Introduction

The goal of Transfer Learning is to adapt a Pre-Trained model for a Source task (the "base" model) to solve a new Target task.

Adapting a base model is typically performed by Fine-Tuning

- allowing the weights of the base model (and any additional "head") layers to adapt
- by training with a relatively small number of examples from the Target task.

Although Fine-Tuning is effective, there is a problem, especially with LLM base models

- LLM models can have a very large number N of parameters
- They are increasingly deep: number of stacked Transformer blocks n_{layers} is growing
    - latency in training

Even training on a small number of Target task examples is expensive in time and memory.

The question we address in this module

- Can we adapt a base model *without* modifying *all* of the parameters of the base model ?

We will refer to this problem as *Parameter Efficient Transfer Learning*

- or *Parameter Efficient Fine-Tuning* when Fine-Tuning is used as the method for adaptation

We want the number of *adapted* parameters to be small relative to the total number of base model parameters.

We will use this fraction as a metric in comparing adaptation methods.

We note that the number of parameters in a Transformer is $N = \mathcal{O}\left(n_{\text{layers}} * d^2\right)$

- where d is the internal dimension of the Transformer
- calculations may be found in [our notebook (Transformer.ipynb#Number-of-parameters)](Transformer.ipynb#Number-of-parameters) and [here (https://arxiv.org/pdf/2001.08361.pdf#page=6)](https://arxiv.org/pdf/2001.08361.pdf#page=6)

Motivation for Parameter Efficient Transfer Learning

A base model may have a large number of parameters (e.g., an LLM)

- Adapting *all* the parameters may require large quantities of time and space
- Reducing the number of adapted parameters may have efficiency advantages

Beyond the obvious efficiency advantage

- there is a space advantage
- the specialization of the Base Model to a Target Task can be represented by the small number of adapted parameters

This means that the parameters of the same base model can be *shared*

- across models for different Target tasks
- with one set of separate (but small) adapted parameters for each Target

This is also potentially a way to enable per-user instances of a Target task

- with user-specific training examples kept private to each user's instance

Adapters

References

- Parameter Efficient Transfer Learning for NLP (https://arxiv.org/pdf/1902.00751.pdf)
- LLM Adapters (https://arxiv.org/pdf/2304.01933.pdf)

Adapters are modules (implemented as Neural Networks)

- that are inserted into the existing modules (layers) of the base model.

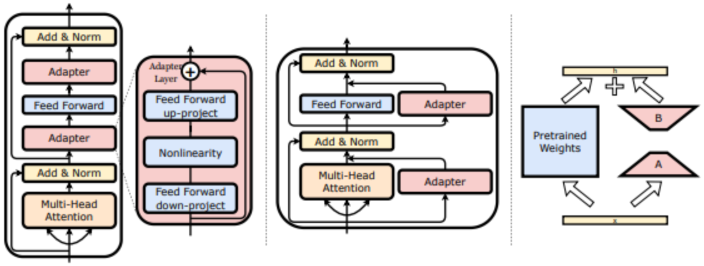
In the general case:

- we can insert one or more adapters *anywhere* within the NN comprising the base model.

Within a *single* Transformer block, typical arrangements are

- Series
    - Adapter inserted between modules
- Parallel
    - Adapter inserted parallel to a module
        - provided an alternate path *by-passing* the module

Various Adapter designs



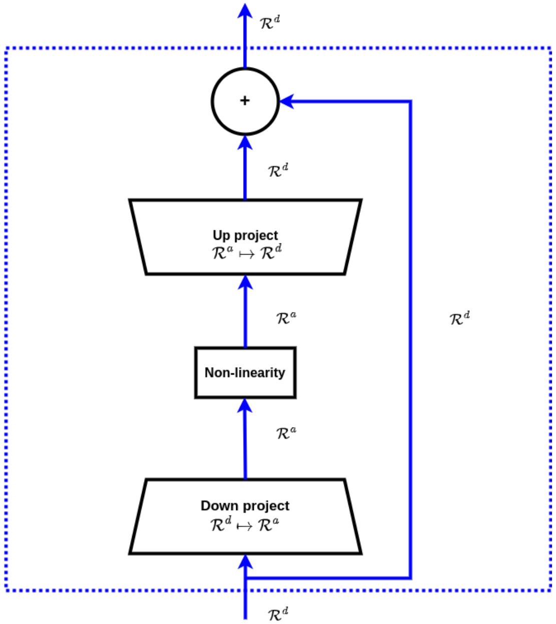
(a) Series Adapter (b) Parallel Adapter (c) LoRA

