Parameter Efficient Fine-Tuning (PEFT) of a Large Language Model on a GPU

Wasu
Hugo Legrand

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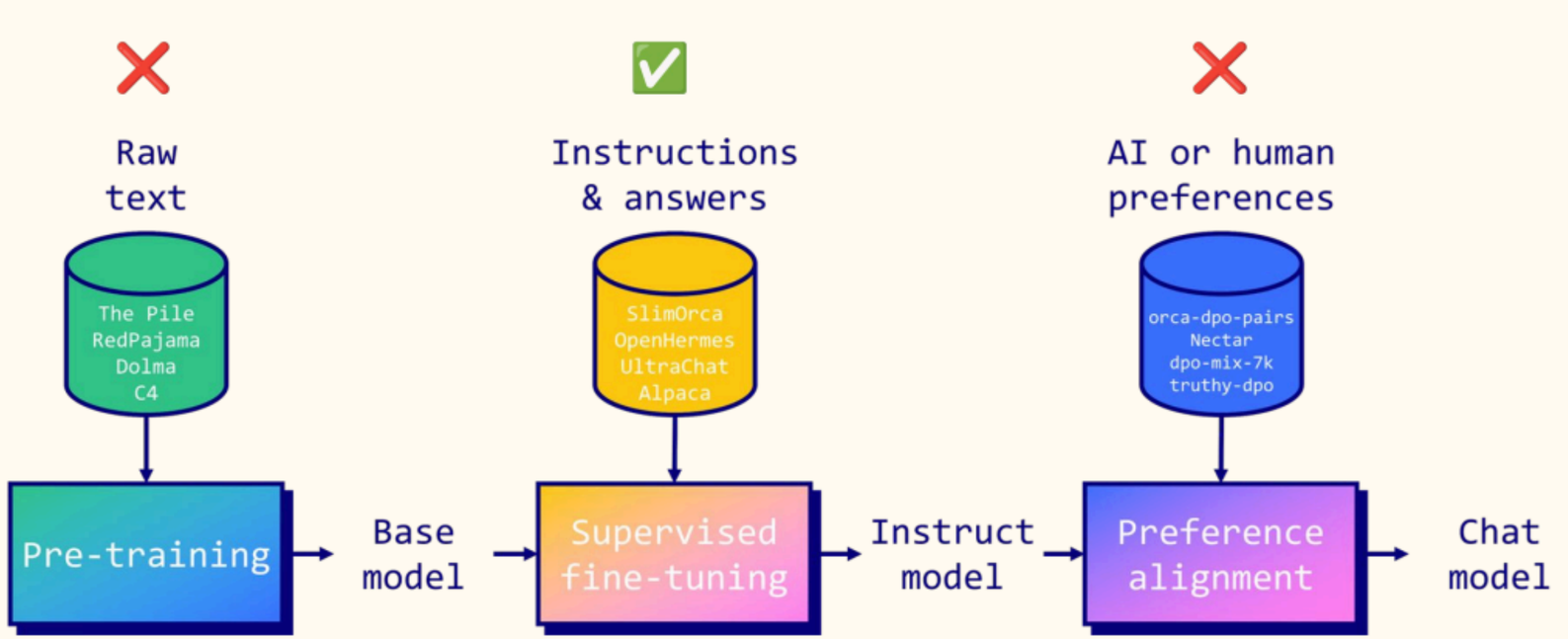
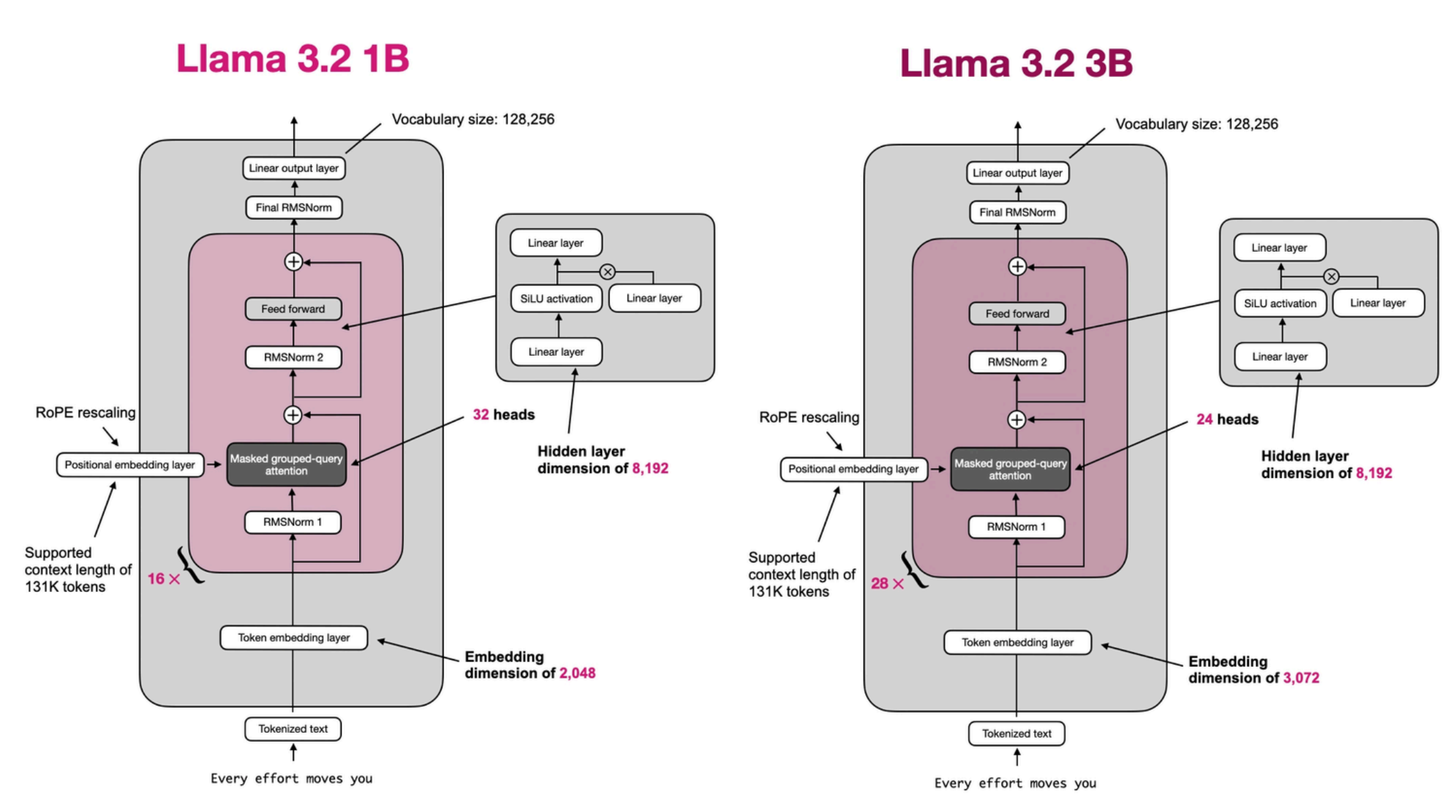
Introduction



