Foundational Models

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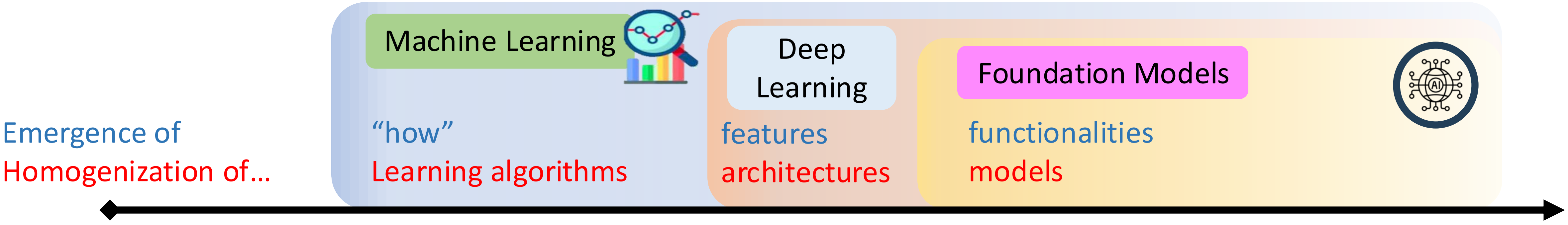
Foundational Models



- Coined in 2021, it references the recent paradigm shift to develop a single model that can implicitly support many downstream tasks.

Bommasani et al. On the Opportunities and Risks of Foundation Models. arXiv 2021

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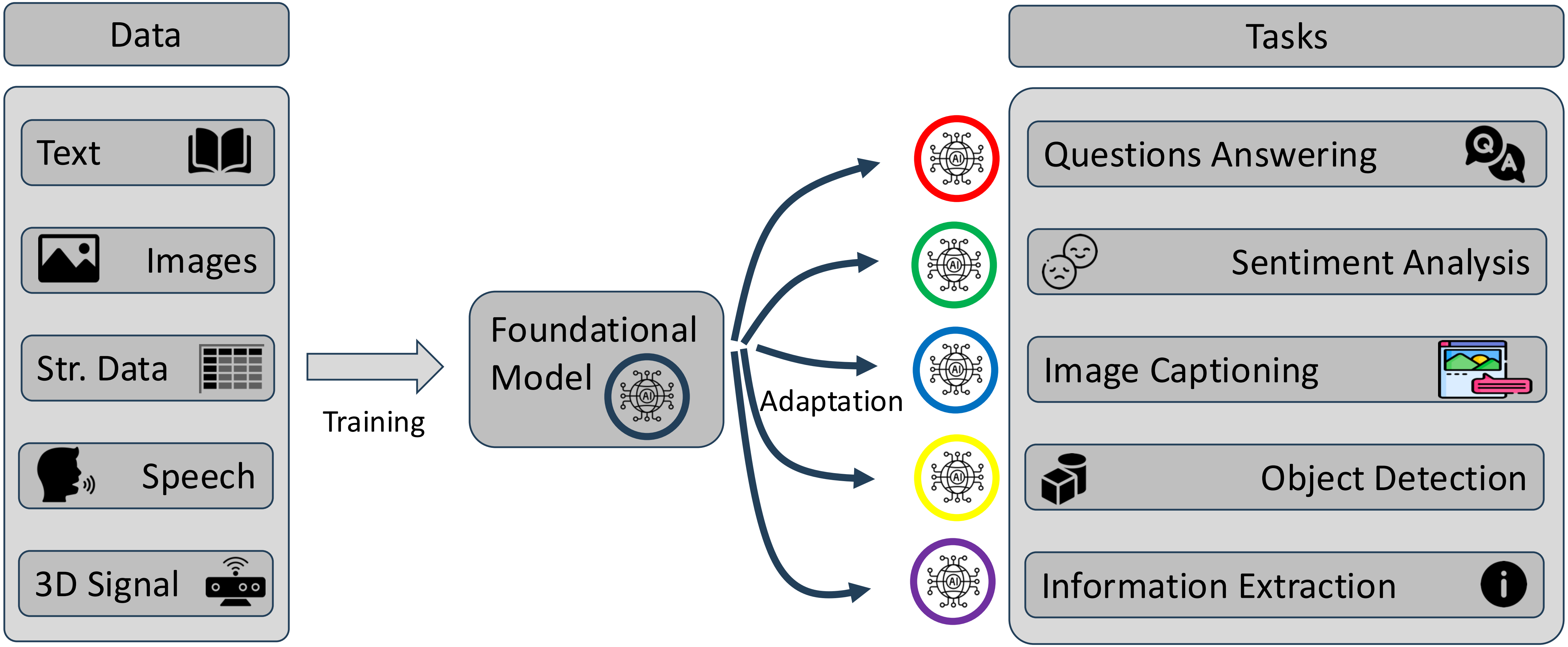

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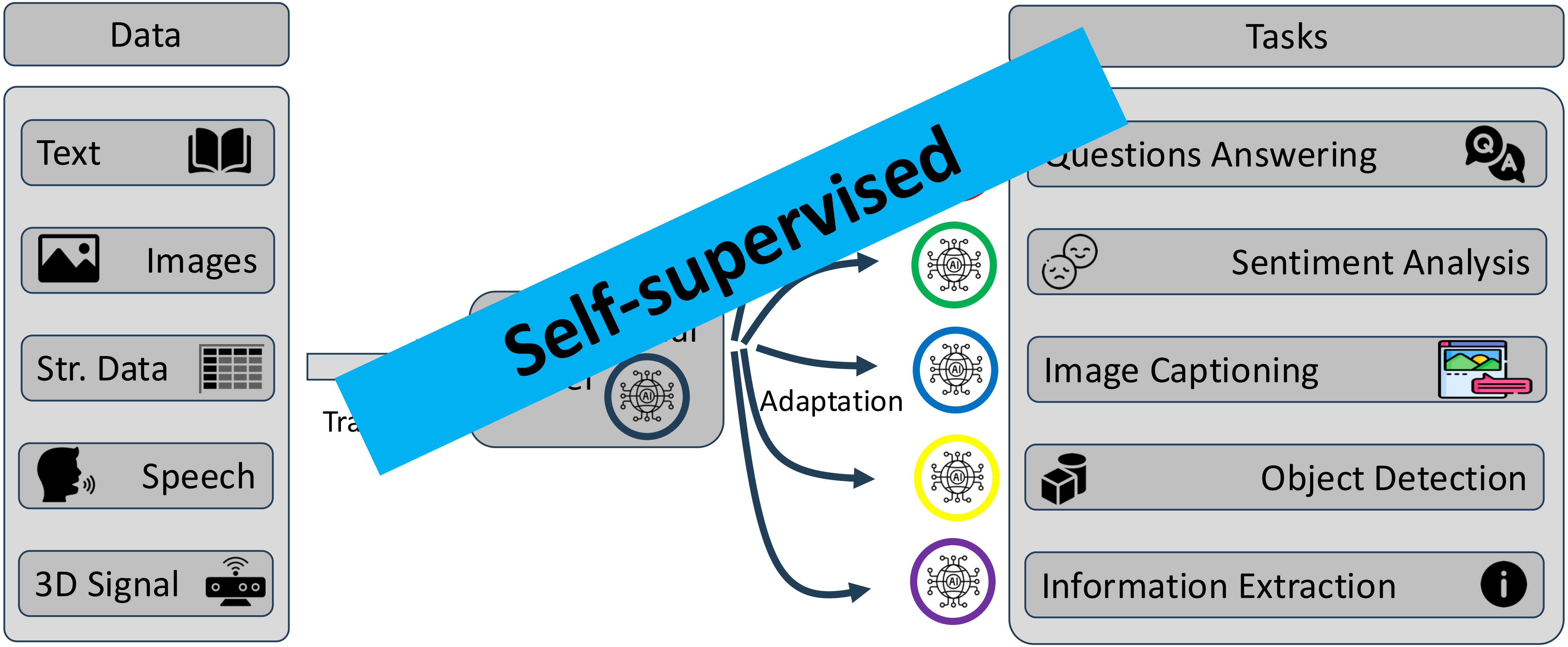

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Beyond Pretraining and Fine-Tuning Paradigm

Pre-Training

Large unlabelled datasets
(e.g. Wikipedia, BookCorpus)

Self-supervised training
(hours to days)

→ Pre-Trained Weights →

Fine-Tuning

Smaller labelled datasets
(SQuAD, MNLI Similarity)

Task-specific fine-tuning
(minutes to hours)

→ Fine-tuned Weights →

Inference

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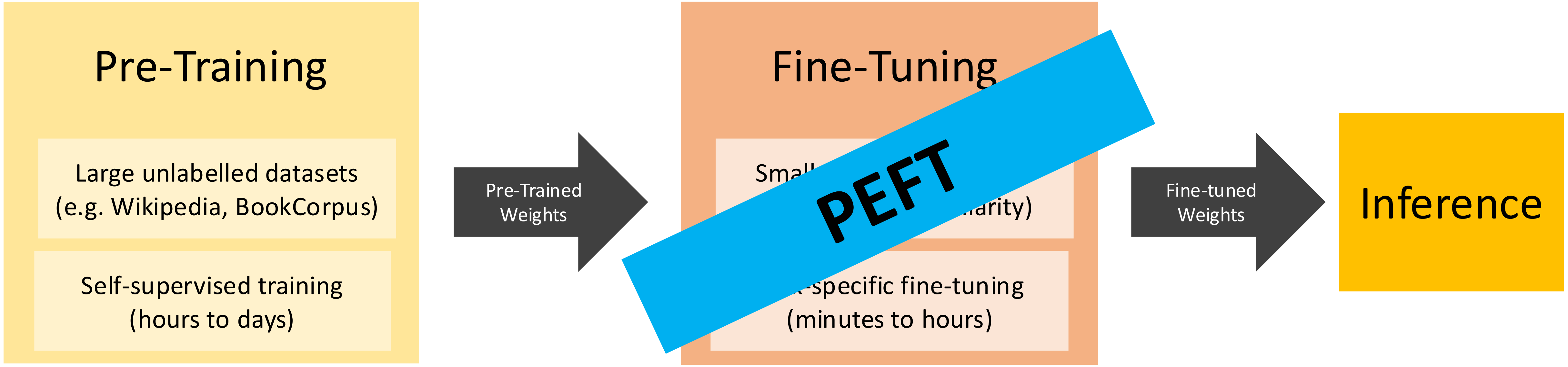

Neural Architecture for Foundational Models

Transformers

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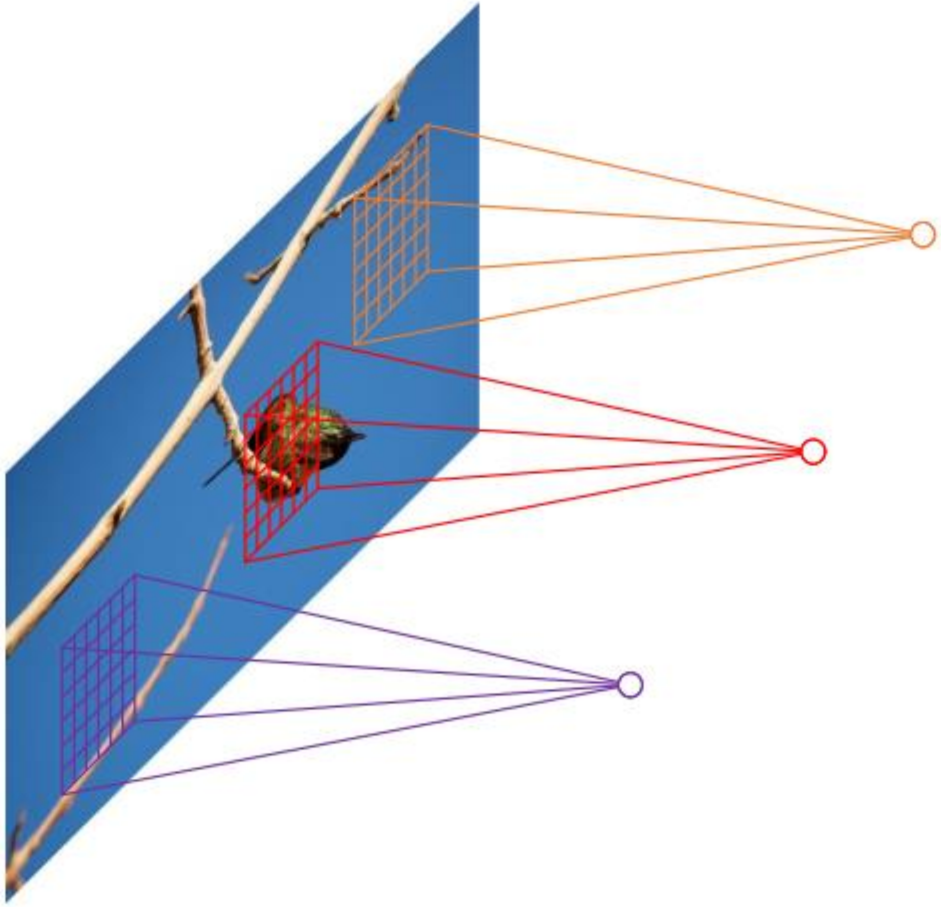
CNNs as Pattern Detector



- Convolutional layers are locally connected
- a filter/kernel/window slides on the image or the previous map
- the position of the filter explicitly provides information for localizing
- local spatial information w.r.t. the window is encoded in the channels

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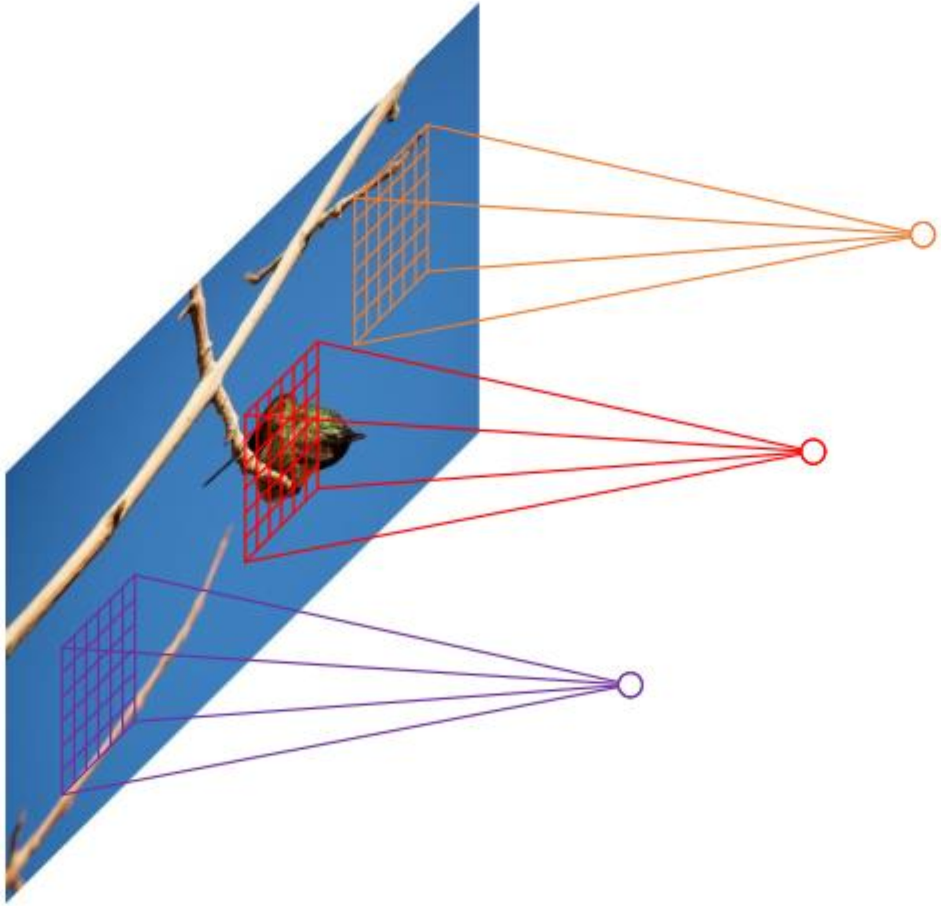
CNNs for Translation Invariance Features



- Convolutional layers share weights spatially leading to translation-invariant features
- Translation-invariance: a translated region will produce the same response at the correspondingly translated position
- A local pattern's convolutional response can be re-used by different candidate regions

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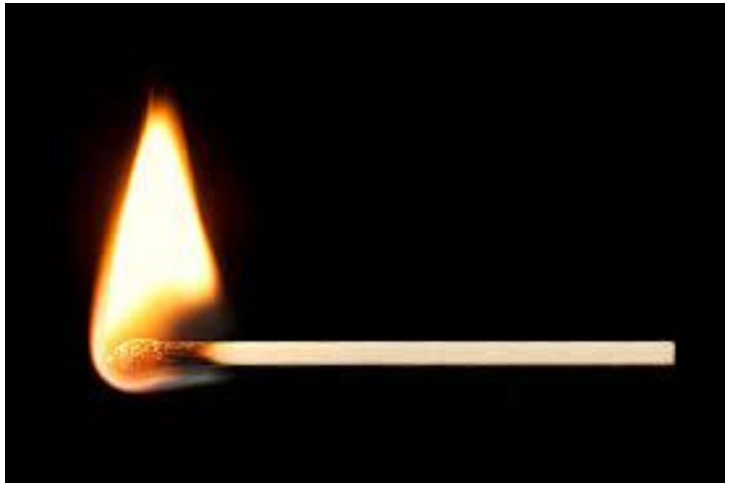
Limitations of CNN's Inductive Bias



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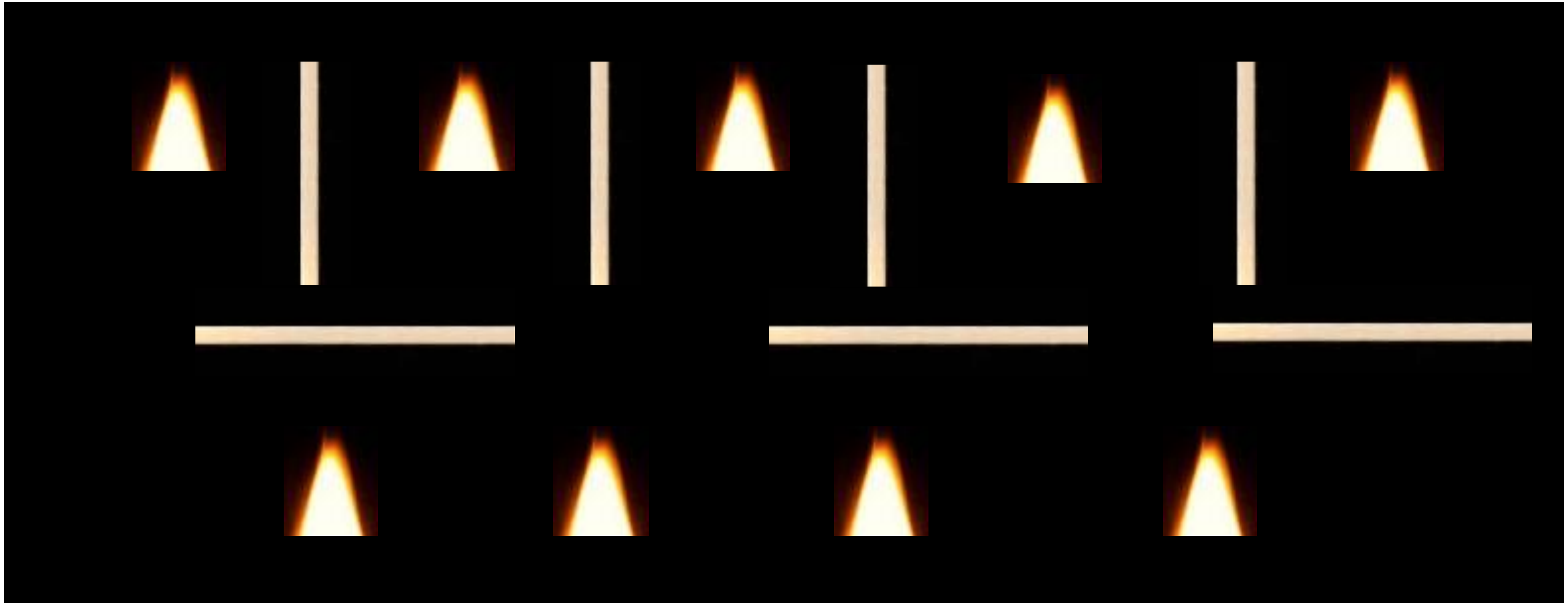

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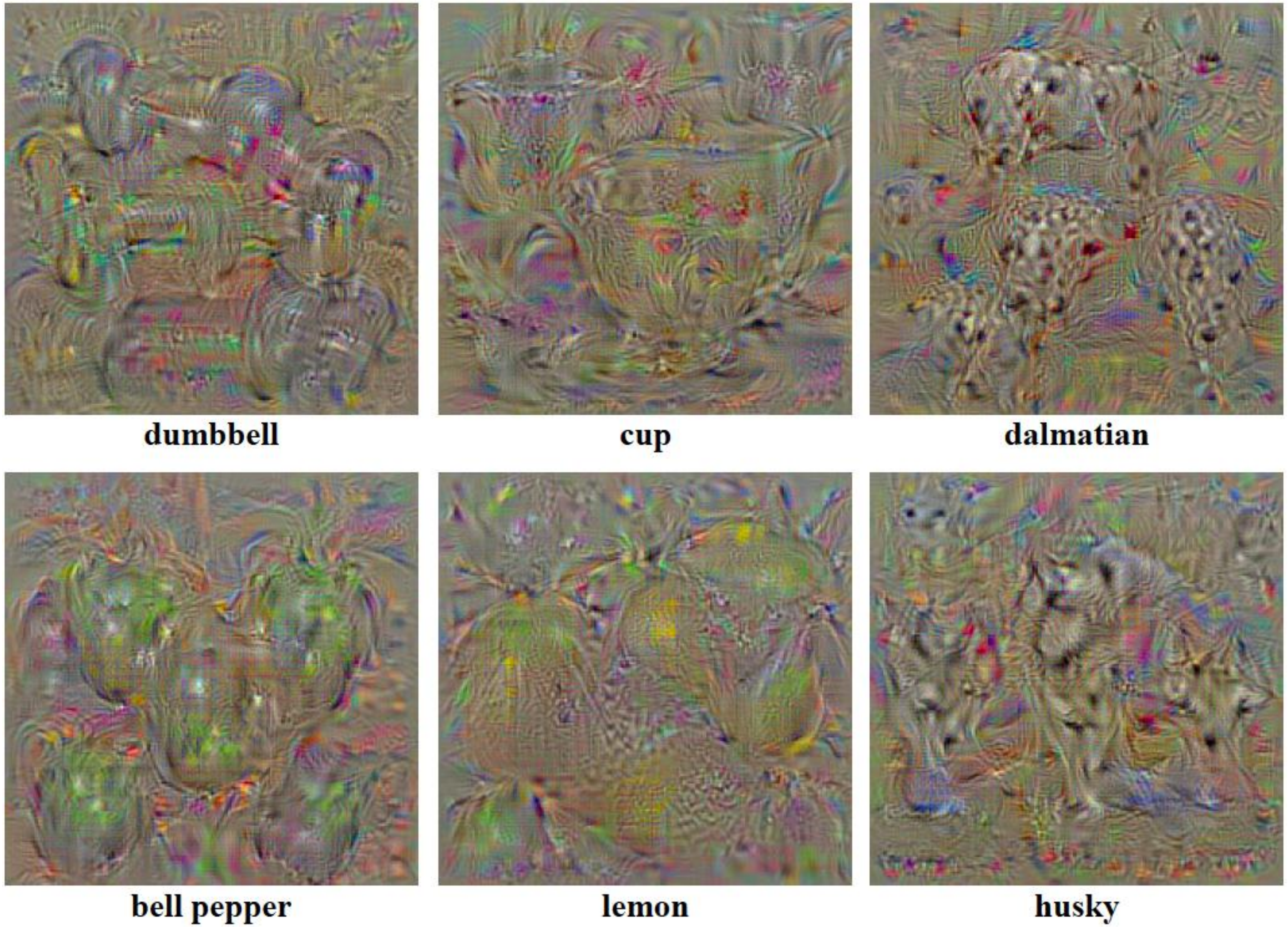
What is a Class to a CNN



Karen Simonyan, Andrea Vedaldi, and Andrew Zisserman
Deep Inside Convolutional Networks: Visualising Image Classification Models and Saliency Maps

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Alternate Paradigm: Attention

What is attention

- In psychology attention is defined as the cognitive ability of humans to focus on the relevant things while processing a lot of information.

Attention mechanism in neural networks tries to do the same, by focusing on the few important things/regions among many.

