Phase 3: LLaMA2 Model Training

Implementations

1. Initial Setup

For intinial testing, the decoder layer is set to be only one.

```
model_args.n_layers = 1  # for debugging purposes we only use 1 layer
```

In the `model.py` file, remove all the `start_pos` variables in forward functions and replace them with 0. This is because we removed the KV-caching and `start_pos` is no longer needed.

Besides, I changed the max sequence length so that it can fit for the Alpaca data:

```
max_seq_len: int = 512      # modify to a larger max_seq_len
```

2. End-to-End Instruction Tuning Flow

Code was provided with the assignment. The classes included `SupervisedDataset(Dataset)` and `DataCollatorForSupervisedDataset`. The main part our modification focused on is the `train()` function.

I also add helper functions `start_timer()` and `end_timer_and_print()` to record the runtime and memory usage.

```
def start_timer():
    global start_time
    gc.collect()
    torch.cuda.empty_cache()
    torch.cuda.reset_max_memory_allocated()
    torch.cuda.synchronize()
    start_time = time.time()


def end_timer_and_print(local_msg=""):
    torch.cuda.synchronize()
    end_time = time.time()
    print("\n" + local_msg)
    print("Total runtime = {:.3f} sec".format(end_time - start_time))
    print("Peak memory usage = {} MBytes".format(torch.cuda.max_memory_allocated()/1000))
```

3. Training Iteration Loop

Code was provided. The crucial change to replace HuggingFace's object with Alpaca's repo is inside the `train()` function. After assigning the paths of our model and data, we extracted the labels and logits within the bath according to the format of Alpaca data.

4. Gradient Accumulation and Mixed Precision Training

For mixed precision, I followed the instructions of AMP Example. `GradScaler` was utilized to prevent gradient vanishing. `Autocast` set the demanding `dtype` to be `torch.float16` for the cuda during training.

Changes are made in the `finetuning.py` file:

```
scaler = GradScaler()   # scale the gradient

    for epoch in range(5):
        for i, batch in enumerate(dataloader):
            input_ids = batch['input_ids'].to("cuda")
            labels = batch['labels'].to("cuda")

            # auto mixed precision
            with autocast(dtype=torch.float16):
                logits = model(input_ids)

                shift_logits = logits[..., :-1, :].contiguous()
                shift_labels = labels[..., 1:].contiguous()
                shift_logits = shift_logits.view(-1, 32000)
                shift_labels = shift_labels.view(-1)

                loss = criterion(shift_logits, shift_labels)

            # exit autocast before backward()
            scaler.scale(loss).backward()
            scaler.step(optimizer)
            scaler.update()
            optimizer.zero_grad()
```

Then, I added the Gradient Accumulation, and assigned `accumulation_steps` to be 8. The gradient is only accumulated and backwarded when reaching this amount of steps:

```
    accumulation_steps = 8
    scaler = GradScaler()

    for epoch in range(5):
        for i, batch in enumerate(dataloader):
            input_ids = batch['input_ids'].to("cuda")
            labels = batch['labels'].to("cuda")
```

```
            # auto mixed precision
            with autocast(dtype=torch.float16):
                logits = model(input_ids)

                shift_logits = logits[..., :-1, :].contiguous()
                shift_labels = labels[..., 1:].contiguous()
                shift_logits = shift_logits.view(-1, 32000)
                shift_labels = shift_labels.view(-1)

                # loss should be devided by accumulation_steps
                loss = criterion(shift_logits, shift_labels) / accumulation_steps

            # exit autocast before backward()
            scaler.scale(loss).backward()

            # accumulate gradient
            if (i + 1) % accumulation_steps == 0:
                scaler.step(optimizer)
                scaler.update()
                optimizer.zero_grad()
```

5. LoRA Linear Layer Module

The file `lora.py` was created based on the official instructions. I copied the classes `LoRALayer()` and `Linear(nn.Linear, LoRALayer)` from the official code, so that I can convert the model using RoLA Linear modules.

```
import torch
import torch.nn as nn
import torch.nn.functional as F
import math

class LoRALayer():
    def __init__():
        ...

class Linear(nn.Linear, LoRALayer):
    def __init__():
        ...
    def reset_parameters(self):
        ...
    def train(self, mode: bool = True):
        ...
    def forward(self, x: torch.Tensor):
        ...
```

Then in the `model.py` file, I modified the way Q and V are projected in the `Attention` class:

```
from llama.lora import Linear as LoRALinear

...

class Attention(nn.Module):
    """Multi-head attention module."""
    def __init__(self, args: ModelArgs):

        ...

        # LoRA Linear
        self.wq = LoRALinear(args.dim, args.n_heads * self.head_dim,
                             merge_weights=False, bias=False)
        self.wv = LoRALinear(args.dim, self.n_kv_heads * self.head_dim,
                             merge_weights=False, bias=False)

        # origin code
        # self.wq = nn.Linear(args.dim, args.n_heads * self.head_dim, bias=False)
        # self.wv = nn.Linear(args.dim, self.n_kv_heads * self.head_dim, bias=False)

        self.wk = nn.Linear(args.dim, self.n_kv_heads * self.head_dim, bias=False)
        self.wo = nn.Linear(args.n_heads * self.head_dim, args.dim, bias=False)
```

