Carnegie Mellon University

Recitation: HW3
10-423/10-623

23rd February 2024

Agenda

- In context learning, COT
- LoRA
- Instruction Fine Tuning
- Code Walkthrough and Implementation Details

Learning from Small Data

How can we learn from a small amount of data?

Learning from Small Data

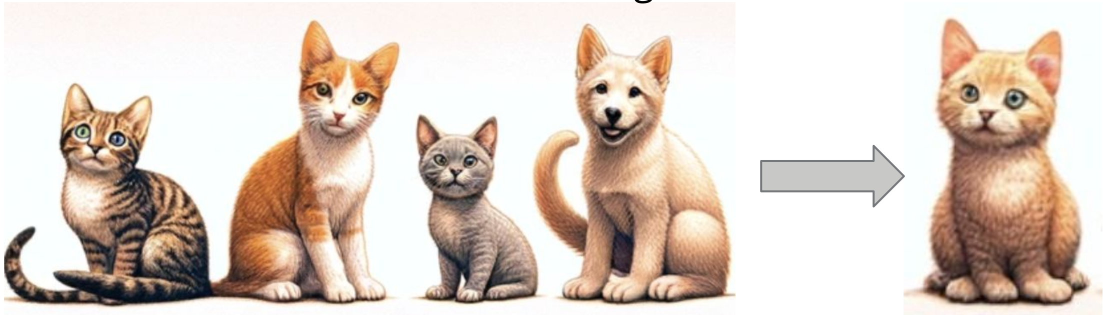
How can we learn from a small amount of data?

Few-Shot learning

Zero-Shot learning

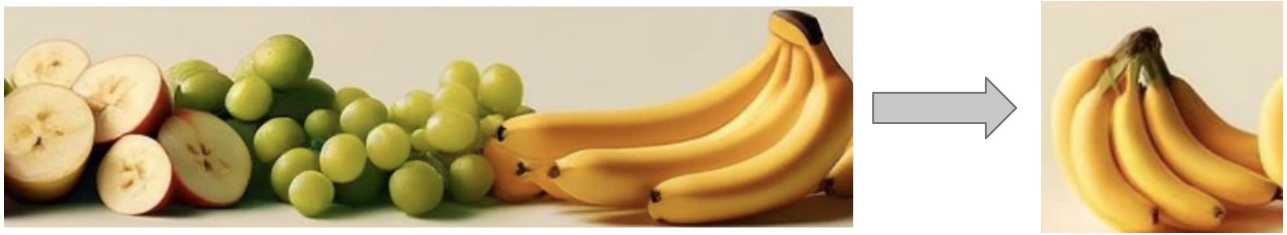
What is Few-Shot Learning?

What is Few-Shot Learning?



Cat Cat Cat Dog

?



Apple Grape Banana

?

What is ZERO-Shot Learning?

Cat Cat Cat Dog

?

Apple Grape Banana

?

What is ZERO-Shot Learning?

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How to Approach Few-Shot Learning?

How to Approach Few-Shot Learning?

One Answer: Meta Learning

What is Meta Learning?

What is Meta Learning?

Learning to Learn?

What is Meta Learning?

Learning to Learn?

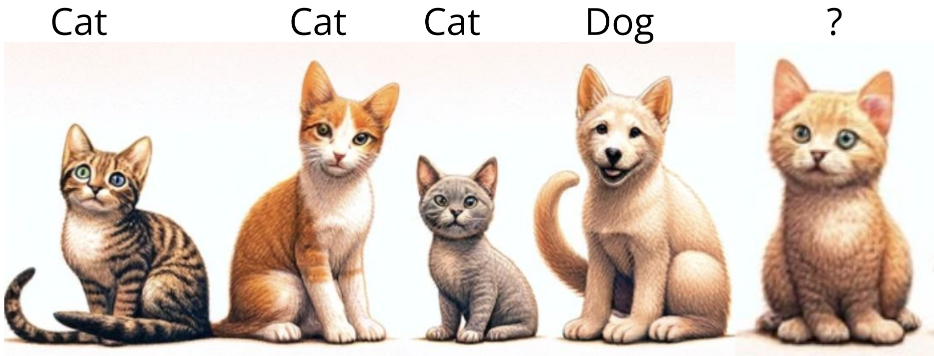
Optimize Few-Shot Learning Performance

What is Meta Learning?

Learning to Learn?

Optimize Few-Shot Learning Performance

Train input example

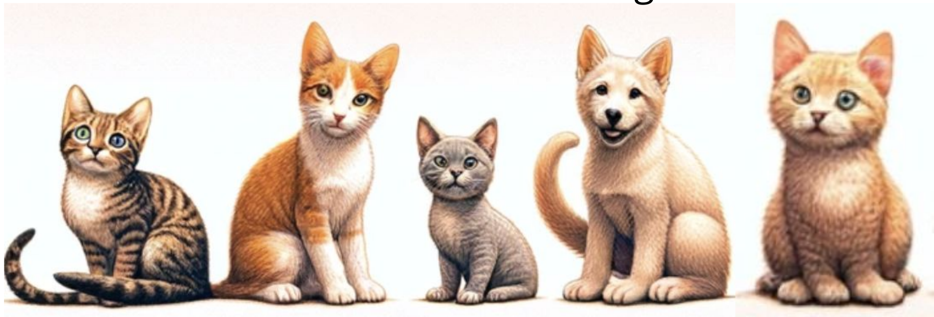


What is Meta Learning?

Learning to Learn?

Optimize Few-Shot Learning Performance

Train input example

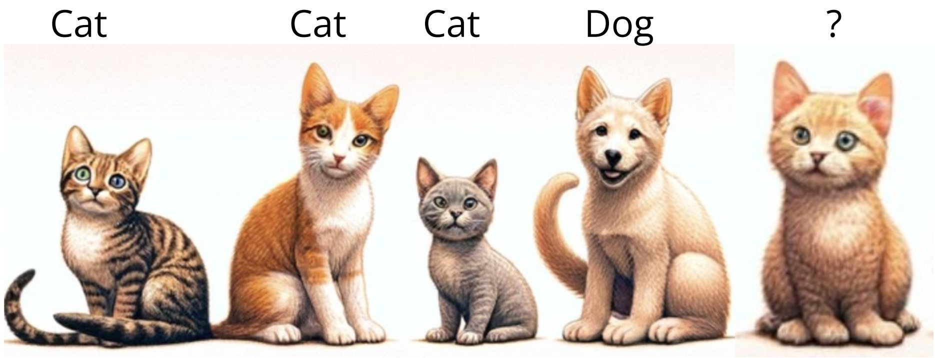


Train target example

Cat

How Can We Solve This Problem?

