自然語言處理與應用
Natural Language Processing and Applications

如何訓練大模型？輕量化微調方法
Parameter-efficient Fine-tuning (PEFT)

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Course GitHub

Slido # NLP_0505

The Revolution of ChatGPT

ChatGPT came out in November, 2022.

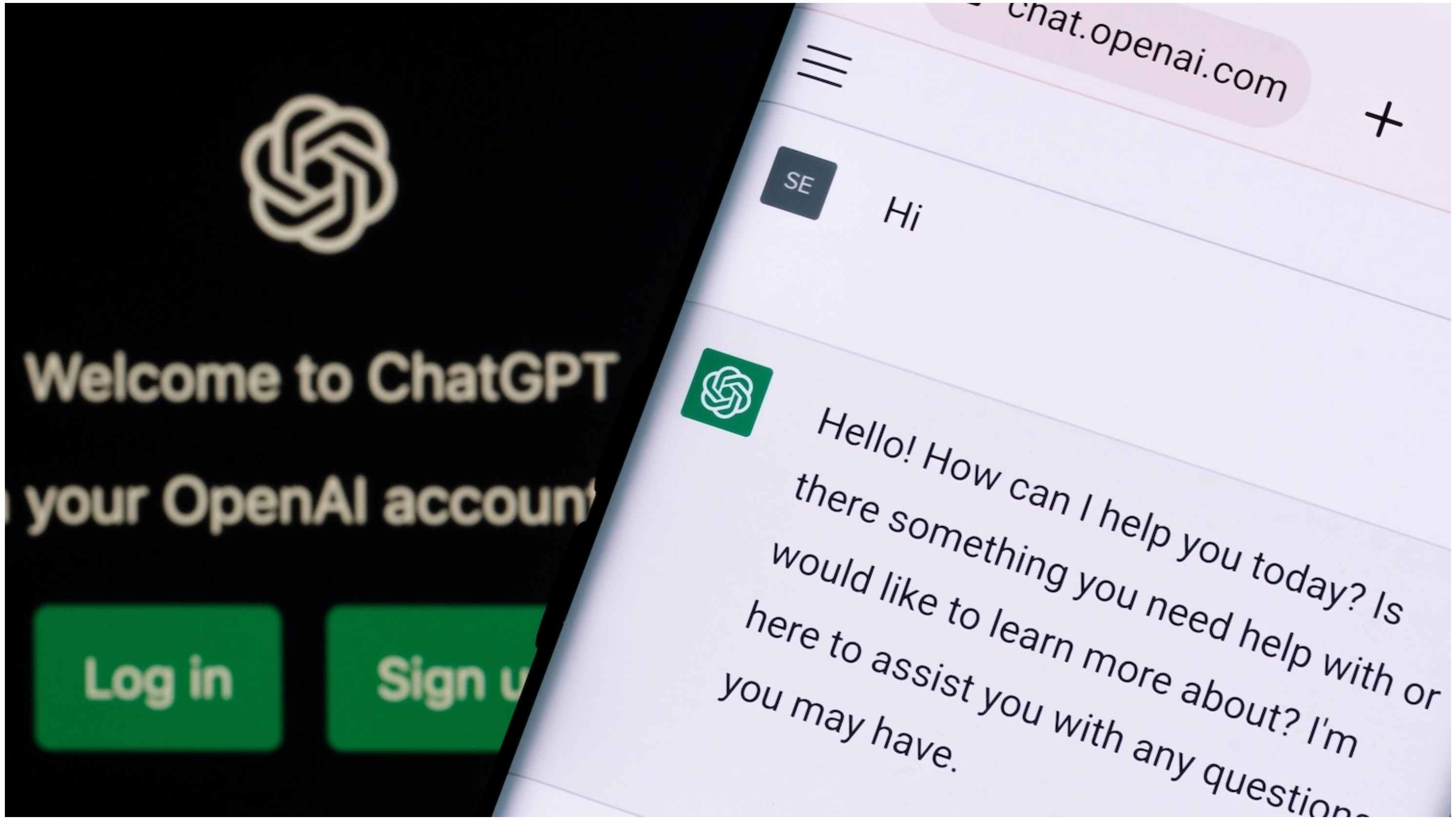
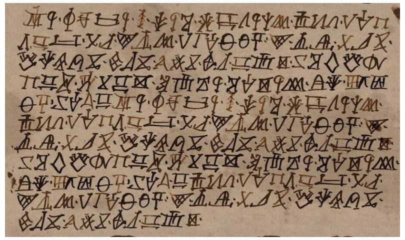


Figure source: https://poole.ncsu.edu/thought-leadership/article/lets-chat-about-chatgpt/
https://openai.com/index/chatgpt/

讓大型語言模型適用於你的任務？

翻譯、聊天、寫故事 ...

