DeepLorIA

Mastering Large Language Models: Efficient Techniques for Fine-Tuning

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DeepLorIA Network

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About Me

2nd-year PhD student - Knowledge-Enhanced Language Models

Research Focus

- Controlled Conversational Models through Conversation-Dedicated Ontology
- *Keywords: Large Language Models (LLMs), Conversational Agents, Ontologies, Fine-Tuning*

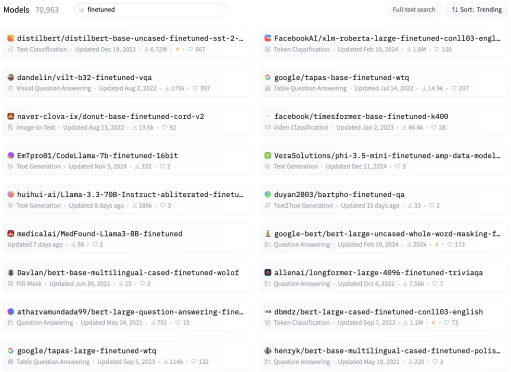
Experience in LLM fine-tuning

- Run pre-defined fine-tuning setups (Causal Language Modeling, Classification,...)
- Develop new fine-tuning pipelines to consider external knowledge
- Focus on textual modality

Experimenting LLM Fine-Tuning

Many successful LLM fine-tunings?

`https://huggingface.co/`



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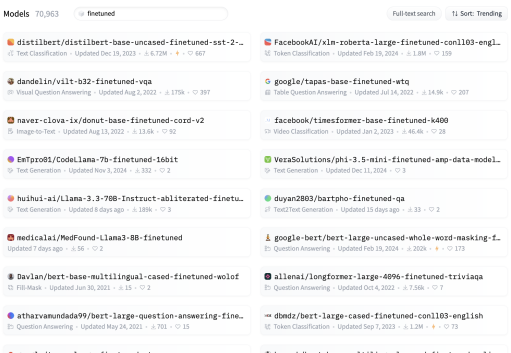
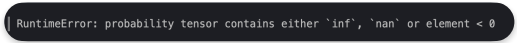
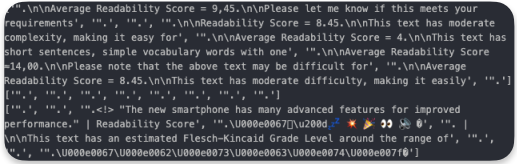
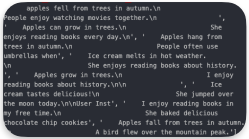
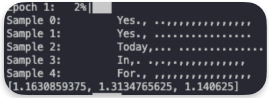


Fine-tuning LLMs in real life?









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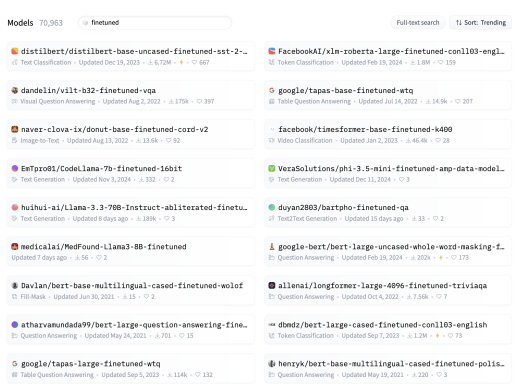

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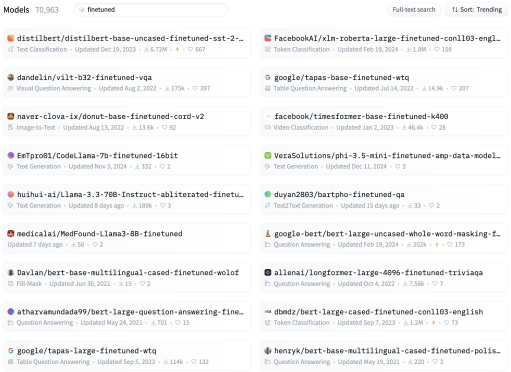

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Deep-Learning-Based Sequence Modeling: Recurrent Models (1)