Train input example



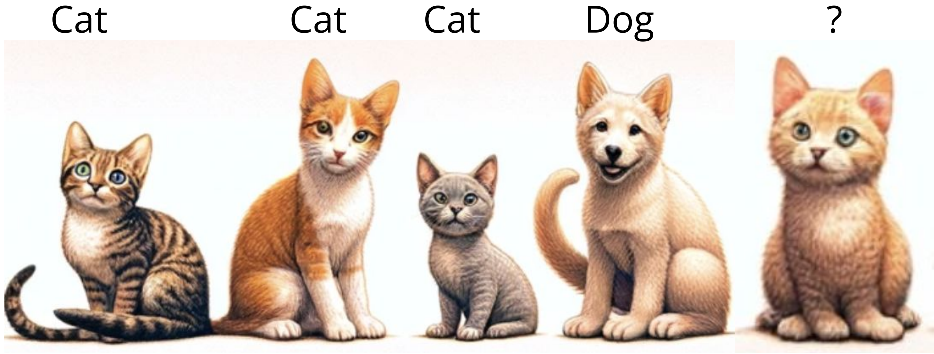
Train target example

Cat

How Can We Solve This Problem?

One Answer: Treat Like Regular Supervised Learning

Train input example



Train target example

Cat

How Can We Solve This Problem?

One Answer: Treat Like Regular Supervised Learning

Train input example

Cat Cat Cat Dog ?

Tranformer/ RNN

Train target example

Cat

What is In-Context Learning?

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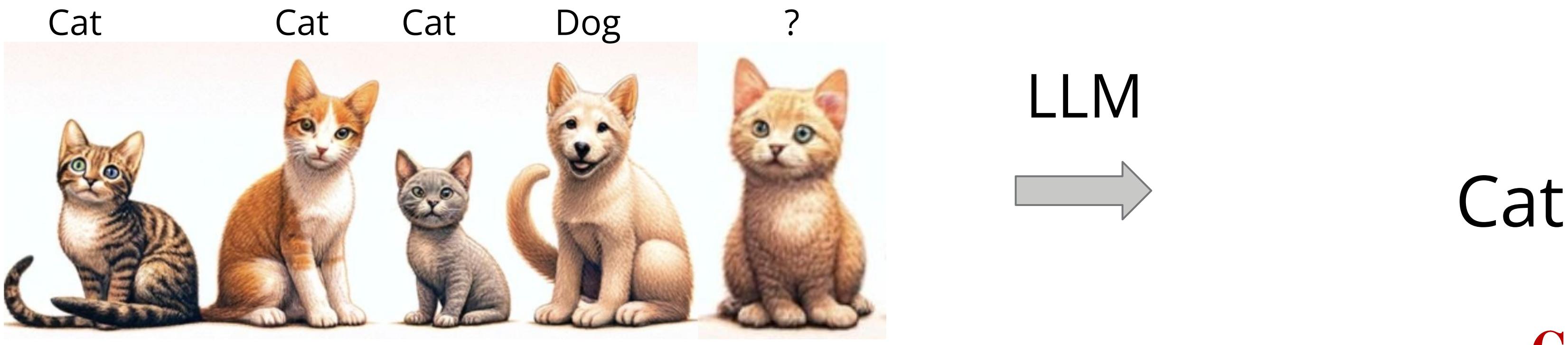


Cat Cat Cat Dog ?

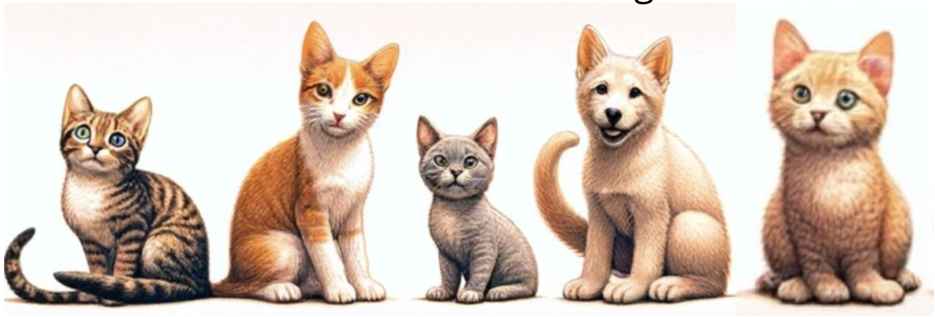
LLM

Cat

What is In-Context Learning?

LLMs “know how to learn” even though we didn’t “learn to learn”!

Cat Cat Cat Dog ?



Cat

Can We Improve In-Context Learning Using Prompt Engineering?

Cat Cat Cat Dog ?

LLM

Cat

Can We Improve In-Context Learning Using Prompt Engineering?

Cat because stripes

Cat because whiskers

Cat because nose

Dog because eyes

?

LLM

Cat because eyes

Can We Improve In-Context Learning Using Prompt Engineering?

"Chain-of-thought prompting"

Cat because stripes

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Dog because eyes

?

LLM

Cat because eyes

Can We Improve In-Context Learning Using Prompt Engineering?

