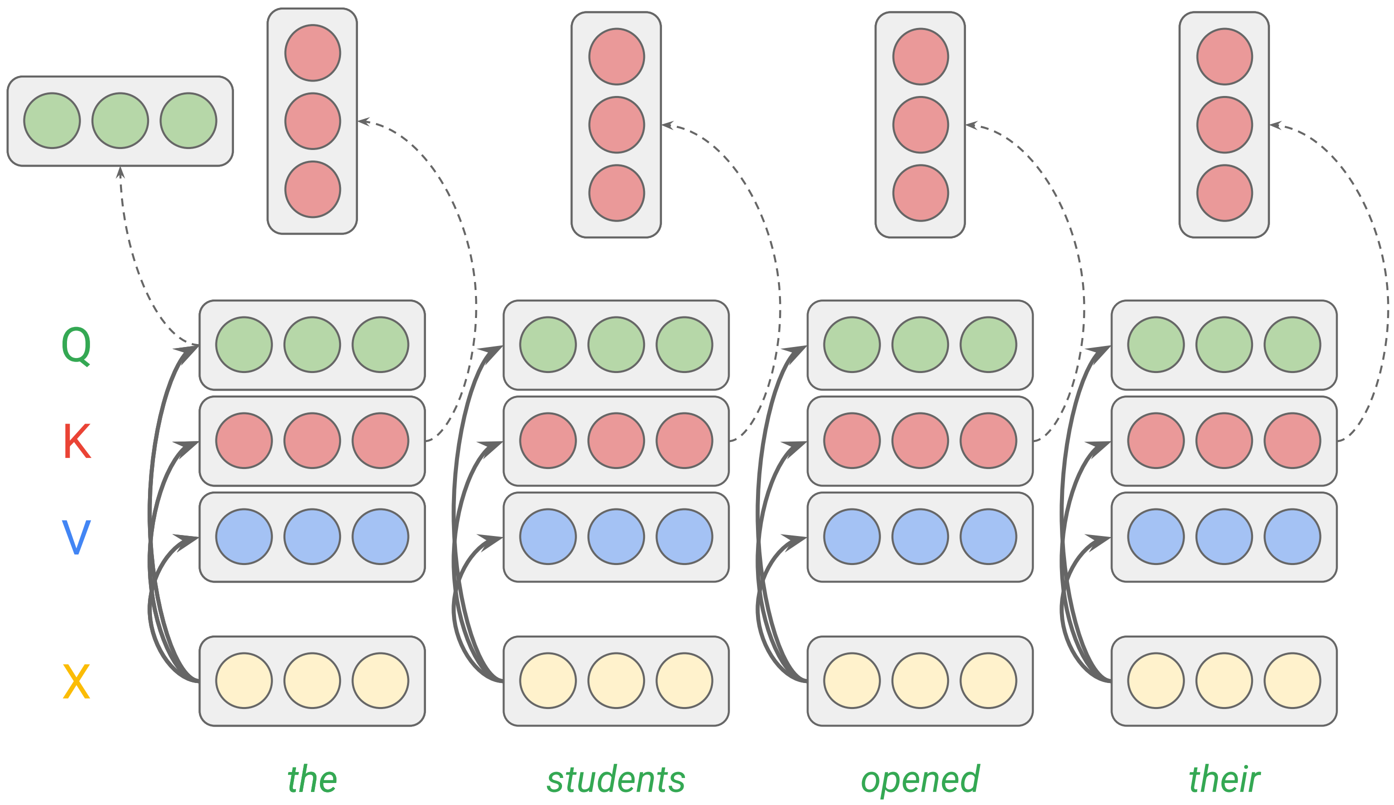
$$Q = X \cdot W_Q$$

$$K = X \cdot W_K$$

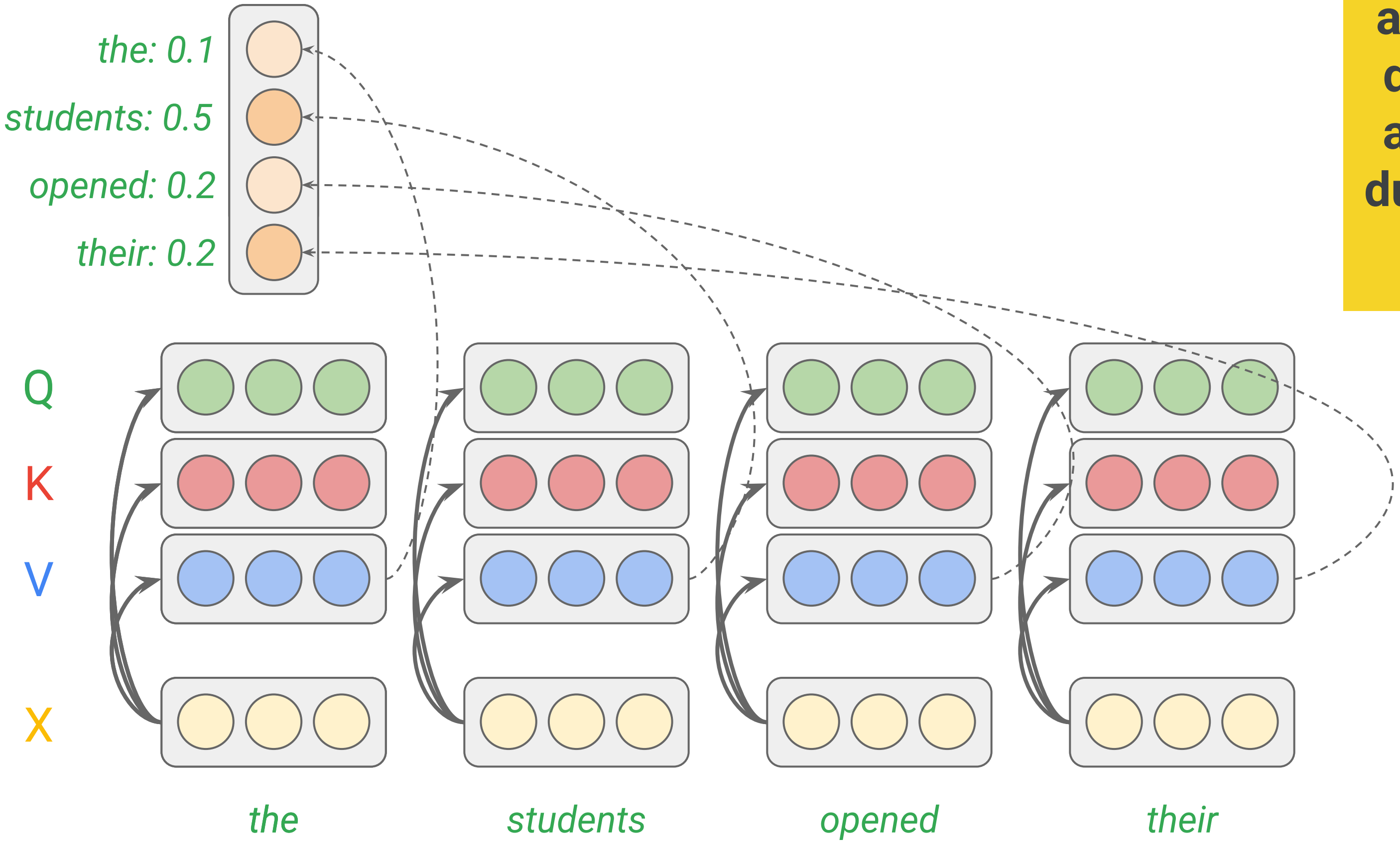
$$V = X \cdot W_V$$

linear projections

Self-attention (cont'd)

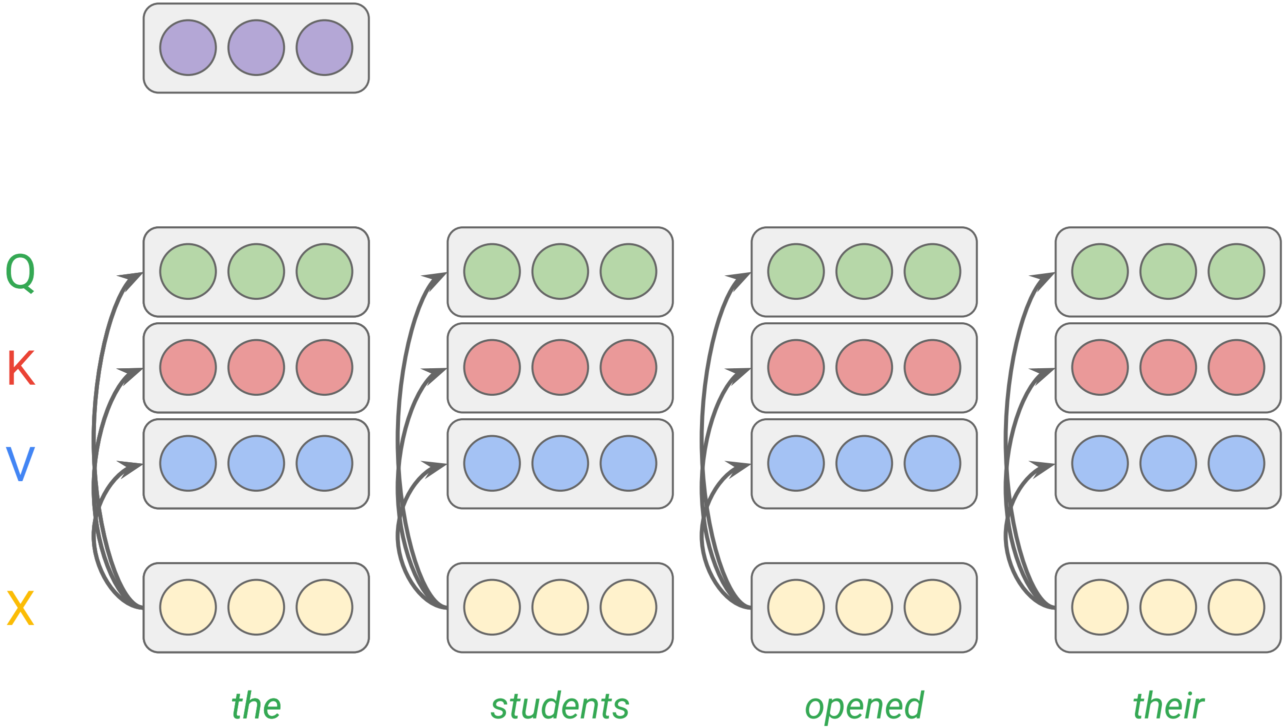


Self-attention (cont'd)



