Parameter Efficient Fine-Tuning (PEFT)

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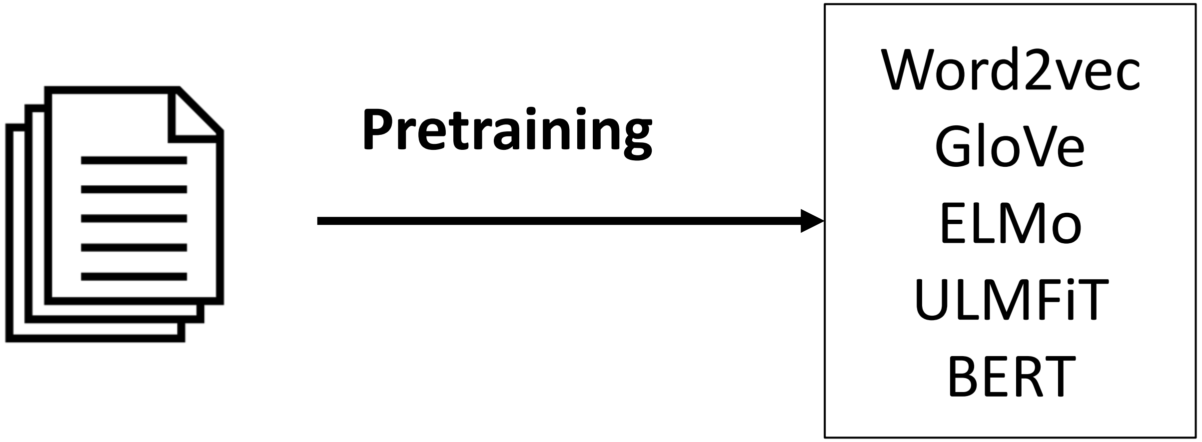
Introduction to Large Language Models

Transfer Learning Before the LLM Era



Adapted from [NAACL 2019 Transfer learning tutorial]

Transfer Learning Before the LLM Era

Pretraining →

Word2vec
GloVe
ELMo
ULMFiT
BERT

Fine-tuning →

classification
sequence labelling
question answering
....

Adapted from [NAACL 2019 Transfer learning tutorial]

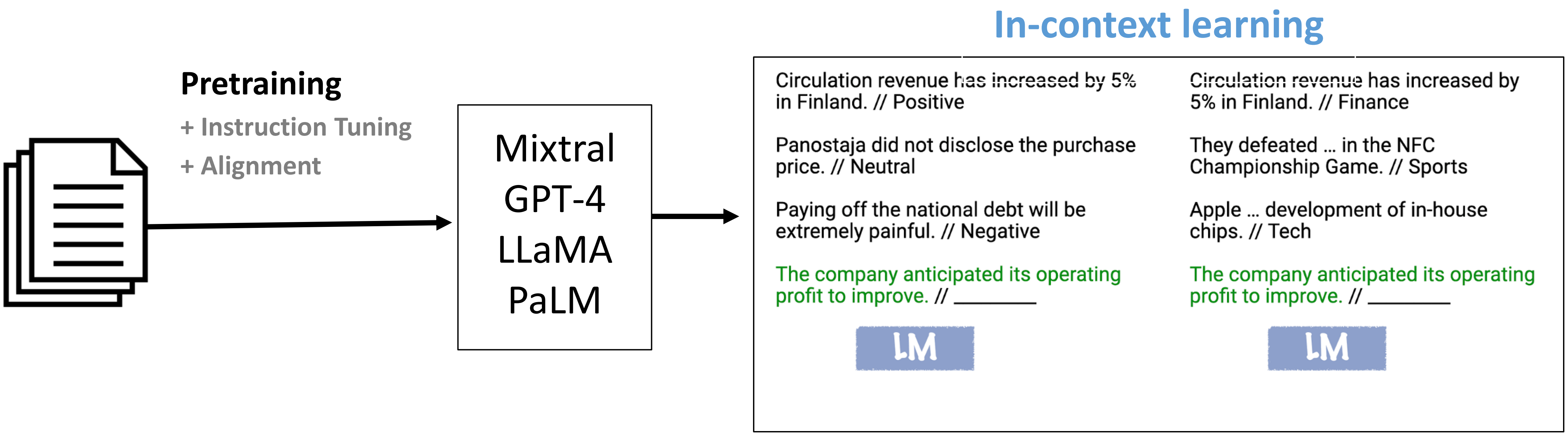
Transfer Learning in the LLM Era

Pretraining

+ Instruction Tuning
+ Alignment

Mixtral
GPT-4
LLaMA
PaLM

Transfer Learning in the LLM Era



- In-context learning has mostly replaced fine-tuning in large models
- In-context learning is very useful if we don't have direct access to the model, for instance, if we are using the model through an API.

Downsides of In-context Learning

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3. **Lack of clarity** regarding what the model learns from the prompt. Even random labels work [Min et al., 2022]!

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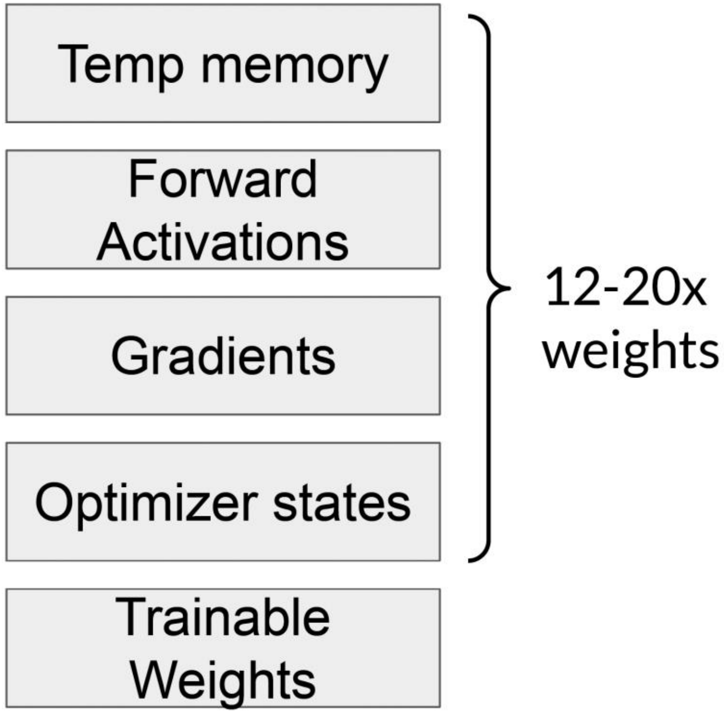
3. **Lack of clarity** regarding what the model learns from the prompt. Even random labels work [Min et al., 2022]!
4. **Inefficiency:** The prompt needs to be processed *every time* the model makes a prediction.

Why is Full Fine-tuning in LLM Challenging?



1. Hardware Requirements

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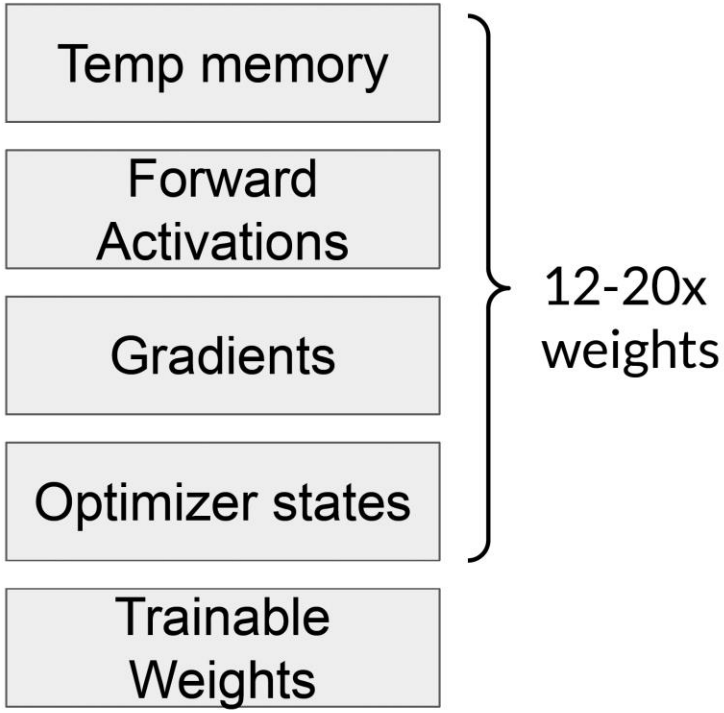