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Attention Layer

Inputs:

Query vector: Q (Shape: $\mathrm{N_Q} \times D_Q$)

Input vectors: X (Shape: $N_X \times D_Q$)

Key matrix: $W_K (Shape: D_X \times D_Q)$

Value matrix: $W_V (Shape: D_X \times D_V)$

Computation:

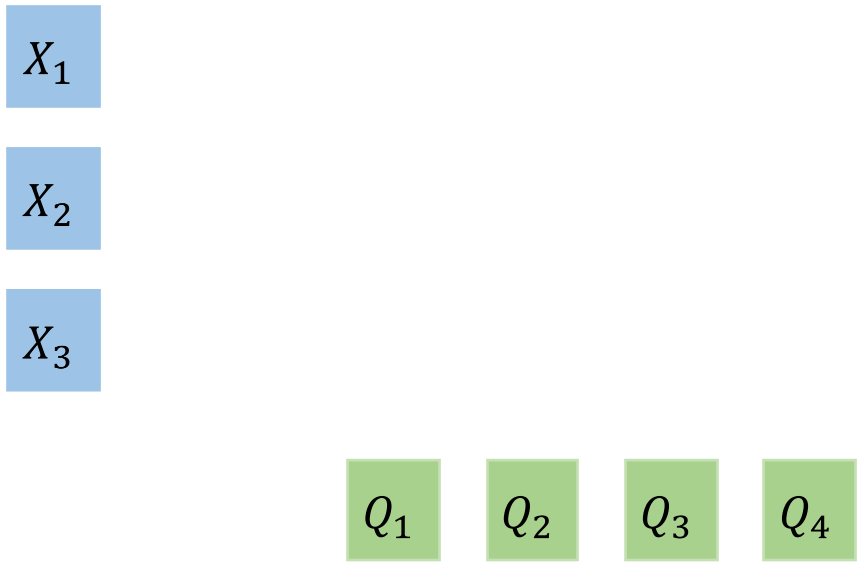
Key vectors: $K = XW_K$ $(Shape: N_X \times D_Q)$

Value Vectors: $V = XW_V$ $(Shape: N_X \times D_V)$

Similarities: $E = \frac{QK^T}{\sqrt{D_Q}}$ $(Shape: N_Q \times N_X)$, $E_{i,j} = (Q_i \cdot K_j)/\sqrt{D_q}$

Attention weights: $A = \mathrm{softmax}(E, \mathrm{dim} = 1)$ (Shape: $N_Q \times N_X$)

Output vectors: $Y = AV$ $(Shape: N_Q \times D_X)$ $Y_i = \Sigma_j A_{i,j} V_j$



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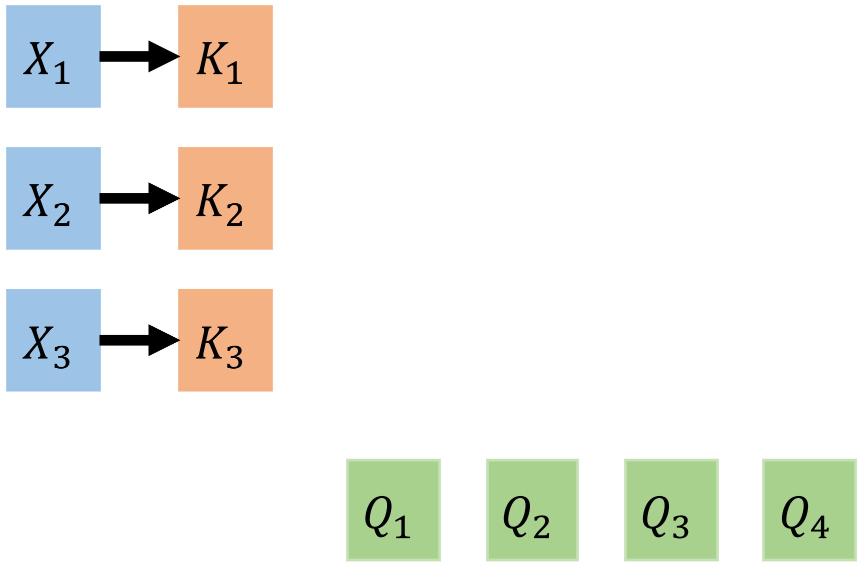

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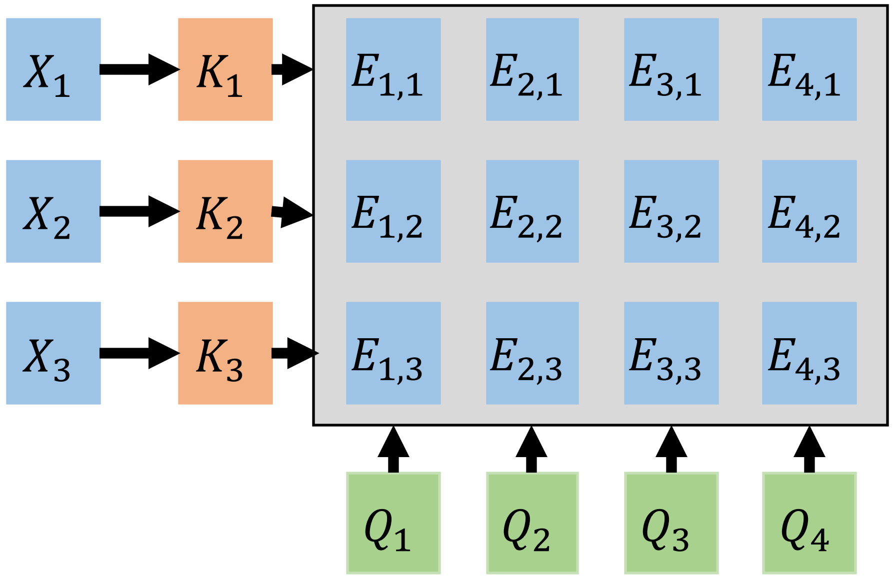

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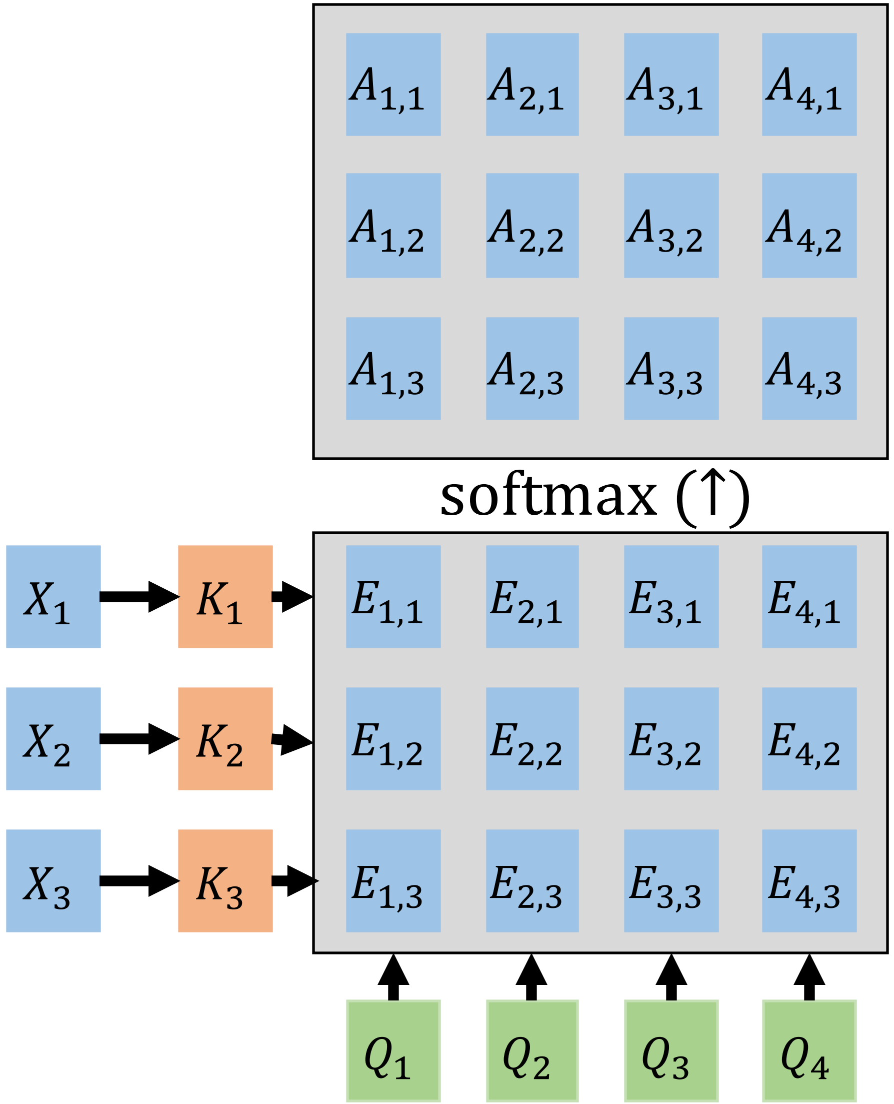

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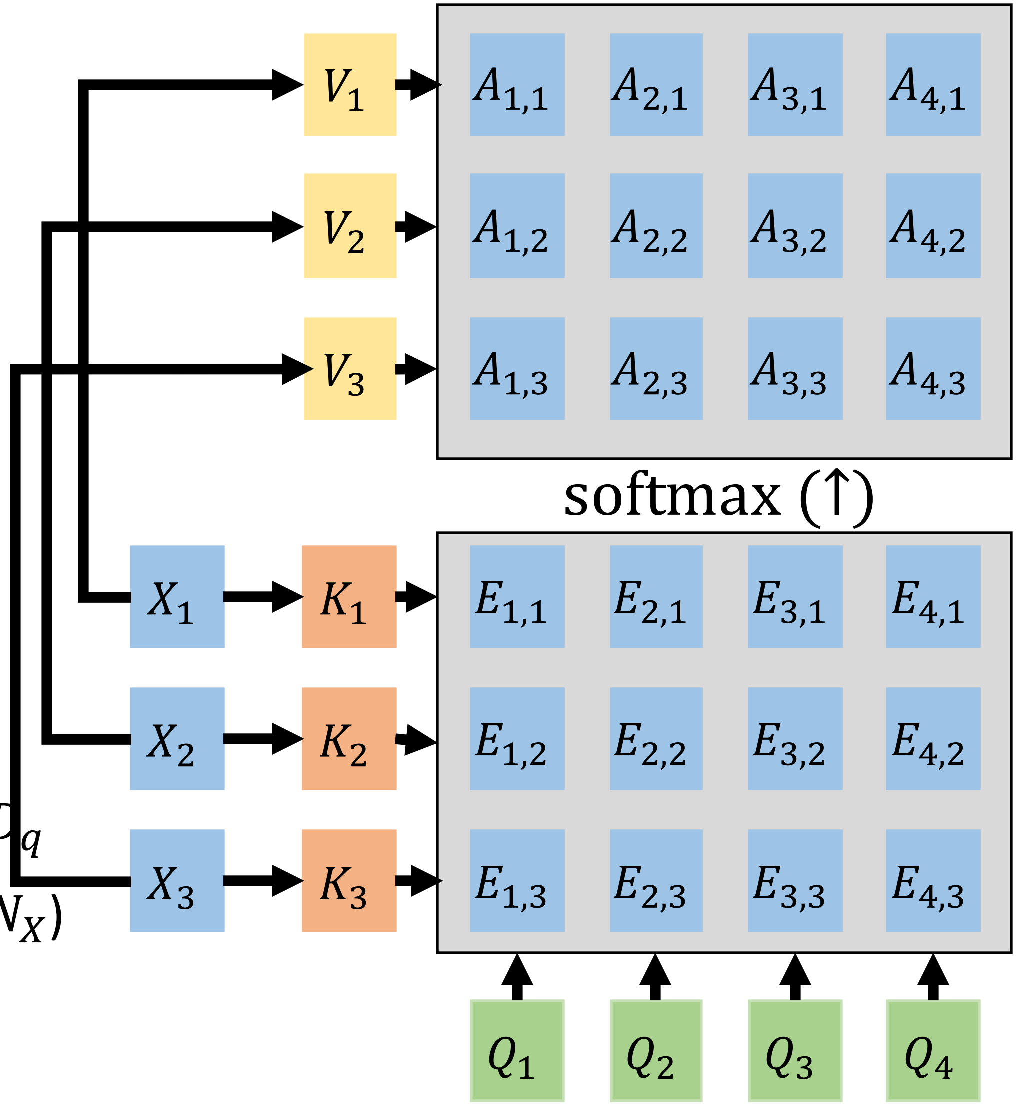

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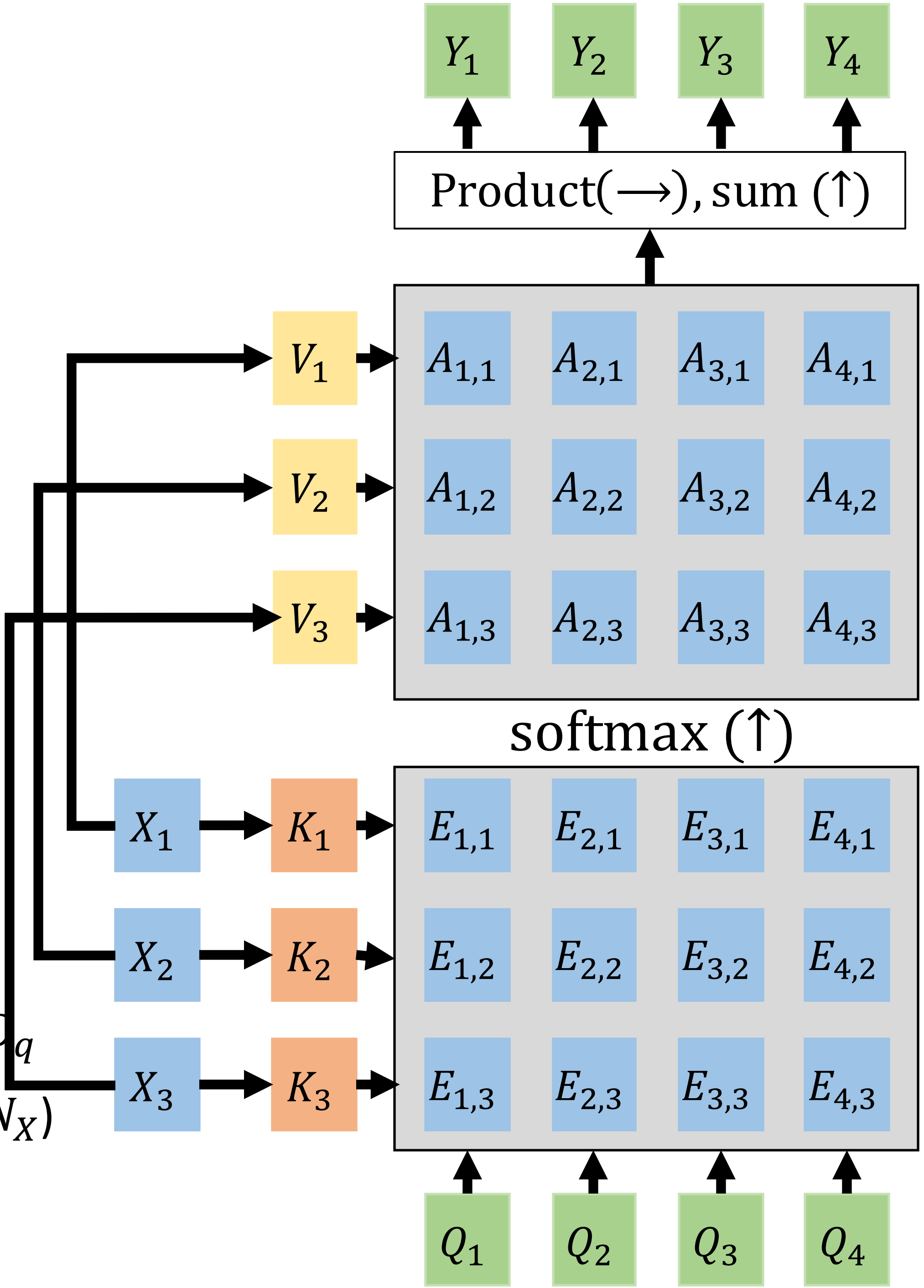

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Self-Attention Layer

One query per input vector

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X_1 X_2 X_3

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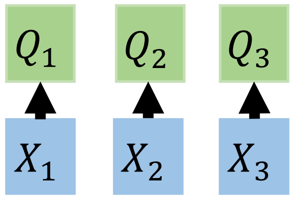

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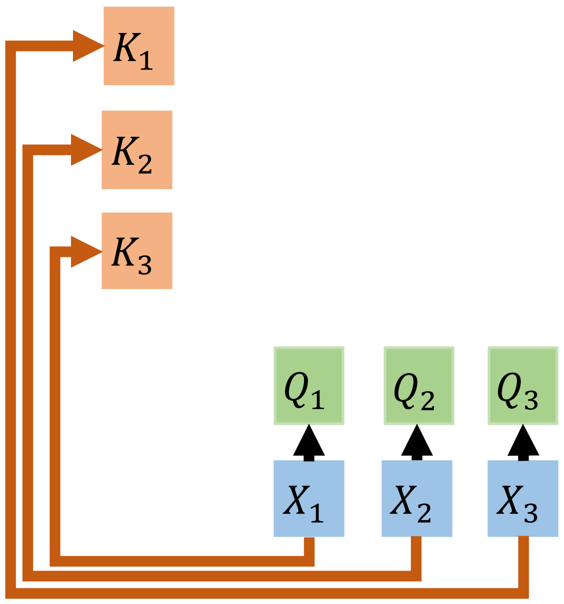

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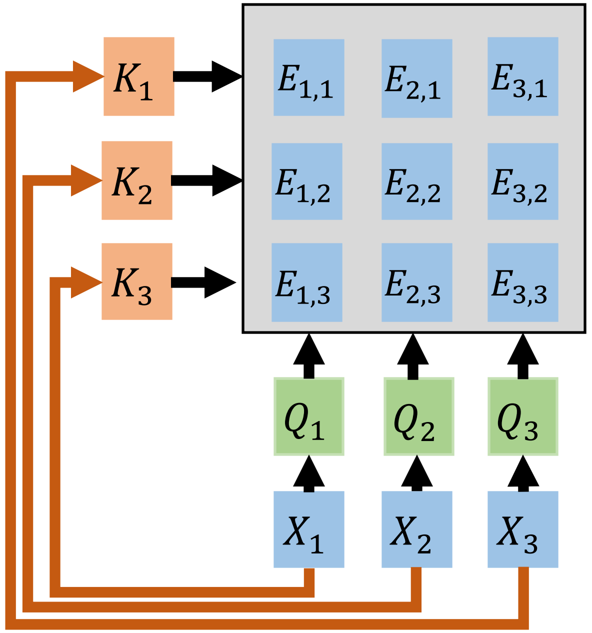

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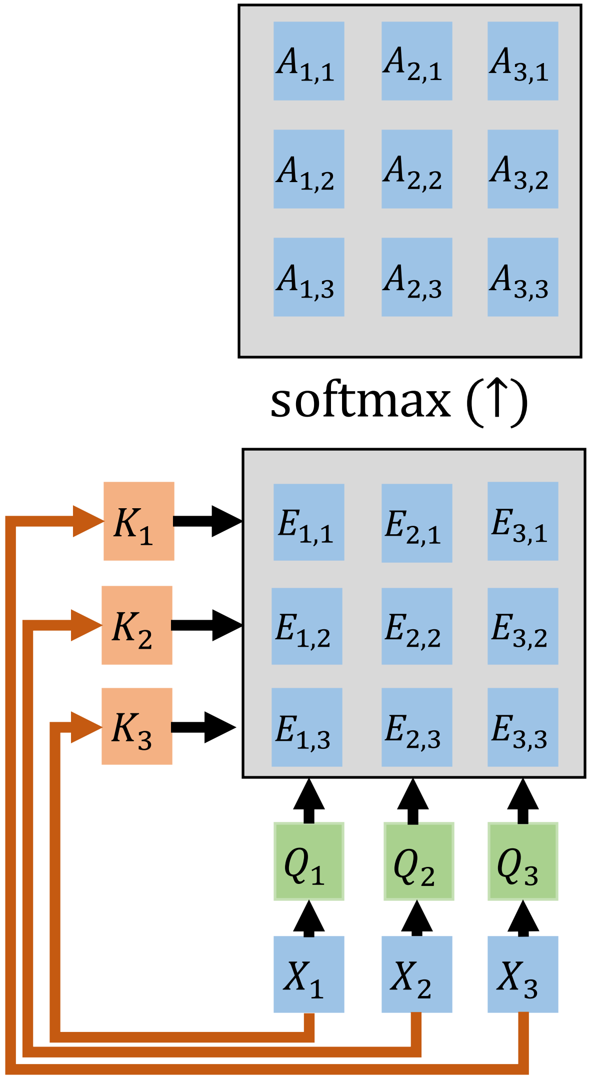

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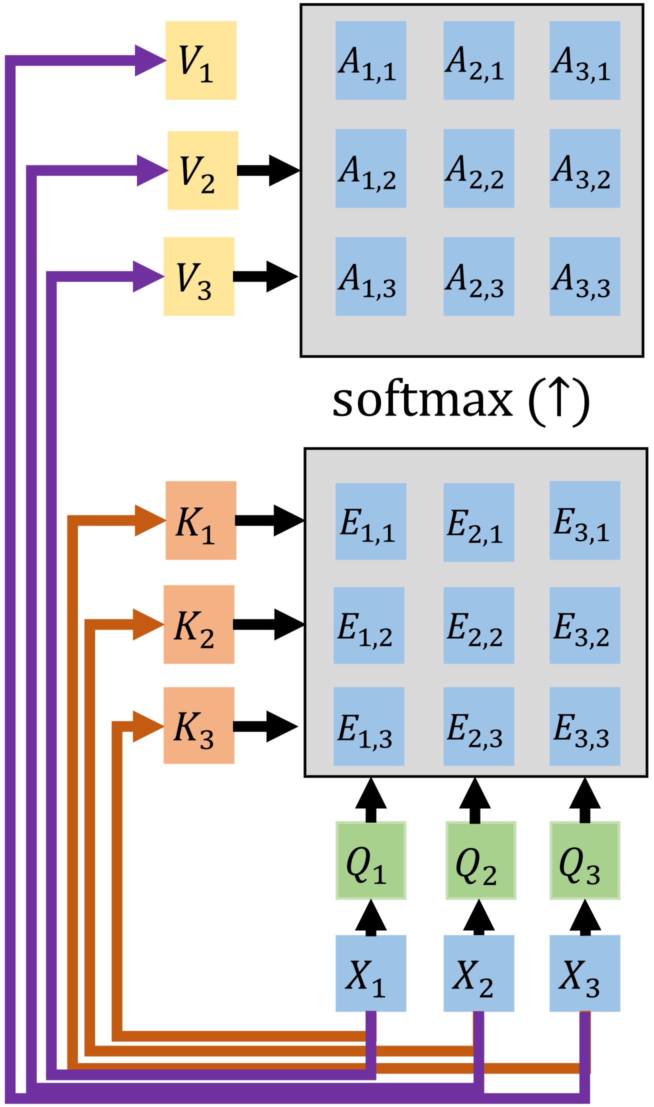

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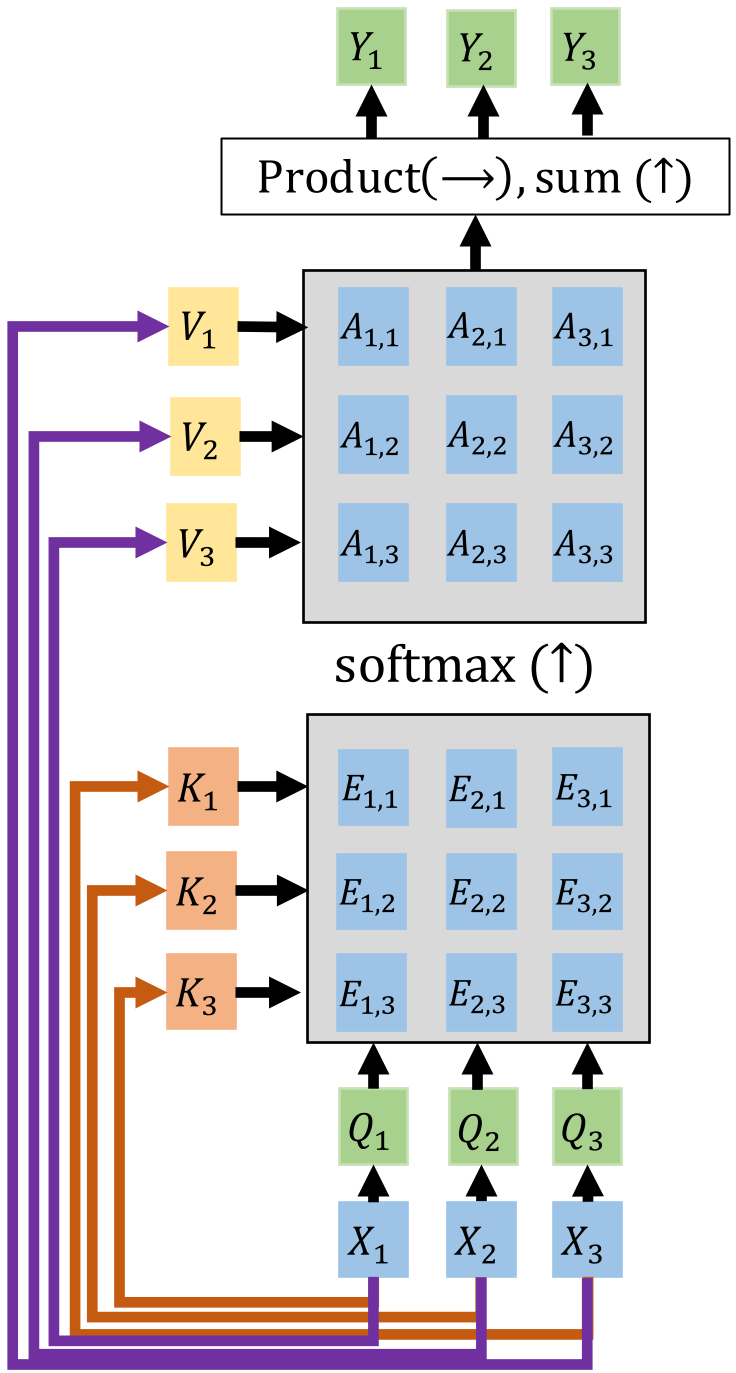

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Multi-head Self-Attention Layer

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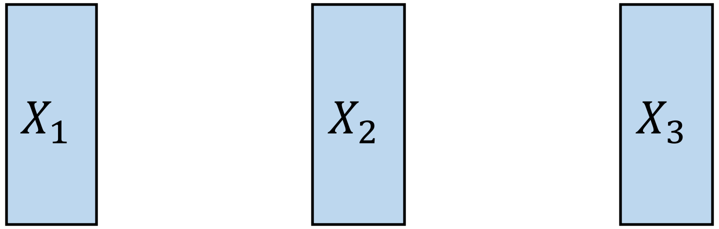

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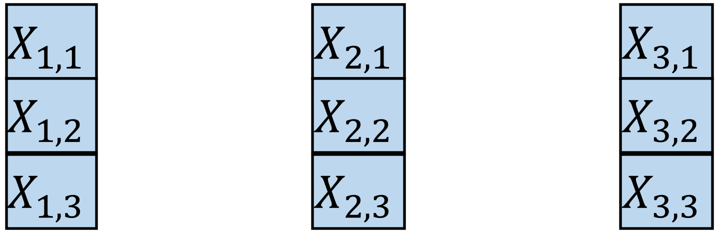

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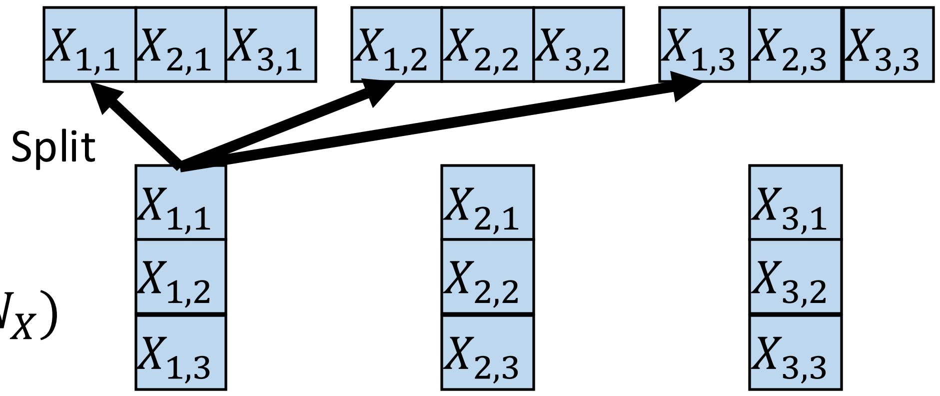
Similarities: $E = \frac{QX^T}{\sqrt{D_Q}} \ (Shape: \ N_X \times N_X) E_{i,j} = (Q_i \cdot K_j)/\sqrt{D_q}$

Attention weights: $A = softmax(E, \mathrm{dim} = 1) \ (Shape: \ N_X \times N_X)$

Output vectors: $Y = AV \ (Shape: \ N_X \times D_V) Y_i = \Sigma_j A_{i,j} V_j$



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Multi-head Self-Attention Layer

Inputs:

Input vectors: X (Shape: $N_X \times D_Q$)

Key matrix: $W_K (Shape: D_X \times D_Q)$

Value matrix: $W_V (Shape: \ D_X \times D_V)$

Query matrix: $\mathbf{W}_Q$ (Shape: $\mathrm{D}_Q \times D_Q$)

Computation:

Query Vectors $Q = XW_Q$

Key vectors: $K = XW_K \ (Shape: \ N_X \times D_Q)$

Value Vectors: $V = XW_V \ (Shape: \ N_X \times D_V)$

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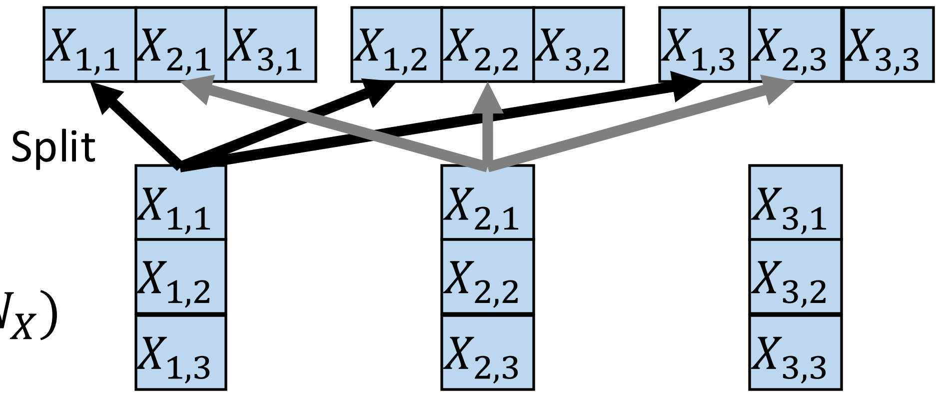

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Query matrix: $\mathbf{W}_Q$ (Shape: $\mathrm{D}_Q \times D_Q$)

Computation:

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Key vectors: $K = XW_K\ (Shape:\ N_X \times D_Q)$