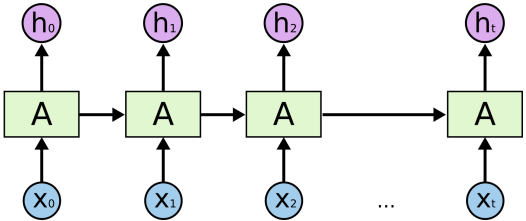

Figure 1 – Illustration of the Recurrent Neural Network (RNN, [18, 10]) architecture[1]

- ✓ Keep token order
- ✓ Handle variable-length sequences
- ✓ Parameter sharing across the sequence

- ✗ Exploding and vanishing gradient
- ✗ Long-term dependencies
- ✗ Slow computing, no parallelization

[1] Olah, C. (2015). Understanding LSTM Networks. https://colah.github.io/posts/2015-08-Understanding-LSTMs/

Deep-Learning-Based Sequence Modeling: Recurrent Models (2)

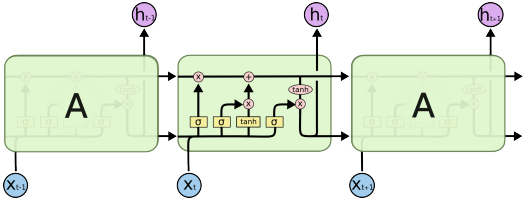

Figure 2 – Illustration of the Long Short Term Memory Neural Network (LSTM, [7]) architecture[2]

- ✓ Keep token order
- ✓ Handle variable-length sequences
- ✓ Parameter sharing across the sequence
- ✓ No exploding/vanishing gradient
- ✓ Long-term dependencies
- ✗ Slow computing, no parallelization

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Attention Principle [1] and Transformer Model [20]

From Transformer-Based Models to Large Language Models (LLMs)

LLMs scale Transformers by stacking encoders and/or decoders together

- Parallelizable and optimized versions exist (e.g. quantization)
- Enable deeper and broader knowledge representation
- Large context window allows for more accurate generation

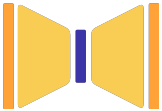

Figure 3 – Full Transformer

Figure 4 – Encoder

Figure 5 – Decoder

From Transformer-Based Models to Large Language Models (LLMs)

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Fine-tuning adapts an LLM to a specific task through further parameter updates

- Can be performed with any LLM structure, but:
  - There are *required structures* for some specific tasks
  - There are *preferred models* for some specific tasks

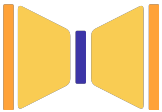

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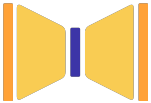
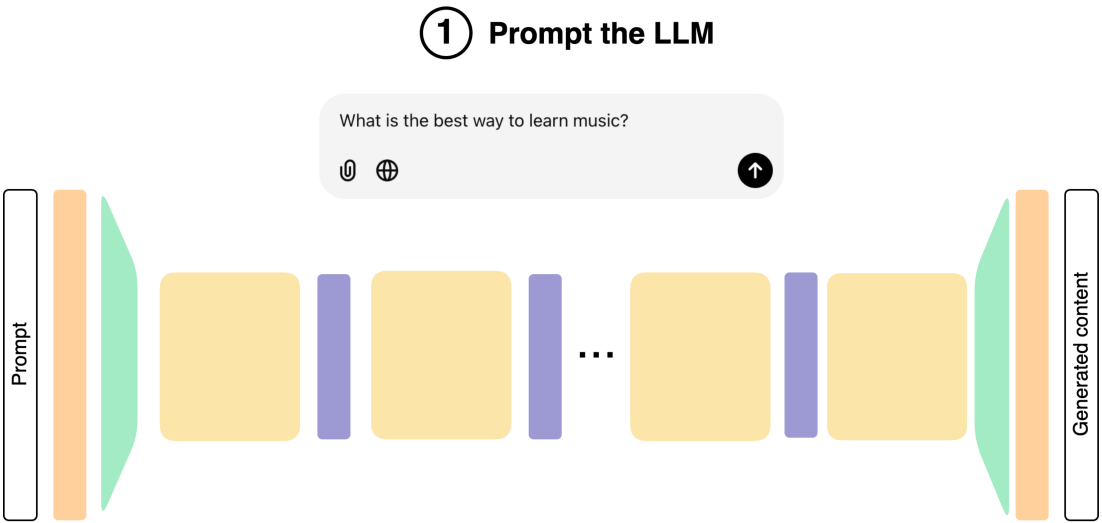
Figure 5 – Decoder

What Use-Cases of LLMs?