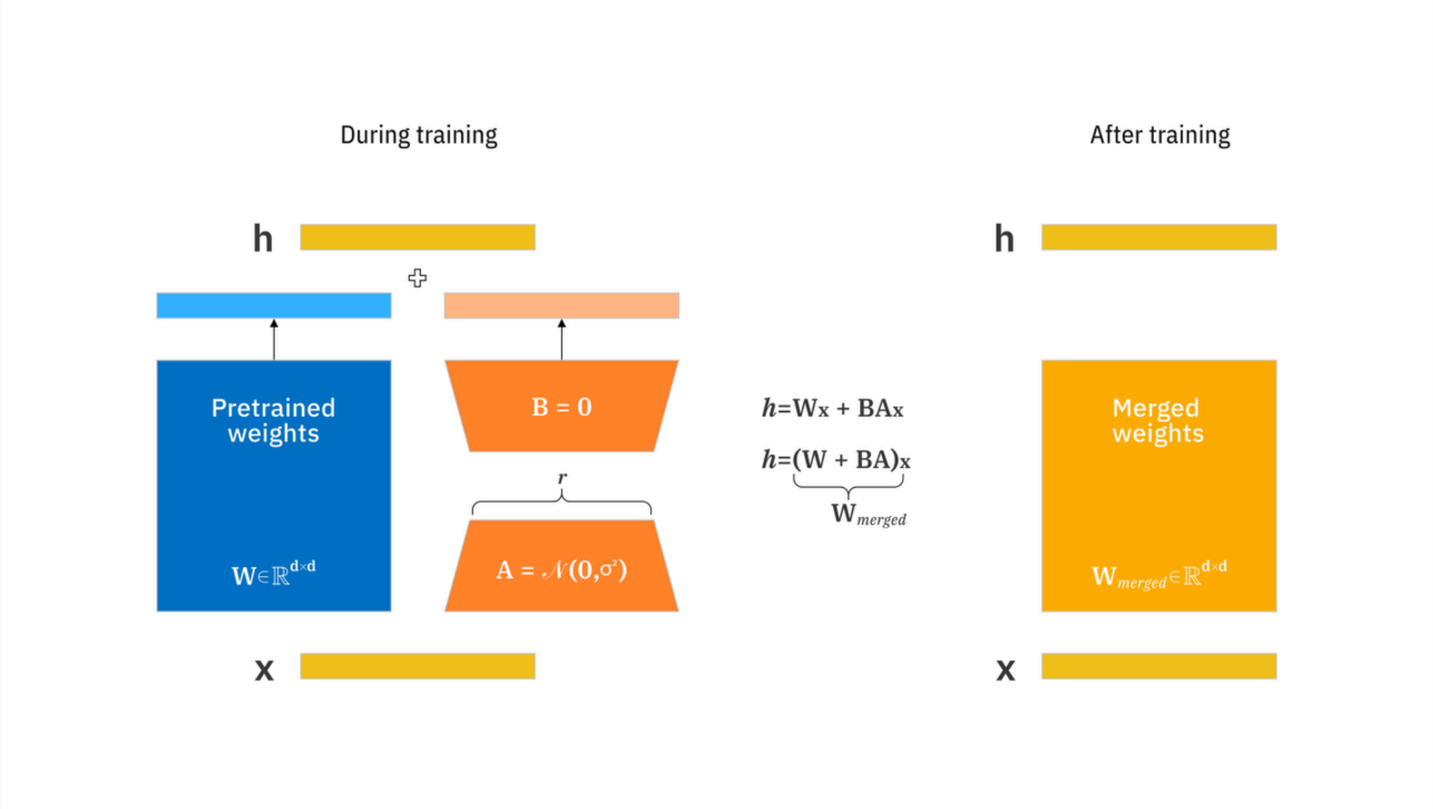
- Dataset: Finetome 100K dataset
- Model: Unsloth/Llama-3.2
- Technique for PEFT: LoRA
- UI: Huggingface Gradio