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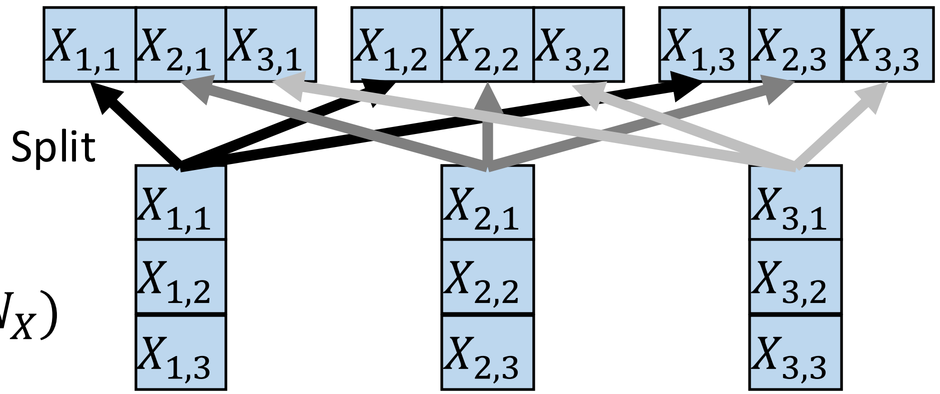

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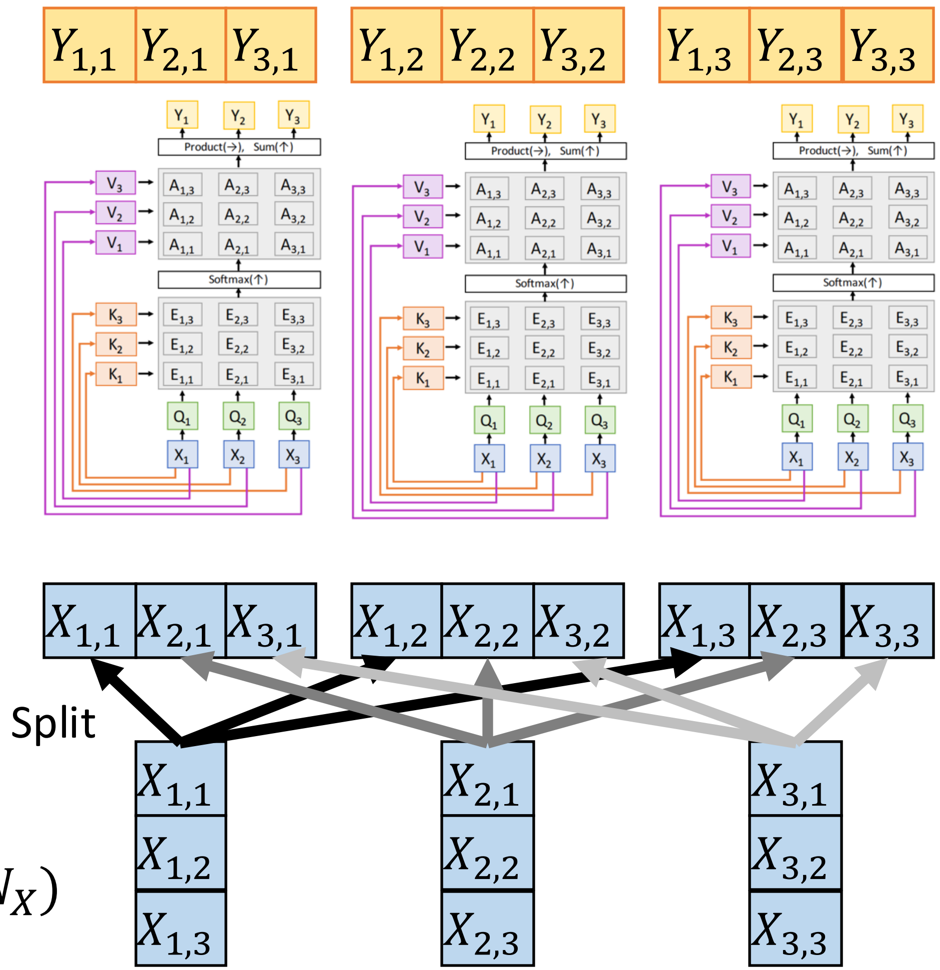
Attention weights: $A = softmax(E, \dim = 1)$ $(Shape: N_X \times N_X)$

Output vectors: $Y = AV$ $(Shape: N_X \times D_V) Y_i = \Sigma_j A_{i,j} V_j$

Run self-attention in parallel on each set of input vectors (different weights per head)



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Multi-head Self-Attention Layer

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Key matrix: $W_K (Shape: D_X \times D_Q)$

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Query matrix: $\mathbf{W}_\mathrm{Q}$ (Shape: $\mathrm{D_Q} \times D_Q$)

Computation:

Query Vectors $Q = XW_Q$

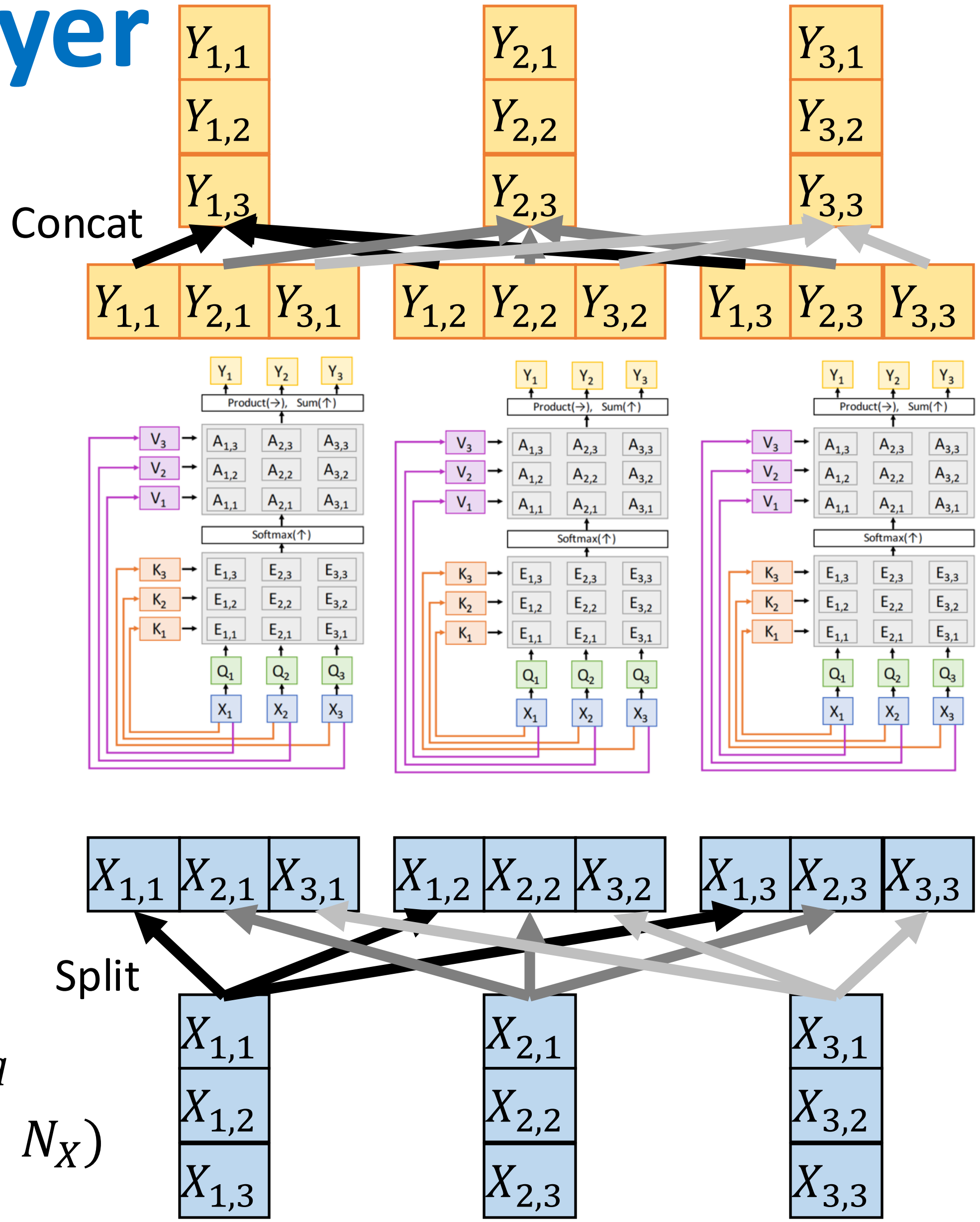
Key vectors: $K = XW_K\ (Shape: N_X \times D_Q)$

Value Vectors: $V = XW_V\ (Shape: N_X \times D_V)$

Similarities: $E = \frac{QX^T}{\sqrt{D_Q}}\ (Shape: N_X \times N_X) E_{i,j} = (Q_i \cdot K_j)/\sqrt{D_q}$

Attention weights: $A = softmax(E, \mathrm{dim} = 1)\ (Shape: N_X \times N_X)$

Output vectors: $Y = AV\ (Shape: N_X \times D_V) Y_i = \Sigma_j A_{i,j} V_j$



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Multi-head Self-Attention Layer

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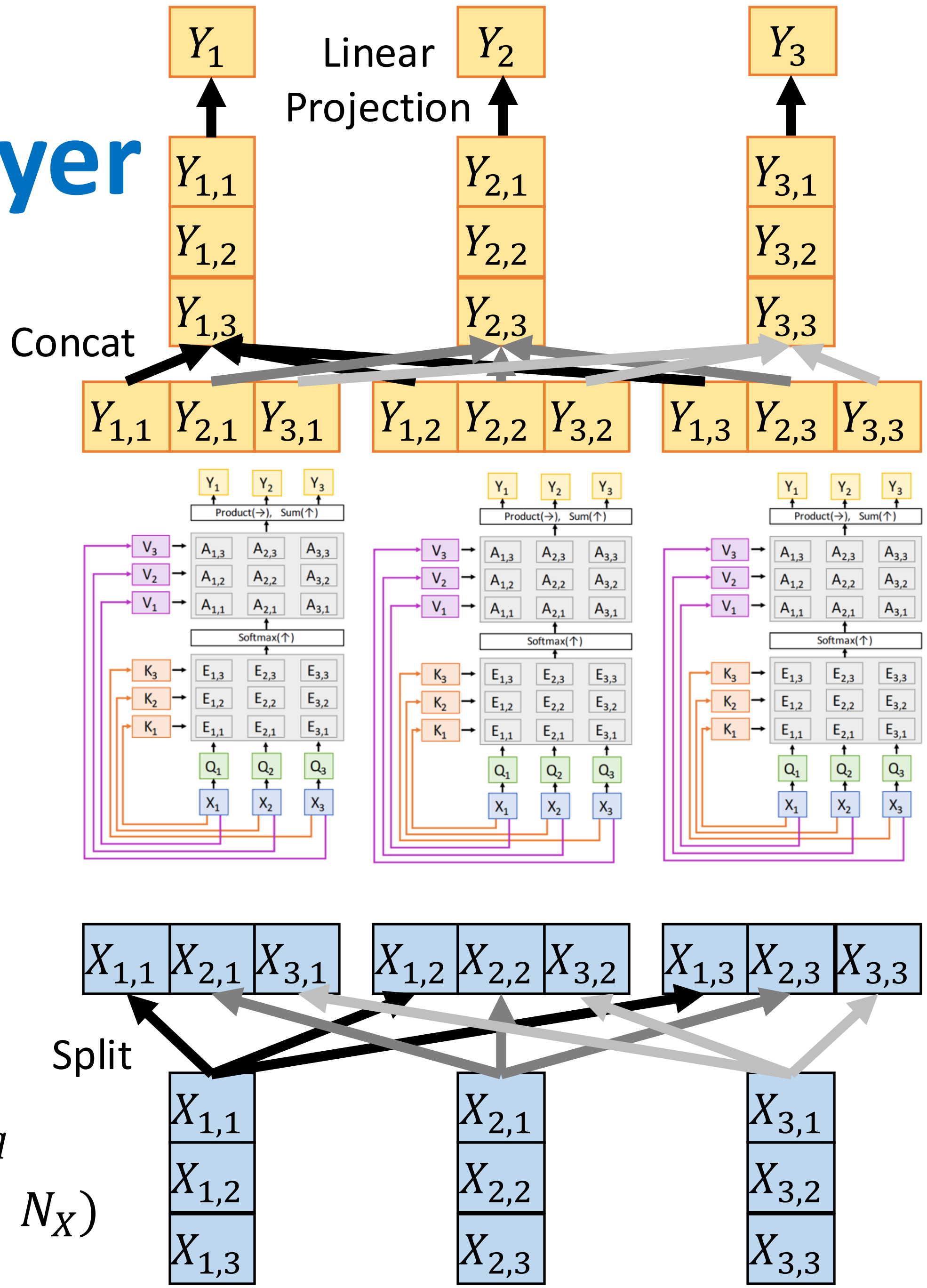

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The Transformer

X_1 X_2 X_3 X_4

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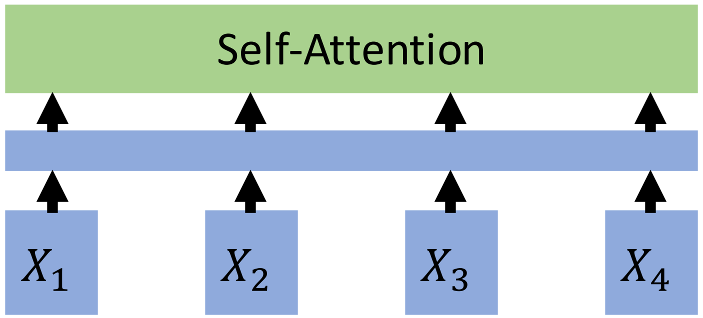
The Transformer



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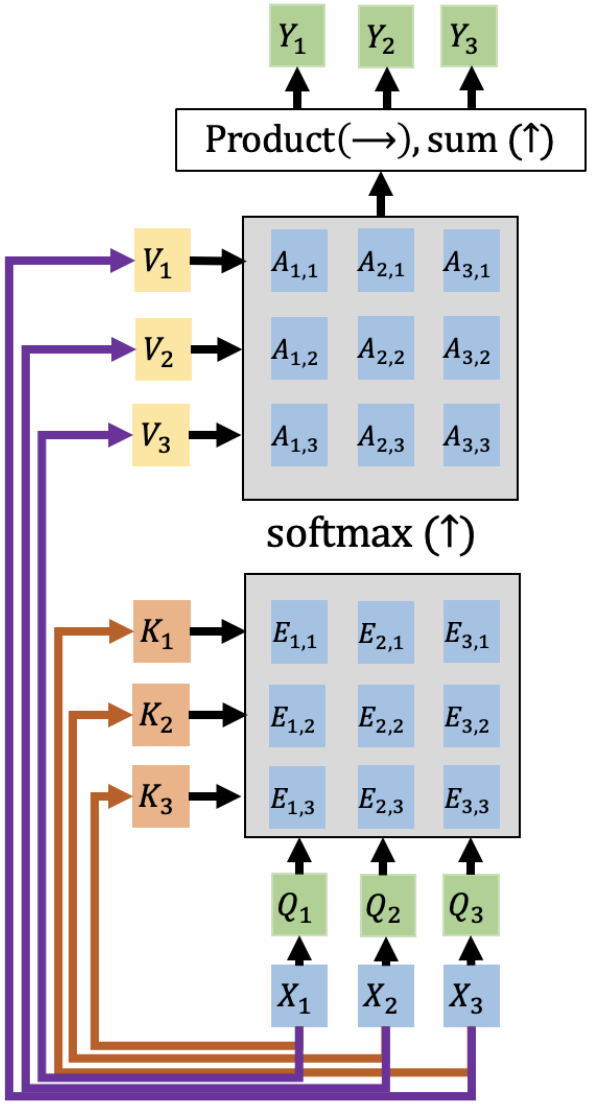
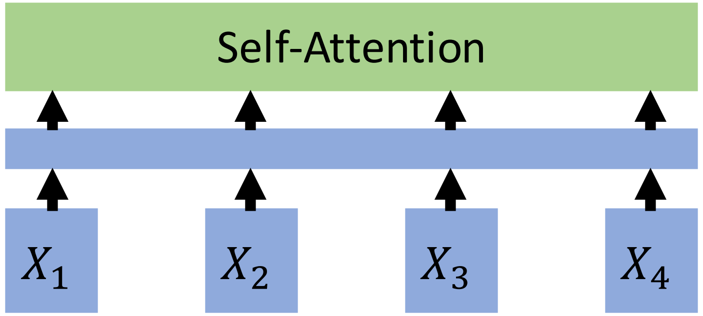
The Transformer



Self-Attention



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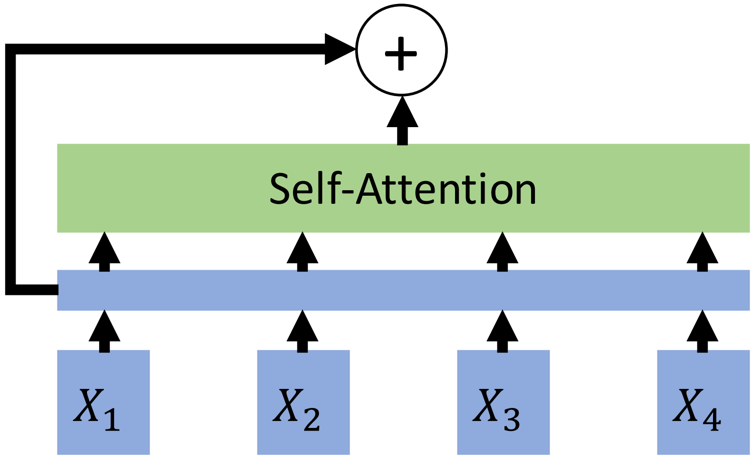
The Transformer

Residual connection
All vectors interact with each other



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The Transformer

Residual connection
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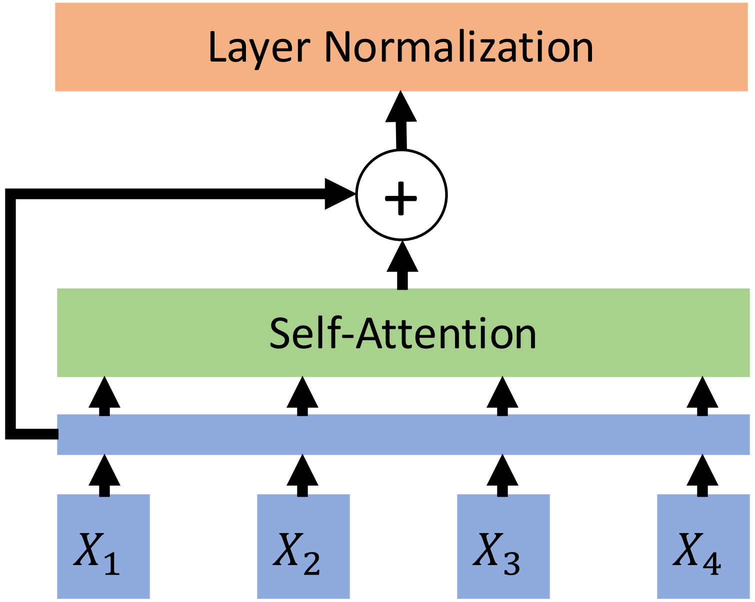

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The Transformer

Layer Normalization:

Given $h_1, \ldots, h_N$ (Shape: C)
scale: γ (Shape: C)
shift: β (Shape: C)

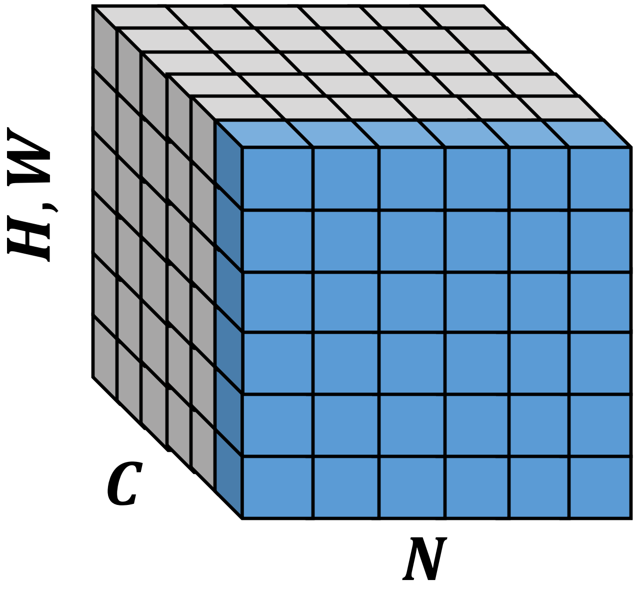
$$\mu_i = \frac{\Sigma_j h_{i,j}}{C} \text{ (scalar)}$$

$$\sigma_i = \left(\frac{\Sigma_j (h_{i,j} - \mu_i)^2}{C}\right)^{1/2} \text{ (scalar)}$$

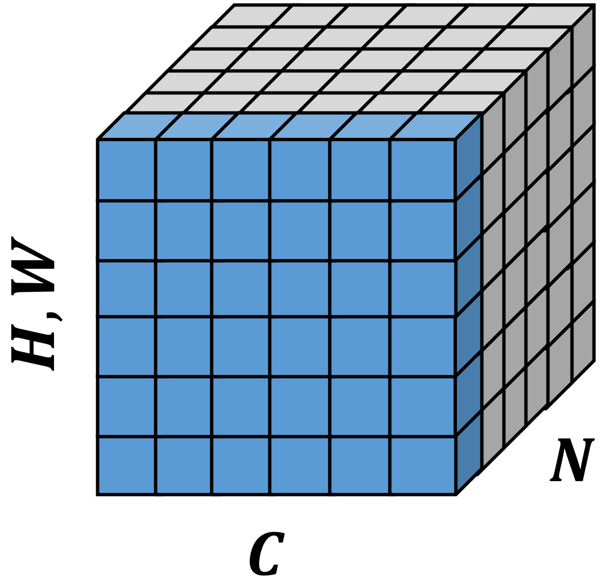
$$z_i = \frac{h_i - \mu_i}{\sigma_i}$$

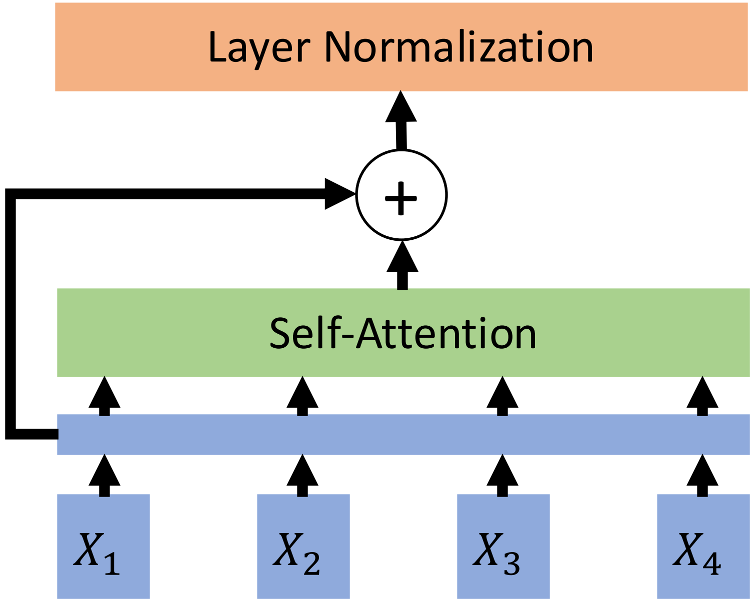
$$y_i = \gamma * z_i + \beta$$

Batch Norm



Layer Norm

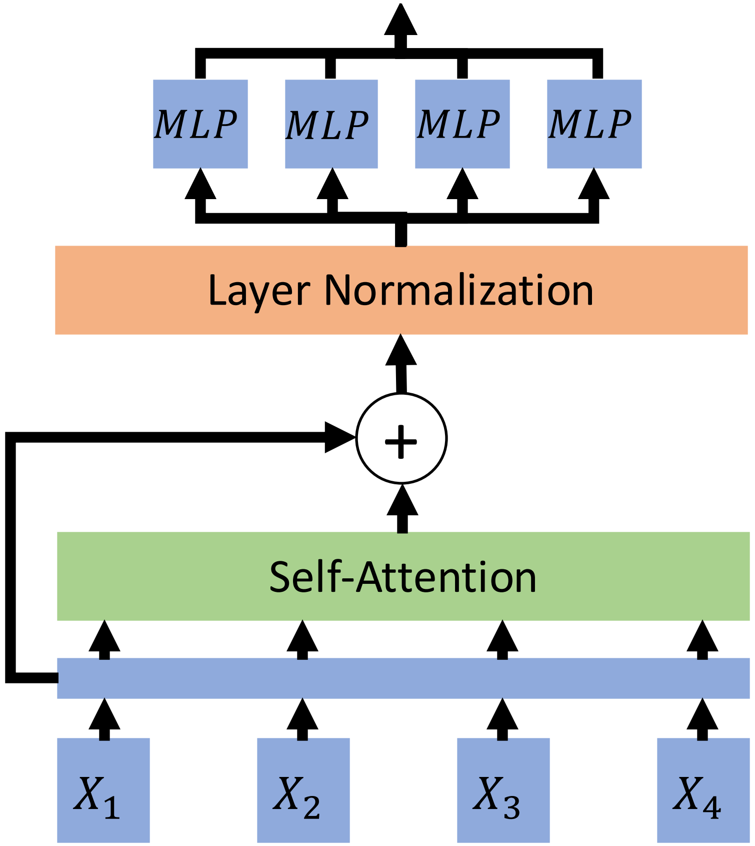




The Transformer

MLP: independently on each vector

Residual connection
All vectors interact with each other

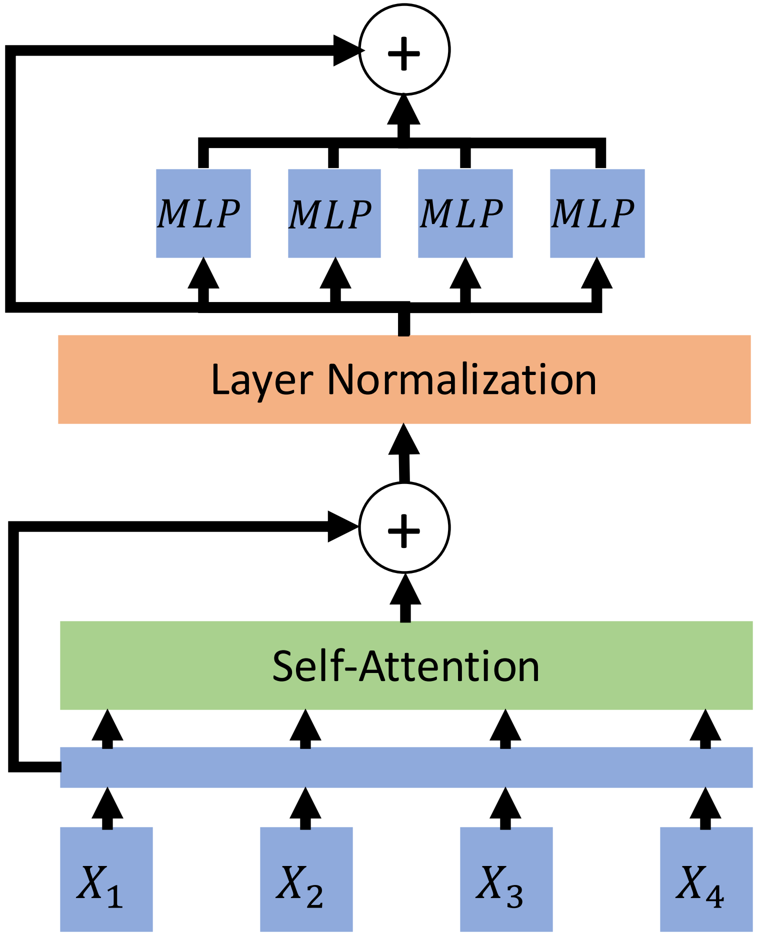


The Transformer

Residual connection

MLP: independently on each vector

Residual connection
All vectors interact with each other



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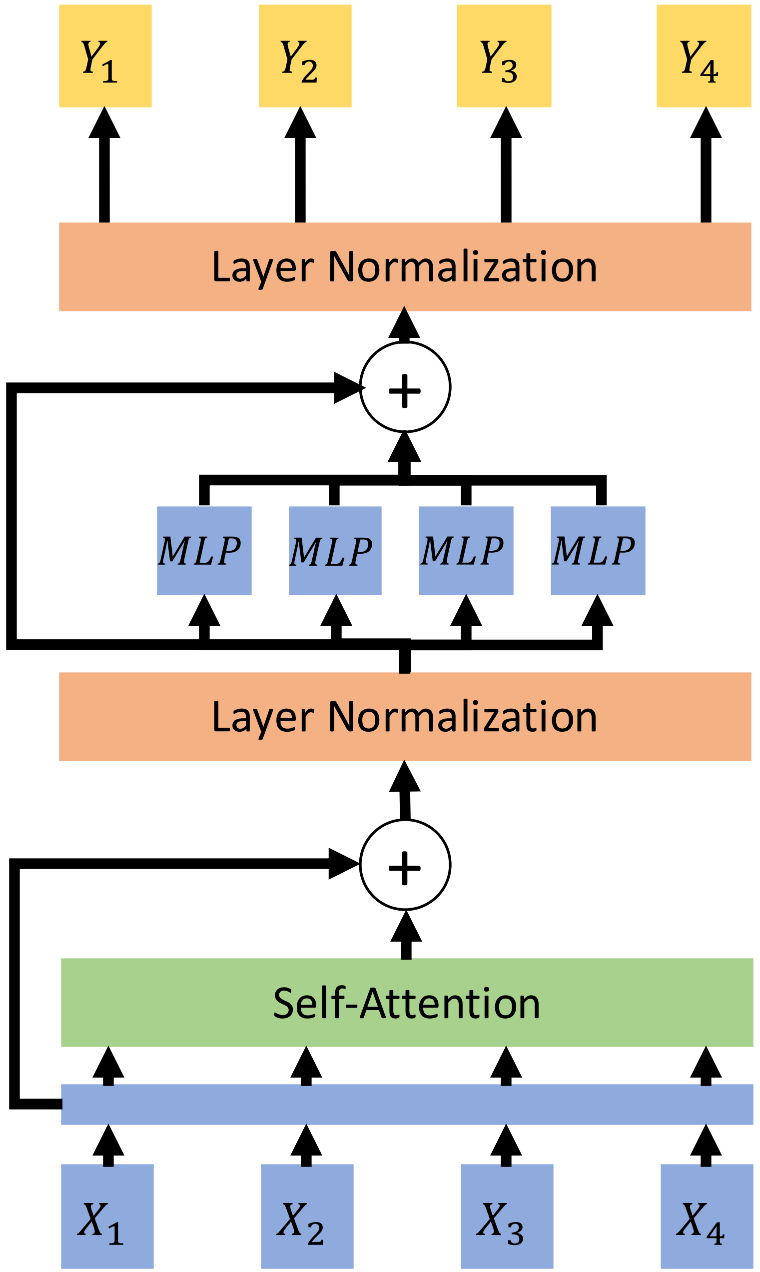
The Transformer