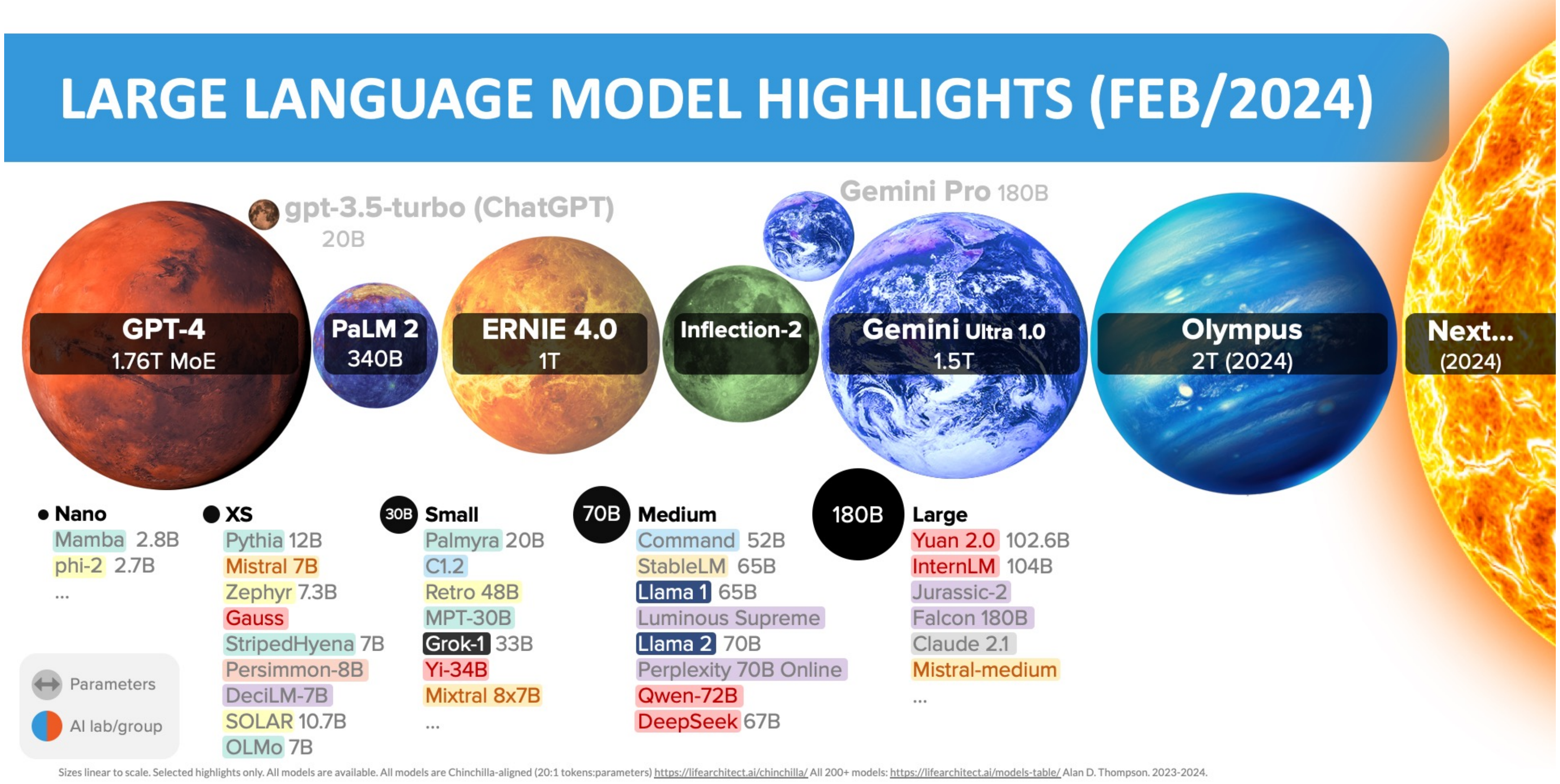


醫學資料、少數語言、網路上查不到的知識

解決方案：Fine-tuning 語言模型

Figure source:
https://gameofthrones.fandom.com/wiki/High_Valyrian?file=Nekesse_Valyrio.jpg

Full Fine-tuning (全微調) LLM 的困境



Source: Inside language models (from GPT-4 to PaLM) – Dr Alan D. Thompson – Life Architect

GPU Memory Estimated (Model weights)

以 Llama 2-7B 為例，且儲存參數的精度為 float 32 (FP32)：

在 float 32 (FP32) 的情況下，1 個參數需要 4 bytes 儲存

-> 7B = 70億個參數 = 70,000,000,000 * 4 bytes = (扣掉3個逗號從B換成GB) 280GB

Introduction to Quantization

(這頁只是示意圖，數值不精準)

$$\begin{bmatrix} -0.4 & 1.3 & 3.73 \\ -4.7 & -3.2 & -6.4 \\ 8.5 & 14.3 & 13.5 \end{bmatrix} \xrightarrow[\text{FP32} \to \text{int8}]{\text{降低儲存精度}} \begin{bmatrix} 0 & 1 & 4 \\ -5 & -3 & -6 \\ 9 & 14 & 14 \end{bmatrix}$$

36 bytes

32-bit floating point (FP32): 1個值需要**4個bytes**才能儲存

8 bytes

8-bit Integer (int8): 1個值需要**1個bytes**才能儲存

誤差：
$$\begin{bmatrix} 0.4 & -0.3 & 0.27 \\ -0.3 & 0.2 & 0.4 \\ 0.5 & -0.3 & 0.5 \end{bmatrix}$$

NLP

GPU Memory Estimated (Model weights)

以 Llama 2-7B 為例，且儲存參數的精度為 float 32 (FP32)：

在 float 32 (FP32) 的情況下，1 個參數需要 4 bytes 儲存

-> 7B = 70億個參數 = 70,000,000,000 * 4 bytes = (扣掉3個逗號從B換成GB) 280GB

模型	**參數量**	**Memory (FP32)**	**Memory (FP16)**
DeepSeek v3	685B	2740 GB	1370 GB
Llama 4 Scout	109B	436 GB	218 GB
GPT-2 XL	1.5B	6 GB	3 GB

