LLM Foundations

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Overview

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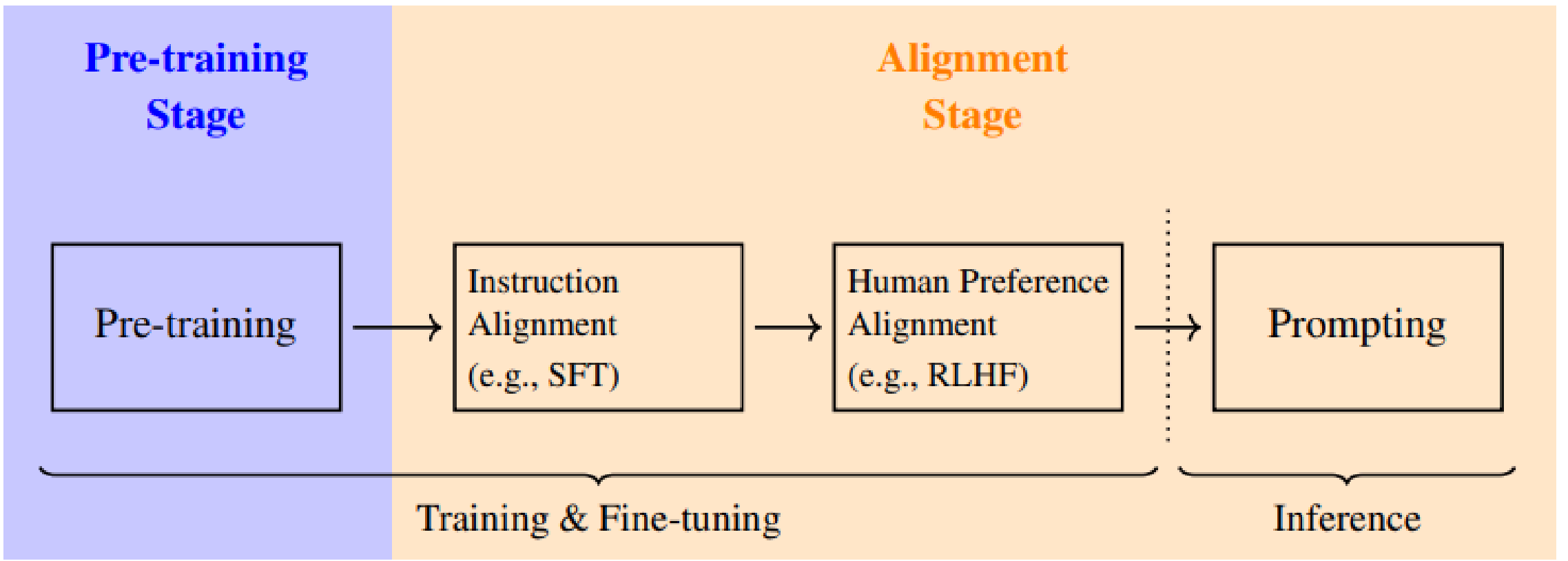

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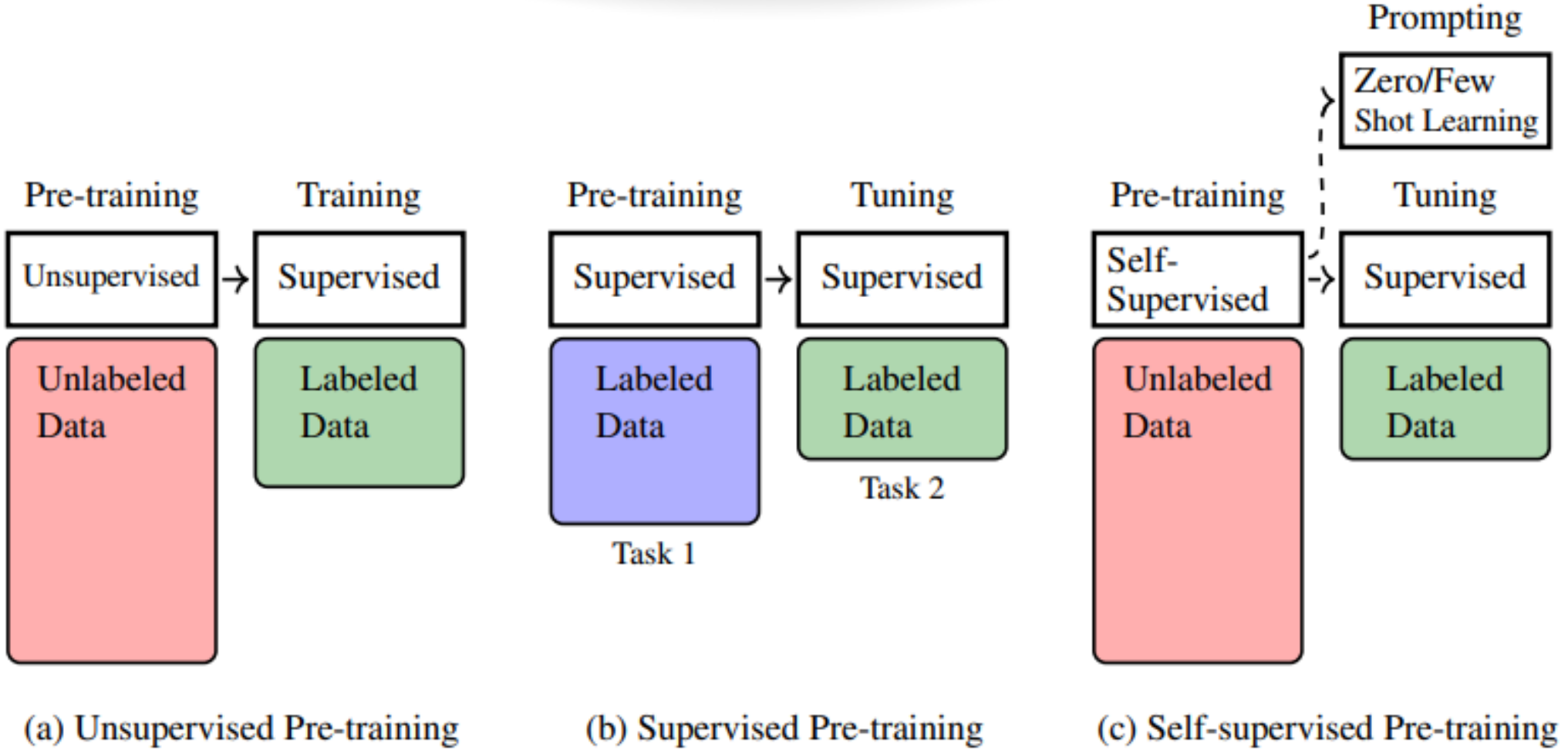
Pre-training types



(a) Unsupervised Pre-training (b) Supervised Pre-training (c) Self-supervised Pre-training