Residual connection

MLP: independently on each vector

Residual connection
All vectors interact with each other

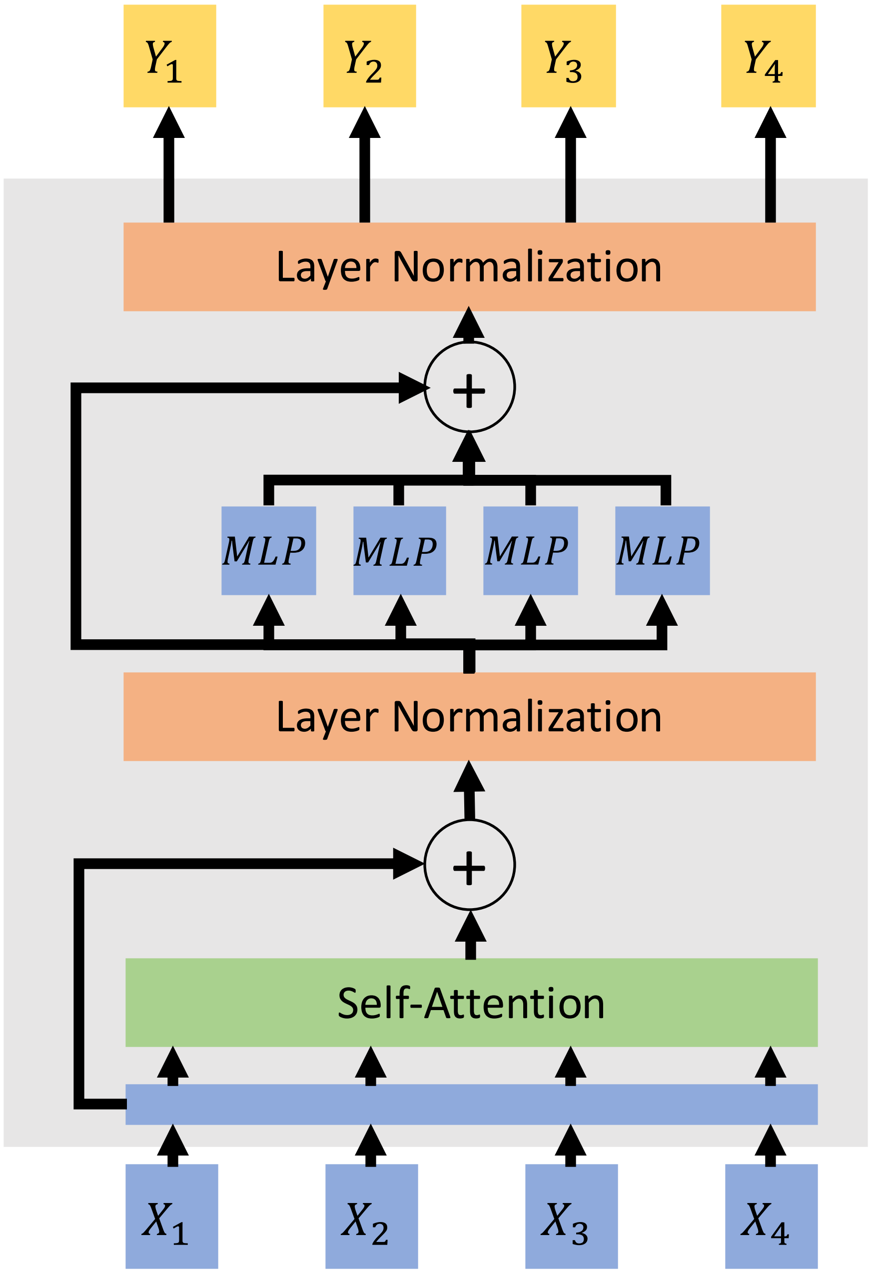


The Transformer

Transformer Block:

- **Input:** Set of vectors x
- **Output:** Set of vectors y

- Self-attention is the only interaction between vectors!
- Layer norm and MLP work independently per vector
- Highly scalable, highly parallelizable



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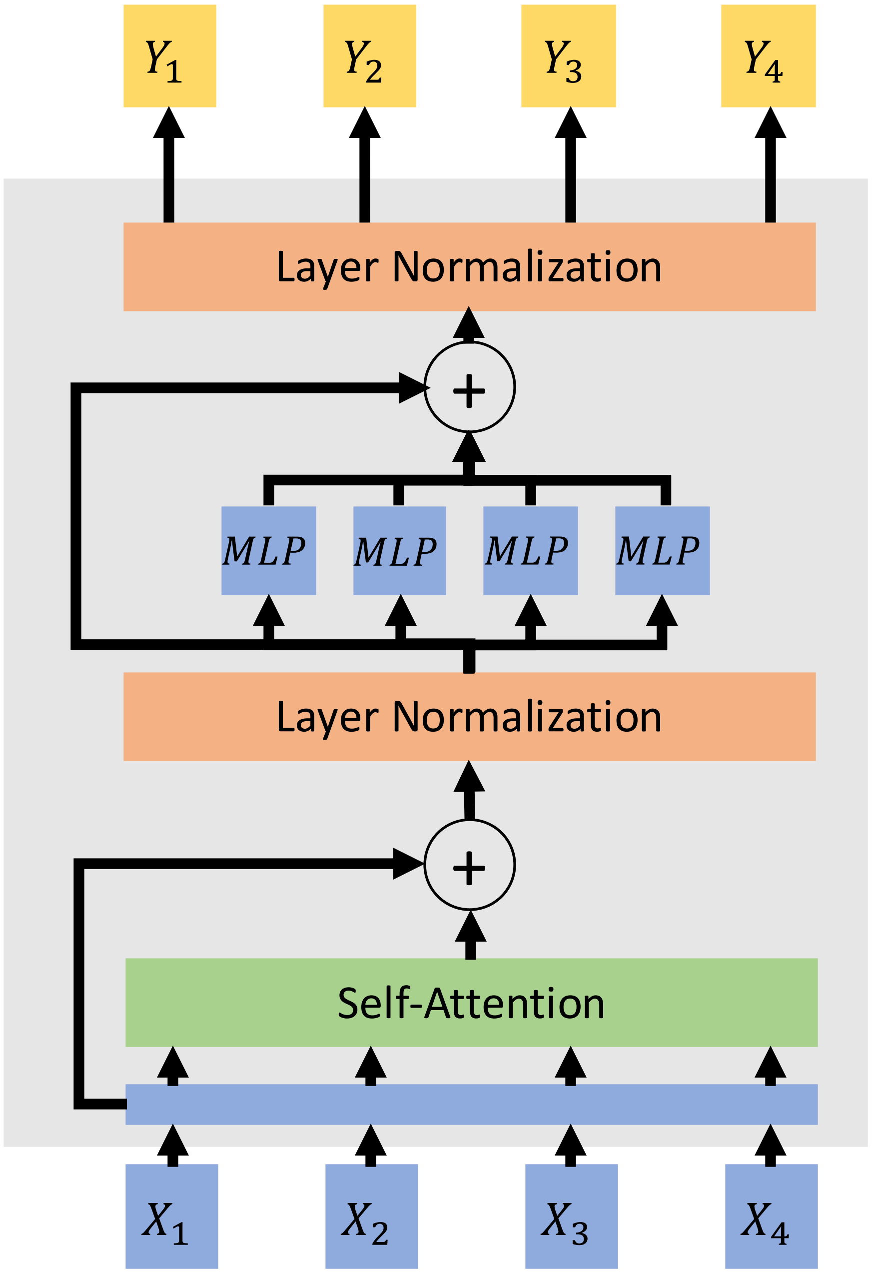
Post-Norm Transformer

- Layer Normalization is after the residual connections

- Gives more stable training, commonly used in practice



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The Transformer

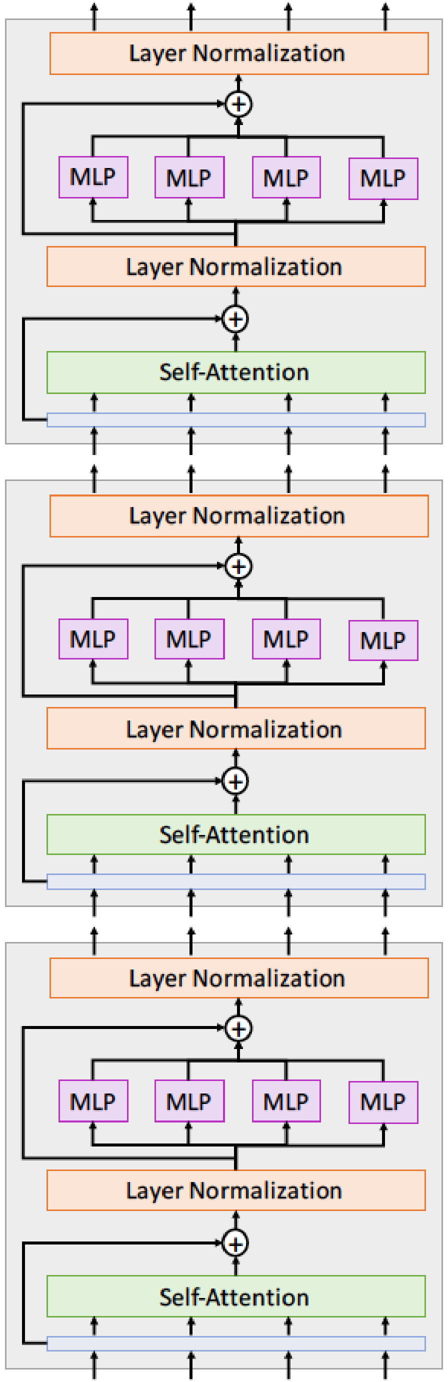
Transformer Block:

- **Input:** Set of vectors x
- **Output:** Set of vectors y

A **Transformer** is a sequence of transformer blocks

Vaswani et al:
12 blocks, $D_Q = 512$, 6 heads

- Self-attention is the only interaction between vectors!
- Layer norm and MLP work independently per vector
- Highly scalable, highly parallelizable



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The Transformer: Transfer Learning

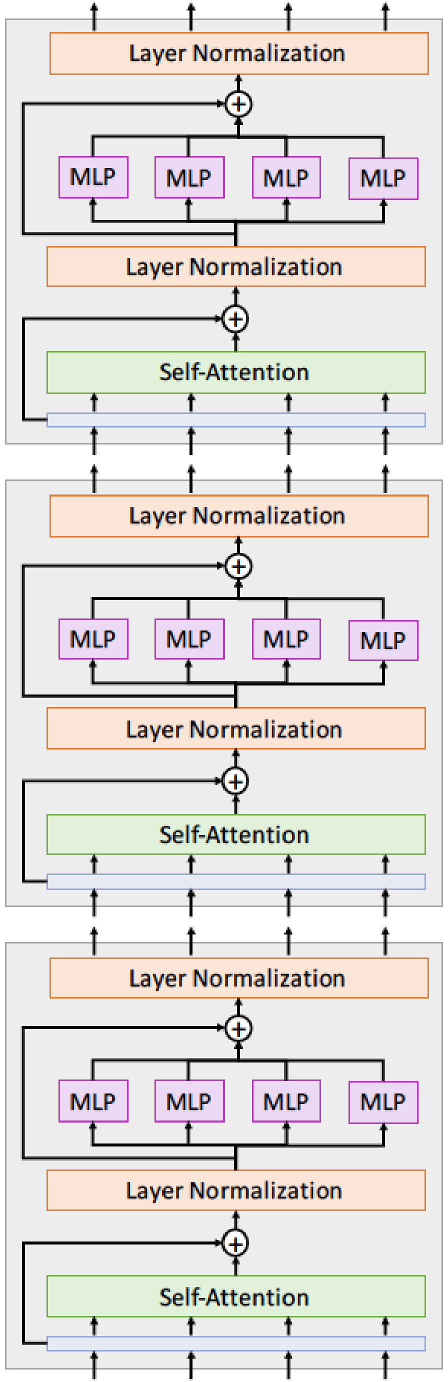
"ImageNet Moment for Natural Language Processing"

Pretraining:

- Download a lot of text from the internet
- Train a giant Transformer model for language modeling

Finetuning:

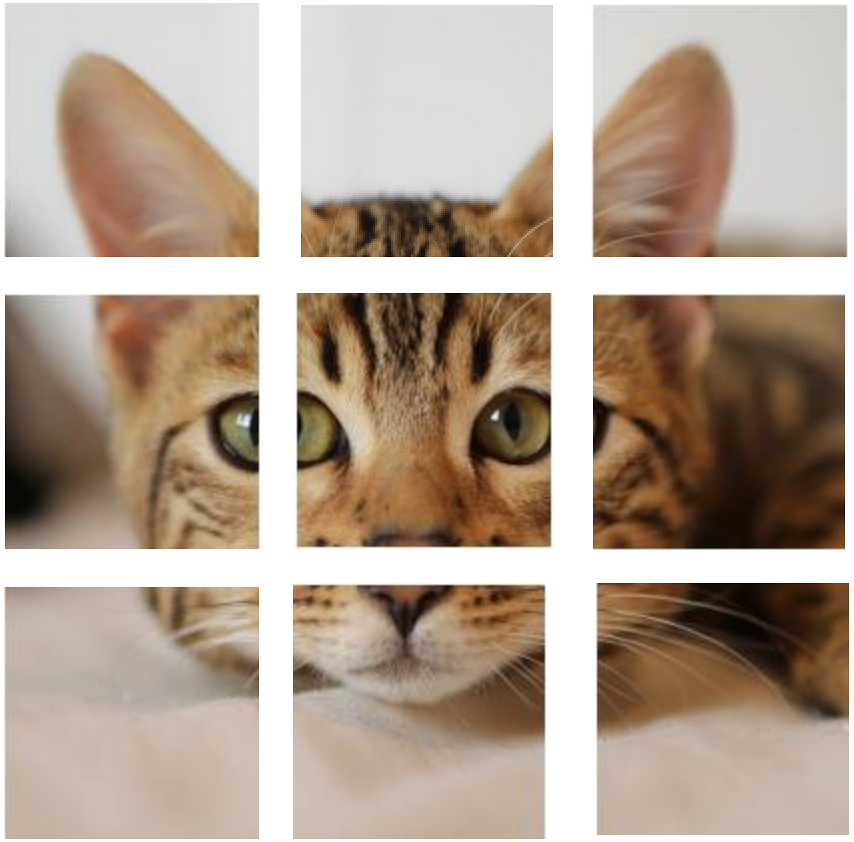
- Fine-tune the Transformer on your own NLP task



Vision Transformer (ViT)

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

Vision Transformer (ViT)



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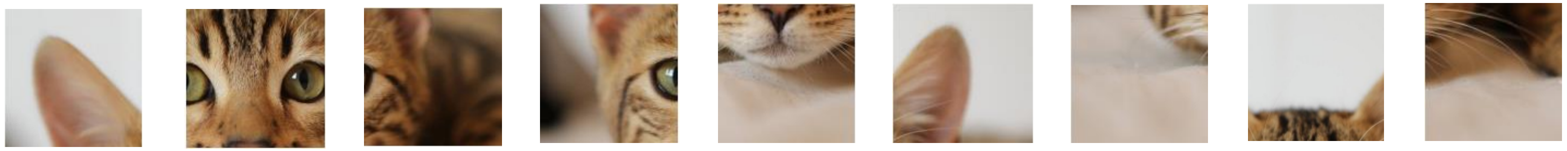
Vision Transformer (ViT)

N input patches, each of shape $3 \times 16 \times 16$



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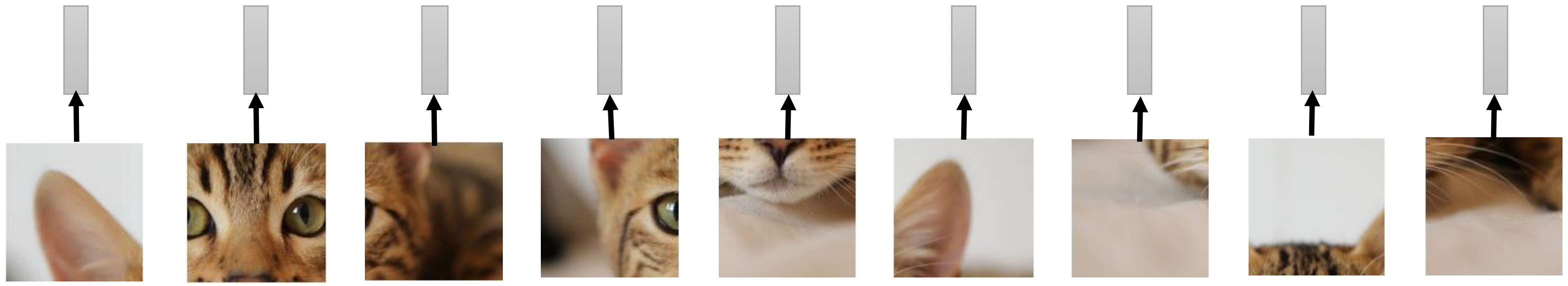
Vision Transformer (ViT)

Linear projection to
D-dimensional vector

N input patches, each
of shape $3 \times 16 \times 16$



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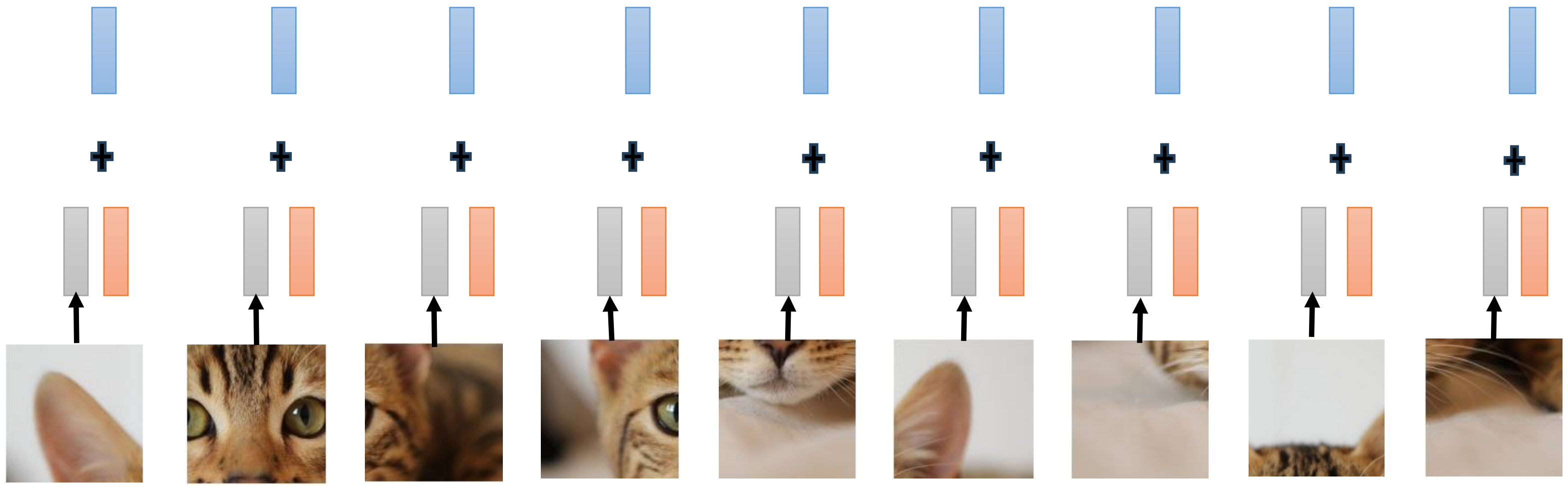
Vision Transformer (ViT)

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

N input patches, each of shape $3 \times 16 \times 16$



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Vision Transformer (ViT)

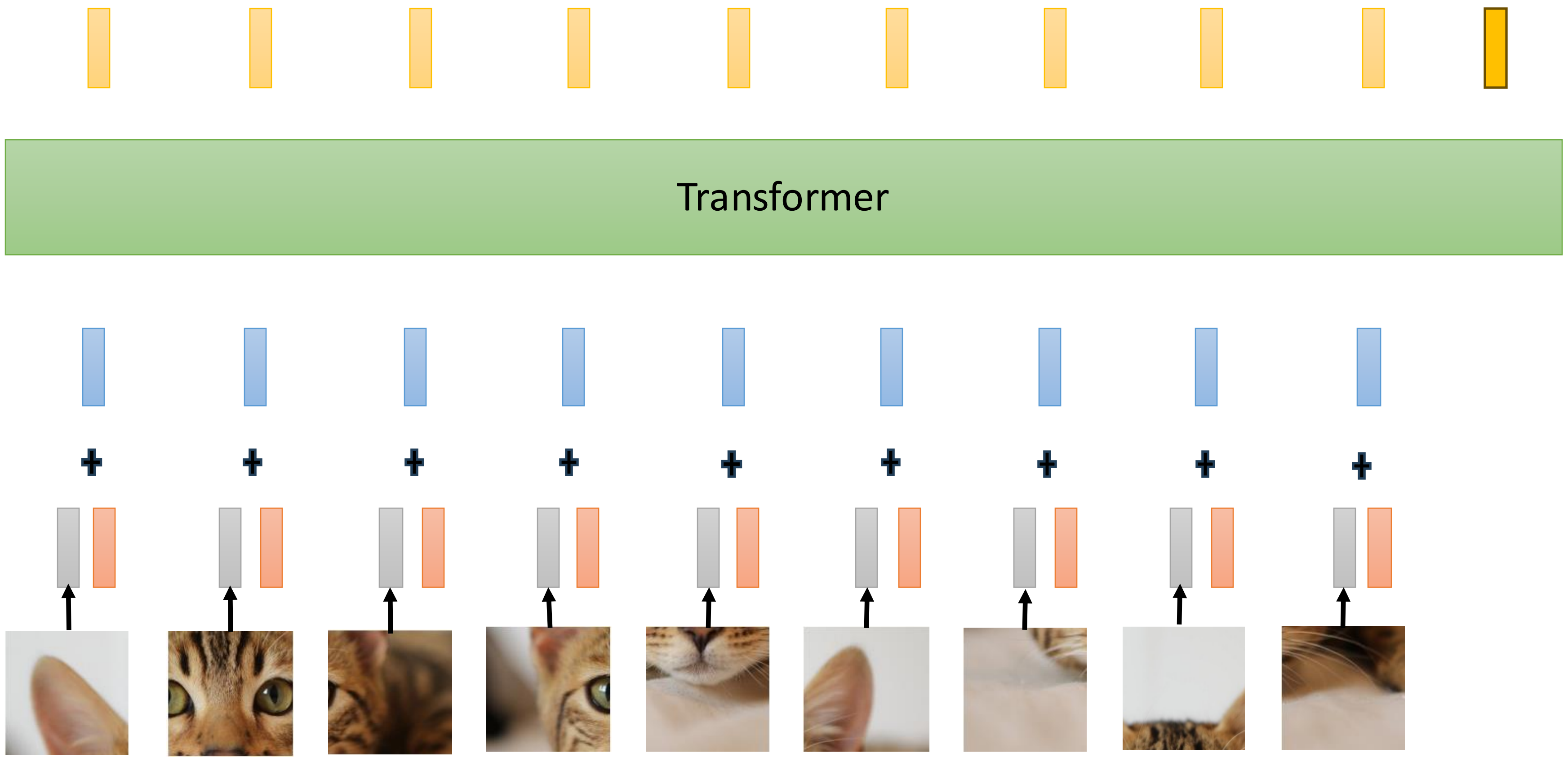
Output vectors

Exact same as
NLP Transformer!