"Chain-of-thought prompting"
(a better example)

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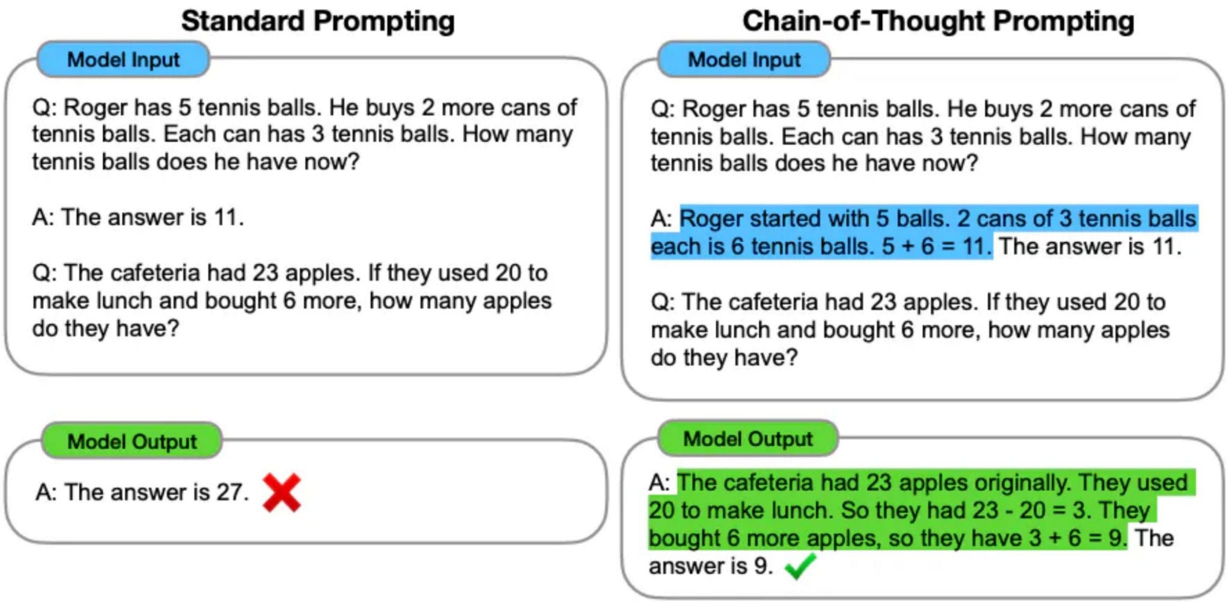
"Chain-of-thought prompting"
(a better example)



Standard Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The answer is 27. ✗

Chain-of-Thought Prompting

Model Input

Q: Roger has 5 tennis balls. He buys 2 more cans of tennis balls. Each can has 3 tennis balls. How many tennis balls does he have now?

A: Roger started with 5 balls. 2 cans of 3 tennis balls each is 6 tennis balls. 5 + 6 = 11. The answer is 11.

Q: The cafeteria had 23 apples. If they used 20 to make lunch and bought 6 more, how many apples do they have?

Model Output

A: The cafeteria had 23 apples originally. They used 20 to make lunch. So they had 23 - 20 = 3. They bought 6 more apples, so they have 3 + 6 = 9. The answer is 9. ✓

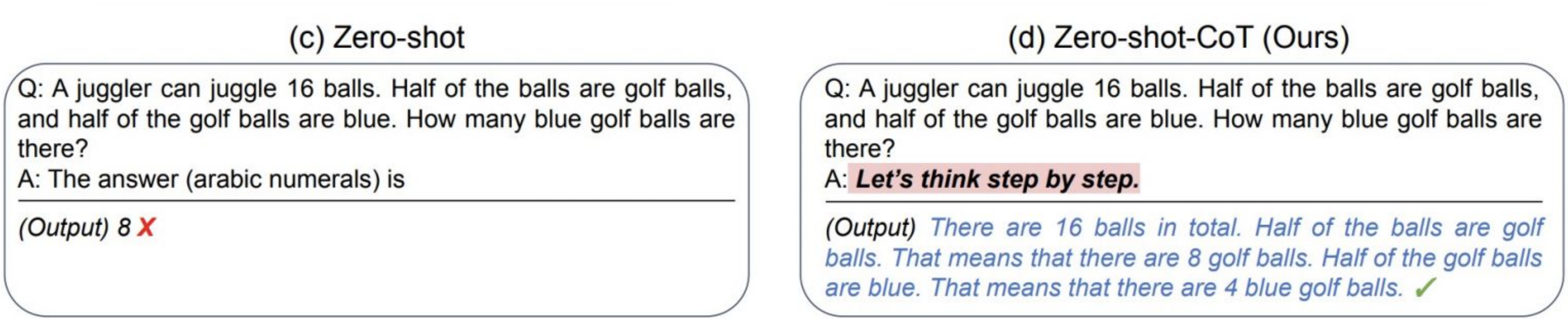
Problem with Few-Shot Learning: Context is Expensive

Problem with Few-Shot Learning: Context is Expensive

We can improve zero-shot learning with prompt engineering

Problem with Few-Shot Learning: Context is Expensive

We can improve zero-shot learning with prompt engineering



(c) Zero-shot

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: The answer (arabic numerals) is

(Output) 8 ✗

(d) Zero-shot-CoT (Ours)

Q: A juggler can juggle 16 balls. Half of the balls are golf balls, and half of the golf balls are blue. How many blue golf balls are there?
A: ***Let's think step by step.***

(Output) There are 16 balls in total. Half of the balls are golf balls. That means that there are 8 golf balls. Half of the golf balls are blue. That means that there are 4 blue golf balls. ✓

Adapting LLMs for Specific Tasks using Fine Tuning

- Although pre-trained language models like GPT possess vast language knowledge, they lack specialization in specific areas.

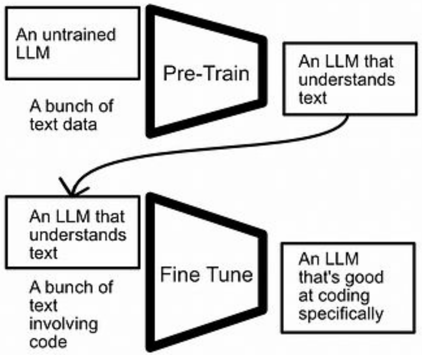
- Fine-tuning addresses this limitation by allowing the model to learn from domain-specific data to make it more accurate and effective for targeted applications.

What is Full Fine Tuning?

- Full fine-tuning is the process of training the entire model on the task-specific data.

- This means all the model layers are adjusted during the training process.

- BUT, is this always computationally feasible?


An untrained LLM
A bunch of text data
Pre-Train
An LLM that understands text
An LLM that understands text
A bunch of text involving code
Fine Tune
An LLM that's good at coding specifically

Limitations of Full Fine Tuning

- Total Training Memory for a model includes the following: Model + Optimiser + Activations + Gradients

- When full fine tuning, gradient needs to be calculated for every parameter. And in full precision training(fp32), the gradient for each parameter takes up 4 bytes of memory.

