Natural Language Understanding, Generation, and Machine Translation

Lecture 27: Parameter-Efficient Fine-Tuning

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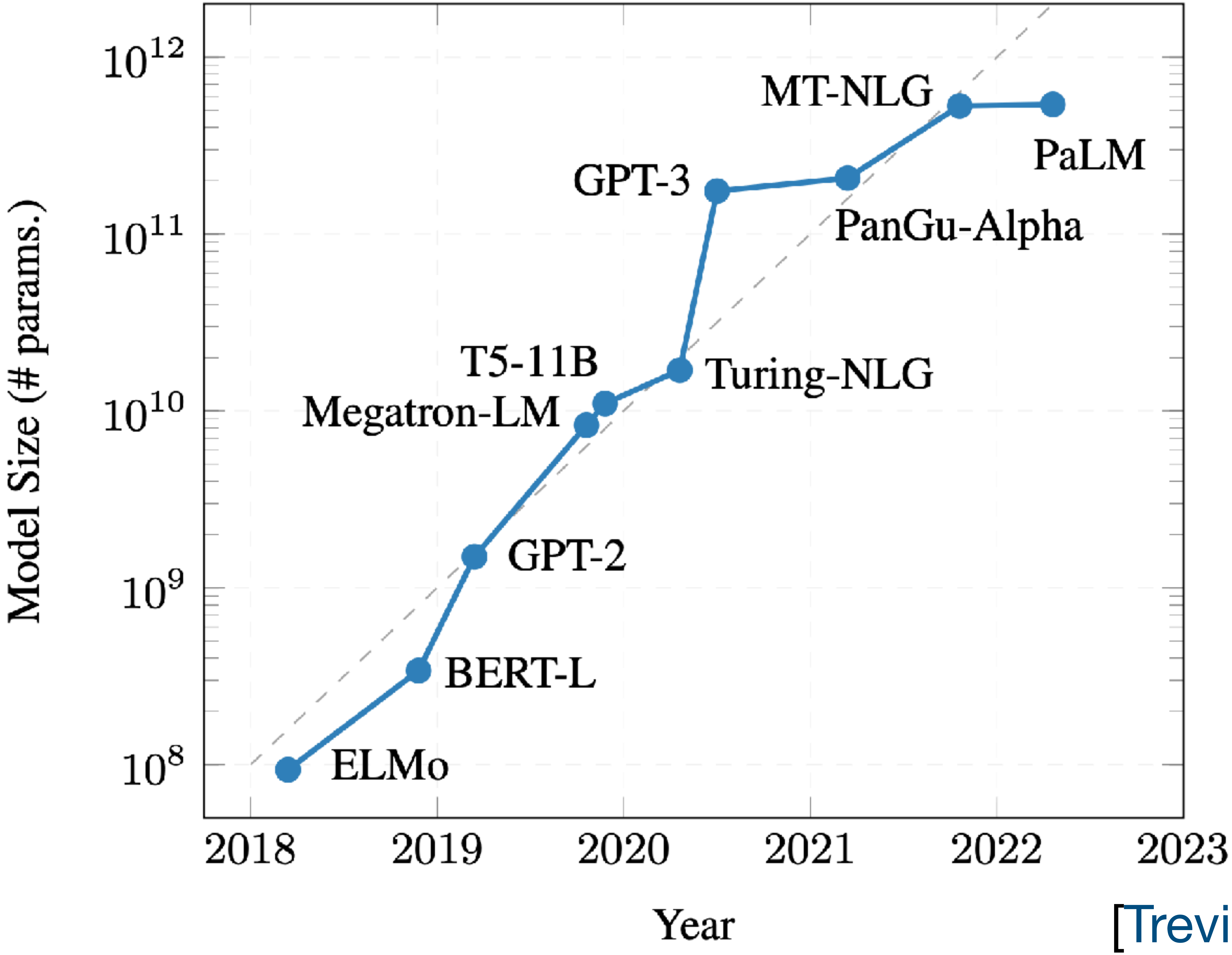
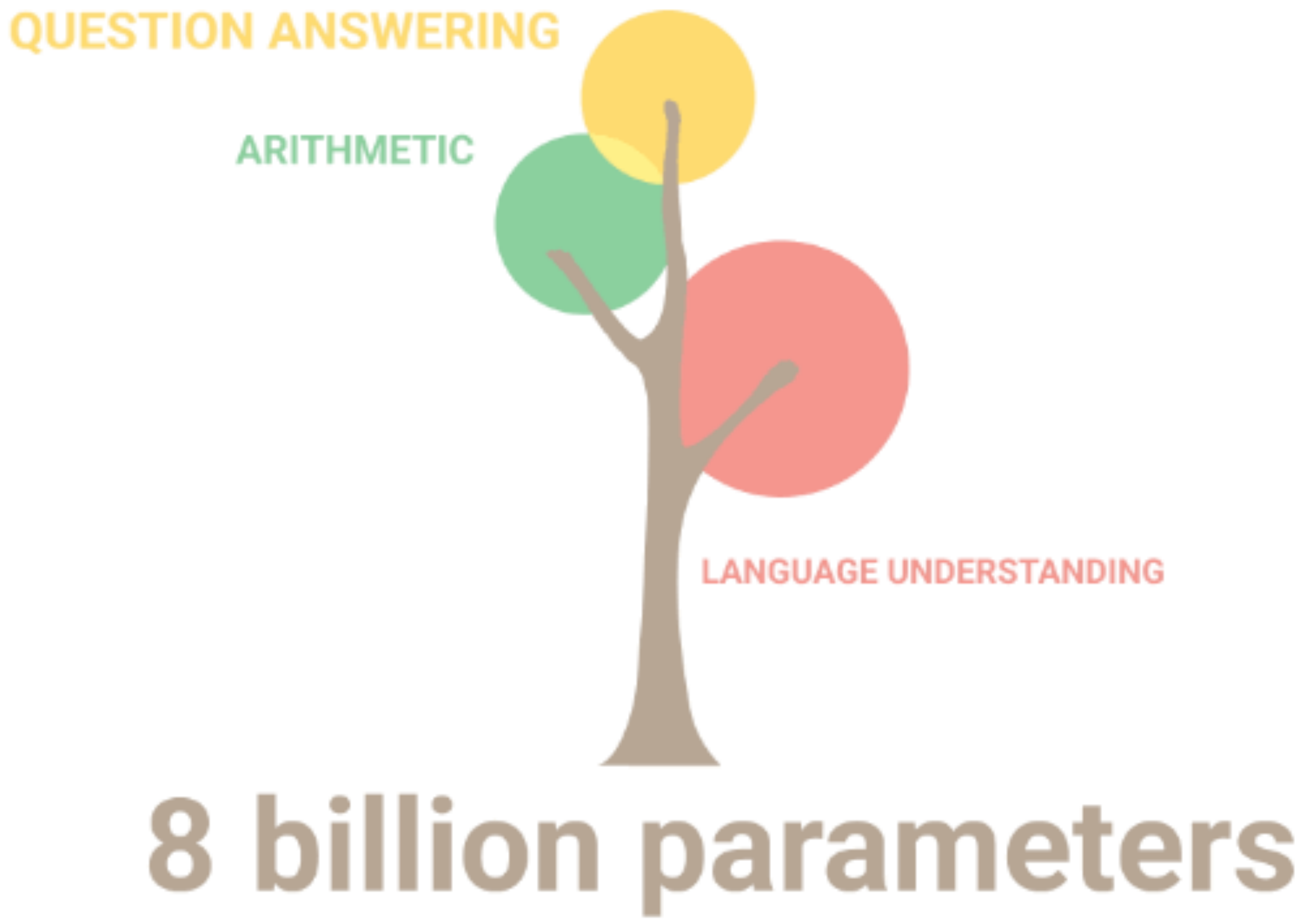
Evolution of Pre-Trained Language Models



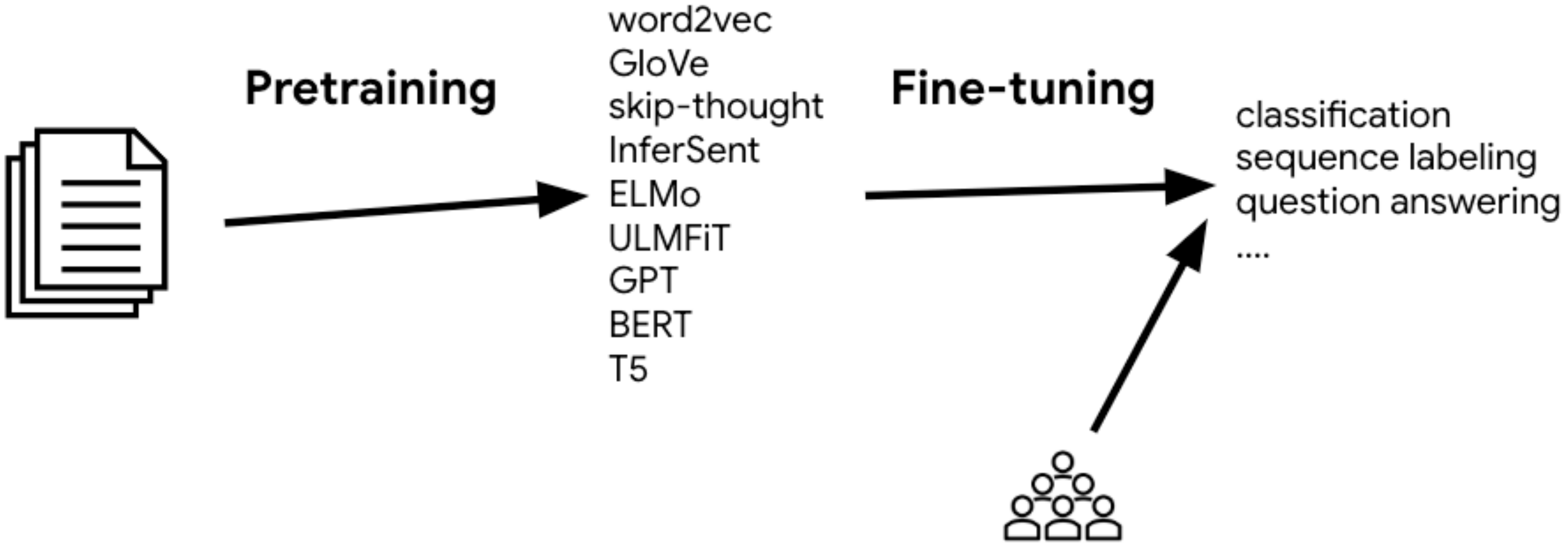
[Treviso et al., 2022]

Evolution of Pre-Trained Language Models



Transfer Learning in the Era of LLMs

- With increasing model size, fine-tuning becomes increasingly expensive
- The standard transfer learning formula breaks down



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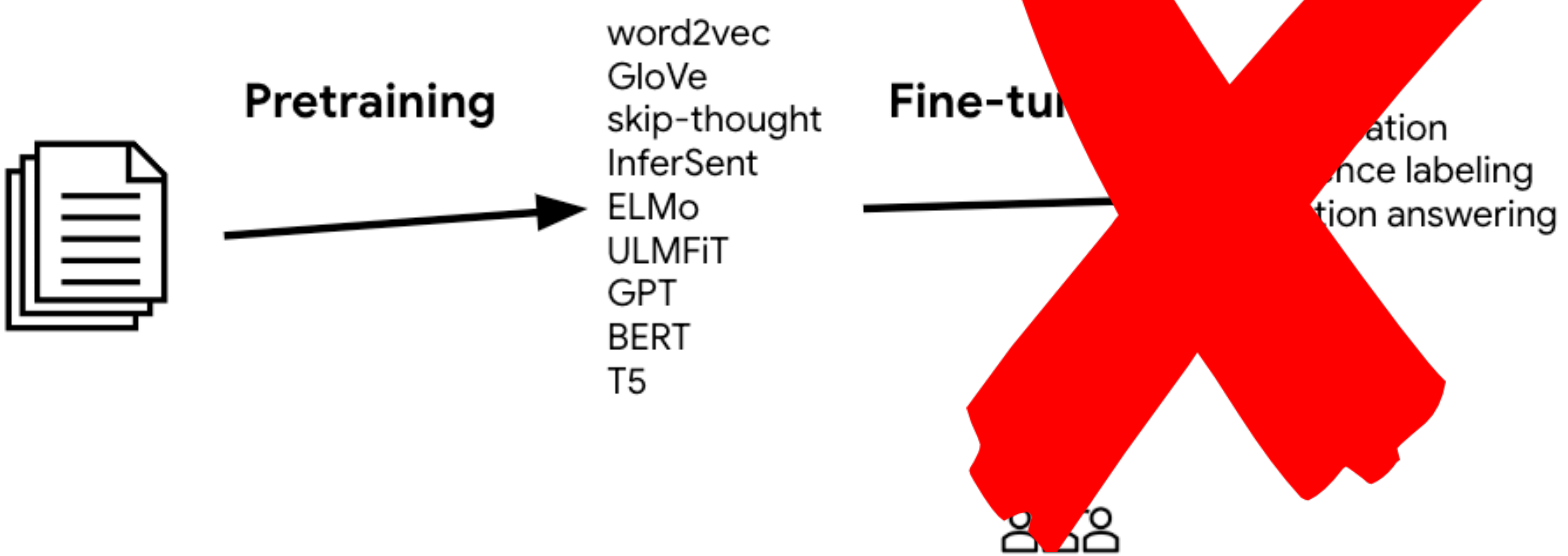

In-Context Learning

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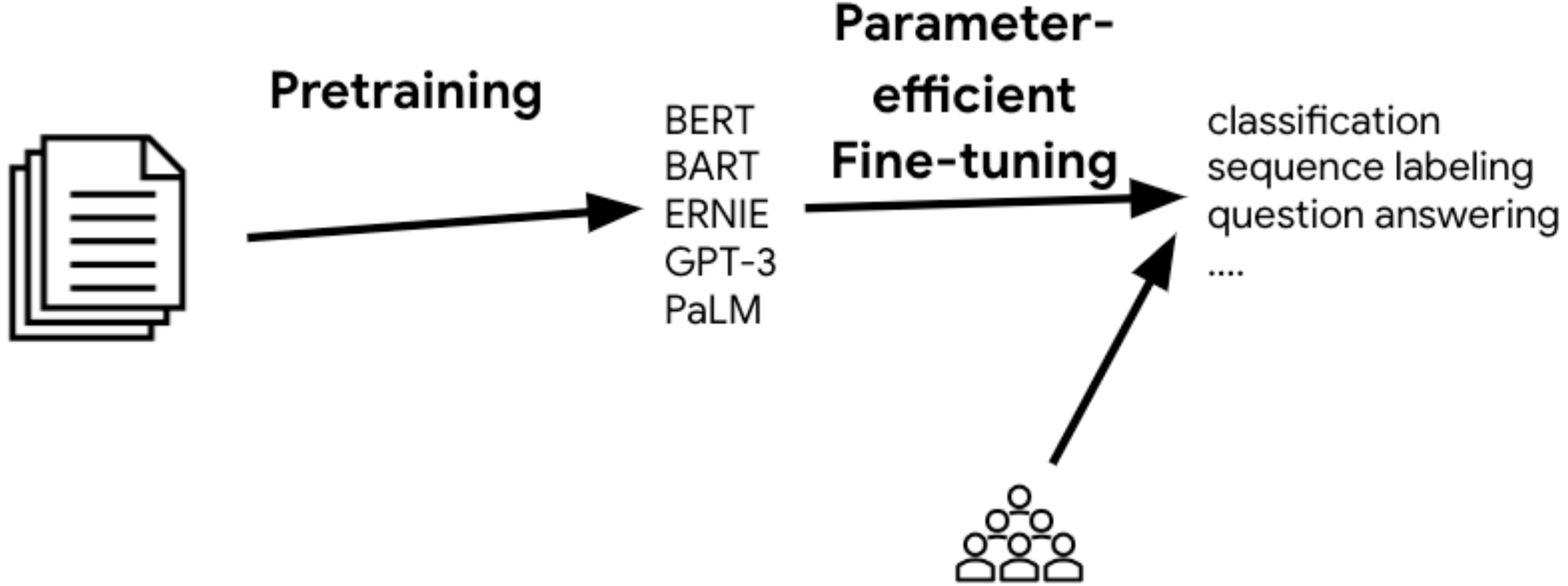
Sensitivity to the wording of the prompt [Webson & Pavlick, 2022], order of examples — e.g., see [Zhao et al., 2021; Lu et al., 2022]

Lack of clarity regarding what the model learns from the prompt — even random label can provide non-trivial results [Min et al., 2022]!

Fine-Tuning → Parameter-Efficient Fine-Tuning



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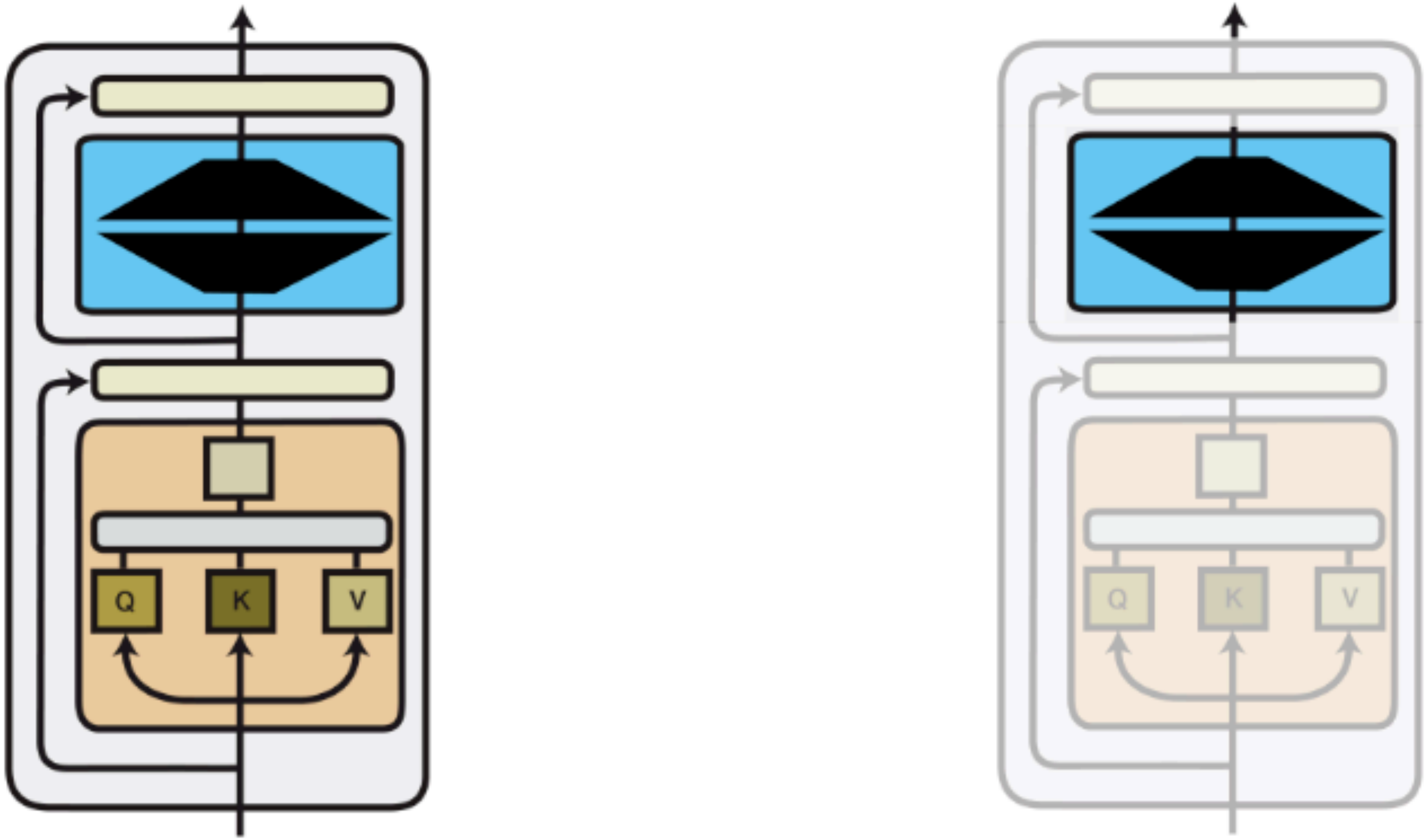

Full Fine-tuning
Update **all model parameters**

Parameter-efficient Fine-tuning
Update a **small subset** of model parameters

Fine-Tuning → Parameter-Efficient Fine-Tuning

Parameter-Efficient Fine-Tuning (PEFT) is not really a new idea!