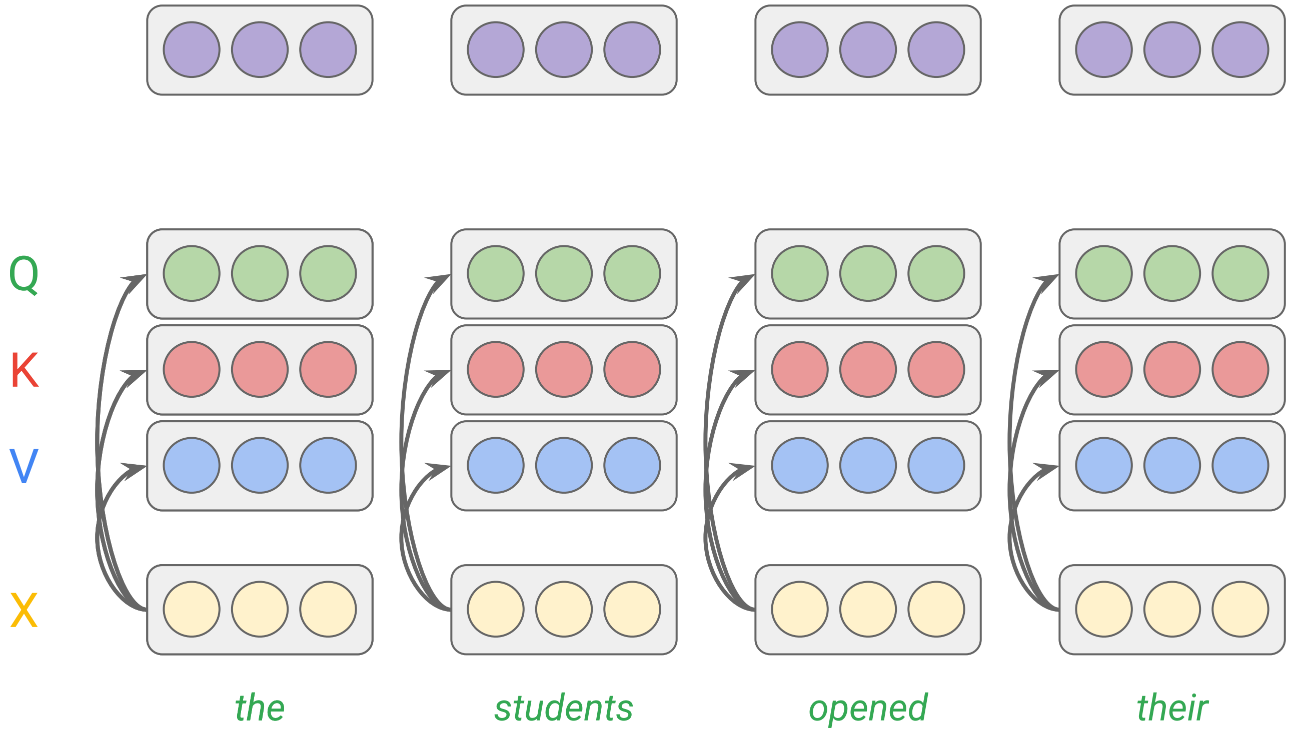
all **computations are parallelized during training and sequential during inference**

Self-attention (cont'd)



all **computations are parallelized during training and sequential during inference**

Self-attention (cont'd)



all **computations are parallelized during training and sequential during inference**

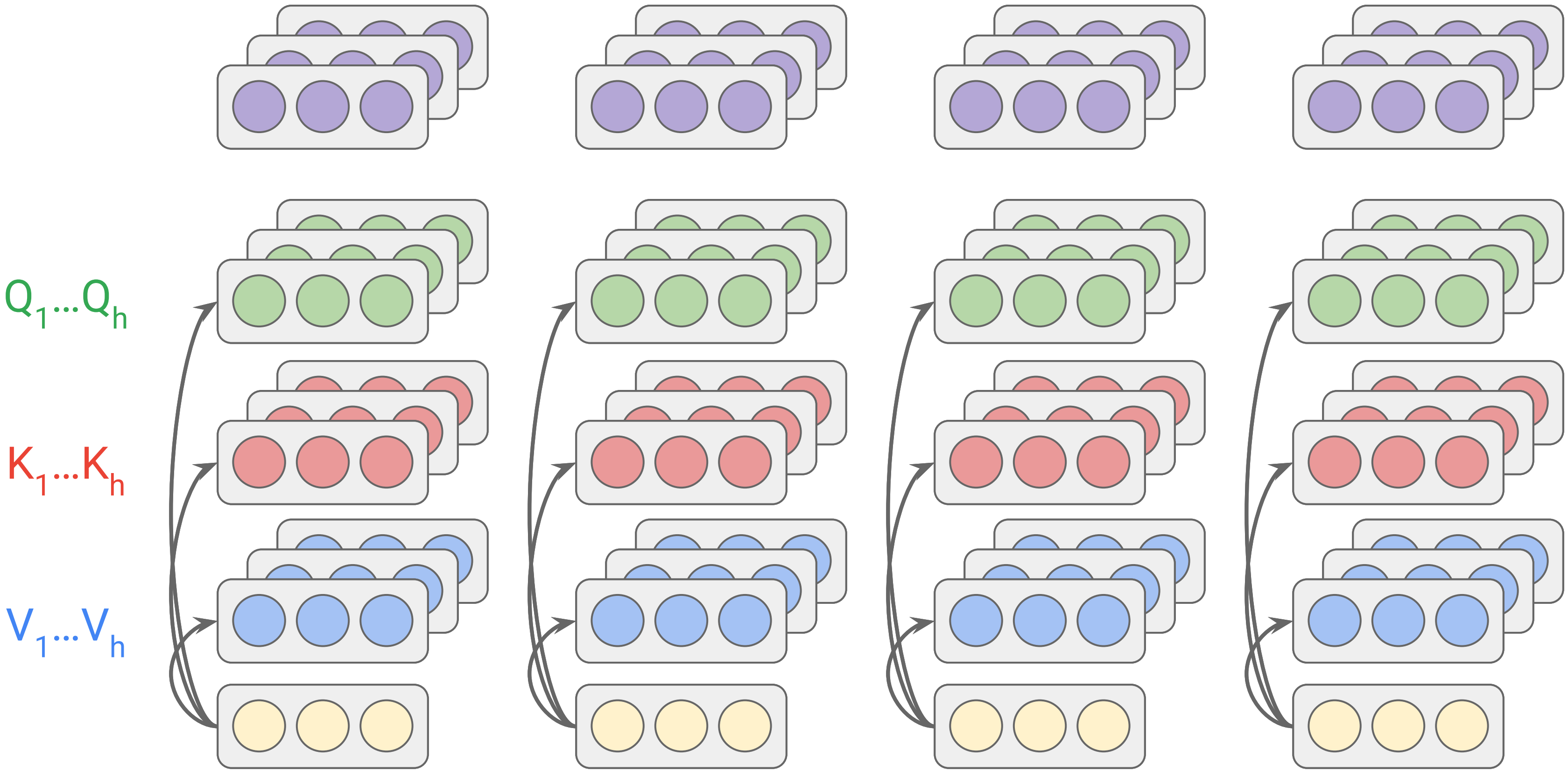
All computations are parallelized

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

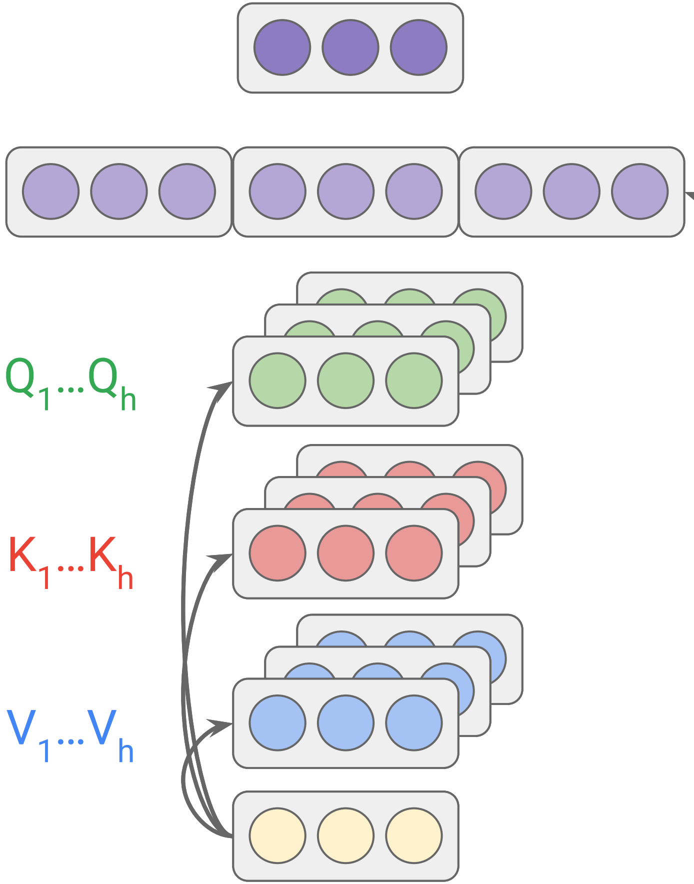
d_k: scaling factor

large products push the softmax function into regions where it has extremely small gradients

Multi-head attention



Multi-head attention (cont'd)



$$O = [head_1;head_2;\dots;head_h] \cdot W_O$$

These output values are concatenated and once again projected

$$\mathrm{MultiHead}(Q, K, V) = \mathrm{Concat}(\mathrm{head}_1, \ldots, \mathrm{head}_h) W_O$$

where

$$\mathrm{head}_i = \mathrm{Attention}(QW_{Q_i}, KW_{K_i}, VW_{V_i})$$

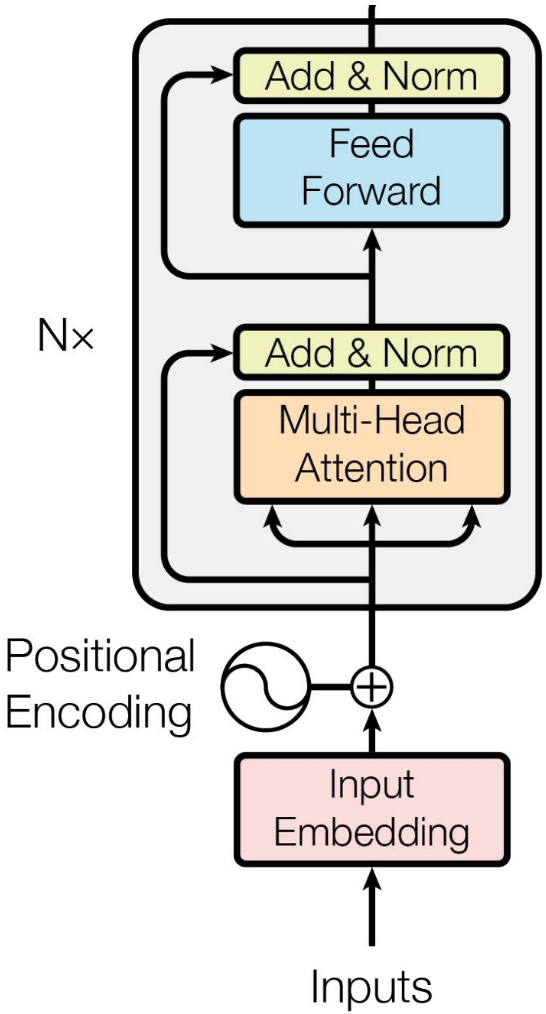
The projections are parameter matrices:

$$W_{Q_i} \in \mathbb{R}^{d_{\mathrm{model}} \times d_k}, W_{K_i} \in \mathbb{R}^{d_{\mathrm{model}} \times d_k}, W_{V_i} \in \mathbb{R}^{d_{\mathrm{model}} \times d_v}$$

and

$$W_O \in \mathbb{R}^{hd_v \times d_{\mathrm{model}}}.$$

In the Transformer paper, they employ $h = 8$ parallel attention layers, or heads. For each of these, they use $d_k = d_v = \frac{d_{\mathrm{model}}}{h} = 64$. Due to the reduced dimension of each head, the total computational cost is similar to that of single-head attention with full dimensionality.