Model: Llama-3.2



- Llama 3.2 collection is a collection of pretrained and instruction-tuned generative models in 1B and 3B sizes.
- Llama 3.2 instruction-tuned text only models are optimized for multilingual dialogue use cases, including agentic retrieval and summation tasks.
- Problems
  - Computational Cost
  - Model Collapse
  - Catastrophic forgetting

Technique for PEFT : LoRA (Low-Rank Adaptation)



- Freeze the original weights and parameters of the model as they are.
- Add a lightweight addition, called a low-rank matrix, which is applied to new inputs to get results specific to the context.
- LoRA utilizes the concept of lower-rank matrices to make the model training process extremely efficient and fast.

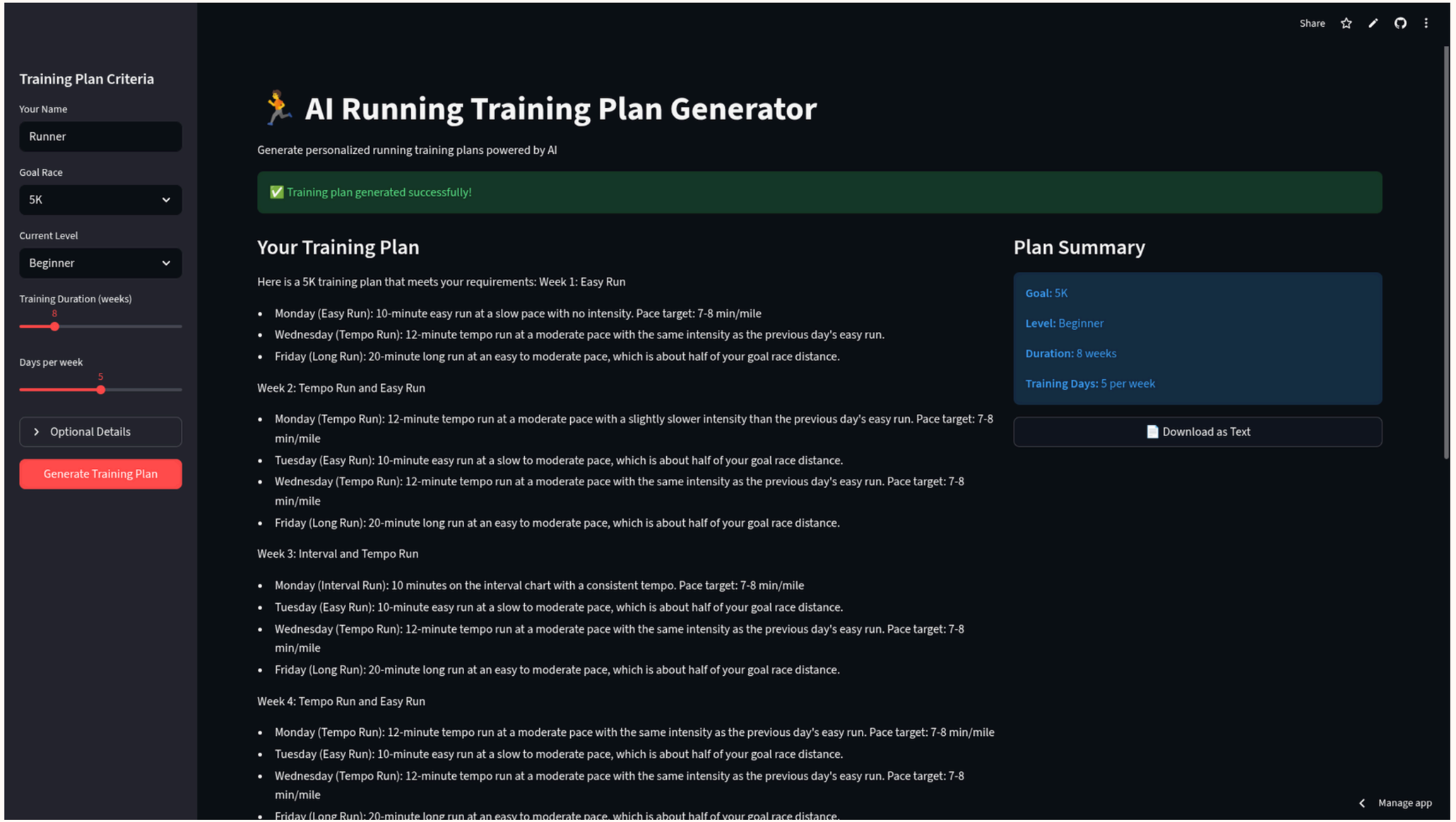
Additional Technique: Checkpoint

```
trainer = SFTTrainer(
    model = model,
    tokenizer = tokenizer,
    train_dataset = dataset,
    dataset_text_field = "text",
    max_seq_length = max_seq_length,
    data_collator = DataCollatorForSeq2Seq(tokenizer = tokenizer),
    dataset_num_proc = 2,
    packing = False, # Can make training 5x faster for short sequences.
    args = TrainingArguments(
        per_device_train_batch_size = 2,
        gradient_accumulation_steps = 4,
        warmup_steps = 5,
        num_train_epochs = 1, # Set this for 1 full training run.
        # max_steps =None,
        learning_rate = 2e-4,
        fp16 = not is_bfloat16_supported(),
        bf16 = is_bfloat16_supported(),
        logging_steps = 1,
        save_steps = 250,
        save_total_limit = 2,
        save_strategy = 'steps',
        optim = "adamw_8bit",
        weight_decay = 0.01,
        lr_scheduler_type = "linear",
        seed = 3407,
        output_dir = drive_output_dir,
        report_to = "none", # Use this for WandB etc
        resume_from_checkpoint = resume_from_checkpoint,
    ),
)
```