Figure 1: A detailed illustration of the model architectures of three different adapters: (a) Series Adapter (Houlsby et al., 2019), (b) Parallel Adapter (He et al., 2021), and (c) LoRA (Hu et al., 2021).

Attribution: https://arxiv.org/pdf/2304.01933.pdf#page=2

Here is a diagram of a common adapter

Adapter



The dimensions of the input and output of the adapter

- are the same d (common vector dimension) used for all layers in a Transformer
- facilitates inserting adapters anywhere in the Transformer

The usual architecture

- usually two modules, with a bottleneck of dimension $a < d$
    - Project down to reduced dimension; Project up to original dimension
- skip connection around the two projection modules

We are already familiar with adaptation via Adapter-like modules

- adding a new "head" layer to a head-less base model
    - often a Classifier to adapt the base model to the particular Target classes
- [Feature based transfer learning (NLP_Language_Models.ipynb#Other-uses-of-a-Language-Model:-Feature-based-Transfer-Learning)](NLP_Language_Models.ipynb#Other-uses-of-a-Language-Model:-Feature-based-Transfer-Learning)
    - feeding the representation created by the base model to another module.
- these are not technically adapters
    - input and output dimensions don't match
    - architecture may differ

Regardless of where Adapters are placed

- they derive a new function g from the function f computed by the base model

Formally:

- f_Θ denotes the function computed by the base model which is parameterized by $\mathbf{\Theta}$
- $g_{\Theta,\Phi}(\mathbf{x})$ denotes the function computed by the adapted model
    - $\mathbf{\Phi}$ are the Adapter parameters
    - $\mathbf{\Theta}$ are the base model parameters

Adapter Tuning occurs when we train only the parameters Φ of the Adapter modules

- on a small number of examples from the Target task
- freezing the parameters of the base model

During epoch t of Adapter Tuning, we learn $\Phi_{(t)}$

- initialing $\Phi_{(0)}$ such that
$$g_{\Theta,\Phi_{(0)}}(\mathbf{x}) \approx f_{\Theta}(\mathbf{x})$$
- can be achieved by setting $\Phi = 0$
    - because of the skip connection, the adapter output becomes $f_{\Theta}(\mathbf{x})$

Bottleneck size

Since Adapter Tuning does not change base model parameters Θ,

- the space used depends on the size of Φ
- this is the key to adapting the base model using a small number of parameters

The number of parameters of the projection components of the Adapter are $\mathcal{O}\left(d * a\right)$, multiplied by the number k of Adapters.

Recall that a number of parameters in a Transformer are $\mathcal{O}\left(n_{\text{layers}} * d^2\right)$.

Expressing the size of Φ as a fraction of the size of Θ:

$$\begin{aligned}
r &= \frac{|\Phi|}{|\Theta|} \\
&\approx \frac{d * a * n_{\text{layers}}}{n_{\text{layers}} * d^2} && \text{since} \\
& |\Phi| = \mathcal{O}\left(d * a * n_{\text{layers}}\right) \text{ assuming } k = n_{\text{layers}} \\
& |\Theta| = \mathcal{O}\left(n_{\text{layers}} * d^2\right) \text{ for a Transformer} \\
&\approx \frac{a}{d}
\end{aligned}$$

For reference, $d = 12,288$ for GPT-3; a is chosen to satisfy a target for r

- e.g., $r = 0.1\%$, results in bottleneck size $a = 12$

In experiments (https://arxiv.org/pdf/1902.00751.pdf#page=4), the the botttleck was varied

$$a \in \{2, 4, 8, 16, 32, 64\}$$

so typical a is a fraction of 1%.