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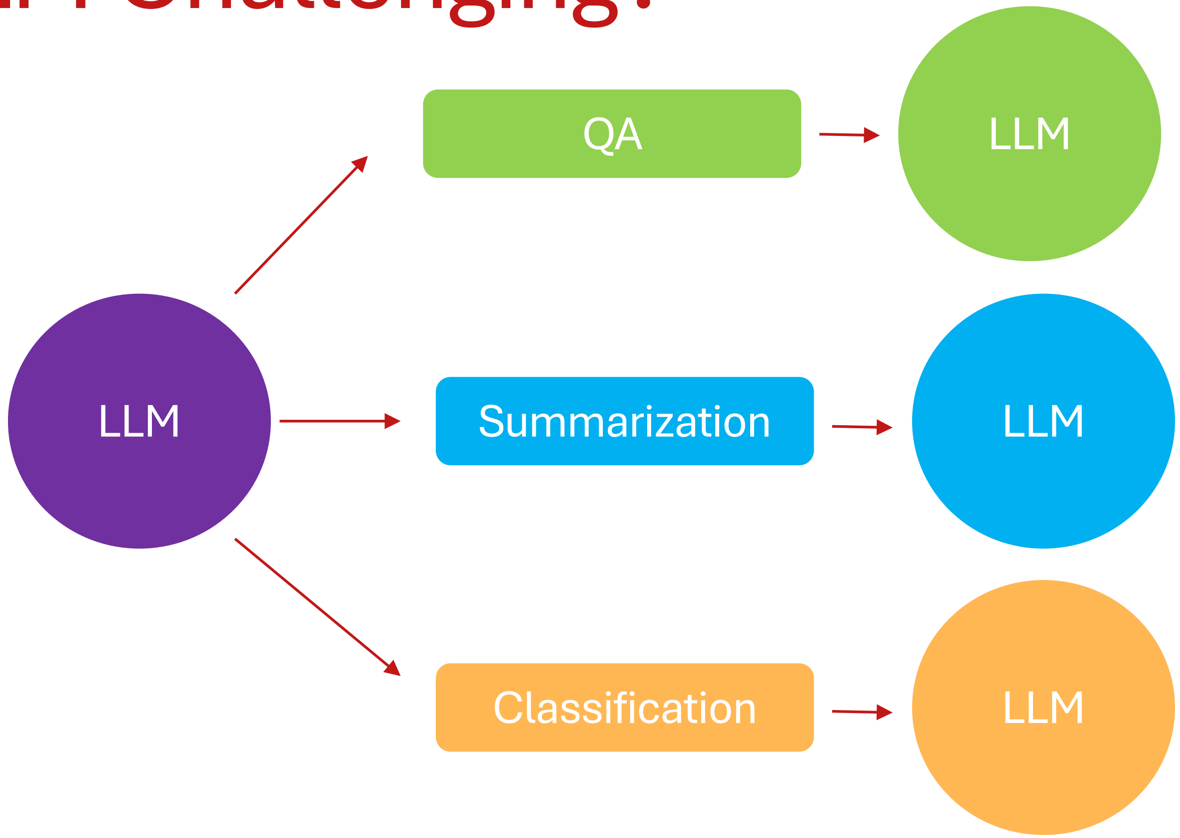
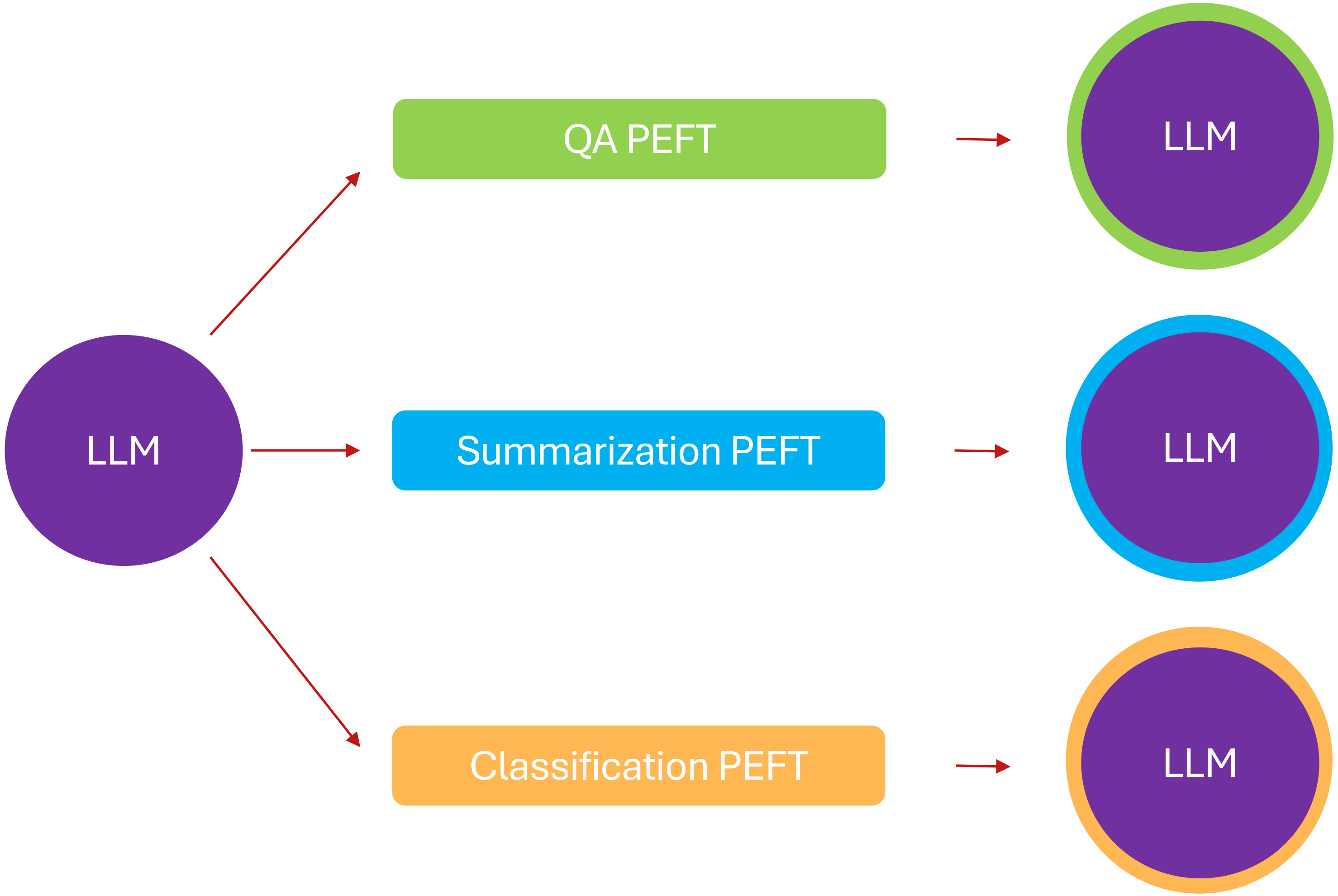


2. Storage

Parameter Efficient Fine Tuning (PEFT)



PEFT Advantages

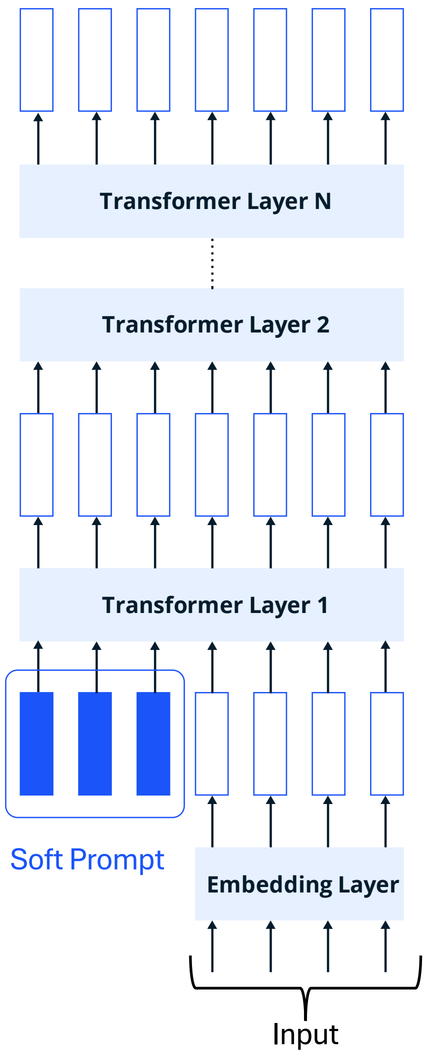
- Reduced computational costs
  - requires fewer GPUs and GPU time
- Lower hardware requirements
  - works with smaller GPUs & less memory
- Better modelling performance
  - reduces overfitting by preventing catastrophic forgetting
- Less storage
  - majority of weights can be shared across different tasks

PEFT Techniques

- (Soft) Prompt Tuning
- Prefix Tuning
- Adapters
- Low Rank Adaptation

Comparison with Other PEFT Methods:
Method What's Tuned? Injected Where?
Prefix Tuning Key/Value prefixes In the attention layers
Prompt Tuning Input token embeddings At the input layer
Adapter Tuning Small feed-forward networks Between transformer layers
LoRA Low-rank matrices Inside attention weights

(Soft) Prompt Tuning (Lester et al. 2021)



- prepends a trainable tensor to the model's input embeddings, creating a soft prompt
- for a specific task, only a small task-specific soft prompt needs to be stored
- soft prompt tuning is significantly more parameter-efficient than full-finetuning