Add & Norm
Feed Forward
Nx
Add & Norm
Multi-Head Attention
Positional Encoding
Input Embedding
Inputs

Bias term

$$h = \sigma(\mathbf{W}x + b)$$

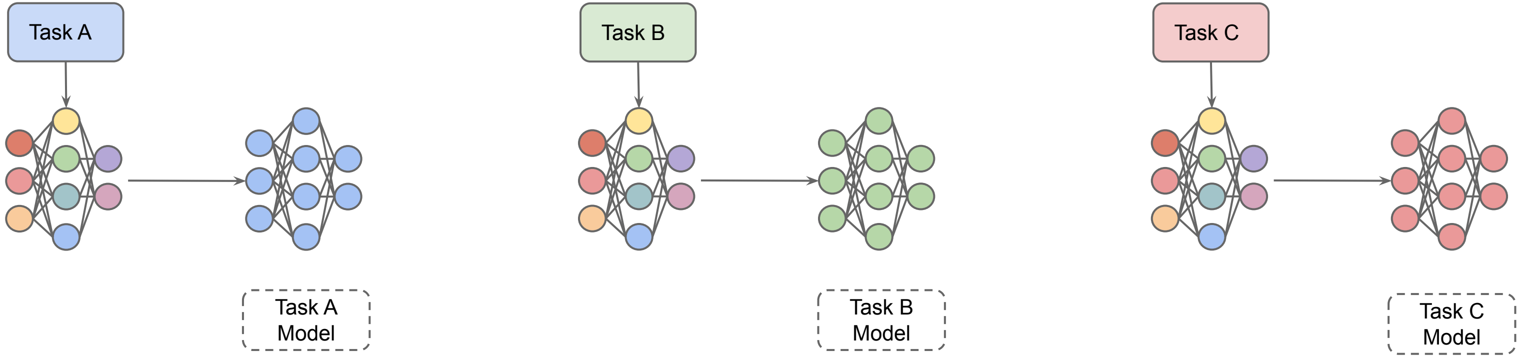
bias term

Model parameters (weights)

- Weight matrices
  - E.g., W_Q , W_K, W_V, W_O
- Bias terms

Limitations of full model tuning

Limitations of full model tuning



The Power of Scale for Parameter-Efficient Prompt Tuning

Brian Lester*   Rami Al-Rfou   Noah Constant
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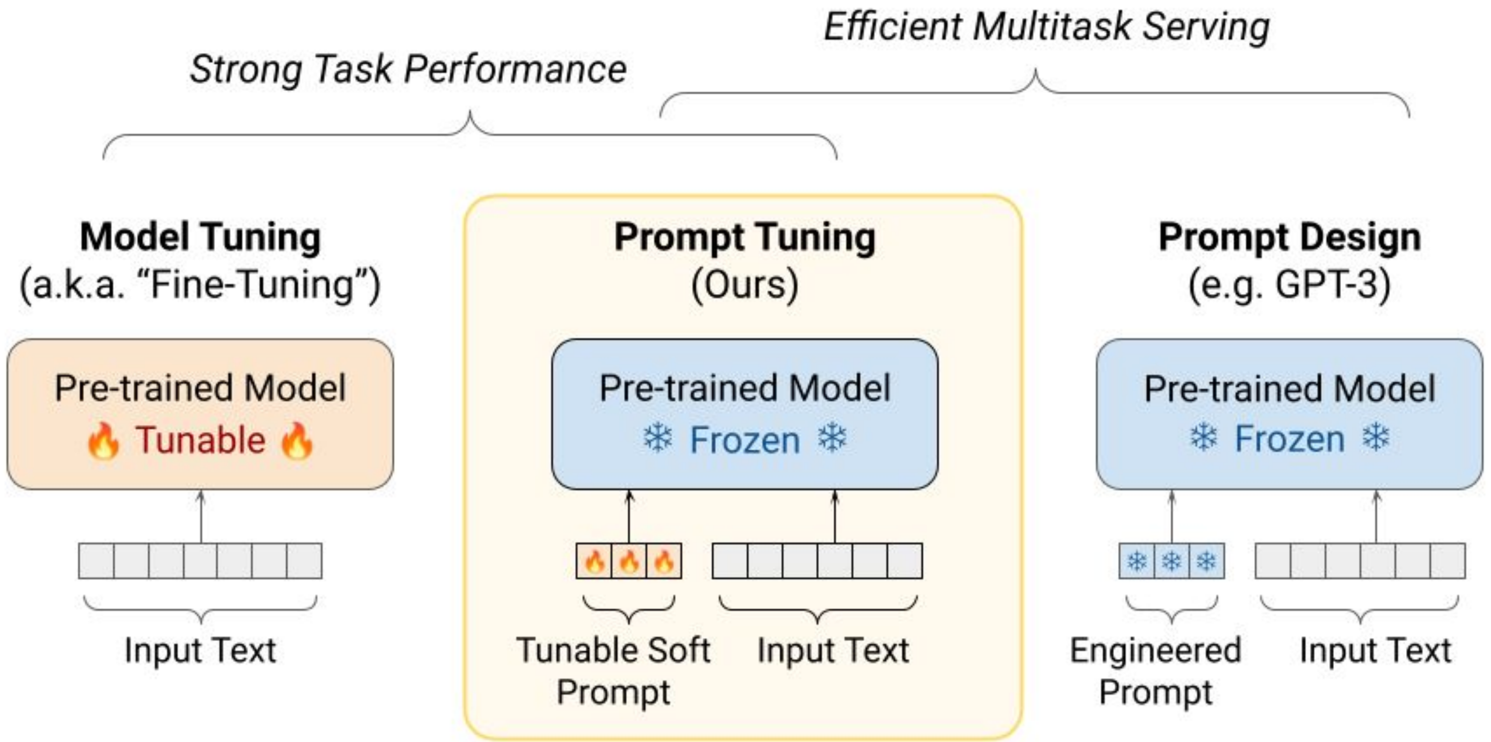
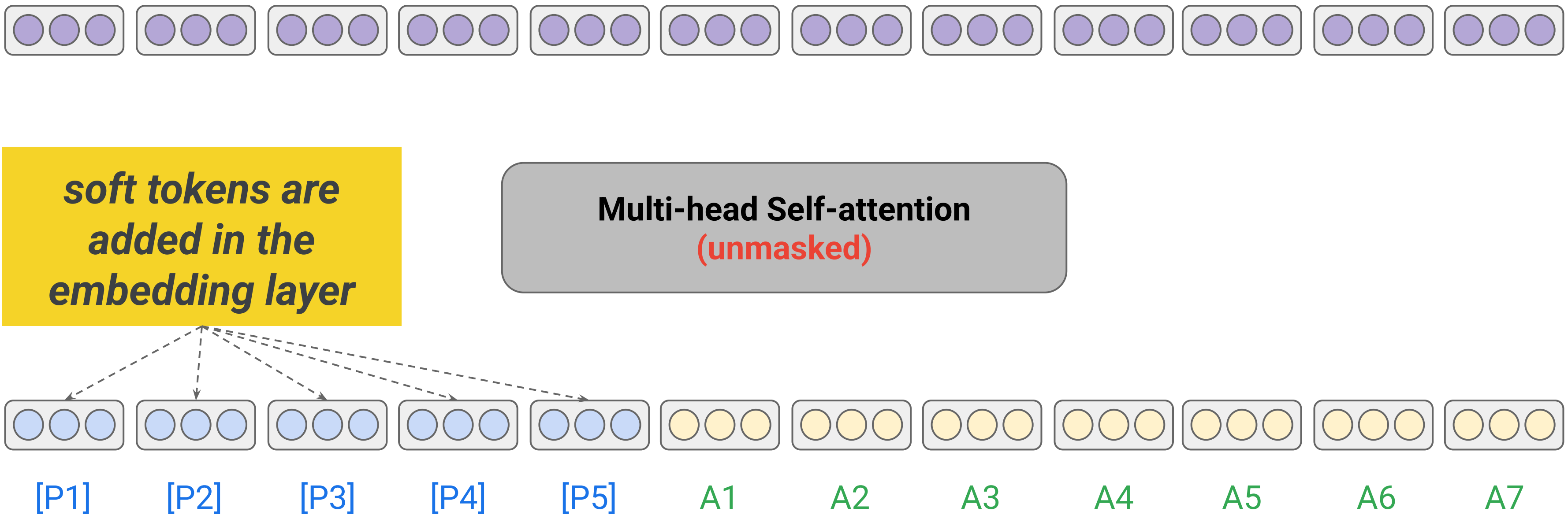
Soft prompt tuning



["The Power of Scale for Parameter-Efficient Prompt Tuning" by Lester et al. (2021)]