- Updating the last layer of the model was common in computer vision [Donahue et al., 2014]. In NLP, people experimented with static (frozen) and non-static (trainable) [Kim, 2014]
- ELMo did not fine-tune word embeddings [Peters et al., 2018]

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In practice, **fine-tuning everything** seems to work better in practice — why go back o fine-tuning **only** some parameters?

- Fine-tuning everything is **impractical** with large models
- LLMs nowadays are massively over-parameterised — PEFT matches full fine-tuning in downstream accuracy

Some Notation

Let $f_\theta : \mathscr{X} \mapsto \mathscr{Y}$ be a neural network, which can be decomposed into a **composition of functions** $f_{\theta_1} \odot f_{\theta_2} \odot \ldots \odot f_{\theta_n}$, where each function has parameters θ_i with $i \in \{1,\ldots,n\}$.

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Concatenation

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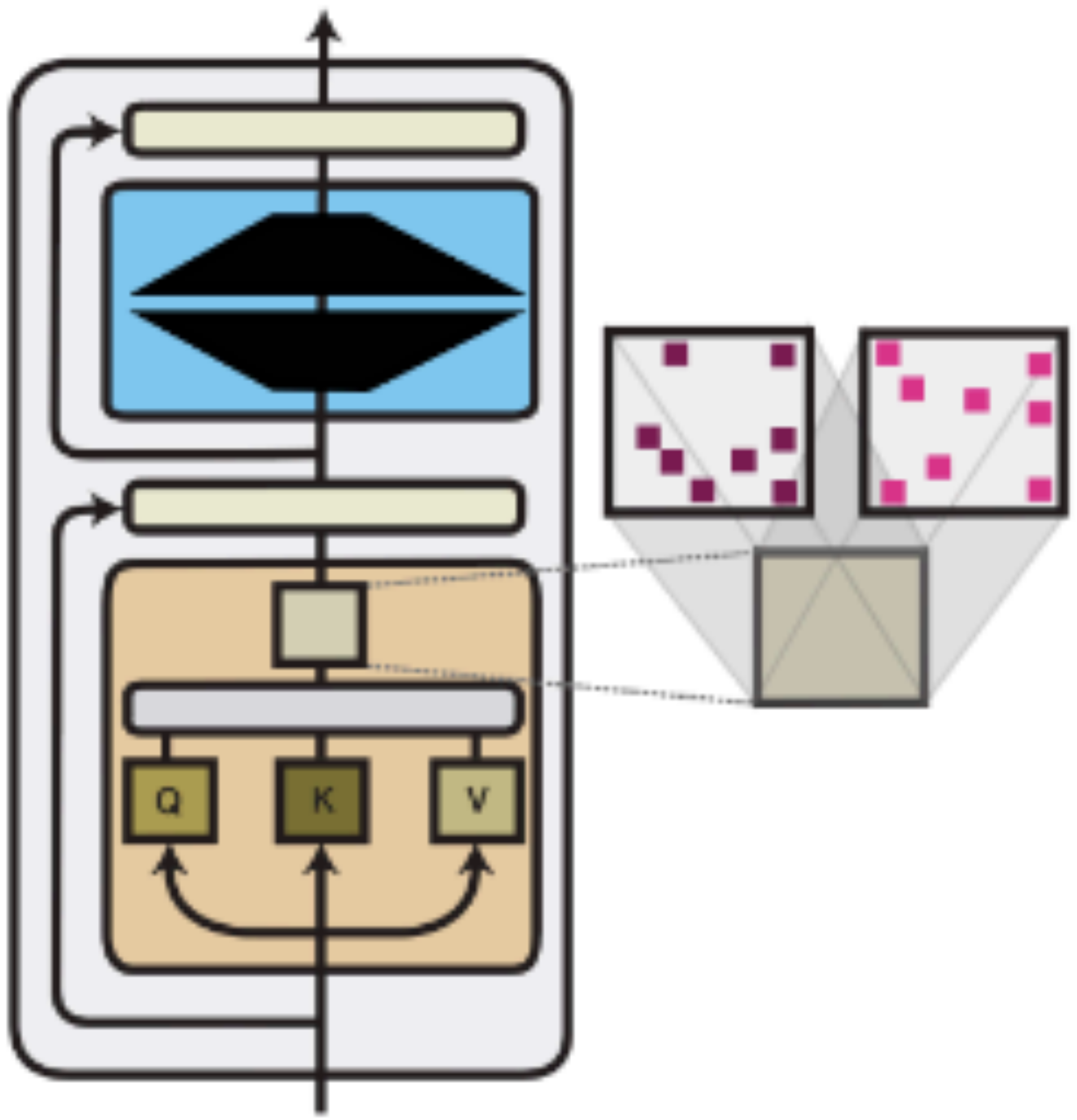
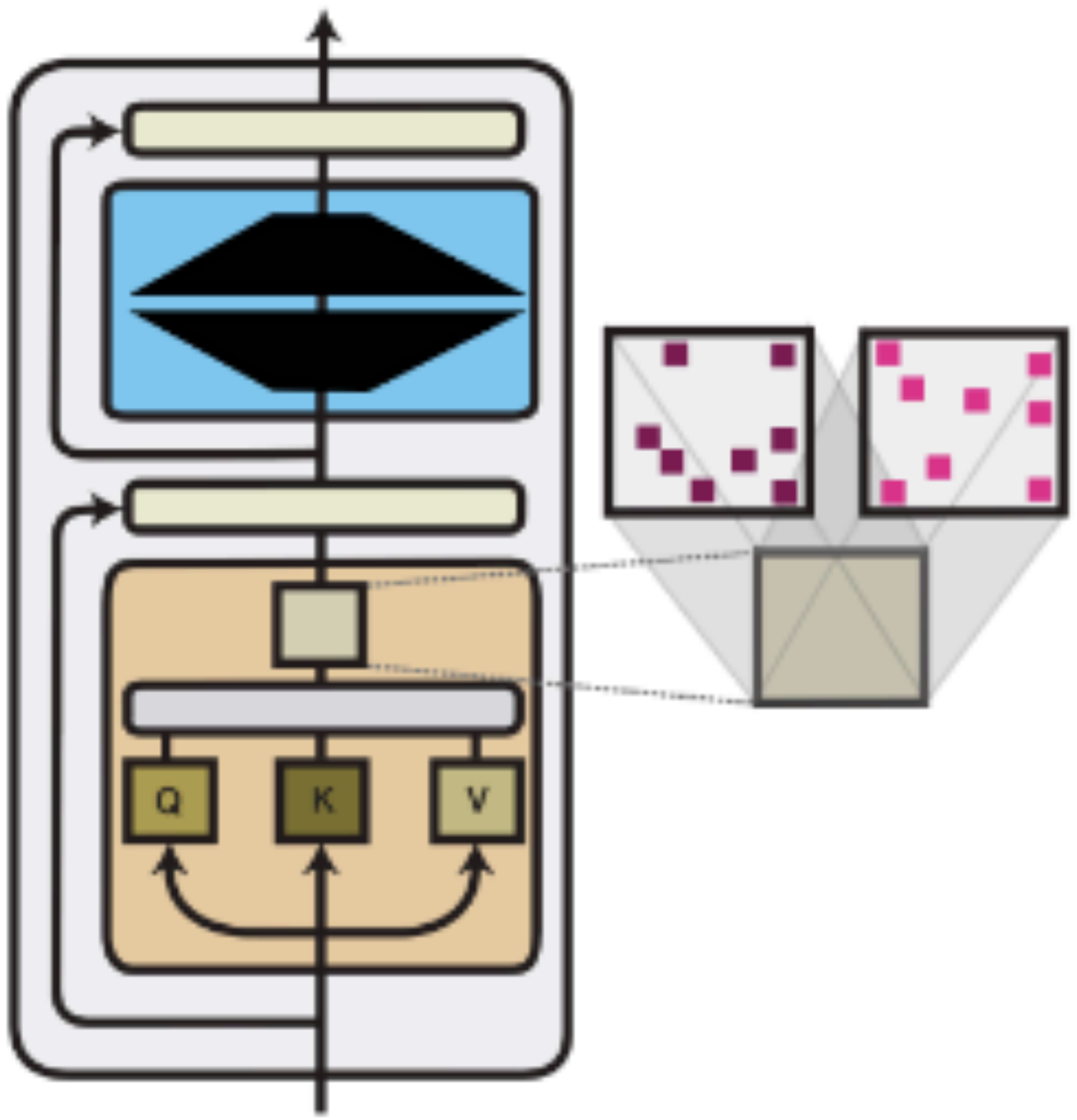
Typically, only module parameters ϕ are updated while θ is fixed

Composition Functions



Parameter Composition

Composition Functions



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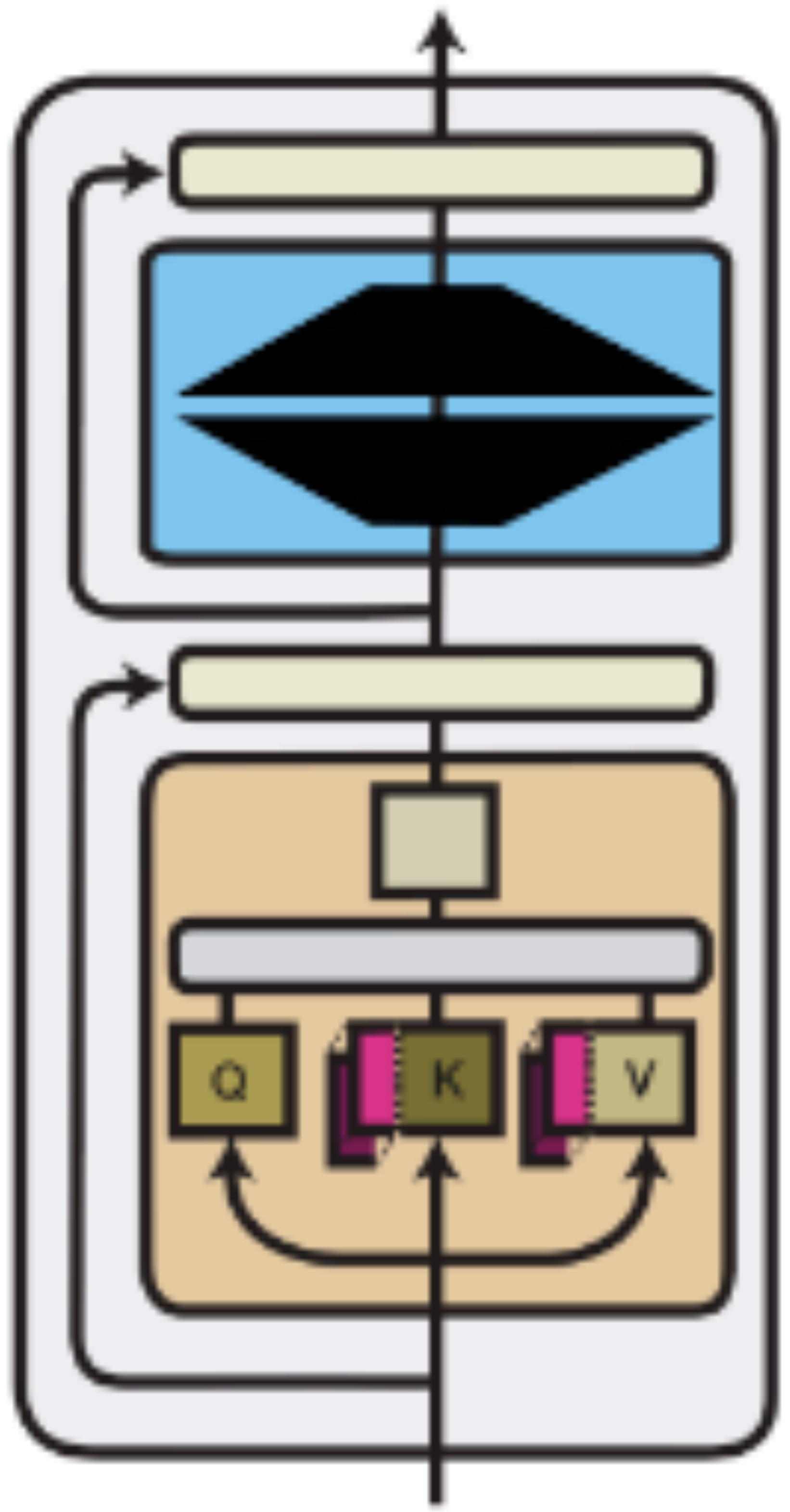

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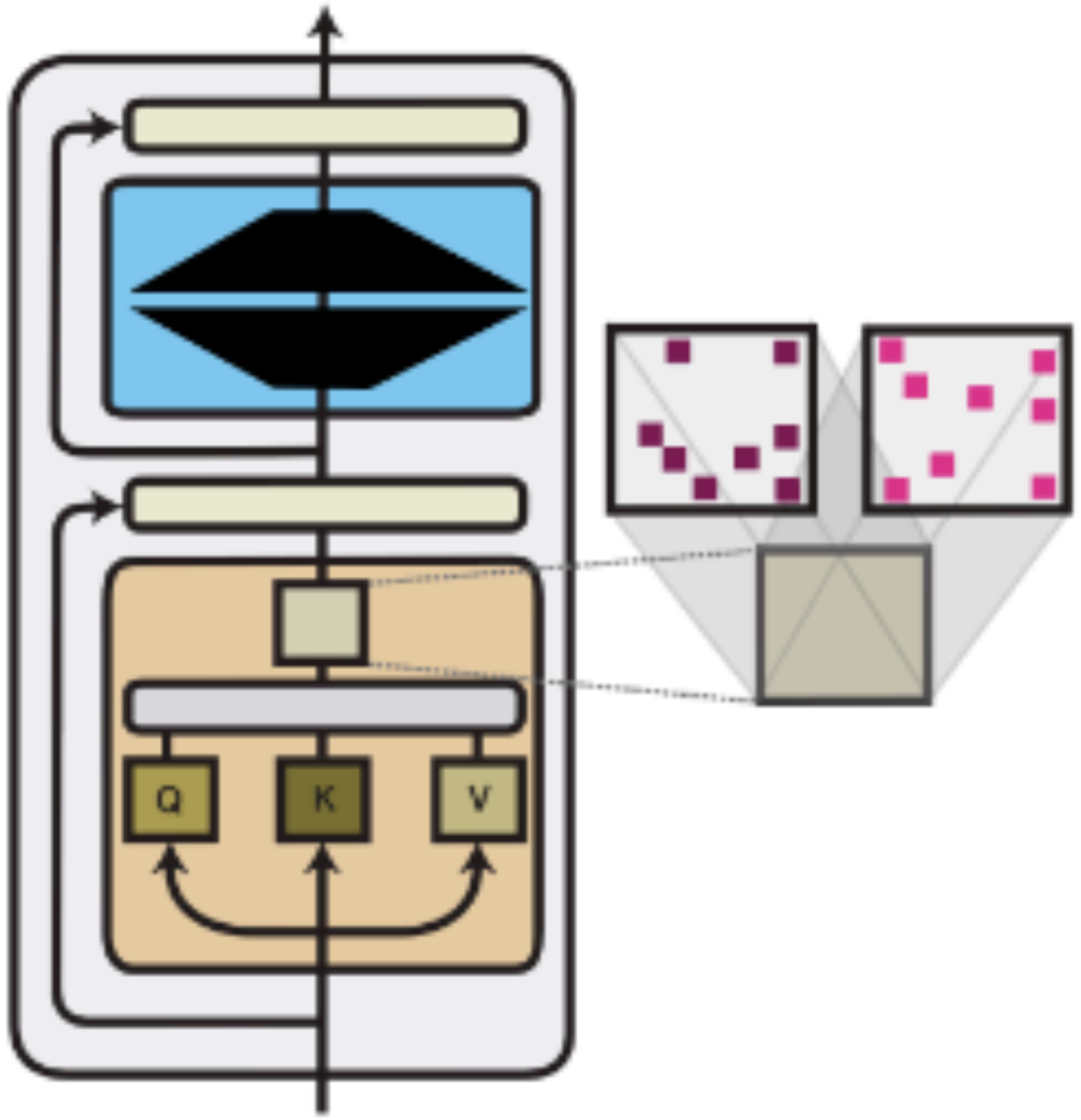

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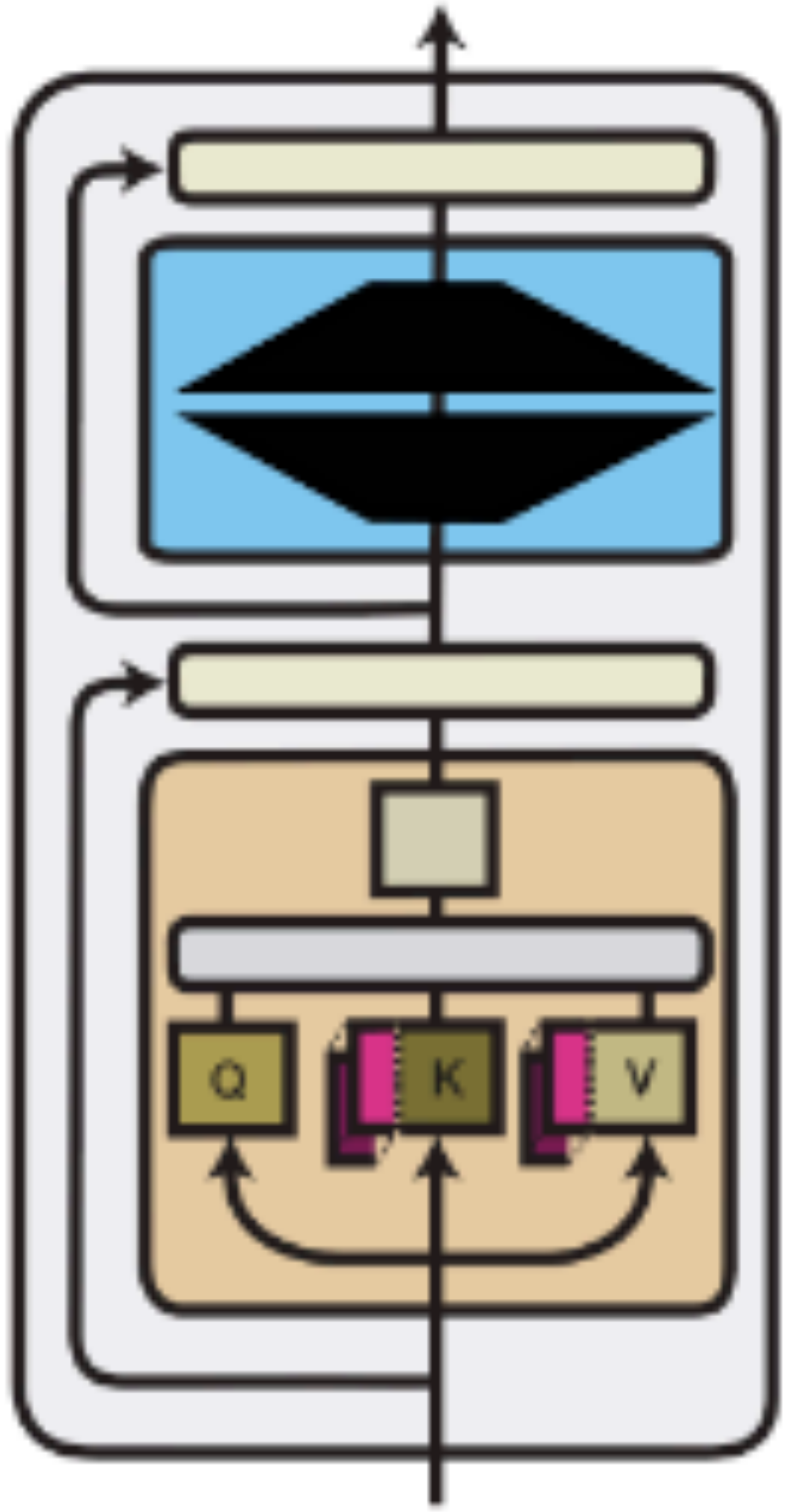