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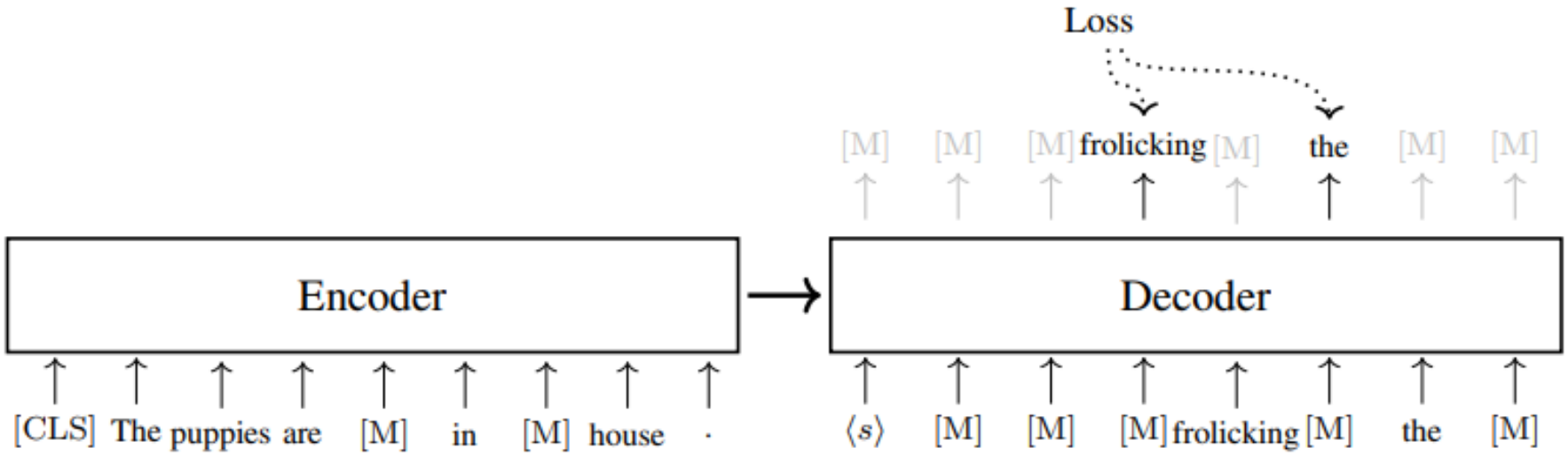
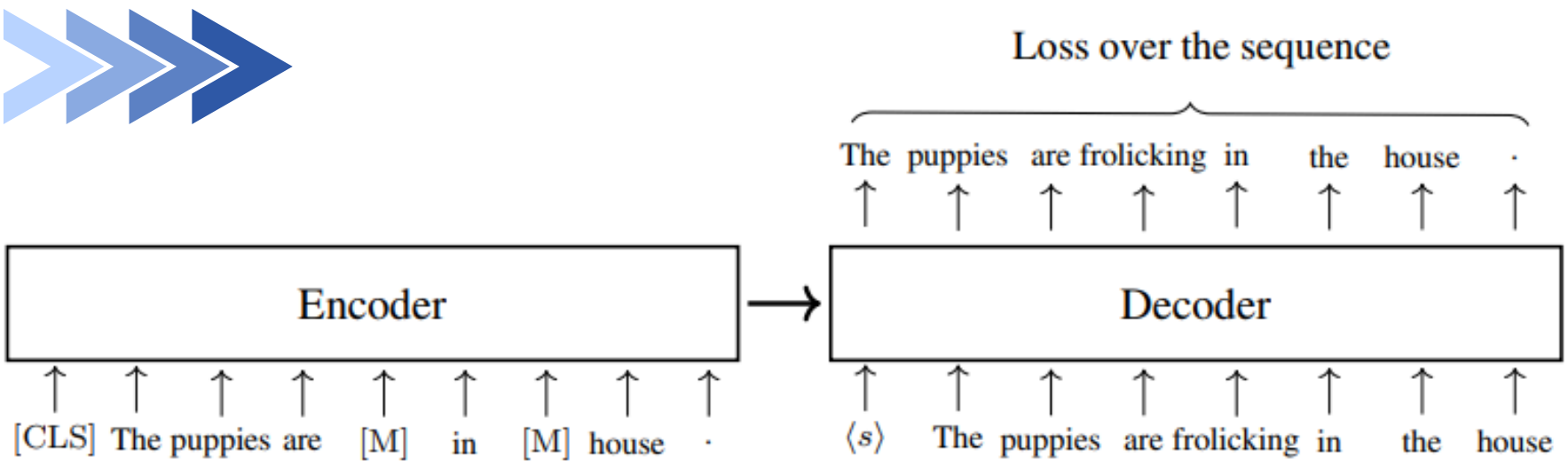
Encoders &Decoders



(a) Training an encoder-decoder model with BERT-style masked language modeling



(b) Training an encoder-decoder model with denoising autoencoding

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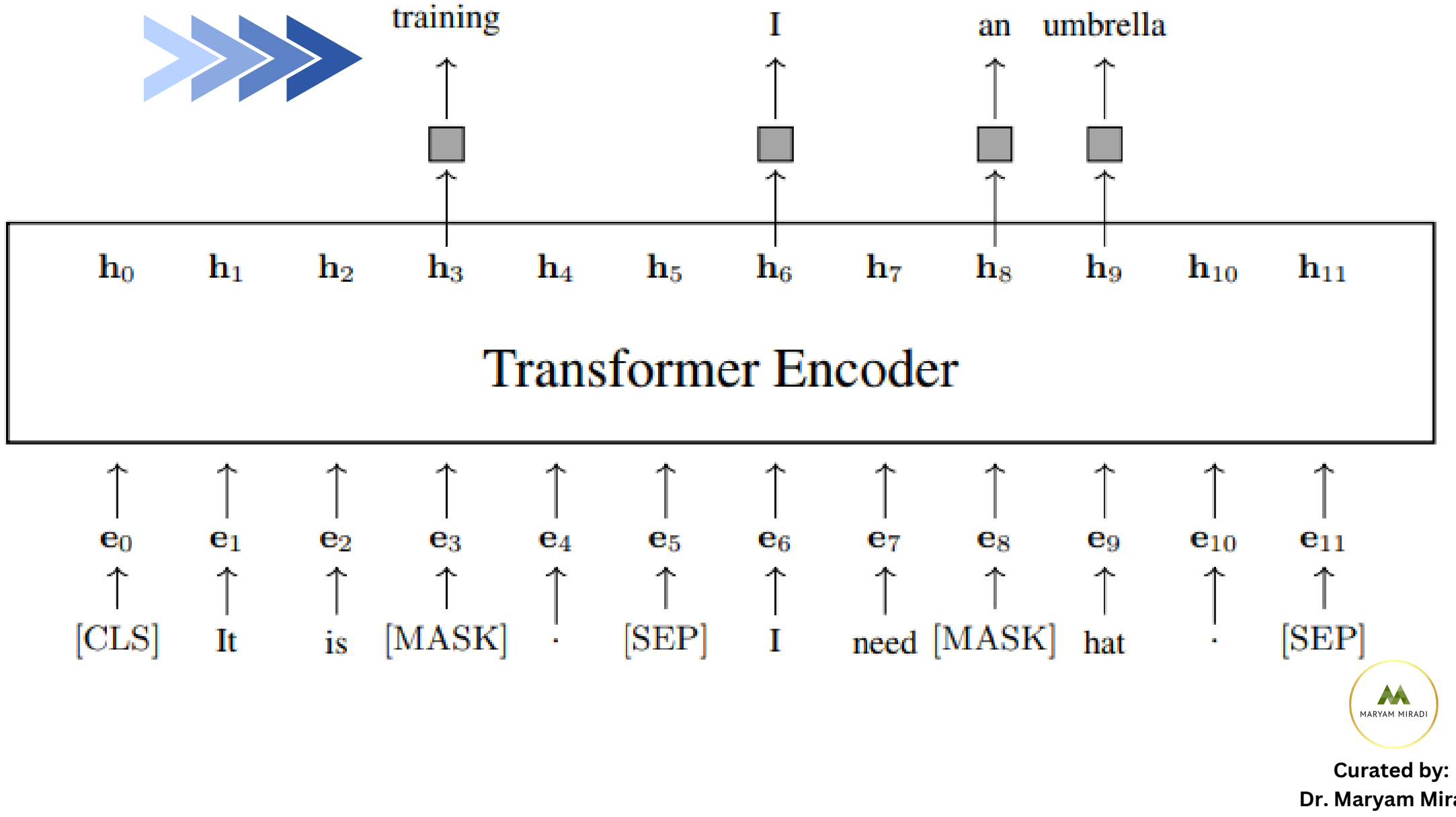
Transformers