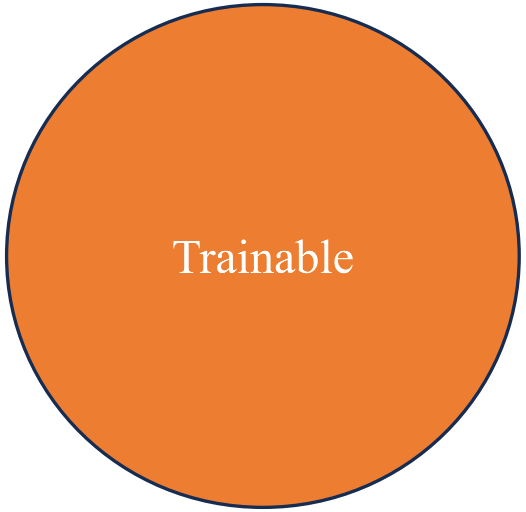
GPU Memory Estimated (Full Fine-tuning)

Llama 2-7B 16-bit float, max_length (seq) = 4096, hidden_size = 4096, batch_size (bs) = 1		
	算法	**Memory**
CUDA	-	~1 GB
Model weights	size(float) * $N_{parameter}$	13.03 GB
Gradients	size(float32) * $N_{trainable}$	26.06 GB
Hidden states	~size(float) * seq * hidden_size * L	1.07 GB
Optimizer states (Adam)	2 * size(float) * $N_{trainable}$	26.06 GB

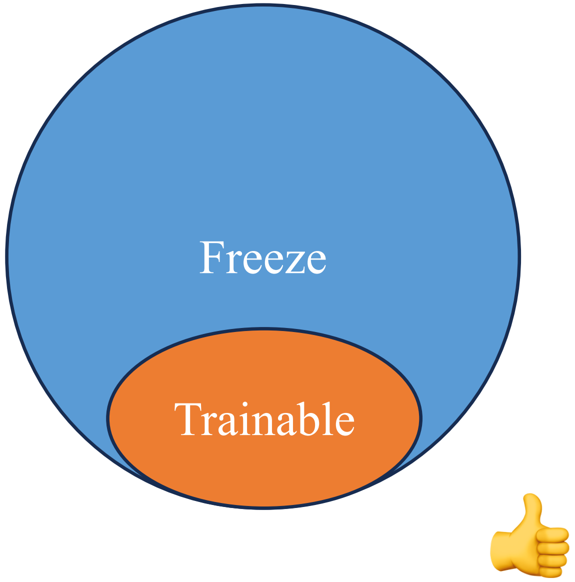
L : Number of layers in model (eq. 32 layers)

Estimate: 67.22 GB
*NVIDIA 5090: 32GB

有沒有可能只微調 LLM 一部分的參數呢？



Full Fine-tuning
Update **all model parameters**



Parameter-efficient Fine-tuning (PEFT)
Update a **small subset** of model parameters

GPU Memory Estimated (PEFT)

- 假設我們只更新 2% 的參數

Llama 2-7B 16-bit float, max_length (seq) = 4096, hidden_size = 4096, batch_size (bs) = 1		
	算法	Memory
CUDA	-	~1 GB
Model weights	size(float) * $N_{parameter}$	13.03 GB
Gradients	size(float32) * $N_{trainable}$	13.03*0.02 = 0.2606 GB
Hidden states	~size(float) * seq * hidden_size * L	1.07 GB
Optimizer states (Adam)	2 * size(float) * $N_{trainable}$	0.5212 GB

L : Number of layers in model (eq. 32 layers)