- Since fine-tuning the LLM requires high computational resources (like GPU)
- So, We use free-GPU from Colab, T4-GPU.
- However, T4-GPU and allowable session time of Colab is still not enough for training. So, we utilized checkpoint technique.

Results

link: https://training-plan-generator.streamlit.app

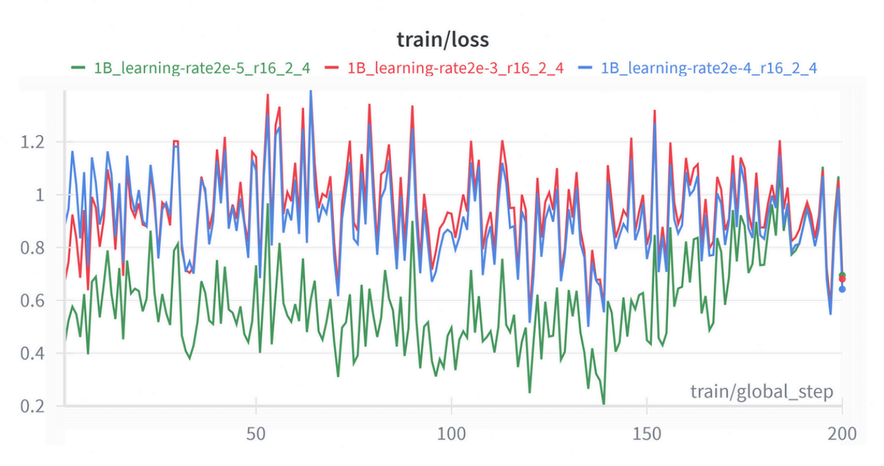


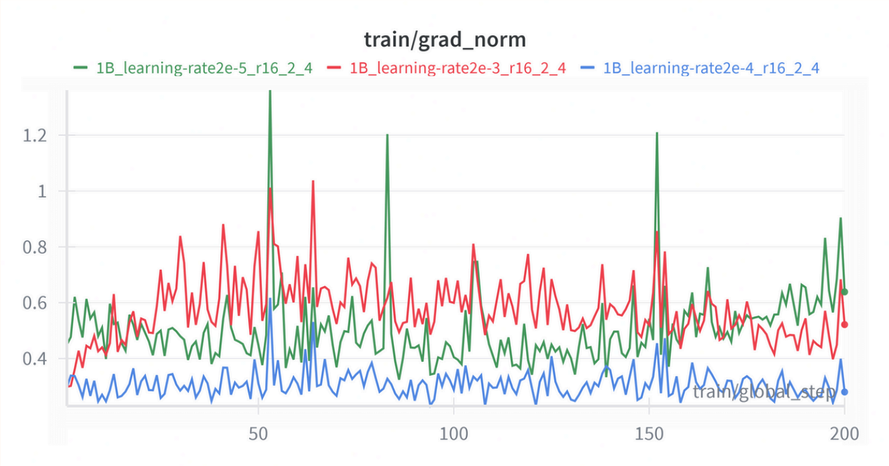
Improvement

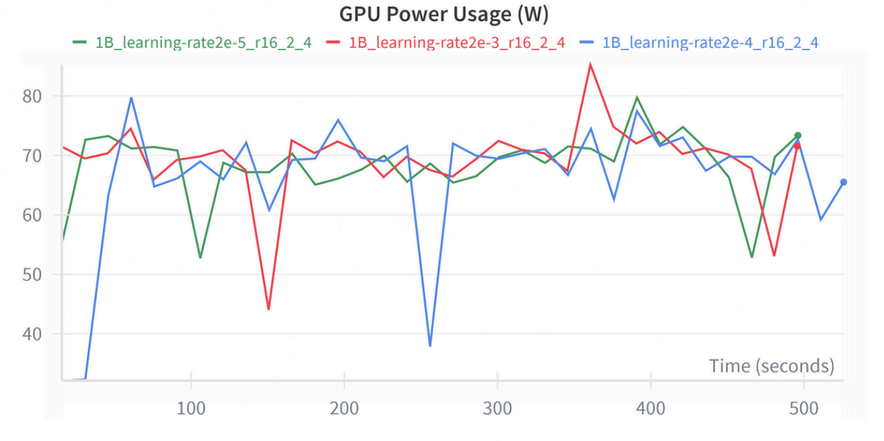
- Model-centric-approach
  - Tuning hyperparameters (Rank of LoRA, Learning Rate, etc)
  - Comparing Llama 3.2 1B/3B
- Objective
  - To improve the performance of the LLM.
  - To study the effects of hyperparameters.