- Now imagine training a 13B parameter model. 13B * 4bytes = 52 Gigabytes of memory is required for the gradients alone!

- What about the time required to backpropagate through ALL these parameters?

Spending an insane amount to finetune foundation models

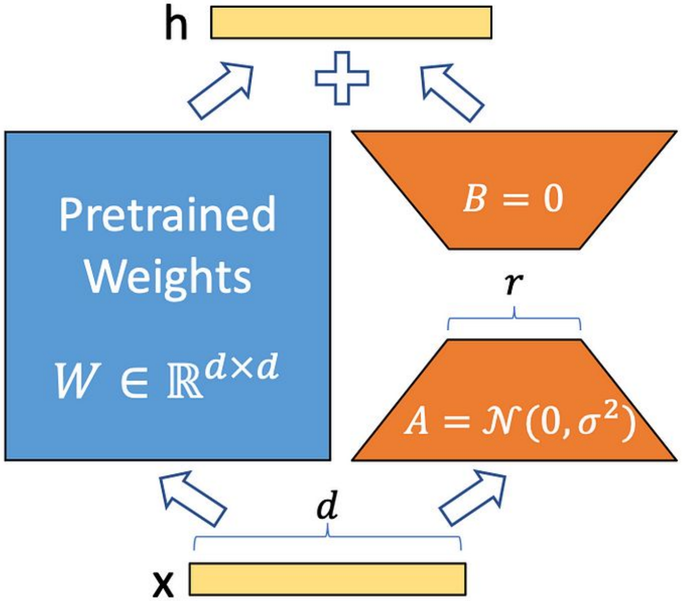
Using LoRA to finetune foundation models

LoRA: Low Rank Adaptation

- LoRA addresses some of the drawbacks of full fine-tuning.

- **How?**

  By freezing the pre-trained model weights and injecting trainable rank decomposition matrices into each layer of the Transformer architecture.


h
Pretrained Weights
$W \in \mathbb{R}^{d \times d}$
$B = 0$
r
$A = \mathcal{N}(0, \sigma^2)$
d
x

LoRA Explained

- LoRA reimagines fine tuning not as learning better parameters, but as adjustments required to the existing parameters to make them better.

$$\overbrace{W_{\mathtt{ft}}}^{\text{Finetuned Weights}} = \underbrace{W_{\mathtt{pt}}}_{\text{Pretrained Weights}} + \overbrace{\Delta W}^{\text{Weight Update}}$$

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LoRA Explained

- LoRA hinges on the following concepts:

1. Pre-trained language models have a low “intrinsic dimension”. They can still learn efficiently despite a random projection to a smaller subspace.

2. If you have a large matrix, with a significant degree of linear dependence (and thus a low intrinsic dimension), you can express that matrix as a factor of two comparatively small matrices.

$$W_0x + \Delta W x = W_0 x + BAx$$

LoRA Explained

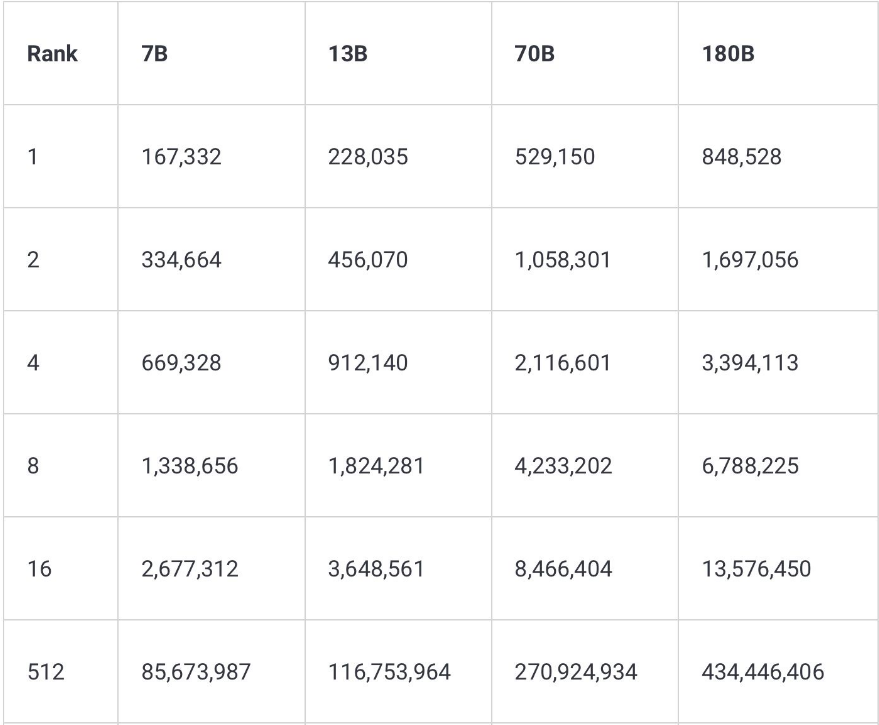
- How are we saving memory with LoRA?

  The full 5x5 matrix above has 25 values in it, whereas if we count the values in the decomposed matrices, there are just 10 (5 + 5).

- As the matrix we are trying to approximate gets larger and larger(delta W), we work with a smaller and smaller proportion of values in our decomposed matrices(A and B), compared to the full-size matrix.

$$\Delta W$$

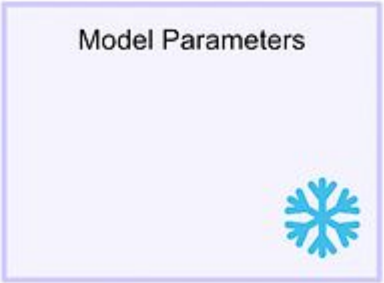
$$\begin{bmatrix}1\\3\\7\\-4\\2\end{bmatrix} \times \begin{bmatrix}5&1&-1&3&4\end{bmatrix} = \begin{bmatrix}5&1&-1&3&4\\15&3&-3&9&12\\35&7&-7&21&28\\-20&-4&4&-12&-16\\10&2&-2&6&8\end{bmatrix}$$



Rank	7B	13B	70B	180B
1	167,332	228,035	529,150	848,528
2	334,664	456,070	1,058,301	1,697,056
4	669,328	912,140	2,116,601	3,394,113
8	1,338,656	1,824,281	4,233,202	6,788,225
16	2,677,312	3,648,561	8,466,404	13,576,450
512	85,673,987	116,753,964	270,924,934	434,446,406