Estimate: 15.88 GB

*NVIDIA 4060 Ti: 16 GB

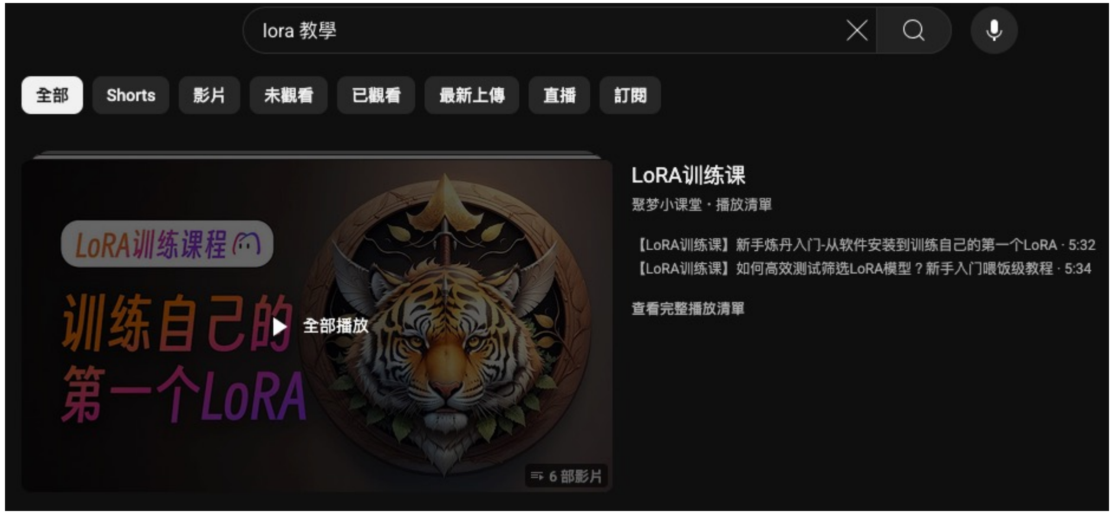
PEFT Outline

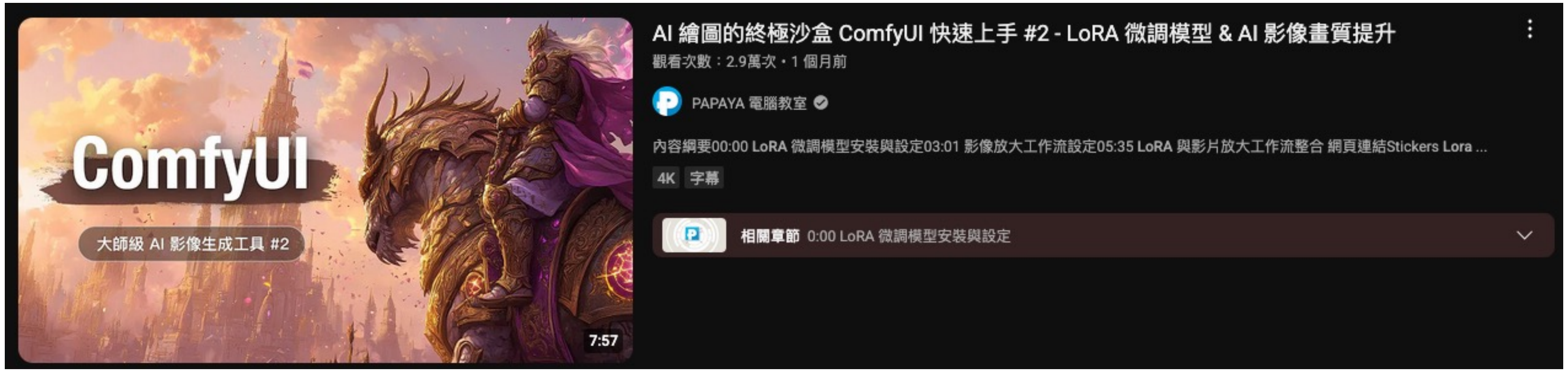
[Adapters] [LoRA] [Prefix-Tuning] [BitFit]