Model Structure	Task Examples	Model examples
	• Summarization • Machine Translation • Question Answering	• BART [11], mBART [12] • T5 [17], Flan-T5 [3] • bert2BERT [2]
	• Sequence Embedding • Text Classification • Regression	• BERT [5], mBERT [15] • RoBERTa [13] • DistilBERT [19]
	• Text Completion • Text Generation • Code Generation	• GPT-3.5, GPT-4o • Llama-3 [6] • Qwen2.5 [16]

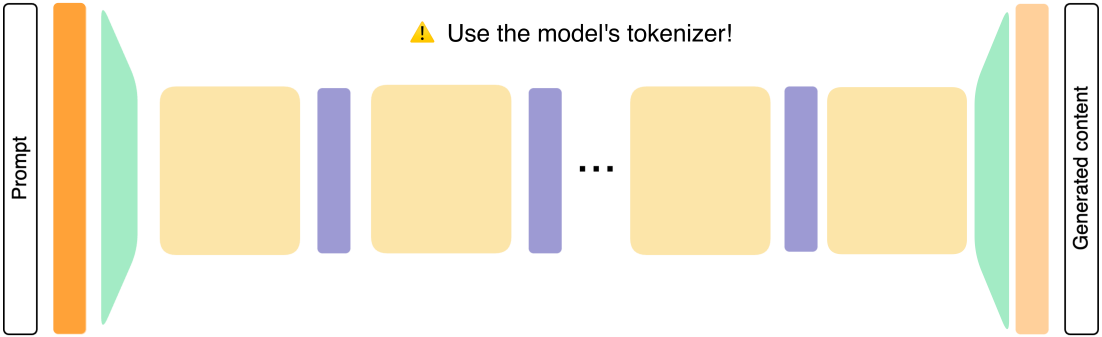
Inside a Decoder-Only LLM



② Tokenize the Prompt Content

"What is the best way to learn music?"
[531, 9, 45, 22, 3316, 2444, 34, 2172, 334]

⚠ Use the model's tokenizer!