Pre-training



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BERT

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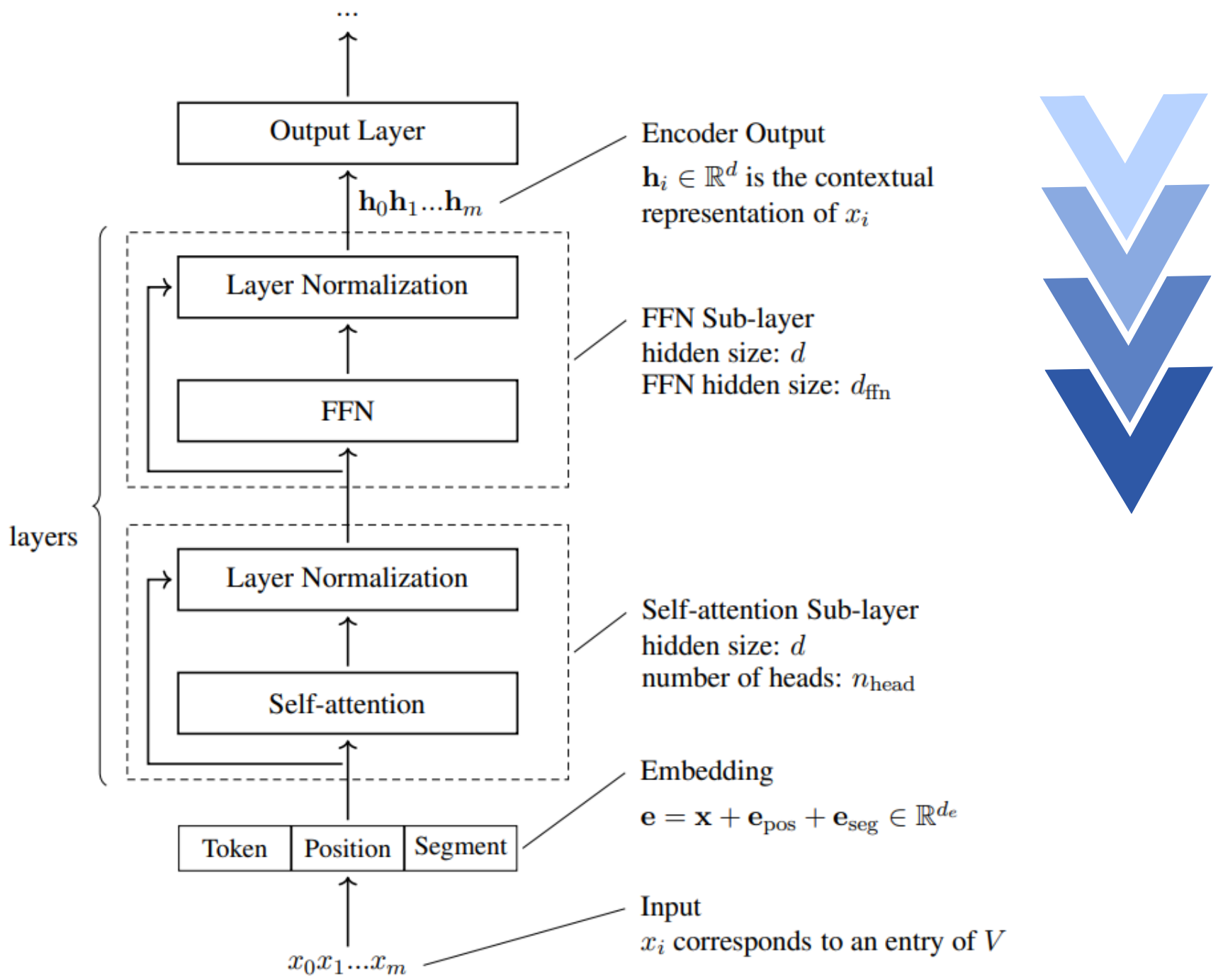

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Transformer-decoder architecture

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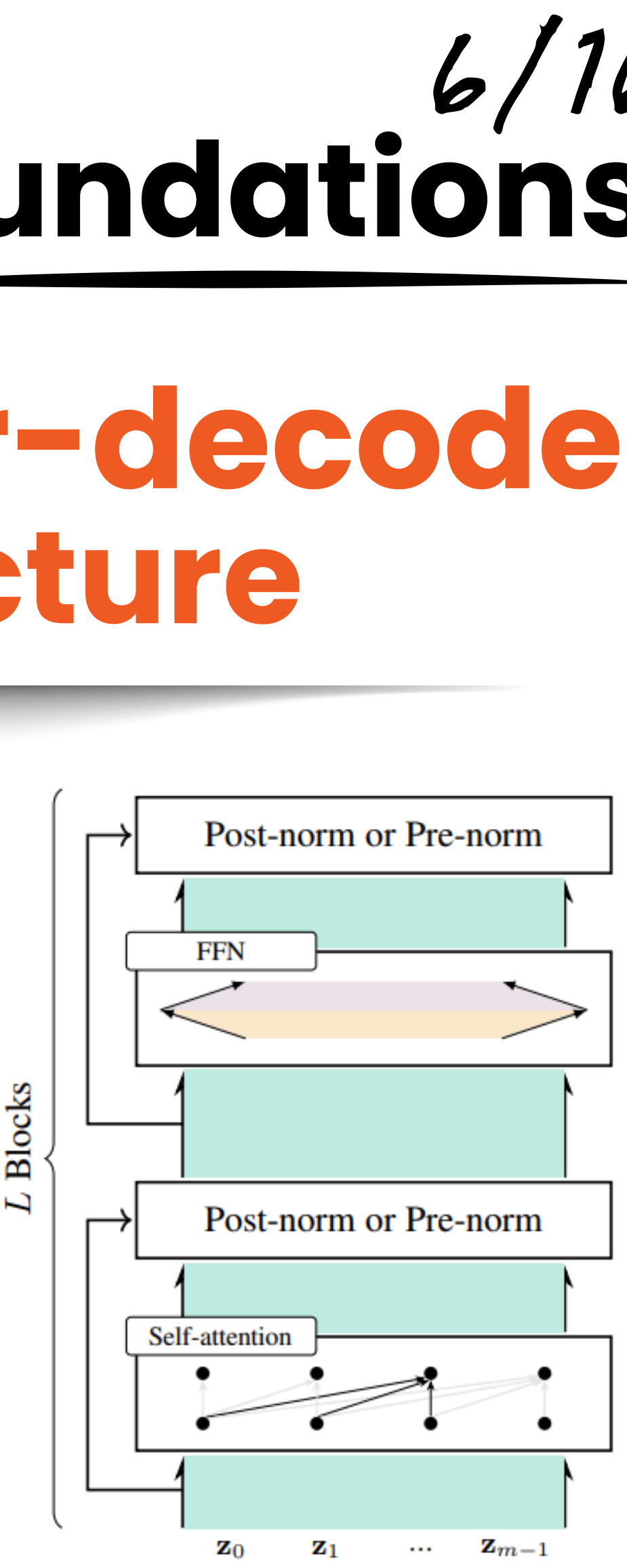

