CS769 Advanced NLP

Parameter-Efficient Fine-Tuning

…and other ways to bypass costly fine-tuning.

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Goals for Today

- What is PEFT and why do we care about it?
- Classes of PEFT methods
- Adapters & $(IA)^3$
- Prefix-tuning & Prompt-tuning
- LoRA & Q-LoRA
- Bonus: Alternate methods for tuning-free adaptation

Background: Open-source LMs

- Language models are becoming larger over time, so it's computationally expensive to fine-tune these open-source LMs

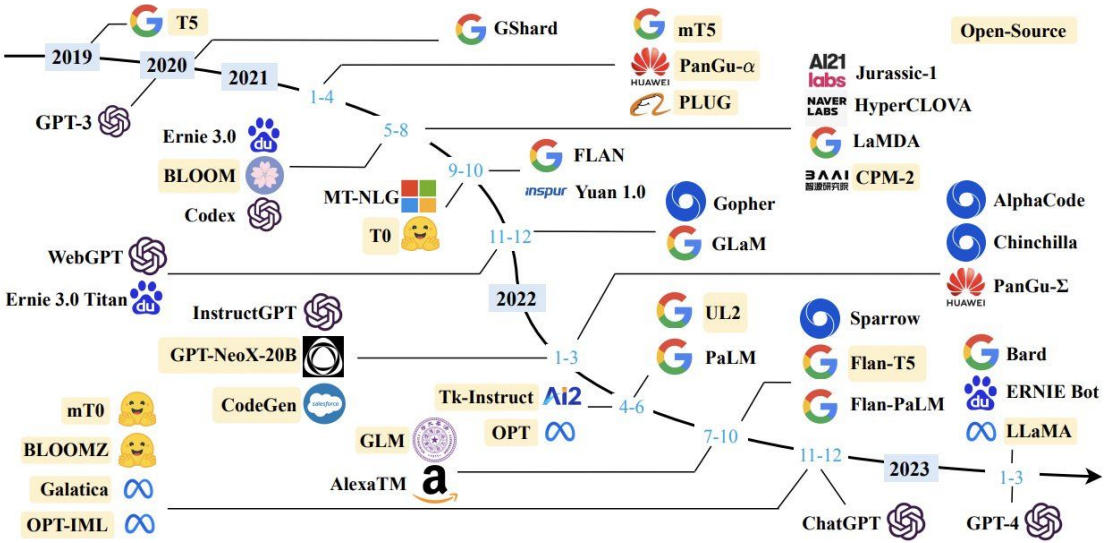
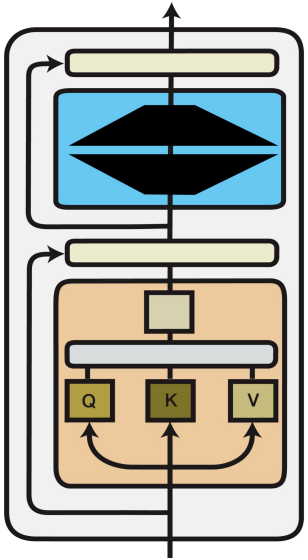


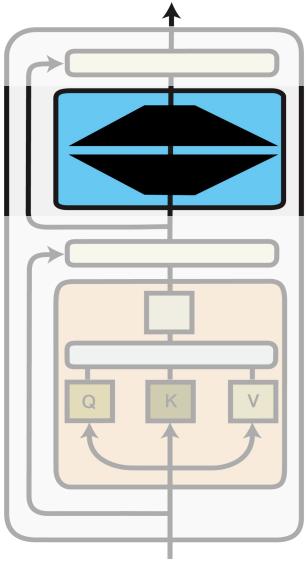
Fig. 1. A timeline of existing large language models (having a size larger than 10B) in recent years. We mark the open-source LLMs in yellow color.

From Fine-tuning to Parameter-efficient Fine-tuning



Full Fine-tuning

Update **all model parameters**



Parameter-efficient Fine-tuning

Update a **small subset** of model parameters

Slide from: EMNLP 2022 Tutorial on *Modular and Parameter-Efficient Fine-Tuning for NLP Models*

Motivation: Why PEFT?

- PEFT: Fine-tune a small amount of model parameters (instead of the entire model) on a small dataset of downstream tasks. Other parameters are frozen.
- Benefits:
  - Reduce the computational and storage costs
  - Mitigate catastrophic forgetting — forgetting often occur when the model changes a lot after fine-tuning. PEFT can be regarded as a regularization on the difference between the two checkpoints before and after PEFT.
  - Easy to update models to new data and facts
  - Better performance in low-data regimes
  - Comparable performance to full fine-tuning

To PEFT or not to PEFT?
PEFT vs Fine-Tuning

	PEFT	Full Fine-tuning
Learnable parameters		
Training Performance		
Training Data		
Training Time		
Overfitting / forgetting		

To PEFT or not to PEFT?
PEFT vs Fine-Tuning

	PEFT	**Full Fine-tuning**
Learnable parameters	A small subset	Entire model
Training Performance		
Training Data		
Training Time		
Overfitting / forgetting		

To PEFT or not to PEFT?
PEFT vs Fine-Tuning

	PEFT	**Full Fine-tuning**
Learnable parameters	A small subset	Entire model
Training Performance	Close to fine-tuning	…is fine-tuning :P
Training Data		
Training Time		
Overfitting / forgetting		

To PEFT or not to PEFT?
PEFT vs Fine-Tuning

	PEFT	**Full Fine-tuning**
Learnable parameters	A small subset	Entire model
Training Performance	Close to fine-tuning	…is fine-tuning :P
Training Data	Small	Large
Training Time		
Overfitting / forgetting		

To PEFT or not to PEFT?
PEFT vs Fine-Tuning

	PEFT	**Full Fine-tuning**
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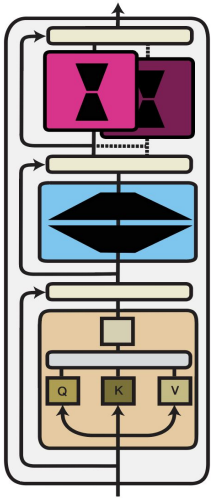
Training Data	Small	Large
Training Time	Faster	Longer training time
Overfitting / forgetting		

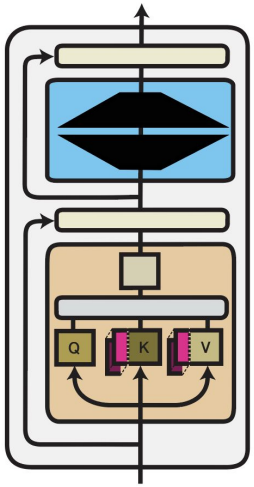
To PEFT or not to PEFT?
PEFT vs Fine-Tuning

	PEFT	**Full Fine-tuning**
Learnable parameters	A small subset	Entire model
Training Performance	Close to fine-tuning	…is fine-tuning :P
Training Data	Small	Large
Training Time	Faster	Longer training time
Overfitting / forgetting	Less prone to overfitting	More prone to overfitting

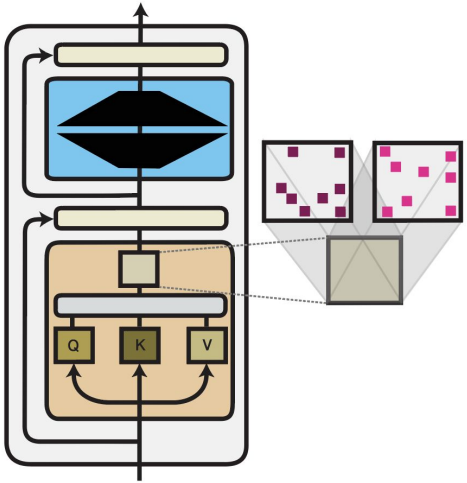
Three Computation Functions



Function Composition



Input Composition



Parameter Composition

Slide from: EMNLP 2022 Tutorial on *Modular and Parameter-Efficient Fine-Tuning for NLP Models*

Three Computation Functions

Let a neural network $f_\theta : \mathcal{X} \rightarrow \mathcal{Y}$ be decomposed into a composition of functions:

$f_{\theta_1} \odot f_{\theta_2} \odot \cdots \odot f_{\theta_l}$ Each has parameters $\theta_i, i = 1, \ldots, l$

A module with parameters ϕ can modify the *i*-th sub-function as follows:

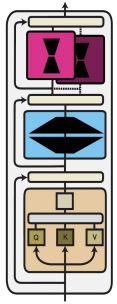
1. Function composition: $f'_i(\boldsymbol{x}) = f_{\theta_i} \odot f_\phi(\boldsymbol{x})$ Function composition
2. Input composition: $f'_i(\boldsymbol{x}) = f_{\theta_i}([\boldsymbol{x}, \phi])$ Concatenation
3. Parameter composition: $f'_i(\boldsymbol{x}) = f_{\theta_i \oplus \phi}(\boldsymbol{x})$ Interpolation, e.g., element-wise addition

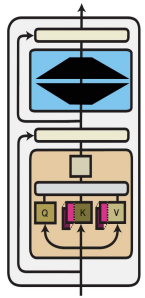
In practice, typically only the module parameters ϕ are updated while θ is fixed.