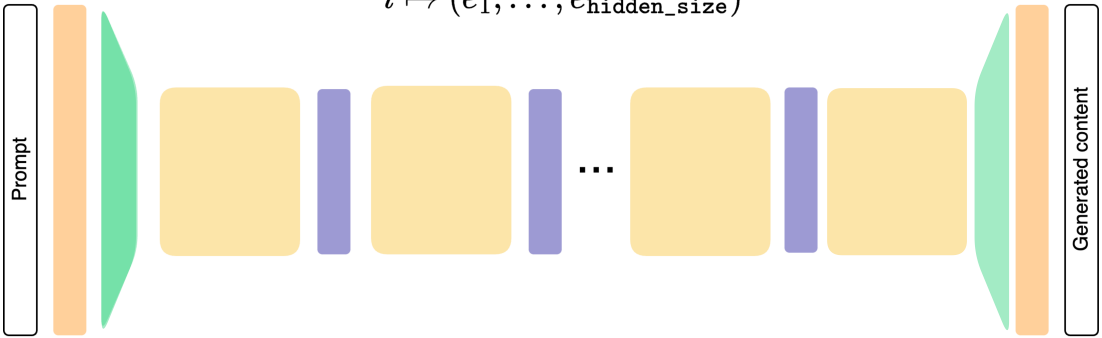


Inside a Decoder-Only LLM

③ Apply an Embedding layer

`Embedding(vocab_size, hidden_size)`

$$i \mapsto (e_1, \ldots, e_{\texttt{hidden\_size}})$$



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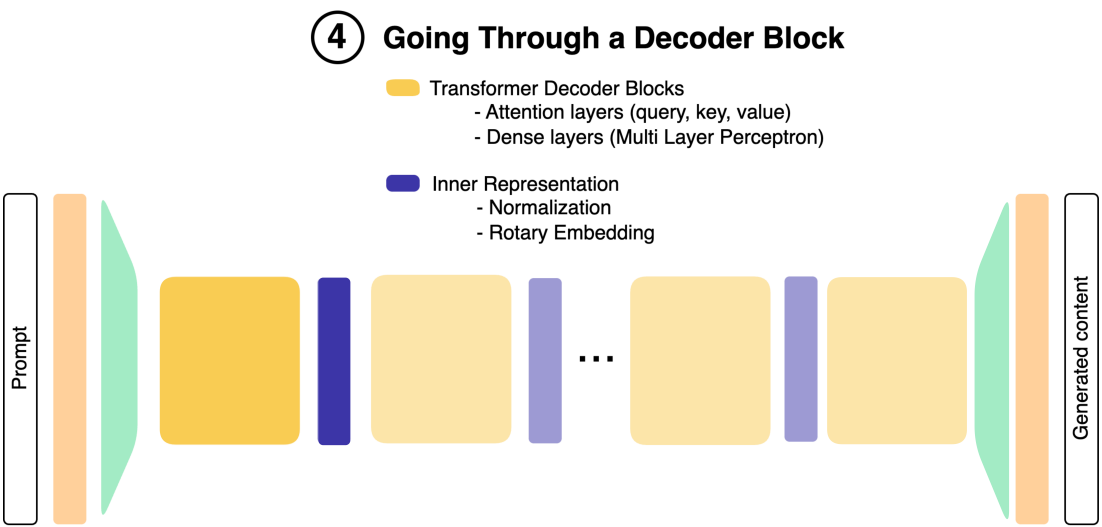

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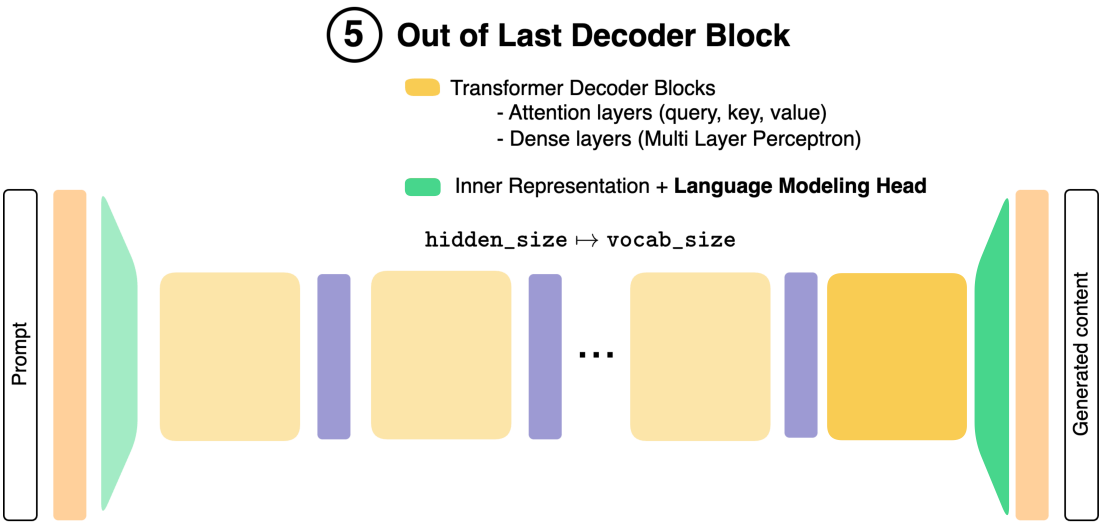
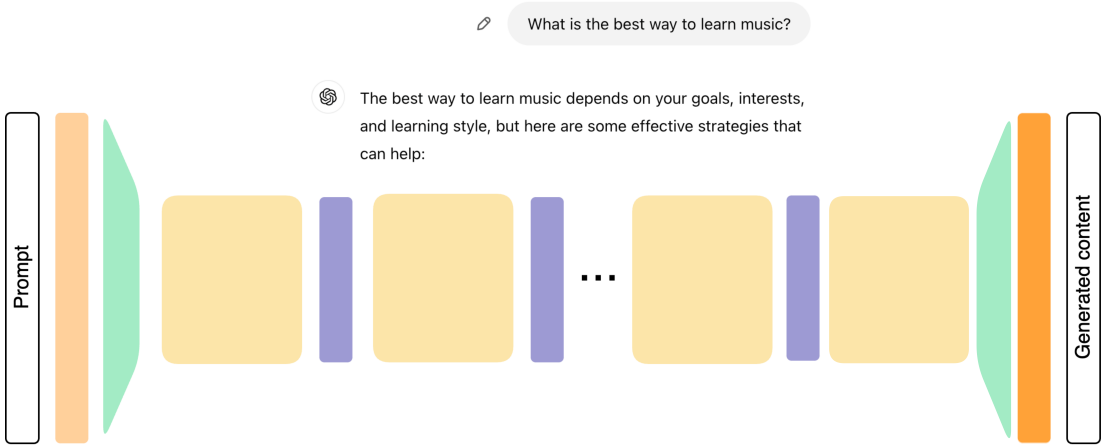
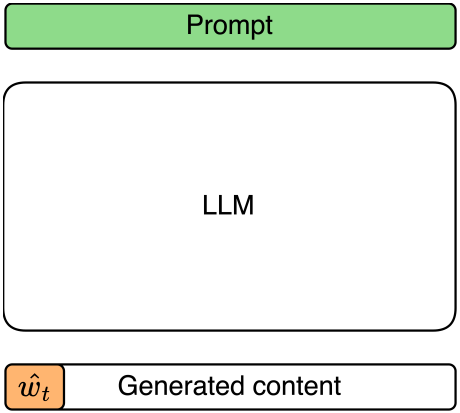