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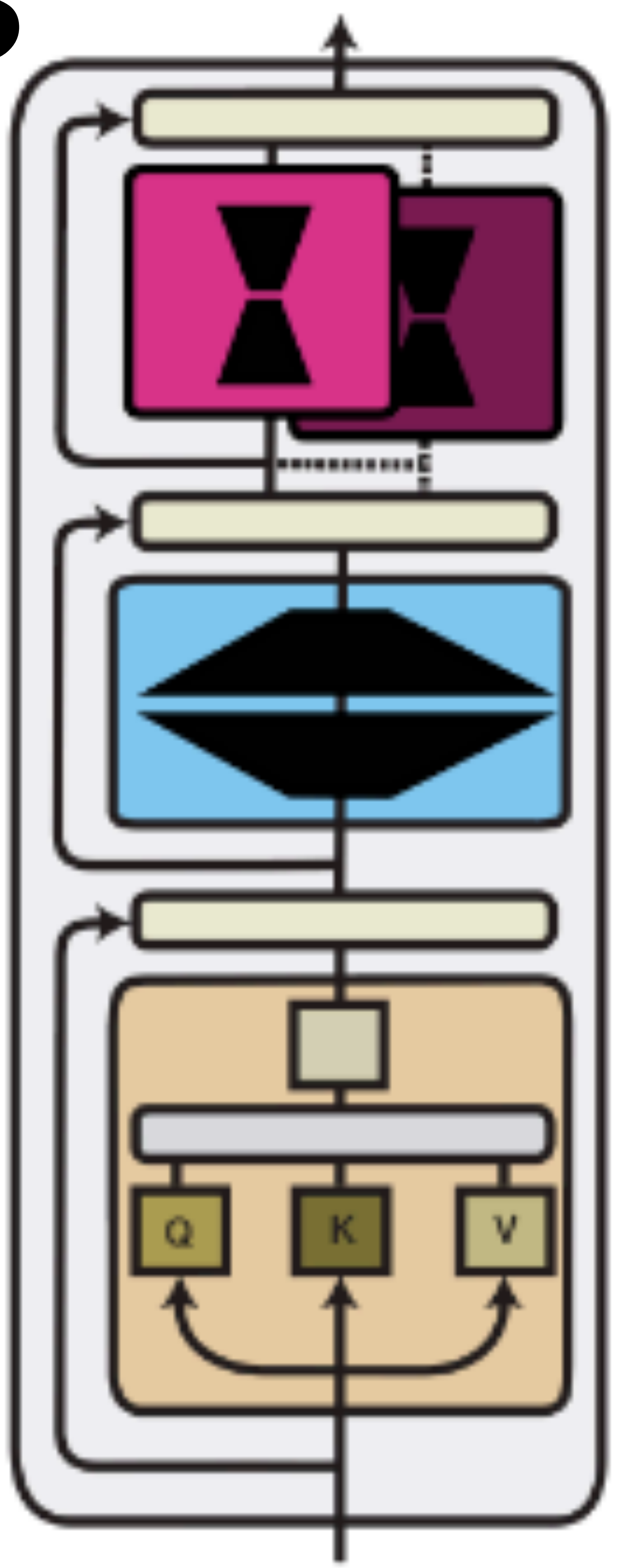

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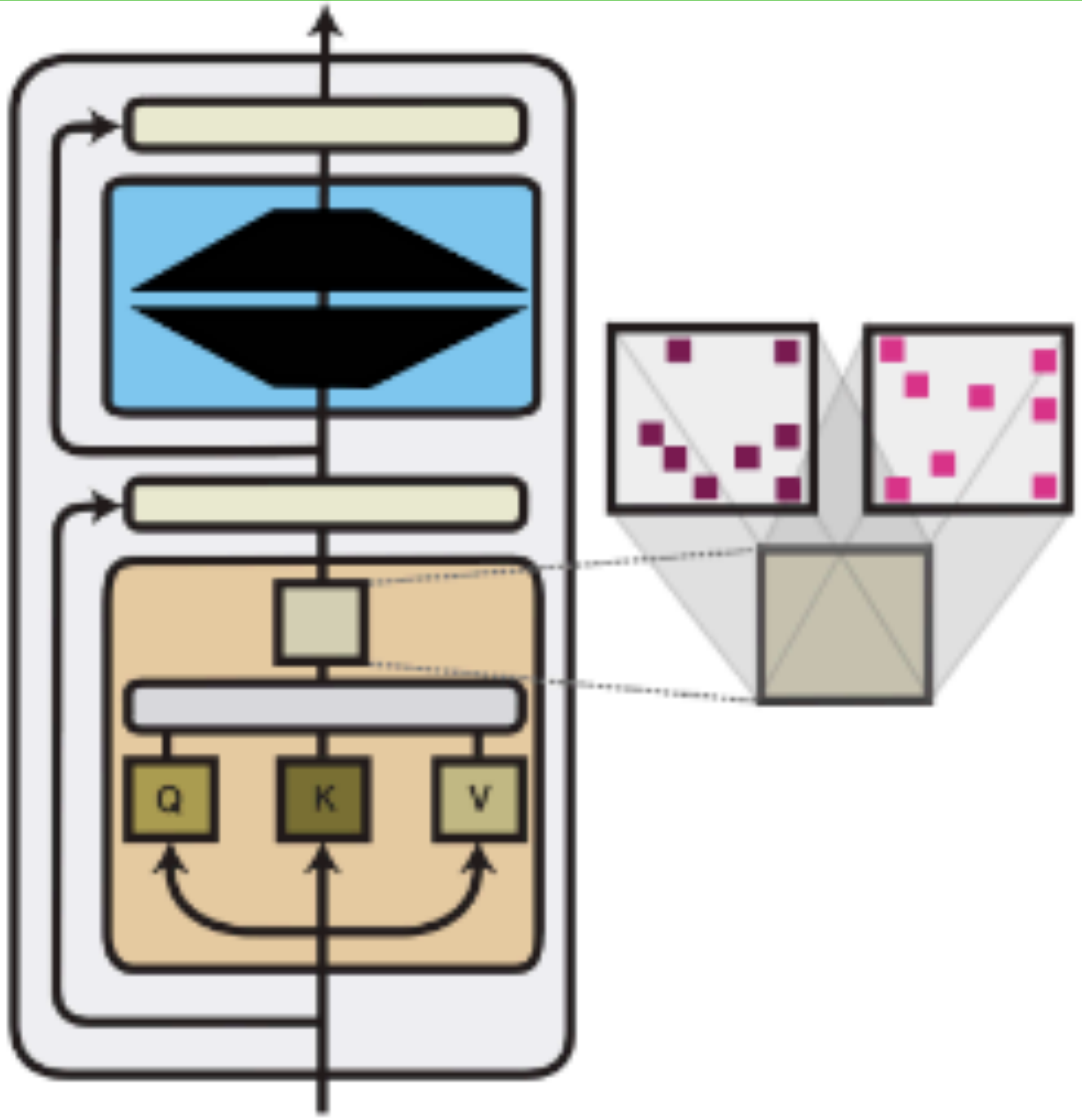

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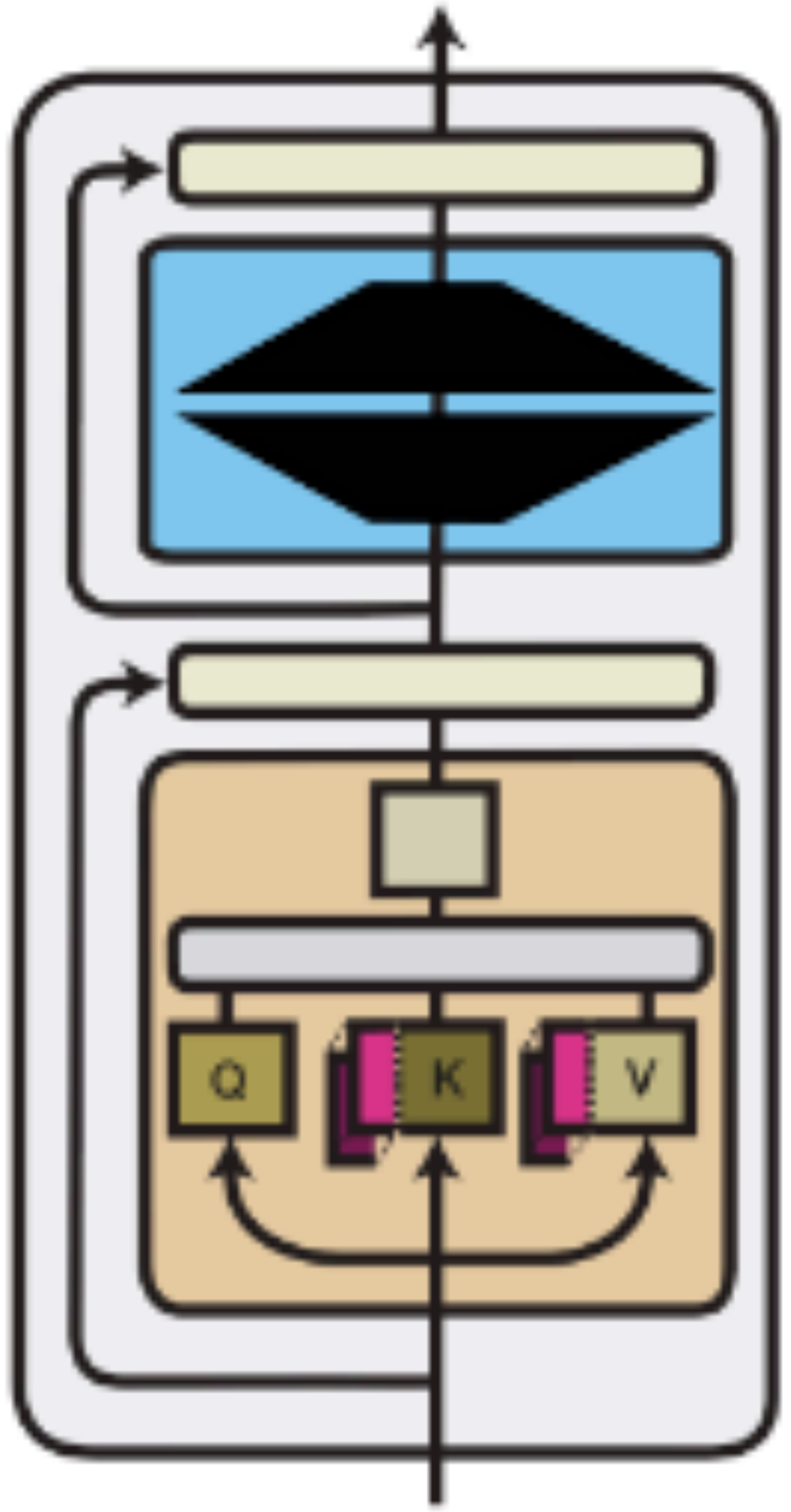

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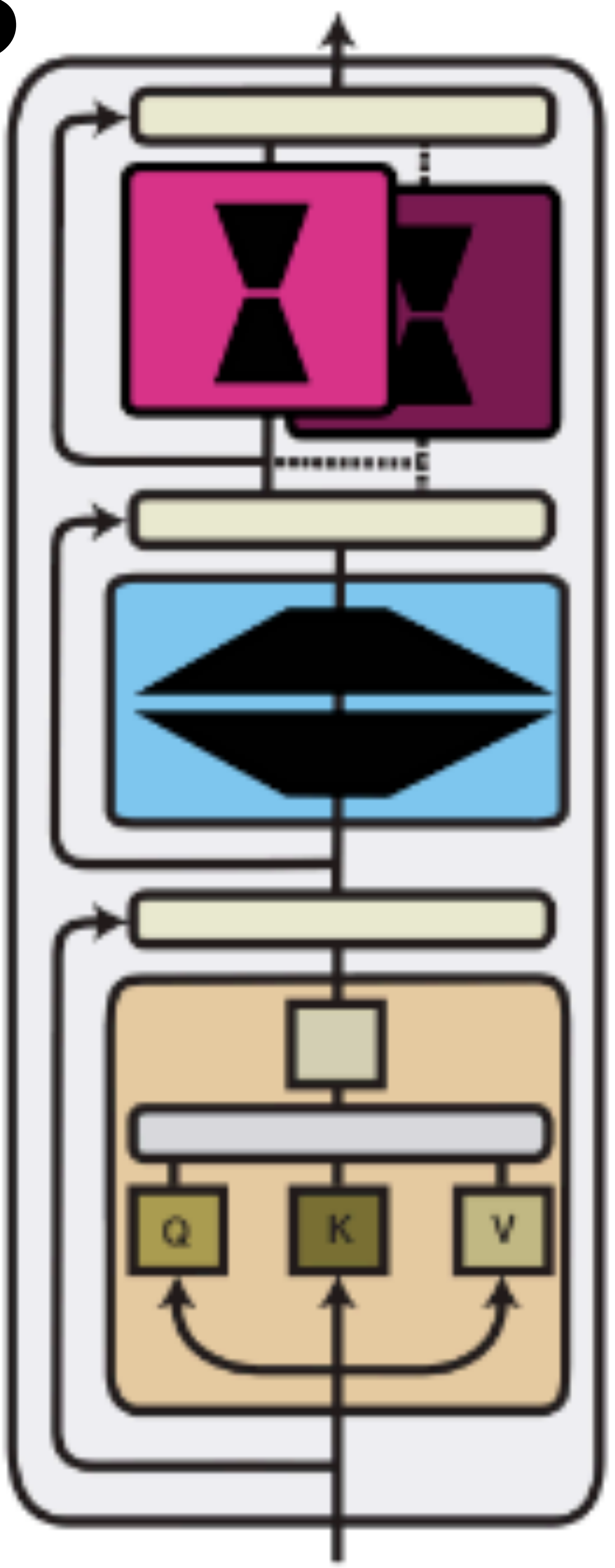
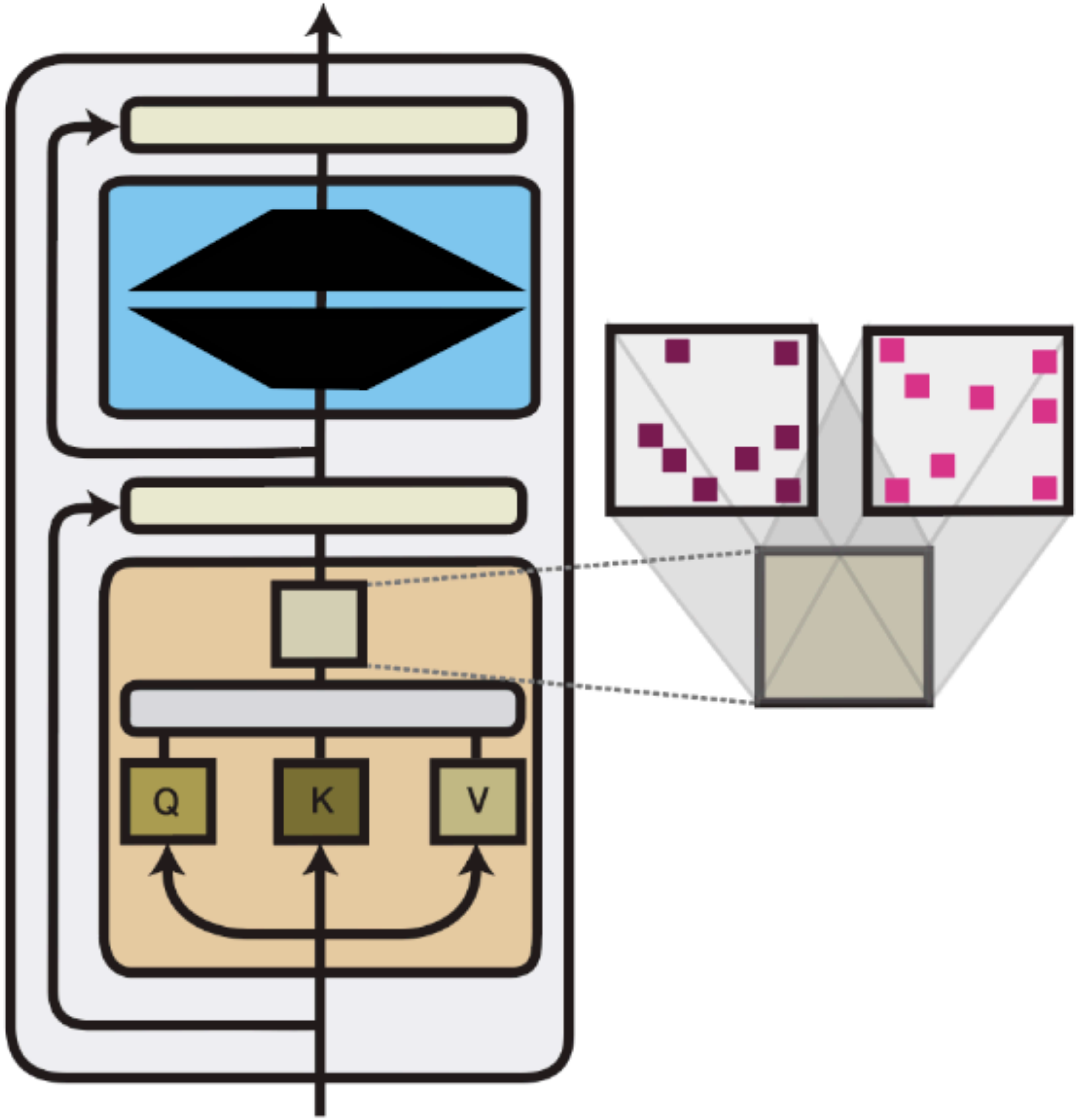