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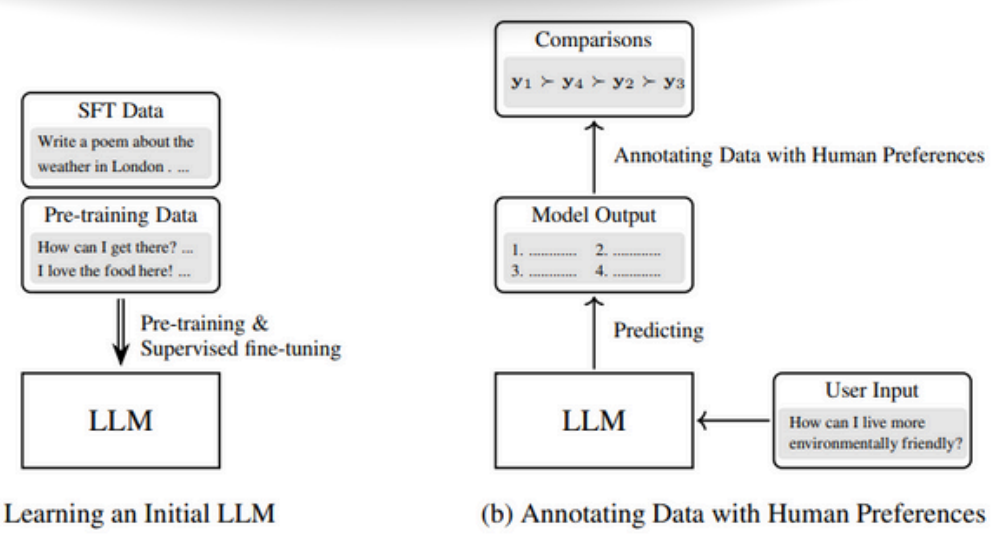
RLHF



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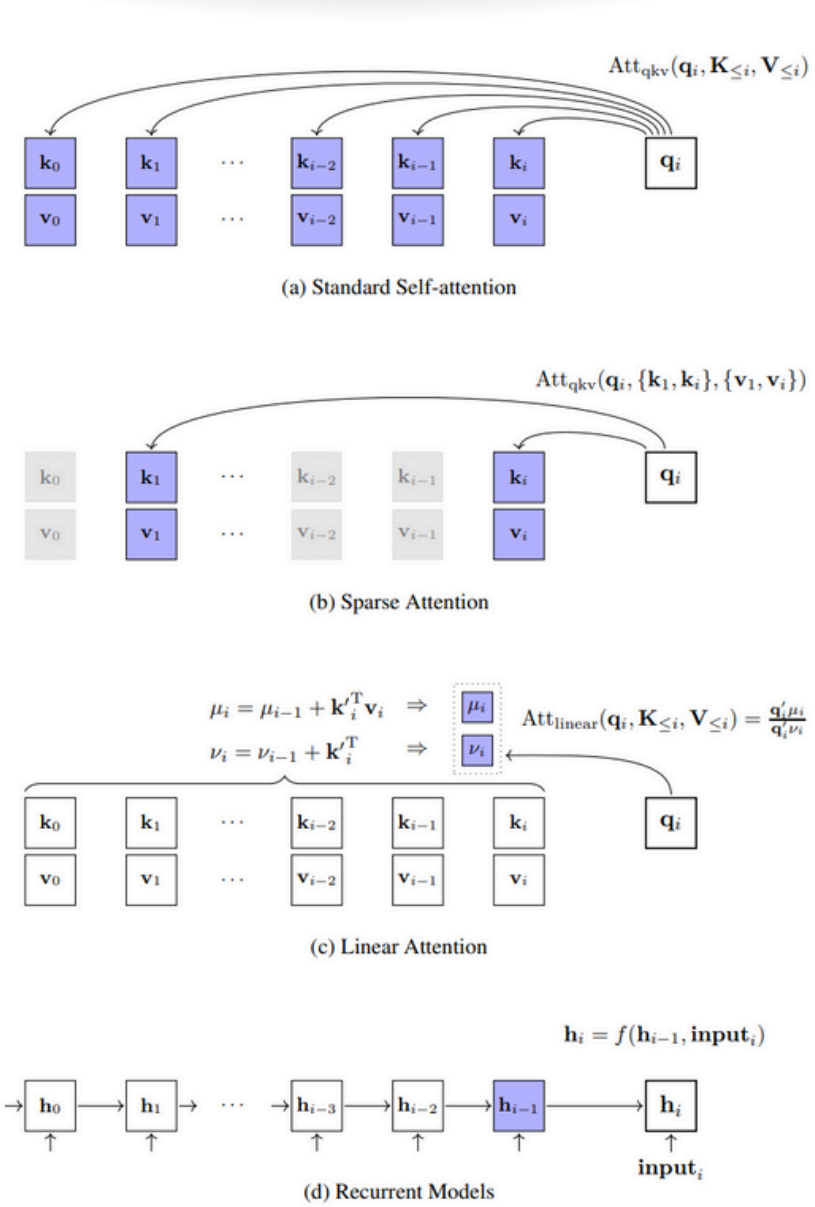
Attention