Inside a Decoder-Only LLM

6 Decode Generated Tokens in Natural Language



The Autoregressive Principle

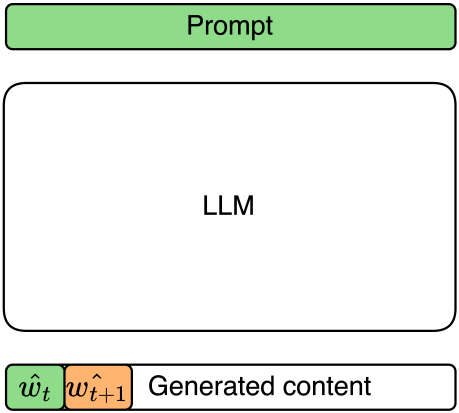


Context

Predicted token

$$\hat{w}_t = \arg\max_{w_i} P(w_i | w_1, w_2, \ldots, w_{t-1})$$

The Autoregressive Principle



Context
Predicted token

$$\hat{w_{t+1}} = \arg\max_{w_i} P(w_i | w_1, w_2, \ldots, w_t)$$

- **Top p**: adjust the range of tokens to consider regarding their probability.
- **Top k**: choose among the k more likely tokens. Default is 1 (most likely token).
- **Temperature:** control "creativity" by adding random noise to select less likely tokens.

How Large are Large Language Models?

Model	Parameters	Layers	Context Size
Gemini 1.5	200B?	-	10M
GPT-4 turbo	1.8T	120	128k
Claude 2.1	12B	-	200k

Table: Some *closed-source* model specifications

Model	Parameters	Layers	Context Size
Llama 3.3	70B	80	128k
Phi 4	14B	40	16k
Qwen 2.5	0.5B-72B	24-80	32k - 128k
Mistral-v0.3	7B	32	32k

Table: Some *open-weights* model specifications

Side remark: most LLMs called "open-source" are actually open-weights!

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Side remark: most LLMs called "open-source" are actually open-weights!

- Most models involve several gigabytes in RAM GPU to perform inference
- Updating each parameter value during fine-tuning would be too costly

$\longrightarrow$ fine-tuning should be **efficient**

Fine-Tuning as an *Affinage*: the Cheese Analogy

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Cow / Raw milk

Milk preparation

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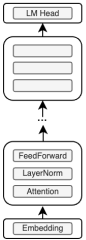
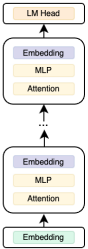
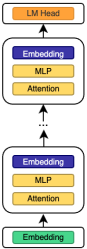


Textual data / Raw model

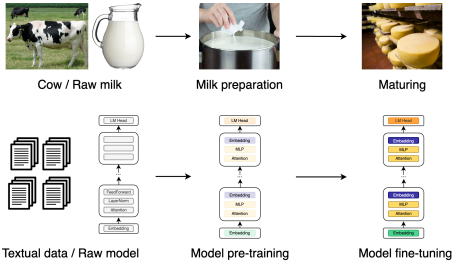


Model pre-training



Model fine-tuning

Fine-Tuning as an *Affinage*: the Cheese Analogy



Fine-tuning, as cheese maturing phase, modifies **in place** its given instance.