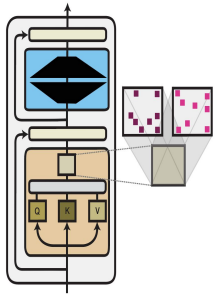
Slide from: EMNLP 2022 Tutorial on *Modular and Parameter-Efficient Fine-Tuning for NLP Models*

Three Computation Functions

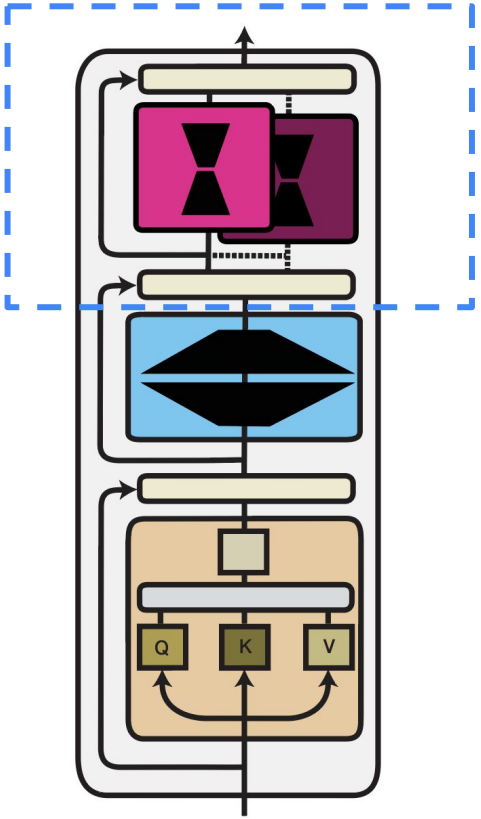
	Function Composition	Input Composition	Parameter Composition
Example Methods	Adapters, $(IA)^3$	Prompt Tuning, Prefix Tuning	LoRA, QLoRA
Impact on Model Size	Additional modules in layers	Context window of model is increased	No increase in model size
Performance	Matches or outperforms fine-tuning	Good with large models	Good







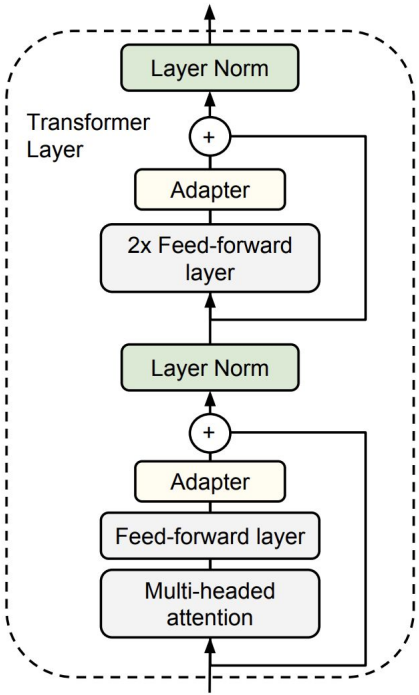
Function Composition: Adapters, $(IA)^3$

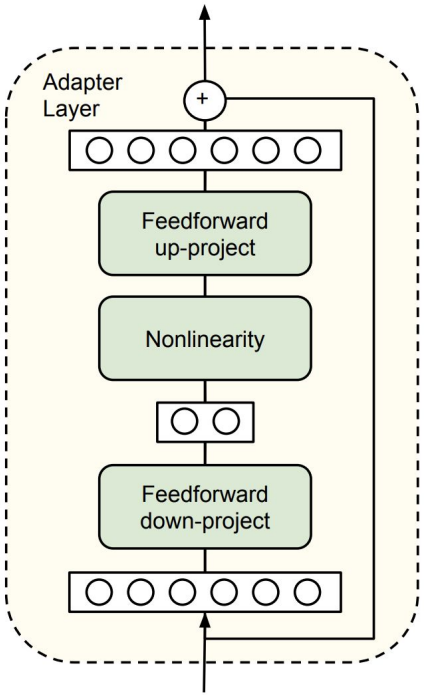


Adapter

- An adapter is a MLP network.
- Add an adapter after the feed-forward layer in each Transformer layer

$$f_{\phi_i}(\boldsymbol{x}) = W^U(\sigma(W^D\boldsymbol{x}))$$

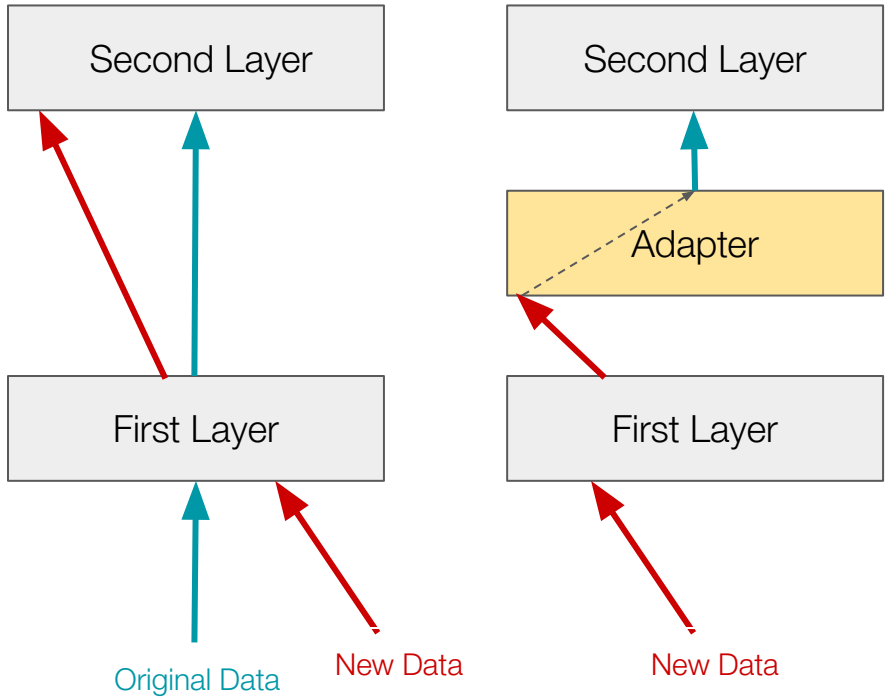




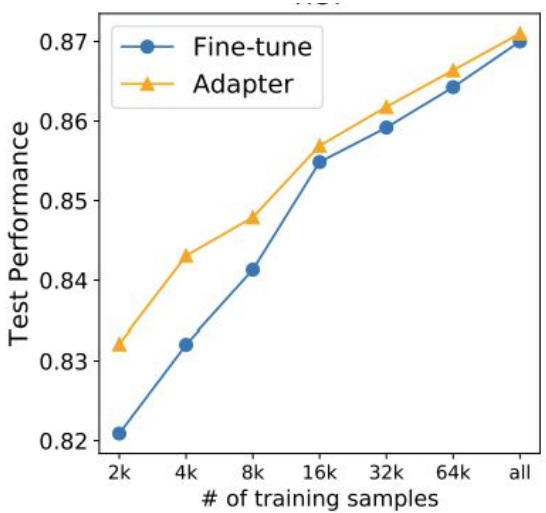
Houlsby et al ICML 2019. Parameter-Efficient Transfer Learning for NLP. https://arxiv.org/pdf/1902.00751.pdf

Why does this work? One Possible Intuition

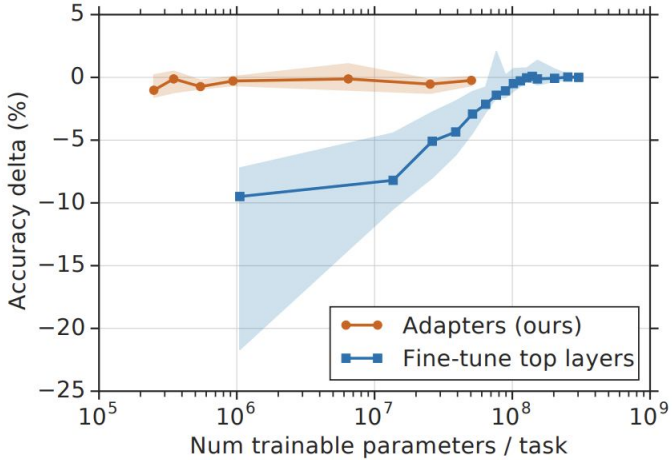
- Oversimplified setting: Each layer is a matrix which transforms the input to a new space
- Adapters help “reroute” the data embeddings to what the upper layer expects



Adapters vs Full Fine-tuning



Adapters ~> FT with less data

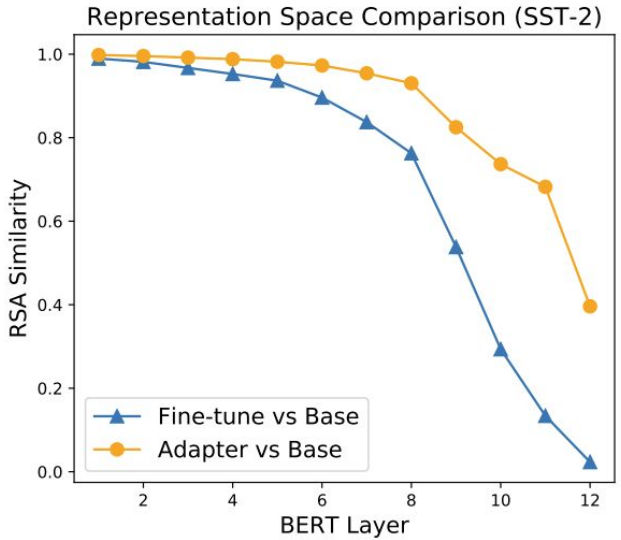


Adapters > FT with less params

He et al. ACL 2021. On the Effectiveness of Adapter-based Tuning for Pretrained Language Model Adaptation. https://arxiv.org/abs/2106.03164
Houlsby et al ICML 2019. Parameter-Efficient Transfer Learning for NLP. https://arxiv.org/pdf/1902.00751.pdf