[The effect of varying a (https://arxiv.org/pdf/1902.00751.pdf#page=7)](https://arxiv.org/pdf/1902.00751.pdf#page=7) are shown in the orange line in the diagram below

- the horizontal axis is the total number of trainable parameters, which is linear in a
- it seems to show that increasing the size of the bottleneck does not impact performance greatly

The table also compares adaptation via Adapters to adaptation by Fine-Tuning only the top layers of the base model

- the total number of trainable parameters increases with the number of top layers fine-tuned
- the results show that adaptation via Adapters is better than Fine Tuning top layers
    - *unless* we Fine-Tune *many* top layers

Adapter vs Fine Tuning

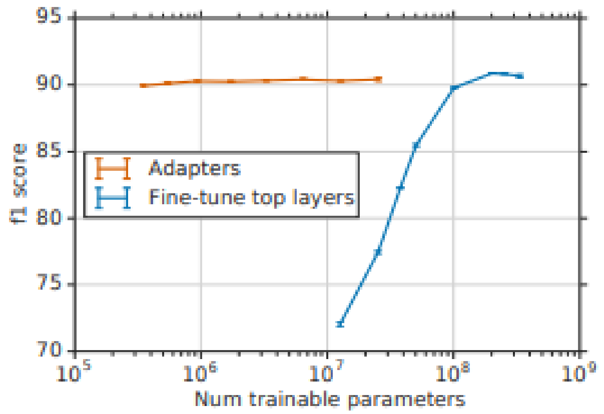


Figure 5. Validation accuracy versus the number of trained parameters for SQuAD v1.1. Error bars indicate the s.e.m. across three seeds, using the best hyperparameters.

Attribution: https://arxiv.org/pdf/1902.00751.pdf#page=7

Adapter placement

Recall that Transformer blocks are usually stacked into n_{layers} in a Transformer for an LLM.

Initially, Adapters were placed at *each* level of the stack.

However, [experiments (https://arxiv.org/pdf/1902.00751.pdf#page=8)](https://arxiv.org/pdf/1902.00751.pdf#page=8) show that the most impactful adapters are located at the *top* of the stack.

In the study, adapters are *removed* within a span of levels of the stacked blocks.

- the models are **not re-trained** after removing the adapters

The horizontal/vertical axes indexes the *end/start* of the span.

Columns 7 and beyond indicates the removing adapters does not decrease performance

- until the adapter at level 7 is removed

The last column indicates that the largest performance decrease occurs

- when removing the single adapater at the top level

Adapter placement

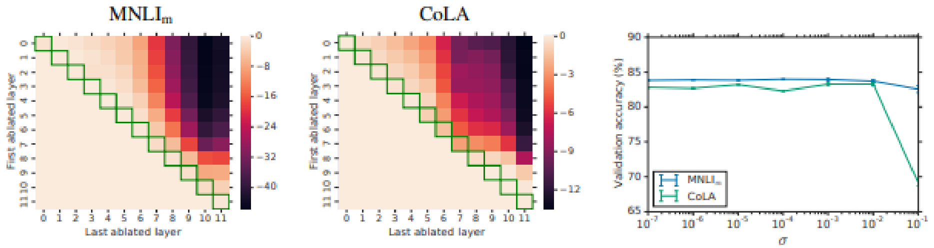


Figure 6. **Left, Center:** Ablation of trained adapters from continuous layer spans. The heatmap shows the relative decrease in validation accuracy to the fully trained adapted model. The y and x axes indicate the first and last layers ablated (inclusive), respectively. The diagonal cells, highlighted in green, indicate ablation of a single layer's adapters. The cell in the top-right indicates ablation of all adapters. Cells in the lower triangle are meaningless, and are set to 0%, the best possible relative performance. **Right:** Performance of BERT$_{\text{BASE}}$ using adapters with different initial weight magnitudes. The x-axis is the standard deviation of the initialization distribution.