LoRA: Low-Rank Adaptation

https://huggingface.co/docs/peft/index

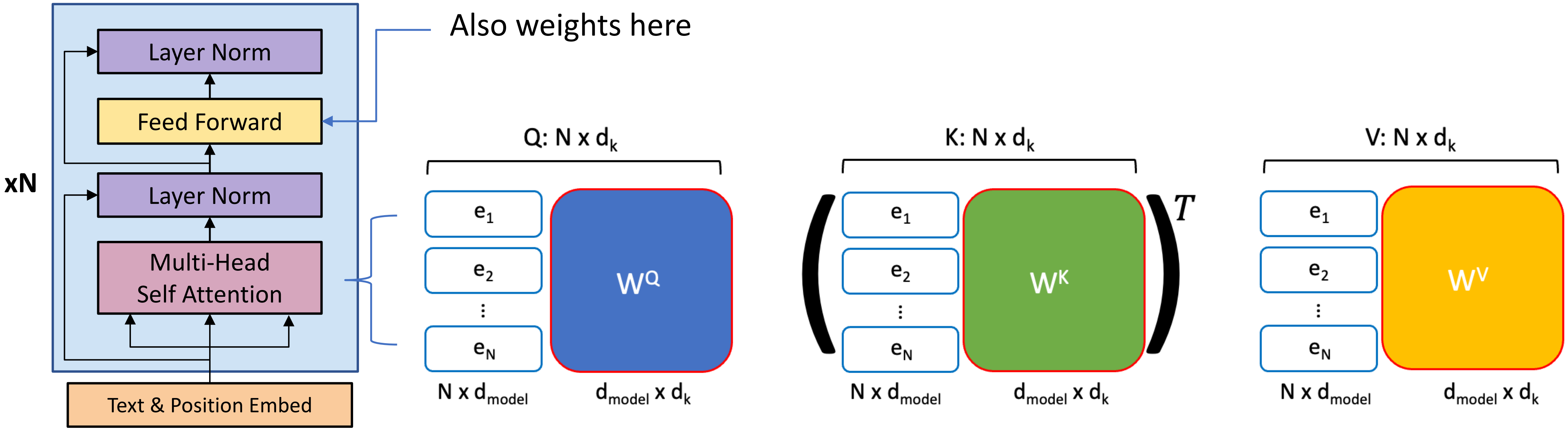
LoRA is common …





[Prerequisite] Weights in Transformer layers

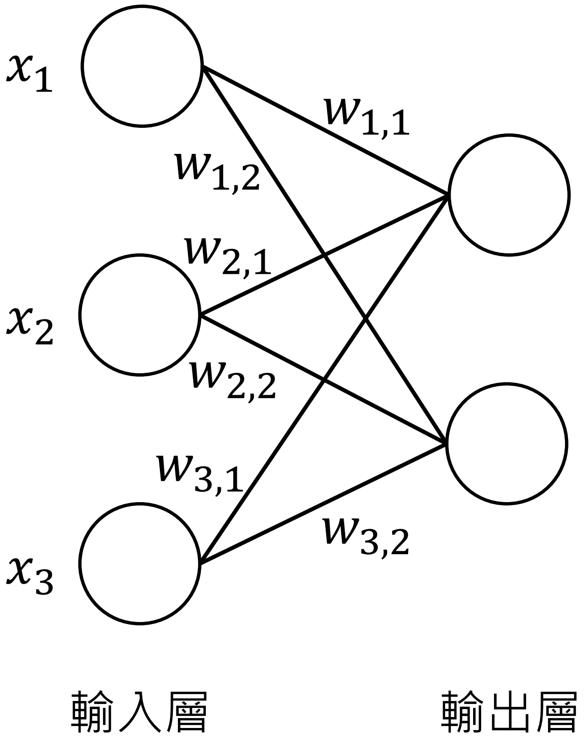
Transformer layers



$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V$$

NLP

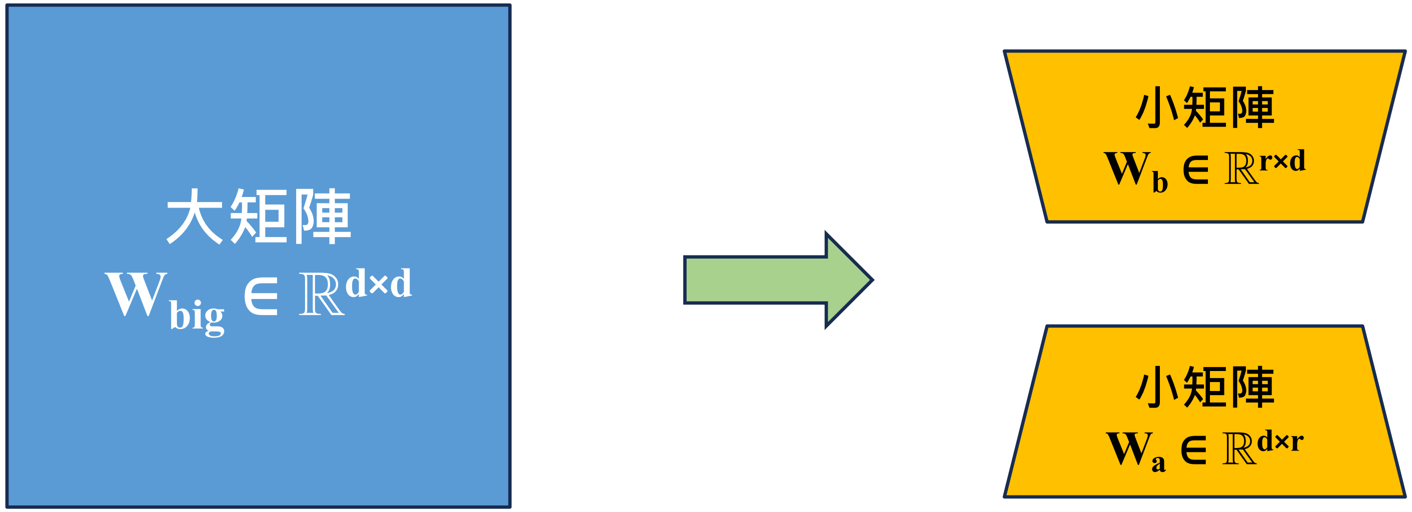
[Recap] MLP is composed of weight matrices



$$
\begin{bmatrix} x_1 & x_2 & x_3 \end{bmatrix} \times \boxed{\begin{bmatrix} w_{1,1} & w_{1,2} \\ w_{2,1} & w_{2,2} \\ w_{3,1} & w_{3,2} \end{bmatrix}} + \text{bias}
$$