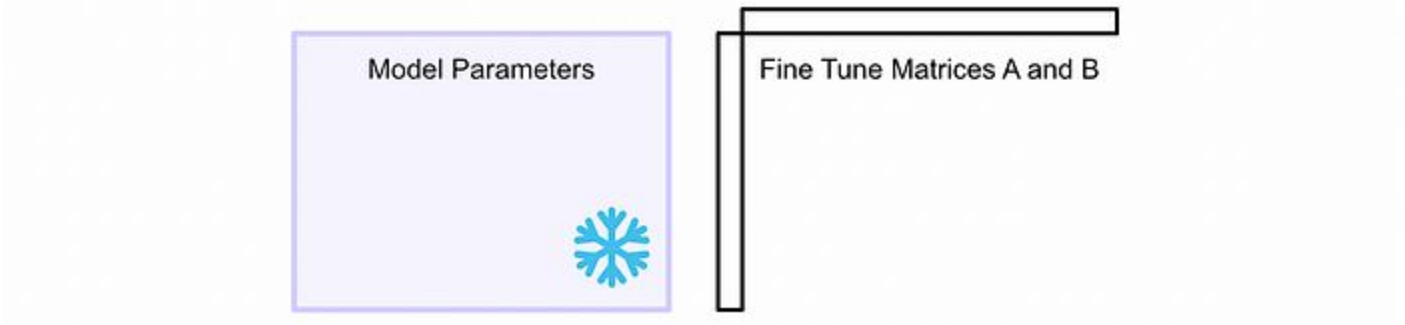
How Does LoRA Work?

- So, first, we freeze the model parameters. We'll be using these parameters to make inferences, but we won't update them.



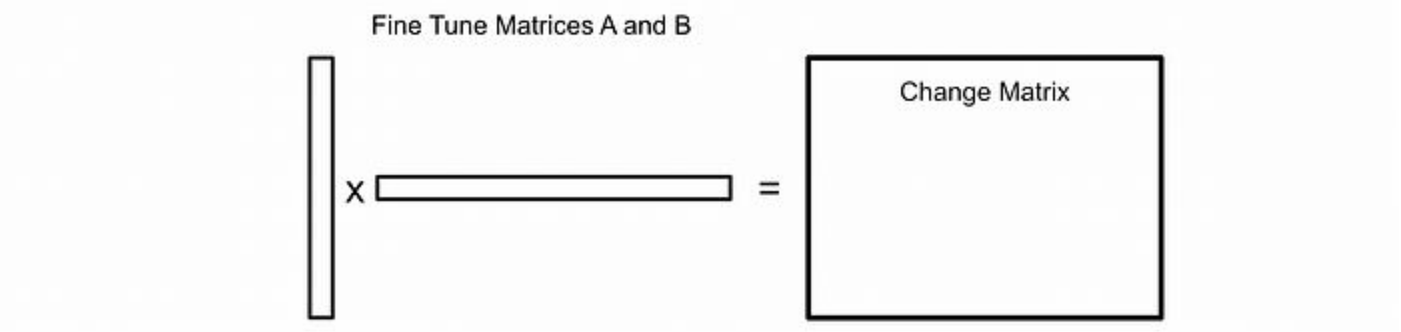
How Does LoRA Work?

- Then we create two matrices. These are sized in such a way that, when they're multiplied together, they'll be the same size as the weight matrices of the model we're fine tuning.



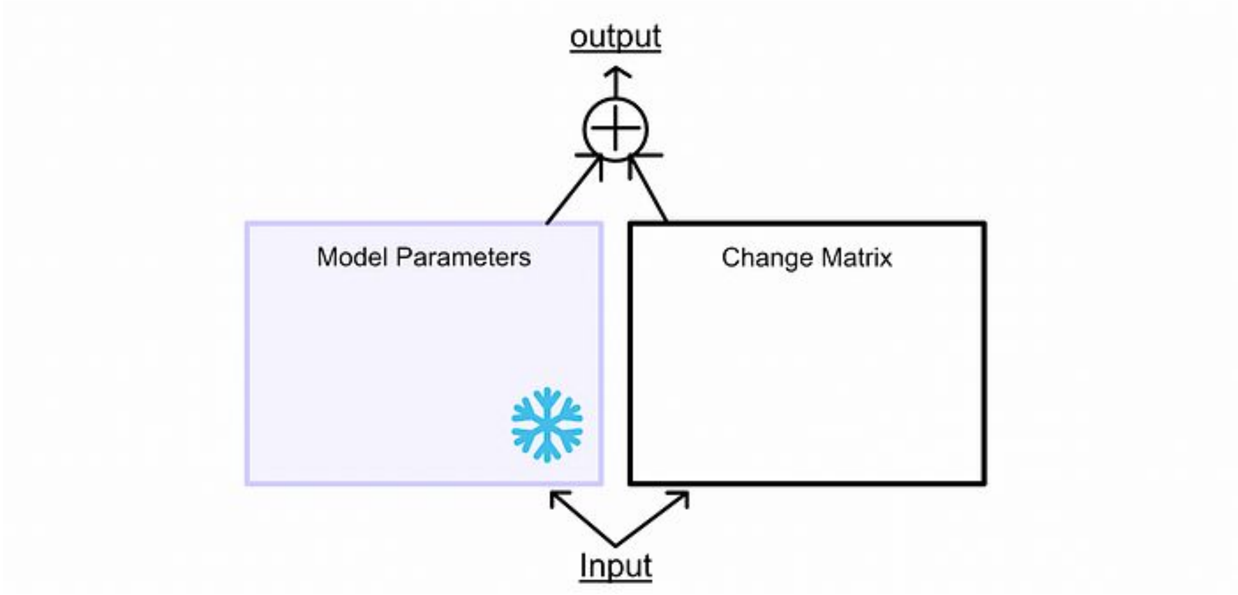
How Does LoRA Work?