Attribution: https://arxiv.org/pdf/1902.00751.pdf#page=8

This is interesting

- Recall, our hypothesis of Deep learning is that increasing levels of abstraction of the inputs are created as layers become deeper
- The early layers create representations that transfer across most tasks
- The deepest layer representations are most task-specific

The decrease in performance corresponding to deeper layers

- may indicate that the Target task specific adaptation
- occurs in the region which we associate most with the Source task

LoRA

References

- [LoRA:Low Rank Adaptation of Large Language Models (https://arxiv.org/pdf/2106.09685.pdf)](https://arxiv.org/pdf/2106.09685.pdf)

Additional reading

- [Intrinsic Dimensionality Explains the Effectiveness of Language Model Fine-Tuning (https://arxiv.org/abs/2012.13255)](https://arxiv.org/abs/2012.13255)

Videos

Code is PyTorch but *idea* is portable to Keras.

- [video: paper (https://www.youtube.com/watch?v=dA-NhCtrrVE)](https://www.youtube.com/watch?v=dA-NhCtrrVE)
- [video: code (https://www.youtube.com/watch?v=iYr1xZn26R8)](https://www.youtube.com/watch?v=iYr1xZn26R8)

The Adapter method of Fine Tuning uses a module involving

- Down projecting to a lower dimension
- Up projecting back to the original dimension
- with an intervening non-linearity
- where the projections are achieved via Dense layers

We now show the Low Rank Adaptation (LoRA) method that is similar

- Down and Up Projections
- without an intervening non-linearity
- where the projections are achieved via matrix multiplication

Let $\mathbf{W}$ denote the parameters of the Pre-Trained Model.

Fine-Tuning updates the parameters to

$$\mathbf{W}' = \mathbf{W} + \Delta\mathbf{W}$$

The usual method is to use Gradient Descent to create a sequence of parameter updates

- one per mini-batch
- equal to negative one times the learning-rate scaled gradient of the Loss

$$\begin{aligned}
\mathbf{W}_{(0)} & = & \mathbf{W} \\
\text{update}_t & = & -\alpha_t * \frac{\partial \mathcal{L}_{\mathbf{W}_{(t-1)}}}{\partial \mathbf{W}_{(t-1)}} \\
\mathbf{W}_{(t)} & = & \mathbf{W}_{(t-1)} + \text{update}_t
\end{aligned}$$

$$\Delta\mathbf{W} = \sum_t \text{update}_t$$

LoRA uses a different method

- using Gradient Descent to approximate the *cumulative* change $\Delta\mathbf{W}$.

Illustrating LoRA on the embedding matrices of an Attention Layer

Although the method works on all types of layers, it is easiest to illustrate in a very particular sub-component of an Attention layer.

This is a component that

- implements the multiplication of
- vector $\mathbf{x}$ of dimension $d = d_{\text{model}}$
- by a matrix $\mathbf{W}$ of dimensions $(d \times d)$
- where $\mathbf{W}$ are updatable *parameters* of the model

$$h = \mathbf{W} * \mathbf{x}$$

This component appears multiple times in an Attention layer.

Recall that an Attention layer matches query q against each key k of key/value pair (k, v) in a Soft Lookup, producing an output o.

But each of q, k, v, o can be projected/embedded by matrices query, key, values (Attention_Lookup.ipynb#Projecting-queries,-keys-and-values), and output (Attention_Lookup.ipynb#Projecting-the-lookup-result) respectively

$$
\begin{aligned}
q &= \mathbf{W}_Q * q \\
k &= \mathbf{W}_K * k \\
v &= \mathbf{W}_V * v \\
o &= \mathbf{W}_O * o
\end{aligned}
$$

Each of these projections is an instance of the operation that we are illustrating.

We will use $\mathbf{W}$ to denote the $(d \times d)$ matrix and $\mathbf{x}$ to denote the value being embedded.