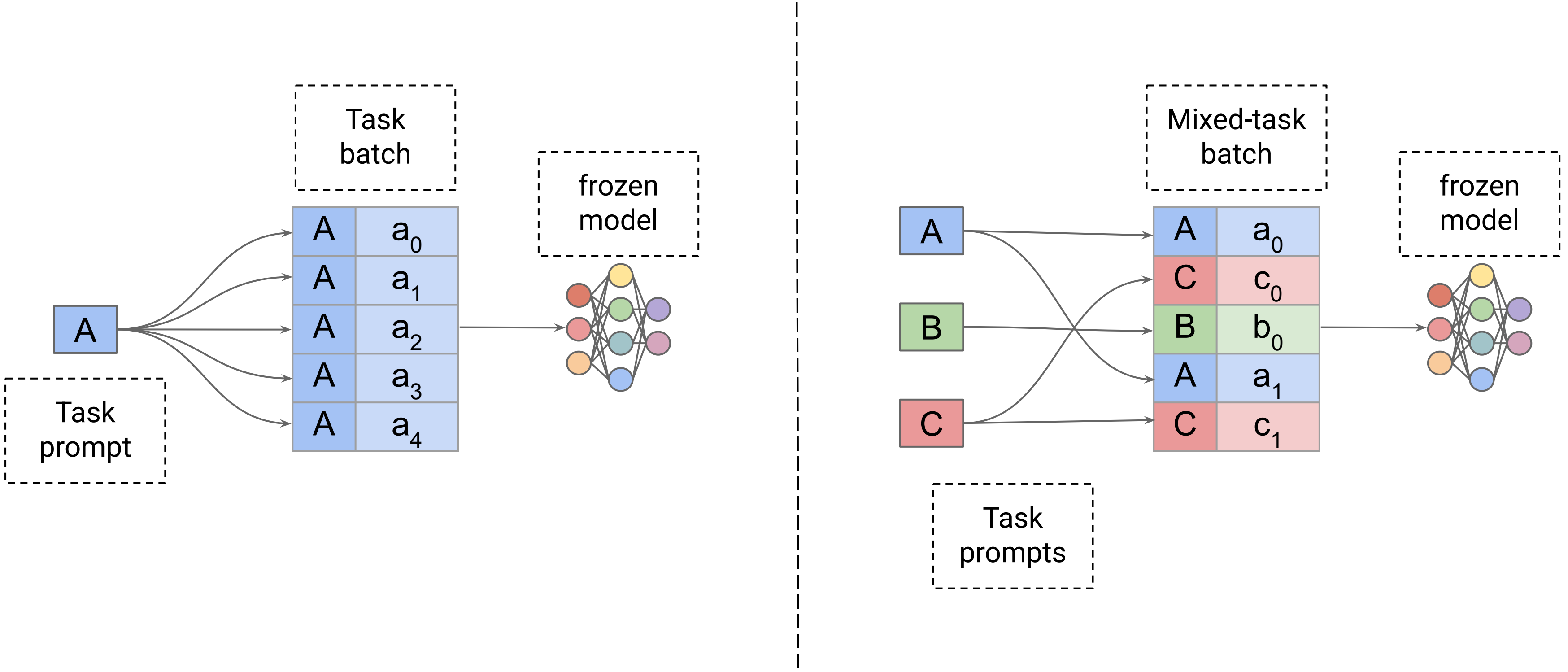
Soft prompt



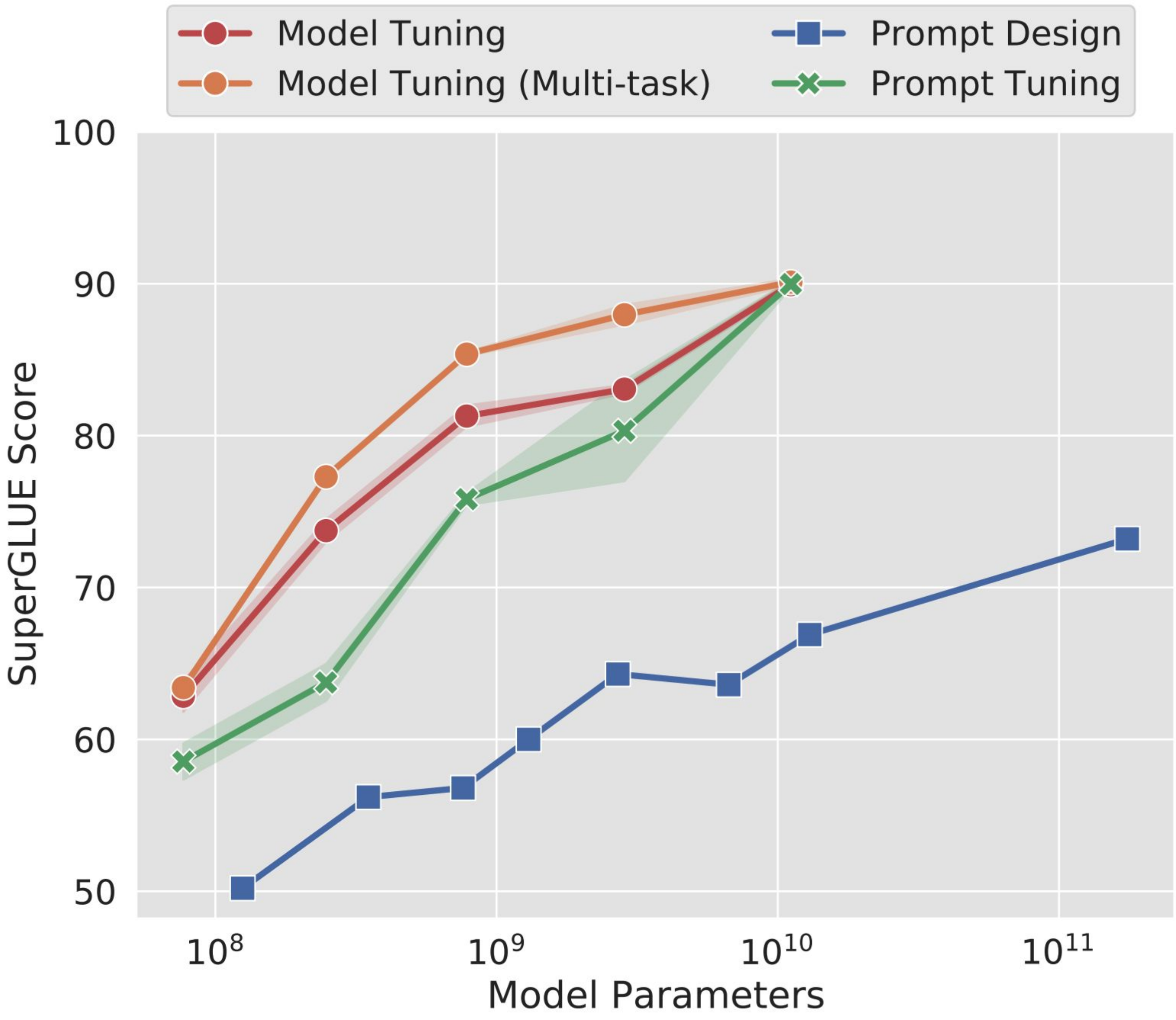
soft tokens are added in the embedding layer
Multi-head Self-attention
(unmasked)
[P1]
[P2]
[P3]
[P4]
[P5]
A1
A2
A3
A4
A5
A6
A7