$$
\mathbb{R}^{1\times 3} \qquad \mathbb{R}^{3\times 2} \qquad \mathbb{R}^{2}
$$

[Prerequisite] 矩陣分解

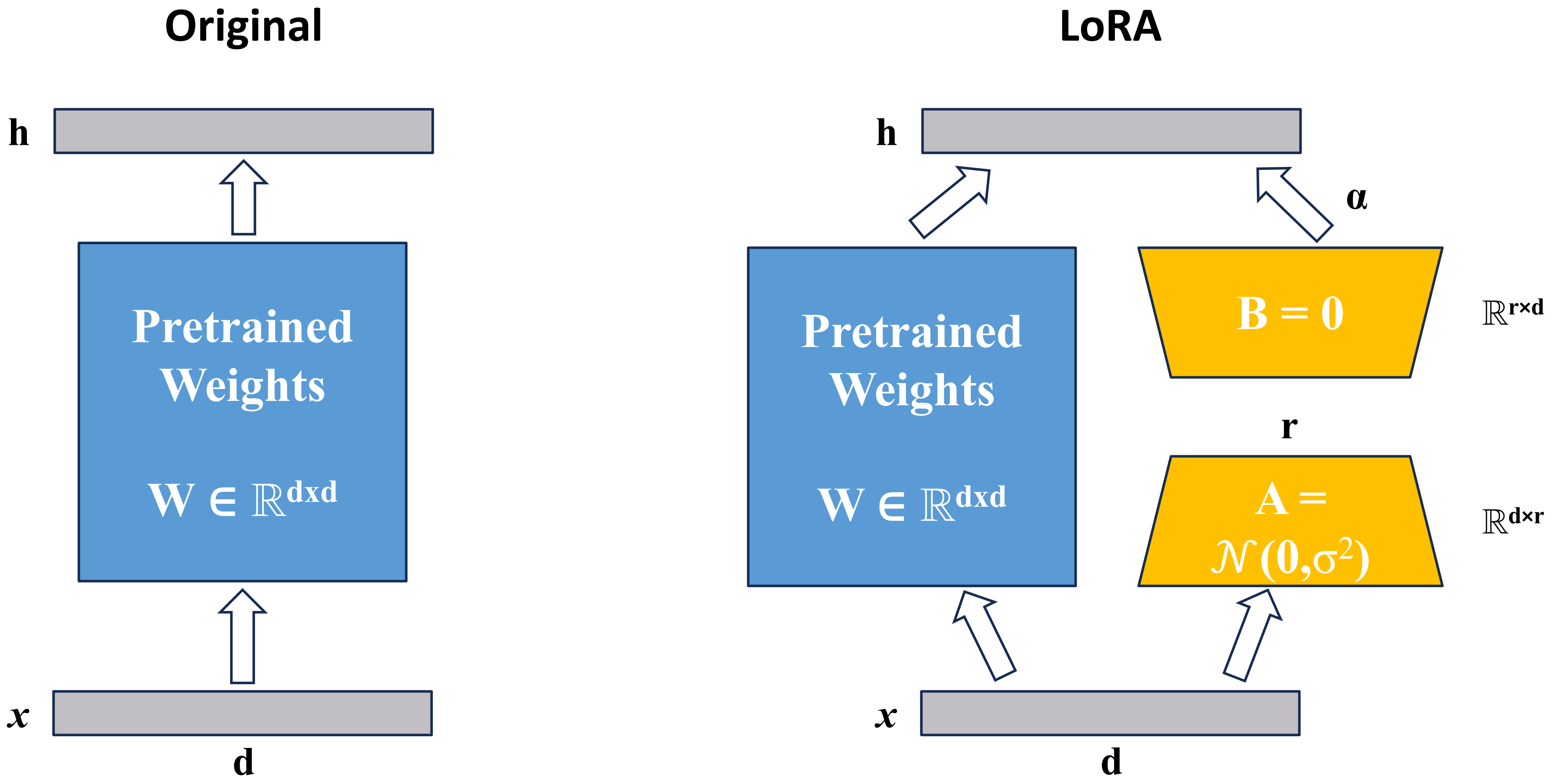


$d = 1000$ | $r = 10$

參數量	1000*1000 = 1百萬	1000*10 + 10*1000 = 20000

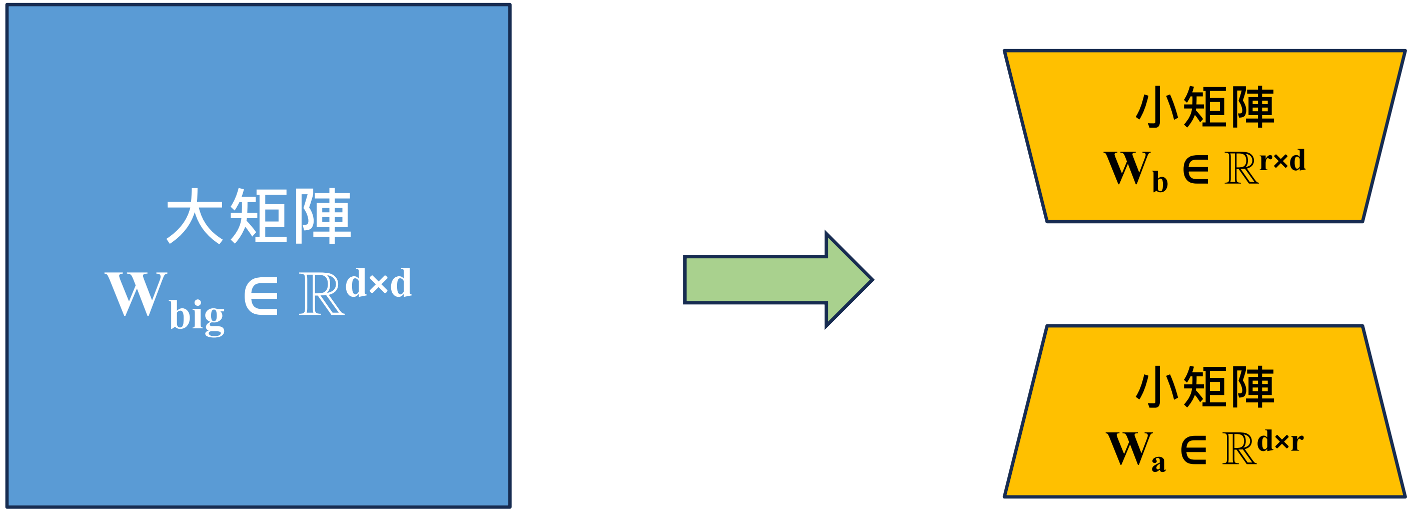
LoRA: Low-Rank Adaptation

只有黃色部分會被訓練
α 是超參數



Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

為什麼 LoRA 要這樣做？



$d = 1000$

$r = 10$

參數量	1000*1000 = 1百萬	1000*10 + 10*1000 = 20000
	訓練參數太多	訓練參數少，僅有 2%

Low-Rank 的部分在哪？(1)

$$\begin{array}{cccc} ✅ & ✅ & & ✅ \\ \end{array}$$

$$\begin{bmatrix} \boxed{\begin{matrix}1\\0\\0\end{matrix}} & \boxed{\begin{matrix}0\\1\\0\end{matrix}} & \begin{matrix}-1\\2\\0\end{matrix} & \boxed{\begin{matrix}0\\0\\1\end{matrix}} \end{bmatrix}$$