Improvement Result: Tuning Hyperparameters (Learning Rate)

- Base Case: Llama 3.2 1B, per_device_train_batch_size = 2, gradient_accumulation_steps = 4, r = 16
- Learning Rate: varying 2e-3, 2e-4, 2e-5

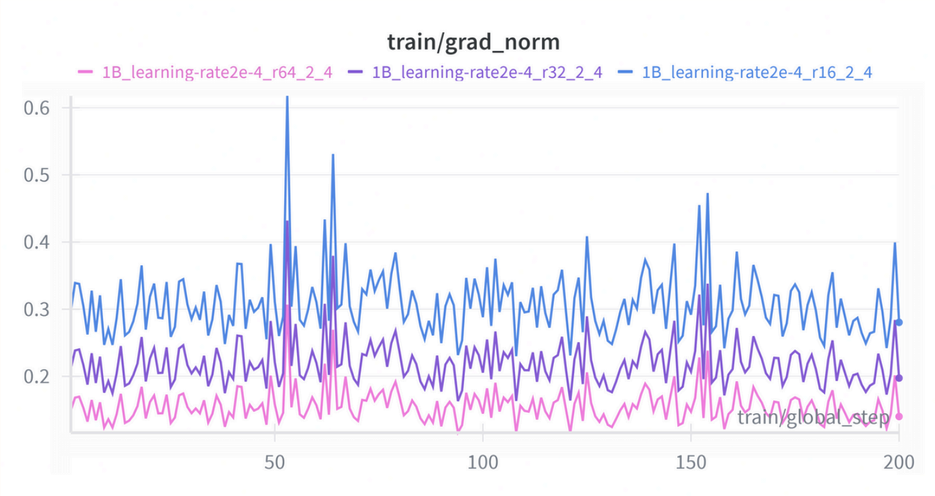


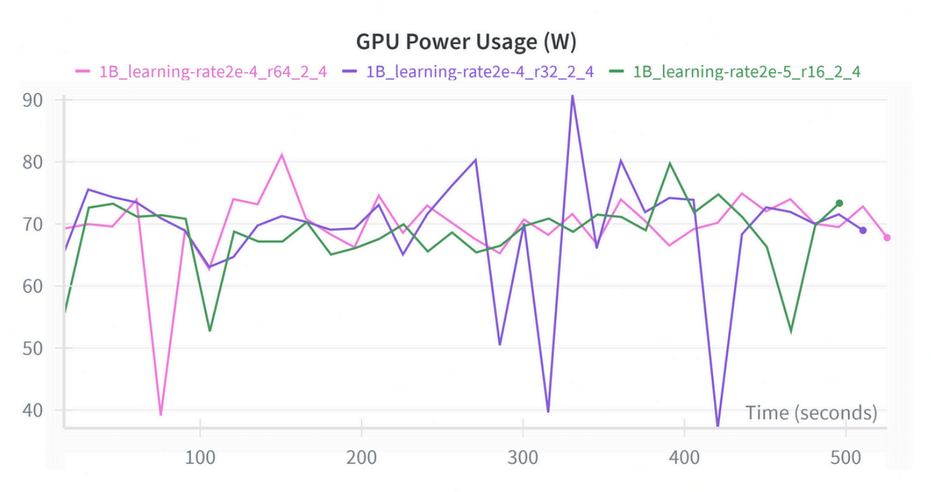




Improvement Result: Tuning Hyperparameters (Rank of LoRA)

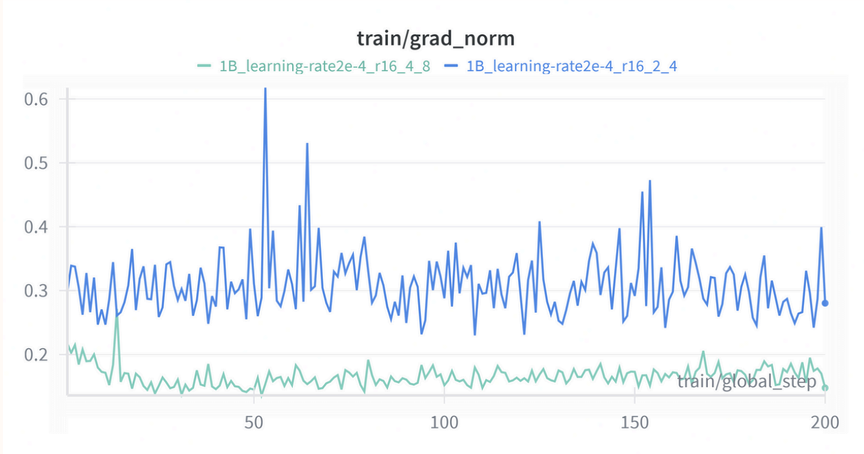
- Base Case: Llama 3.2 1B, per_device_train_batch_size = 2, gradient_accumulation_steps = 4, r = 16
- Rank: r = 16, 32, 64