Add positional embedding: learned D-dim vector per position

Linear projection to D-dimensional vector

N input patches, each of shape $3 \times 16 \times 16$



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Add positional
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Linear projection to
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N input patches, each
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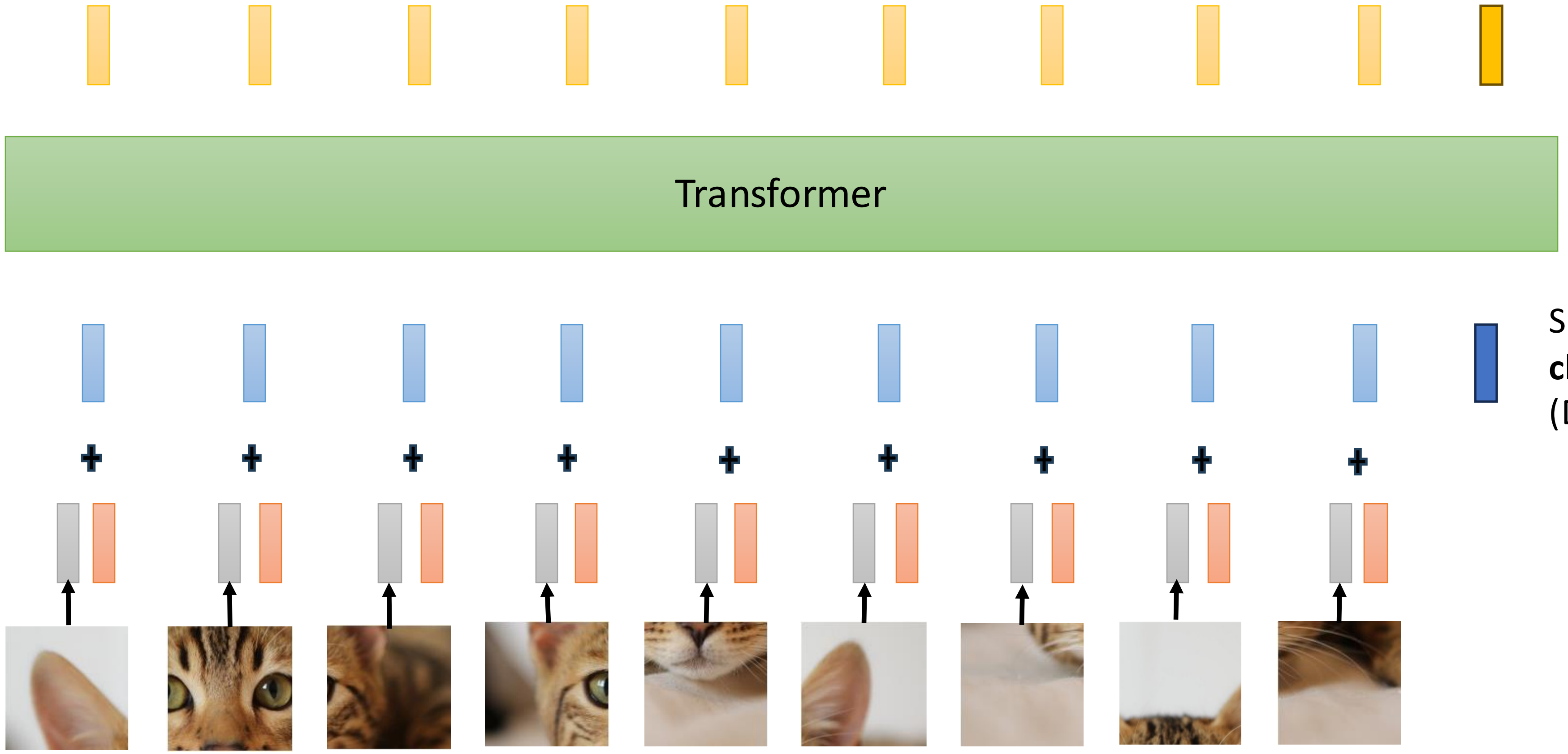

Special extra input:
classification token
(D dims, learned)

Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

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Vision Transformer (ViT)

Computer vision model with
no convolutions!

Linear projection to C-dim vector of predicted class scores

Output vectors

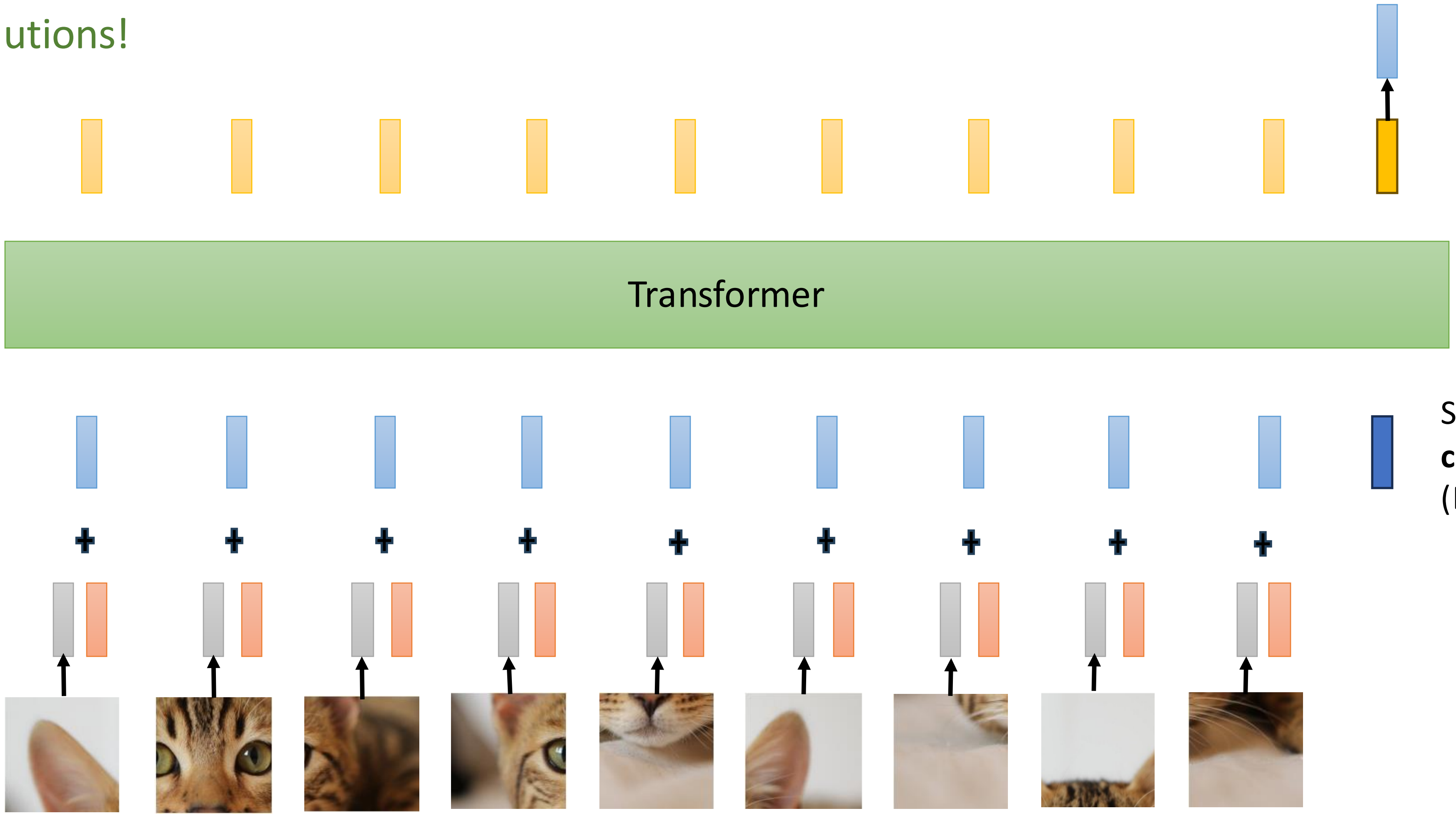
Exact same as NLP Transformer!

Add positional embedding: learned D-dim vector per position

Special extra input: **classification token** (D dims, learned)

Linear projection to D-dimensional vector

N input patches, each of shape 3x16x16



Dosovitskiy et al, “An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale”, ICLR 2021

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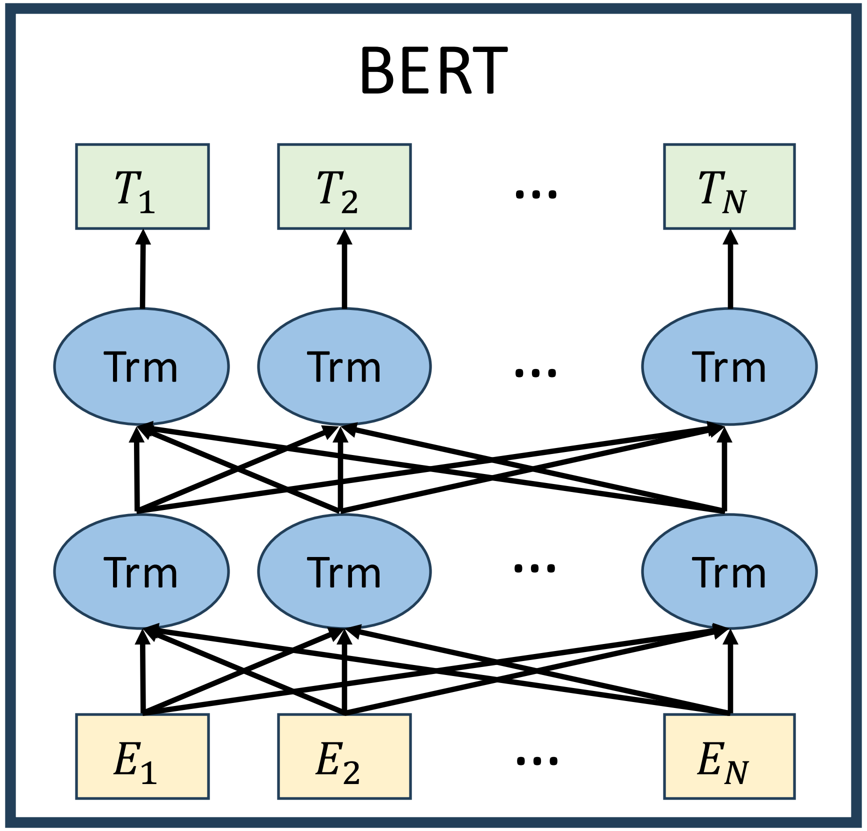
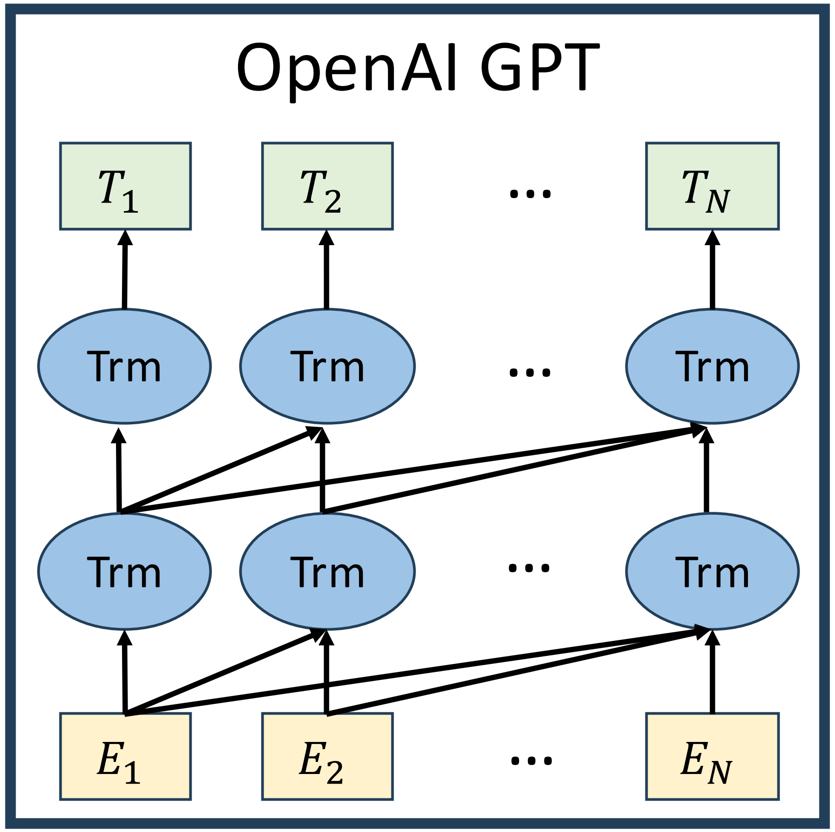
Pretraining Transformers: BERT Vs GPT





Parameter Efficient Fine-Tuning (PEFT)

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Full Fine-tuning in Foundational Models

Model Name	η_{params}	η_{layers}	d_{model}	η_{heads}	d_{head}	Batch Size	Learning Rate
GPT-3 Small	125M	12	768	12	64	0.5M	$6.0\ X 10^{-4}$
GPT-3 Medium	350M	24	1024	16	64	0.5M	$3.0\ X\ 10^{-4}$
GPT-3 Large	760M	24	1536	16	96	0.5M	$2.5\ X\ 10^{-4}$
GPT-3 XL	1.3B	24	2048	24	128	IM	$2.0\ X\ 10^{-4}$
GPT-3 2.7B	2.7B	32	2560	32	80	IM	$1.6\ X\ 10^{-4}$
GPT-3 6.7B	6.7B	32	4096	32	128	2M	$1.2\ X\ 10^{-4}$
GPT-3 13B	13.0B	40	5140	40	128	2M	$1.0\ X\ 10^{-4}$
GPT-3 175B or "GPT-3"	175.0B	96	12288	96	128	3.2M	$0.6\ X\ 10^{-4}$

Brown et al. Language Models are Few-Shot Learners. NeurIPS 2020.
McCandlish et al. An Empirical Model of Large-Batch Training

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Full Fine-tuning in Foundational Models

Temp Memory

Forward Activations

Gradients

Optimizer States

Trainable Weights

12-20x weights

1. Hardware Requirements

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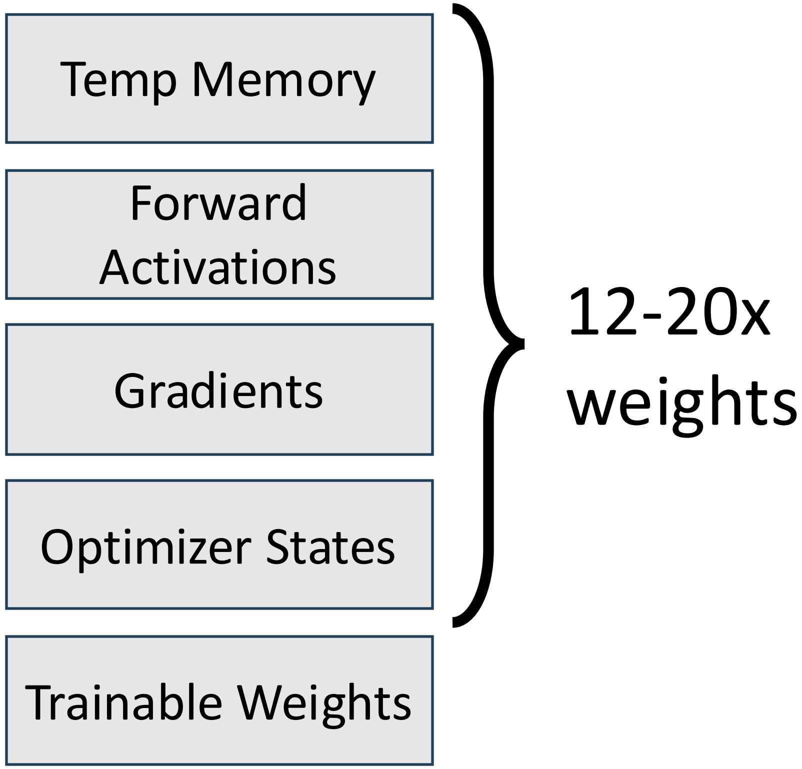
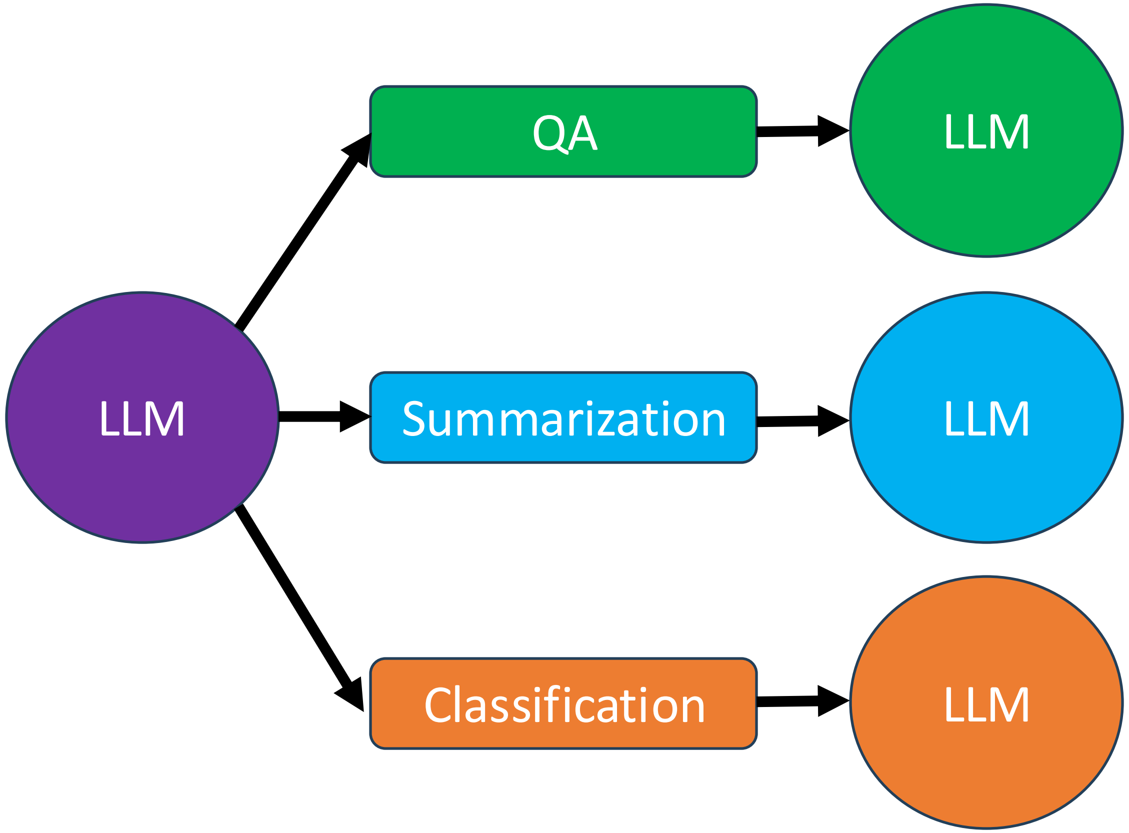
Full Fine-tuning in Foundational Models



1. Hardware Requirements



2. Storage

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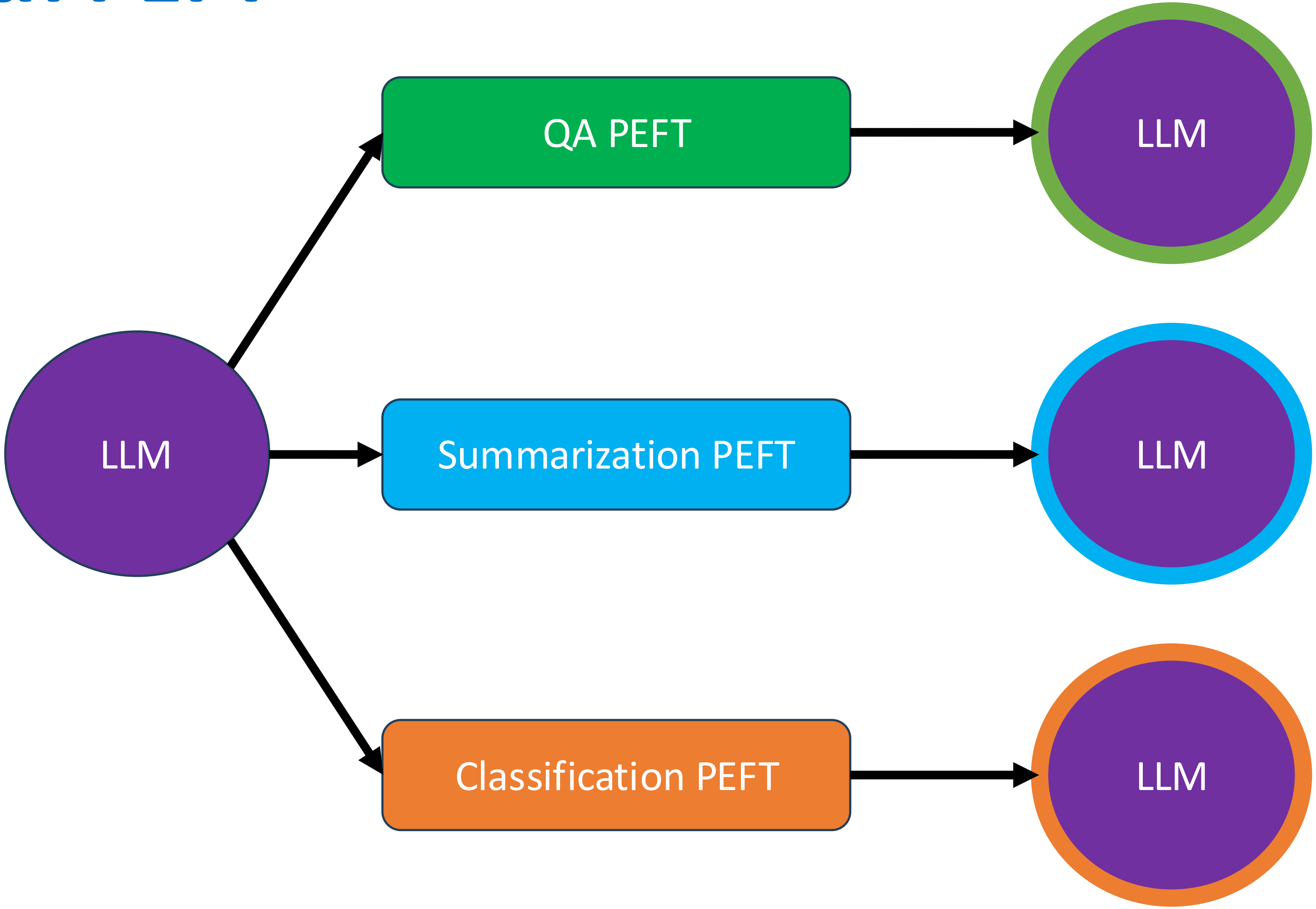
With PEFT



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PEFT Benefits

- **Reduced computational costs**
  - Requires fewer GPUs and GPU time
- **Lower hardware requirements**
  - Works with smaller GPUs & less memory
- **Better modelling performance**
  - Reduces overfitting by preventing catastrophic forgetting
- **Less storage**
  - Majority of weights can be shared across different tasks

Prompts

- Prompts include instructions and, optionally, examples (latter called “In-Context Learning”)

- **Zero Shot:** The model predicts the answer given only a natural language description of the task. No gradient updates are performed.

```
Translate English to French:

cheese =>
```

Brown et al. Language Models are Few-Shot Learners. NeurIPS 2020.

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Prompts

- Prompts include instructions and, optionally, examples (latter called "In-Context Learning")

- **Single Shot:** In addition to the task description, the model sees a single example of the task. No gradient updates are performed.

```
Translate English to French:

sea otter => loutre de mer

cheese =>
```

Brown et al. Language Models are Few-Shot Learners. NeurIPS 2020.

Prompts

- Prompts include instructions and, optionally, examples (latter called "In-Context Learning")

- **Few Shot:** In addition to the task description, the model sees a **few** examples of the task. No gradient updates are performed.

```
Translate English to French:
sea otter => loutre de mer
peppermint => menthe poivre
plush giraffe => giraffe peluche
cheese =>
```

Brown et al. Language Models are Few-Shot Learners. NeurIPS 2020.

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What Prompts to Use?

- Chain-of-thought (COT) prompting can help by guiding model to show its intermediate reasoning steps!

Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

The answer is 27.

incorrect

Chain of Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9.

Challenge: What Prompts to Use?

Why COT prompting works? Examples may reveal the target output format as performance still improves with invalid examples; e.g.

COT	Originally, Leah had 32 chocolates and her sister had 42. So in total they had 32 + 42 = 74. After eating 35, they had 74 - 35 = 39 pieces left in total. The answer is 39.	Julie is reading a 120-page book. Yesterday, she read 12 pages and today, she read 24 pages. So she read a total of 12 + 24 = 36 pages. Now she has 120 - 36 = 84 pages left. Since she wants to read half of the remaining pages, she should read 84 / 2 = 42 pages. The answer is 42
Invalid Reasoning **Yet, correct answer**	Originally, Leah had 32 chocolates, and her sister had 42. So her sister had 42 – 32 = 10 chocolates more than Leah had. After eating 35, since 10 + 35 = 45, they had 45 – 6 = 39 pieces left in total. The answer is 39.	Yesterday, Julie read 12 pages. Today, she read 12 * 2 = 24 pages. So she read a total of 12 + 24 = 36 pages. Now she needs to read 120 - 36 = 84 more pages. She wants to read half of the remaining pages tomorrow, so she needs to read 84/2 = 42 pages tomorrow. The answer is 42.

Brown et al. Language Models are Few-Shot Learners. Neurips 2020.

PEFT Techniques

- P-Tuning
- Prefix Tuning
- Adapters
- Low Rank Adaptation

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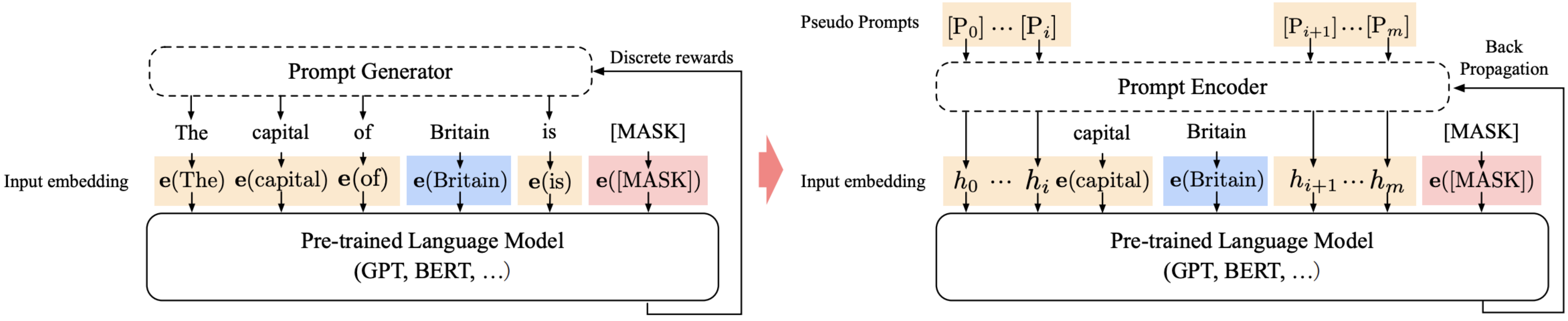
P-Tuning

- Appends a trainable tensor to the model's input embeddings, creating a soft prompt.
- The model weights of the LLM are frozen.
- In contrast to the regular (hard) prompt tuning, in (soft) prompt tuning the prompts are vectors instead of discrete prompts.



(a) Discrete Prompt Search (b) P-tuning

Liu et al. GPT Understands, Too. CoRR abs/2103.10385. 2021

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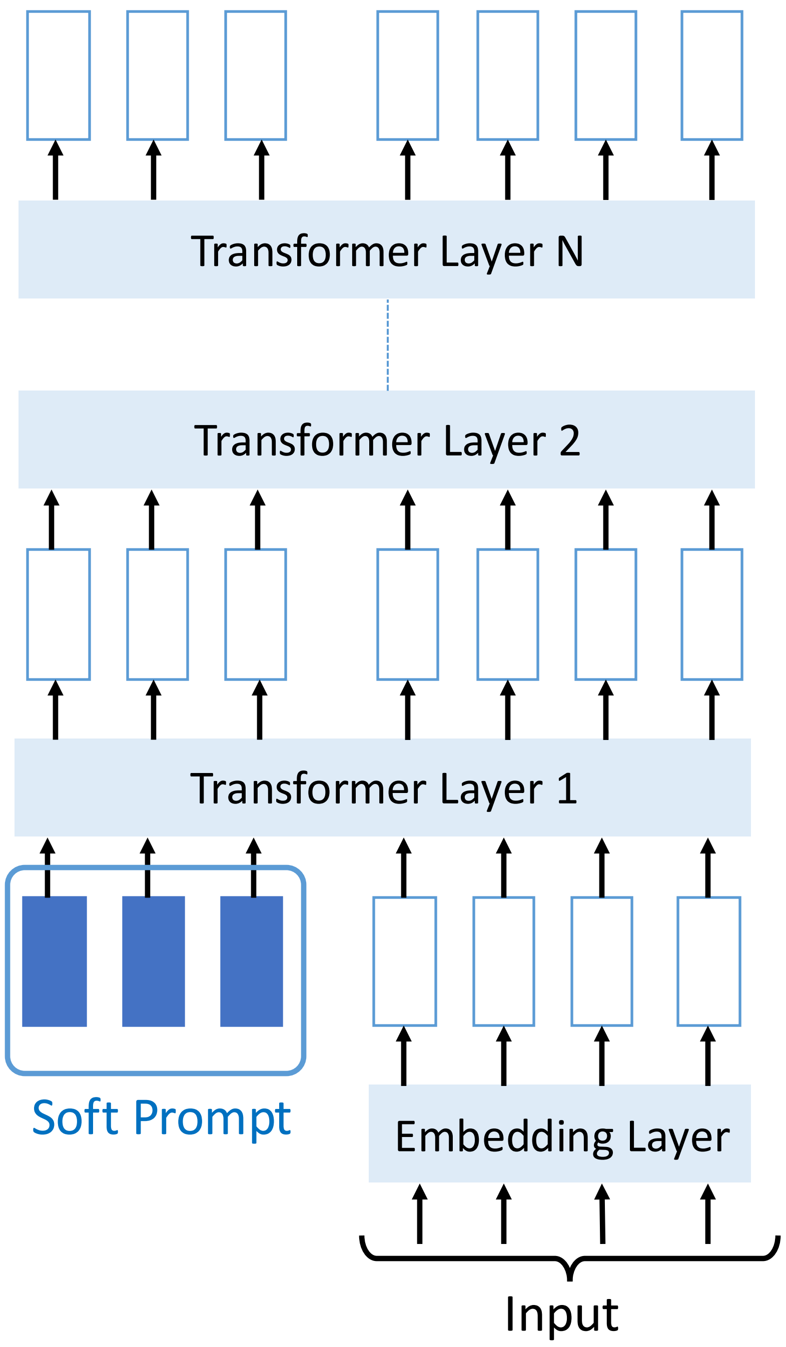
P-Tuning

- Treats prompt as a set of learnable parameters that are updated by backpropagation.