Function Composition

Parameter Composition

Sparse Subnetworks, where module parameters ϕ are enforced to be *sparse*



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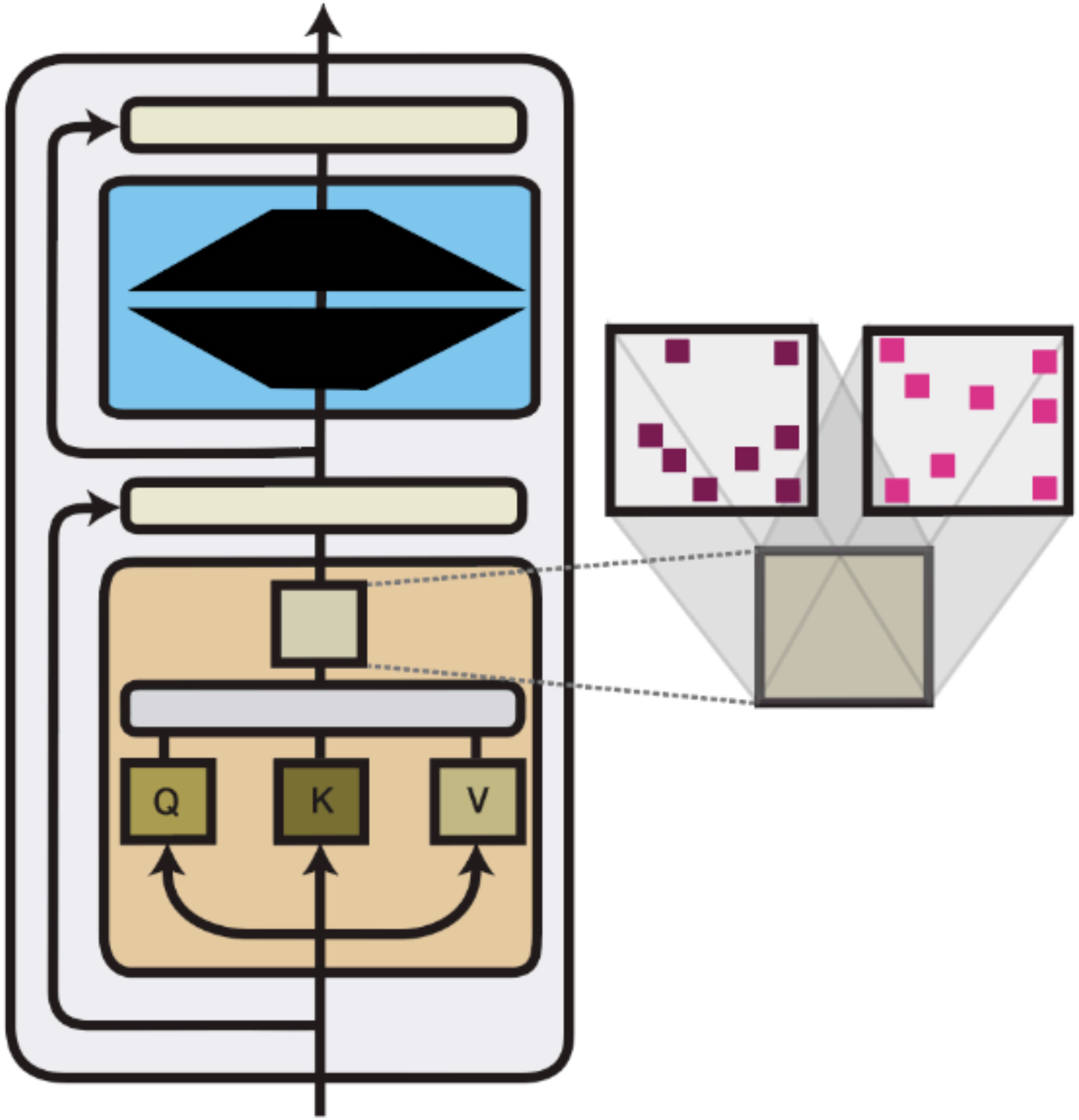
Structured Composition, where we impose a structure on the weights θ_i that we select — e.g., we update the weights belonging to a *pre-defined group*



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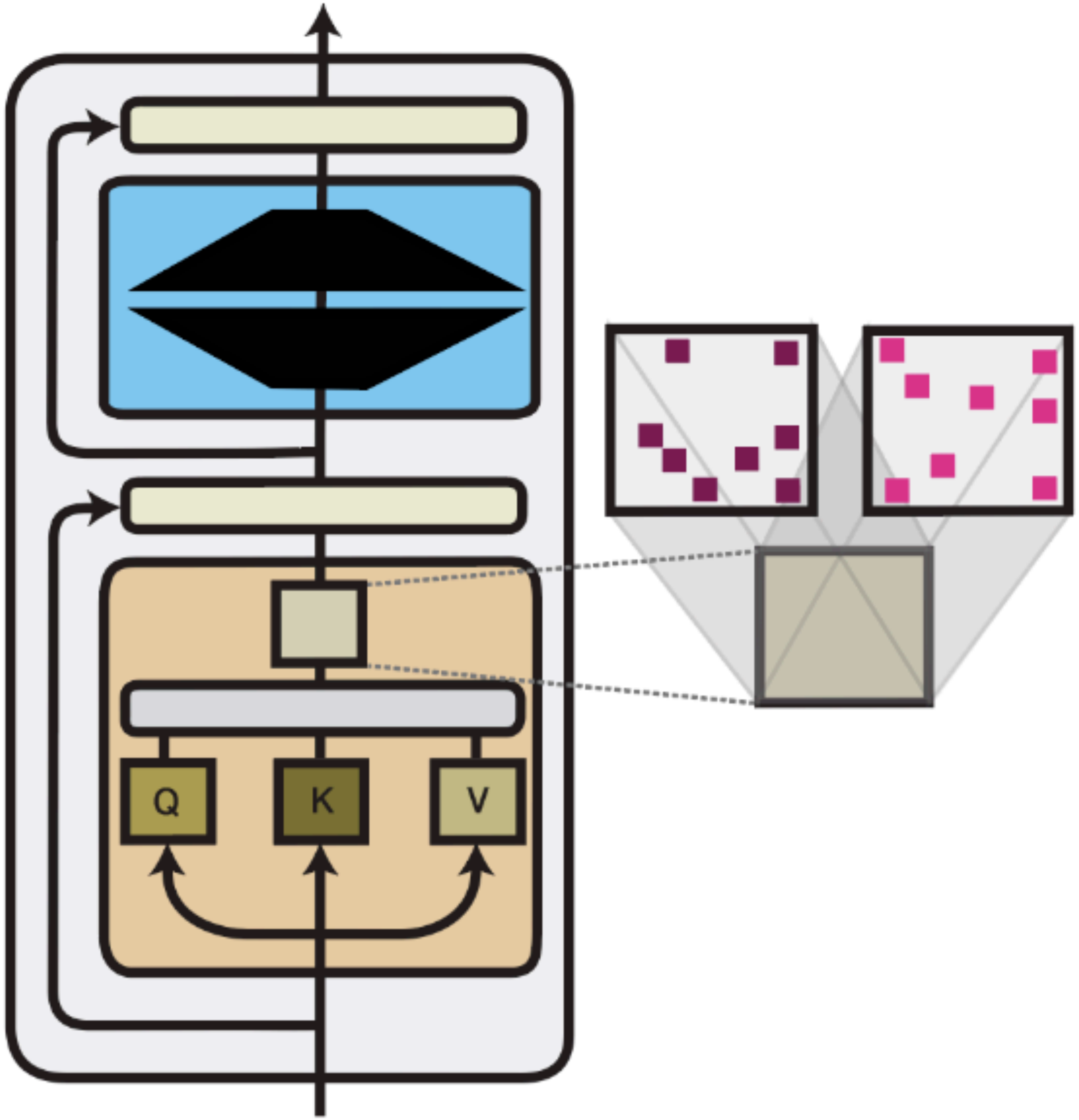
Structured Composition, where we impose a structure on the weights θ_i that we select — e.g., we update the weights belonging to a *pre-defined group*

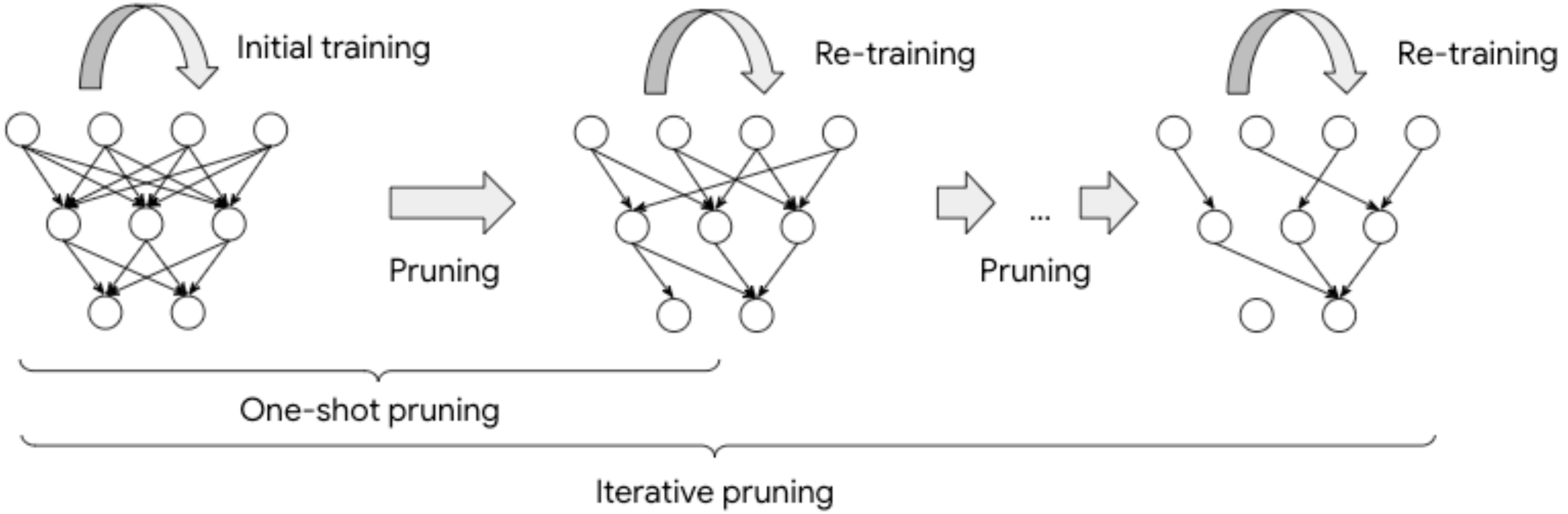
Low-Rank Composition, where the module parameters ϕ lie in a *low-dimensional space*



Parameter Composition — Sparse Subnetworks

A common inductive bias on module parameters ϕ is **sparsity**: when we do $g_i = f_{\theta_i \cdot \phi}(x)$ (element-wise product), we mask part of the neural network f

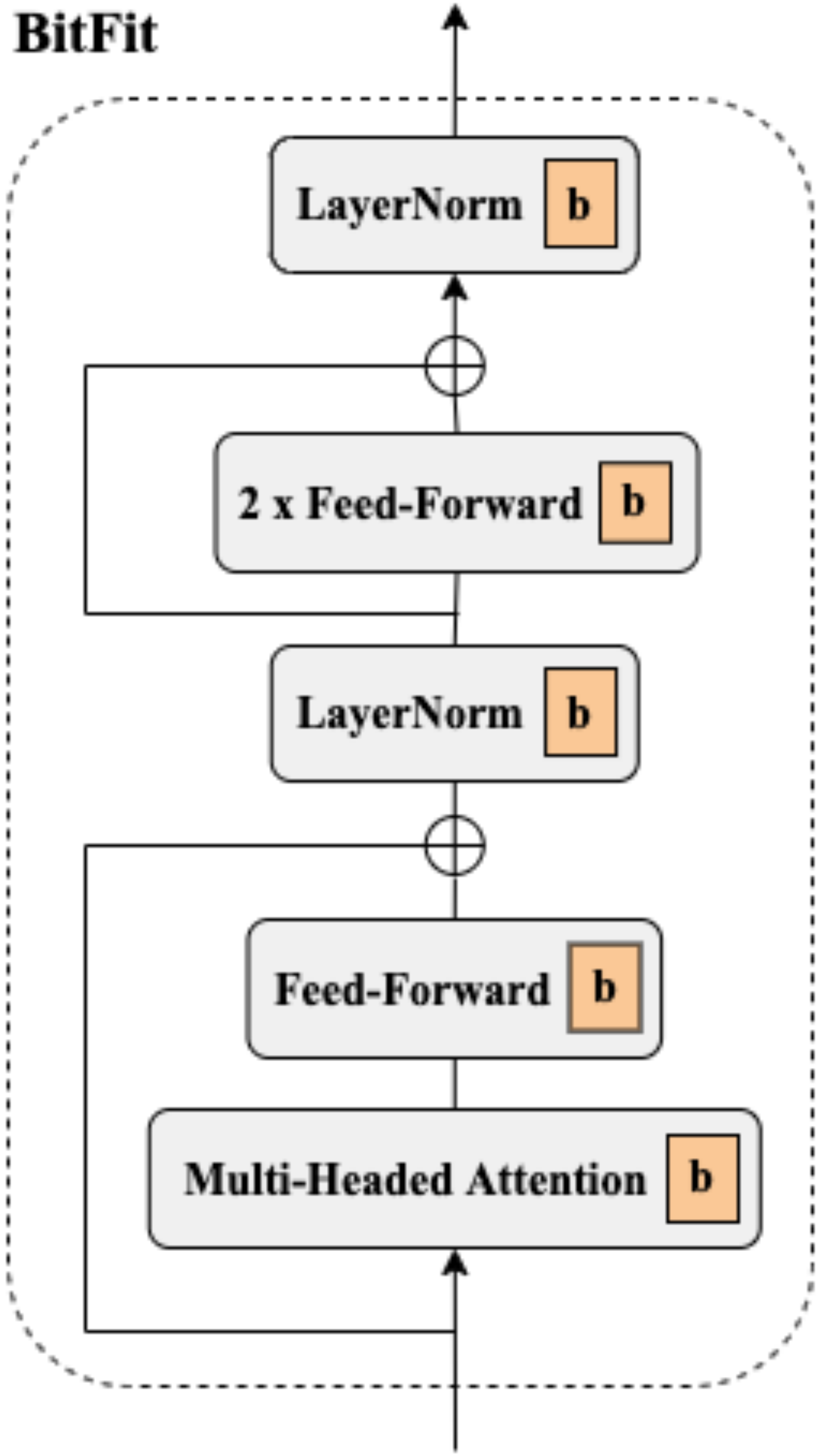
Most common sparsity method: **pruning** — e.g., see [Han et al., 2017]



Parameter Composition — Structured Composition

We can impose a structure on the weights that we select: we only modify the weights that are **associated in a pre-defined group** $\mathscr{G}$, for example, a layer, a group of layers, or more fine-grained components

Example: only update bias vectors — BitFit [Ben-Zaken et al., 2022]



Parameter Composition — Low-Rank Composition

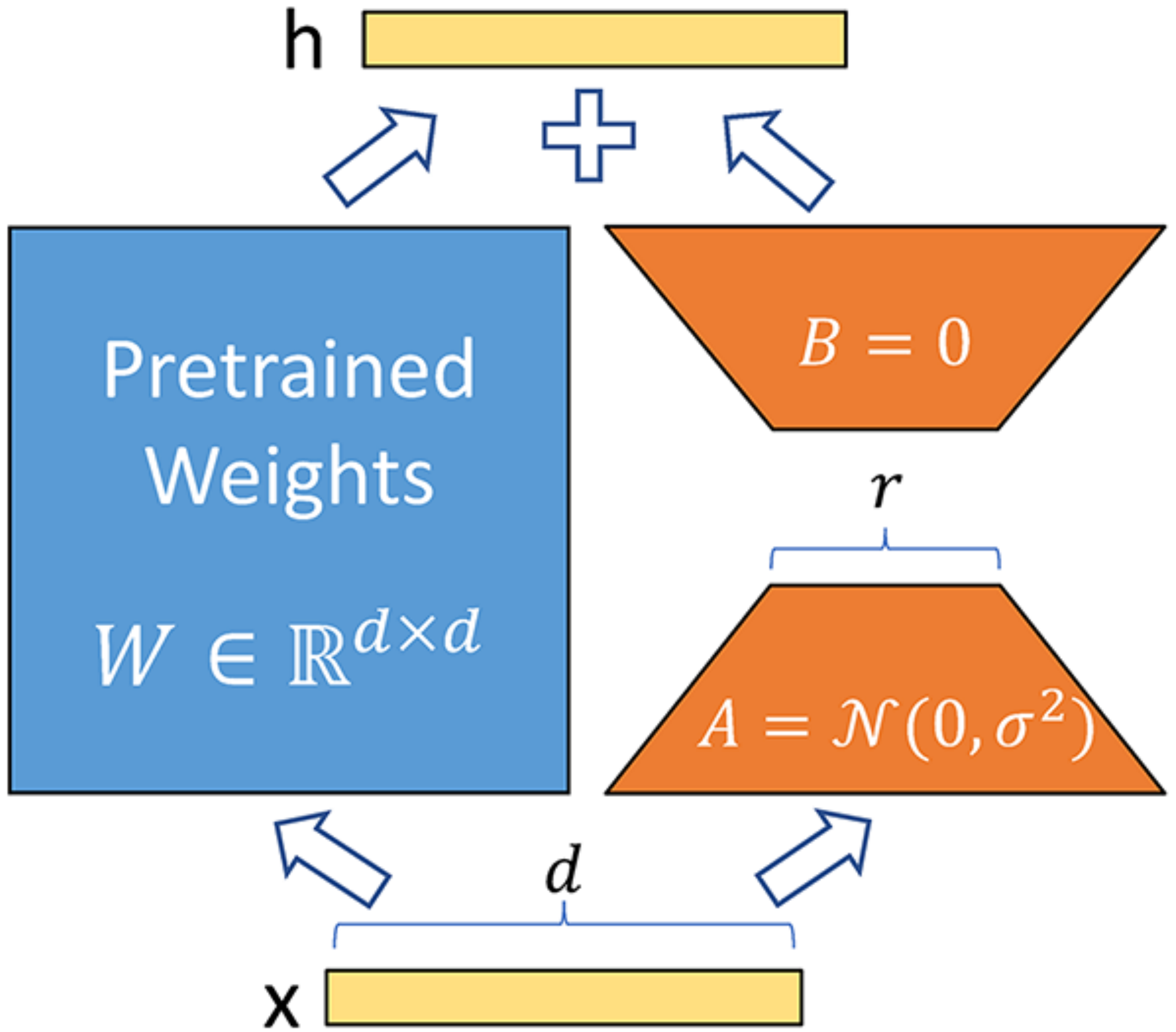
Another useful inductive bias: module parameters ϕ should **lie in a low-dimensional space.** Li et al., 2018 show that models can be optimised in a low-dimensional, randomly oriented subspace rather than the full parameter space

Low-rank fine-tuning takes the form $g = f_{\theta + P\phi}$ where $P \in \mathbb{R}^{D \times d}$ — with a dense matrix of shape $D \times d$, this scales as $\mathcal{O}(Dd)$ in time and storage

Parameter Composition — LoRA

Low-Rank Adaptation — instead of learning a low-rank factorisation via a random matrix P, we can learn the projection matrix directly

LoRA [Hu et al., 2022] learns two matrices $B \in \mathbb{R}^{d \times r}$ and $A \in \mathbb{R}^{r \times k}$ that are applied to the self-attention weights:



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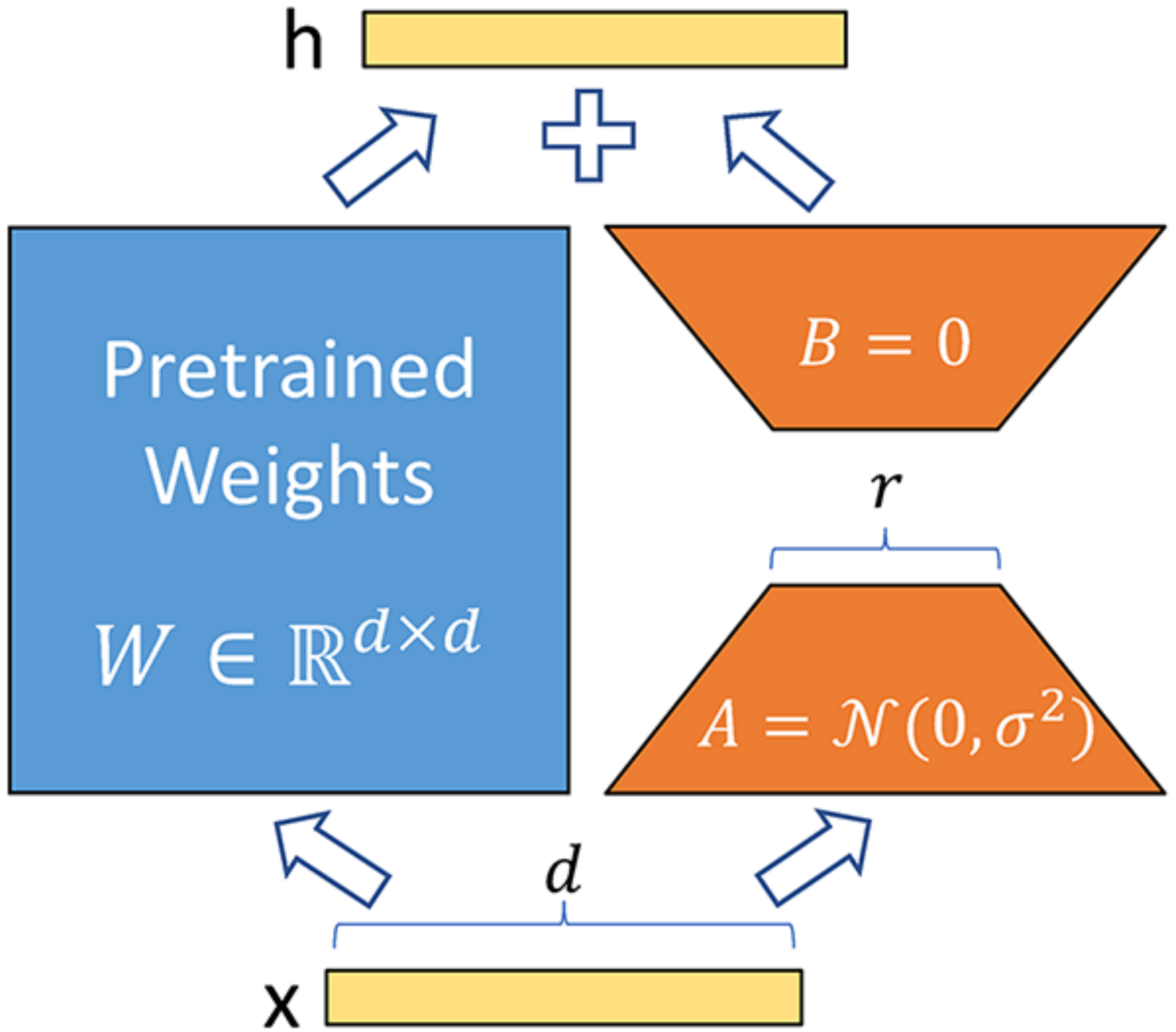
$$h = \left[W_0 + \underbrace{\Delta W}_{\text{Update to parameters } W_0}\right] x = \left[W_0 + BA\right] x$$



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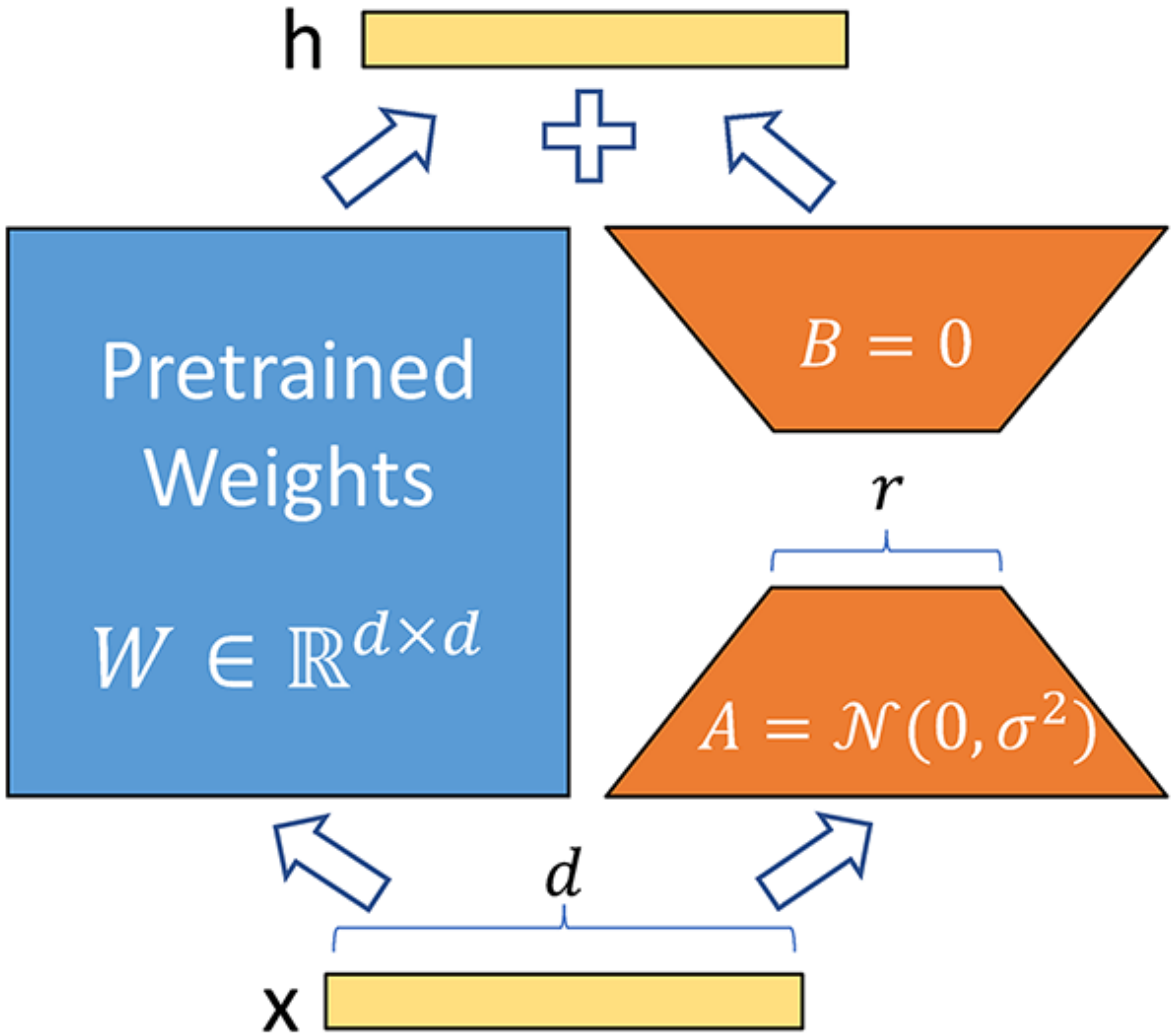

In our notation:

$$g_i = f_{\theta_i + B_i A_i}, \forall f_i \in \mathcal{G}$$

Parameter Composition — LoRA

Applying LoRA to a Transformer layer — remember how Transformers work:

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

$$\text{with } \text{Attention}(Q\boxed{W_{Q,i}}, K\boxed{W_{K,i}}, V\boxed{W_{V,i}}) \text{ and } \text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^\top}{\sqrt{d_k}}\right)$$

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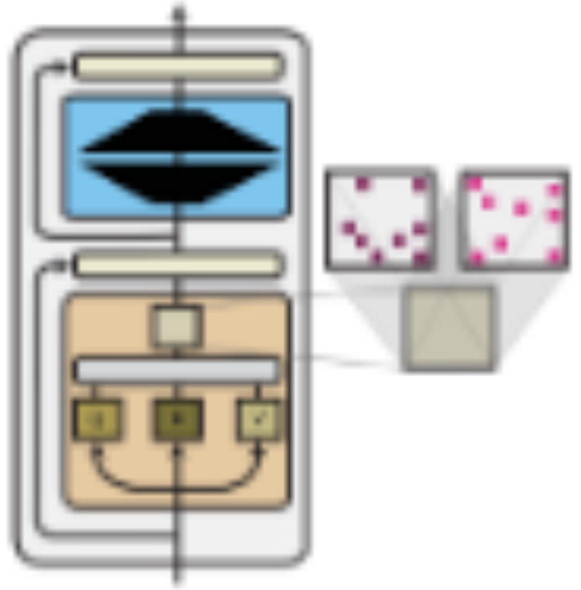
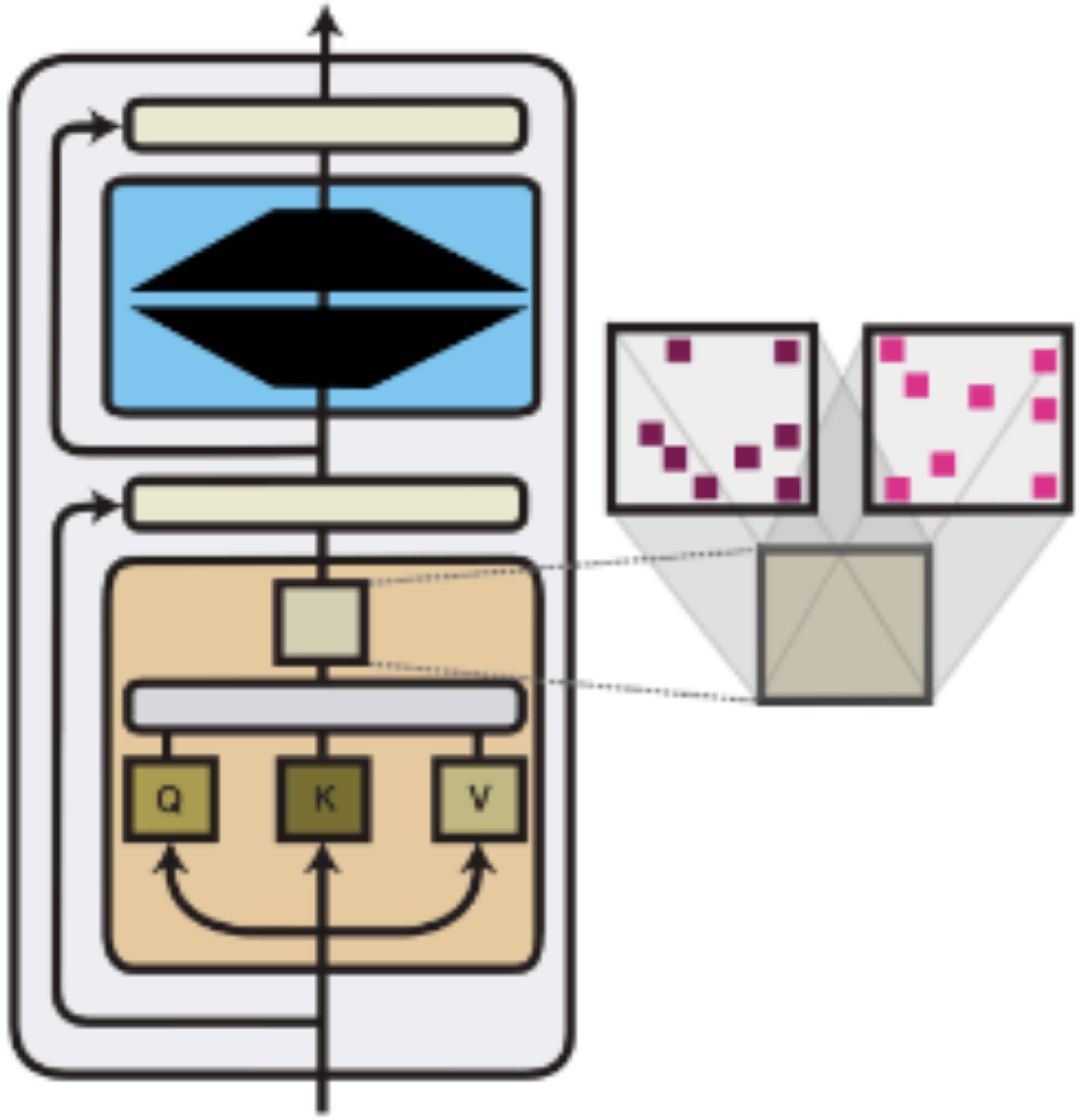
We can use LoRA to adapt the weights $W_{Q,i}$, $W_{K,i}$, and/or $W_{V,i}$ — in the case of $W_{Q,i}$, the updated weights will be:

$$\begin{aligned}\widetilde{W_{Q,i}} &= W_{Q,i} + \Delta W_{Q,i} \\ &= W_{Q,i} + B_{Q,i}A_{Q,i} \text{ with } B \in \mathbb{R}^{d \times r}, A \in \mathbb{R}^{r \times k}\end{aligned}$$

Computation Functions — Comparison

	Parameter efficiency	Training efficiency	Inference efficiency	Performance
Parameter composition 	Methods such as LoRA require < 3% of parameters	Pruning requires re-training iterations	Does not increase the model size	E.g., LoRA achieves strong performance
	+	-	++	+

Composition Functions



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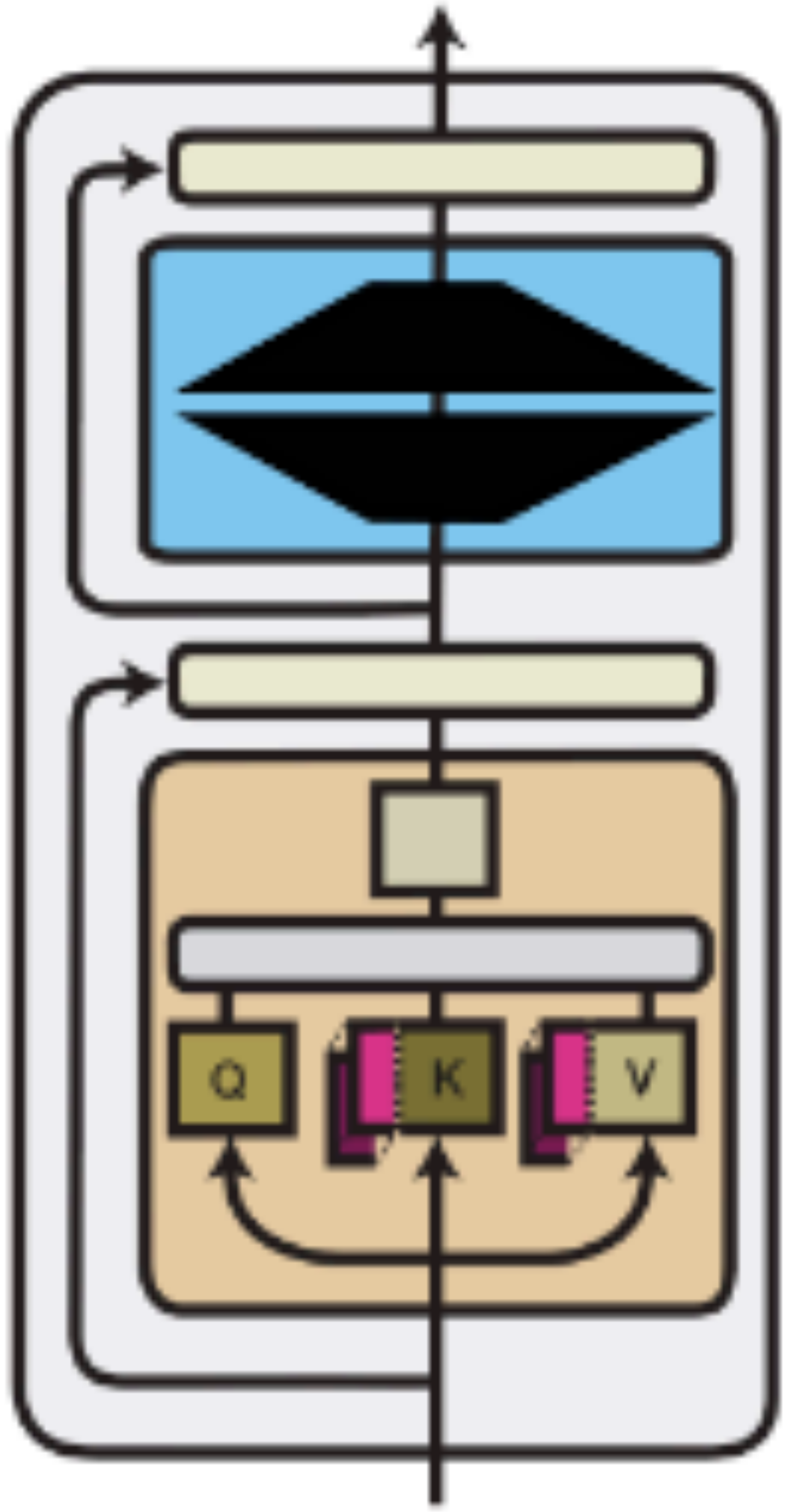
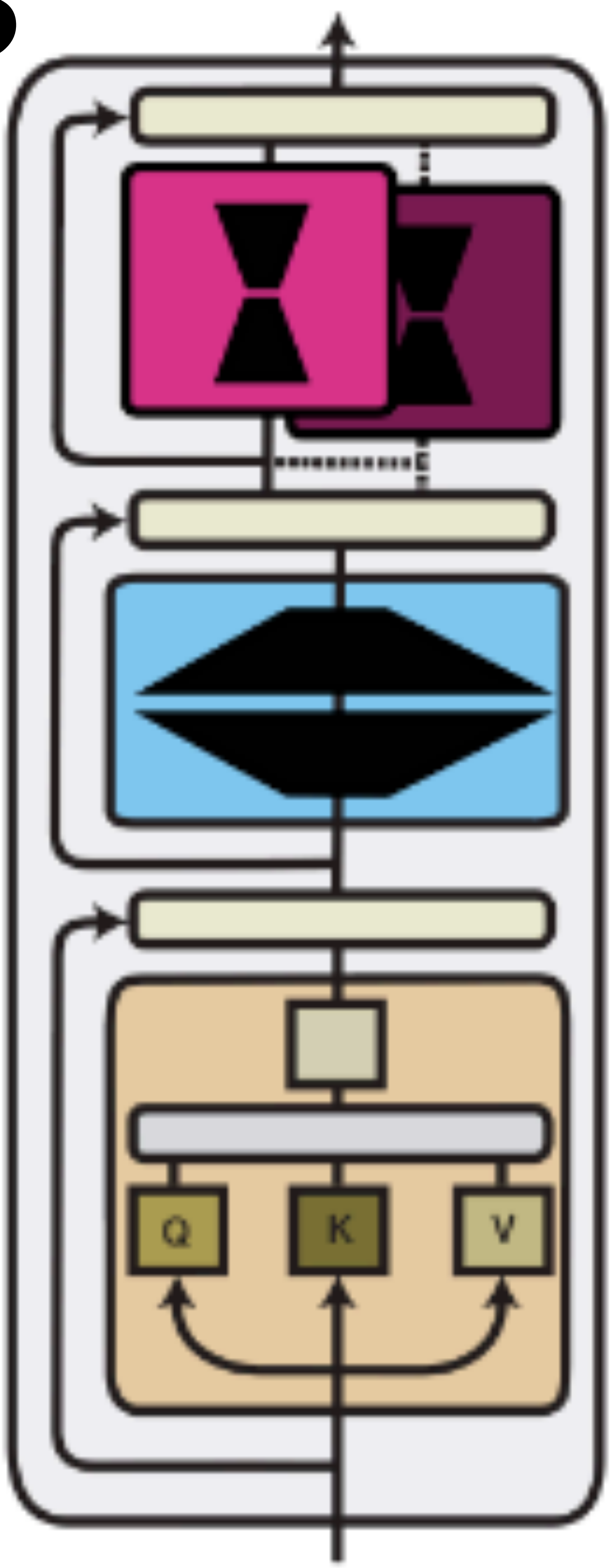