Types



(a) Standard Self-attention

(b) Sparse Attention

(c) Linear Attention

(d) Recurrent Models

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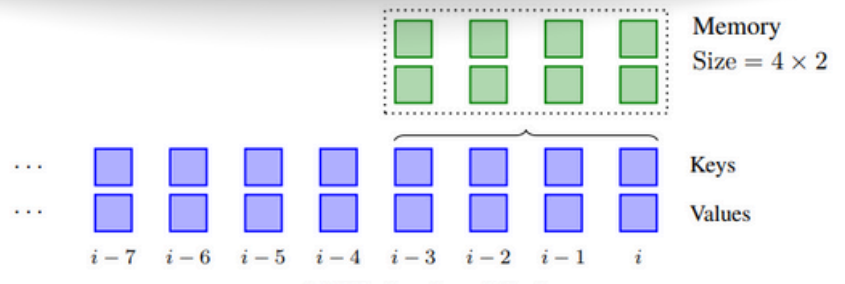
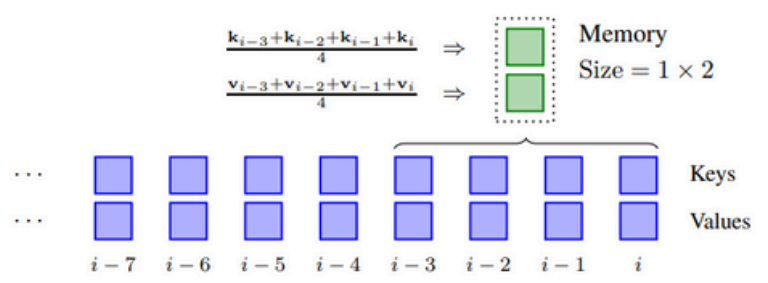
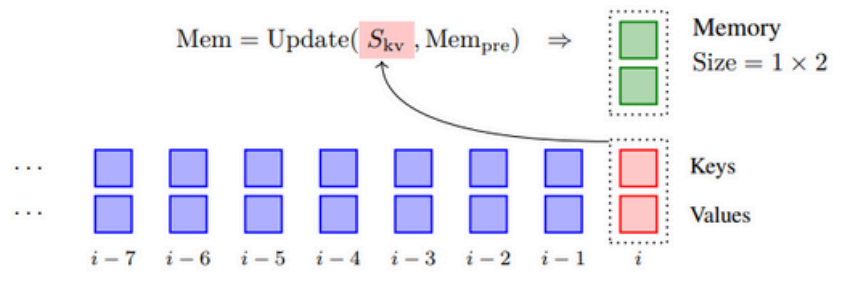
Memory



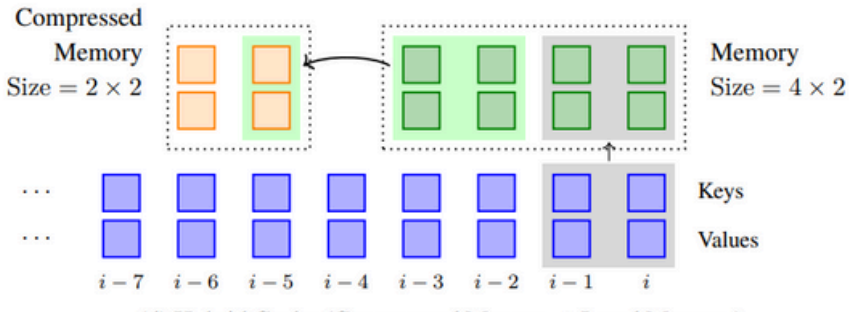
(a) Window-based Cache



(b) Moving Average-based Cache



(c) Recurrent Network as Cache



(d) Hybrid Cache (Compressed Memory + Local Memory)

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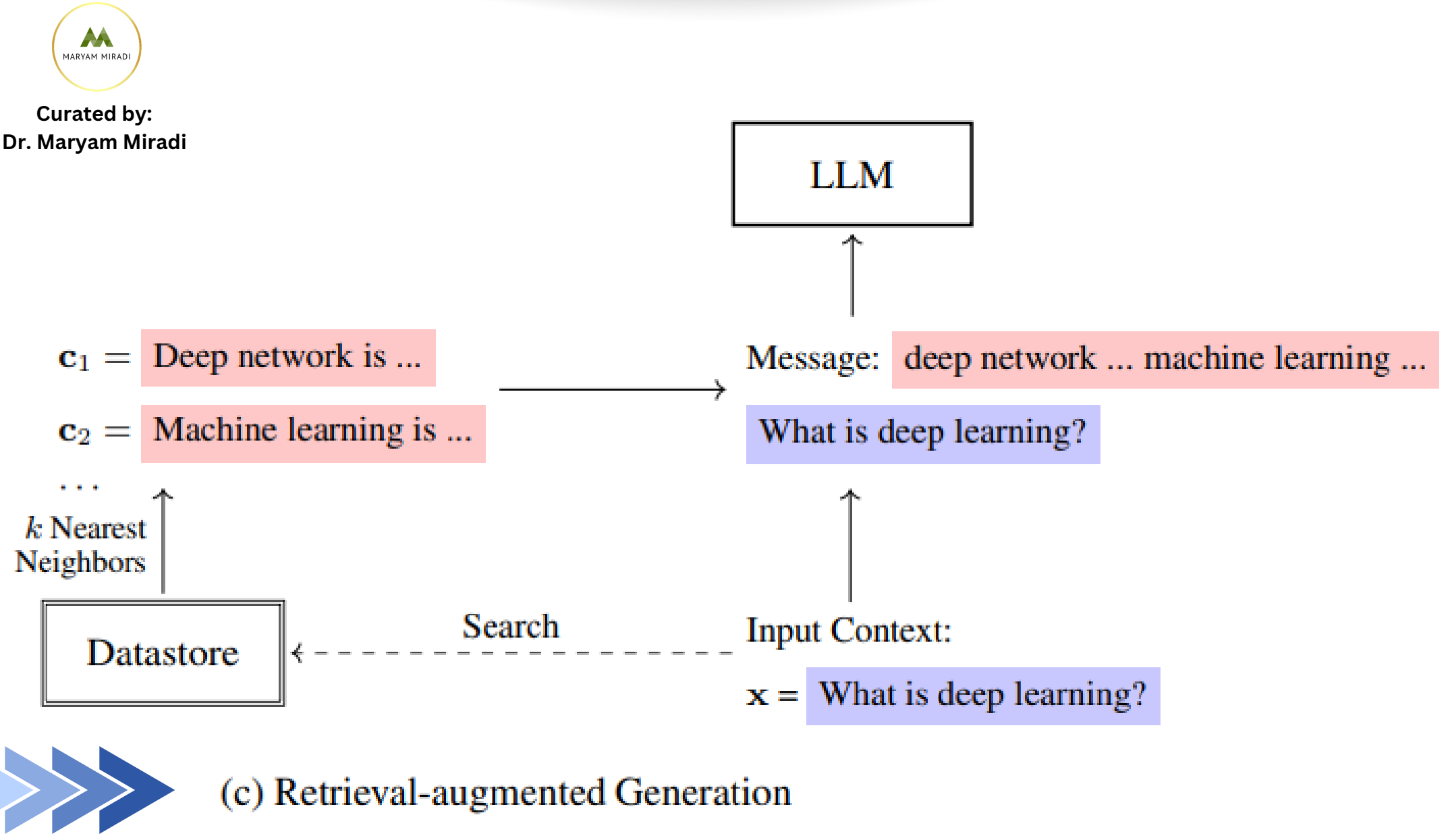