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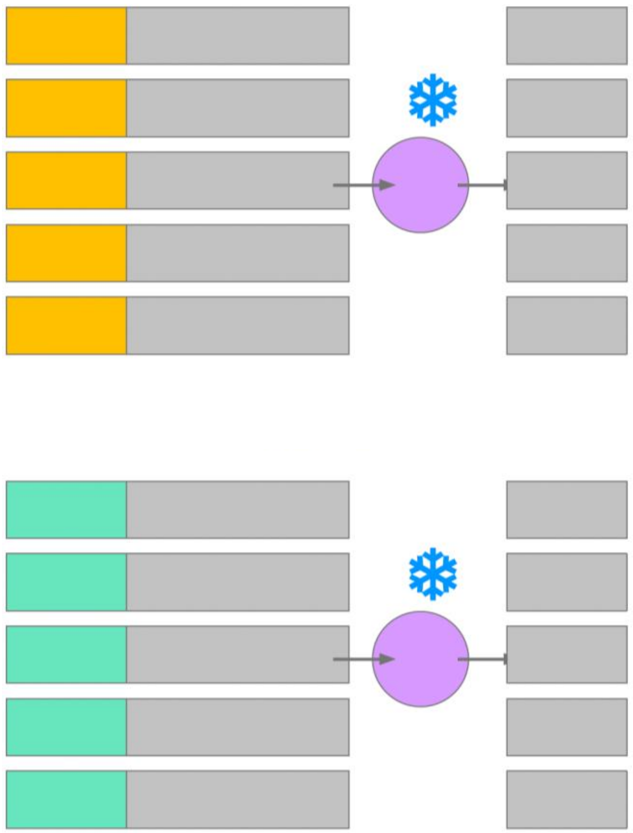
(Soft) Prompt Tuning: Multi-Task Serving

Adapted from DeepLearning.AI

Training

Task A

Task B



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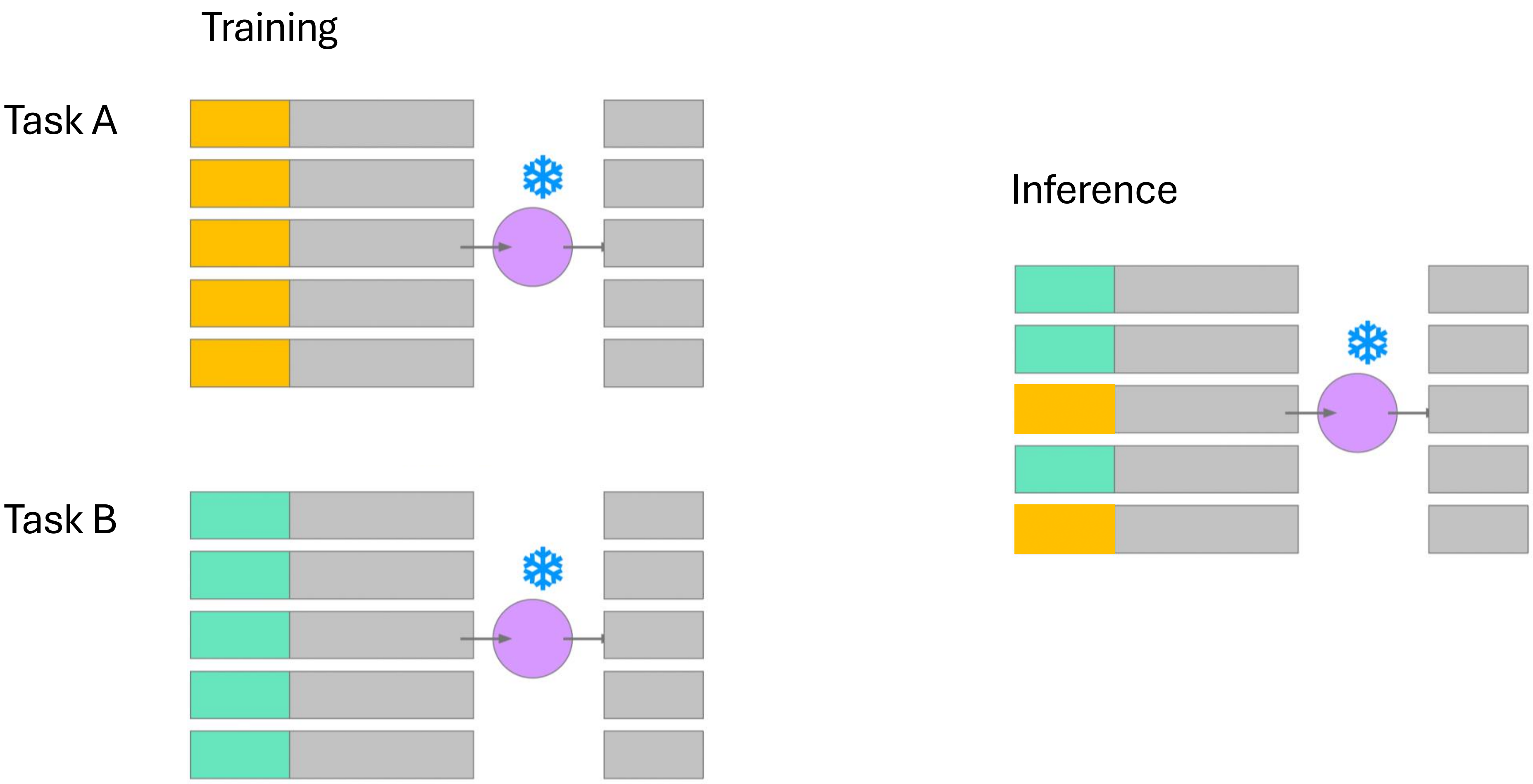

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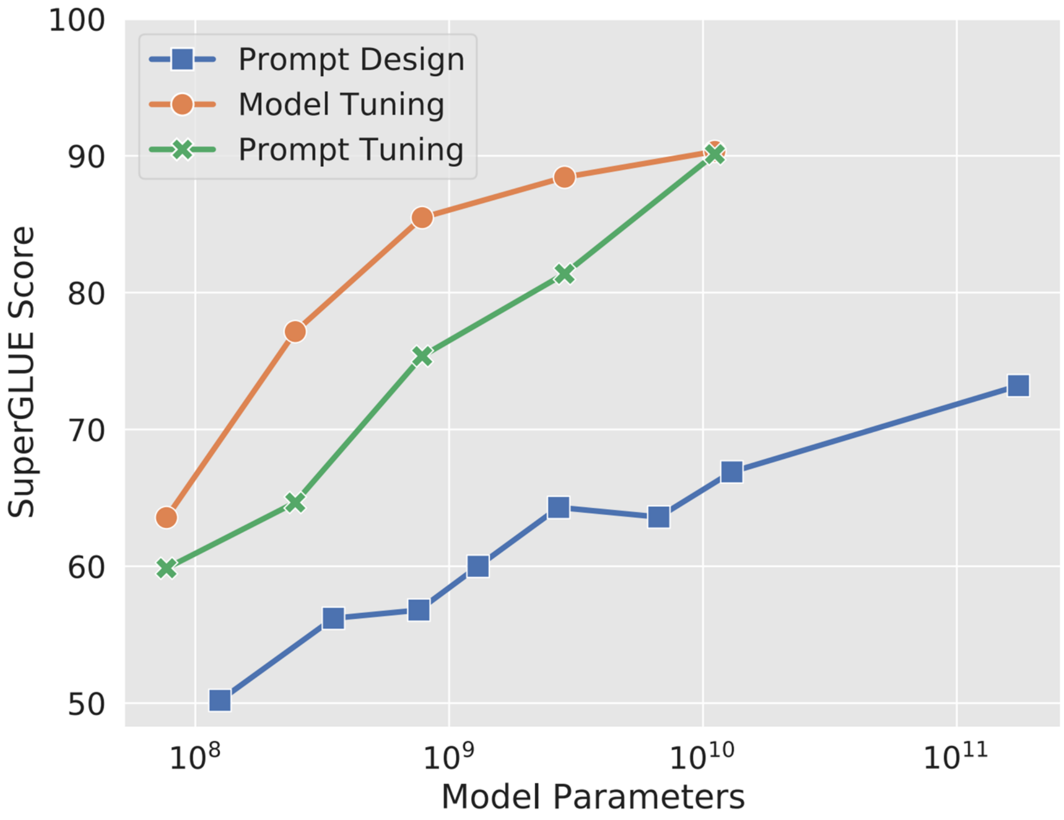
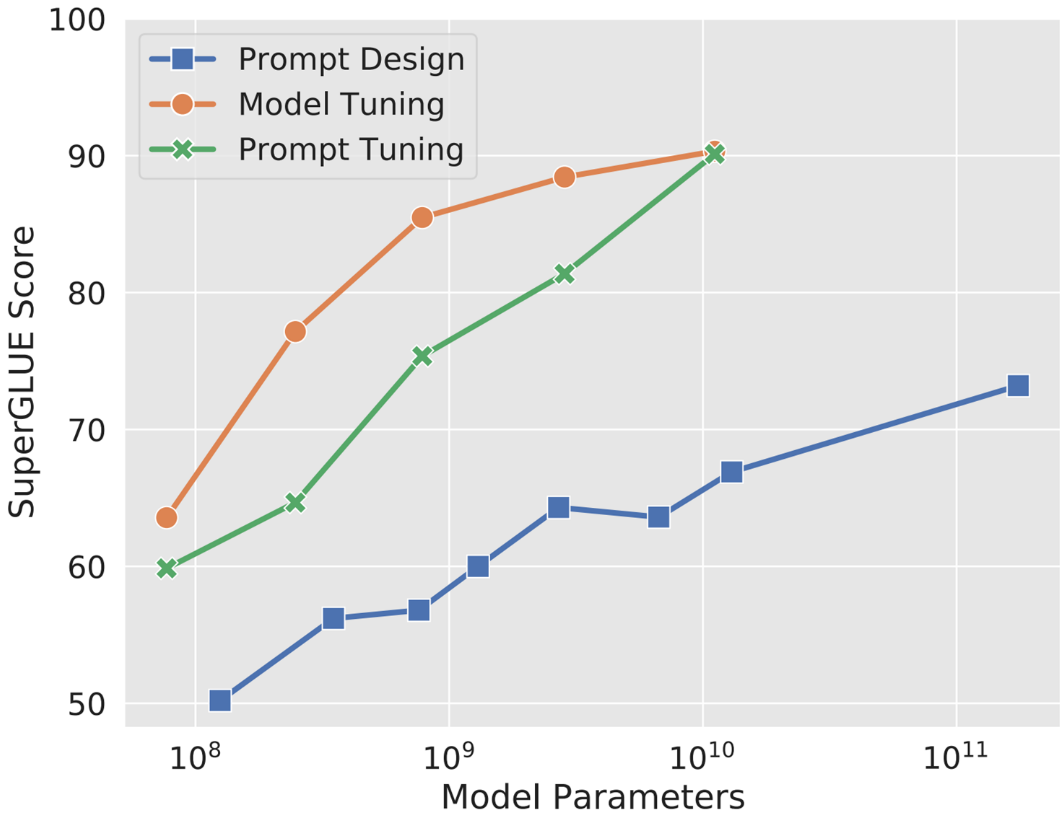