Input Composition

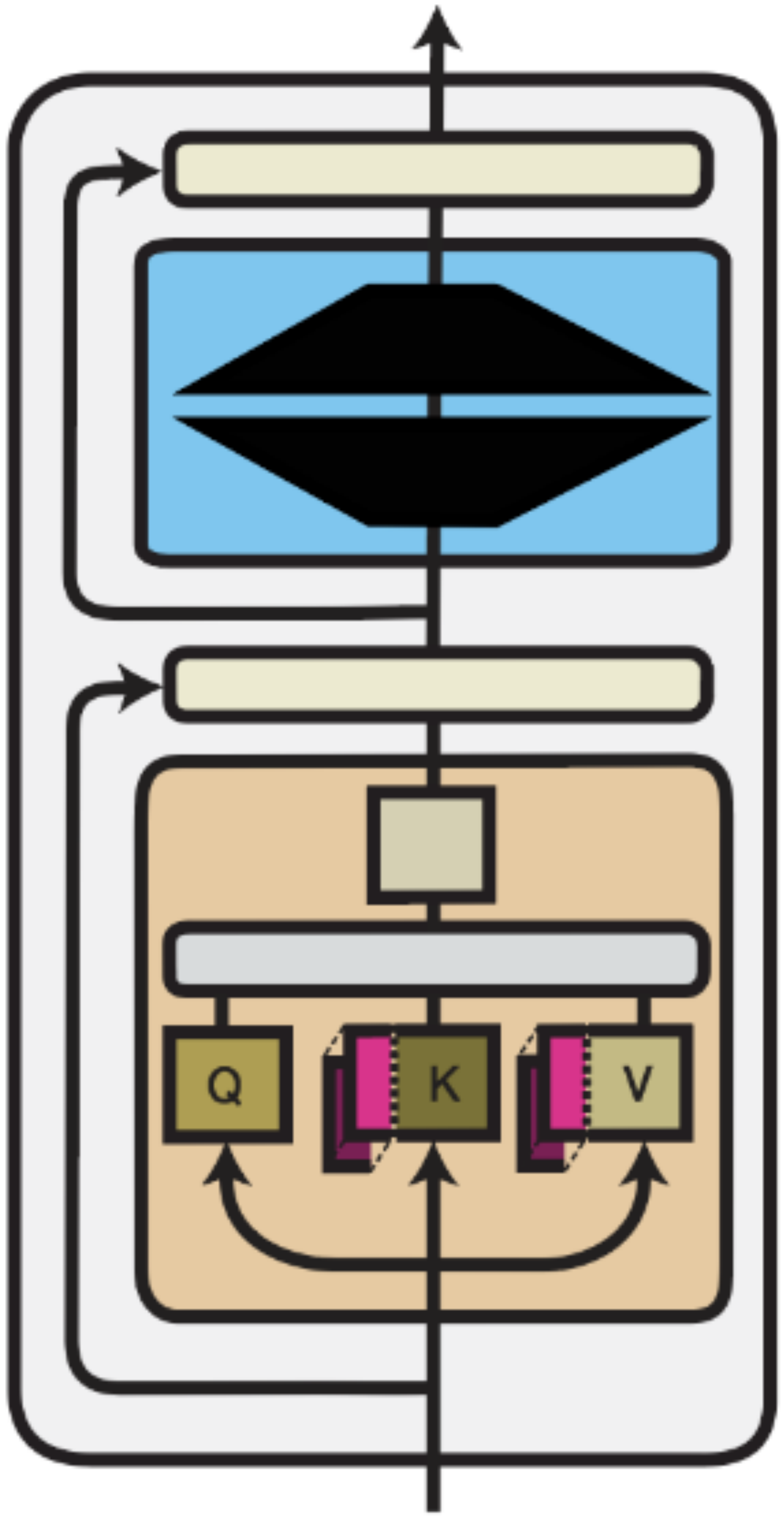


Function Composition

Input Composition

Idea — augment the input of the model with a learnable vector ϕ:

$$g_i(x) = f_{\theta_i}\left(\left[\phi_i, x\right]\right)$$



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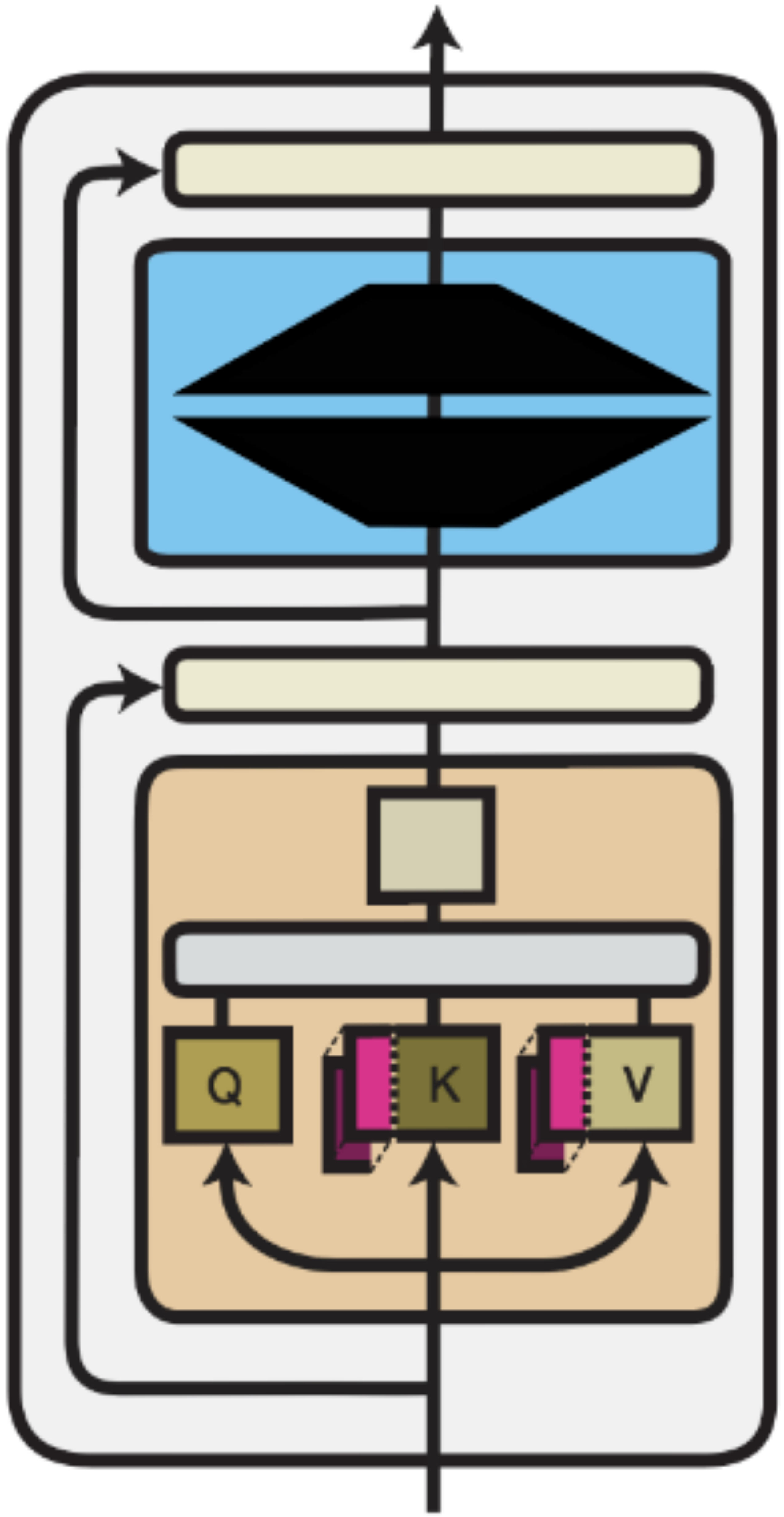
Input Composition and Prompting — standard prompting can be seen as finding a discrete text prompt that, when embedded using the model's embedding layer, yields ϕ_i



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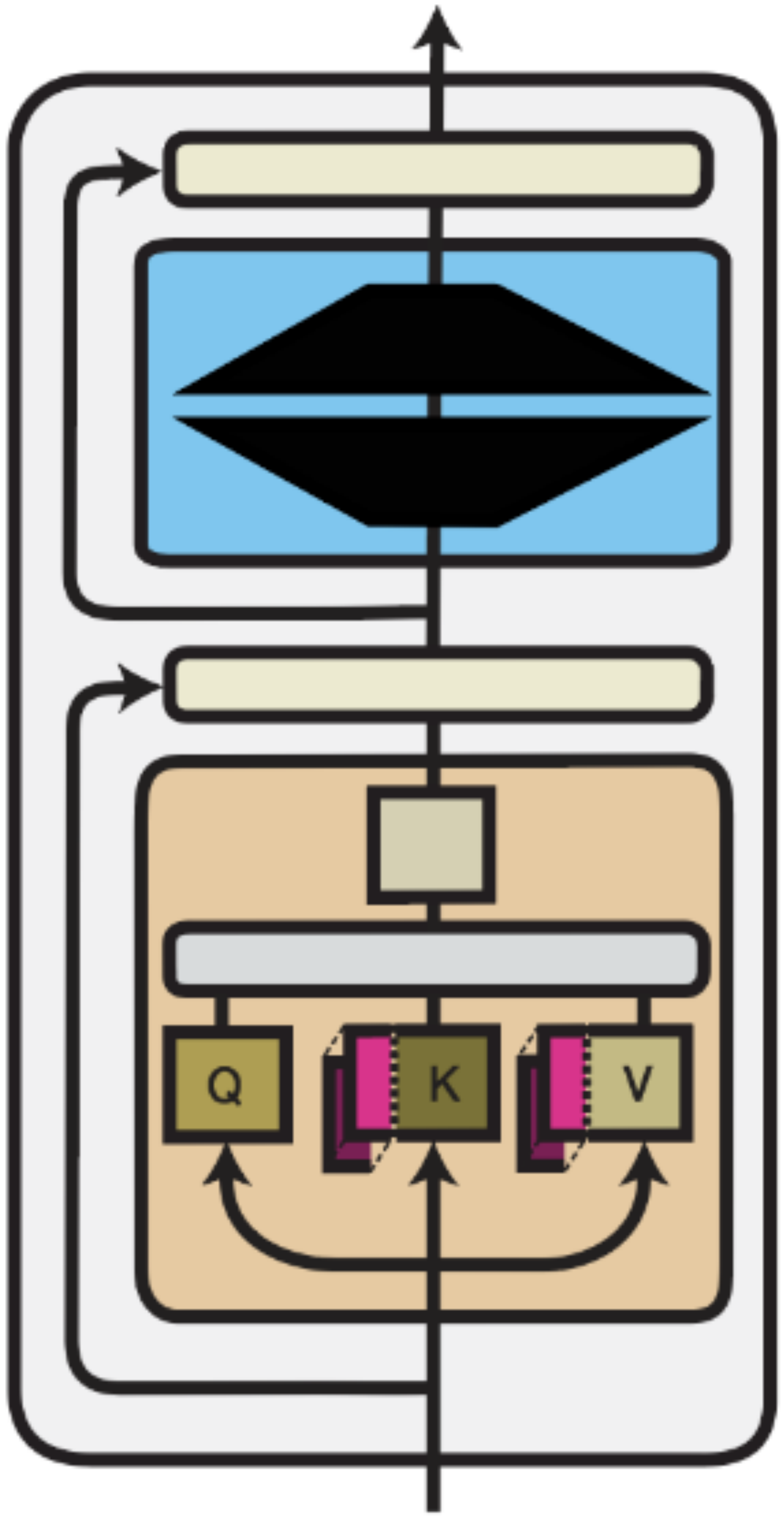
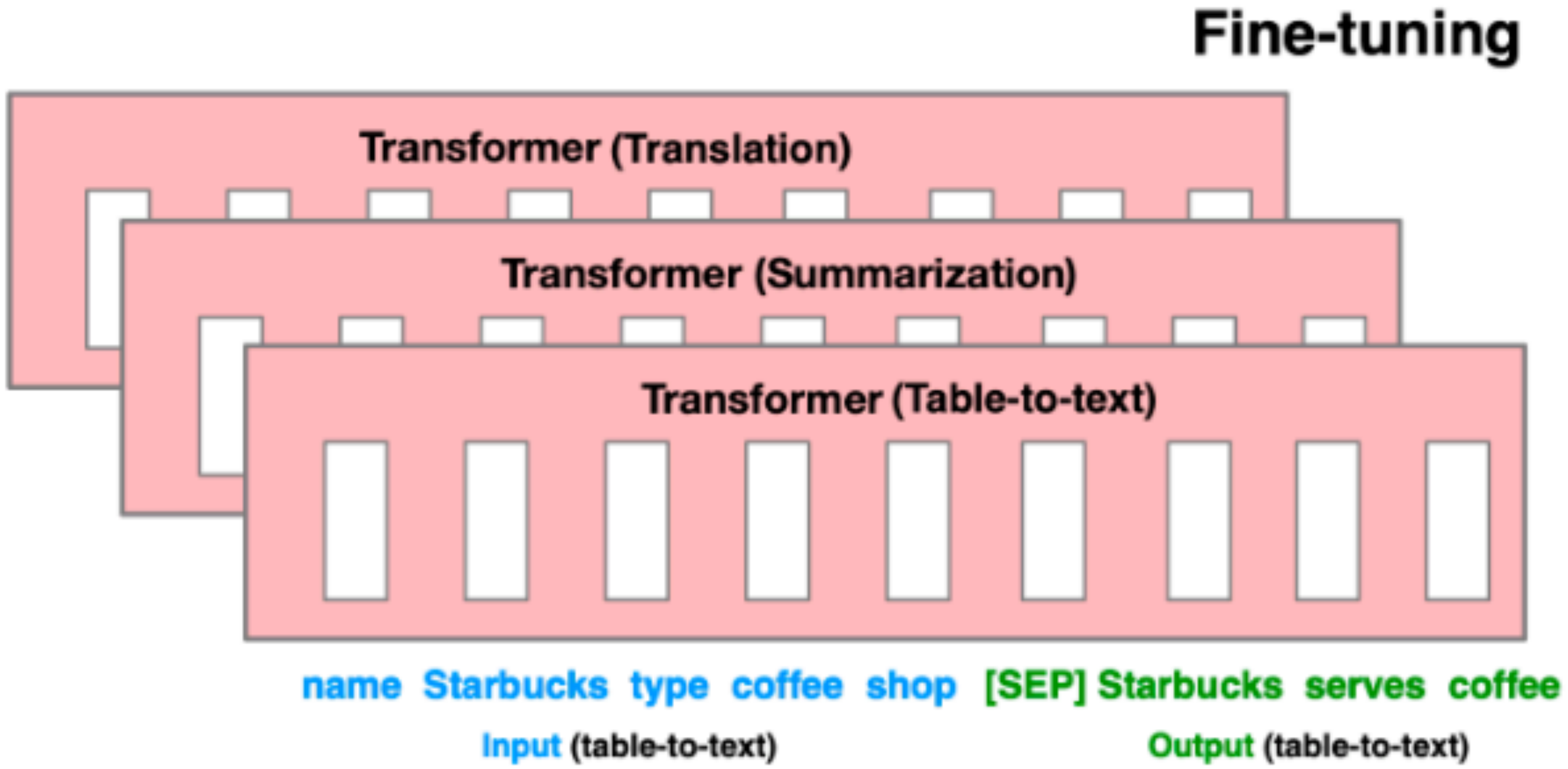
However, models tend to be sensitive to the choice of the prompt [Webson and Pavlick, 2022] and the order of examples [Zhao et al., 2021; Lu et al., 2022]



Prompt Tuning

Idea — we can directly learn a *continuous prompt* ϕ which is pre-pended to the input [Liu et al., 2021; Hambardzumyan et al., 2021; Lester et al., 2021]



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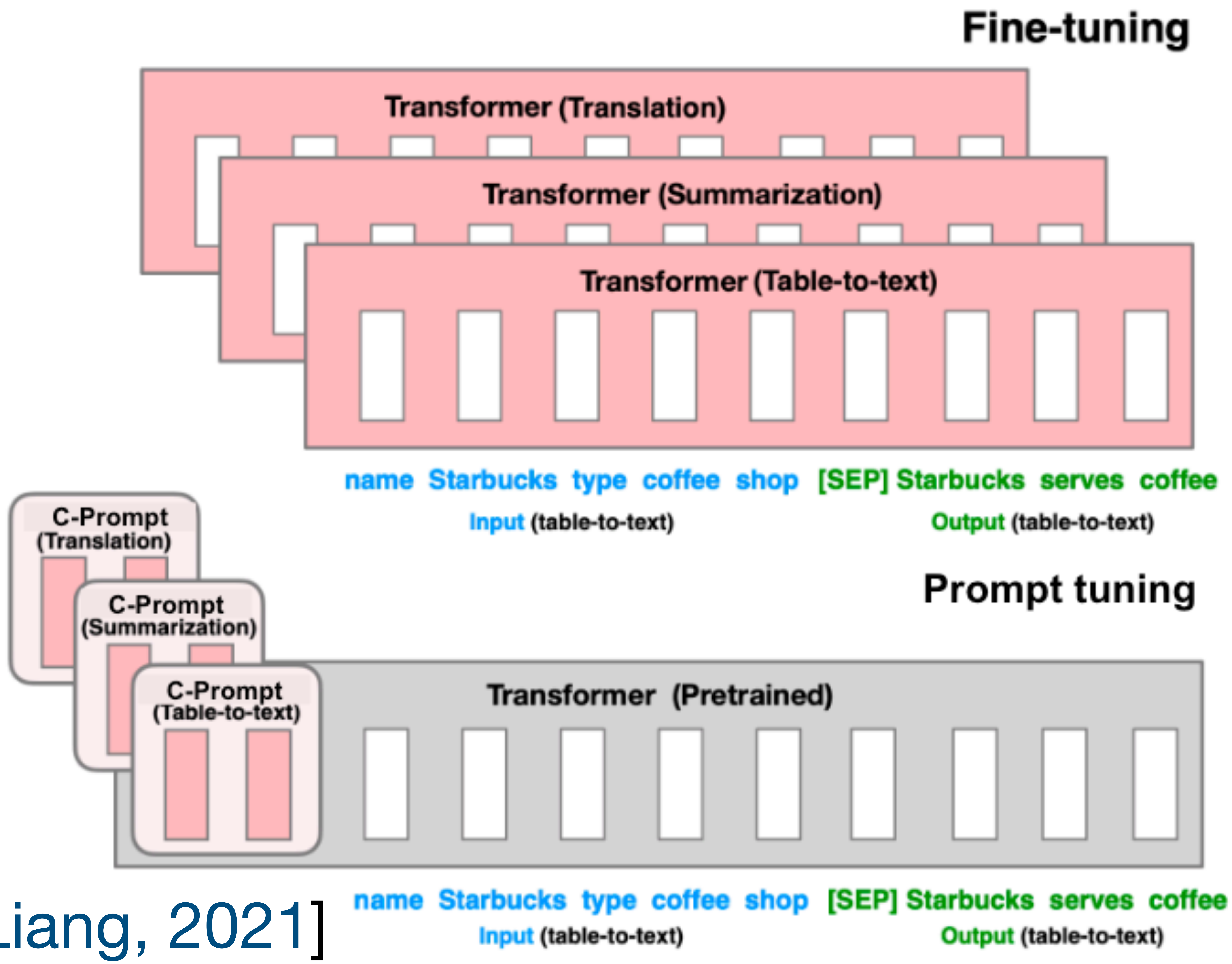
Here the module parameters ϕ is typically a matrix consisting of a sequence of continuous prompt embeddings