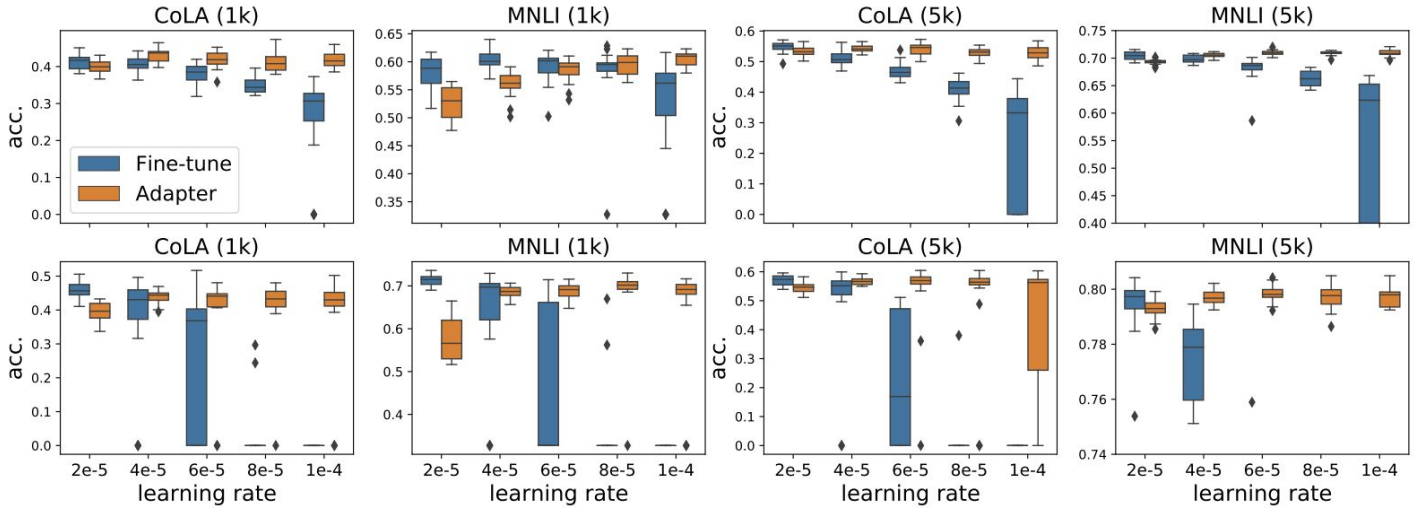
Adapters vs Full Fine-tuning

- In practice, Adapters change the embeddings less than fine-tuning



He et al. ACL 2021. On the Effectiveness of Adapter-based Tuning for Pretrained Language Model Adaptation. https://arxiv.org/abs/2106.03164

Adapters vs Full Fine-tuning



Adapters are less sensitive to hyperparameters like learning rate

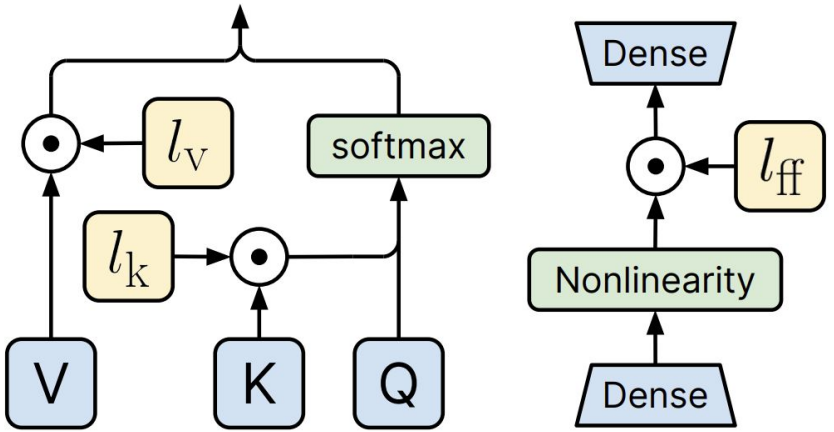
He et al. ACL 2021. On the Effectiveness of Adapter-based Tuning for Pretrained Language Model Adaptation. https://arxiv.org/abs/2106.03164

$(IA)^3$

- Instead of learning a function, even rescaling via element-wise multiplication can be powerful:

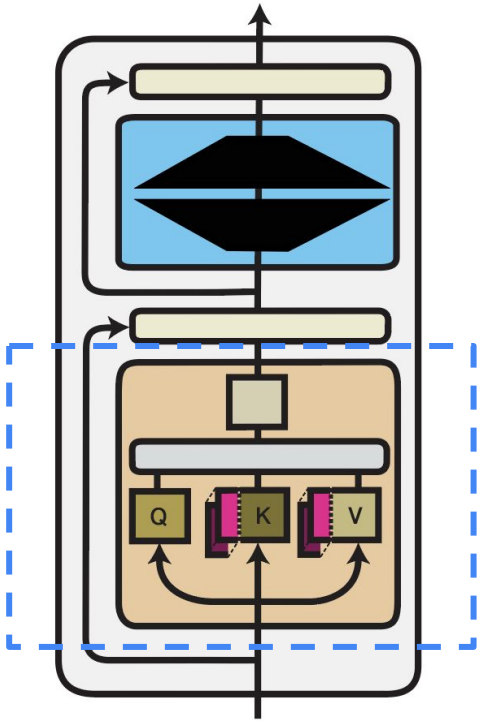
$$f_i'(\boldsymbol{x}) = f_{\theta_i}(\boldsymbol{x}) \circ \phi_i$$

- Allows the model to select parameters that are more and less important for a given task



Liu et al NeurIPS 2022. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. https://arxiv.org/abs/2205.05638

Input Composition: Prompt-tuning, Prefix-tuning

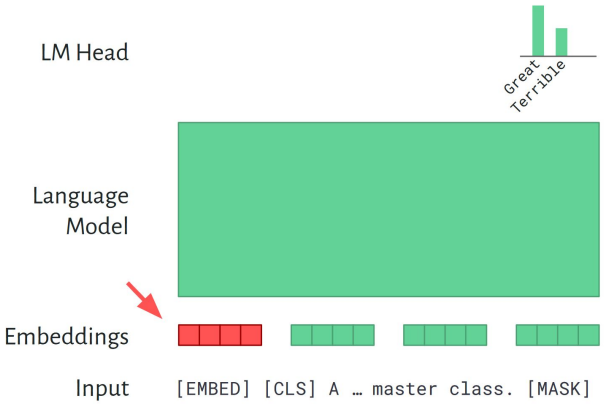


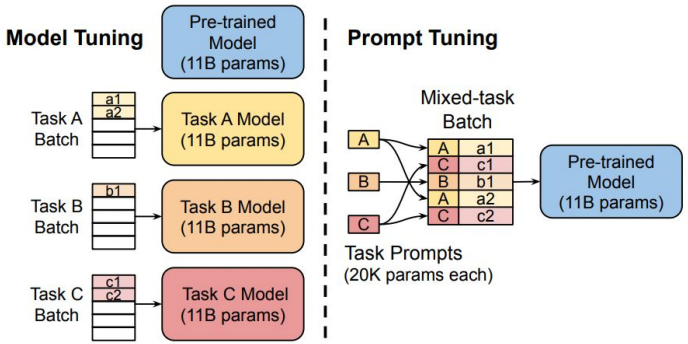
Motivation: Prompting!

- Prompting with text: Prepending instructive words or demonstrations before the actual test input
- Standard prompting can be seen as finding a discrete text prompt that—when embedded using the model's embedding layer—yields ϕ_i
- However, models are sensitive to the formulation of the prompt and to the order of examples
- Why not skip the words and directly learn an appropriate ϕ_i?

Prompt Tuning

- Prompt tuning only updates a small task-specific prompt parameters for each task, enables mixed task inference.
- Fine-tuning (Model tuning): make a task-specific copy of the entire pre-trained LMs for each task, and inference must be performed in separate batches.