- For a specific task, only a small task-specific soft prompt needs to be stored

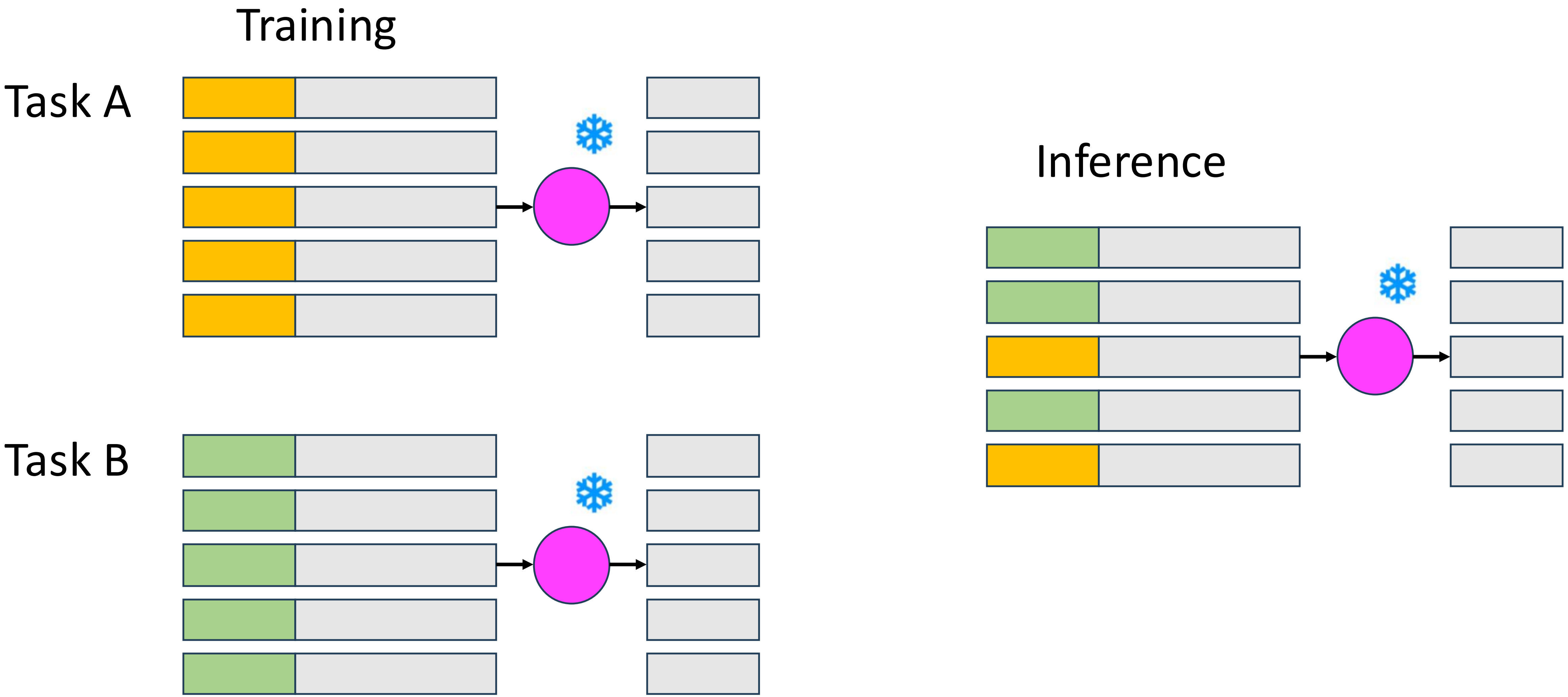
- Significantly more parameter-efficient than full-finetuning

- Additionally, a prompt encoder can also be used which can be an LSTM or a Multi-Layer Perceptron.



Lester et al., The Power of Scale for Parameter-Efficient Prompt Tuning. EMNLP 2021.

P-Tuning



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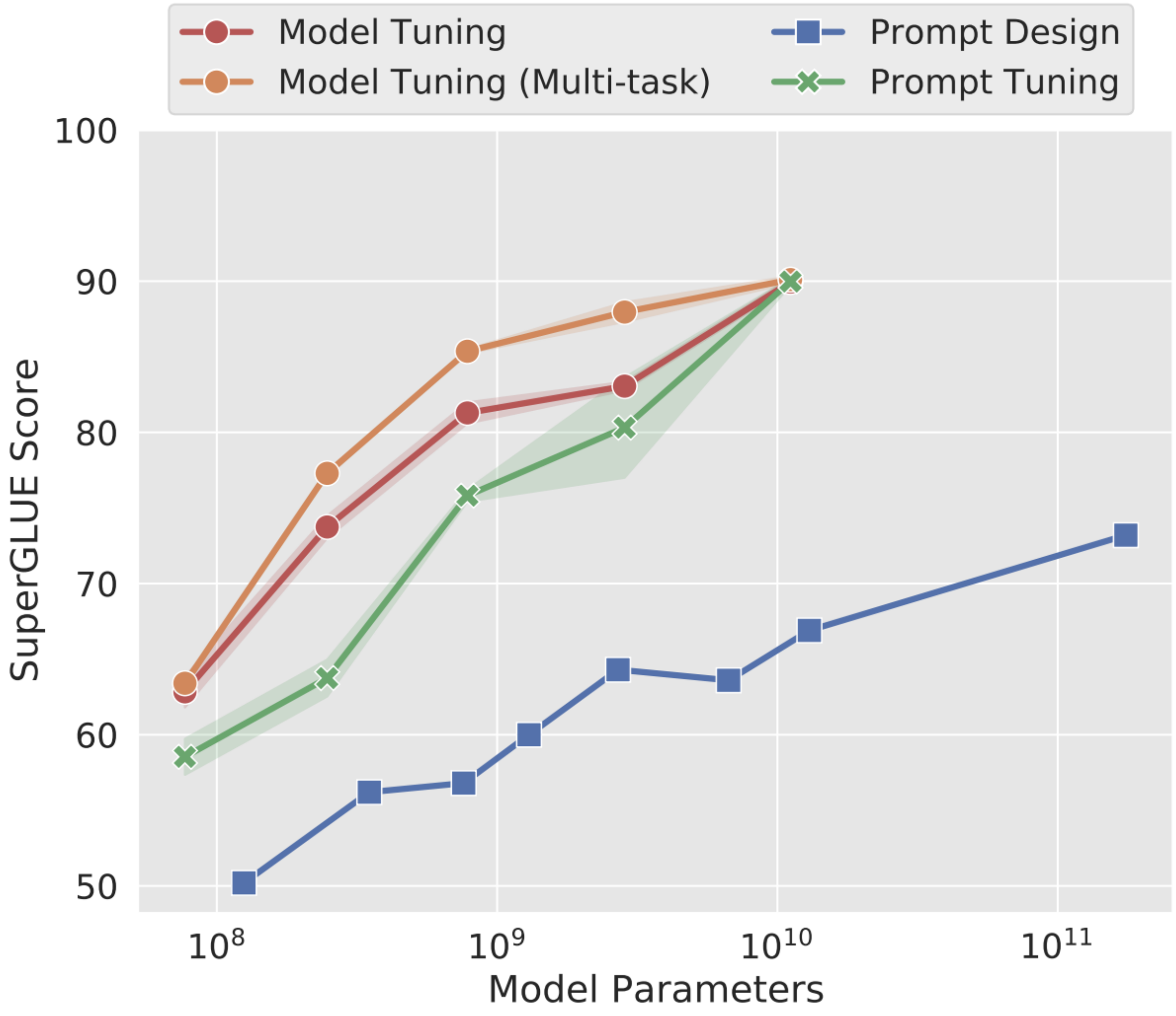
(Soft) Prompt Tuning: Pros and Cons

- May perform poorly at smaller model sizes and on harder tasks.
- Increasing prompt length improves the performance but increasing beyond 20 tokens may only yield marginal gains.



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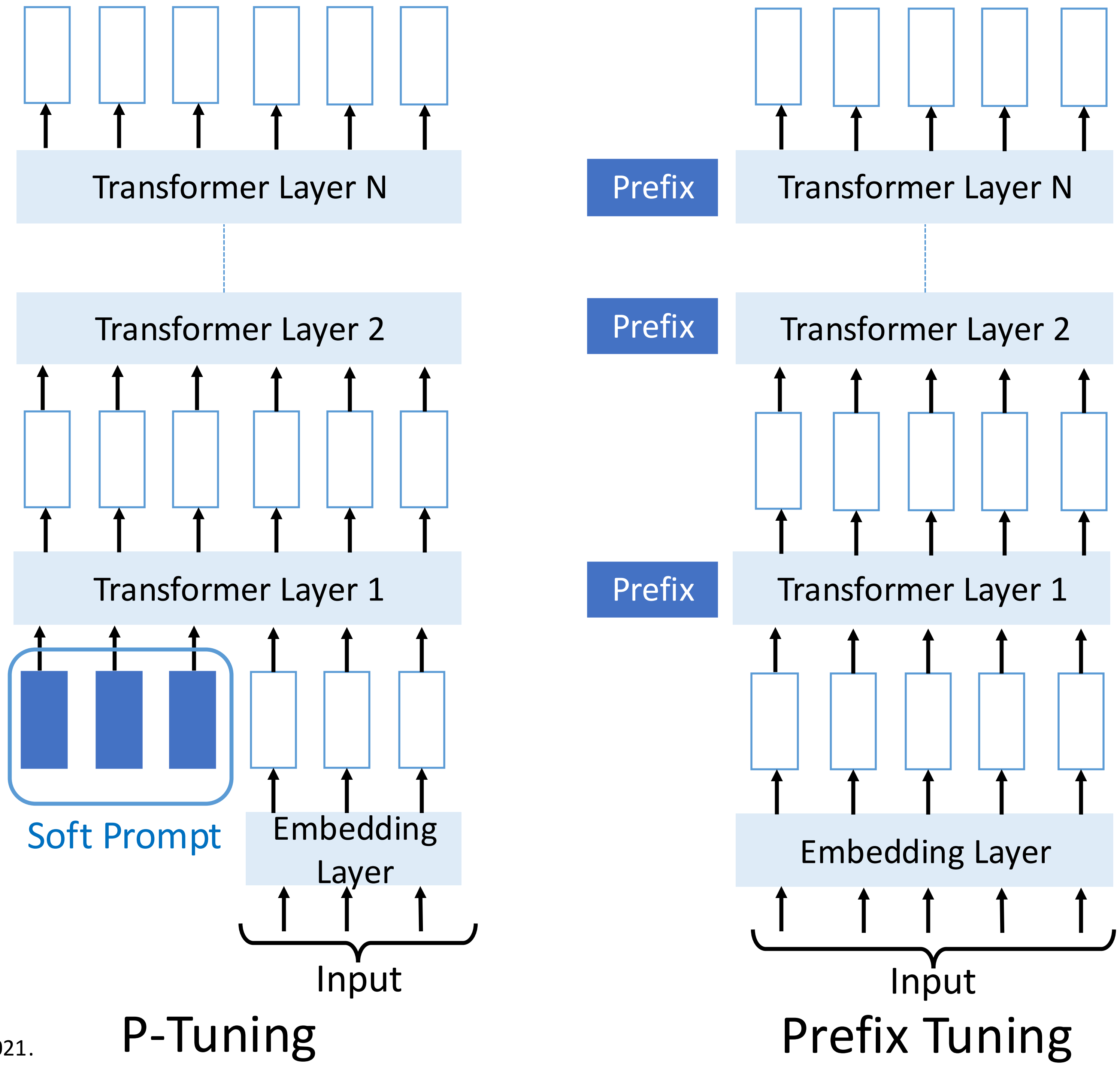
Prefix Tuning

- Add a trainable tensor to **<u>each</u>** transformer block instead of only the input embeddings, as in soft prompt tuning.
- Add learnable component to each K/V vectors.



Li and Liang, Prefix-Tuning: Optimizing Continuous Prompts for Generation. 2021.

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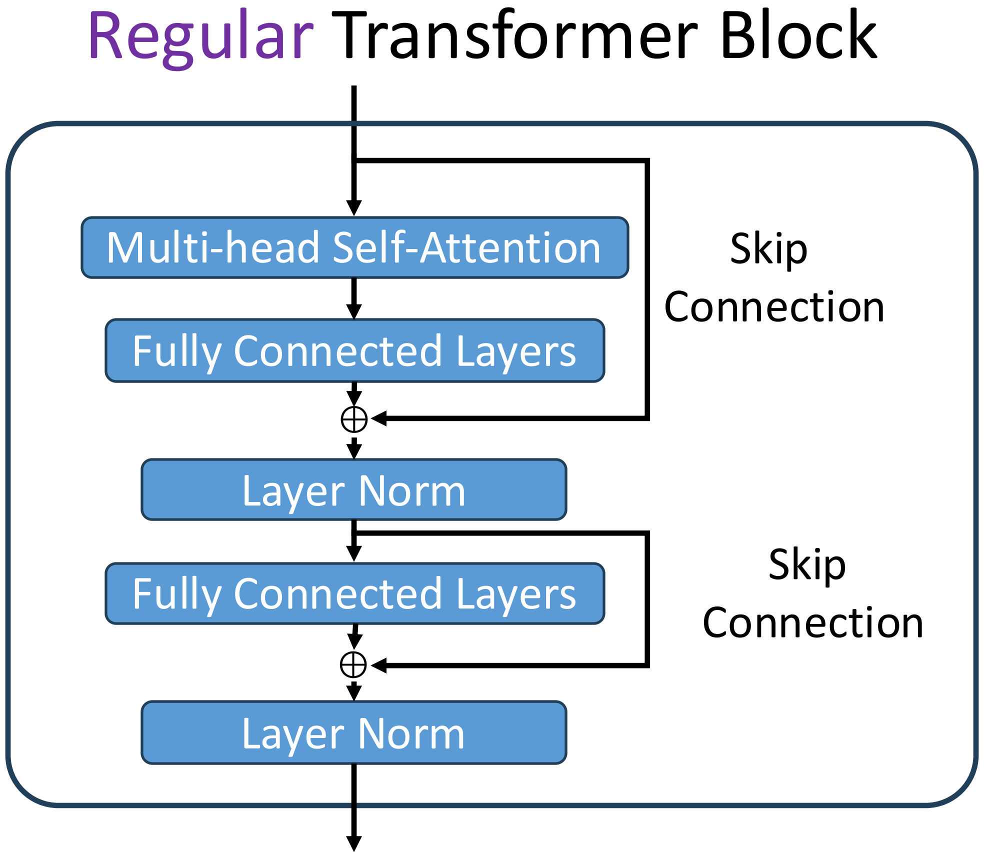
Prefix Tuning



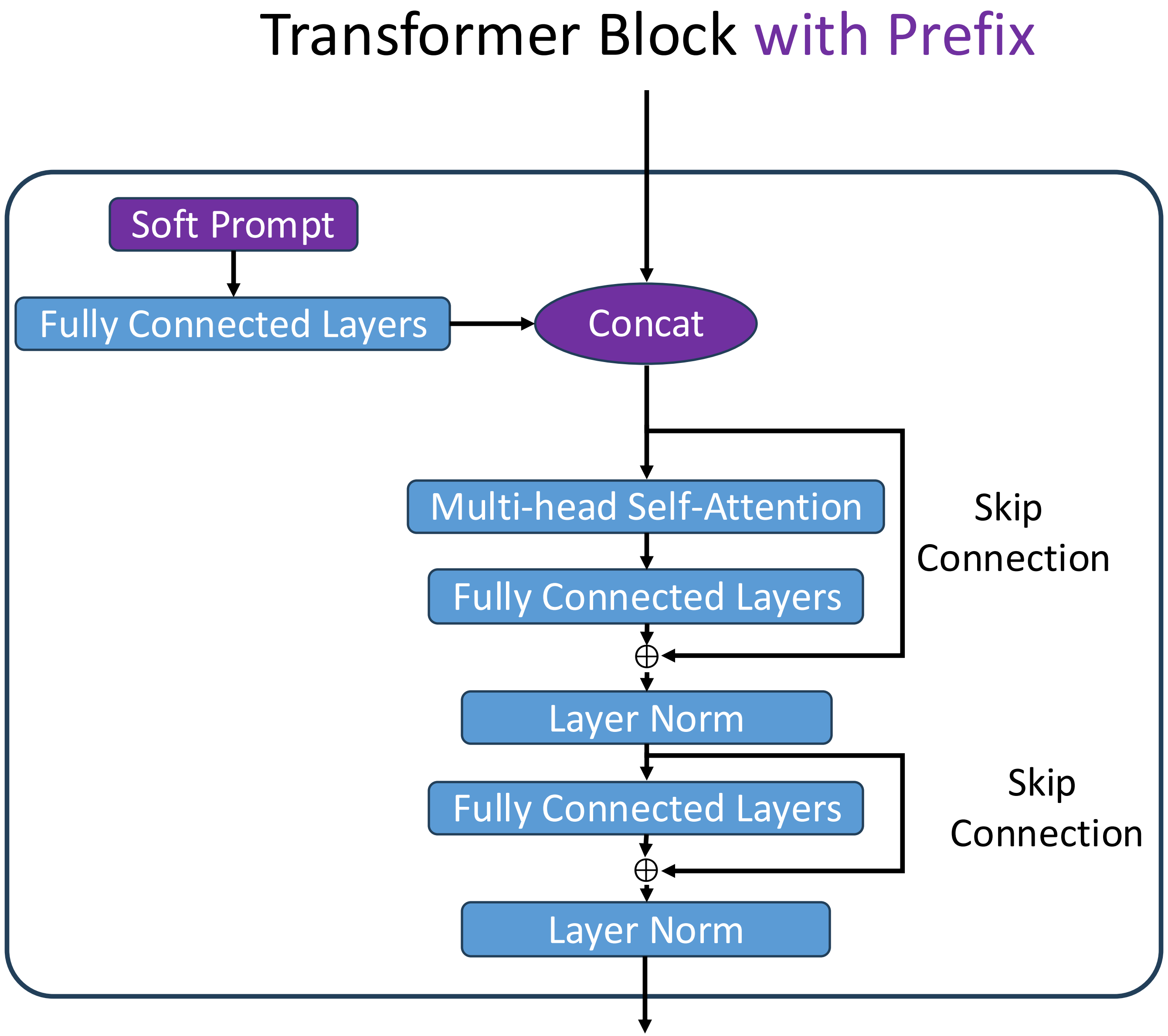


Image Credit: https://sebastianraschka.com/blog/2023/llm-finetuning-llama-adapter.html

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Adapter

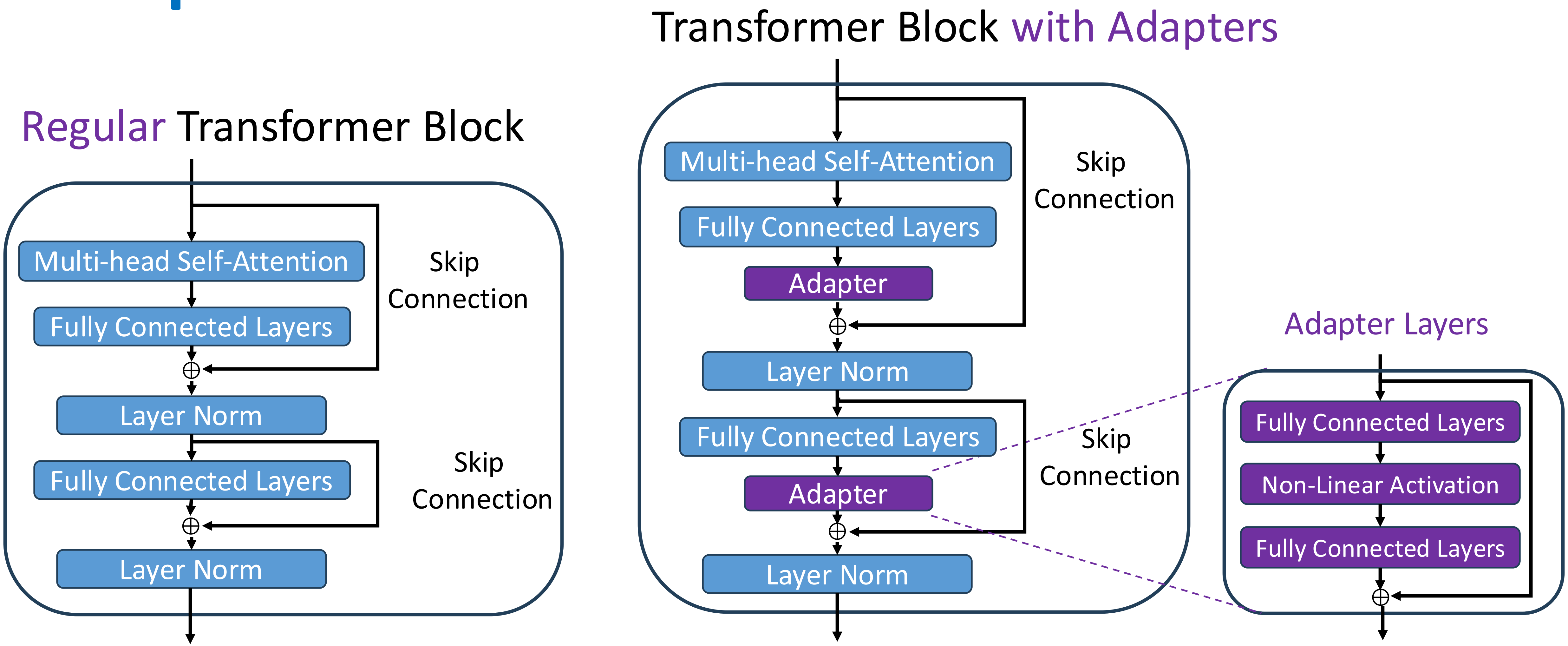

Image Credit: https://sebastianraschka.com/blog/2023/llm-finetuning-llama-adapter.html

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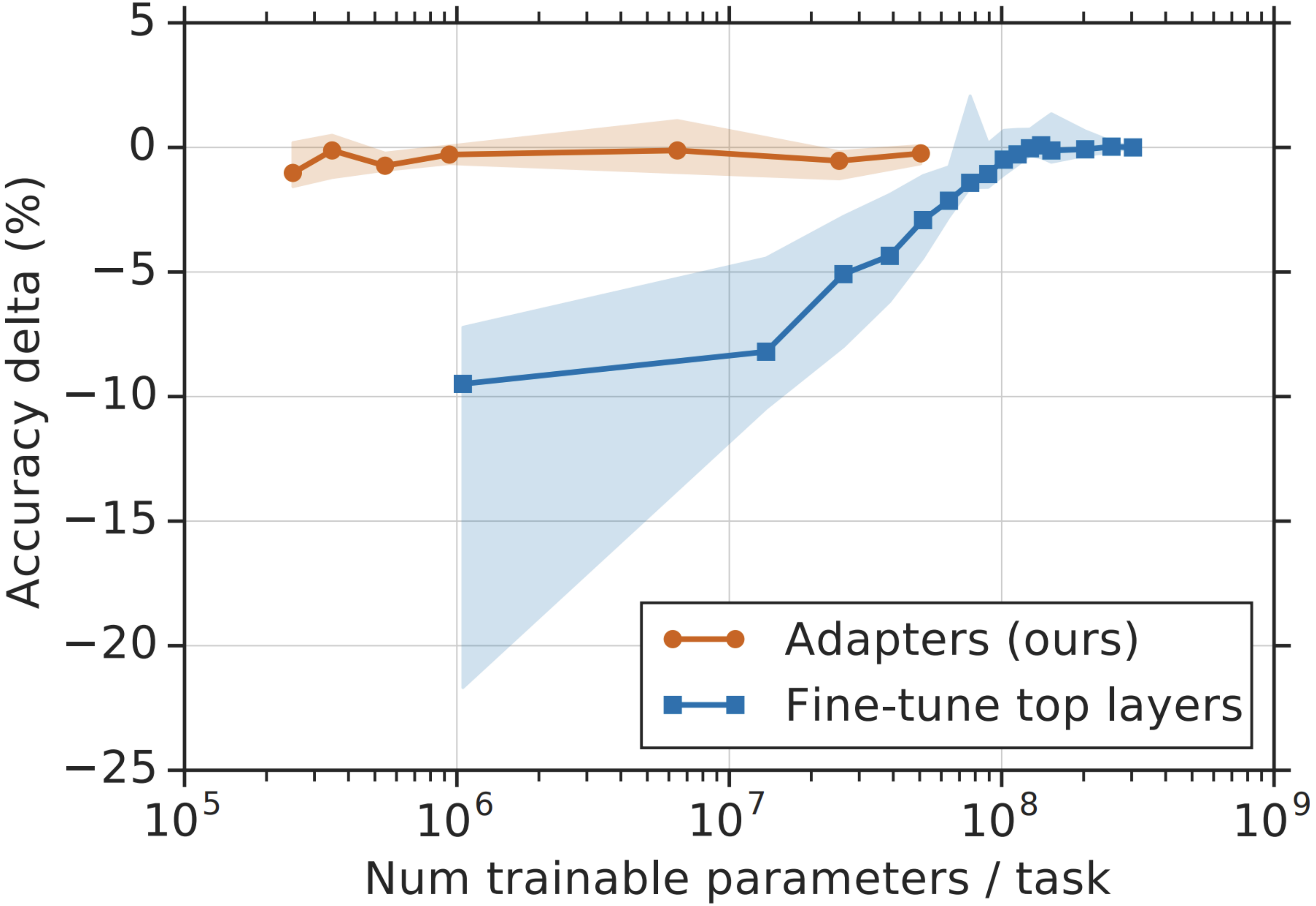
Adapter

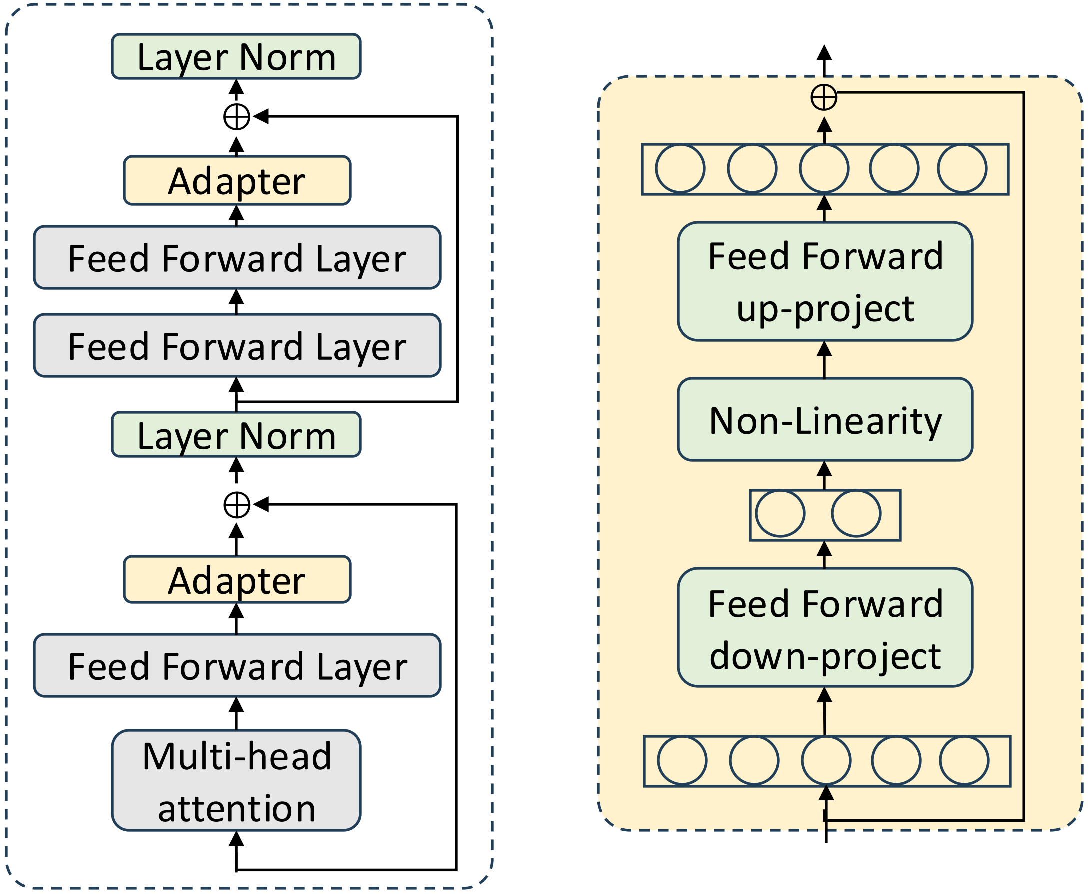


Houlsby et al., Parameter-Efficient Transfer Learning for NLP. 2019.