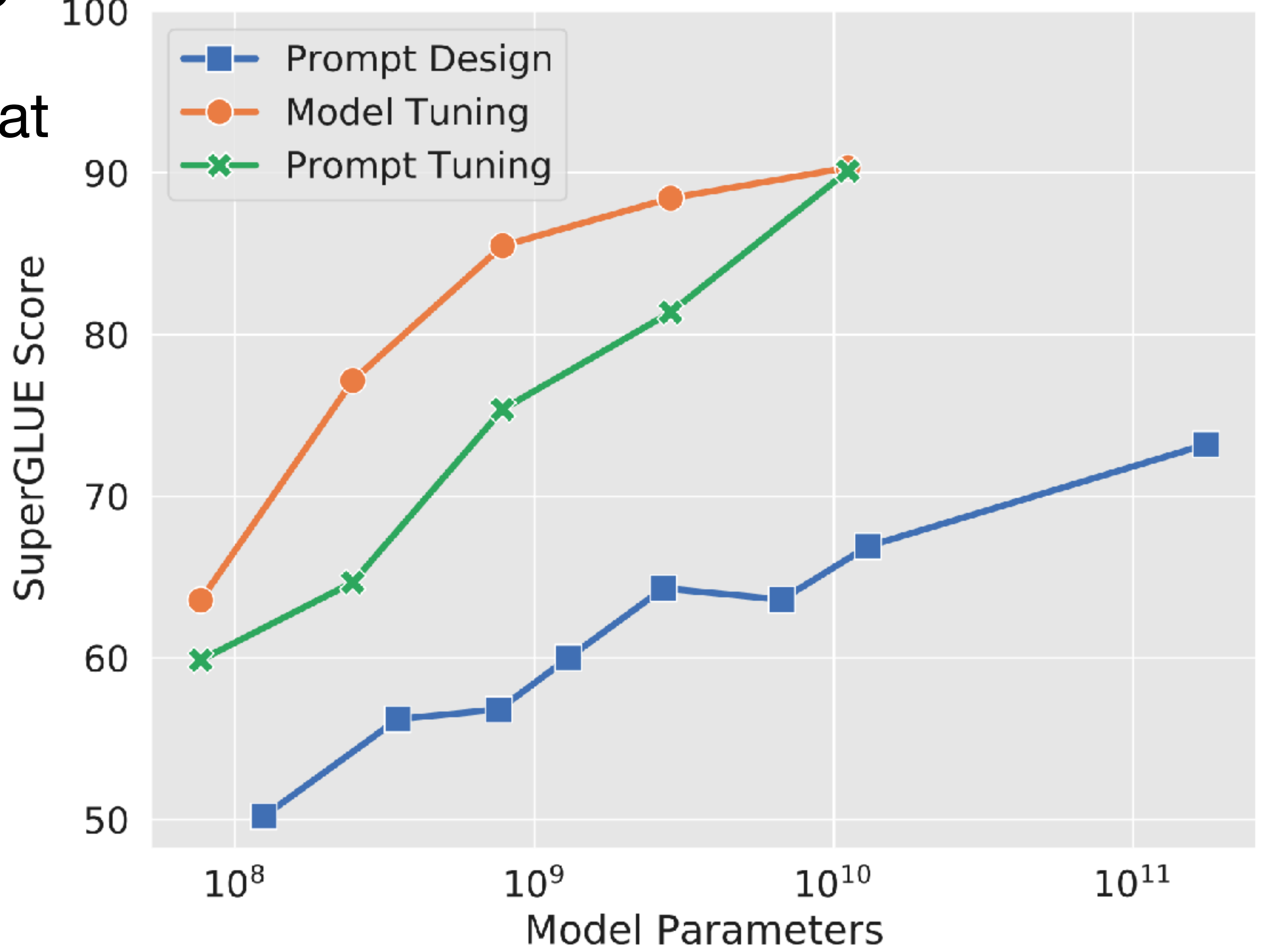


[Li and Liang, 2021]

Prompt Tuning Works Well at Scale

Only using trainable parameters at the input layer limits its capacity for adaptation

→ Prompt tuning performs poorly at smaller model sizes and on harder tasks [Mahabadi et al., 2021; Liu et al., 2022]



Prompt tuning vs. Standard fine-tuning and prompt design across T5 models of different sizes [Lester et al., 2021]

Multi-Layer Prompt Tuning

Instead of learning the module parameters ϕ_i only at the input layer, we can learn them at *every layer of the model* [Li and Jiang, 2021; Liu et al., 2022]

In practice, continuous prompts ϕ_i are concatenated with the keys and values in the self-attention layer [Li and Jiang, 2021]

Prompt tuning

Multi-layer prompt tuning

Computation Functions — Comparison

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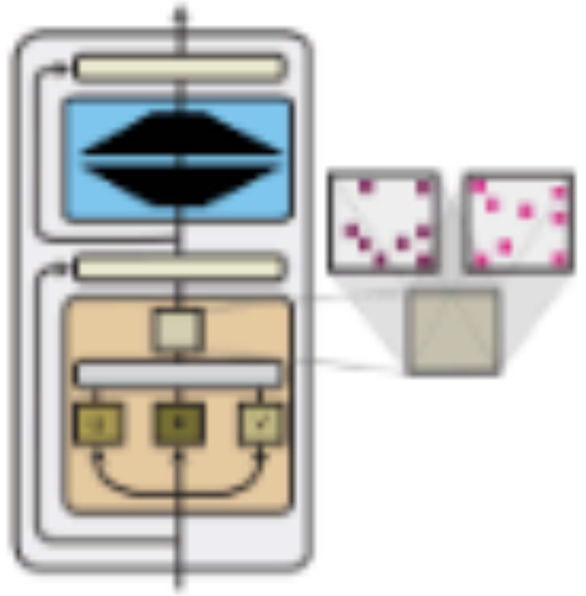
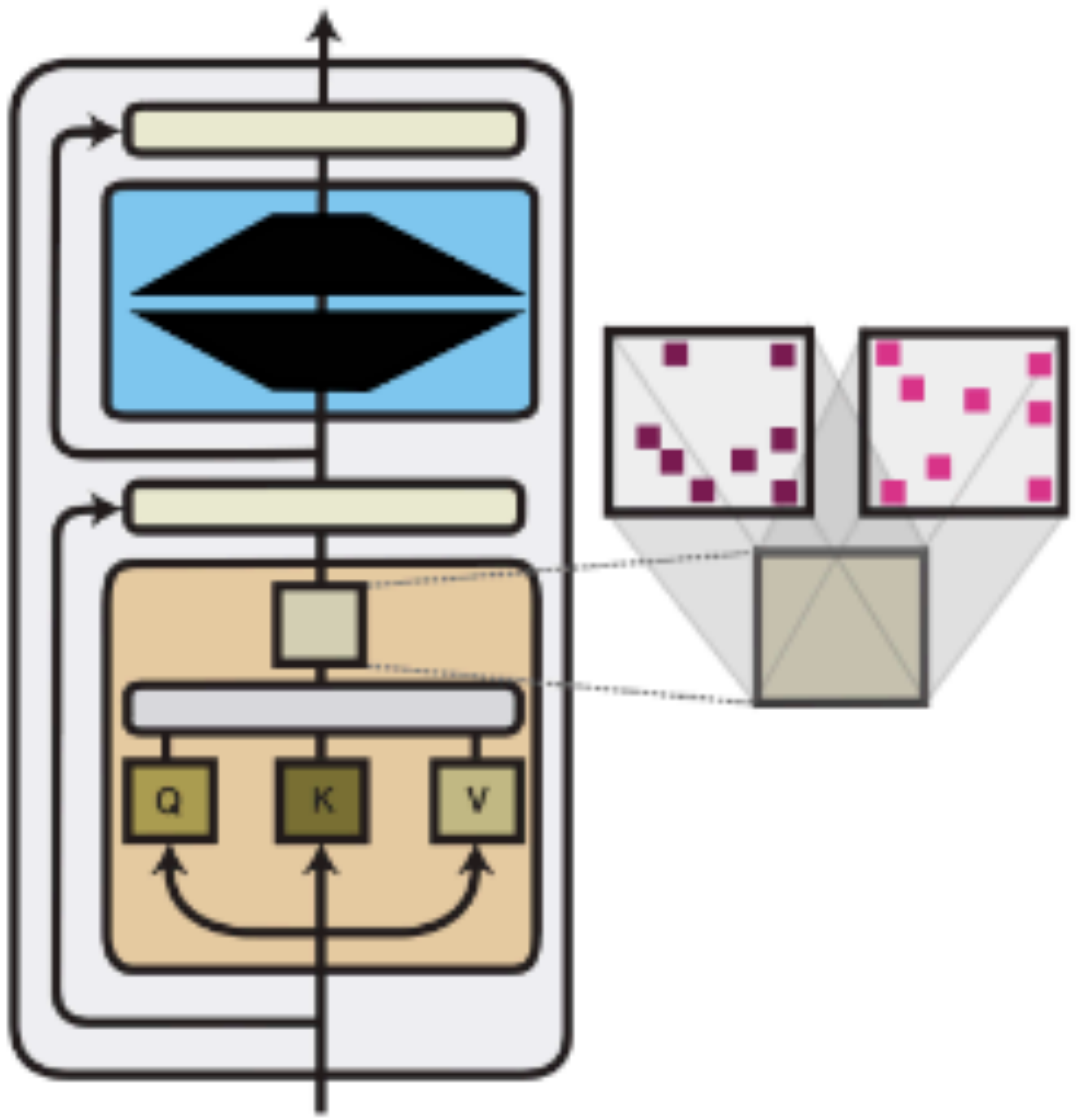
Parameter composition 	+	-	++	+
Input composition 	Only add a small number of parameters	Extend the model's context window		Requires large models to perform well
	++	--	--	-

Composition Functions



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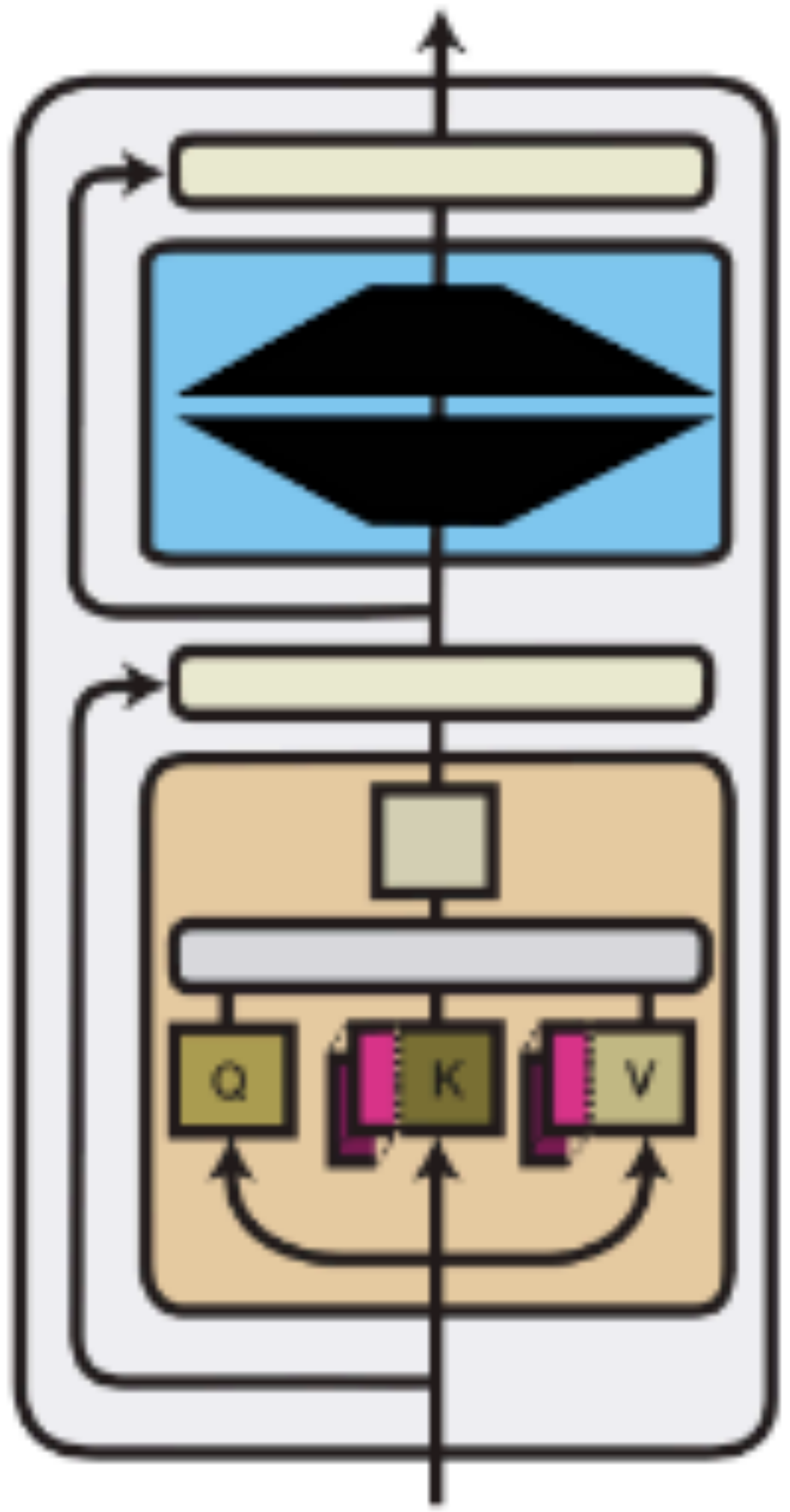

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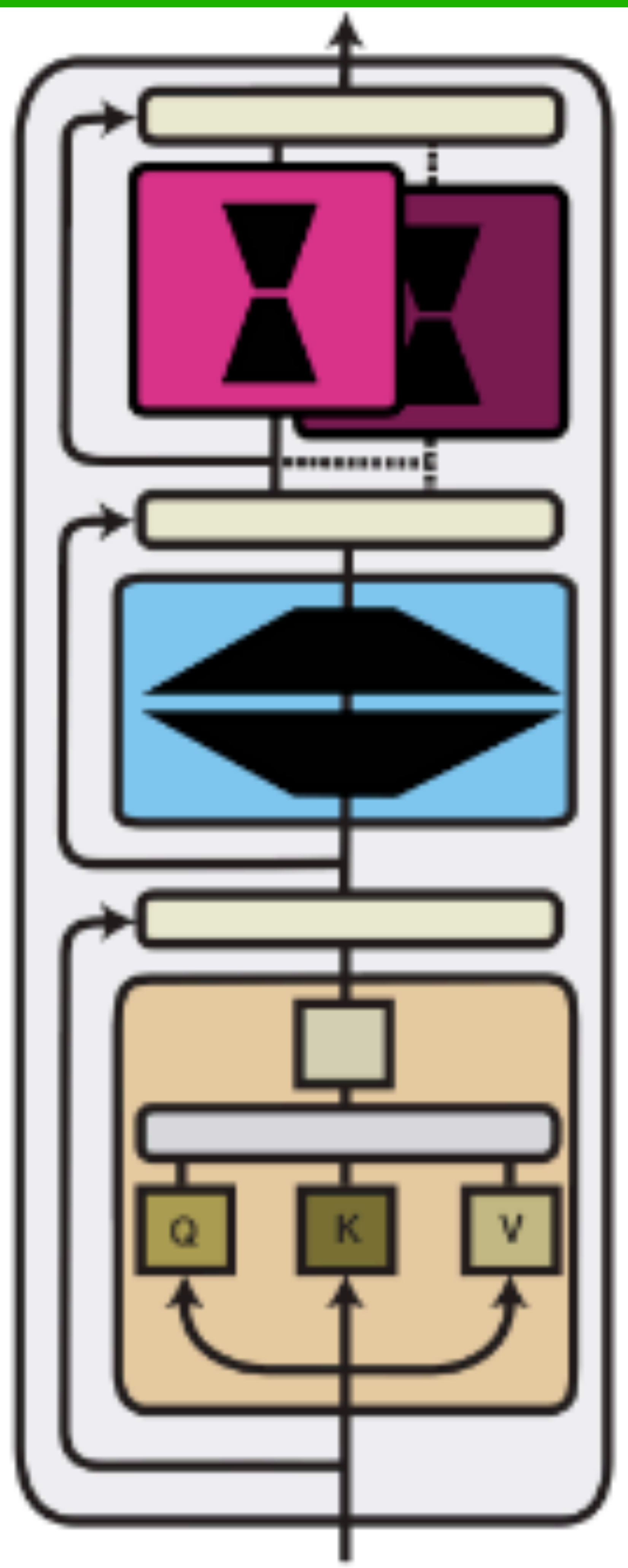


Function Composition

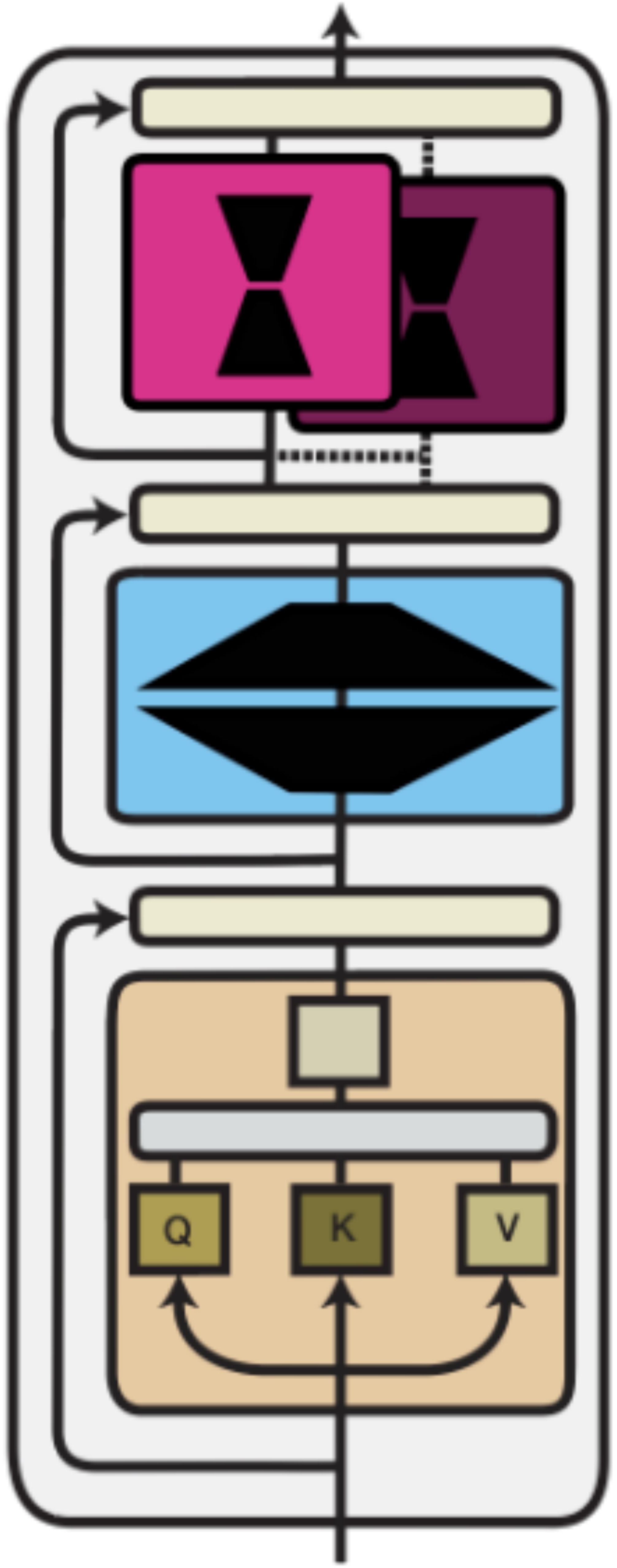
Function Composition

Function composition augments a model's functions with *new task-specific functions*:

$$g_i(x) = f_{\theta_i} \odot f_\phi(x)$$

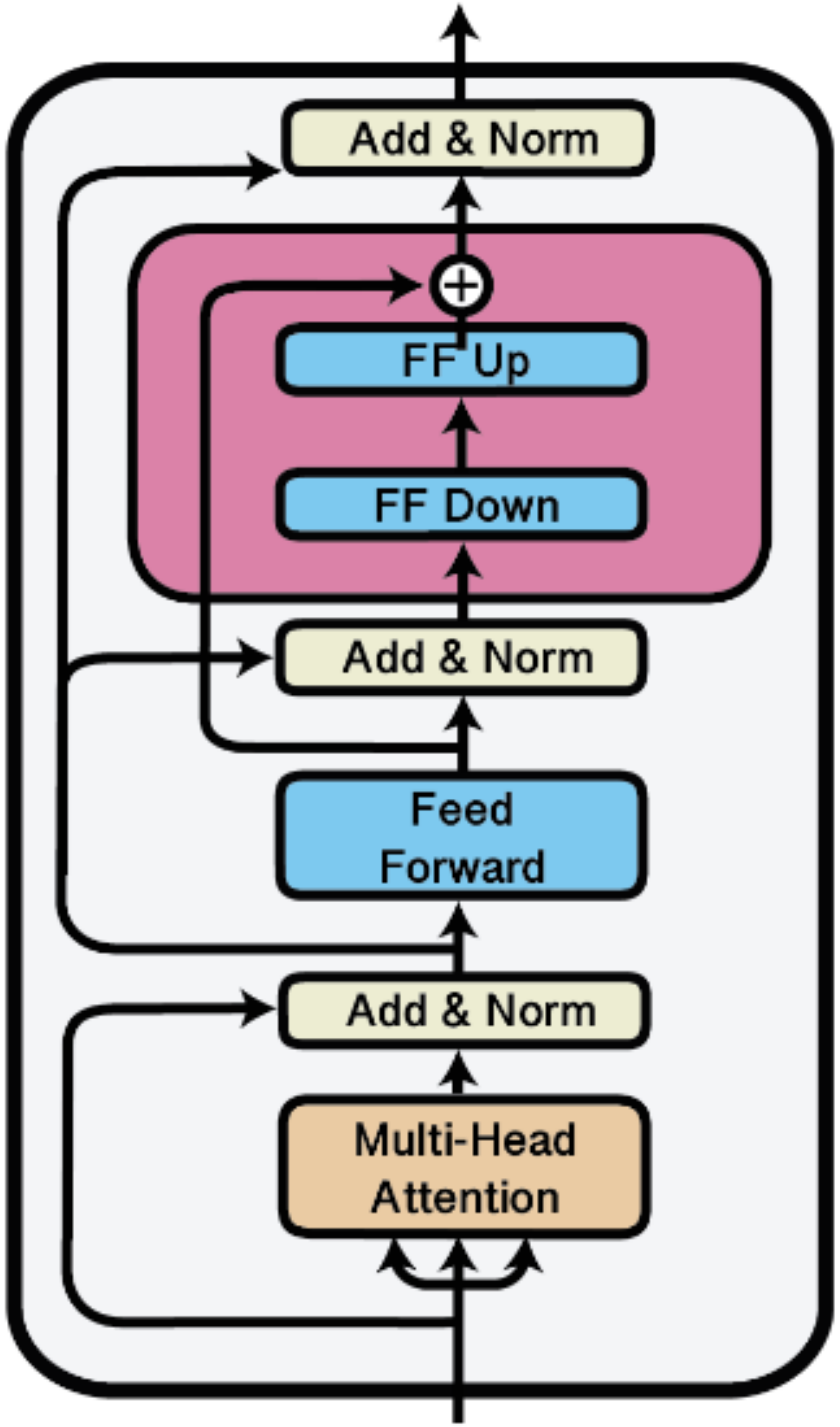
Commonly used in multi-task learning, where we have multiple task-specific models composed together — e.g., see the surveys in [Ruder, 2017; Crawshaw, 2020]