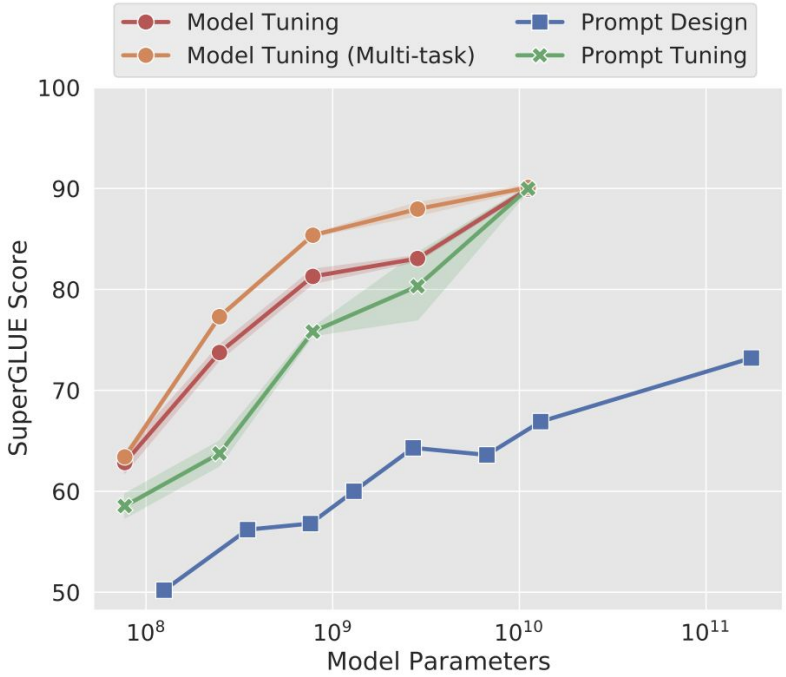




Lester et al. EMNLP 2021. The Power of Scale for Parameter-Efficient Prompt Tuning. https://arxiv.org/abs/2104.08691

Prompt Tuning vs Model Tuning

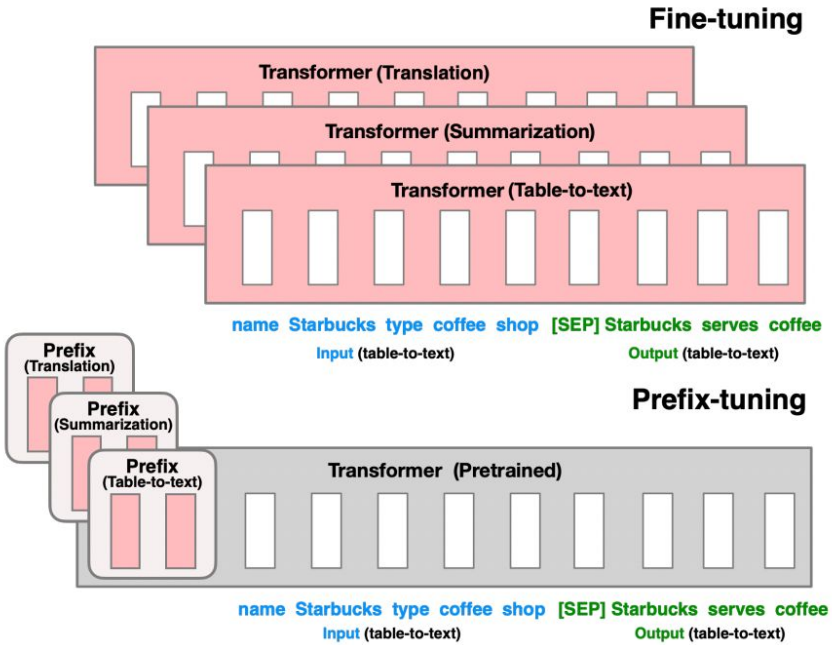
- As model size increases (e.g., T5-XXL 11B model), prompt tuning of T5 (green curve) matches the performance of (full) model tuning (red/orange curves) on SuperGLUE.
- Prompt design: few-shot in-context prediction by GPT-3 (blue curve) is still way worse than fine-tuning.



Prefix Tuning / Multi-Layer Prompt Tuning

- Add learnable parameters at the beginning of the input sequence over all Transformer layers.
- Use different prefix parameters for different tasks, and keep the other parameters frozen

$$z = [\textsc{Prefix}; x; y]$$



Li et al. ACL 2021. Prefix-Tuning: Optimizing Continuous Prompts for Generation. https://arxiv.org/pdf/2101.00190.pdf

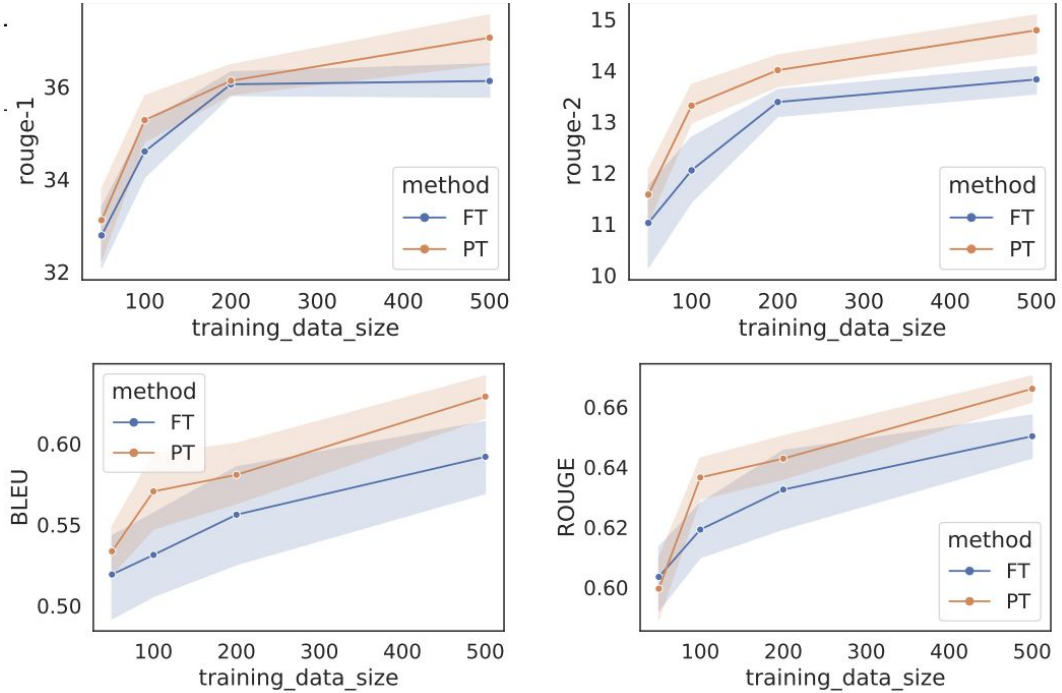
Effective on NLG tasks w/ 0.1% parameters

- Evaluate on three table-to-text generation datasets: E2E, WebNLG, and DART
- Continuous prompts in later layers are more important

	E2E					WebNLG									DART					
	BLEU	NIST	MET	R-L	CIDEr	BLEU			MET			TER ↓			BLEU	MET	TER ↓	Mover	BERT	BLEURT
						S	U	A	S	U	A	S	U	A						
GPT-2$_{\text{MEDIUM}}$																				
FINE-TUNE	68.2	8.62	**46.2**	71.0	2.47	**64.2**	27.7	46.5	**0.45**	0.30	0.38	**0.33**	0.76	0.53	46.2	**0.39**	**0.46**	**0.50**	**0.94**	**0.39**
FT-TOP2	68.1	8.59	46.0	70.8	2.41	53.6	18.9	36.0	0.38	0.23	0.31	0.49	0.99	0.72	41.0	0.34	0.56	0.43	0.93	0.21
ADAPTER(3%)	68.9	8.71	46.1	71.3	2.47	60.4	**48.3**	54.9	0.43	**0.38**	**0.41**	0.35	**0.45**	**0.39**	45.2	0.38	**0.46**	**0.50**	**0.94**	**0.39**
ADAPTER(0.1%)	66.3	8.41	45.0	69.8	2.40	54.5	45.1	50.2	0.39	0.36	0.38	0.40	0.46	0.43	42.4	0.36	0.48	0.47	**0.94**	0.33
PREFIX(0.1%)	**69.7**	**8.81**	46.1	**71.4**	**2.49**	62.9	45.6	**55.1**	0.44	**0.38**	**0.41**	0.35	0.49	0.41	**46.4**	0.38	**0.46**	**0.50**	**0.94**	**0.39**
GPT-2$_{\text{LARGE}}$																				
FINE-TUNE	68.5	8.78	46.0	69.9	2.45	**65.3**	43.1	55.5	**0.46**	0.38	**0.42**	**0.33**	0.53	0.42	**47.0**	**0.39**	0.46	**0.51**	**0.94**	**0.40**
Prefix	**70.3**	**8.85**	**46.2**	**71.7**	**2.47**	63.4	**47.7**	**56.3**	0.45	**0.39**	**0.42**	0.34	**0.48**	**0.40**	46.7	**0.39**	**0.45**	**0.51**	**0.94**	**0.40**
SOTA	68.6	8.70	45.3	70.8	2.37	63.9	52.8	57.1	0.46	0.41	0.44	-	-	-	-	-	-	-	-	-

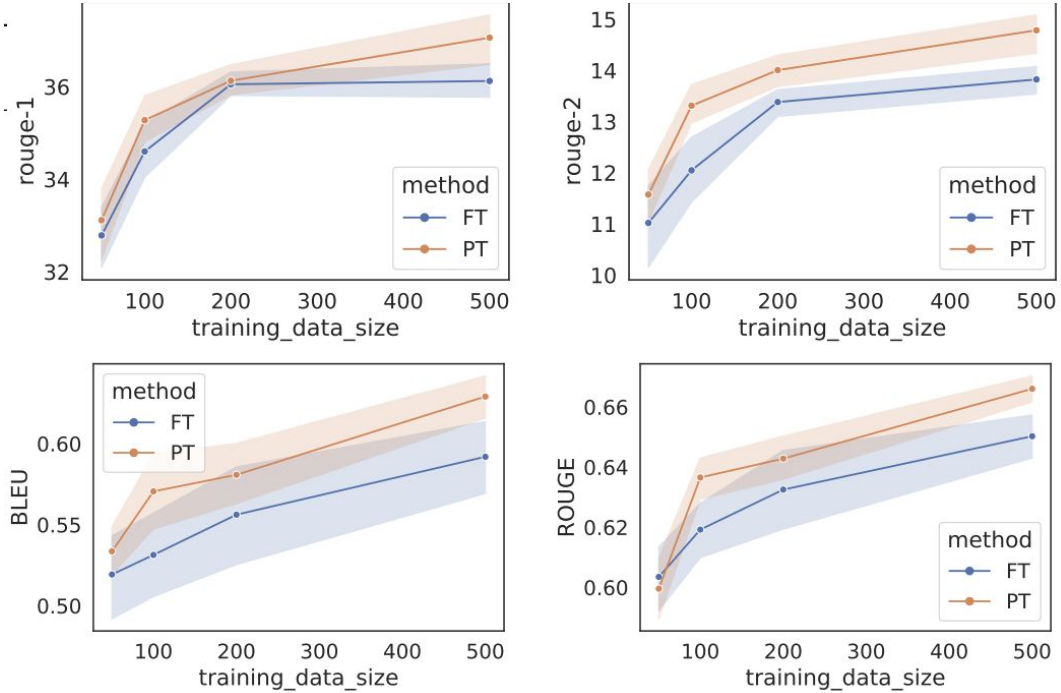
Low-Data Setting

- Performs comparative to fine-tuning in low-data regimes
- Cool! But why?