- i.e., $\mathbf{W}$ will be one of $\{\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V, \mathbf{W}_O\}$

Aside

Here are the equations for Multi Head Attention, for reference

$$
\begin{aligned}
\text{MultiHead}(QK, V) &= \text{Concat}(\text{head}_1, \ldots, \text{head}_{n_{\text{head}}})\ \mathbf{W}_O \\
\text{head}_j &= \text{Attention}(Q * \mathbf{W}_Q^{(j)}, K * \mathbf{W}_K^{(j)}, V * \mathbf{W}_V^{(j)}) \\
\text{Attention}(Q, K, V) &= \text{softmax}\left(\frac{Q * K^T}{\sqrt{d}}\right) V
\end{aligned}
$$

Computing $\Delta\mathbf{W}$

The Pre-Trained model has $\mathbf{W}$ equal to an initial value

$$\mathbf{W} = \mathbf{W}_0$$

After Fine-Tuning, $\mathbf{W}$ becomes

$$\mathbf{W}' = \mathbf{W}_0 + \Delta\mathbf{W}$$

LoRA does not **learn** $\Delta \mathbf{W}$ directly.

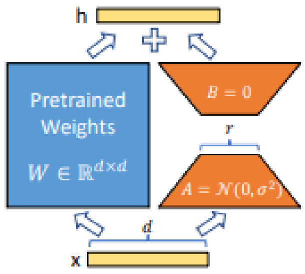
Instead, it creates two learnable parameter matrices A, B:

out		down project		up project
$\Delta \mathbf{W}$	=	A	*	B
$(d \times d)$		$(d \times r)$		$(r \times d)$

where $r \leq \text{rank}(\Delta \mathbf{W})$

That is, it *factors* $\Delta \mathbf{W}$ into the product of two low rank matrices A, B

LoRA adapting Pre-Trained matrix W



Attribution: https://arxiv.org/pdf/2106.09685.pdf#page=1

This arrangement results in

$$\begin{aligned}
h &= \mathbf{W}_0 * \mathbf{x} && \text{the left branch} \\
&\quad + (A * B) * \mathbf{x} && \text{the sum operator on top} \\
&= \mathbf{W}_0 * \mathbf{x} + \Delta\mathbf{W} * \mathbf{x} && \Delta\mathbf{W} = A * b \\
&= (\mathbf{W}_0 + \Delta\mathbf{W}) * \mathbf{x} && \text{distributive property} \\
&= \mathbf{W}' * \mathbf{x} && \mathbf{W}' = \mathbf{W}_0 + \Delta\mathbf{W}
\end{aligned}$$

Thus, the output is $\mathbf{W}' * \mathbf{x}$, satisfying the goal of adapting $\mathbf{W}$ to $\mathbf{W}'$.

The resulting number of parameters

- is $2 * d * r$ parameters
- rather than d^2

So, not only is the representation of $\mathbf{\Delta W}$ smaller, there are fewer parameters to Fine-Tune.

Matrix B is initialized to 0 so that

- when Fine-Tuning begins
- the initial $\mathbf{\Delta W} = A * B = 0$
- A, B get updated during Fine-Tuning
    - by gradient descent on the elements of the matrices

Note the similarity to the Adapter used in a Parallel arrangement.

The advantage of the Parallel arrangement compared to a Series arrangement

- the Series introduces an added layer
- each time it appears
- which slows *inference*

The Parallel arrangement used in LoRA does not introduce latency at inference time.

How big does r have to be ?

Not much ! Values of $r \leq 2$ seem to do very well in an experiment

The accuracy reported when $r = 2$ is almost the same as when $r = 64$

LoRA: accuracy versus rank r

7.2 WHAT IS THE OPTIMAL RANK r FOR LORA?

We turn our attention to the effect of rank r on model performance. We adapt $\{W_q, W_v\}$, $\{W_q, W_k, W_v, W_c\}$, and just W_q for a comparison.

	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

Table 6: Validation accuracy on WikiSQL and MultiNLI with different rank r. To our surprise, a rank as small as one suffices for adapting both W_q and W_v on these datasets while training W_q alone needs a larger r. We conduct a similar experiment on GPT-2 in Section H.2.

Attribution: https://arxiv.org/pdf/2106.09685.pdf#page=10

Results

How do the various adaptation methods compare according to the authors ?

LoRa with 37.7MM parameters ($.02\%$ of GPT-3) *outperforms* full Fine-Tuning.