(c) Retrieval-augmented Generation

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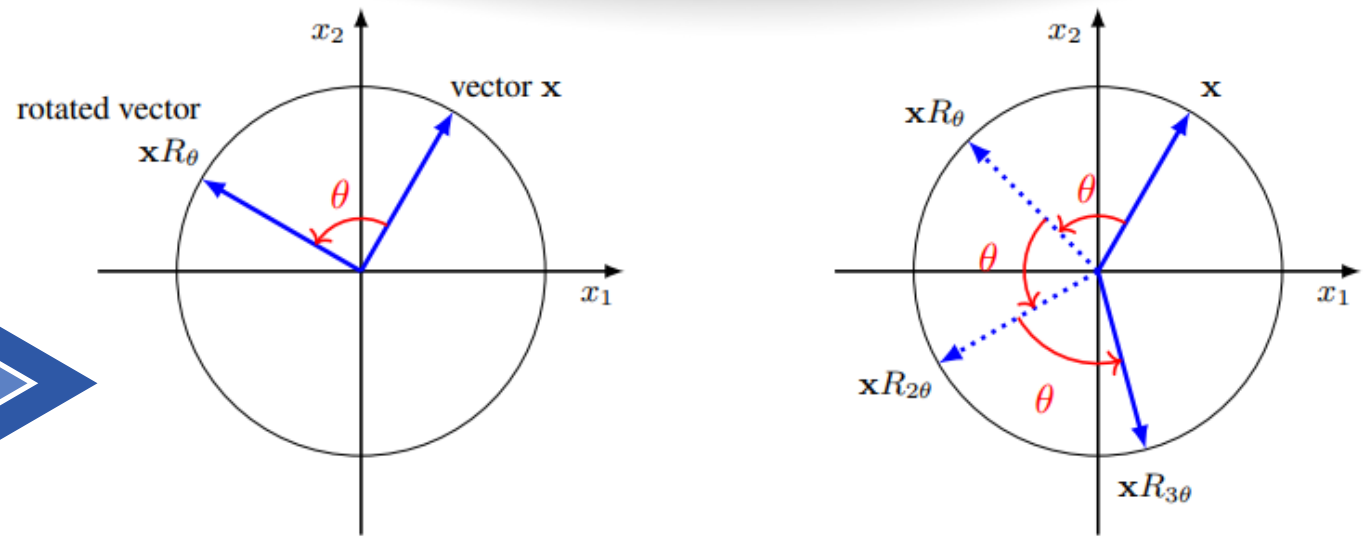
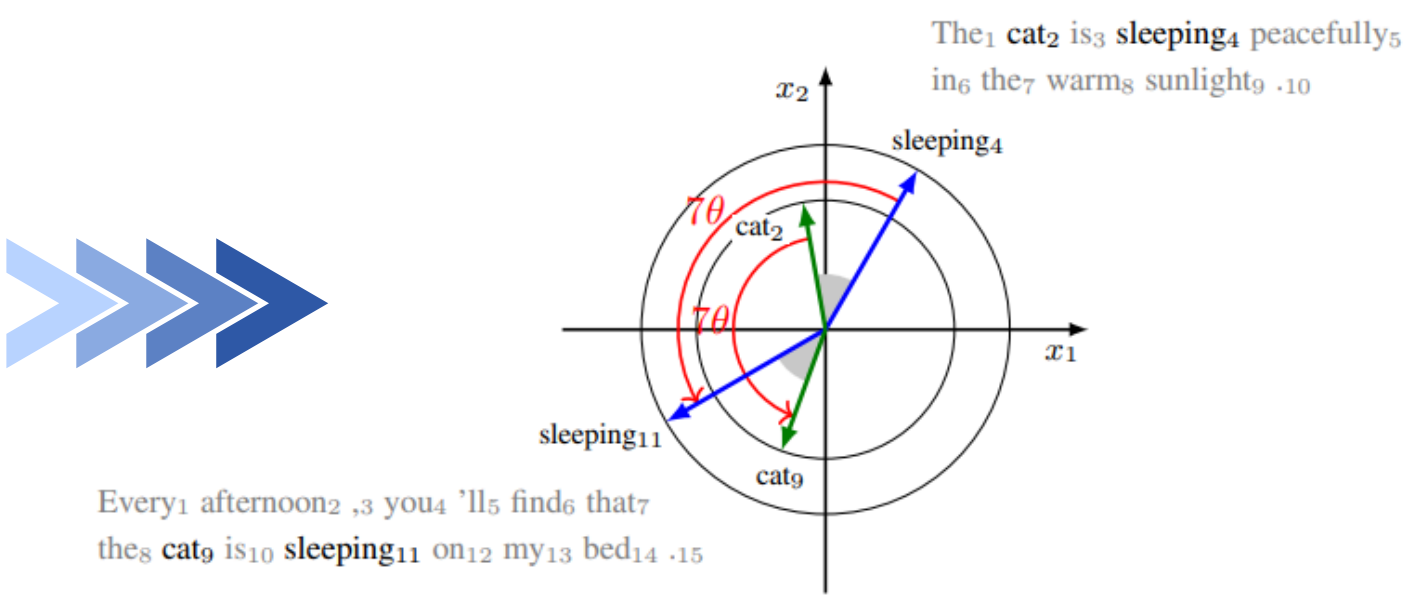
Embedding