Prompt tuning vs standard full fine-tuning across T5 models of different sizes [Lester et al., 2021]

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

(Soft) Prompt Tuning



Prompt tuning vs standard full fine-tuning across T5 models of different sizes [Lester et al., 2021]

- Prompt tuning performs poorly at smaller model sizes and on harder tasks [Mahabadi et al., 2021; Liu et al., 2022]
- increasing prompt length improves the performance and increasing beyond 20 tokens only yields marginal gains

(Soft) Prompt Tuning

Dataset	Domain	Model	Prompt	Δ
SQuAD	Wiki	94.9 ±0.2	94.8 ±0.1	−0.1
TextbookQA	Book	54.3 ±3.7	**66.8** ±2.9	+12.5
BioASQ	Bio	77.9 ±0.4	**79.1** ±0.3	+1.2
RACE	Exam	59.8 ±0.6	**60.7** ±0.5	+0.9
RE	Wiki	88.4 ±0.1	**88.8** ±0.2	+0.4
DuoRC	Movie	**68.9** ±0.7	67.7 ±1.1	−1.2
DROP	Wiki	**68.9** ±1.7	67.1 ±1.9	−1.8

F1 mean and stddev for models trained on SQuAD and evaluated on out-of-domain datasets from the MRQA 2019 shared task [Houlsby et al., 2019]

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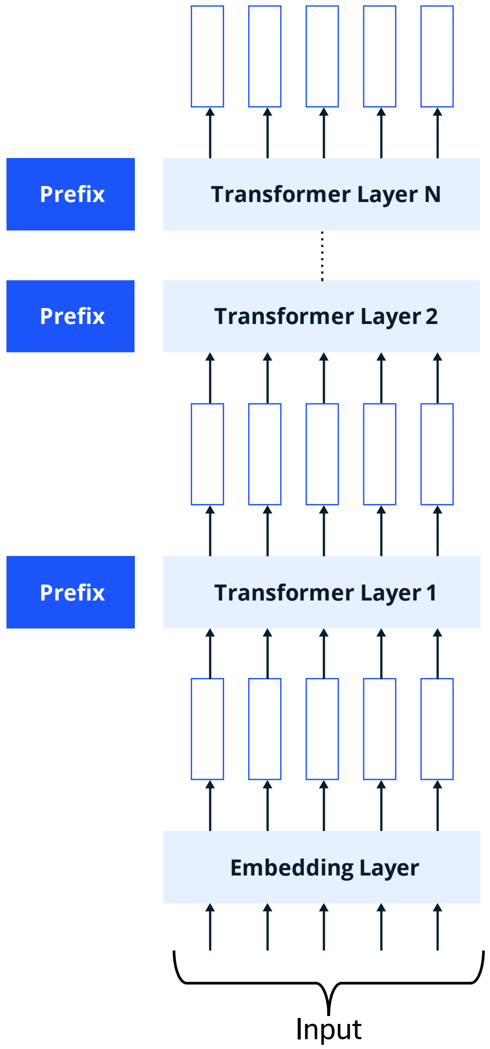
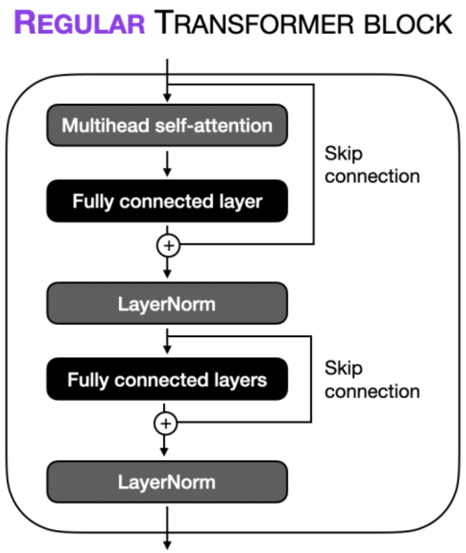
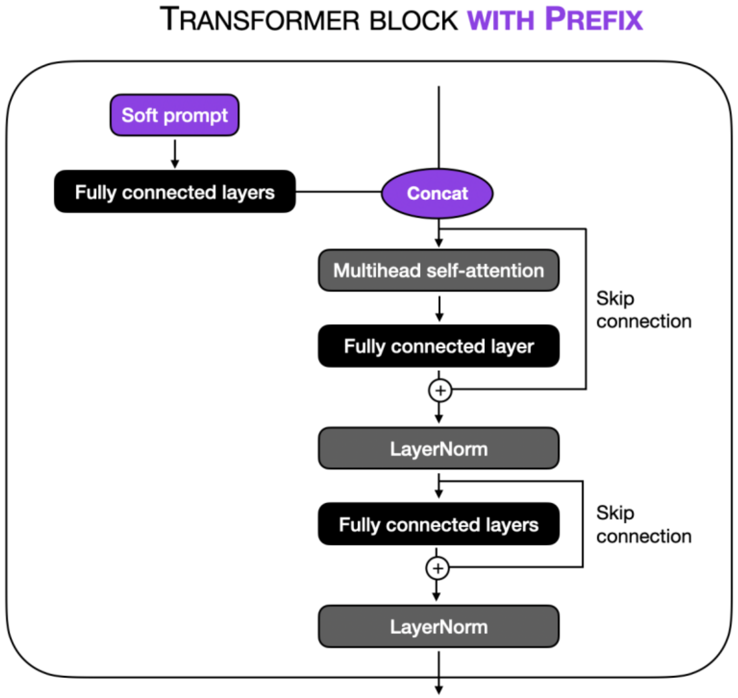
Prefix Tuning (Li & Liang 2021)