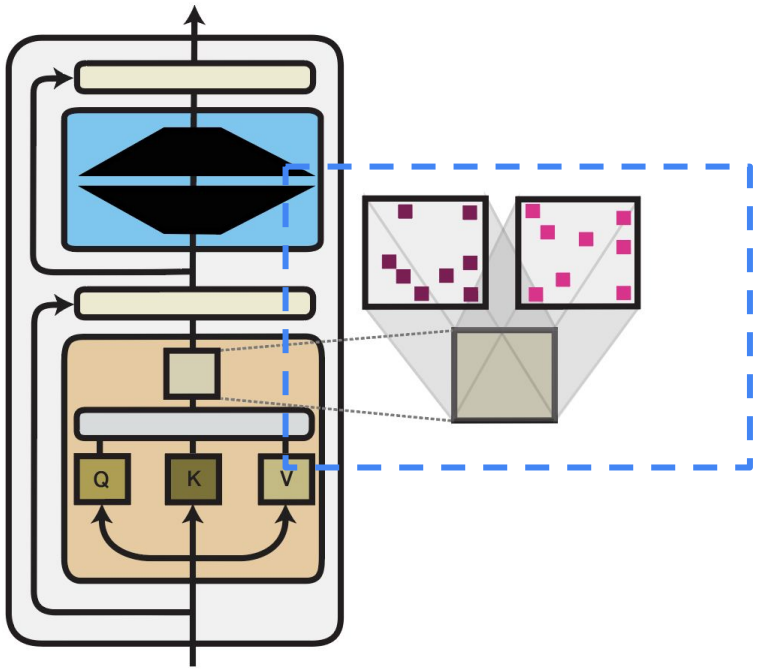


Low-Data Setting

- Performs comparative to fine-tuning in low-data regimes
- Cool! But why?
- Fine-tuning is likely overfitting.



Parameter Composition: LoRA and Q-LoRA



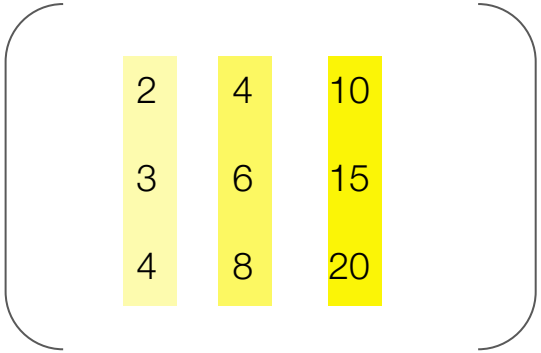
LoRA

- First, what is the ***rank*** of a matrix?

$$\begin{pmatrix} 2 & 4 & 10 \\ 3 & 6 & 15 \\ 4 & 8 & 20 \end{pmatrix} \qquad \begin{pmatrix} 2 & 5 & 11 \\ 3 & 7 & 16 \\ 4 & 9 & 21 \end{pmatrix}$$

Low Rank Adaptation

- First, what is the rank of a matrix?



Rank = 1

Rank = 3

Full-rank

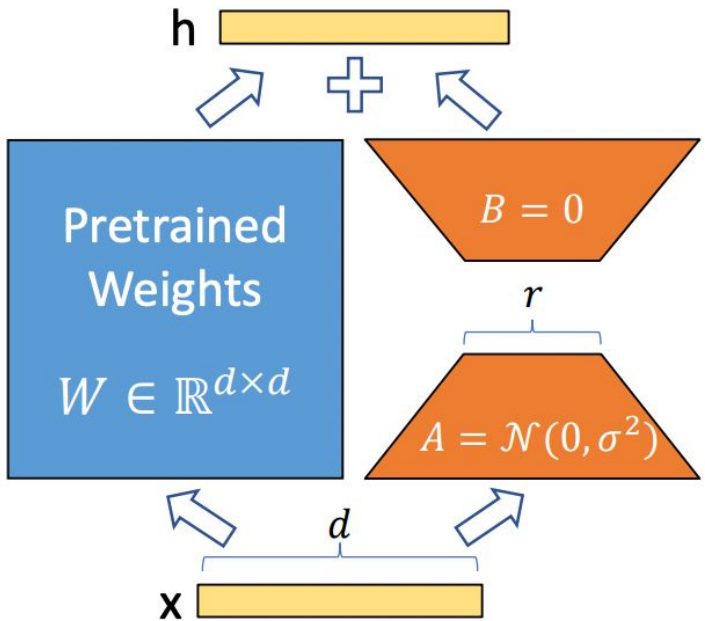
Low Rank Adaptation

- Approximate the self-attention update of a learnable weight by a low-rank matrix

$$\Delta W = BA$$

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

- The initial update is 0
- After training, the updates are added back to the original checkpoint. So, the inference cost of the updated checkpoint is the same as the original checkpoint.



Hu et al. ICLR 2021. LoRA: Low-Rank Adaptation of Large Language Models. https://arxiv.org/pdf/2106.09685.pdf

Setting up LoRA with HuggingFace:

Code demo here!

```
PeftModel(
  (base_model): LoraModel(
    (model): GPT2LMHeadModel(
      (transformer): GPT2Model(
        (wte): Embedding(50257, 768)
        (wpe): Embedding(1024, 768)
        (drop): Dropout(p=0.1, inplace=False)
        (h): ModuleList(
          (0-11): 12 x GPT2Block(
            (ln_1): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
            (attn): GPT2Attention(
              (c_attn): lora.Linear(
                (base_layer): Conv1D(nf=2304, nx=768)
                (lora_dropout): ModuleDict(
                  (default): Identity()
                )
                (lora_A): ModuleDict(
                  (default): Linear(in_features=768, out_features=64, bias=False)
                )
                (lora_B): ModuleDict(
                  (default): Linear(in_features=64, out_features=2304, bias=False)
                )
                (lora_embedding_A): ParameterDict()
                (lora_embedding_B): ParameterDict()
                (lora_magnitude_vector): ModuleDict()
              )
              (c_proj): Conv1D(nf=768, nx=768)
              (attn_dropout): Dropout(p=0.1, inplace=False)
              (resid_dropout): Dropout(p=0.1, inplace=False)
            )
            (ln_2): LayerNorm((768,), eps=1e-05, elementwise_affine=True)
            (mlp): GPT2MLP(
              (c_fc): Conv1D(nf=3072, nx=768)
              (c_proj): Conv1D(nf=768, nx=3072)
              (act): NewGELUActivation()
              (dropout): Dropout(p=0.1, inplace=False)
            )
          )
```

LoRA works better than other PEFT

- GPT-2 Medium (355M) and Large (774M) models

Model & Method	# Trainable Parameters	E2E NLG Challenge				
		BLEU	NIST	MET	ROUGE-L	CIDEr
GPT-2 M (FT)*	354.92M	68.2	8.62	46.2	71.0	2.47
GPT-2 M ($\text{Adapter}^{\text{L}}$)*	0.37M	66.3	8.41	45.0	69.8	2.40
GPT-2 M ($\text{Adapter}^{\text{L}}$)*	11.09M	68.9	8.71	46.1	71.3	2.47
GPT-2 M ($\text{Adapter}^{\text{H}}$)	11.09M	$67.3_{\pm.6}$	$8.50_{\pm.07}$	$46.0_{\pm.2}$	$70.7_{\pm.2}$	$2.44_{\pm.01}$
GPT-2 M (FT^{Top2})*	25.19M	68.1	8.59	46.0	70.8	2.41
GPT-2 M (PreLayer)*	0.35M	69.7	8.81	46.1	71.4	2.49
GPT-2 M (LoRA)	0.35M	$\mathbf{70.4}_{\pm.1}$	$\mathbf{8.85}_{\pm.02}$	$\mathbf{46.8}_{\pm.2}$	$\mathbf{71.8}_{\pm.1}$	$\mathbf{2.53}_{\pm.02}$
GPT-2 L (FT)*	774.03M	68.5	8.78	46.0	69.9	2.45
GPT-2 L ($\text{Adapter}^{\text{L}}$)	0.88M	$69.1_{\pm.1}$	$8.68_{\pm.03}$	$46.3_{\pm.0}$	$71.4_{\pm.2}$	$\mathbf{2.49}_{\pm.0}$
GPT-2 L ($\text{Adapter}^{\text{L}}$)	23.00M	$68.9_{\pm.3}$	$8.70_{\pm.04}$	$46.1_{\pm.1}$	$71.3_{\pm.2}$	$2.45_{\pm.02}$
GPT-2 L (PreLayer)*	0.77M	70.3	8.85	46.2	71.7	2.47
GPT-2 L (LoRA)	0.77M	$\mathbf{70.4}_{\pm.1}$	$\mathbf{8.89}_{\pm.02}$	$\mathbf{46.8}_{\pm.2}$	$\mathbf{72.0}_{\pm.2}$	$2.47_{\pm.02}$