Advantages of soft prompt tuning

Parameter-efficient tuning & mixed-task inference



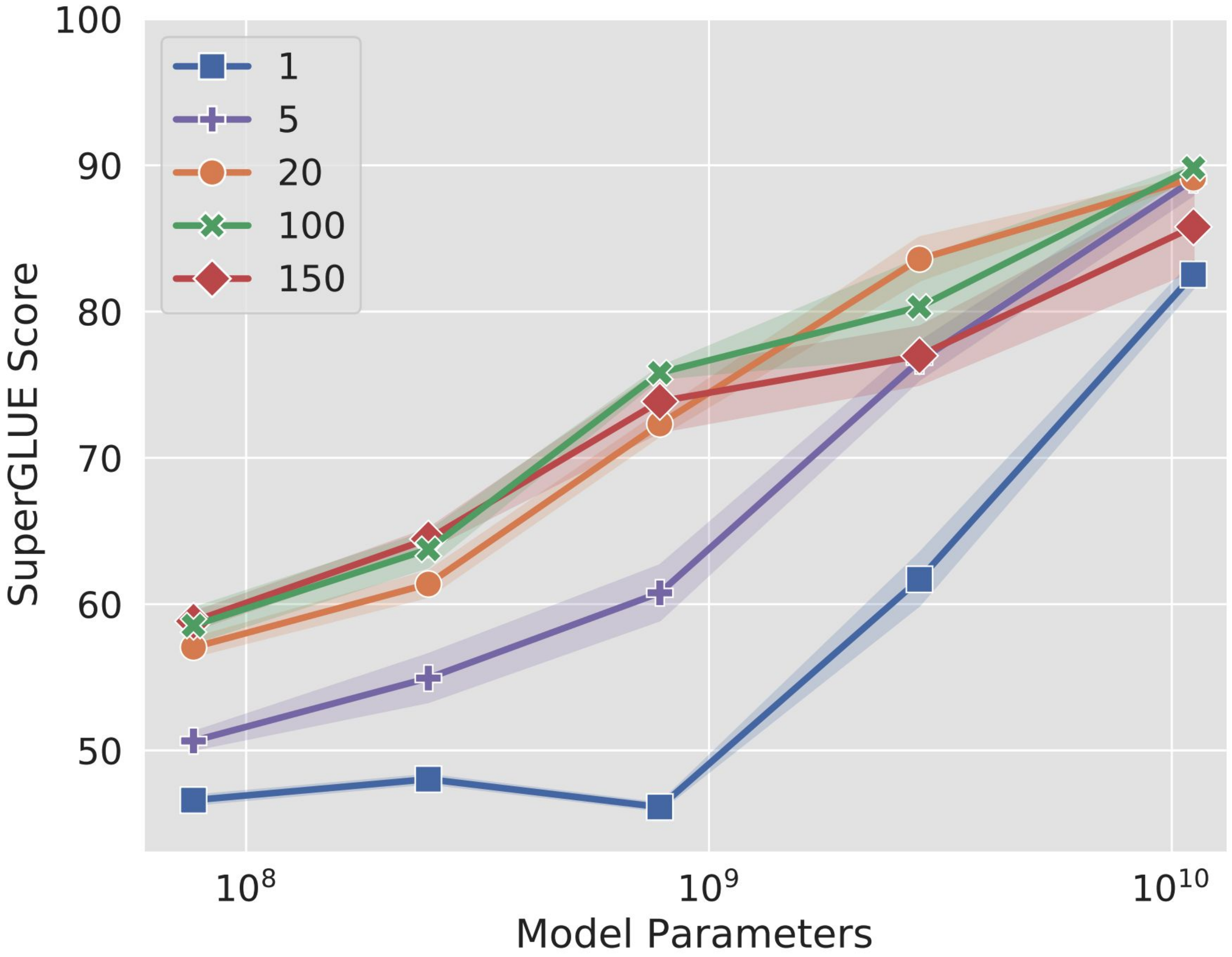
Improvement with Scale



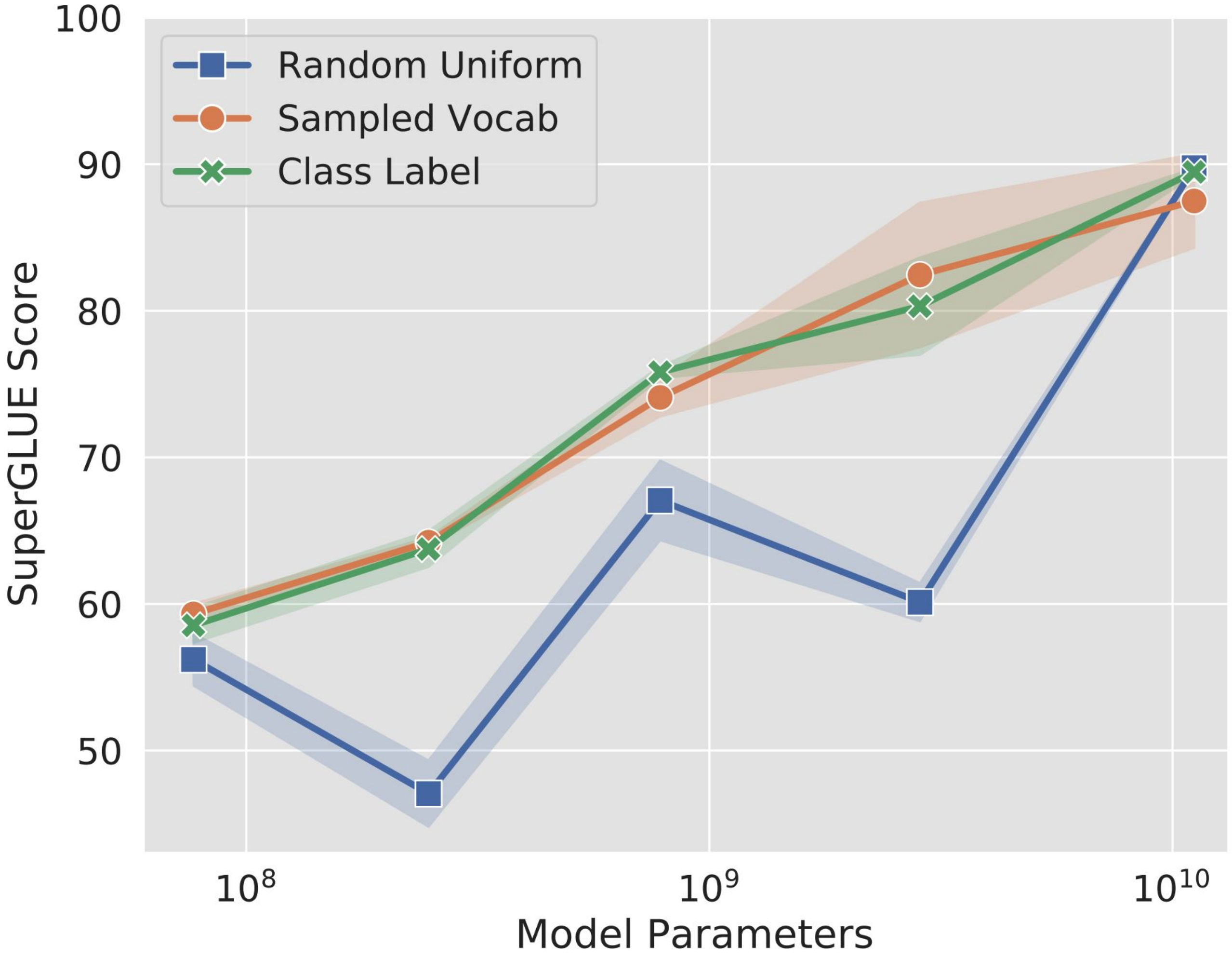
Resilience to domain shift

Train	Eval	Tuning	Accuracy	F1
QQP	MRPC	Model	73.1 ±0.9	81.2 ±2.1
		Prompt	**76.3** ±0.1	**84.3** ±0.3
MRPC	QQP	Model	74.9 ±1.3	**70.9** ±1.2
		Prompt	**75.4** ±0.8	69.7 ±0.3