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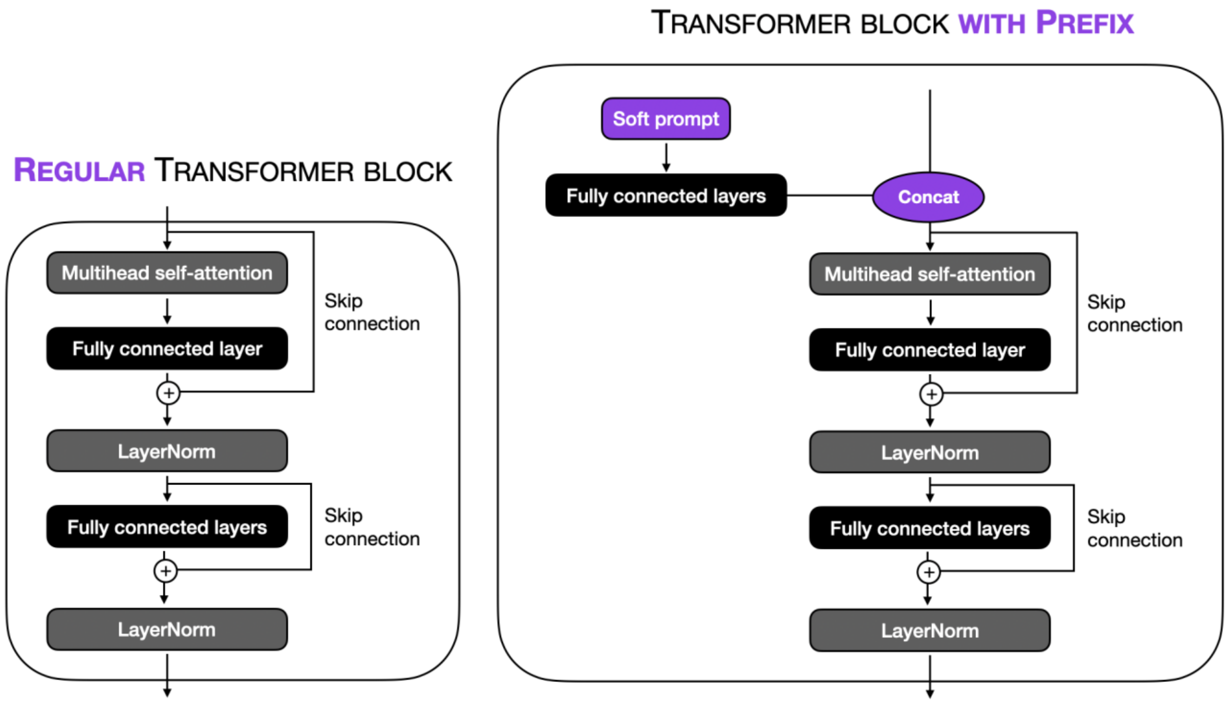
Prefix Tuning (Li & Liang 2021)

Let P denote the prefix sequence and $|P|$ denote the length of the prefix sequence



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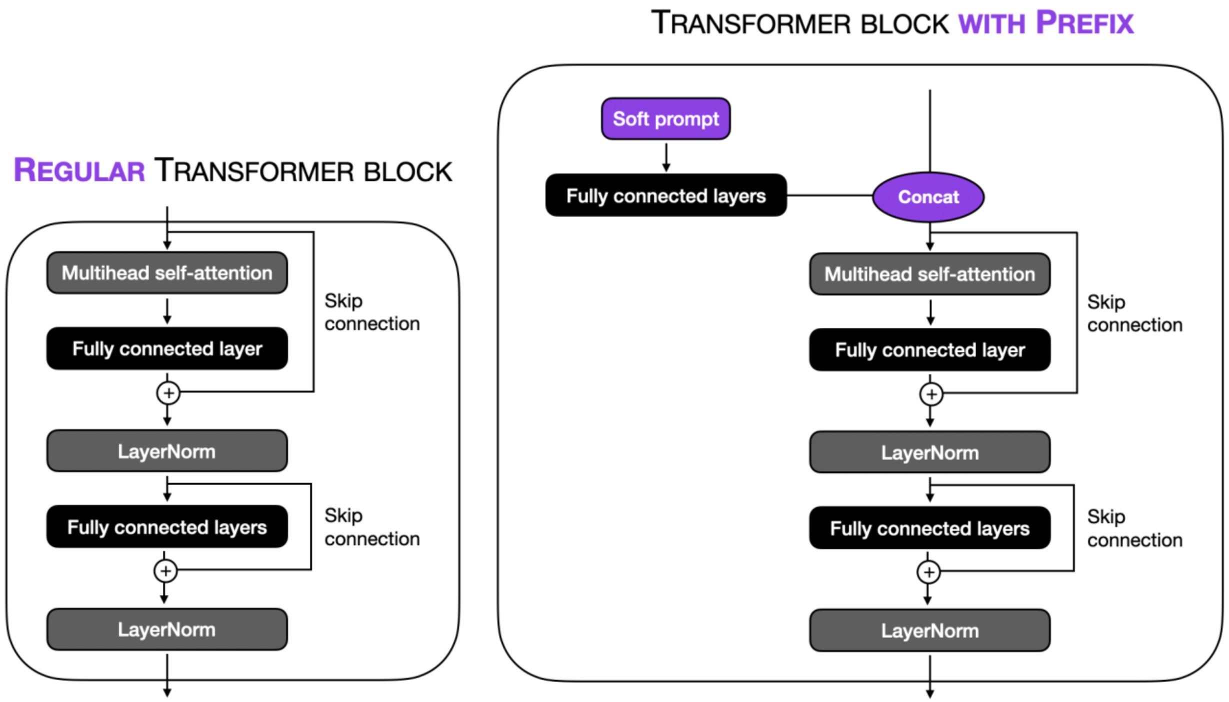

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Let f_θ denote the prefix token p_i to hidden state h_i mapping

$$h_i = f_\theta\,(p_i)$$

f_θ dimensions are $|P|$ x dimension(h_i)

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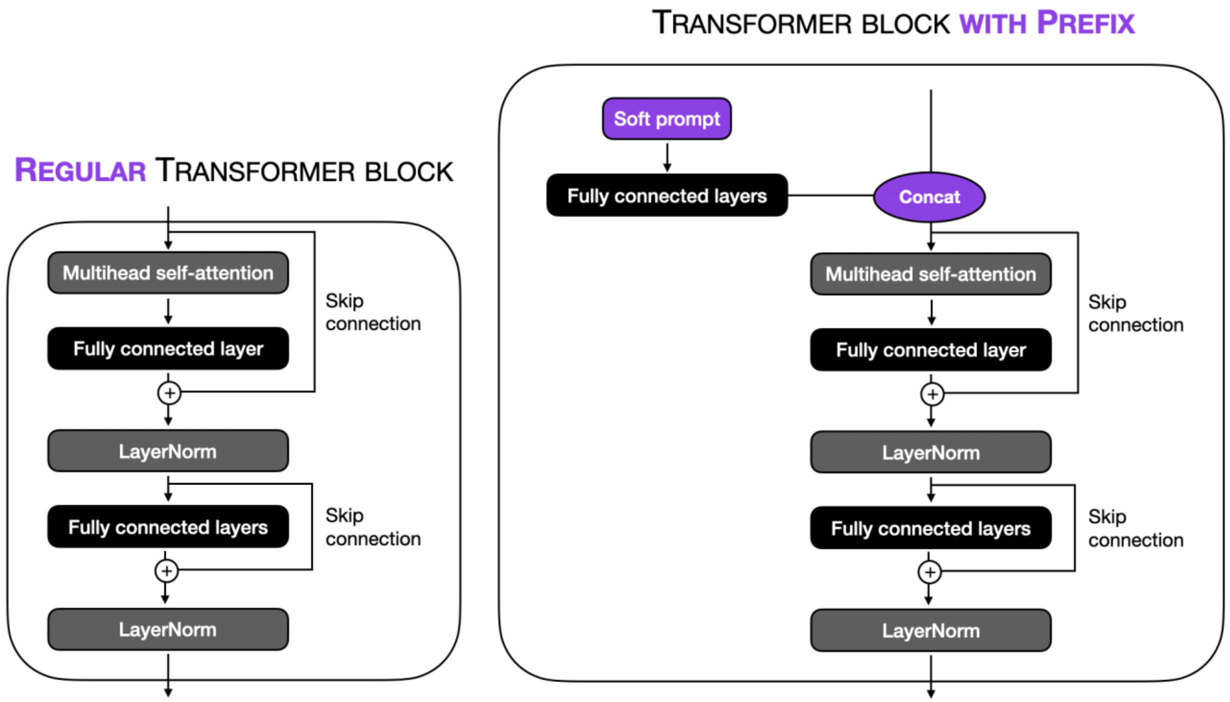

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Unstable Optimization Fix:

$$f_\theta(p_i) = MLP_\theta(f'_\theta(p_i))$$

- f'_θ is smaller than f_θ
- MLP_θ is a large FFN

Prefix Tuning (Li & Liang 2021)

Experimental Setup:

- GPT-2 for table-to-text generation
- BART for summarization

Results:

- by learning only 0.1% of the parameters, prefix-tuning obtains comparable performance to full fine tuning
- extrapolates better to examples with topics unseen during training