Why does this work? Intrinsic Dimensions

- Intrinsic Dimensionality: Smallest *d* for which models achieve 90% of original accuracy
  - Intrinsic dimensionality decreases during pre-training
  - Larger models have lower intrinsic dimensionality
- Essentially, weights are already low rank. So the new updates can be low rank too.
- Models can be optimized in a low-dimensional, randomly oriented subspace rather than the full parameter space

Standard fine-tuning:

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

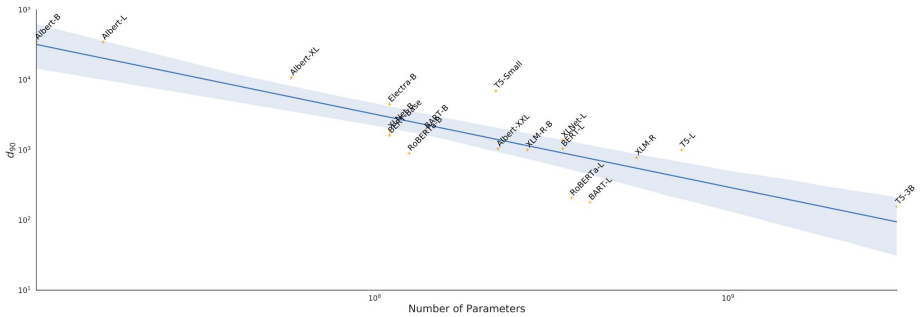
Low-rank fine-tuning:

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

Li et al. ICLR 2018. Measuring the Intrinsic Dimension of Objective Landscapes. https://arxiv.org/abs/1804.08838
Aghajanyan et al. ACL 2021. Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning. https://arxiv.org/abs/2012.13255

Intrinsic Dimensions

- Pre-training provides a strong initialization, i.e. a good $\theta_0^{(D)}$ in *D* dimensional space
- Due to this, the model only needs to explore a subspace of *d* dimensions during fine-tuning (through $\theta^{(d)}$), to learn the final weights $\theta^{(D)}$



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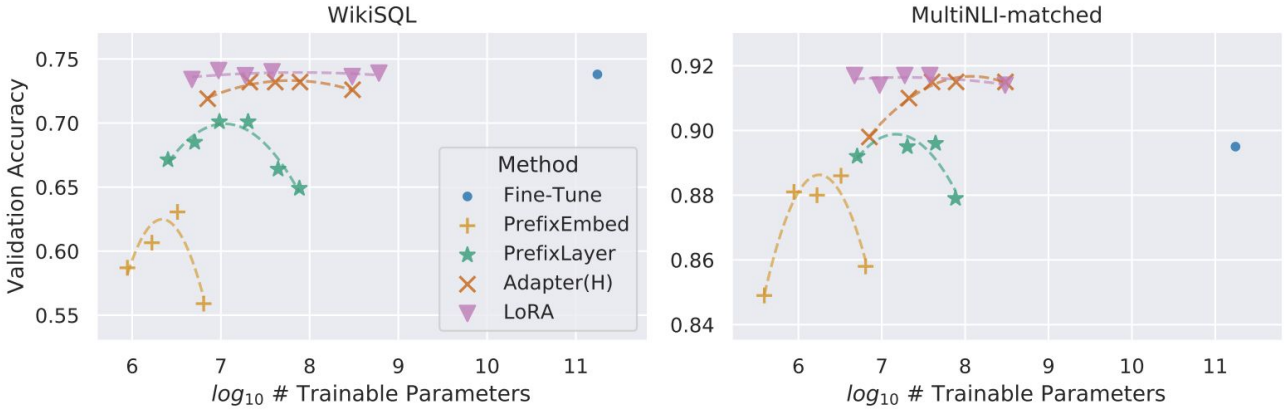
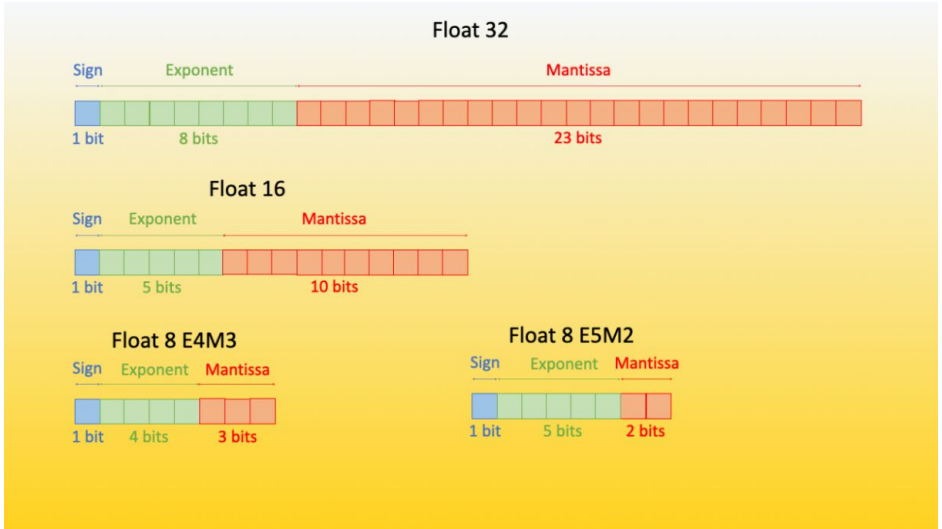
Scale to GPT-3 175 B

- Key benefit is the reduction in memory and storage usage:
  - Do not need to store the gradients of the frozen parameters
  - Reduce the VRAM consumption from **1.2TB to 350GB** during training
  - Use fewer GPUs and fewer I/O operations
- But LoRA still requires forward computation and back-propagation.
  - So, LoRA gives a 25% speedup (not 10x) compared to full fine-tuning.



QLoRA: Further Reduce Memory Usage

- Convert information in a high-precision data type to a low-precision data type
- Allows training a LLM in a single consumer GPU, e.g., 33B LLAMA in a single 24GB GPU



- Example:
  - $25 = 2.5 * 10^1$
  - Mantissa - 2.5
  - Exponent - 1
- Convert to binary for storage

Image source: https://huggingface.co/blog/4bit-transformers-bitsandbytes

QLoRA

- Define a quantization method to convert a 16-bit model into a 4-bit model, using CPU before training
- Store the model weights in a special data type (4-bit NF), and compute the update using another data type (16-bit BF)

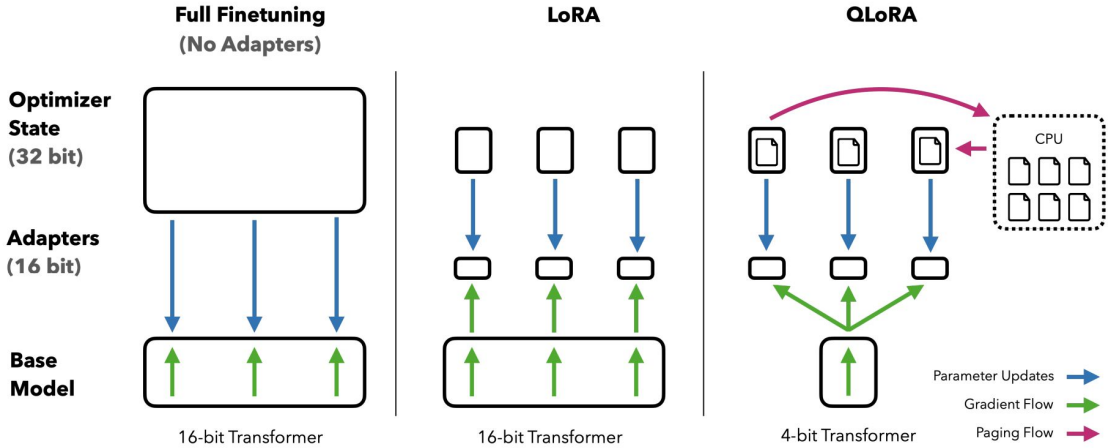


Figure 1: Different finetuning methods and their memory requirements. QLoRA improves over LoRA by quantizing the transformer model to 4-bit precision and using paged optimizers to handle memory spikes.

QLoRA: Background

- **Block-wise k-bit Quantization**: discretize an input from a high-precision representation to a low-precision representation.
  - Example: quantize a 32-bit float tensor into a 8-bit integer tensor with range [-127, 127] with a quantization constant *c* (input dependent).

$$\mathbf{X}^{\text{Int8}} = \text{round}\left(\frac{127}{\text{absmax}(\mathbf{X}^{\text{FP32}})}\mathbf{X}^{\text{FP32}}\right) = \text{round}(c^{\text{FP32}} \cdot \mathbf{X}^{\text{FP32}}),$$

  - Dequantization is the inverse operation:

$$\text{dequant}(c^{\text{FP32}}, \mathbf{X}^{\text{Int8}}) = \frac{\mathbf{X}^{\text{Int8}}}{c^{\text{FP32}}} = \mathbf{X}^{\text{FP32}}$$

QLoRA: Double Quantization

- **Double Quantization**: (1) first quantize the weight matrix, and (2) then further quantize the quantization constants for additional memory savings.
    - Example: using 32-bit constants and a blocksize of 64 for a weight W, quantization constants add 32/64 = 0.5 bits per parameter on average

$$\text{doubleDequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}, \mathbf{W}^{\text{k-bit}}) = \text{dequant}(\text{dequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}), \mathbf{W}^{\text{4bit}}) = \mathbf{W}^{\text{BF16}}$$

Second dequantization

First dequantization

QLoRA

- QLoRA use a single linear layer in the quantized based model with a single LoRA adapter (recall LoRA update: $h = W_0 x + BAx$

$$\mathbf{Y}^{\text{BF16}} = \mathbf{X}^{\text{BF16}} \text{doubleDequant}(c_1^{\text{FP32}}, c_2^{\text{k-bit}}, \mathbf{W}^{\text{NF4}}) + \mathbf{X}^{\text{BF16}} \mathbf{L}_1^{\text{BF16}} \mathbf{L}_2^{\text{BF16}},$$

- Summary: QLoRA has one **storage data type** (usually **4-bit NormalFloat**) and a **computation data type** (**16-bit BrainFloat**). They dequantize the storage data type to the computation data type to perform the forward and backward pass, but they only compute the weight gradients for the LoRA parameters which use 16-bit BrainFloat.