(a) Single-step Rotation

(b) Multi-step Rotation



(c) Angles between embeddings of two tokens at different positions

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Ensembling

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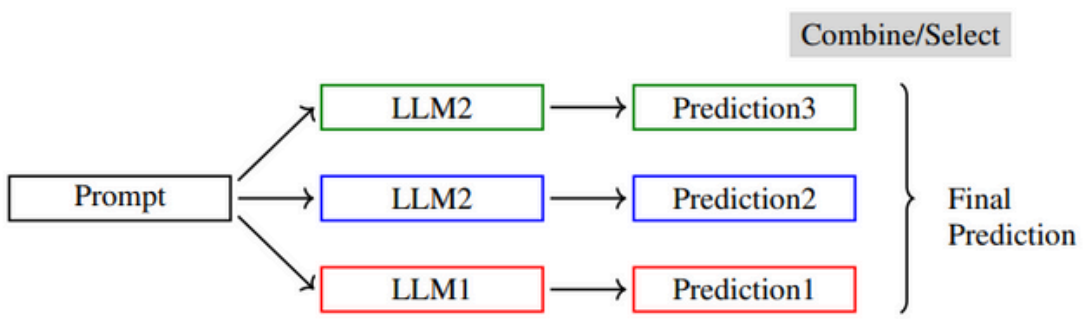
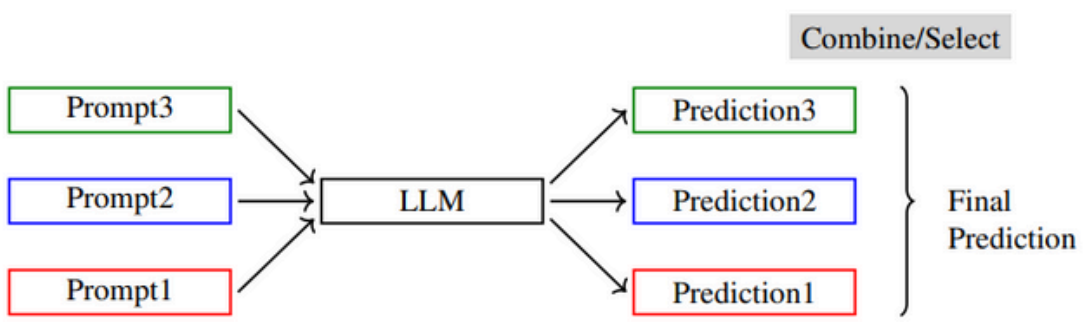
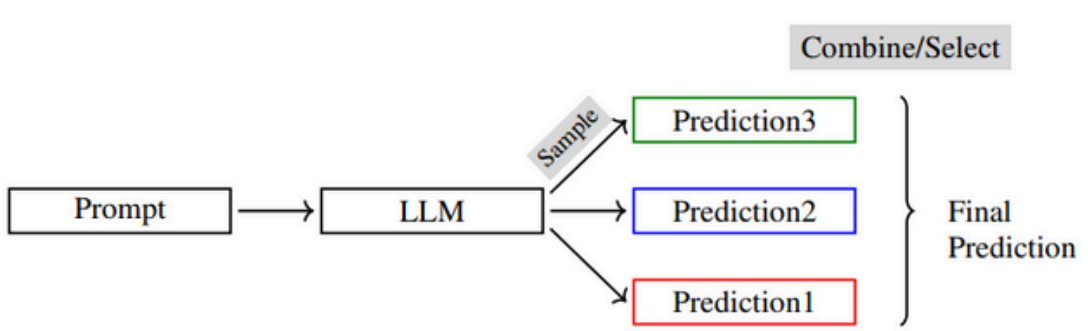


(a) Model Ensembling



(b) Prompt Ensembling



(c) Output Ensembling

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Fine-Tunning

$\text{Loss} = 0$ $\text{Loss} \neq 0$ $\text{Loss} = 0$ $\text{Loss} \neq 0$

$\Pr_\theta(\mathbf{x}^1)$ $\Pr_\theta(\mathbf{y}^1|\mathbf{x}^1)$ $\Pr_\theta(\mathbf{x}^2|\mathbf{x}^1,\mathbf{y}^1)$ $\Pr_\theta(\mathbf{y}^2|\mathbf{x}^1,\mathbf{y}^1,\mathbf{x}^2)$

$\mathbf{x}^1$ $\mathbf{y}^1$ $\mathbf{x}^2$ $\mathbf{y}^2$ ...

User: I've been feeling very tired lately.

Chatbot: I'm sorry to hear that. Besides feeling tired, have you noticed any other symptoms?

User: Yes, I'm also experiencing headaches frequently.

Chatbot: How long have these symptoms been going on?

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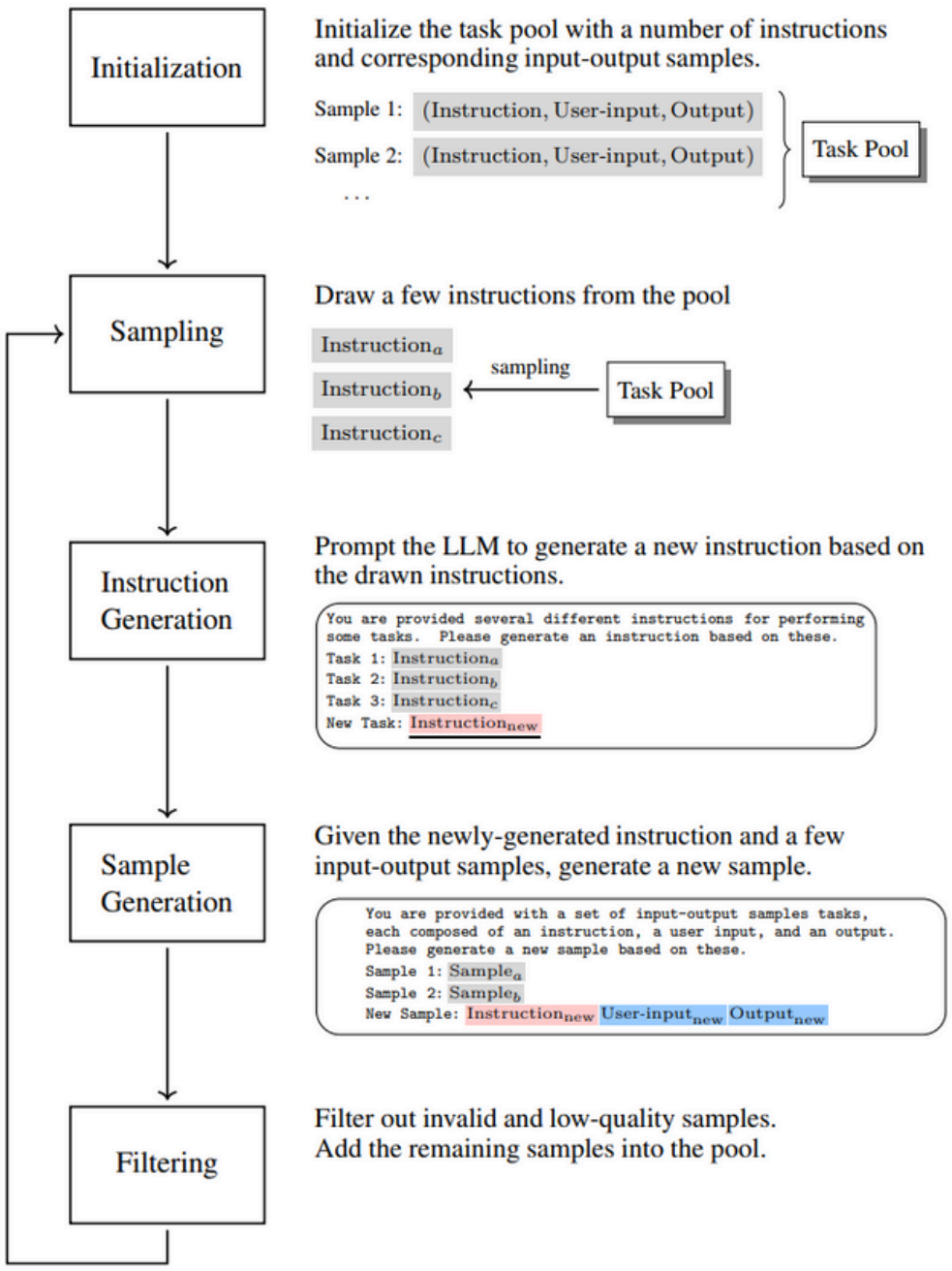
Self-Instruct