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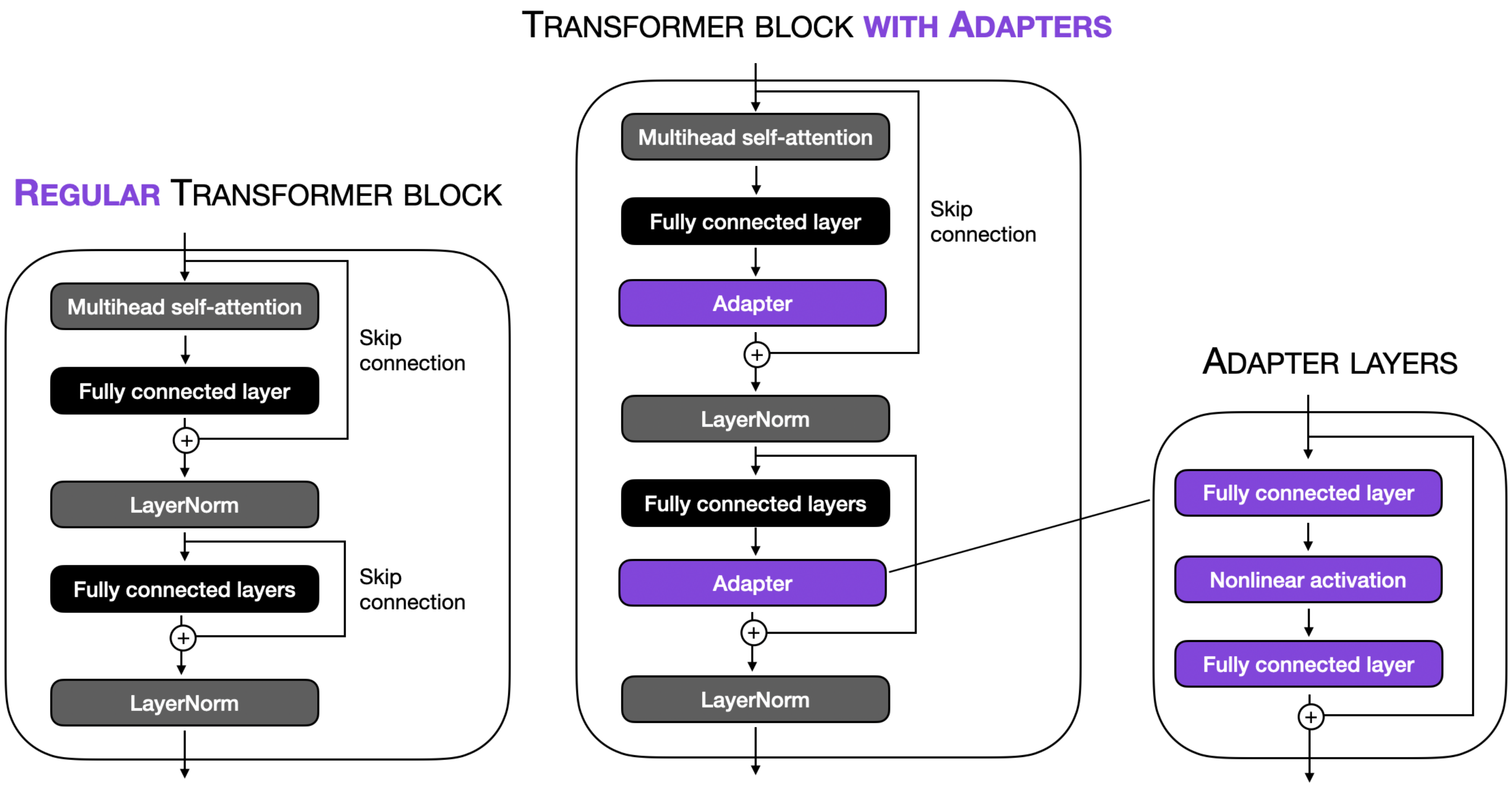
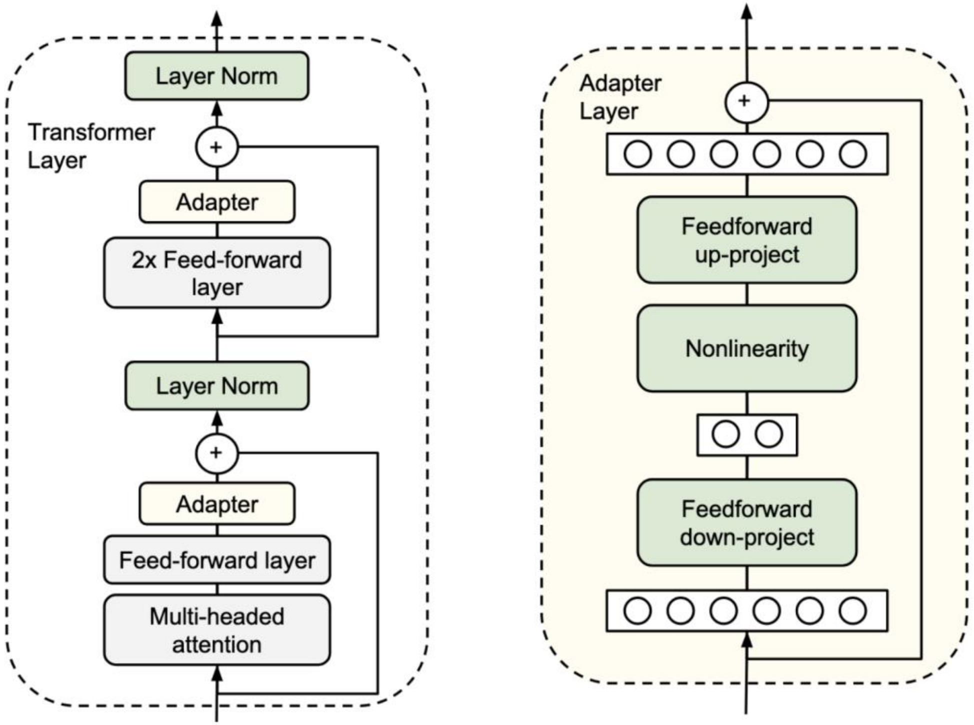
Image Credits: sebastianraschka.com

Adapters (Houlsby et al 2019)



Adapters



Architecture of adapter module and its integration with the transformer [Houlsby et al., 2019]

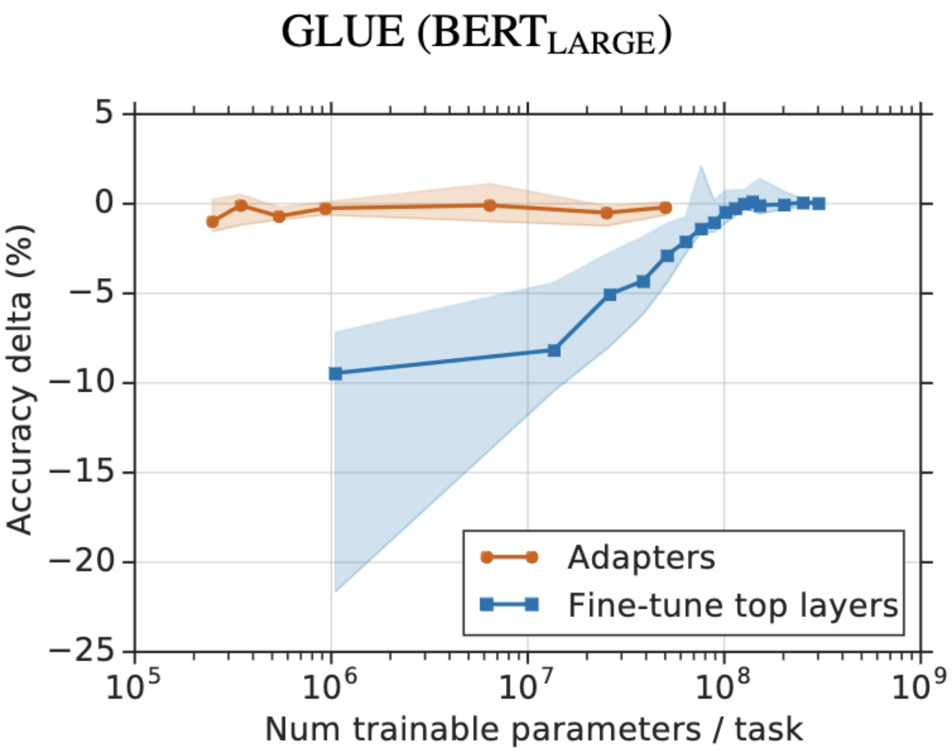
Bottleneck Structure

- significantly reduces the number of parameters
- reduces *d*-dimensional features into a smaller *m*-dimensional vector
- example: *d*=1024 and *m*=24
  - (1024x1024) requires 1,048,576 parameters
  - 2* (1024*24) requires 49,152 parameters
- *m* determines the number of optimizable parameters and hence poses a parameter vs performance trade-off.

Inference Overhead

- Additional adapter in each transformer layer increases the inference latency

Adapters



Accuracy versus the number of trained parameters, aggregated across tasks. The lines and shaded areas indicate the 20th, 50th, and 80th percentiles across tasks. [Houlsby et al., 2021]

- comparable to a fully finetuned BERT model while only requiring the training of 3.6% of the parameters
- when the adapter method is used to tune 3% of the model parameters, the method ties with prefix tuning of 0.1% of the model parameters

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Credit: EMNLP 2022 PEFT Tutorial

Low Rank Composition

- Li et al. [2018] show that models can be optimized in a low-dimensional, randomly oriented subspace rather than the full parameter space

Standard fine-tuning:

$$\theta^{(D)} = \theta_0^{(D)} + \theta_\tau^{(D)}$$

Low-rank fine-tuning:

$$\theta^{(D)} = \theta_0^{(D)} + P\theta^{(d)}$$

A random $D \times d$ projection matrix

Intrinsic Dimensionality (ID)

- Li et al. [2018] refer to the minimum d where a model achieves within 90% of the full-parameter model performance, d_{90} as the intrinsic dimensionality of a task

- Aghajanyan et al. [2021] investigate the intrinsic dimensionality of different NLP tasks and pre-trained models

  - the method of finding the intrinsic dimension proposed by Li et al. (2018) is unaware of the layer-wise structure of the function parameterized by θ

  - Would require about 1TB of memory to store the projection matrix for even BERT based models.