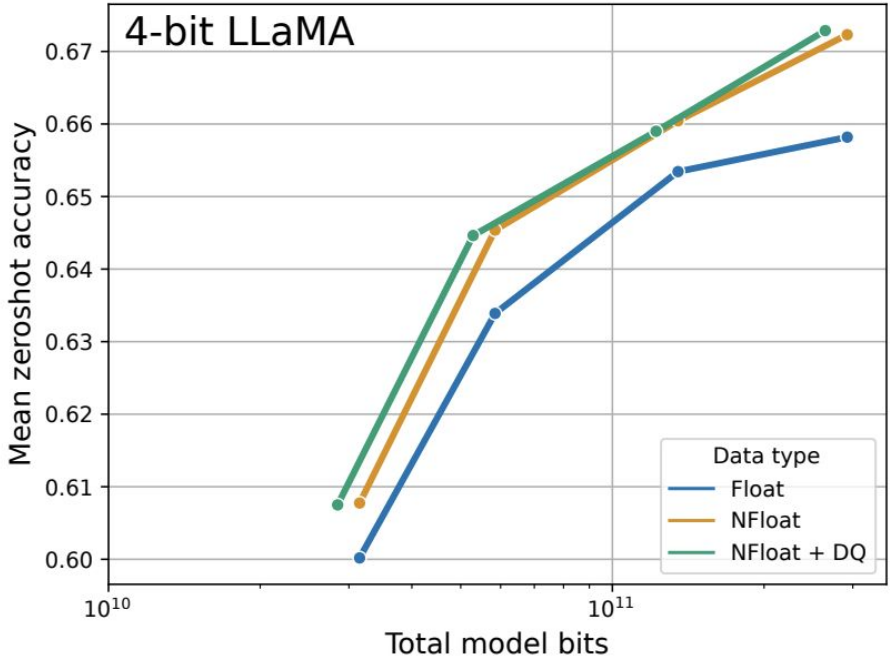
Fine-tuning a LLM in a single GPU

- Fine-tune a 65B LLM on a 48GB GPU (e.g., A6000)
- Fine-tune a 33B LLM on a 24GB GPU (e.g., RTX 3090, RTX 4090, A5000)

Model	Size	Elo
GPT-4	-	1348 ± 1
Guanaco 65B	41 GB	1022 ± 1
Guanaco 33B	21 GB	992 ± 1
Vicuna 13B	26 GB	974 ± 1
ChatGPT	-	966 ± 1
Guanaco 13B	10 GB	916 ± 1
Bard	-	902 ± 1
Guanaco 7B	6 GB	879 ± 1

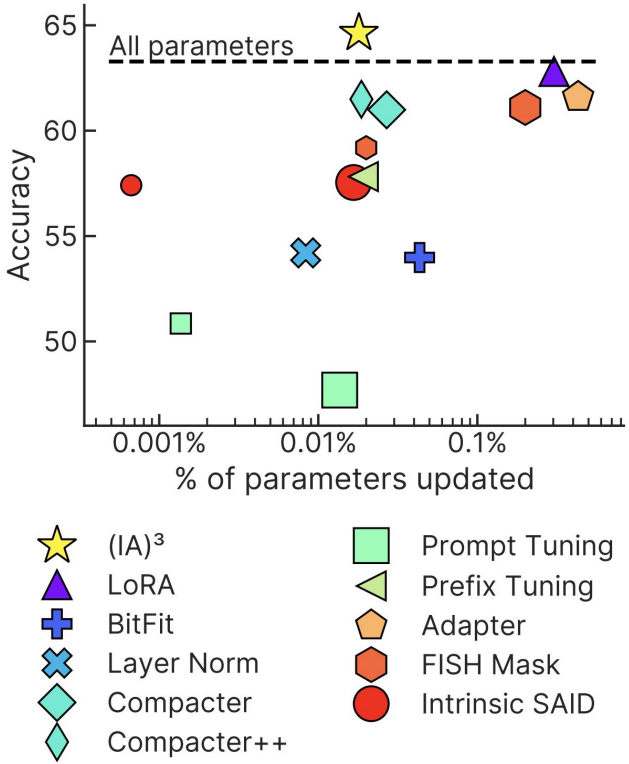
4-bit NF vs 4-bit Floating Point

- Using the same amount of model bits, **4-bit NF** yields better performance than **4-bit Floating point** (orange vs blue curves).
- **Double quantization** reduces the memory footprint without degrading performance (orange vs green curves). For instance, save ~3GB GPU RAM for a 65B LLM



Mean zero-shot accuracy on 5 datasets using LLAMA w/ different 4-bit data type.

Summary: How do these methods compare?



Liu et al NeurIPS 2022. Few-shot parameter-efficient fine-tuning is better and cheaper than in-context learning. https://arxiv.org/abs/2205.05638

Aside:
Other ways to bypass expensive fine-tuning

Alternative Adaptation Methods

- PEFT

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- PEFT
- Prompting, In-Context Learning
- Retrieval Augmented Generation (RAG)

Alternative Adaptation Methods

- PEFT
- Prompting, In-Context Learning
- Retrieval Augmented Generation (RAG)
- Model editing
  - The process of changing knowledge or behaviour of a model, through interventions, instead of any kind of learning
  - Computationally/Parameter cheap
  - Fine-grained control

Why Edit?

- Computationally inexpensive
  - Limited or no new parameters added to model
  - No training or tuning
- Fine-grained control towards targeted facts/behaviours
- Possibly more faithful, due to a more interpretable approach than black box fine-tuning

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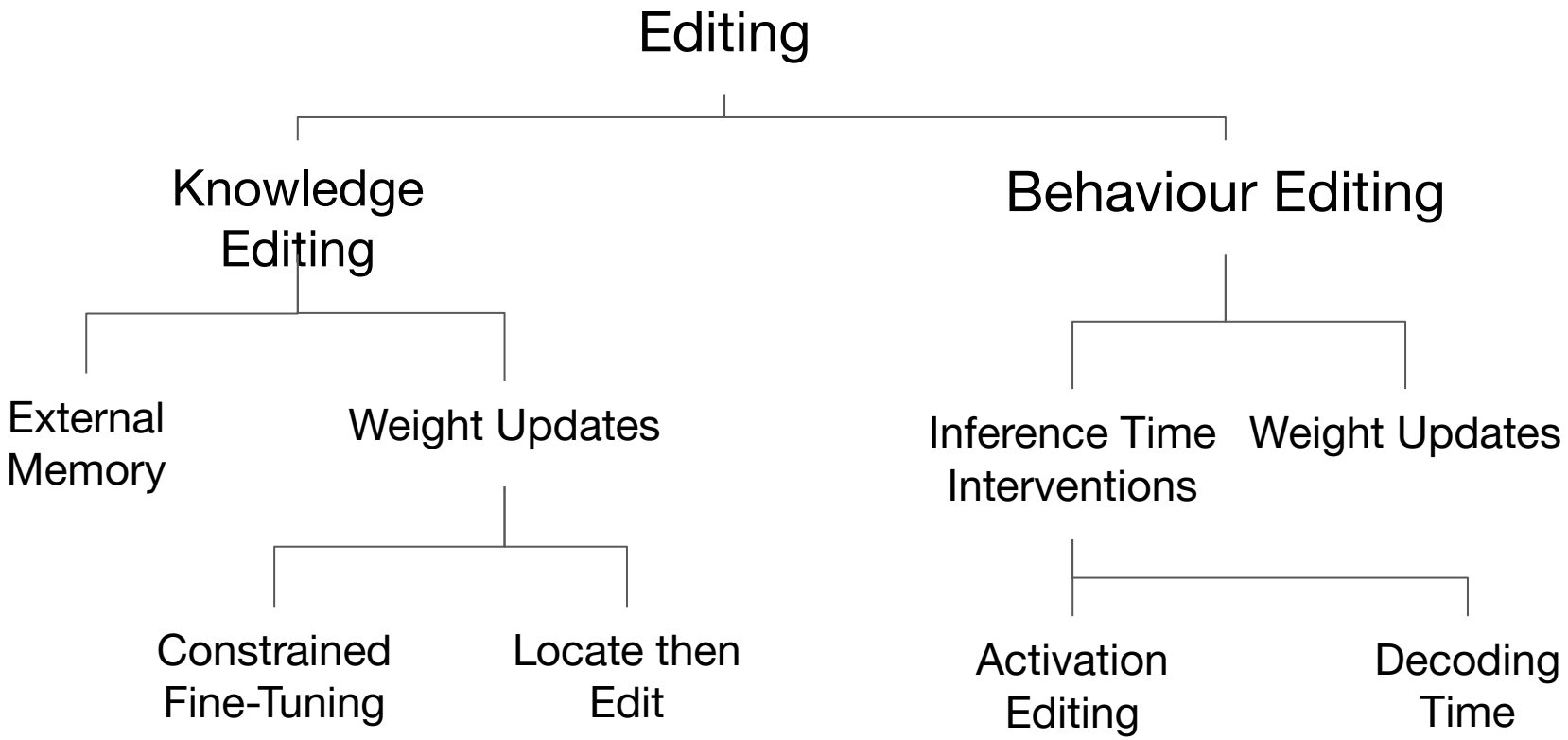
Why Not Edit?