Adapter: Architecture

Bottleneck Structure

- Reduces the number of parameters
- Reduces d-dimensional features into a smaller m-dimensional vector
  - Example: $d = 1024$ and $m = 24$
  - 1024×1024 requires 1,048,576 parameters
  - $2 \times (1024 \times 24)$ requires 49,152 parameters



- m determines the number of optimizable parameters and hence poses a parameter vs performance tradeoff.

Houlsby et al., Parameter-Efficient Transfer Learning for NLP. 2019.

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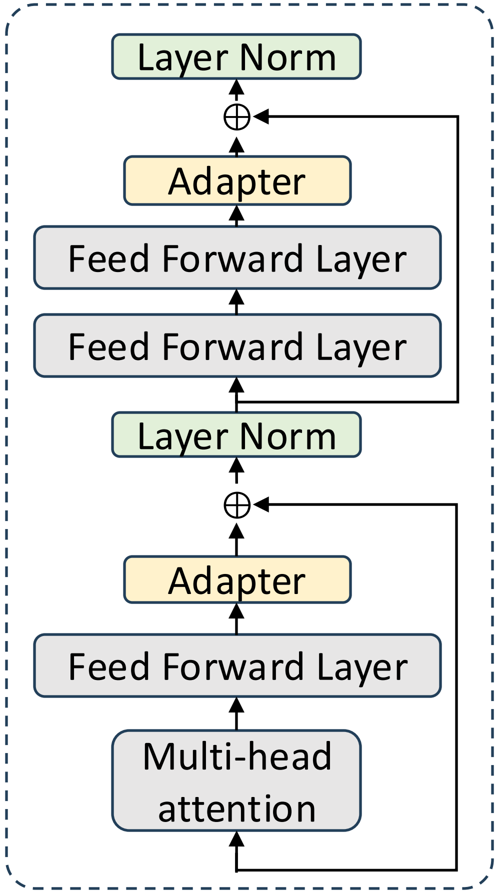
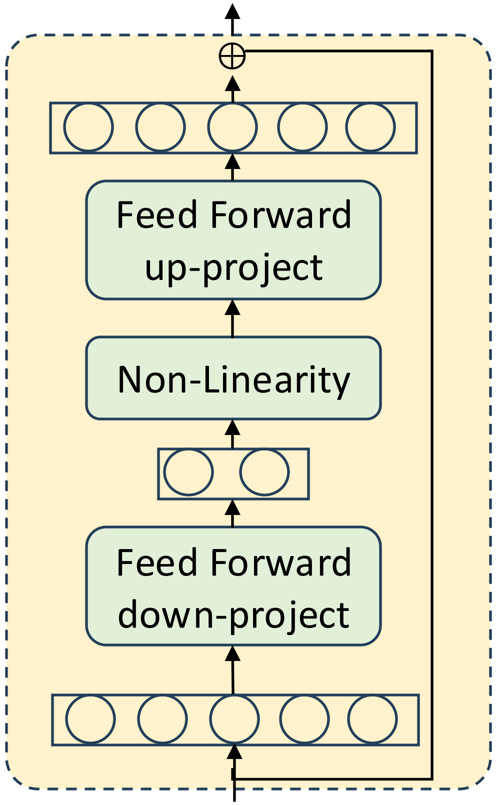
Adapter: Architecture

Inference Overhead

- Additional adapter in each transformer layer increases the inference latency

- Unlike Prompt tuning, same pre-trained model can't be used when fine-tuned with an adapter layer.





Houlsby et al., Parameter-Efficient Transfer Learning for NLP. 2019.

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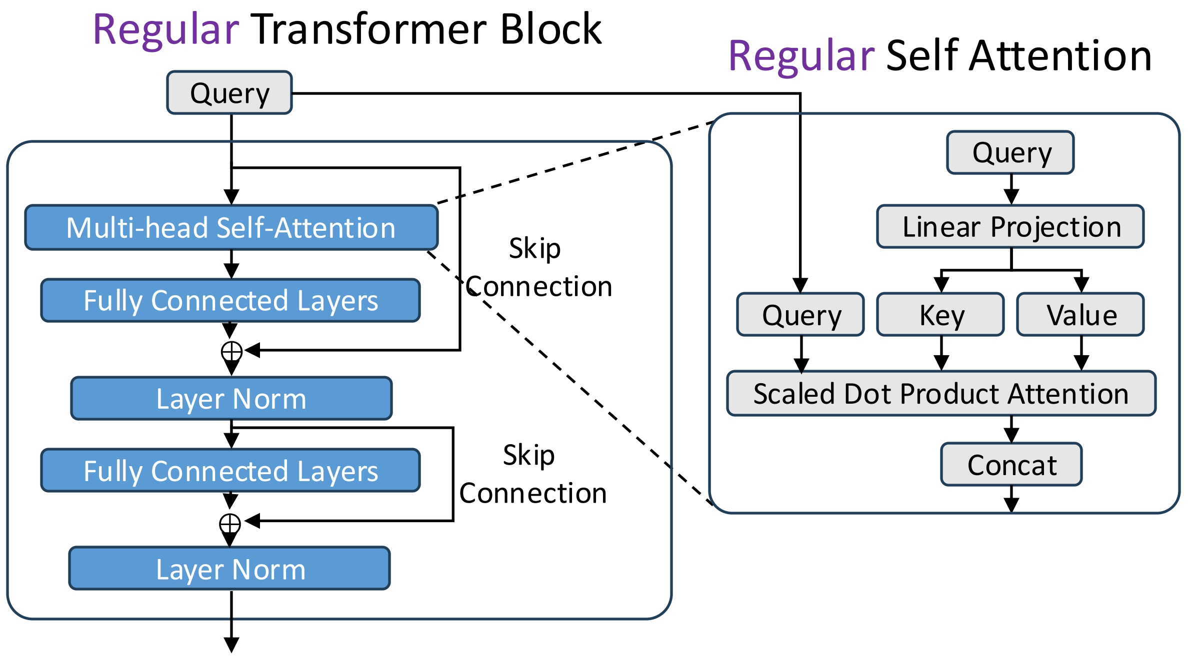
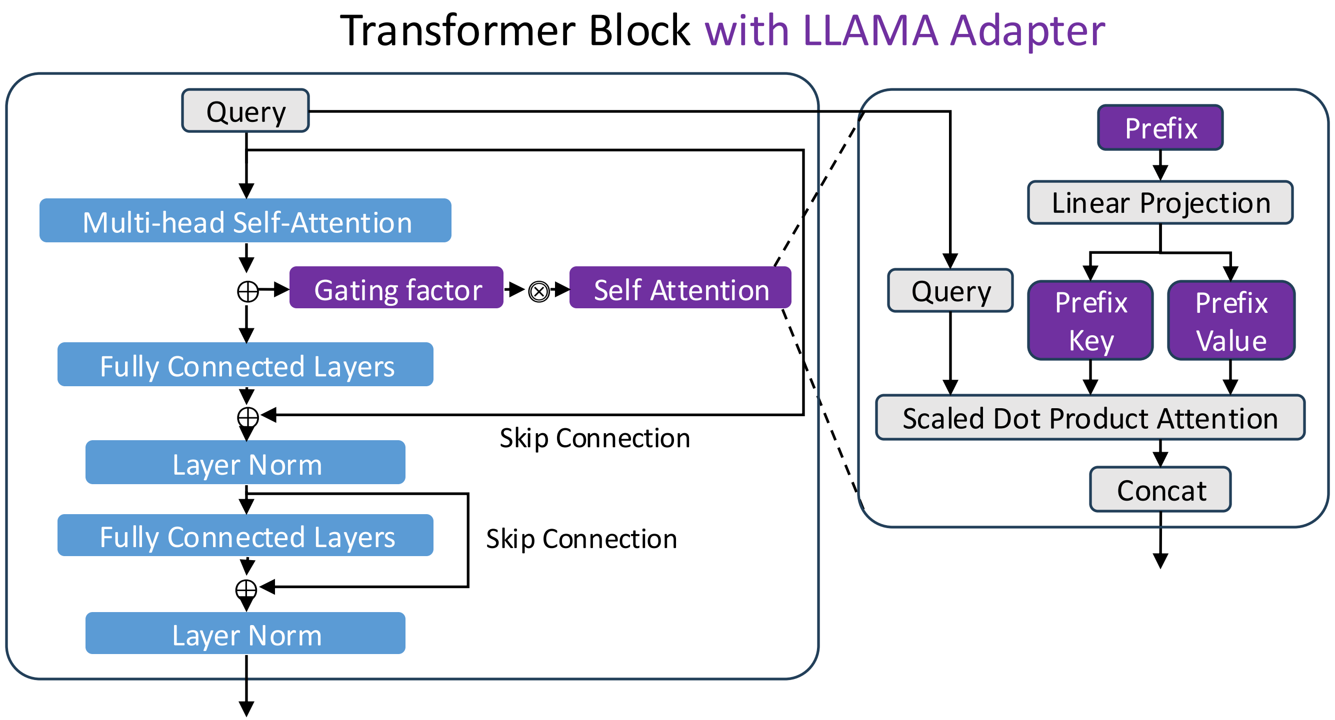
Example: Llama Adapter

- Prepends tunable prompt tensors to the embedded inputs.
- The prefix is learned and maintained within an embedding table rather than being provided externally.
- Each transformer block in the model has its own distinct learned prefix, allowing for more tailored adaptation across different model layers.





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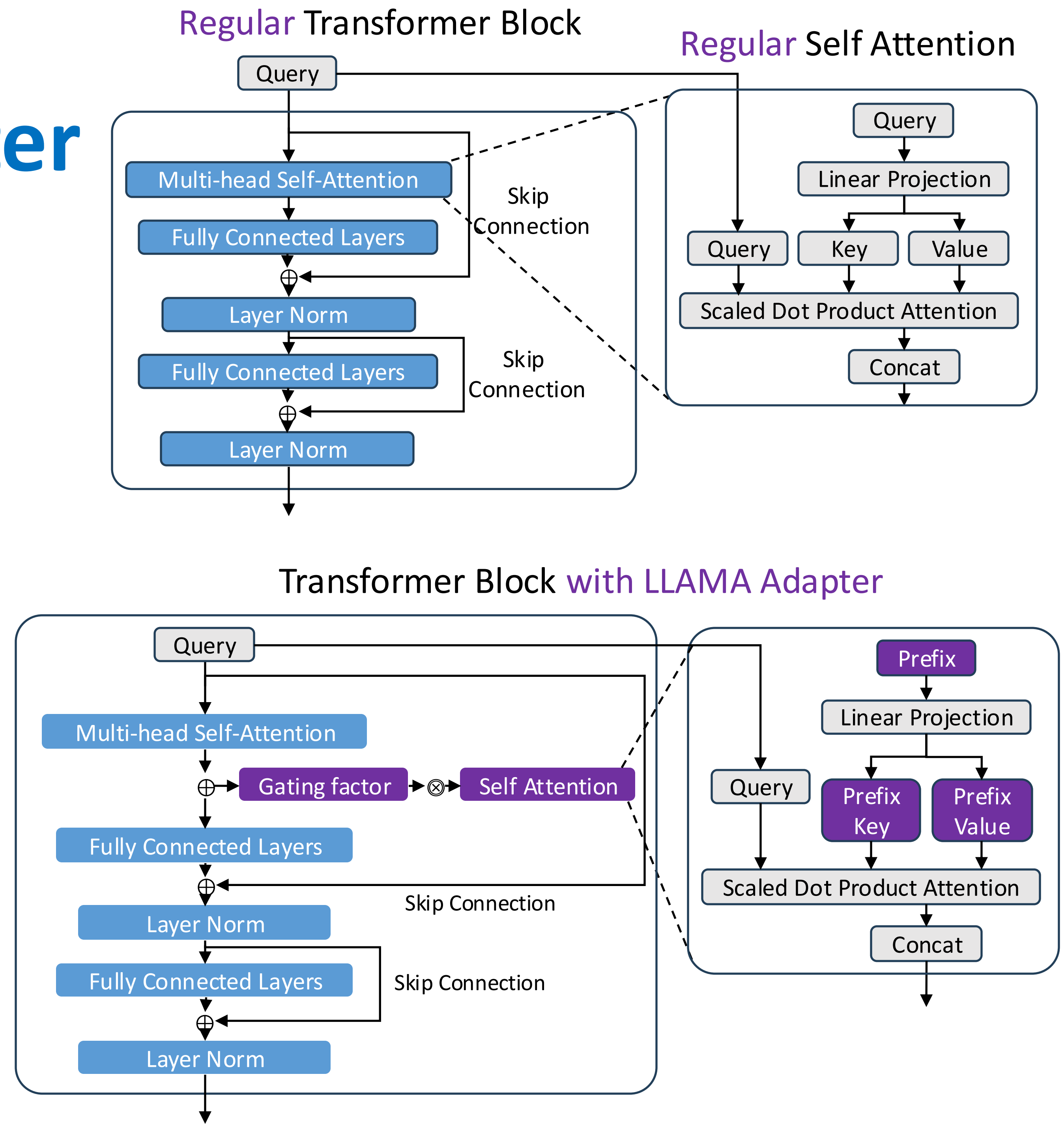
Example: Llama Adapter

- Introduces a zero-initialized attention mechanism coupled with gating.
- Prevents adapters and prefix tuning from potentially disrupting the linguistic knowledge of the pretrained LLM during initial training phases.
- Adds the learnable adaption prompts only to the L topmost transformer layers instead of all transformer layers.



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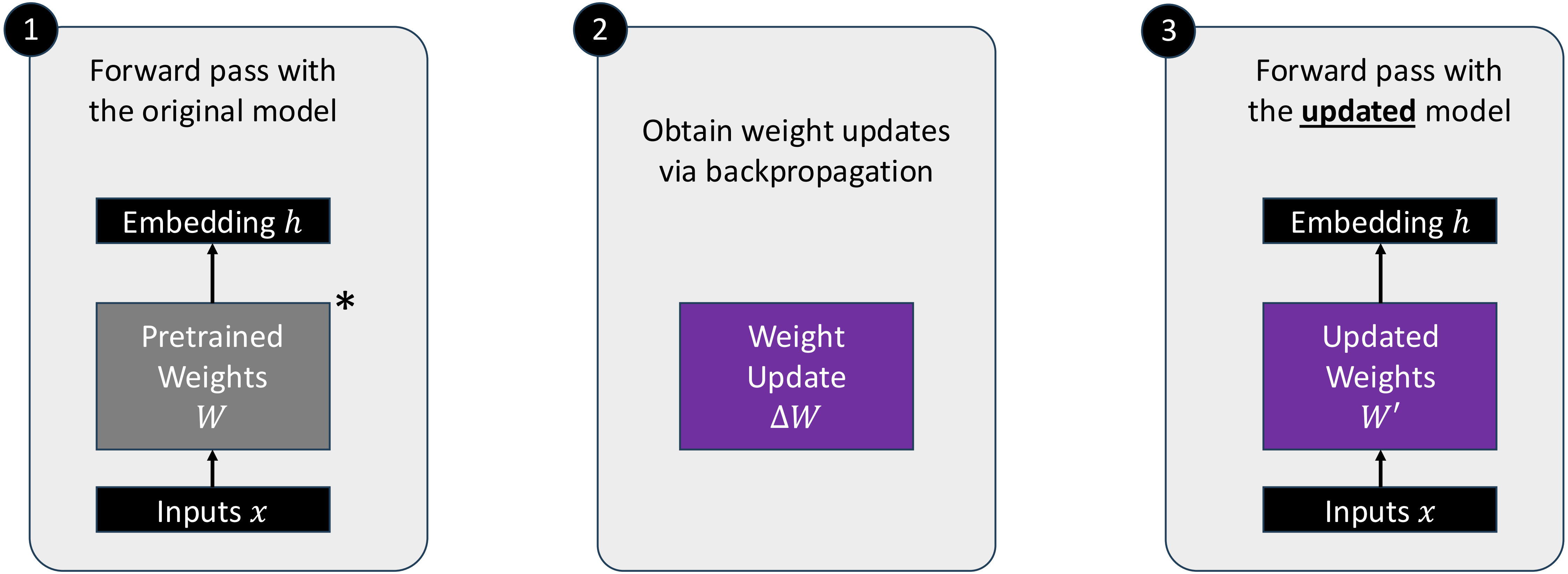
Regular Finetuning



* The pretrained model could be any LLM, e.g. an encoder-style LLM (Like BERT) or a generative decoder-style LLM (like GPT)

https://sebastianraschka.com/blog/2023/llm-finetuning-lora.html

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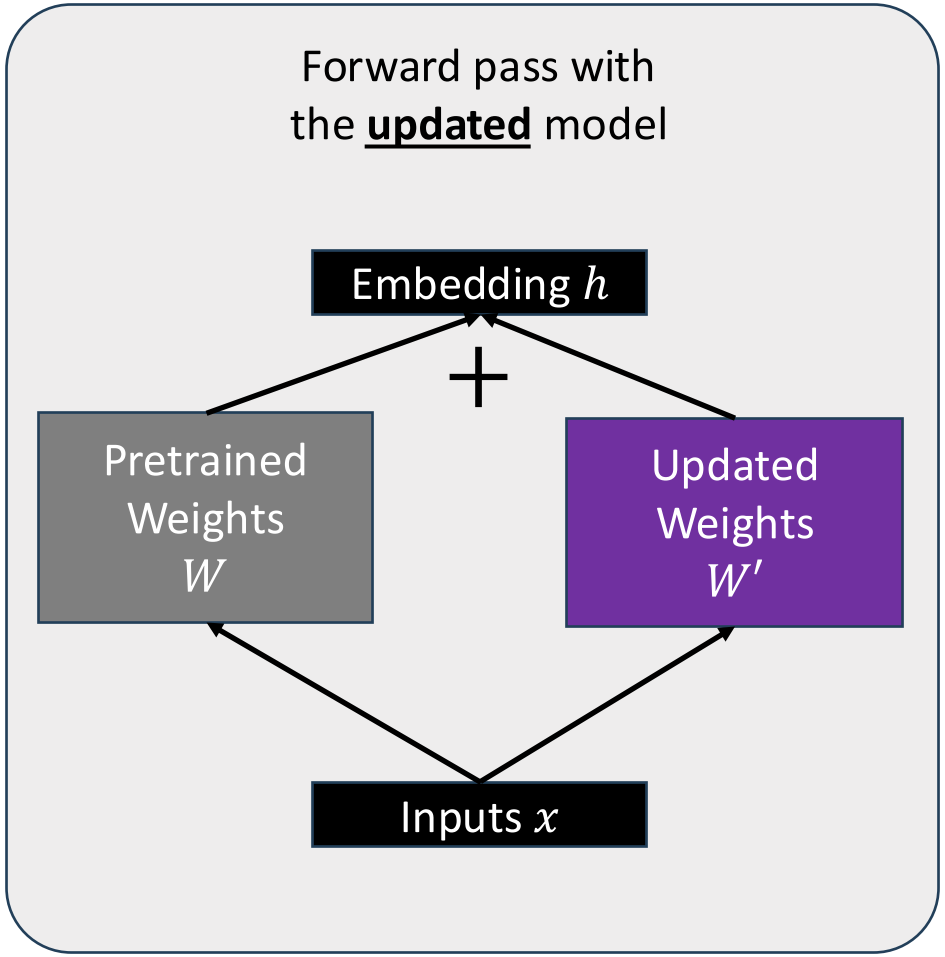
Regular Finetuning: Alternate Visualization



https://sebastianraschka.com/blog/2023/llm-finetuning-lora.html

Intrinsic Dimension

- While the weights of a pretrained model have full rank on the pretrained tasks, pretrained large language models have a low "intrinsic dimension" when they are adapted to a new task.

- By optimizing only 200 trainable parameters randomly projected back into the full space, one can tune a RoBERTa model to achieve 90% of the full parameter performance.

- **Intrinsic dimension of a task**: Minimum dimension/number-of-parameters where a model achieves within 90% of the full-parameter model performance

Aghajanyan et al., Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning. 2020.

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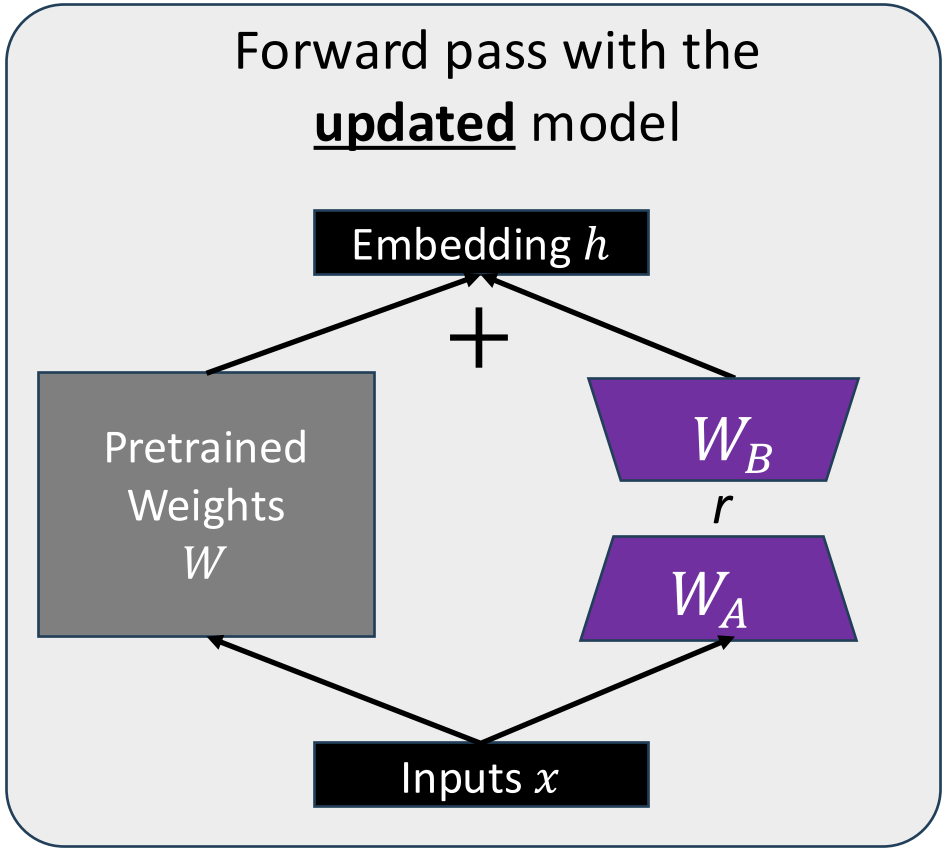
Low Rank Adaptation (LoRA)

LoRA weights W_A and W_B represent ΔW



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

Learns two low-rank matrices A and B that are applied to the self-attention weights

Rank r is a hyperparameter that is used to specify the rank of the low-rank matrices used for adaptation

https://sebastianraschka.com/blog/2023/llm-finetuning-lora.html

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LoRA: Choosing Rank

Smaller Rank r

- Simpler low-rank matrix, and fewer parameters to learn during adaptation.
- Faster training and reduced computational requirements.
- Decreased capacity of the low-rank matrix to capture task-specific information. Lower adaptation quality. Inferior performance

- Rank in LoRA represents trade-off between model complexity, adaptation capacity, and the risk of underfitting or overfitting.
- Important to experiment with different rank values to find the right balance to achieve the desired performance on the new task.

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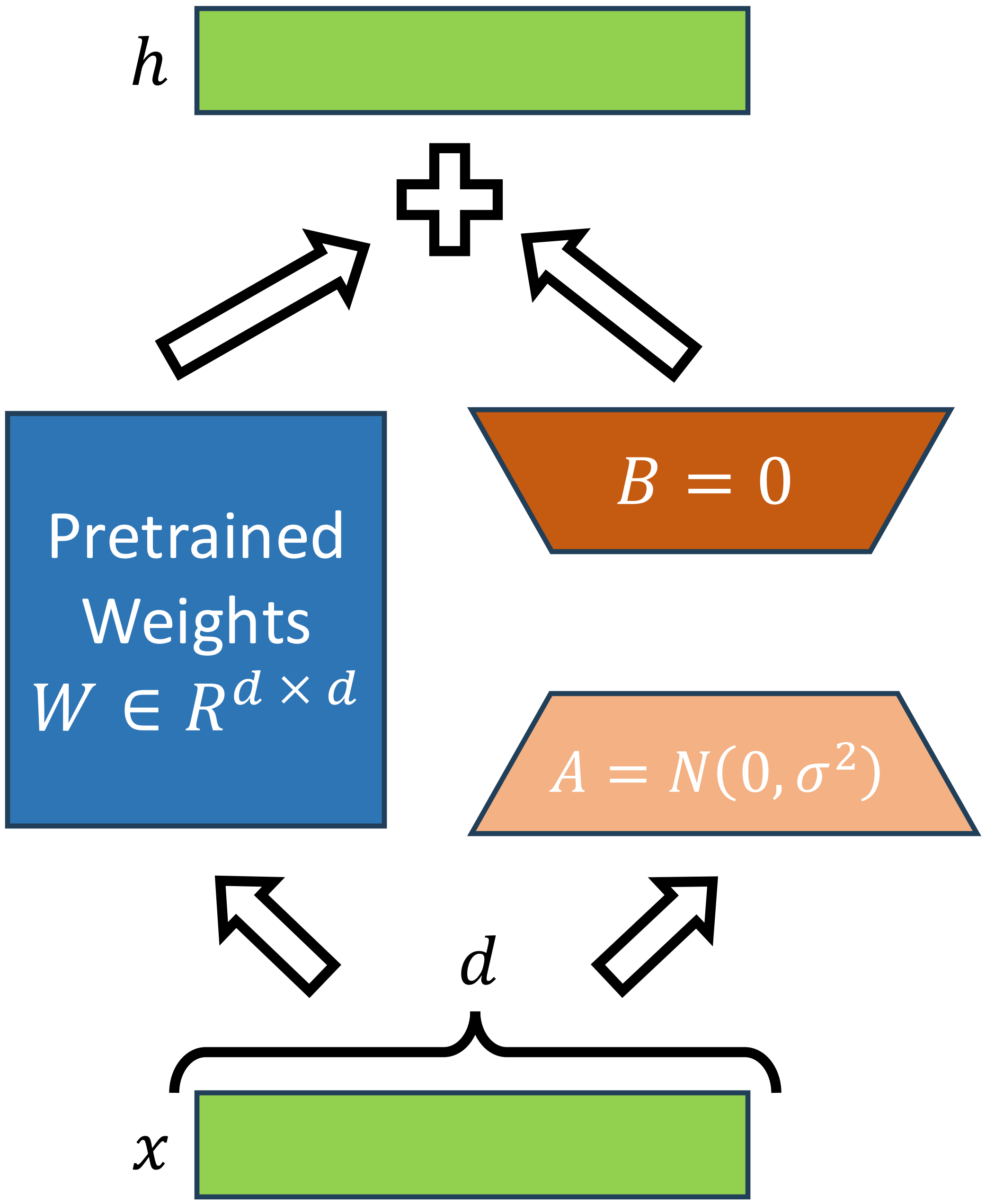
LoRA Weight Initialization

- By setting B to zero, the product $\Delta W = BA$ initially equals zero. This preserves the behavior of the original model at the start of fine-tuning

- Gaussian distribution helps ensure that the values in A are neither too large nor too biased in any direction, which could lead to disproportionate influence on the updates when B begins to change.