Structure-Aware Intrinsic Dimension (SAID)

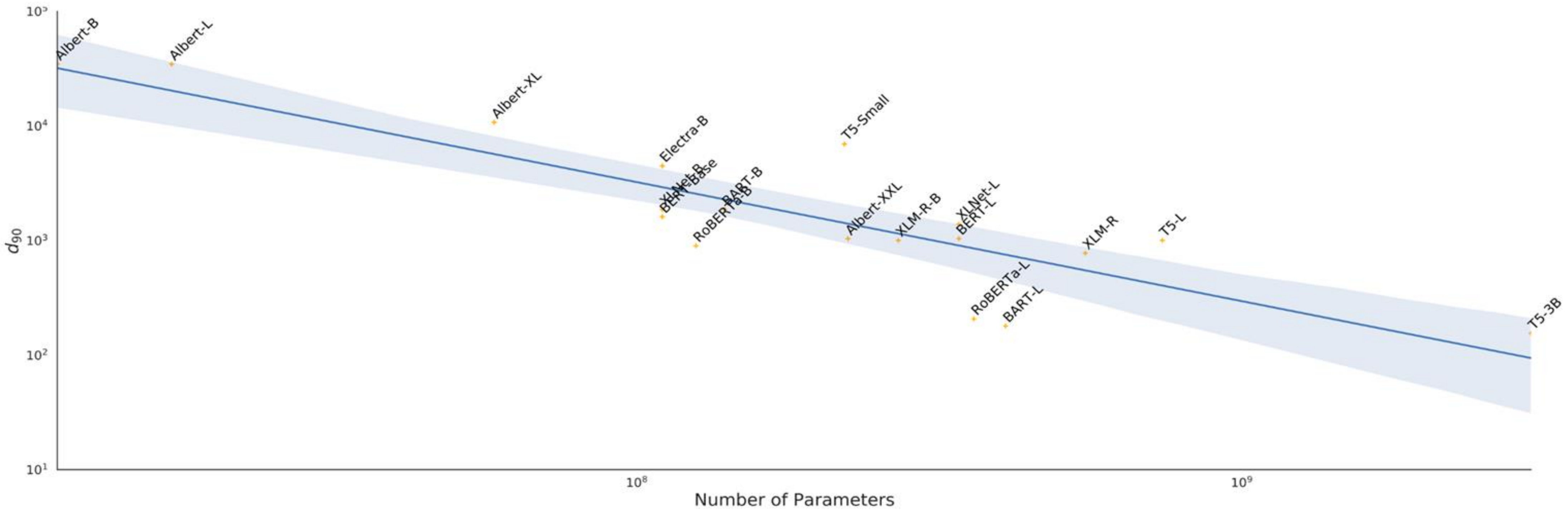
- Aghajanyan et al. [2021] also propose a structure-aware version
- Allocate one scalar λ_i per layer to learn layer-wise scaling:

$$\theta_i^D = \theta_{0,i}^D + \lambda_i P(\theta^{d-m})_i$$

where m is the number of layers in the network

- However, storing the random matrices still requires a lot of extra space and is slow to train [Mahabadi et al., 2021]

Structure-Aware Intrinsic Dimension (SAID)



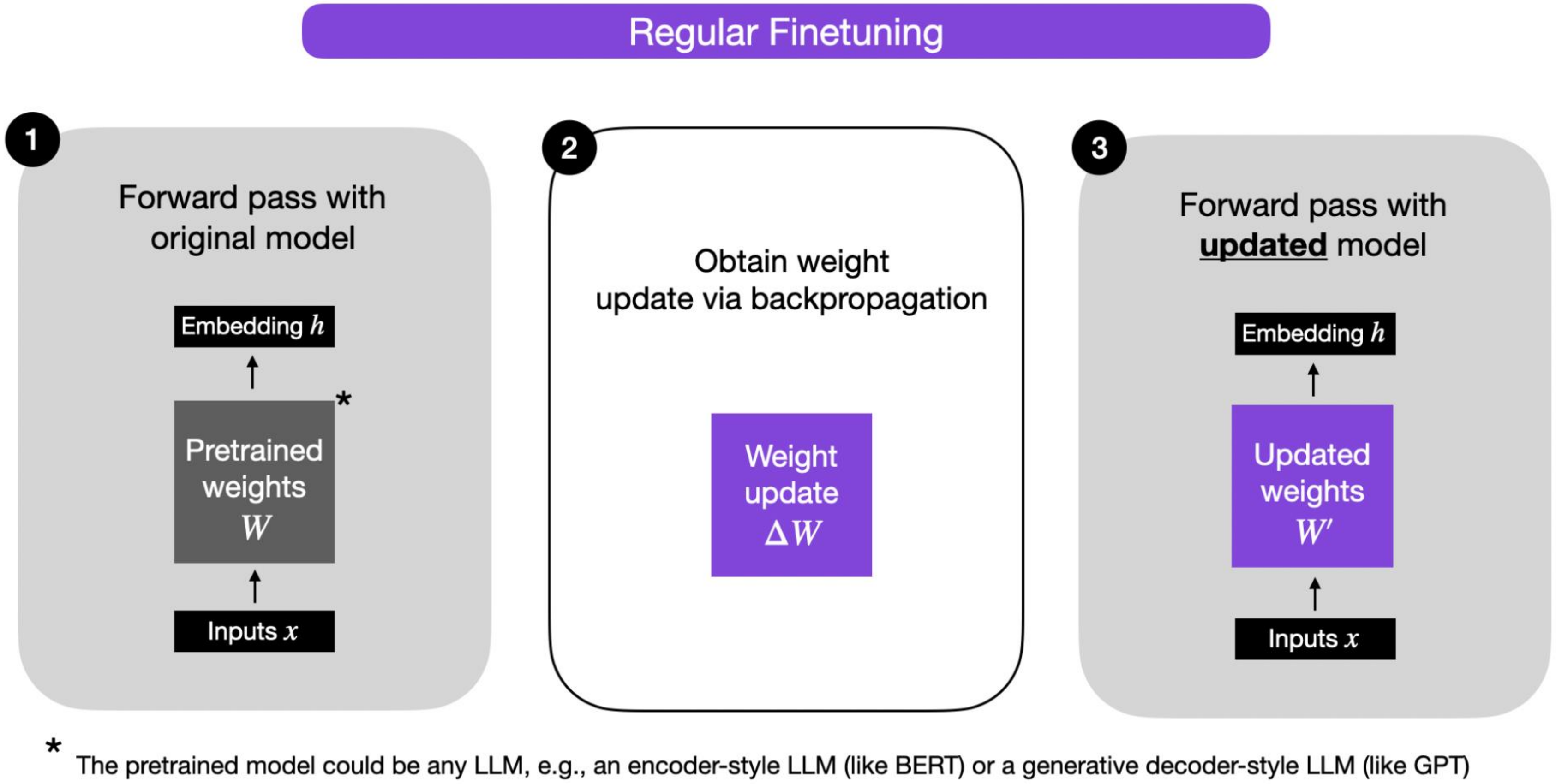
d_{90} on the MRPC dataset for models of different sizes

Structure-Aware Intrinsic Dimension (SAID)

	SAID		ID	
Model	MRPC	QQP	MRPC	QQP
BERT-Base	1608	8030	1861	9295
BERT-Large	1037	1200	2493	1389
RoBERTa-Base	896	896	1000	1389
RoBERTa-Large	**207**	**774**	322	**774**

Estimated d_{90} intrinsic dimension for a set of sentence prediction tasks and common pre-trained models.