However, here we focus on functions that can be added to pre-trained models like LLMs 🙂



Adapters

The main purpose of functions f_{ϕ_i} added to a pre-trained model is to adapt it to a new task — these functions are also known as **adapters**



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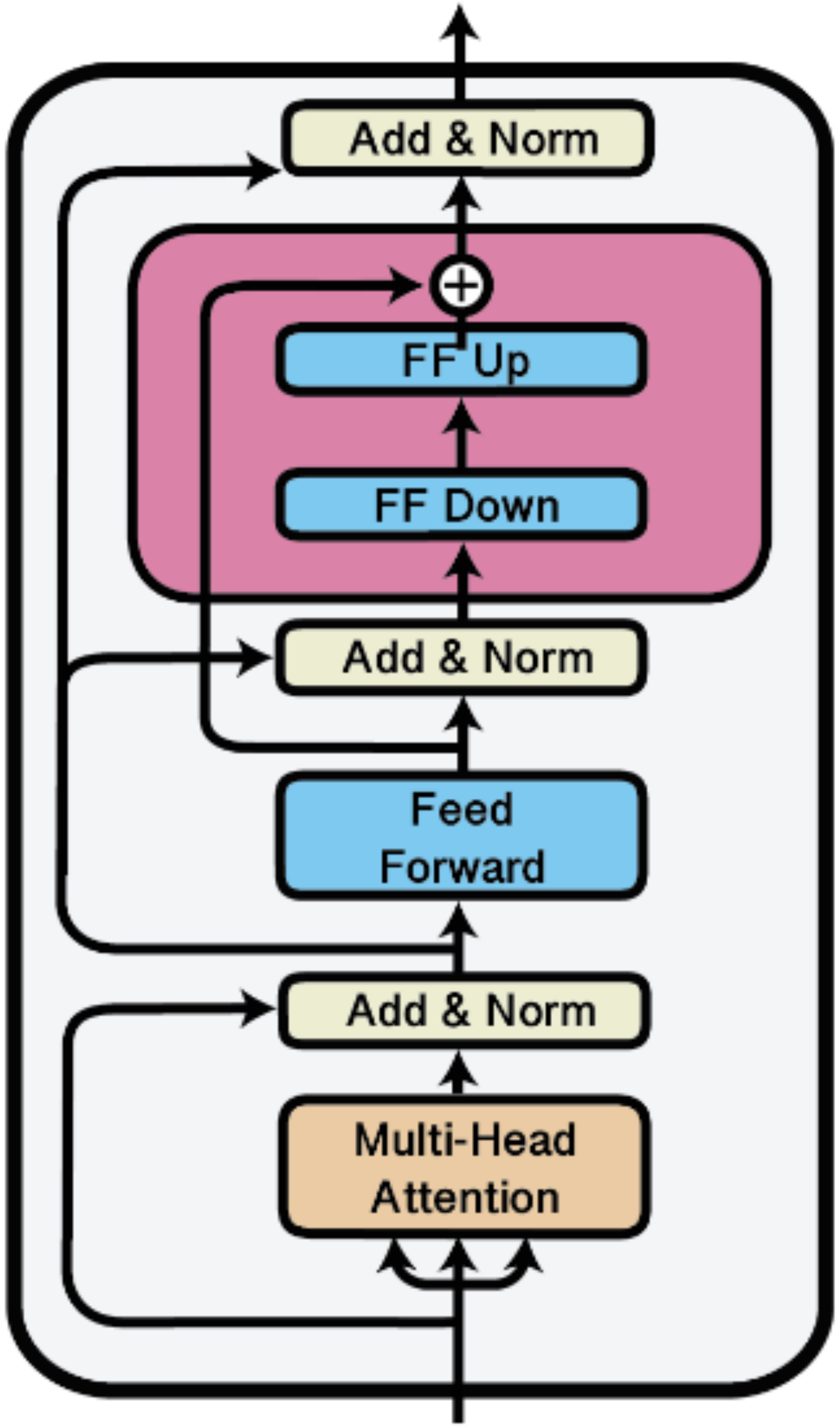
In NLP, an adapter in a Transformer layer typically consists of a feed-forward down-projection $W_D \in \mathbb{R}^{k \times d}$, a feed-forward up-projection $W_U \in \mathbb{R}^{d \times k}$, and an activation function σ [Houlsby et al., 2019]

$$f_{\phi_i}(x) = W_D \left[\sigma \left(W_U x \right) \right]$$



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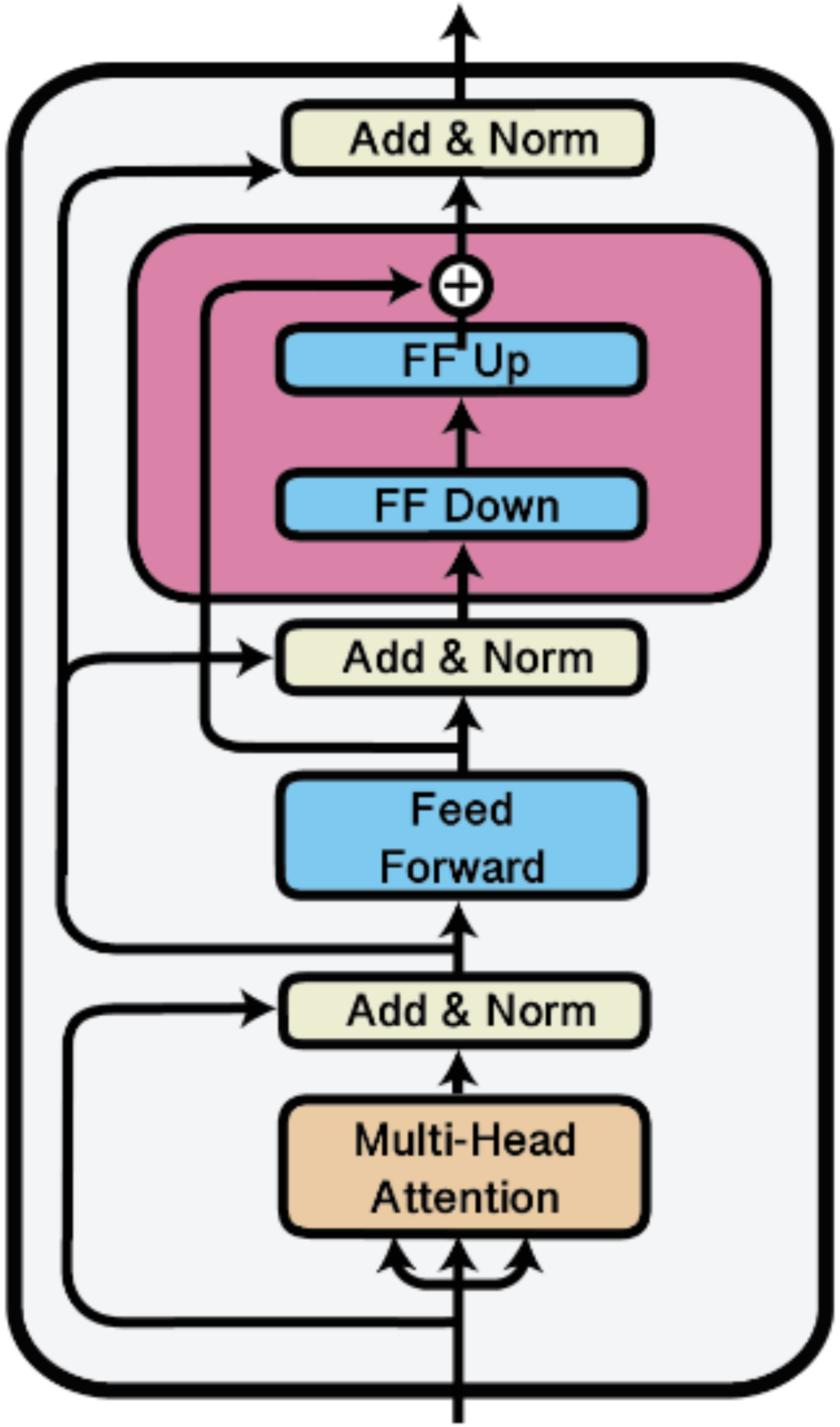
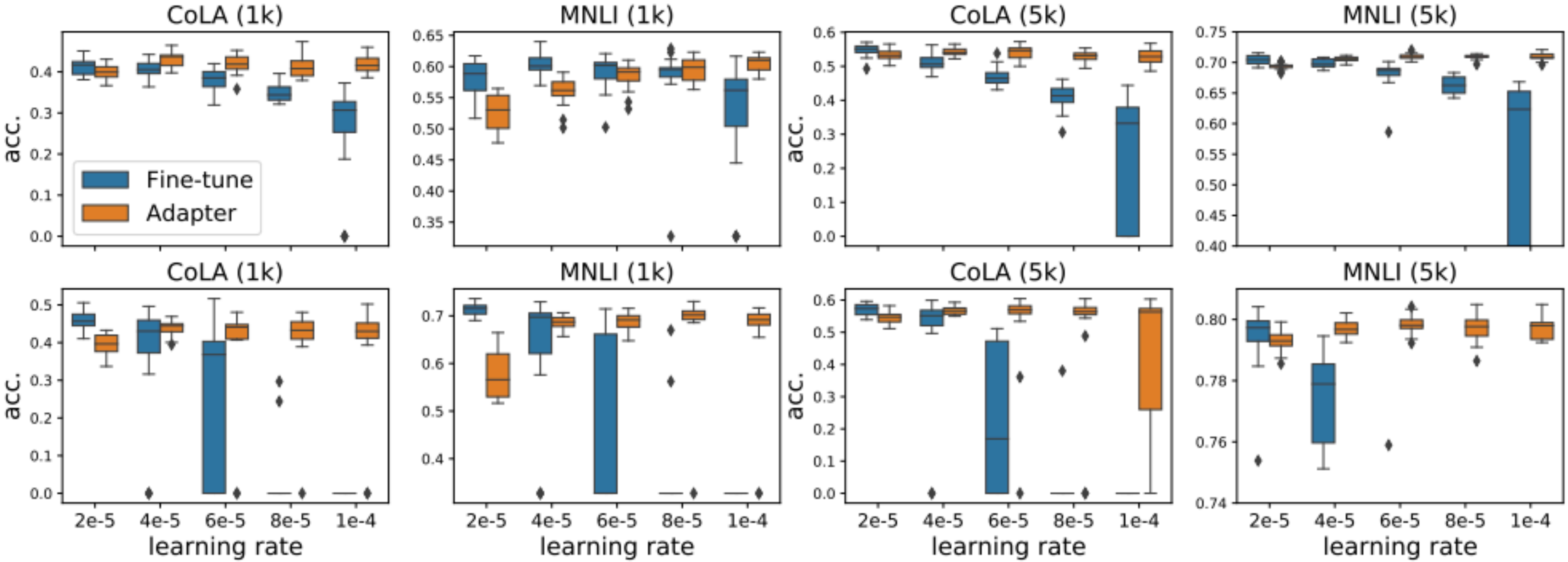
Adapter usually placed after multi-head attention and/or after the feed-forward layer



Benefits of Adapters

Increased robustness [He et al., 2021; Han et al., 2021]



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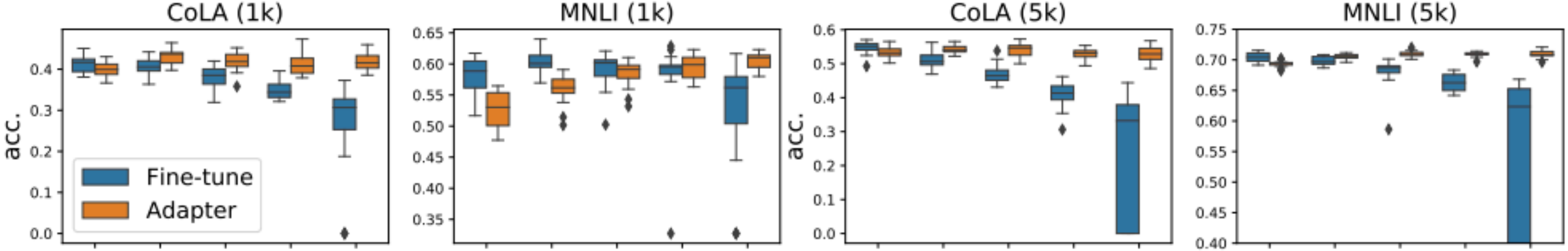
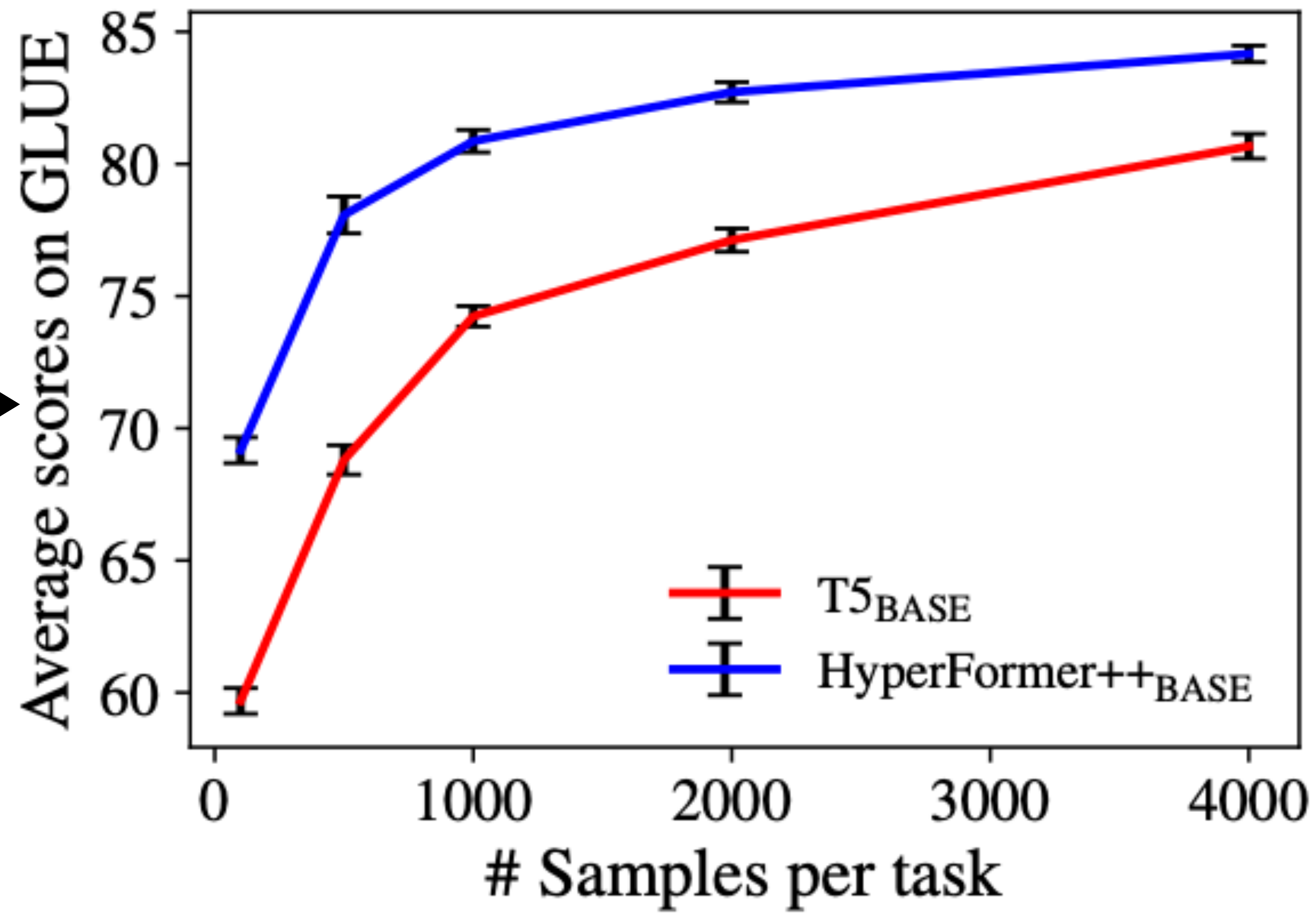
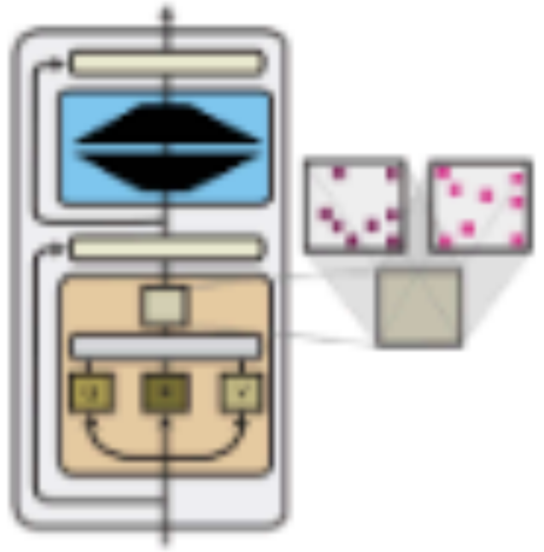


Increased sample efficiency [Mahabadi et al., 2021]

Results on GLUE with different numbers of training examples per task



Computation Functions — Comparison

	Parameter efficiency	Training efficiency	Inference efficiency	Performance
Parameter composition 	+	−	++	+
Input composition 	++	−−	−−	−
Function Composition 	Adapters depend on the hidden size	Does not require gradients of frozen params	New functions increase # of operations	Match or outperform standard fine-tuning
	−	+	−	++