LoRA: Performance, by method of adaptation

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 (Adapter^{H})	7.1M	71.9	89.8	53.0/28.9/44.8
GPT-3 (Adapter^{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

Table 4: Performance of different adaptation methods on GPT-3 175B. We report the logical form validation accuracy on WikiSQL, validation accuracy on MultiNLI-matched, and Rouge-1/2/L on SAMSum. LoRA performs better than prior approaches, including full fine-tuning. The results on WikiSQL have a fluctuation around $\pm 0.5\%$, MNLI-m around $\pm 0.1\%$, and SAMSum around $\pm 0.2/\pm 0.2/\pm 0.1$ for the three metrics.

Attribution: https://arxiv.org/pdf/2106.09685.pdf#page=8

BitFit

References

- [BitFit: Simple Parameter-efficient Fine-tuning for Transformer-based Masked Language-models (https://arxiv.org/pdf/2106.10199.pdf)](https://arxiv.org/pdf/2106.10199.pdf)

Our goal remains

- to fine-tune a base model
- without having to adapt many parameters

LoRA achieves this goal

- by leaving base model parameters unchanged
- adding Adapters
    - training only Adapter weights

This paper takes a different approach

- adapt a *small number* of base model parameters

Surprisingly: just fine-tuning the *bias* terms ("intercept") works pretty well !

To be specific: the bias parameters of Attention lookup layers are modified.

Recall 1

From the [Attention Lookup module (Attention_Lookup.ipynb#Projecting-queries,-keys-and-values)](Attention_Lookup.ipynb#Projecting-queries,-keys-and-values)

- Attention creates queries, keys, and values
  - based on the sequences (states) produced by earlier layers of the Transformer
- Rather than using the raw states of the Transformer as queries (resp., keys/values)
- we can map them through projection/embedding *matrices* $\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V$
  - each mapping matrix shape is $(d \times d)$
  - thus, the mapping preserves the shapes of Q, K, V

- Mapping through these matrices:

out		left		right
Q	=	Q	*	$\mathbf{W}_Q$
$(T \times d)$		$(T \times d)$		$(d \times d)$

K | = | K| | $\boldsymbol{W}_K$ | V | = | V| |$\mathbf{W}_V$ | $(\bar{T} \times d)$ | | $(\bar{T} \times d)$ | | $(d \times d)$

Recall 2

Our notational practice in dealing with the "bias" term

- when computing a dot product $\mathbf{w} \cdot \mathbf{x}$ we add
    - a constant "1" as first element of $\mathbf{x}$ (let's call the augmented vector $\mathbf{x}'$)
    - the bias parameter b as the first element of $\mathbf{w}$ (let's call this $\mathbf{w}'$)

So

$$\mathbf{w} \cdot \mathbf{x} + b = \mathbf{w}' \cdot \mathbf{x}'$$

This paper

- keeps $\mathbf{w}$ frozen
- modifies b

where these terms are parts of $\mathbf{W}_Q, \mathbf{W}_K, \mathbf{W}_V$.

On small to medium fine-tuning datasets

- performance comparable to fine-tuning *all* parameters

on large fine-tuning datasets

- performance comparable to other sparse methods

Conclusion: Fine-Tuning is easy for everyone !

Fine-Tuning a huge model like GPT-3 seemed out of the realm of possibility for individuals or small organizations.

- huge memory requirements
- time intensive
    - even with the *much smaller* number of examples in the Fine-Tuning dataset compared to the Pre-Training datasets

Parameter Efficient Transfer learning shows

- Fine-Tuning is now accessible on consumer grade hardware
- Without negligible loss of performance (maybe even better) than full Fine-Tuning

Our module on [Transformer Scaling (Transformers_Scaling.ipynb)](Transformers_Scaling.ipynb)

- highlighted a trend
- to *smaller* Large Language Models
- with performance matching very large models (like GPT-3).

Combined with Parameter Efficient Fine-Tuning

- it is [now possible to Fine-Tune a model (LLaMA 7B) (https://arxiv.org/pdf/2303.16199.pdf)](https://arxiv.org/pdf/2303.16199.pdf)
- with performance equivalent to GPT-3 (175B parameters)
- using 8 A100 GPU's
- in one hour !

In [2]:

```
print("Done")
```

```
Done
```