- Then we calculate the the change matrix(delta W)



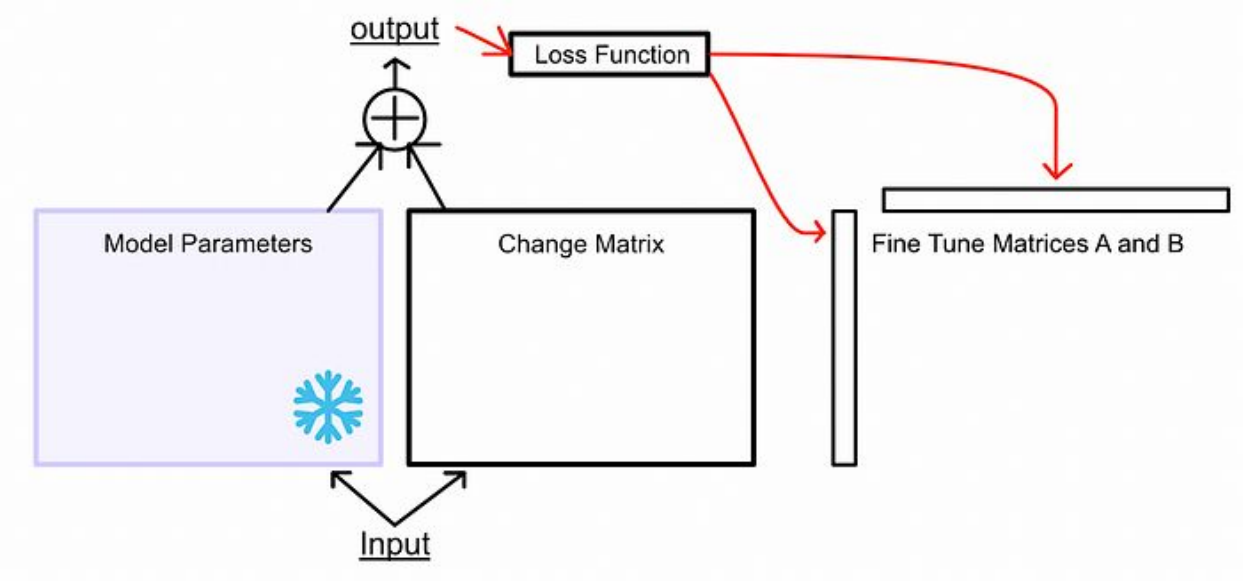
How Does LoRA Work?

- We pass our input through the frozen weights and the change matrix.



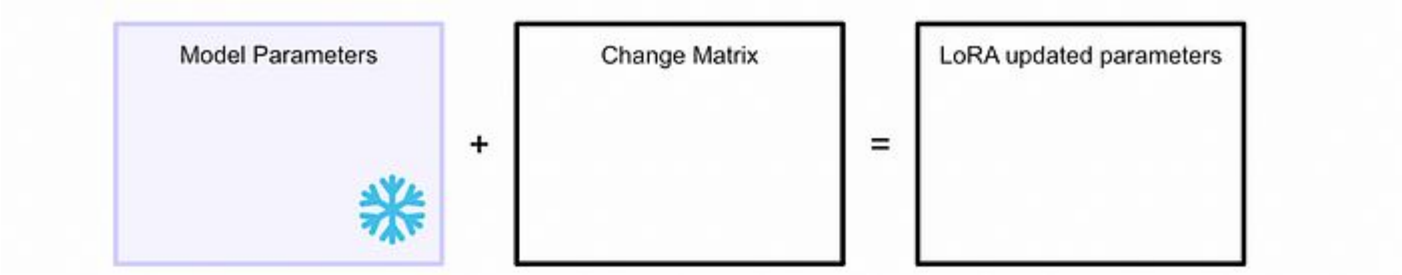
How Does LoRA Work?

- We calculate the loss and update matrices A and B.



How Does LoRA Work?

- At inference time we add the change matrix to the frozen weights and pass the input.

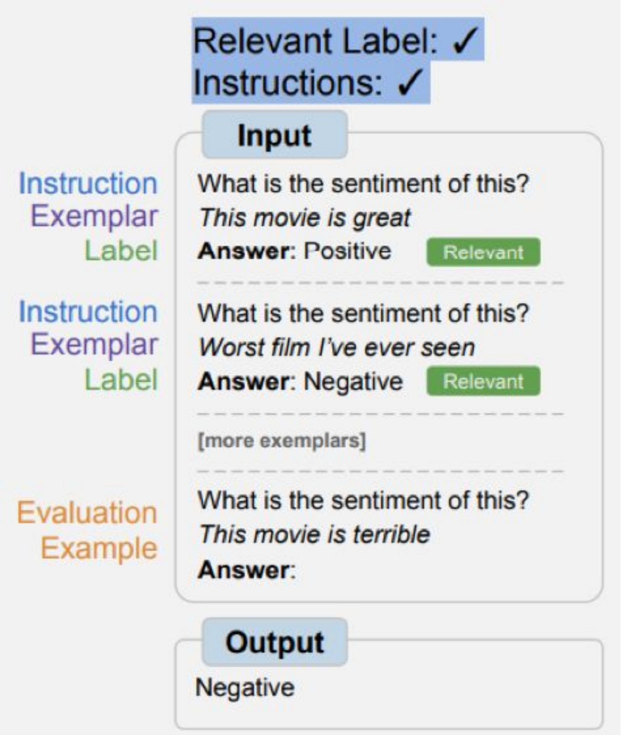


How Does LoRA Work?

- P.S: Don’t forget the scaling factor!

$$h = W_0 x + \frac{\alpha}{r} \Delta W x = W_0 x + \frac{\alpha}{r} B A x$$

Instruction Fine Tuning



Relevant Label: ✓
Instructions: ✓

Input

Instruction
Exemplar
Label

What is the sentiment of this?
This movie is great
Answer: Positive Relevant

Instruction
Exemplar
Label

What is the sentiment of this?
Worst film I've ever seen
Answer: Negative Relevant

[more exemplars]