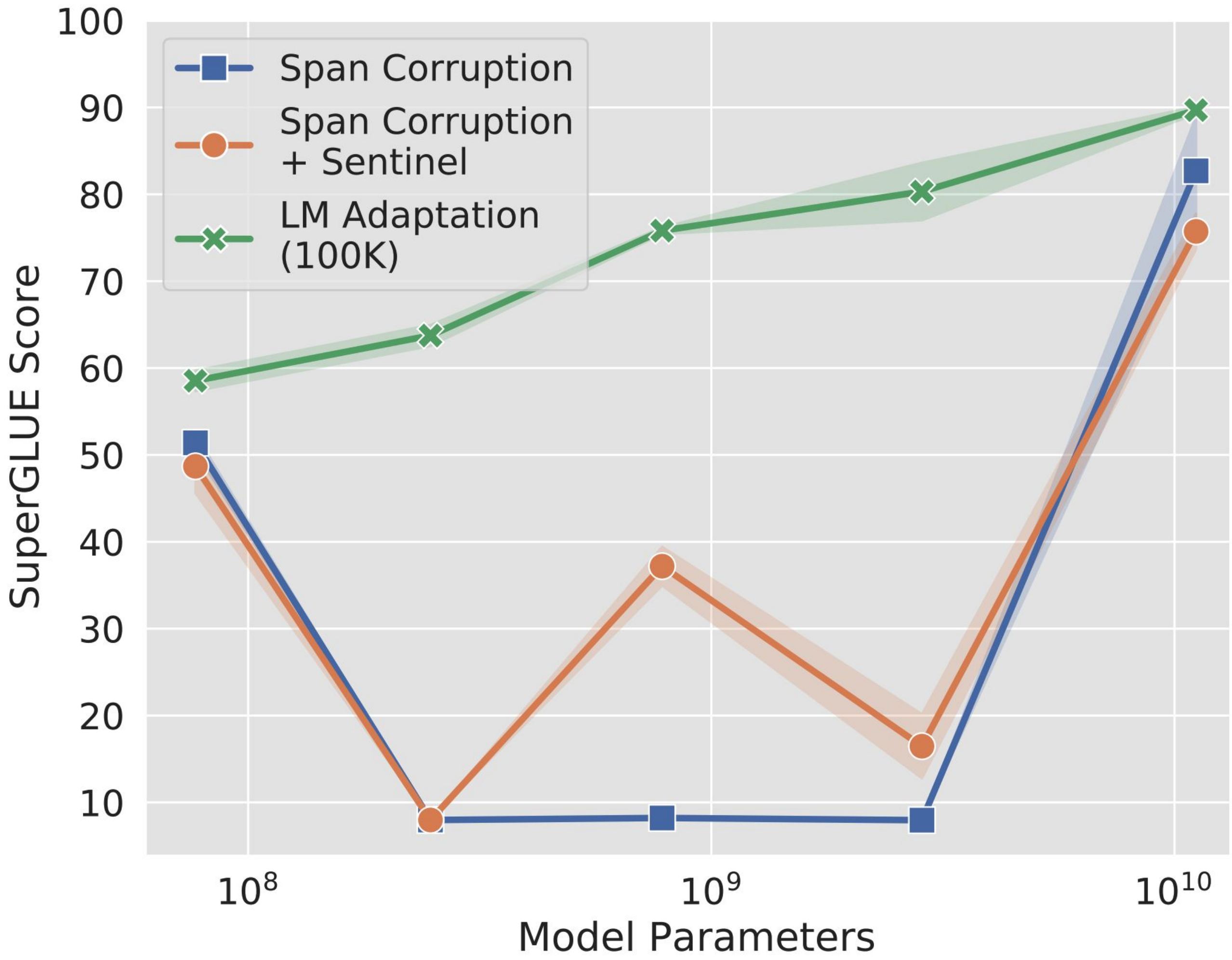
Effect of prompt length



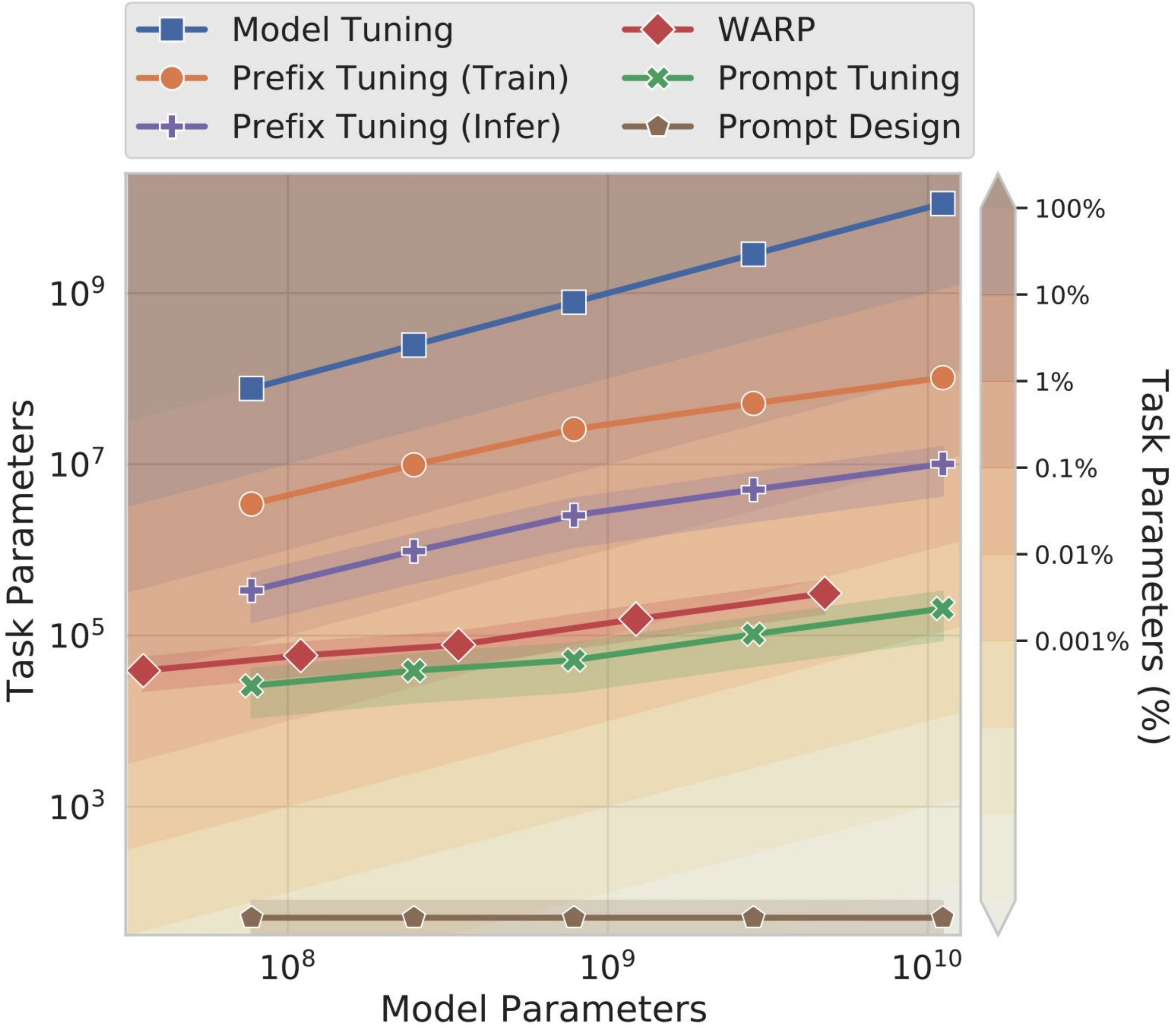
Effect of prompt initialization



Effect of pretraining method



Parameter usage



Interpretability

- the learned prompts taken as sequences show little interpretability

Limitations of soft prompt tuning

SPoT: Better Frozen Model Adaptation through Soft Prompt Transfer

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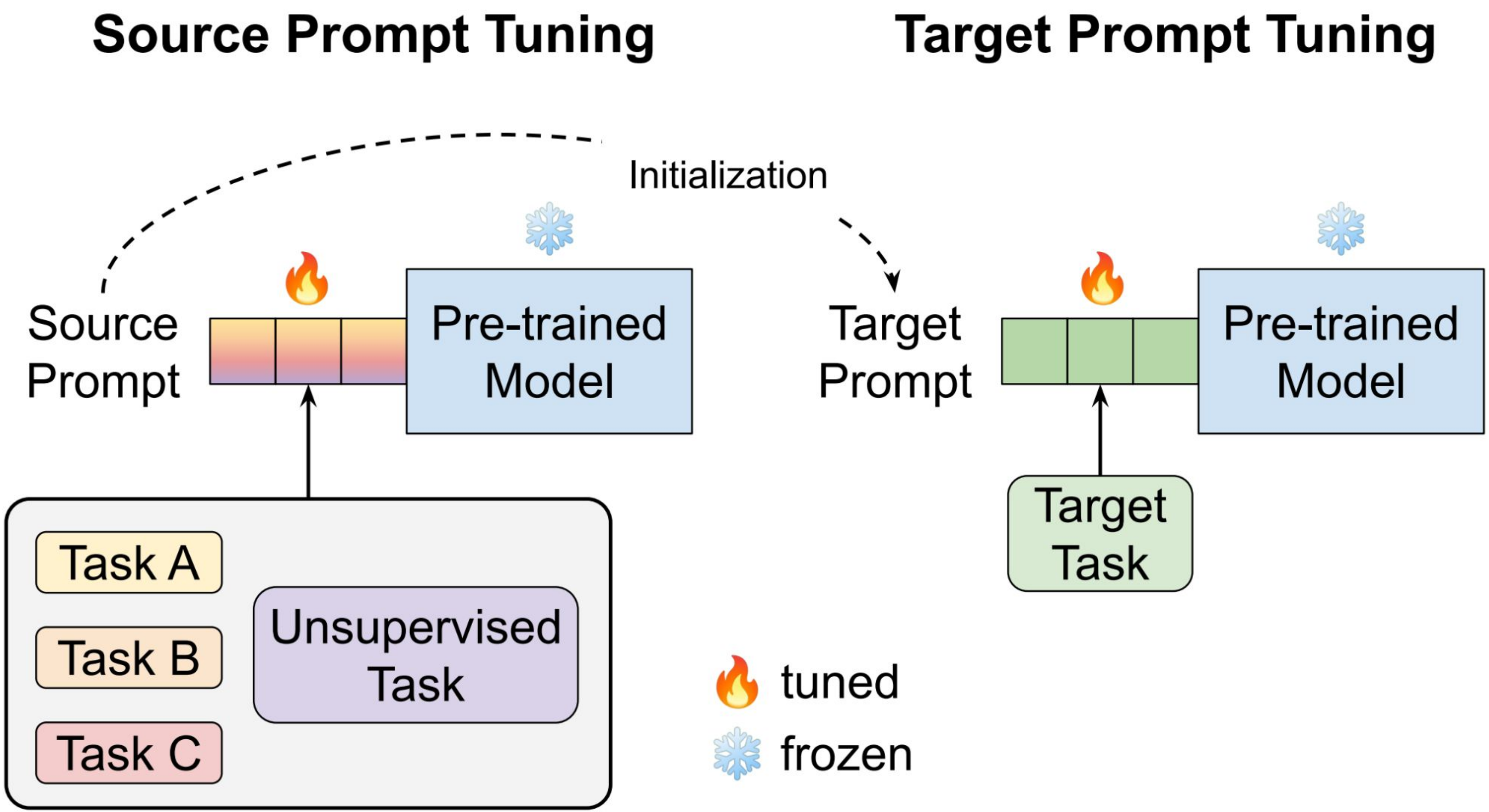
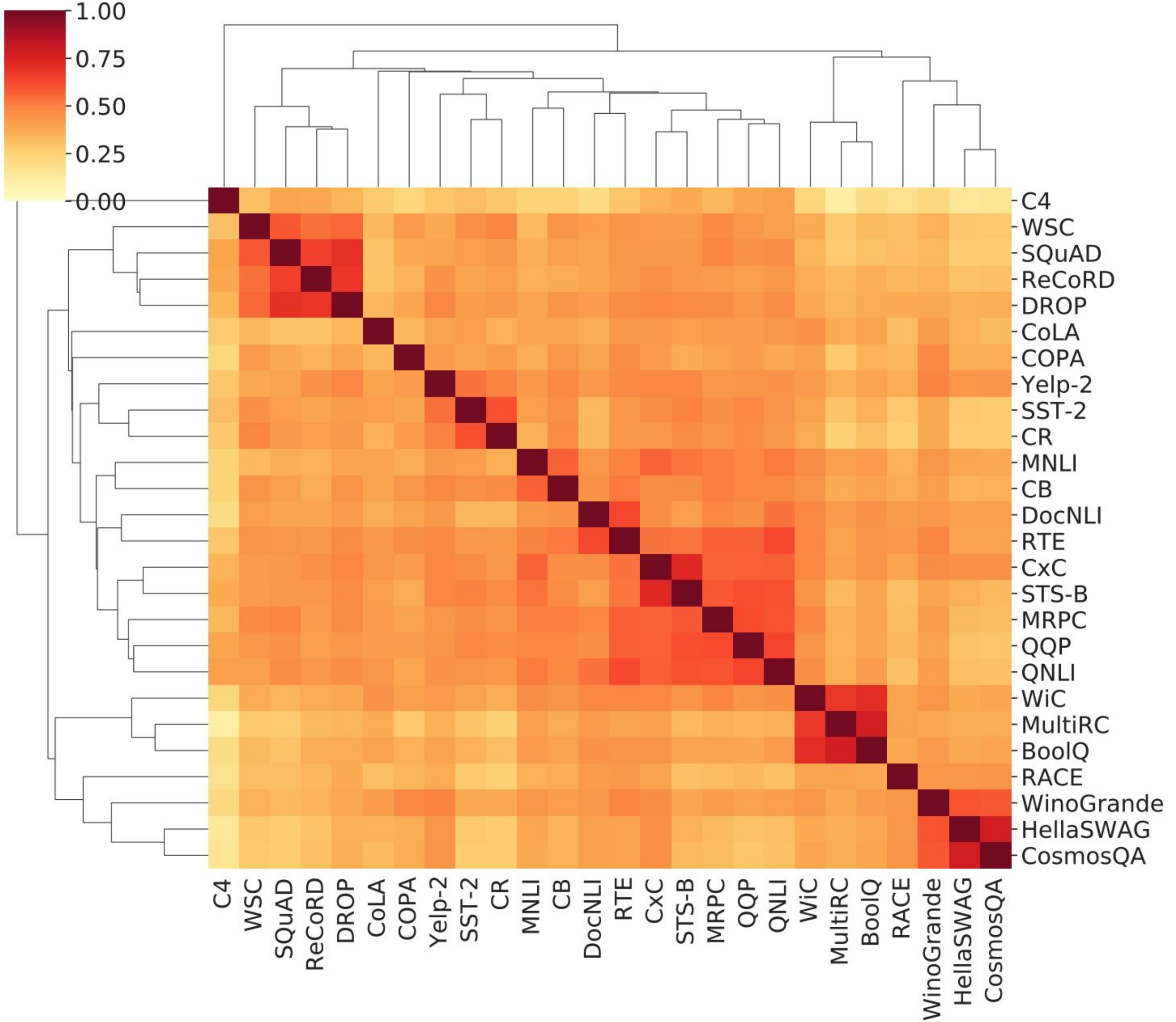
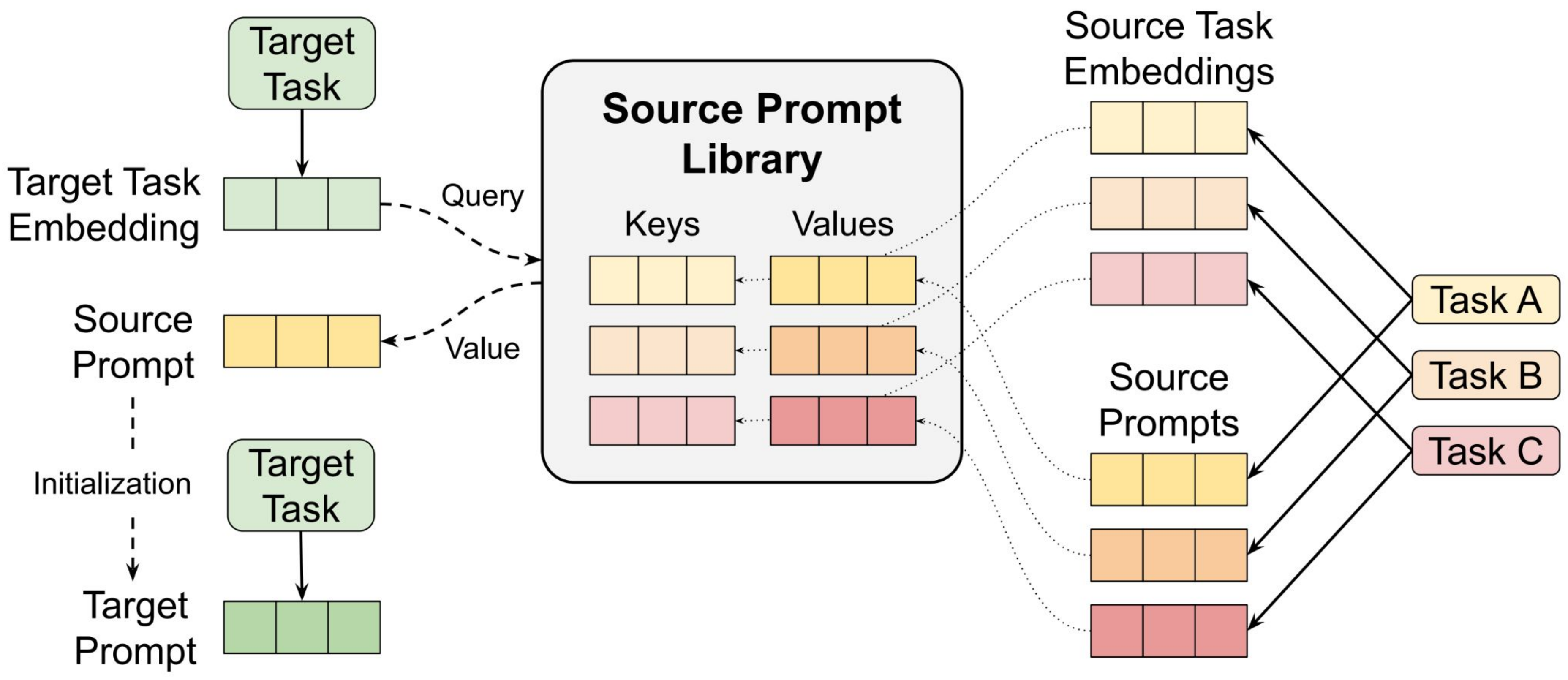
Generic SPoT