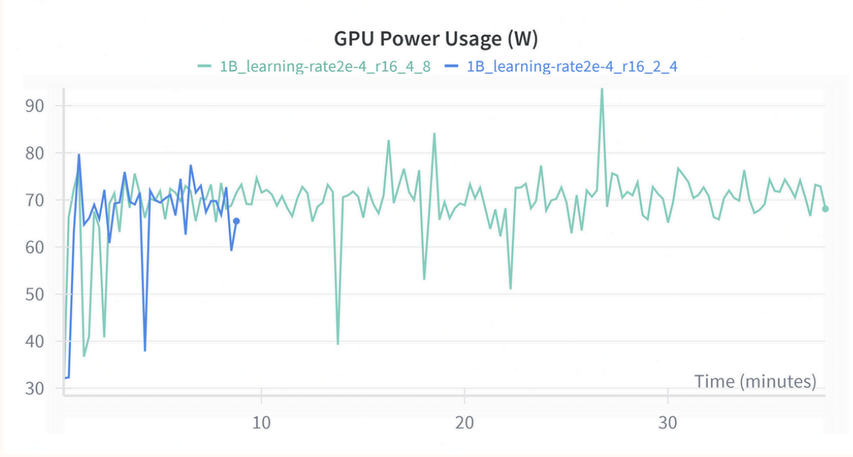




Improvement Result: Tuning Hyperparameters (per_device_train_batch_size, gradient_accumulation_steps)

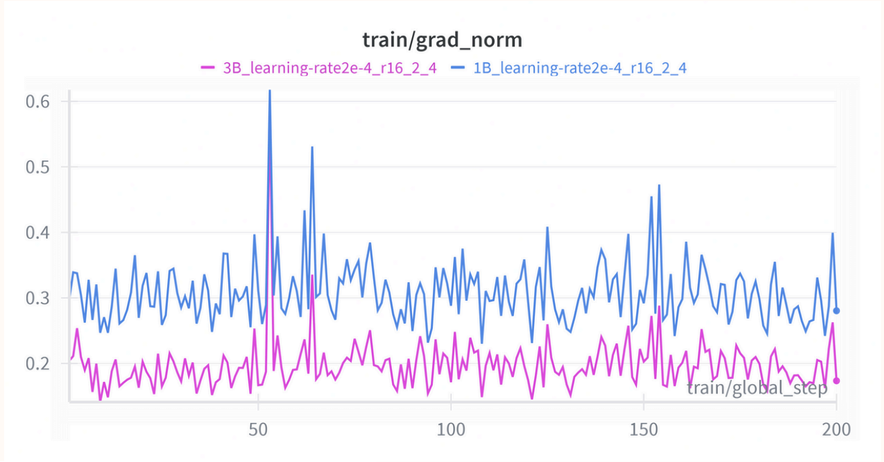
- Base Case: Llama 3.2 1B, per_device_train_batch_size = 2, gradient_accumulation_steps = 4, r = 16
- per_device_train_batch_size = 4, gradient_accumulation_steps = 8