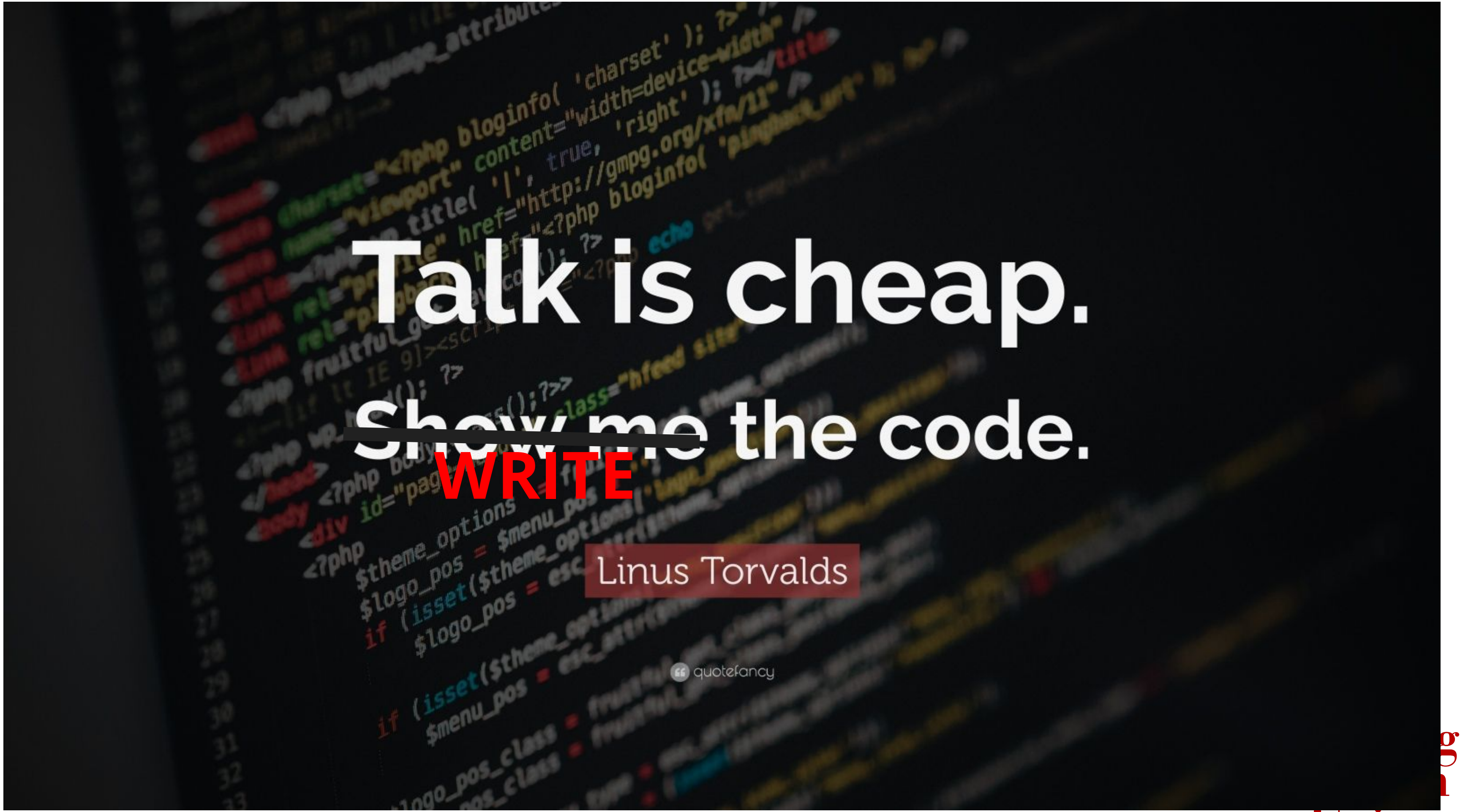
Evaluation
Example

What is the sentiment of this?
This movie is terrible
Answer:

Output

Negative

- Instruction fine-tuning is a technique used to train the model using examples that demonstrate how it should respond to a specific instruction.