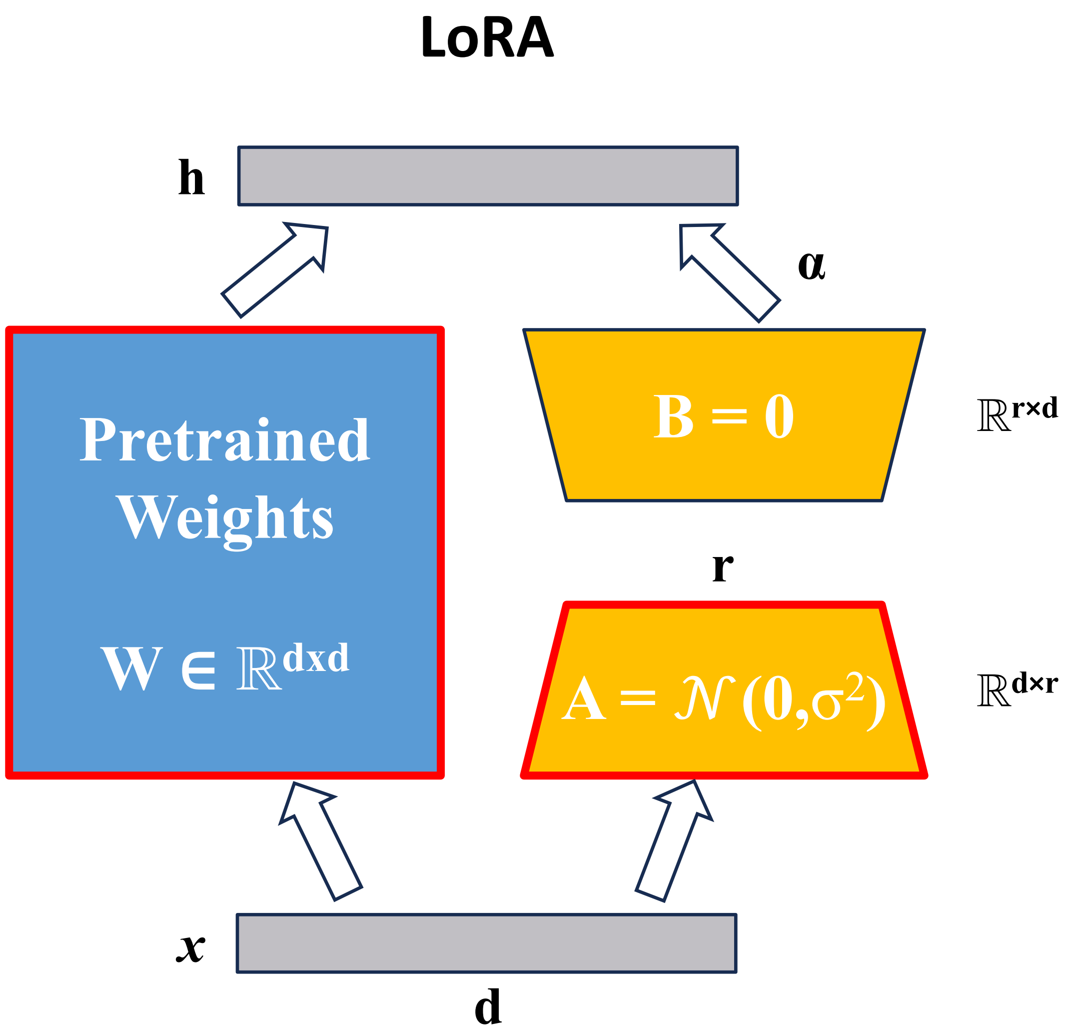
Reduced row-echelon form

✅ : Linearly-independent vectors

rank = 3

rank 大小最多等於 column vectors (或 row vectors) 的數量

Low-Rank 的部分在哪？(2)

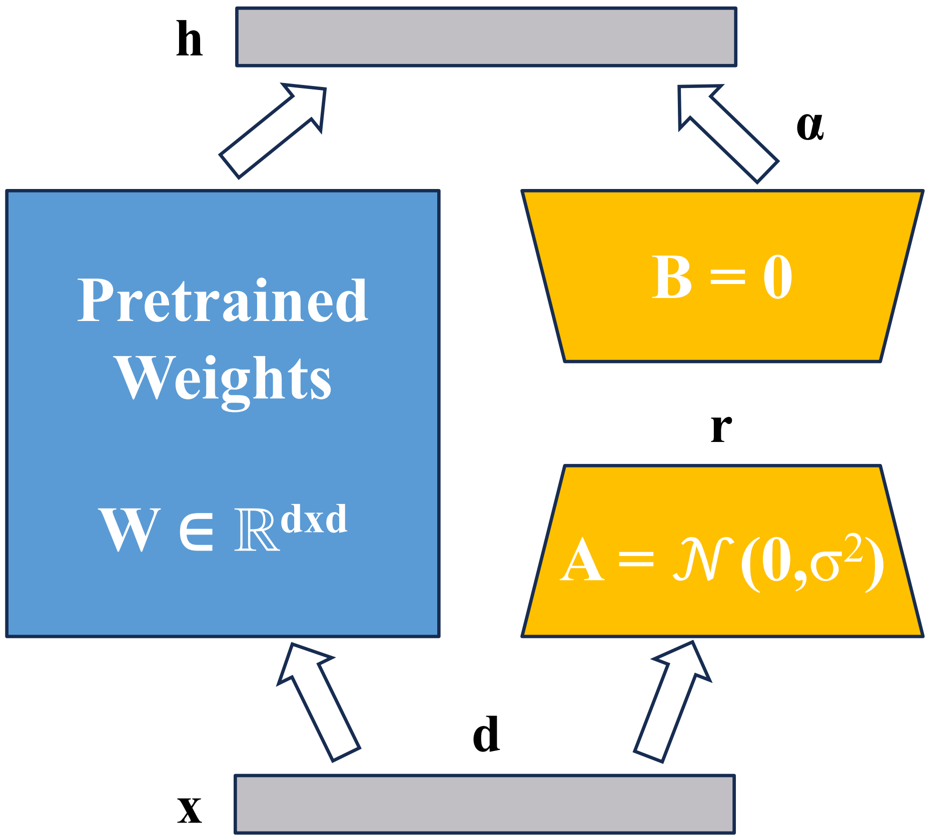


d > r 的情況下 (通常 d>> r)，**A 或 B 的 rank 一定遠小於 W 的 rank**
故為 low-rank 的由來

LoRA: Low-Rank Adaptation (w / pseudo code)