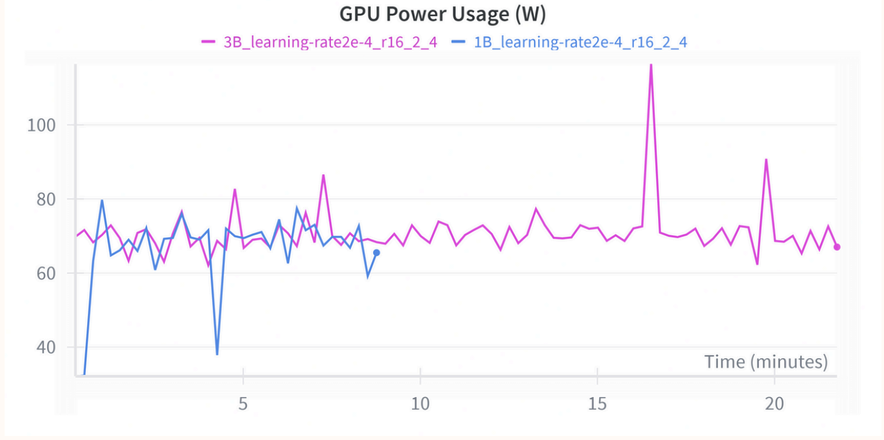




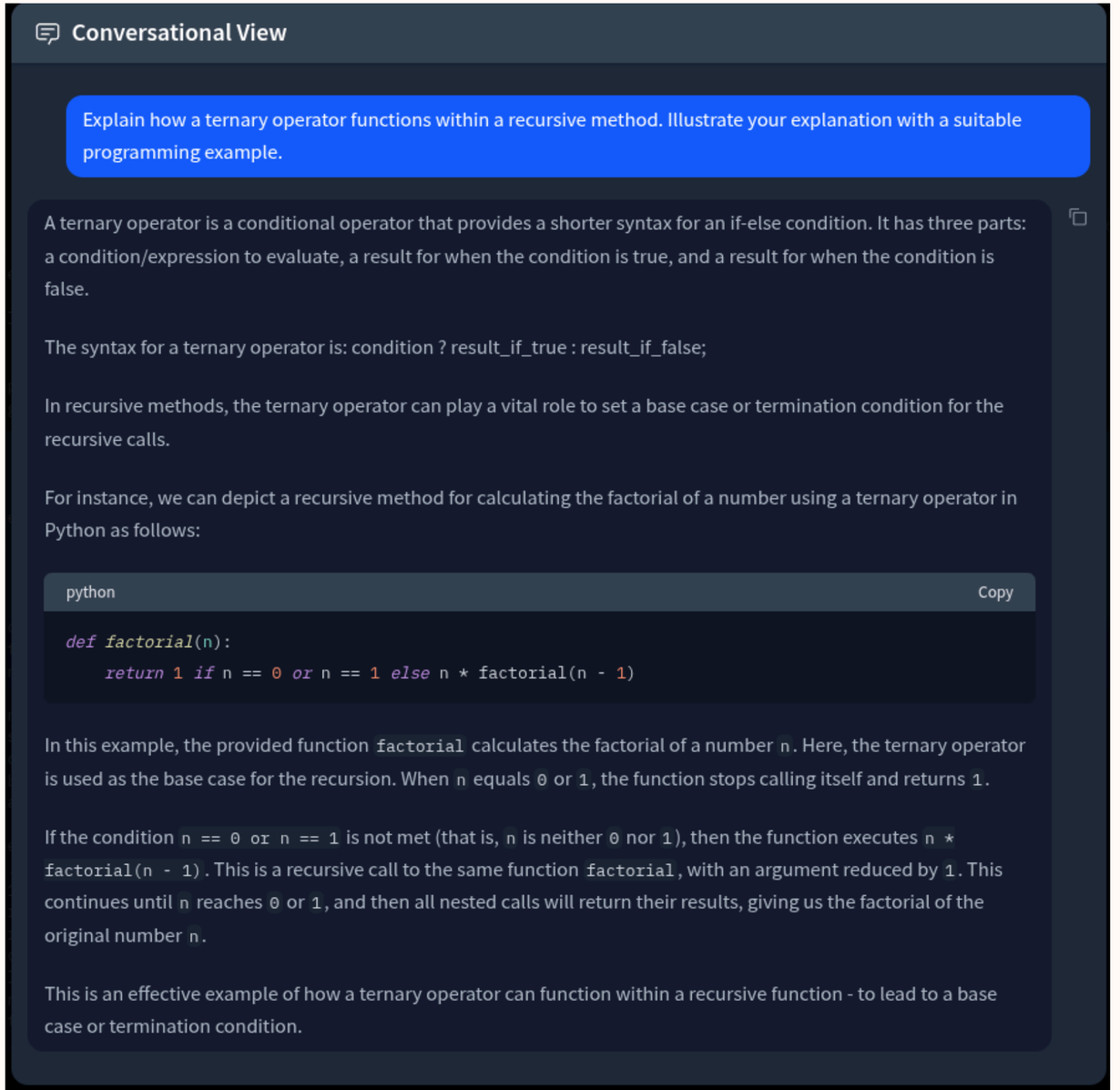
Improvement Result: Changing the model

- Base Case: Llama 3.2 1B, per_device_train_batch_size = 2, gradient_accumulation_steps = 4, r = 16
- Llama 3.2 3B





Evaluation on a rephrased input of the FineTome dataset :



Evaluation on a rephrased input of the FineTome dataset : Base Llama3 1B

Example:

We want to calculate the sum of all elements in a list of integers. We can use recursion to solve this problem. We'll use the ternary operator to simplify the recursive calls.

```
def recursive_sum(lst):
    if len(lst) == 0:
        return 0
    else:
        return lst[0] + recursive_sum(lst[1:])
```

Explanation:

When we use a ternary operator inside a recursive function, it works as follows:

- If the current recursive call returns a value, we discard it and continue with the next recursive call.
- If the current recursive call returns `None` or an empty value, we discard it and use the value from the previous recursive call as the new value.

In our example, the ternary operator allows us to simplify the recursive calls as follows:

```
def recursive_sum(lst):
    if len(lst) == 0:
        return 0
    else:
        first = lst[0]
        second = recursive_sum(lst[1:])
        return first + second if second else first
```

Example Usage:

```
numbers = [1, 2, 3, 4, 5]
result = recursive_sum(numbers)
print(result)  # Output: 15
```

In this example, the recursive function `recursive_sum` is called with the list `numbers` as its argument. The function first checks if the list is empty, in which case it returns 0. Otherwise, it recursively calls itself with the first element of the list (`lst[0]`) and the remaining elements (`lst[1:]`). The ternary operator allows the function to use the first element of the list as the new value in the recursive call, while also returning the sum of the remaining elements. The final result is the sum of all elements in the list.

Evaluation on a rephrased input of the FineTome dataset : Llama3 1B with finetuning

A ternary operator is a concise way to express a conditional statement. When used inside a recursive function, it allows the function to make decisions based on previous computations. Here's how it works:

1. The function takes three parameters: the current value, the condition, and the value to return if the condition is true.
2. The function checks the condition. If it is true, it returns the value to be returned.
3. If the condition is false, the function recursively calls itself with the current value, the condition, and the value to return if the condition is true.
4. The recursive call returns the result of the call, which is then returned to the previous call.

Let's consider an example:

```
def recursive_function(n, condition, value_to_return):
    if condition:
        return value_to_return
    else:
        return recursive_function(n, condition, value_to_return)

result = recursive_function(5, True, 10)
print(result)  # Output: 10
```

In this example, the `recursive_function` takes three parameters: `n` (the current value), `condition` (the condition to check), and `value_to_return` (the value to return if the condition is true). The function checks the condition and returns the value to be returned if the condition is true. If the condition is false, the function recursively calls itself with the current value, the condition, and the value to return if the condition is true. The recursive call returns the result of the call, which is then returned to the previous call.