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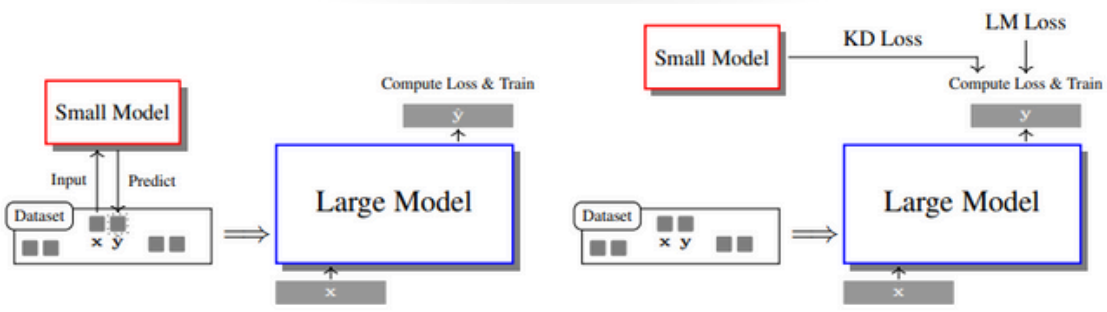
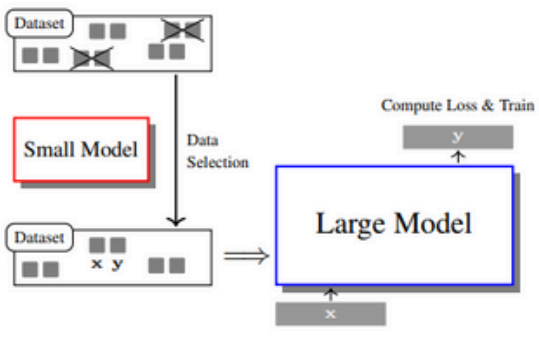
Small-to-Large

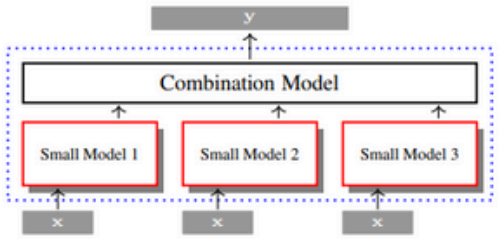


(a) Fine-tuning on data generated by a small model (weak-to-strong generalization)

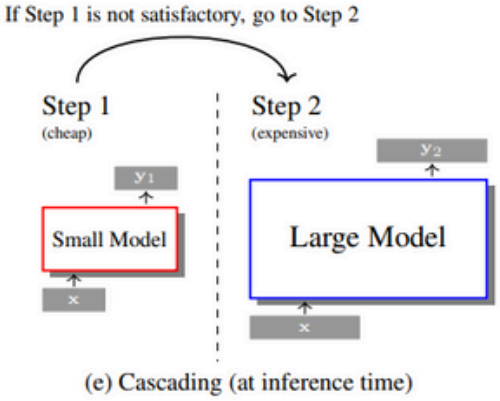
(b) Fine-tuning with KD Loss from a small model (weak-to-strong generalization)



(c) Data selection with a small model



(d) Ensemble of multiple small models



(e) Cascading (at inference time)

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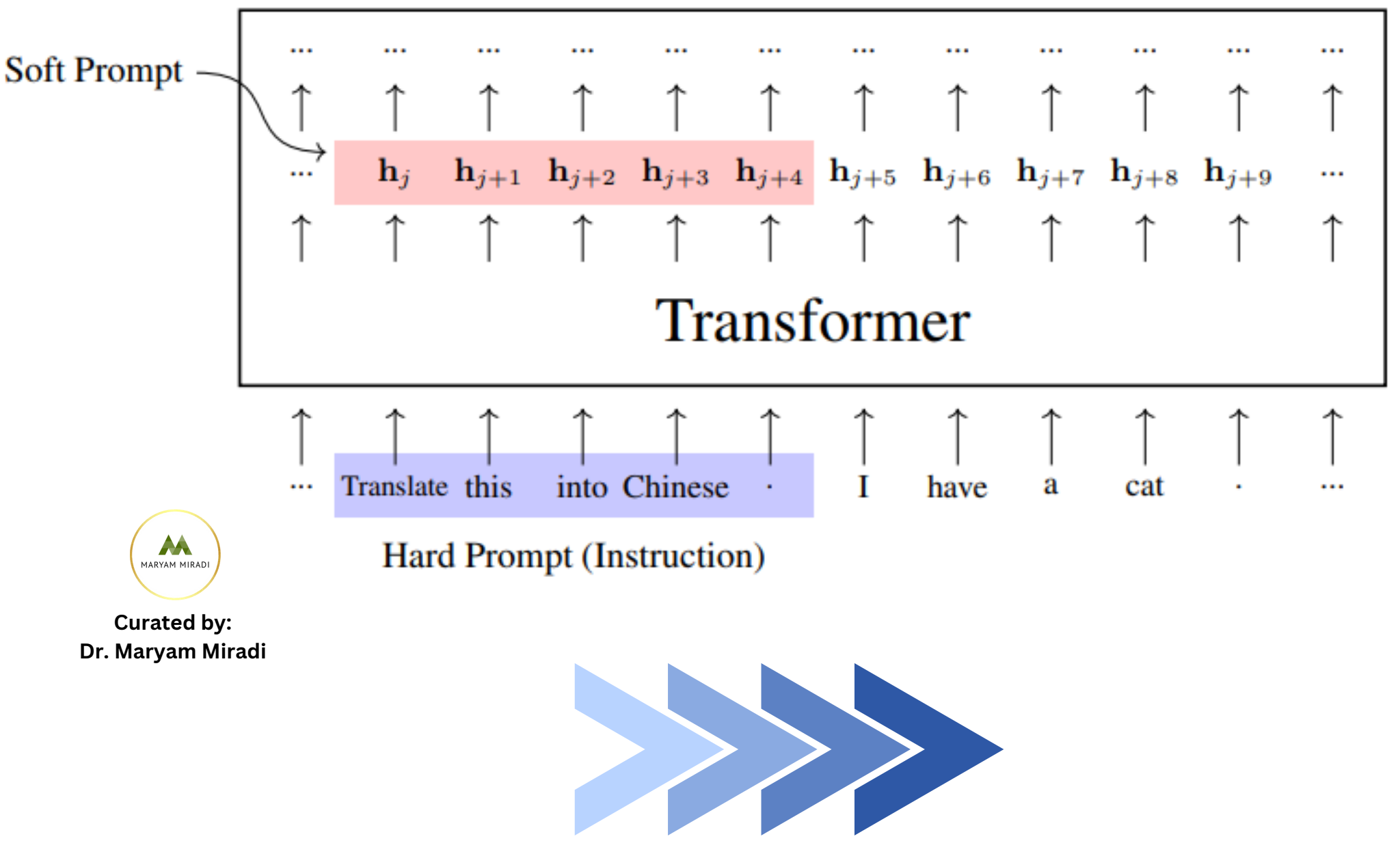
Soft Prompts



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