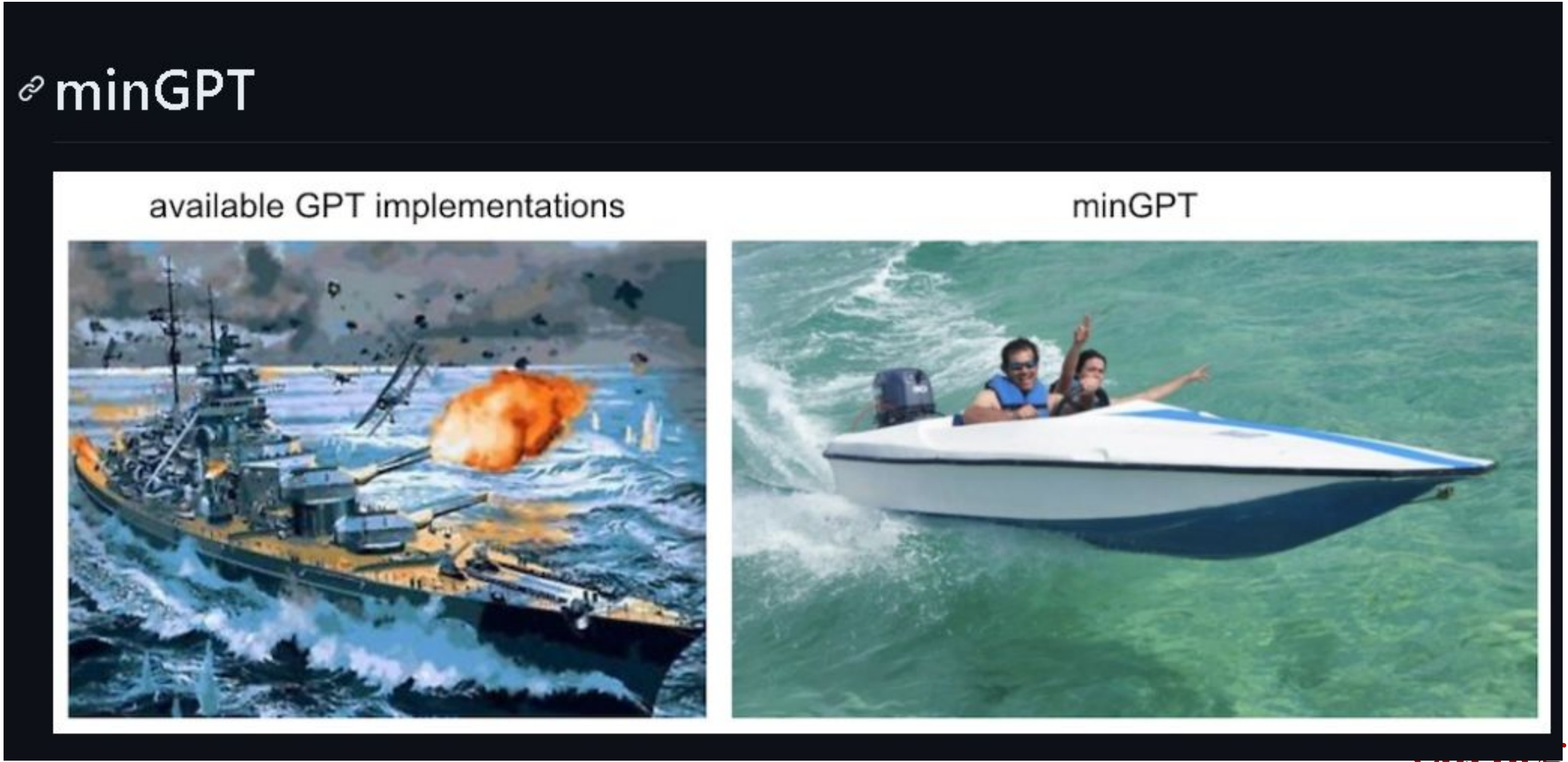


Talk is cheap.

~~Show me~~ WRITE the code.

Linus Torvalds

quotefancy



minGPT

Dataset

Rotten Tomatoes - Movie Review Dataset (Classification)

gpt2 untrained:

“Predict the sentiment of the following text: You are terrible. Label: ”

Response: “ Yes. Murders of this kind…”

Code Structure

-handout

- lora.py
- model.py
- dataloader.py
- train.py
- generate.py
- configs
    - finetune_config_params.py
- configurator.py
- requirements.tx

Code Structure

-handout

- **lora.py** (30-35 lines)

Code Structure

-handout

- **lora.py** (30-35 lines)
- model.py (2 lines)
- dataloader.py (5 lines)
- train.py (1 lines)

Training

Code Structure

-handout

- **lora.py** (30-35 lines)
- model.py (2 lines)
- dataloader.py (5 lines)
- train.py (1 lines)

Training

- generate.py (10 lines)

Evaluation

Lora.py

- only add LoRA to the linear layer
- so we tweak Linear Layer to support LoRA
    - inherit from the Linear Layer
- We should also be able to use this tweaked layer as our normal Linear layer if rank<=0.

Helpful PyTorch functions:

- NN Linear Layer (source code to skim through the existing functions): Link

Lora.py

class LoRALinear(nn.Linear):

- __init__() -> create the parameters (only if lora rank is >0)
    - Helpful PyTorch functions:
        - torch.nn.parameter.Parameter(torch.empty(in_dim, out_dim)) Link
- reset_parameter() -> set the initial values for the parameters
    - Helpful PyTorch functions:
        - torch.nn.init (Link)
- forward() -> called in *each* forward pass of the model
- train() -> called only when model.train() is called
- eval() -> called only when model.eval() is called

Wait but why do we need to (re)implement train and eval?

- How do you know if your weights have been merged in or not?
  - Use self.has_weights_merged
- When do you want your weights to be merged? (train or eval)?
- When do you want your weights to be de-merged? (train or eval)?

- Ensure that your train/eval/forward have weights in the required format (merged/de-merged) - if not, merge/de-merge them

~~I want~~ *The writeup tells me* to do full fine tuning with LoRA layer implemented. How do I do that?

- set r=0
- What this does is it never initializes your lora_a, lora_b matrix
  - so your layer is now the equivalent of Linear.
- Account for this in your train, forward and eval functions! (hint: use self.is_lora())

In LoRA you are only updating lora weight (and no other weights). How do you ensure that in practice?

Implement def mark_only_lora_as_trainable(model)

Hint: iterate through named_parameters() (Link)

Additional Files:

- model.py: add lora to attention layers
- dataloader.py: Write your instruction for fine tuning. Also decide if you want to make your labels more descriptive!

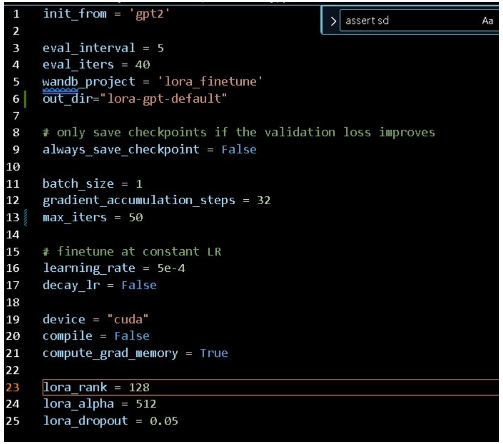
- train.py : make your model actually use lora

```
!python train.py --init_from=”gpt-medium” --out_dir=”gpt_lora_r:16_alpha:32”
```

Where do I change values of my hyperparams?

- Hyperparameters in LoRA: r, alpha, lr, max_iters..

- finetune_config_params.py



```
init_from = 'gpt2'

eval_interval = 5
eval_iters = 40
wandb_project = 'lora_finetune'
out_dir="lora-gpt-default"

# only save checkpoints if the validation loss improves
always_save_checkpoint = False

batch_size = 1
gradient_accumulation_steps = 32
max_iters = 50

# finetune at constant LR
learning_rate = 5e-4
decay_lr = False

device = "cuda"
compile = False
compute_grad_memory = True

lora_rank = 128
lora_alpha = 512
lora_dropout = 0.05
```

- command line (Eg python train.py --init_dir=”lora-pls-work3”)

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Generate.py

- Encouraged to just look at the generations gpt2-untrained vs finetuned gpt2 produces (use get_generation(prompt) method in the generate.py)
- Implement your own accuracy function:
  - Check if LoRA actually produced the labels you told it to
    - *GPT2 (and other small LMs (Even 7B ones)) may have trouble generating EOS and so one hack is to ask it to generate a limited number of tokens and look for labels in the first few characters.*
    - *Often labels generated will be garbage, make sure to consider those as negative predictions in your accuracy function*

```
!python generate.py --init_from=”resume” --out_dir=”gpt_lora_r:16_alpha:32”
```

Thank you!

I just spent our entire AI budget on fine-tuning a model
But at least we have a working model now, right?
We have a working model, right?