Pseudocode:

```
input_dim = 768  # the hidden size of the pre-trained model
output_dim = 768  # the output size of the layer
rank = 8  # The rank 'r' for the low-rank adaptation

W = ... # from pretrained network with shape input_dim x
output_dim

W_A = nn.Parameter(torch.empty(input_dim, rank)) # LoRA weight A
W_B = nn.Parameter(torch.empty(rank, output_dim)) # LoRA weight B

# Initialization of LoRA weights
nn.init.kaiming_uniform_(W_A, a=math.sqrt(5))
nn.init.zeros_(W_B)

def regular_forward_matmul(x, W):
    h = x @ W
return h

def lora_forward_matmul(x, W, W_A, W_B):
    h = x @ W  # regular matrix multiplication
    h += x @ (W_A @ W_B) * alpha # use scaled LoRA weights
return h
```

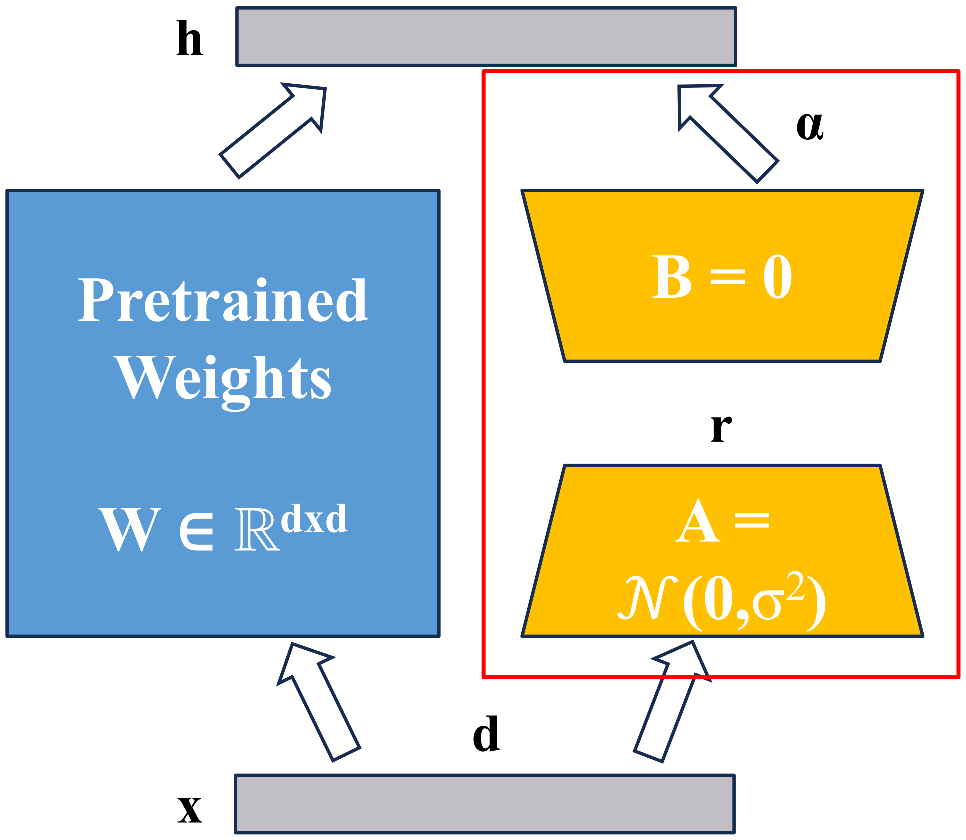


Hu, Edward J., et al. "LoRA: Low-Rank Adaptation of Large Language Models." *International Conference on Learning Representations*. 2021.

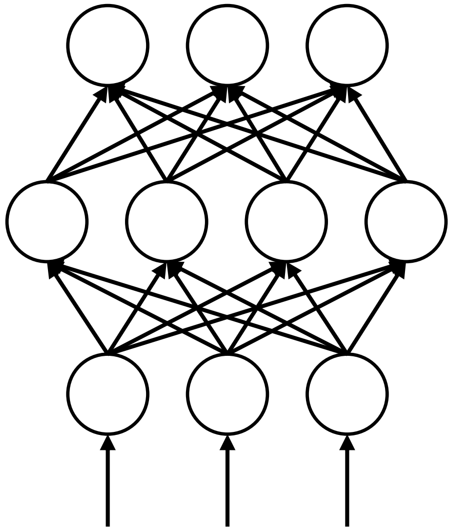
[注意事項] LoRA: Low-Rank Adaptation

- r 的數值大小需要手動調整
  - r 越小，訓練參數量越少
- 相較於原本沒有 LoRA 的模型，

  LoRA 其實會讓 inference 速度變慢



How about model compression?



PEFT vs. Model compression

	PEFT	**Model Compression**
目標	讓模型適應新的任務， 但模型大小不變	加速模型運算或模型儲存空間
相較於原始模型的改變內容	插入少量可訓練參數	減少整體模型結構或權重
參數更新	只更新少量新參數	先減少整體模型結構後針對新的模型進行訓練
使用情境	需要模型學會新的任務時	手機、邊緣裝置

Thank you!

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