Prompt-based task embeddings capture task relationships



Targeted SPoT



Overcoming Catastrophic Forgetting in Zero-Shot Cross-Lingual Generation

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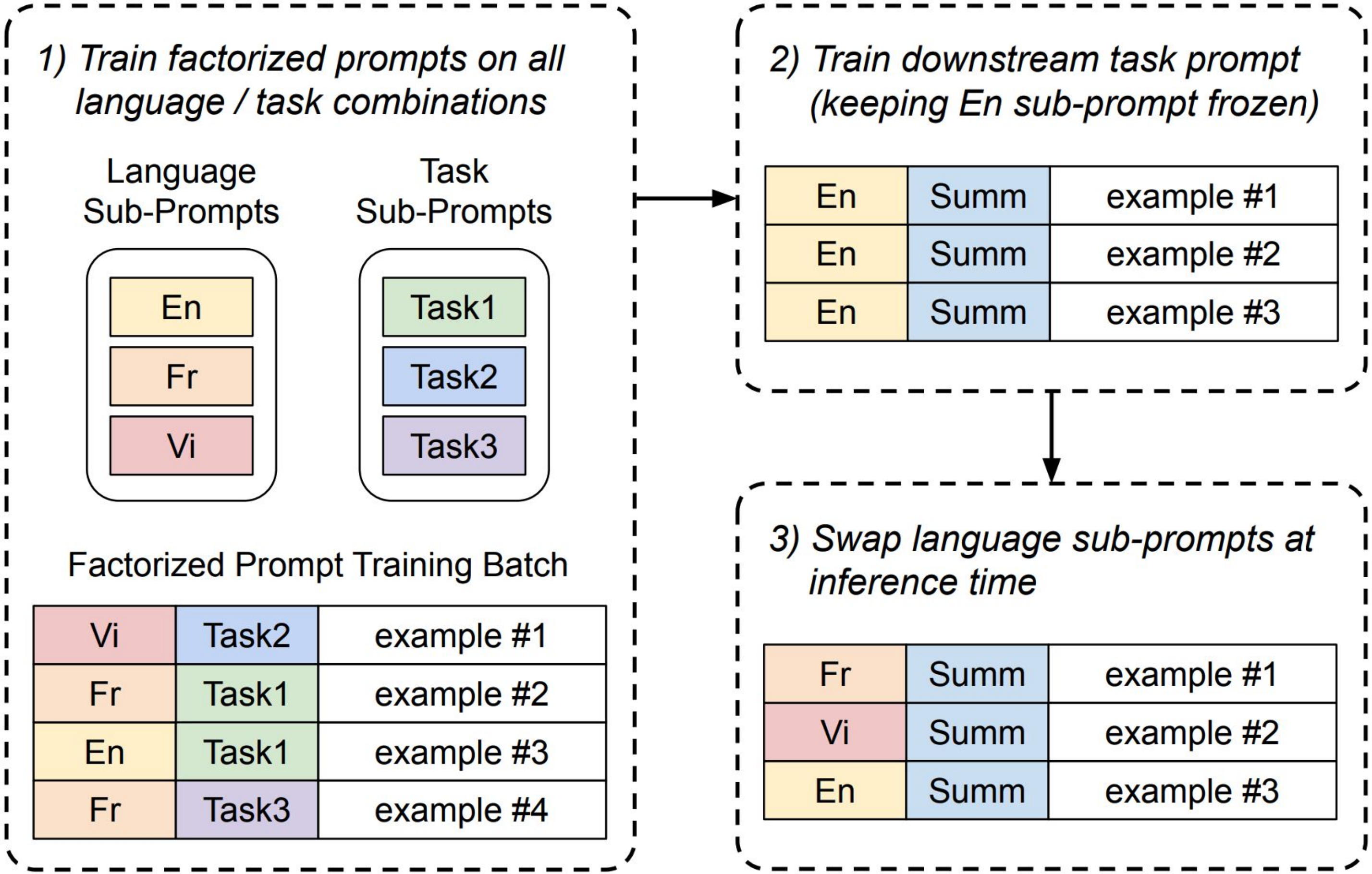
Factorized prompts



BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models

Elad Ben-Zaken[1] **Shauli Ravfogel**[1,2] **Yoav Goldberg**[1,2]
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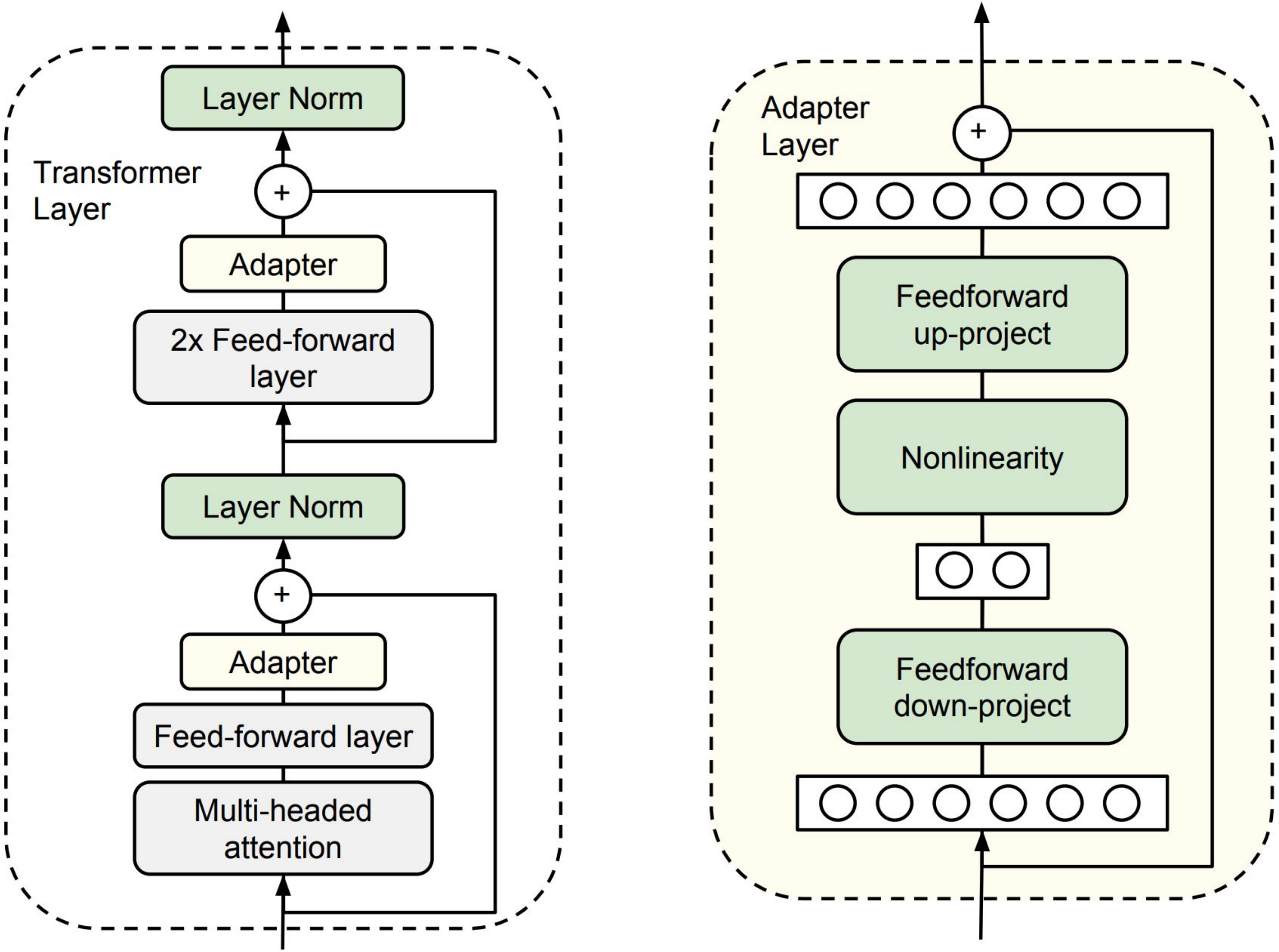
Parameter-Efficient Transfer Learning for NLP

Neil Houlsby [1] Andrei Giurgiu [1 *] Stanisław Jastrzębski [2 *] Bruna Morrone [1] Quentin de Laroussilhe [1]
Andrea Gesmundo [1] Mona Attariyan [1] Sylvain Gelly [1]

Adapters



Layer Norm
Transformer Layer
+
Adapter
2x Feed-forward layer
Layer Norm
+
Adapter
Feed-forward layer
Multi-headed attention
Adapter Layer
+
Feedforward up-project
Nonlinearity
Feedforward down-project

Prefix-Tuning: Optimizing Continuous Prompts for Generation

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LoRA

Algebra review

- The rank of a matrix is the number of linearly independent rows or columns (whichever is smaller)
- A ***full-rank*** matrix refers to a matrix that does not have any constraints on its rank. In other words, it has the maximum possible rank, meaning all of its rows and columns are linearly independent.

