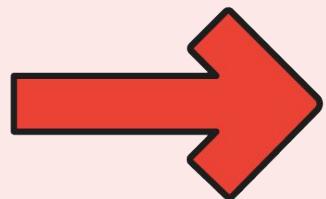




Google Developer Group  
Chandigarh University

# Gemini Study Jams

Session 2 - Supervised PEFT using LoRA

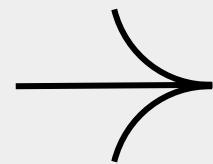
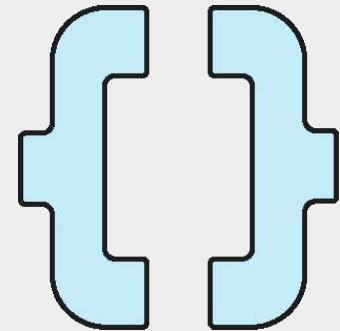


# What will we do today?

1. The main loop of the session will be:

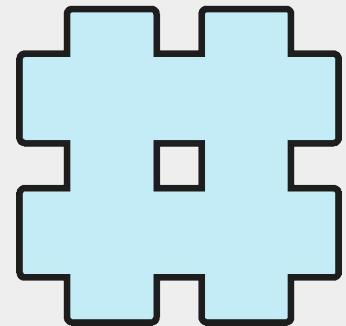
**Code -> Theory -> Code**

2. We will work through the given code and stop and understand the theory behind it at **Exhibitions**.
3. It is **recommended** that you have the file “Session 2 - PEFT with LoRA.ipynb” open.



# E1: LoRA decreases complexity!

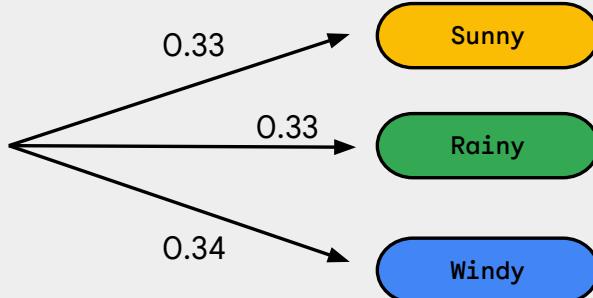
1. During full fine-tuning, **the model is initialized to pre-trained weights  $\Phi$  and updated to  $\Phi + \Delta\Phi$**  by repeatedly following the gradient to maximize the conditional language modeling objective.
2. One of the main drawbacks for full fine-tuning is that **for each downstream task, we learn a different set of parameters  $\Delta\Phi$**  whose dimension  $|\Delta\Phi|$  equals  $|\Phi|$ .
3. This means that for each downstream task, for a model like GPT3,  **$|\Phi| \approx 175 \text{ Billion}$** , storing and deploying many independent instances of fine-tuned models can be challenging, if at all feasible.



# Overly Simplified Visualization : A Sunny Model

## Pre-Trained Model

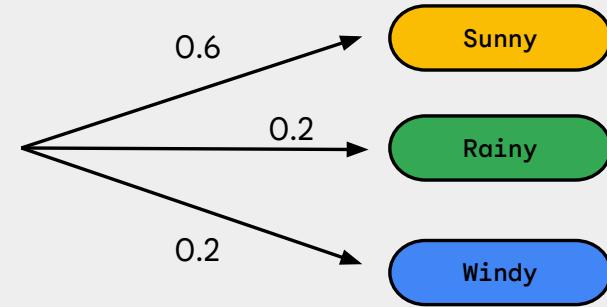
Today is a \_\_\_\_\_ day.



$$\Phi = [0.33, 0.33, 0.34]$$

## Fine Tuned Model

Today is a \_\_\_\_\_ day.



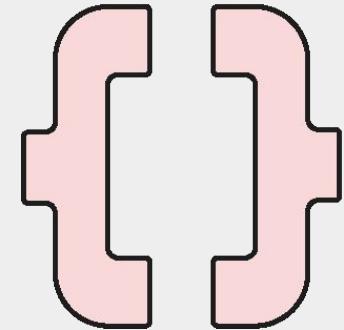
$$\Phi = [0.6, 0.2, 0.2]$$

$$\Delta\Phi = [0.27, -0.13, -0.14]$$

*Now imagine 175 billion parameter updates for GPT3 - unique to each task!*

# E1: LoRA decreases complexity!

1. In LoRA, the task-specific parameter increment  $\Delta\Phi = \Delta\Phi(\Theta)$  is **further encoded by a much smaller-sized set of parameters**  $\Theta$  with  $|\Theta| \ll |\Phi|$ .
2. When the pre-trained model is GPT-3 175B, **the number of trainable parameters  $|\Theta|$  can be as small as 0.01% of  $|\Phi|$** .



Now back to Code!