- Ensure fine-tuning is performed in the right conditions
- Check pre-trained baseline reliability
- Test several (adapted) pre-trained baselines for one fine-tuning experiment

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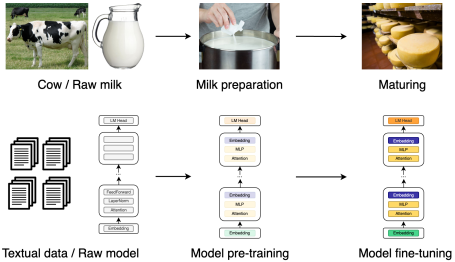

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$\longrightarrow$ fine-tuning should be **stable** and **consistent** with pre-trained baseline

Efficient Fine-Tuning With Adapters [8]

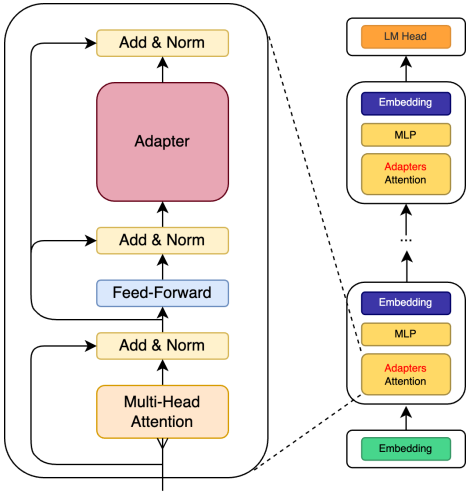

Figure 6 – An attention block with adapters

Adapters layers are inserted to enable parameter-efficient fine-tuning[a]

Common usage:

- Freeze all pre-trained model layers
- Insert trainable MLP layers into attention blocks (query, value) and/or model head

[a] https://huggingface.co/PEFT
[b] https://adapterhub.ml/

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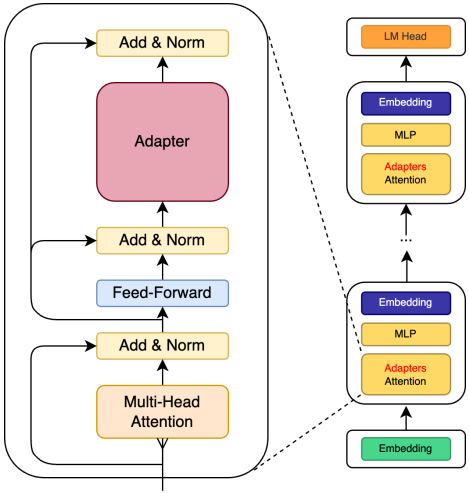

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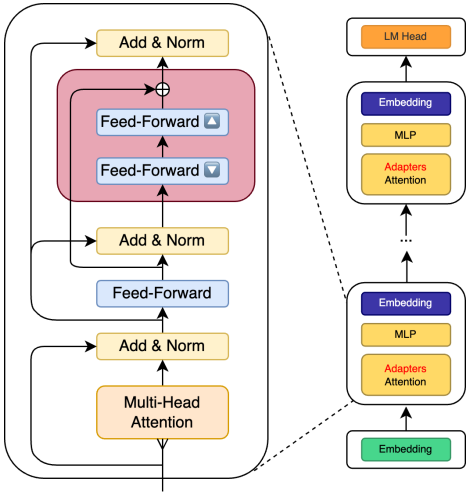
Advantages:

- Fewer param. updates than full fine-tuning
- Helps reduce catastrophic forgetting [14]
- Easy to share fine-tuned models[b]

[a] `https://huggingface.co/PEFT`
[b] `https://adapterhub.ml/`

Efficient Fine-Tuning With LoRA Adapters [9]



LoRA: Low-Rank Adaptation
A specific adapter block structure

- Information from the model can be represented (almost) equally well in a lower dimensional space
- The rank r of the lower dim. space should be determined by hyperparameter tuning
- Quantized versions: QLoRA [4]

Figure 7 – An attention block with LoRA adapters

Wrap-Up

Thanks for your attention!

Figure 8 – Practical session: `https://github.com/B-Gendron/tutorial-deeploria/lab/`

References I

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