LoRA: Low-Rank Adaptation of Large Language Models

Edward Hu* **Yelong Shen*** **Phillip Wallis** **Zeyuan Allen-Zhu**
Yuanzhi Li **Shean Wang** **Lu Wang** **Weizhu Chen**
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Weight changes during model adaptation have a low “intrinsic rank”

- The learned over-parametrized models in fact reside on a low intrinsic dimension
    - intrinsic dimension: the minimal number of variables needed to describe the essential variations in the data

- Many real-world high-dimensional datasets actually lie on or near a lower-dimensional manifold embedded in the high-dimensional space

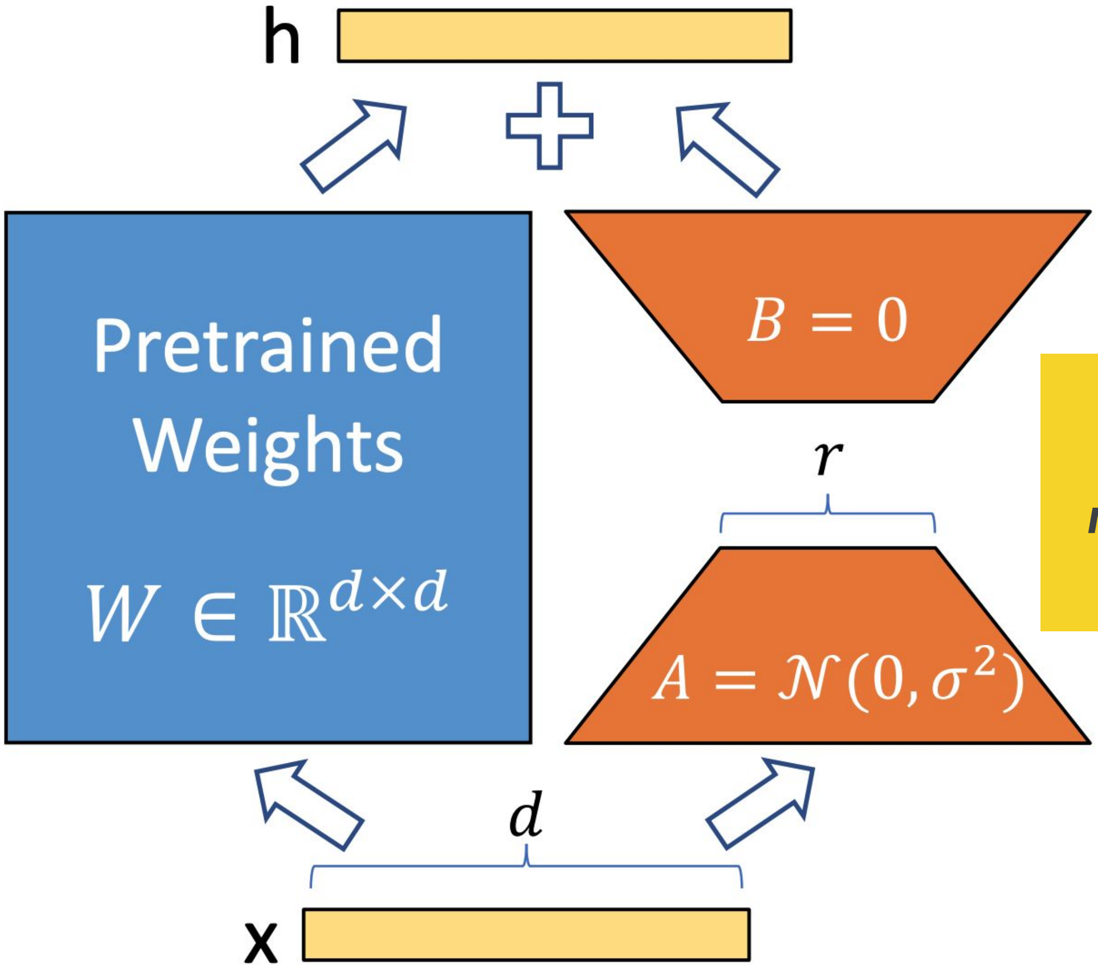
- If a model or function resides in a low intrinsic dimension, then it may be possible to approximate it well with fewer parameters or a lower-dimensional representation, leading to improved generalization and efficiency

For a pre-trained weight matrix $W_0 \in \mathbb{R}^{d \times k}$, we constrain its update by representing the latter with a low-rank decomposition $W_0 + \Delta W = W_0 + BA$, where $B \in \mathbb{R}^{d \times r}$, $A \in \mathbb{R}^{r \times k}$, and the rank $r \ll \min(d, k)$. During training, W_0 is frozen and does not receive gradient updates, while A and B contain trainable parameters. Note both W_0 and $\Delta W = BA$ are multiplied with the same input, and their respective output vectors are summed coordinate-wise.

For $h = W_0 x$, our modified forward pass yields:

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

LoRA



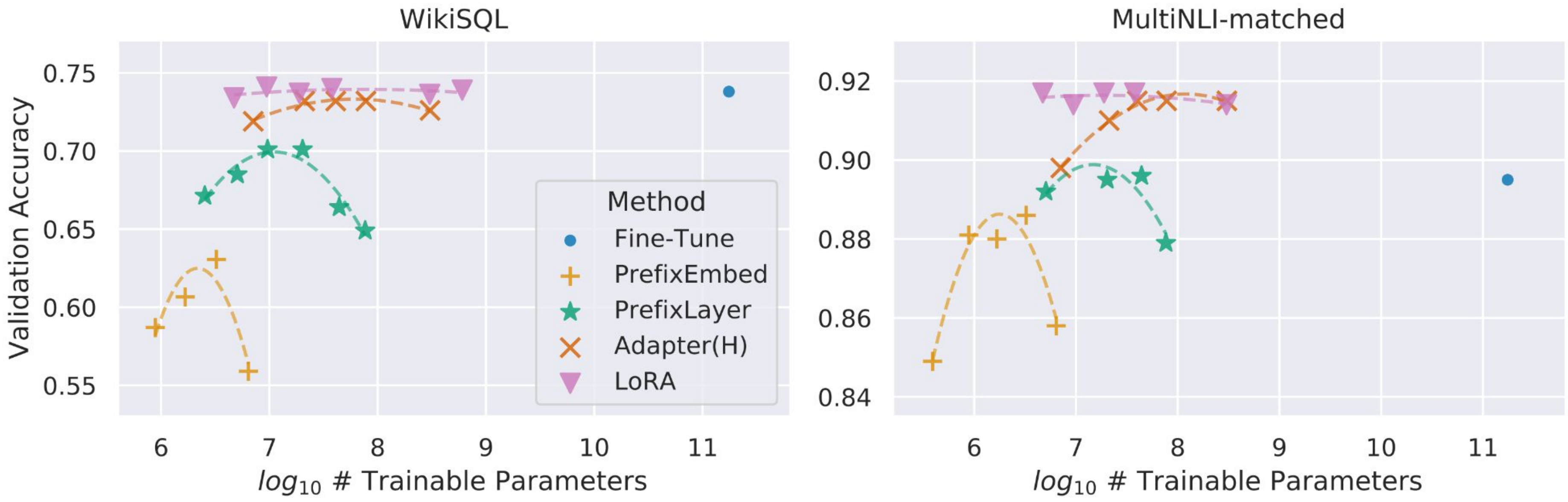
Only rank decomposition matrices A and B are trained

Advantages of LoRA

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**

Model&Method	# Trainable Parameters	WikiSQL	MNLI-m	SAMSum
		Acc. (%)	Acc. (%)	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^{H})	7.1M	71.9	89.8	53.0/28.9/44.8
GPT-3 (Adapter^{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

LoRA exhibits better scalability and task performance



Given a limited parameter budget, which weight matrices should we apply LoRA to?

	# of Trainable Parameters = 18M						
Weight Type	W_q	W_k	W_v	W_o	W_q, W_k	W_q, W_v	W_q, W_k, W_v, W_o
Rank r	8	8	8	8	4	4	2
WikiSQL ($\pm 0.5\%$)	70.4	70.0	73.0	73.2	71.4	**73.7**	**73.7**
MultiNLI ($\pm 0.1\%$)	91.0	90.8	91.0	91.3	91.3	91.3	**91.7**

The effect of rank *r* on model performance

	Weight Type	$r=1$	$r=2$	$r=4$	$r=8$	$r=64$
WikiSQL($\pm 0.5\%$)	W_q	68.8	69.6	70.5	70.4	70.0
	W_q, W_v	73.4	73.3	73.7	73.8	73.5
	W_q, W_k, W_v, W_o	74.1	73.7	74.0	74.0	73.9
MultiNLI ($\pm 0.1\%$)	W_q	90.7	90.9	91.1	90.7	90.7
	W_q, W_v	91.3	91.4	91.3	91.6	91.4
	W_q, W_k, W_v, W_o	91.2	91.7	91.7	91.5	91.4

practical recommendations

of training examples

- < 20: LoRA is difficult to train
- 50: LoRA w/ careful settings can be better than full model fine-tuning; r=1 or 4
- O(100): e.g., 200-500, LoRA is recommended; r=1 or 4
- O(10K): should compare LoRA vs. full model fine-tuning
- Very large (>100K): LoRA can get decent quality to match full model fine-tuning when r is large, e.g., 128 or 512

Limitations of parameter-efficient tuning methods

LoRA Learns Less and Forgets Less

Dan Biderman[1,2], **Jacob Portes**[2], **Jose Javier Gonzalez Ortiz**[2], **Mansheej Paul**[2], **Philip Greengard**[1], **Connor Jennings**[2], **Daniel King**[2], **Sam Havens**[2], **Vitaliy Chiley**[2], **Jonathan Frankle**[2], **Cody Blakeney**[2], **John P. Cunningham**[1]
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[2]**Databricks Mosaic Research** {jacob.portes, j.gonzalez, mansheej.paul, connor.jennings, daniel.king, sam.havens, vitaliy.chiley, jfrankle, cody.blakeney}@databricks.com

LoraHub: Efficient Cross-Task Generalization via Dynamic LoRA Composition

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Thank you!