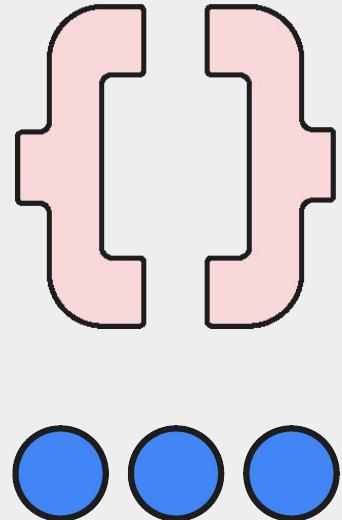


# E2: How does LoRA work?

1. Consider a single Transformer layer, single attention head for clarity.
2. You start with an input sequence:

$X \in \mathbb{R}$  where  $X$  has dimensions  $T * d$  where

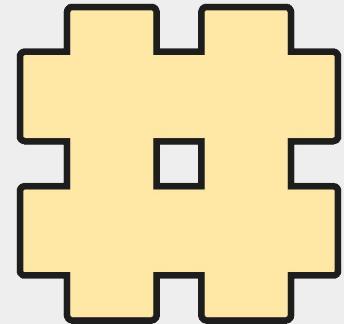
- $T$ : sequence length
  - $d$ : embedding dimension
3. Each token is a row vector in  $X$ .



# E2: How does LoRA work?

1. The attention mechanism does **not** operate directly on  $X$ .
2. Instead, it projects  $X$  into three different representation spaces:
  - **Query (Q)** — “What am I looking for?”
  - **Key (K)** — “What do I contain?”
  - **Value (V)** — “What information do I give if selected?”
3. And then attention is computed using these three.
4. Mathematically:

$$Q = XW(Q) \mid V = XW(V) \mid K = XW(K)$$



# E2: How does LoRA work?

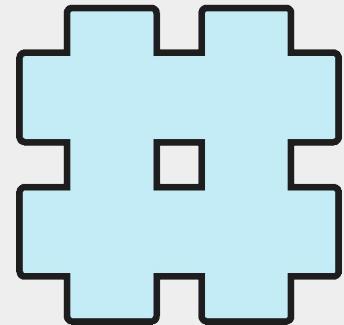
1. During Fine Tuning, the projection matrices are learned as follows:

$$Q = X(W(Q) + \Delta W(Q))$$

2. LoRA **does not change** the attention mechanism.
3. It changes how the projection matrices are *learned*. LoRA enforces:

$$\Delta W(Q) = BA$$

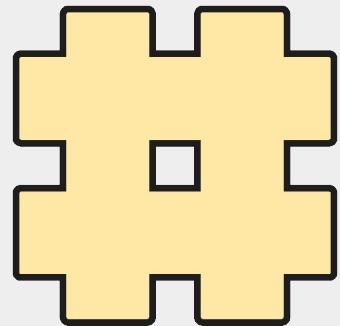
Where A has dims  $r * d$  and B has dimension  $d * r$  where  $r \ll d$ . The original weight matrix  $W(Q)$  is frozen, and only A and B are trained.



# This is a Headline.

This is body copy. Bringing developers together in-person and online. Stay in the know about upcoming events, catch up on content you missed, and connect with Google experts. This is body copy. Bringing developers together in-person and online. Stay in the know about upcoming events, catch up on content you missed, and connect with Google experts. This is body copy. This is body copy.

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# E3: LoRA Evaluation

## (a) Language modeling

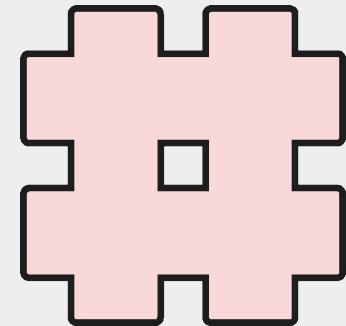
- Perplexity (PPL)
- Negative log-likelihood (NLL)

## (b) Classification / structured prediction

- Accuracy
- Precision / Recall / F1
- ROC-AUC

## (c) Generation tasks

- BLEU, ROUGE, METEOR (summarization, translation)
- Exact Match (EM), F1 (QA)
- Human evaluation (helpfulness, factuality, style adherence)



# E4: Considerations

Choose target layers carefully (Q, V usually most effective)

Select rank  $r$  wisely: low  $r$  captures most gains; high  $r$  has diminishing returns

Tune scaling  $\alpha$  to control update magnitude and stability

Initialize properly (base weights frozen; LoRA starts as no-op)

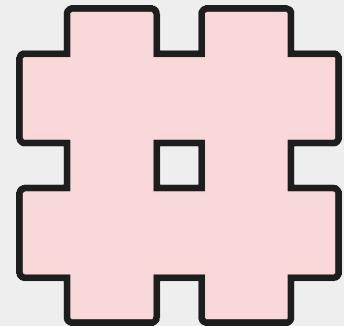
Use higher learning rates; avoid heavy regularization

Best for domain/style adaptation; limited for learning new capabilities

Check in-domain vs out-of-domain generalization

Decide whether to merge adapters at inference

Monitor memory, speed, and perplexity together



# Quiz Time!

# Doubts?

Ask away!



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# Thank You!

Fine Tuning Basics & Supervised Fine Tuning - End