Low Rank Adaptation (LoRA)



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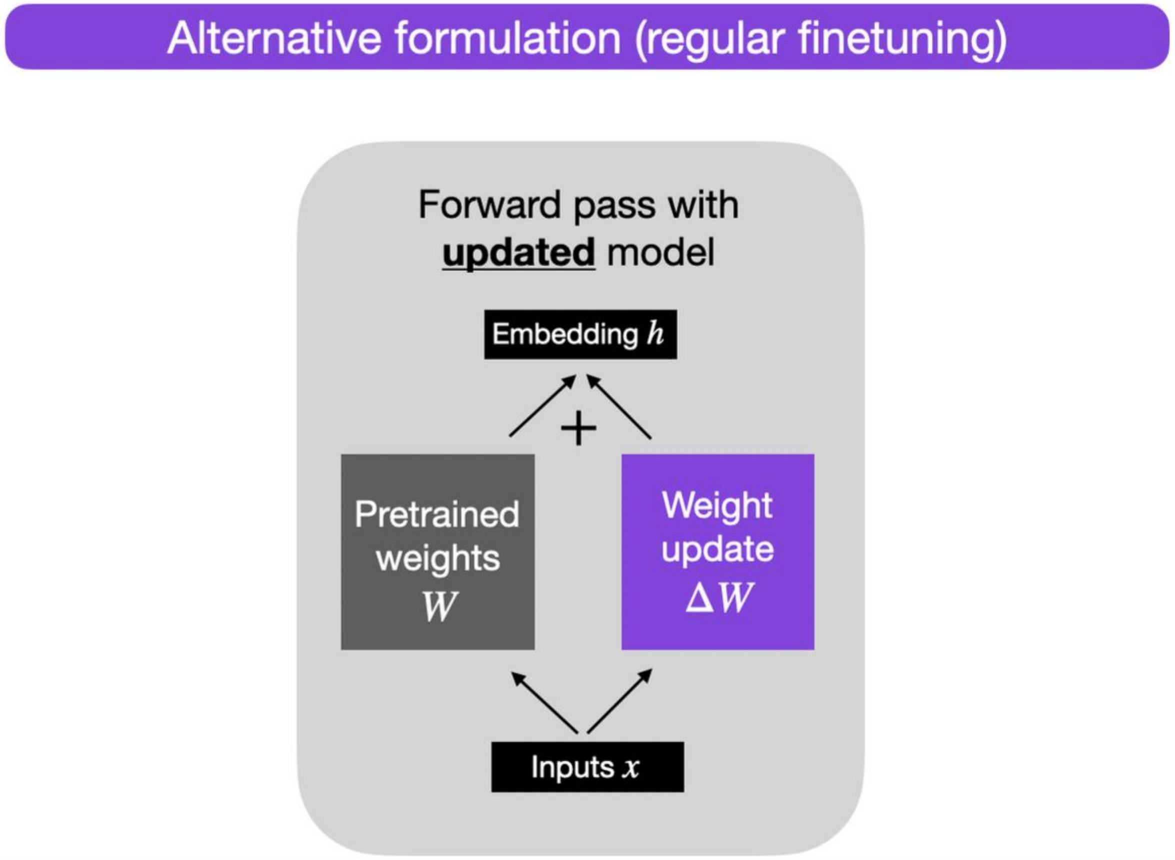

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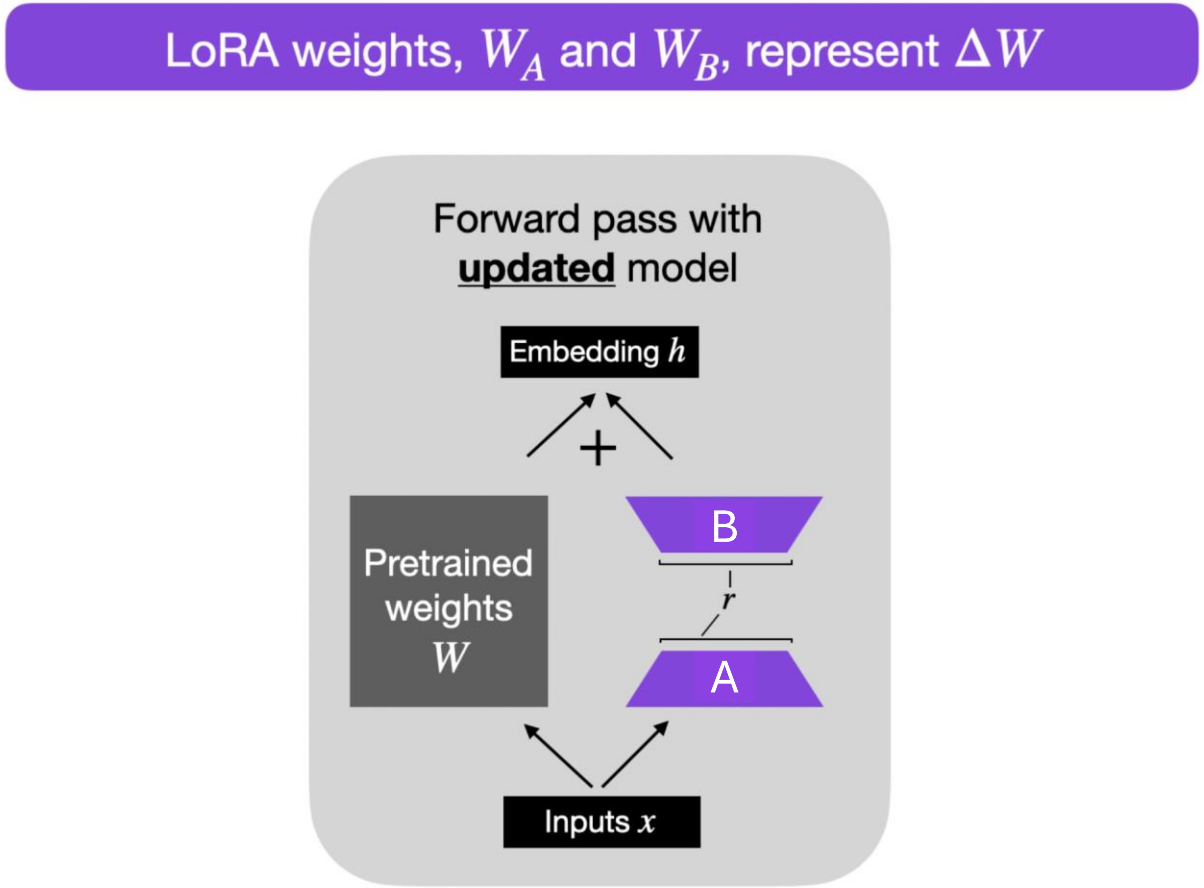


- Instead of learning a low-rank factorization via a random matrix P, we can learn the projection matrix directly - if it is small enough
- Better use of the network structure
- LoRA [Hu et al., 2022] learns two low-rank matrices A and B that are applied to the self-attention weights

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

LoRA

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

Performance of different adaptation methods on GPT-3 175B [Hu et al., 2021]

Effect of Apply LoRA to Weight Matrices in Transformers

	# 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**

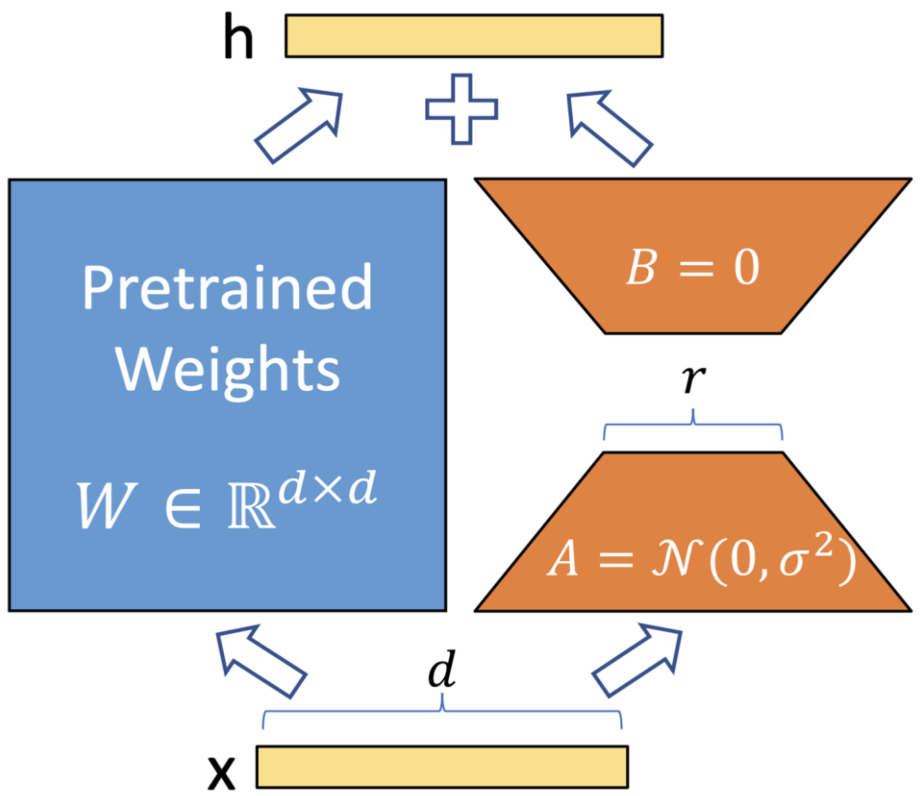
Validation accuracy on WikiSQL and MultiNLI after applying LoRA to different types of attention weights in GPT-3, given the same number of trainable parameters [Hu et al., 2021]

LoRA: Effect of rank on 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

Validation accuracy on WikiSQL and MultiNLI with different rank [Hu et al., 2021]

LoRA Weights Initialization



- By setting B to zero, the product $\Delta W = BA$ initially equals zero. This preserves the behaviour 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

Extensions of LoRA

- QLoRA [Dettmers et al., 2023]
  - backpropagates gradients through 4-bit quantized model for reducing memory usage
- LongLoRA [Chen et al., 2024]
  - sparse local attention to support longer context length during finetuning
- 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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