- Superposition - Knowledge is entangled in models, making it hard to apply targeted interventions
- Still a new field, with no established methods yet
- We don’t yet understand how editing may affect other functionalities of a model

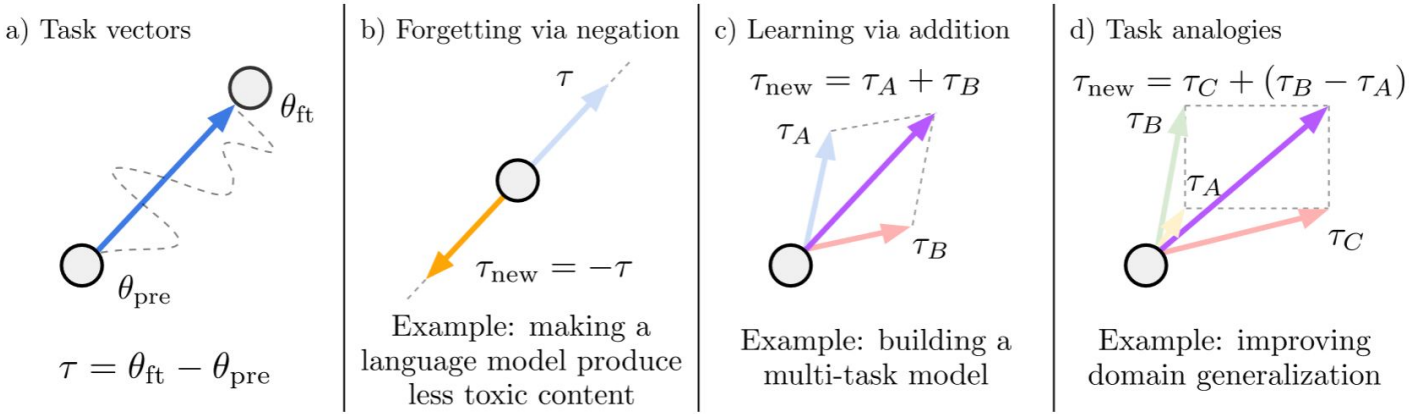


Disclaimer: The Knowledge Editing taxonomy is from the mentioned survey papers. However, the category of Behaviour Editing and its subcategories have been defined as per the presenter's understanding of the literature.

Knowledge Editing for Large Language Models: A Survey (Preprint, 2023)
Editing Large Language Models: Problems, Methods, and Opportunities (EMNLP 2023)
A Comprehensive Study of Knowledge Editing for Large Language Models (Preprint, 2024)

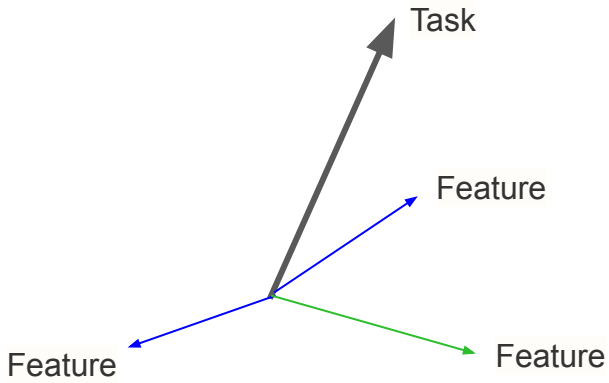
Treating Model Weights as Vectors

- Treating each model as a point in a high dimensional space, training is considered as a vector from the pre-trained point to fine-tuned point

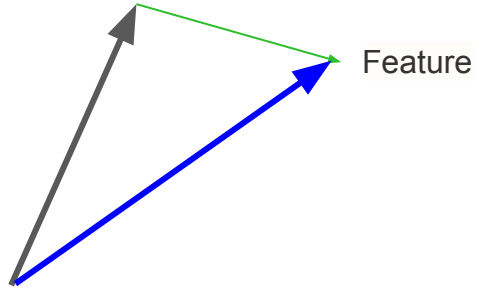


Editing models with task arithmetic. (ICLR, 2022).

More generally, the Linear Representation Hypothesis



Some of these directions correlate with interpretable behaviours!

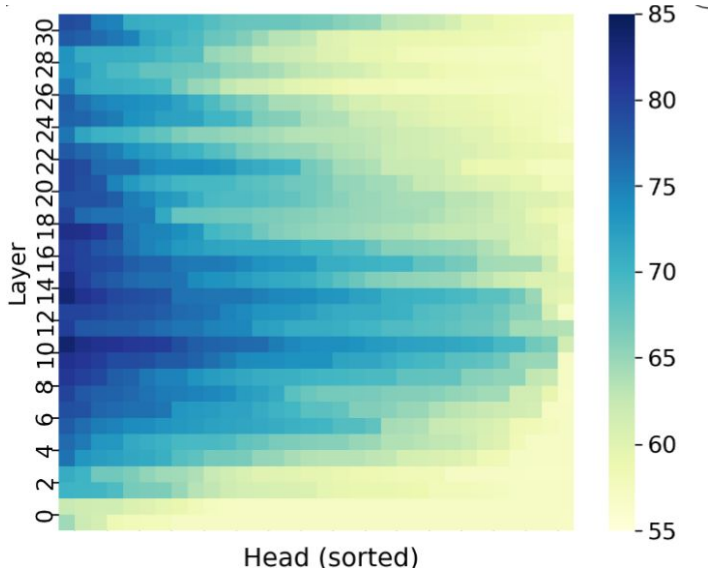


‘Steering’ activations in these directions impacts model performance

Discovering latent knowledge in language models without supervision. (ICLR 2022)
The linear representation hypothesis and the geometry of large language models. (NeurIPS, 2023)
Emergent linear representations in world models of self-supervised sequence models. (EMNLP, 2023)

An example in practice: Steering Attention Heads (ITI)

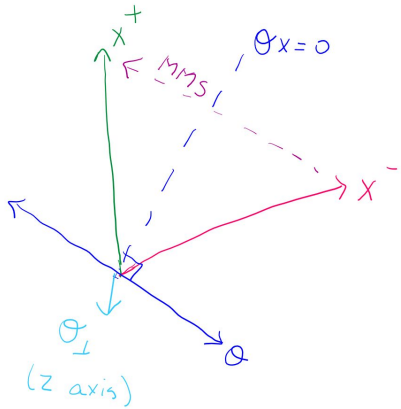
- Generate probing dataset for each attention head in each layer
- $\{q_i, a_i, y_i\}_{i=1}^N \; (y \in \{0,1\} \longrightarrow \{(x_l^h, y)_i\}_{i=1}^N$
- Train binary linear classifier on these datasets
- Significant number of heads (especially in earlier layers) show a high validation accuracy



Inference-Time Intervention: Eliciting Truthful Answers from a Language Model (NeurIPS 2023)

Steering Attention Heads

- Intervention on top ~50 heads of model (for minimal invasiveness)
- Best direction to steer: Vector from centroid of False points to True points
- Modify attention operation:



$$x_{l+1} = x_l + \sum_{h=1}^{H} Q_l^h \, \mathrm{Att}_l^h(P_l^h x_l), \longrightarrow x_{l+1} = x_l + \sum_{h=1}^{H} Q_l^h \left(\mathrm{Att}_l^h(P_l^h x_l) + \alpha \sigma_l^h \theta_l^h \right).$$

Theta - Steering/ truthful direction

Sigma - Std dev of top k head activations, along the truthful direction

Inference-Time Intervention: Eliciting Truthful Answers from a Language Model (NeurIPS 2023)

Steering Attention Heads

With LLaMA models and <100 samples, significantly reduces falsehoods on TruthfulQA (more than SFT and Prompting), and mildly on other distributions.

	True*Info (%)	True (%)	MC acc. (%)	CE	KL
Alpaca	32.5	32.7	27.8	2.56	0.0
Alpaca + ITI	65.1	66.6	31.9	2.92	0.61
Vicuna	51.5	55.6	33.3	2.63	0.0
Vicuna + ITI	74.0	88.6	38.9	3.36	1.41

	True*Info (%)	True (%)	MC acc. (%)	CE	KL
Baseline	30.5	31.6	25.7	2.16	0.0
Supervised Finetuning	36.1	47.1	24.2	2.10	0.01
Few-shot Prompting	49.5	49.5	**32.5**	-	-
Baseline + ITI	43.5	49.1	25.9	2.48	0.40
Few-shot Prompting + ITI	**51.4**	**53.5**	**32.5**	-	-

Table 1: Comparison with baselines that utilize 5% of TruthfulQA to make LLaMA-7B more truthful. CE is the pre-training loss; KL is the KL divergence between next-token distributions pre- and post-intervention. Results are averaged over three runs. We report standard deviations in Appendix D.

Inference-Time Intervention: Eliciting Truthful Answers from a Language Model (NeurIPS 2023)

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