In the example provided, the function is called with `n` equal to 5, `condition` set to `True`, and `value_to_return` set to 10. The function checks the condition and returns the value to be returned if the condition is true. In this case, the condition is true, so the function returns the value 10. The returned value is then printed to the console.

Evaluation on a rephrased input of the FineTome dataset : Base Gemma 270m

Explanation:

A ternary operator (also known as a ternary operator) is a concise and efficient way to evaluate expressions that can be expressed as a series of binary operations. It's designed to be concise and readable, particularly when dealing with simple expressions. It's particularly useful for situations where you need to perform a series of operations, like comparing values, or performing calculations.

How it Works:

The ternary operator evaluates a single expression, and it compares the result with the result of the corresponding operation. If the result is *greater* than the result of the operation, the expression is considered equal to the operation, and the operator is executed. Otherwise, the expression is considered *less than* the result of the operation.

Example:

Let's consider a simple ternary operator that evaluates the expression `2 + 3 * 4`.

1. **Initialization:** The ternary operator is initialized with `0` as the left-hand operand.
2. **Evaluation:** The ternary operator evaluates `2 + 3 * 4`.
3. **Comparison:** The result of the ternary operator is compared to the result of the operation `4`.
4. **Result:** If the result of the ternary operator is greater than 4, the expression is considered equal to the operation. Otherwise, it is considered *less than* the result of the operation.

Code Example:

```
def ternary_operator_expression(expression):
    """
    Evaluates a ternary operator expression.

    Args:
        expression: A string representing the ternary operator expression.

    Returns:
        The result of the ternary operator expression.
    """

    try:
        result = expression
        return result
    except Exception as e:
        print(f"Error evaluating ternary operator expression: {e}")
        return 0  # Return 0 if there's an error
    else:
```

Evaluation on a rephrased input of the FineTome dataset : Base Gemma 270m with finetuning

A ternary operator is a function that takes two input values and returns a value that can be expressed as a ternary sum. It can be used inside a recursive function to evaluate the expression entered into the ternary operator and return the result.

Here's an example in code:

```
def ternary_sum(a, b):
    return ternary_sum_recursive(a, b)

def ternary_sum_recursive(a, b):
    if b == 0:
        return a + b
    elif b == 1:
        return a + a + b
    else:
        return ternary_sum_recursive(a + b, b)

a = 10
b = 15
result = ternary_sum_recursive(a, b)
print(result)
```

In this code, the ternary operator `ternary_sum_recursive` is defined to evaluate the ternary sum of the input `a` and `b`. The ternary sum is defined as `a + b`. The function `ternary_sum_recursive` is declared as `a` and `b`, and its body is declared as `if b == 1: return a + a + b; else: return ternary_sum_recursive(a + b, b);` Where `a + b` represents the ternary sum of the two input values.

The ternary operator uses ternary operators to evaluate the ternary sum of the input values. The ternary sum of the input values is expressed as a ternary sum, which is the sum of the ternary sum of the input values. This function can be used inside a recursive function to evaluate the expression entered into the ternary operator and return the result.

Here is an example of how the ternary operator can be used inside a recursive function:

```
def ternary_sum_recursive(a, b):
    if b == 0:
        return a + b
    elif b == 1:
        return a + a + b
    else:
        return ternary_sum_recursive(a + b, b)
```

In this code, the ternary operator `ternary_sum_recursive` is defined to evaluate the ternary sum of the input values. The ternary sum is defined as `a + b`. The function `ternary_sum_recursive` is declared as `a` and `b`, and its body is declared as `if b == 1

Hyperparameter Tuning with Optuna

```python
def objective(trial):
    # Hyperparameters to tune
    learning_rate = trial.suggest_float("learning_rate", 1e-6, 1e-4, log=True)
    warmup_steps  = trial.suggest_int("warmup_steps", 5, 50)
    weight_decay  = trial.suggest_categorical("weight_decay", [0.0, 0.001, 0.01])
    batch_size    = trial.suggest_categorical("batch_size", [1, 2, 4])
    grad_acc      = trial.suggest_categorical("grad_acc", [1, 2, 4])


    # Load model here

    # Trainer config with sampled params
    training_args = SFTConfig(
        dataset_text_field = dataset_text_field,
        per_device_train_batch_size = batch_size,
        gradient_accumulation_steps = grad_acc,
        learning_rate = learning_rate,
        warmup_steps = warmup_steps,
        weight_decay = weight_decay,

        optim = "adamw_8bit",
        max_steps = 50,          # Hyperband will prune bad configs early
        logging_steps = 10,
        report_to = "none",
        output_dir=f"outputs_trial_{trial.number}",

        save_strategy = "no",    # do NOT save checkpoints during tuning
    )
```

```python
study = optuna.create_study(
    direction="minimize",
    pruner=HyperbandPruner(),
)

study.optimize(
    objective,
    n_trials=10,
    timeout=None,
)
```

Conclusion

- Fine-tuning with Unsloth on a Colab T4 GPU is feasible but comes with several constraints.
- 1-hour session limits and daily usage caps on free Colab slow down training progress.
- Training already takes a long time; these constraints make it even longer and harder to iterate.
- The fine-tuned model actually performed worse, likely due to overfitting on the small new dataset.
- A learning rate too high (or other hyperparameter choices) may have contributed to the performance drop.