LoRA Variants

QLoRA [Dettmers et al., 2023]

- Backpropagates gradients through 4-bit quantized model for reducing memory usage.

LoRA+ [Hayou et al., 2024]

- Different learning rates for the LoRA adapter matrices A and B. Improves finetuning speed.

DyLoRA [Valipou et al., 2023]

- Selects rank without requiring multiple runs of training.

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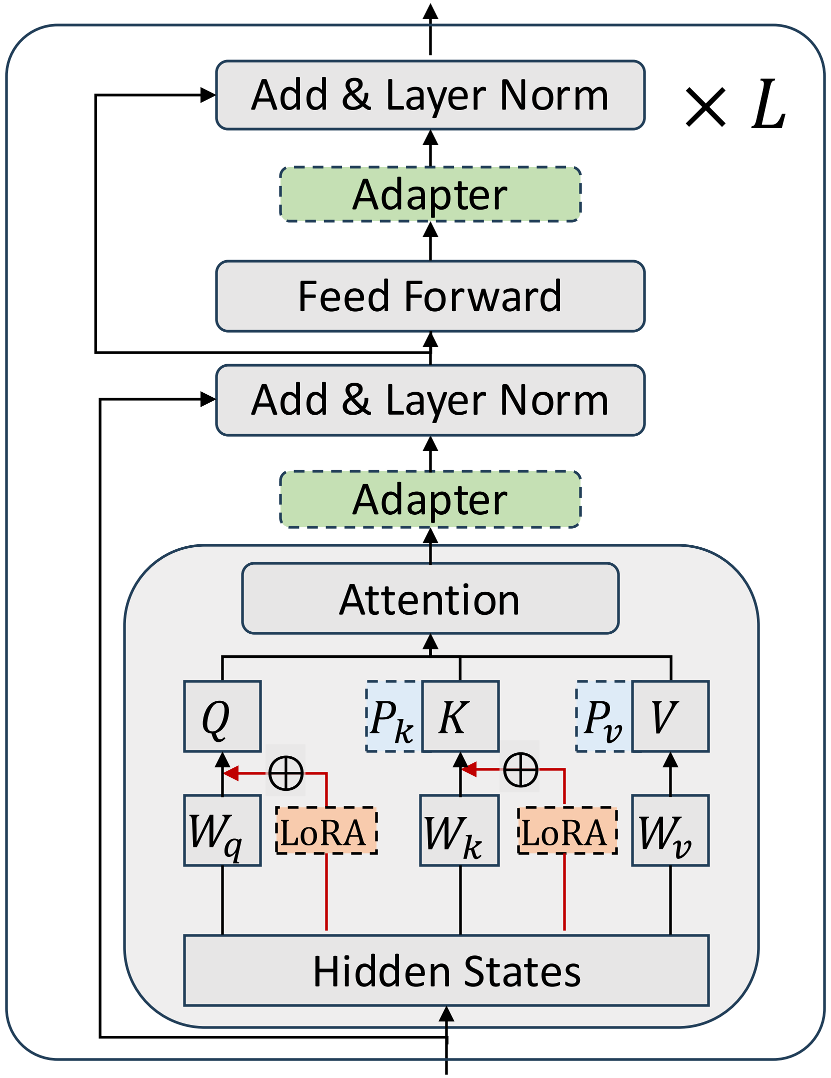
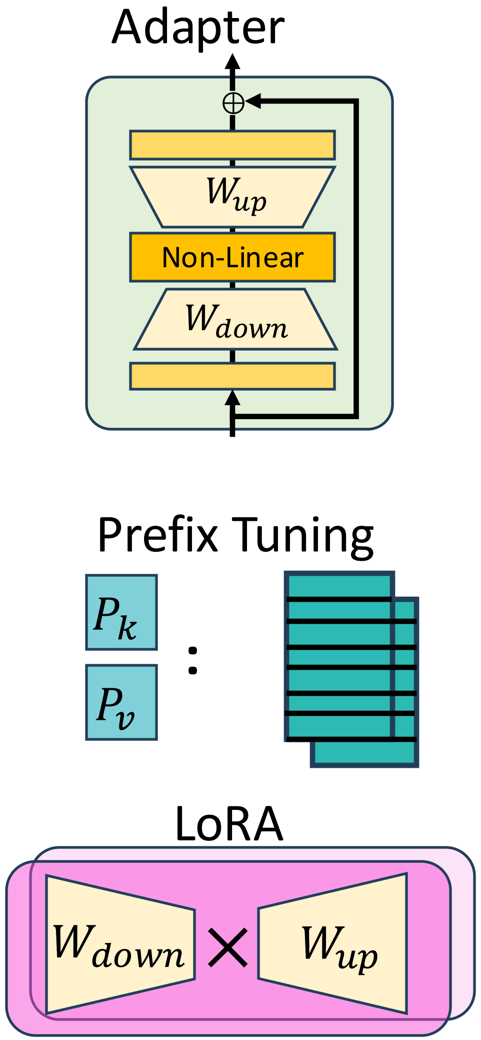
Parameter Efficient Tuning: Summary





He et al. Towards a Unified View of Parameter-Efficient Transfer Learning. ICLR 2022

Computer Vision Applications

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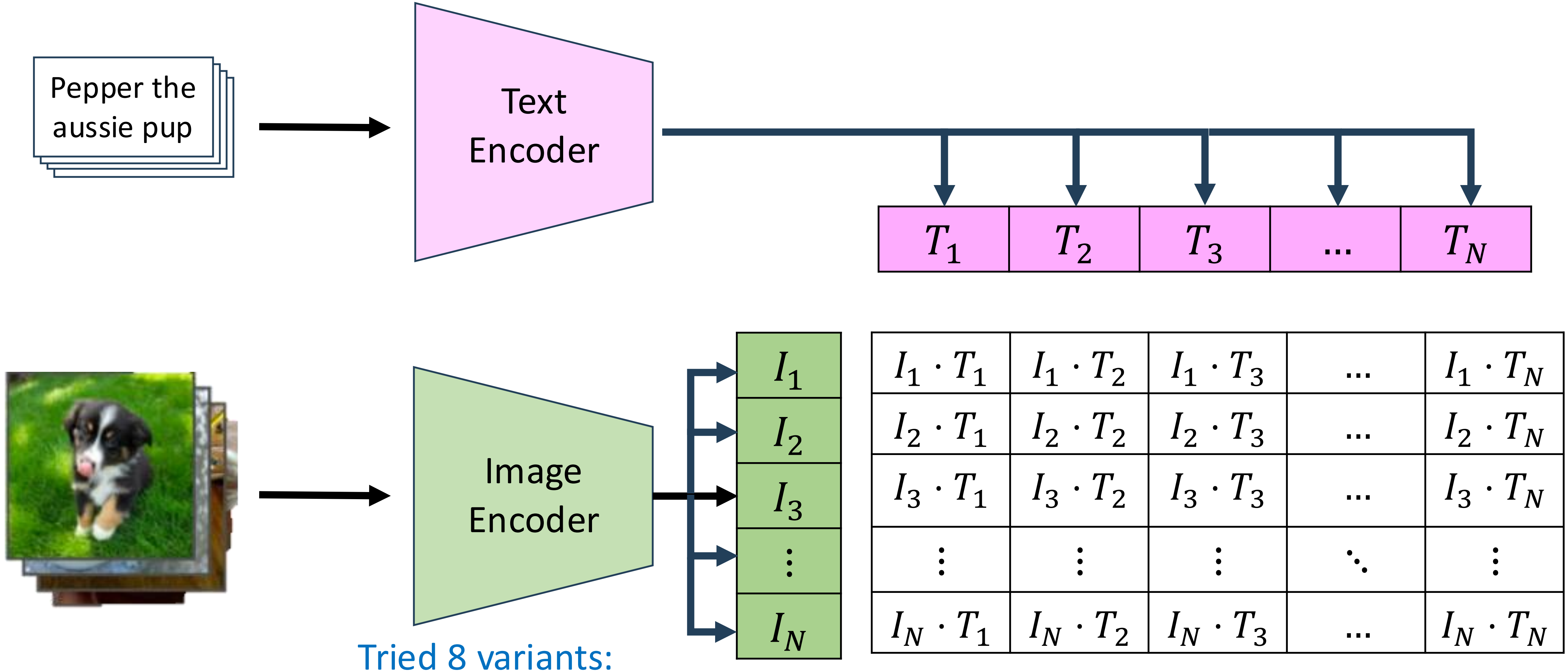
Contrastive Language Image Pre-training (CLIP)

Text Transformer (GPT-2)



Tried 8 variants:
3 VIT and 5 ResNet

Radford et al. Learning Transferable Visual Models From Natural Language Supervision. ICML 2021.

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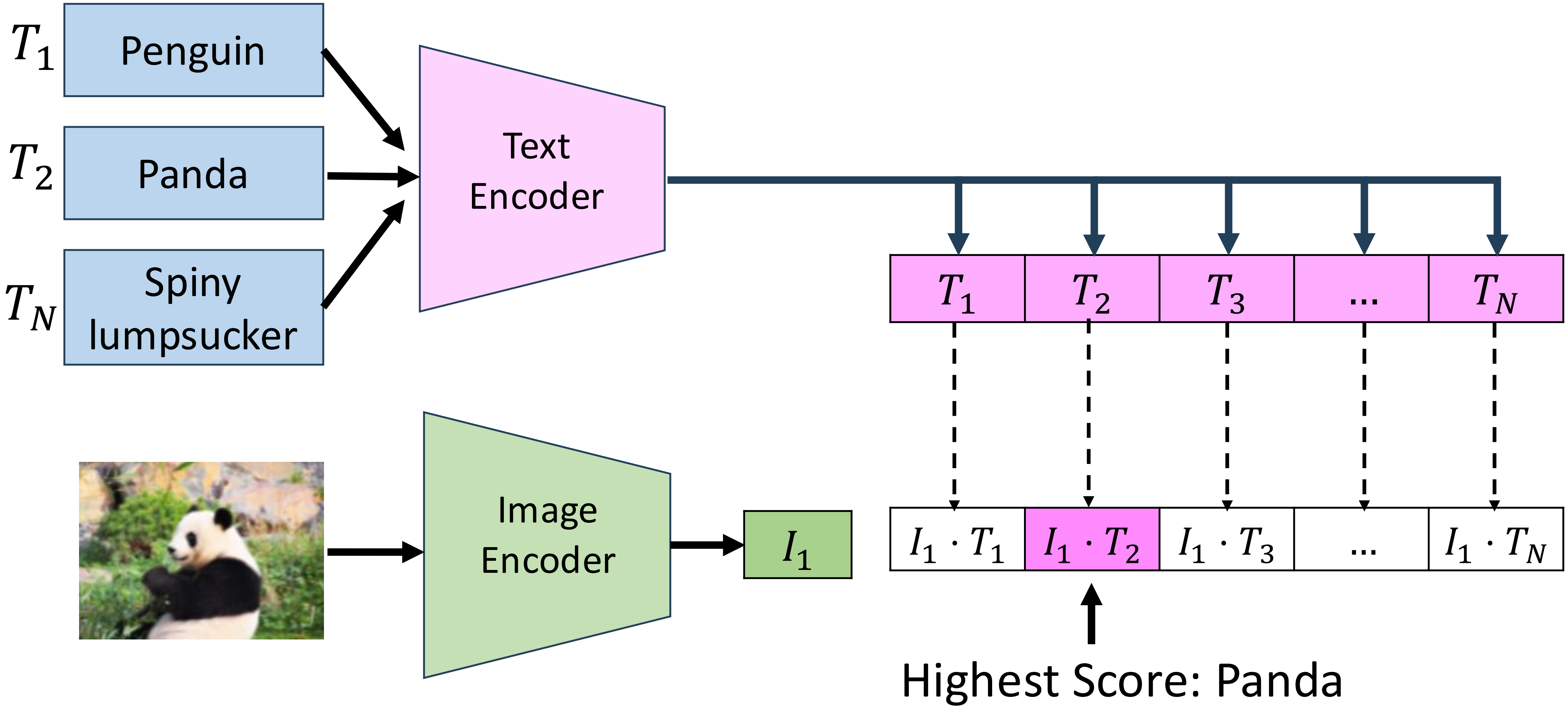
CLIP Inference



https://towardsdatascience.com/understanding-zero-shot-learning-making-ml-more-human-4653ac35ccab

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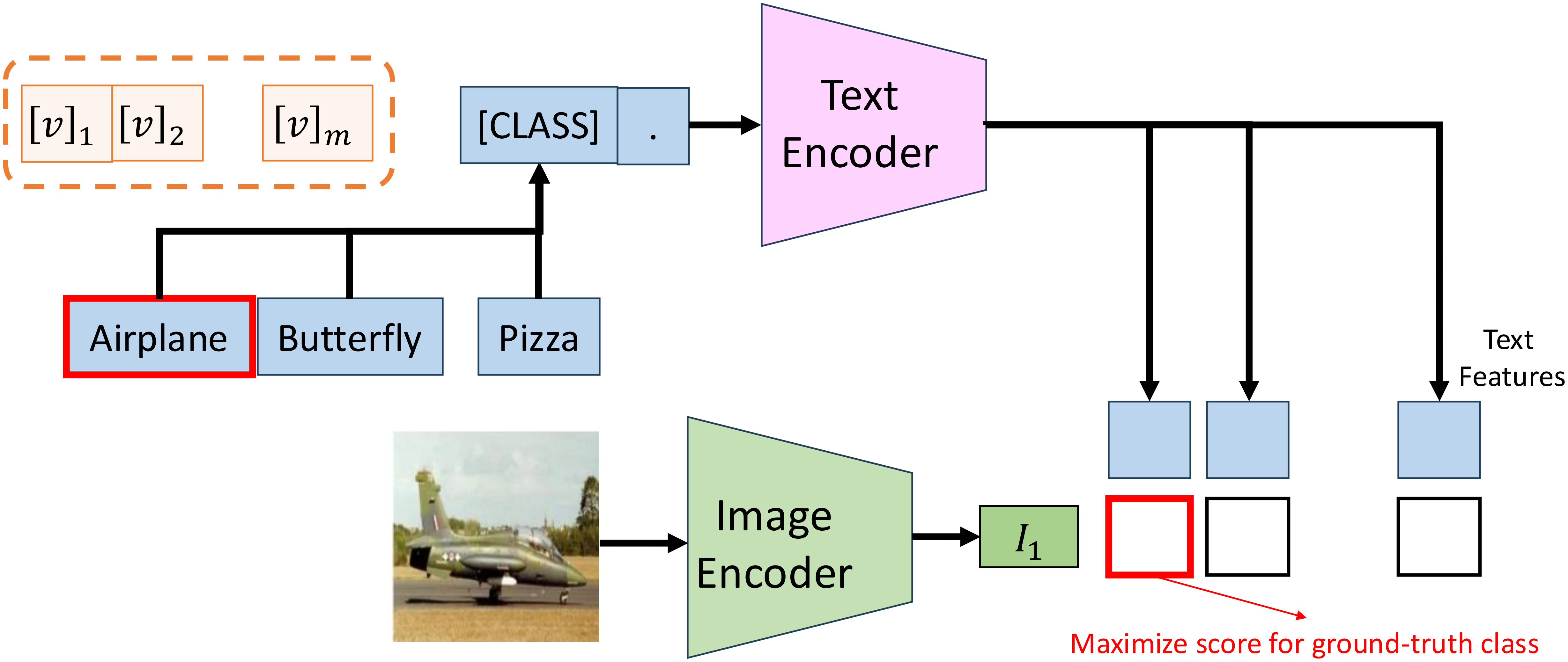
Context Optimization (CoOp)



Zhou et al., Learning to Prompt for Vision-Language Models. 2021.

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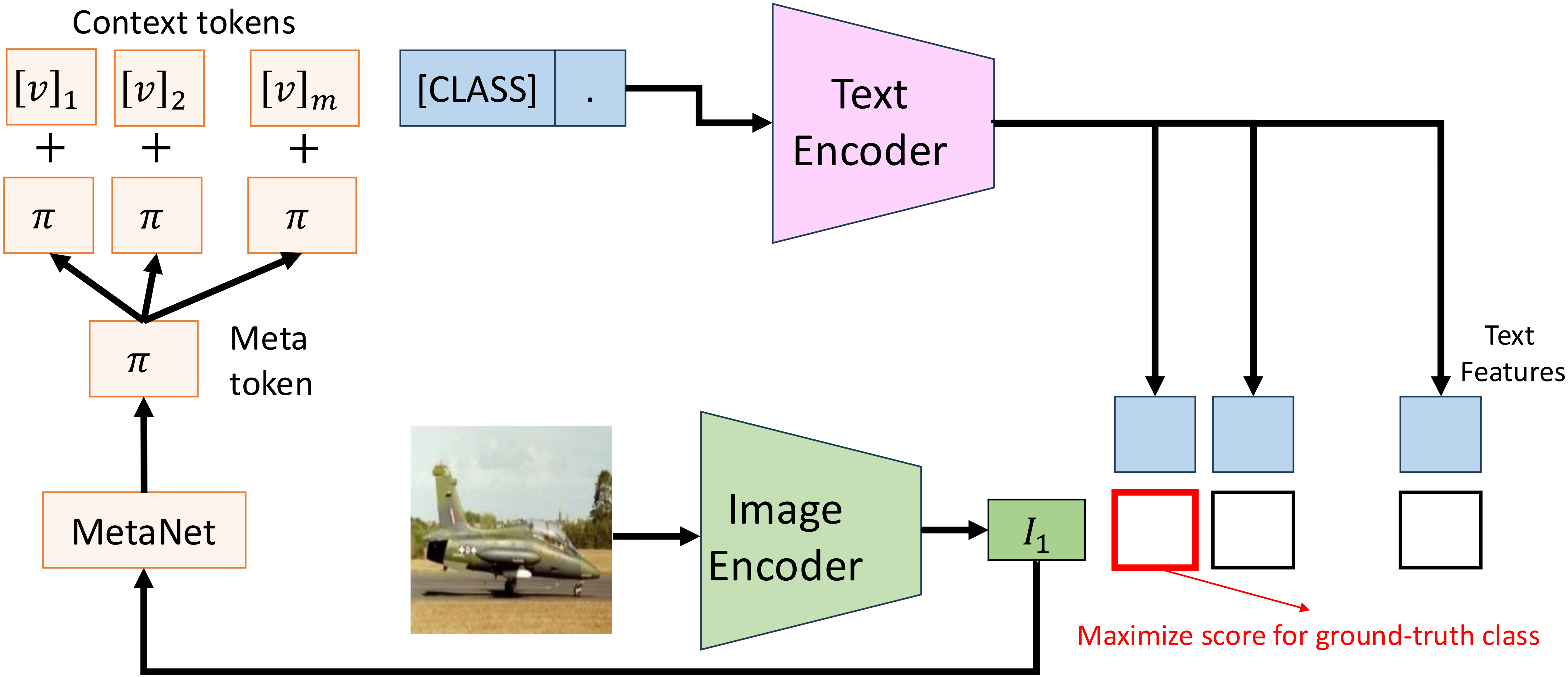
Conditional Context Opt. (CoCoOp)



Zhou et al., Conditional Prompt Learning for Vision-Language Models. CVPR 2022

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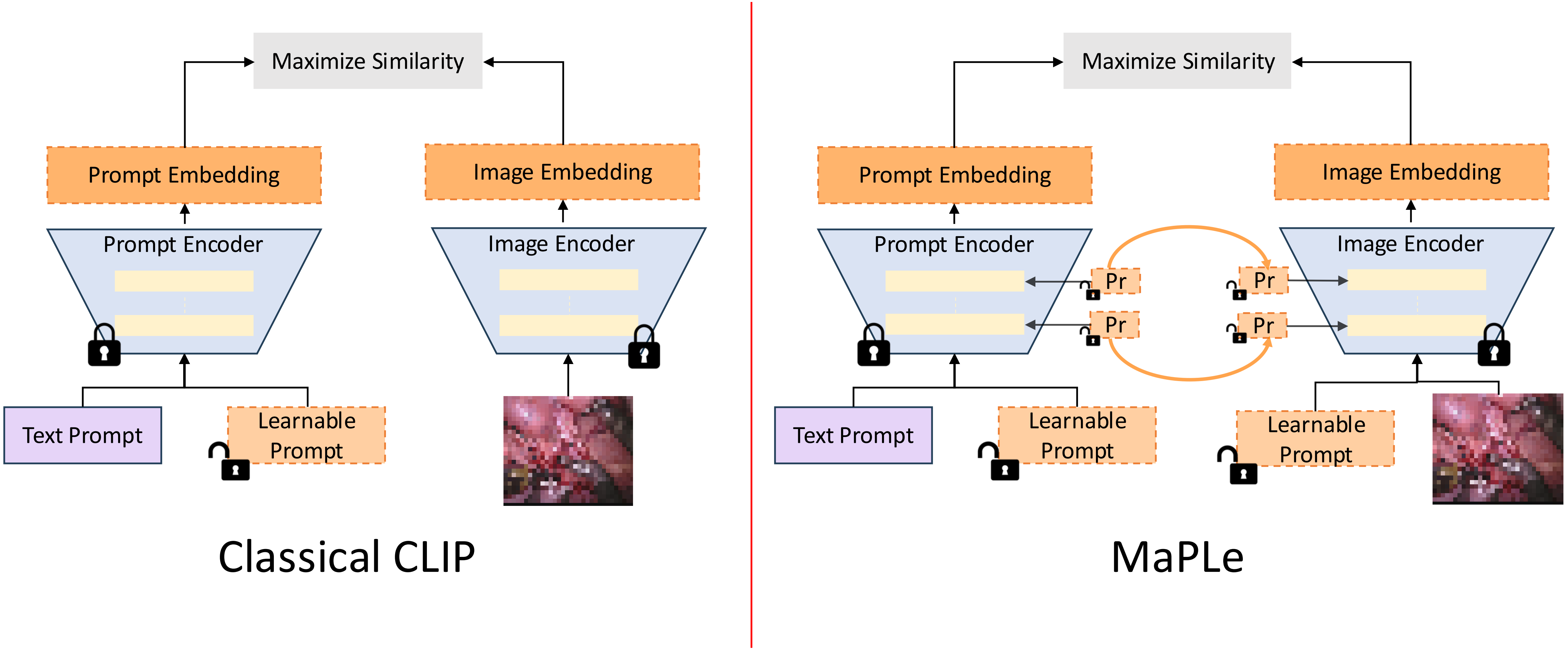
Multi-modal Prompt Learning (MaPLe)



Khattak et al., Multi-modal Prompt Learning (MaPLe). CVPR 2023.

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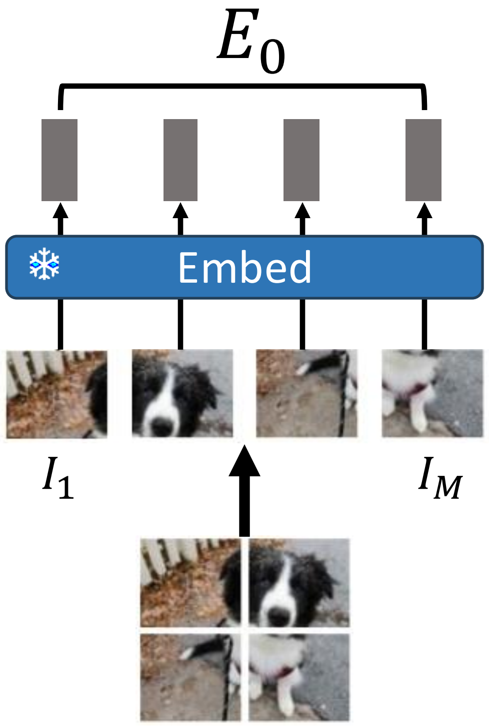
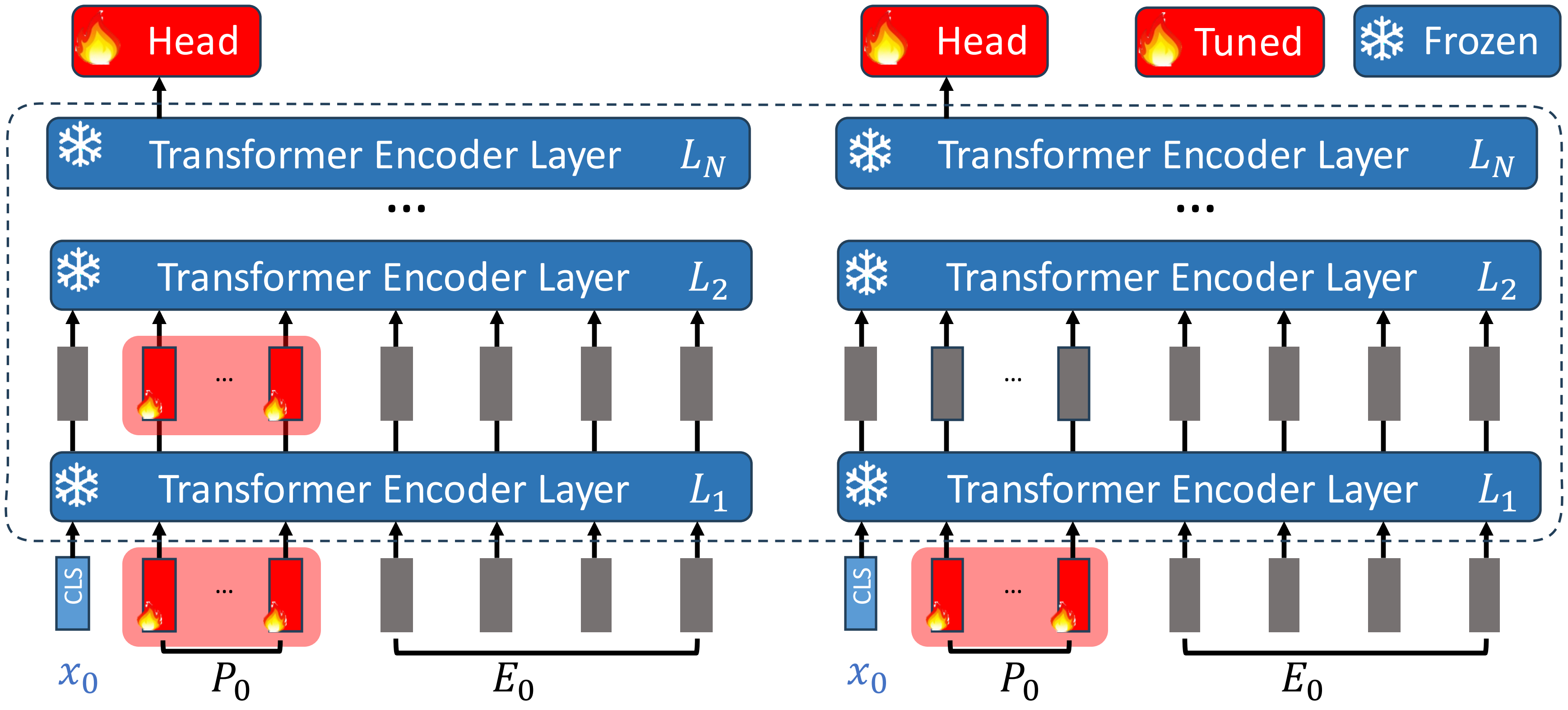
Visual Prompt Tuning

- Learned prompts adapt frozen model (e.g., no fine-tuning required) to different target tasks.





Visual-Prompt Tuning: Deep

Visual-Prompt Tuning: Shallow

Jia et al. Visual Prompt Tuning. ECCV 2022