Also in the `finetuning.py`, de-comment the part related to RoLA weights:

```
    # Freeze model parameters other than lora weights
    for name, params in model.named_parameters():
        if "lora_" in name:
            params.requires_grad = True
        else:
            params.requires_grad = False
```

6. Gradient Checkpointing

Checkpoints were inserted in the `model.py` file. After importing the `checkpoint` in Pytorch, I changed the `forward` function in `TransformerBlock`. I chose to apply the gradient checkpoint for every training layer. Custom attention and feed_forward functions were created in order to separate them from the checkpoint processing:

```
def forward(
    self,
    x: torch.Tensor,
    freqs_cis: torch.Tensor,
    mask: Optional[torch.Tensor],
```

```
):
    def custom_attention(x, freqs_cis, mask):
        return x + self.attention(self.attention_norm(x), freqs_cis, mask)

    def custom_feed_forward(h):
        return h + self.feed_forward(self.ffn_norm(h))

    if self.training:
        h = checkpoint(custom_attention, x, freqs_cis, mask, use_reentrant=False)
        out = checkpoint(custom_feed_forward, h, use_reentrant=False)
    else:
        h = custom_attention(x, freqs_cis, mask)
        out = custom_feed_forward(h)

    return out
```

7. Model Fine-Tuning

The GPU type was switched to A100; the dataset path was changed to the Alpaca 200 samples:

```
data_path = "/project/saifhash_1190/llama2-7b/alpaca_data_200.json"
```

8. Hyperparameters

Set the variables according to the instruction:

```
# set the learning rate to be 1e-5
optimizer = torch.optim.AdamW(model.parameters(), lr=1e-5)
...
# set the batch size to be 1
dataloader = torch.utils.data.DataLoader(
        data_module["train_dataset"],
        batch_size=1,
        collate_fn=data_module["data_collator"],
        shuffle=True,
    )
...
# set the gradient accumulation step to be 8
accumulation_steps = 8
```

For LoRA configuration:

```python
# set r = 16, alpha = 32, and dropout rate = 0.05
class Linear(nn.Linear, LoRALayer):
    def __init__(
            self,
            in_features: int,
            out_features: int,
            r: int = 16,
            lora_alpha: int = 32,
            lora_dropout: float = 0.05,
            merge_weights: bool = True,
            **kwargs
    ):
    ...
```

Table 1

		Grad. Accumulation	Grad. Checkpoint	Mixed Precision	LoRA
Memory	parameter	-	-	↓	↓
	activation	-	↓	↓	↓
	gradient	-	-	↓	-
	optimizer state	↓	-	-	-
Computation		↓	↑	↓	↓

Table 2

While training with 32 layers, techniques without LoRA Linear Layer will all result in an "out of memory error". The table is shown below:

(num of Layers: 32)

GA	OFF				ON			
MP	OFF		ON		OFF		ON	
LoRA	OFF	ON	OFF	ON	OFF	ON	OFF	ON
Peak Mem	-	3.13×10^7	-	4.34×10^7	-	3.13×10^7	-	4.34×10^7
Runtime	-	256.750	-	90.911	-	253.861	-	90.630

Analysis:

1. With LoRA Linear Layer, the trainable parameter reduced to only 0.12%, resulting in significant improvement in efficiency. This is mainly because the changes of weights are mostly low-rank matrices, and LoRA approximates these matrices only according to the rank of the changes. Therefore, the total number of parameters will be largely reduced.
2. The Mixed Precision technique results in a higher peak memory consumption, but saves largely in the runtime. The increased memory consumption may be caused by extra operations for HalfTensor type. Nevertheless, the calculation of float16 data will be much faster in computation.
3. Gradient Accumulation doesn't contribute much to the improvement of the training. This is due to the extremely low percentage of trainable parameters. This technique's influence can't be reflected in such senario.

To see what is the scenario when LoRA is off, I changed the layer to 8 while turning off the LoRA Linear Layer. The table is shown below:

(num of Layers: 8)

GA	OFF		ON	
MP	OFF	ON	OFF	ON
LoRA	OFF			
Peak Mem	3.77×10^7	2.02×10^7	3.77×10^7	2.02×10^7
Runtime	214.698	68.415	125.985	56.547

1. Without the LoRA Linear Layer, the effect of Mixed Precision is similar to before - a higher peak memory consumption, but much lower runtime
2. We can also observe that the Gradient Accumulation, in this case, could make the runtime slower, especially in the situation where the runtime is high. Without the help of LoRA Linear Layer, 100% of the parameters are trainable, and the Gradient Accumulation technique can save the runtime during the backpropagation in a more significant way.

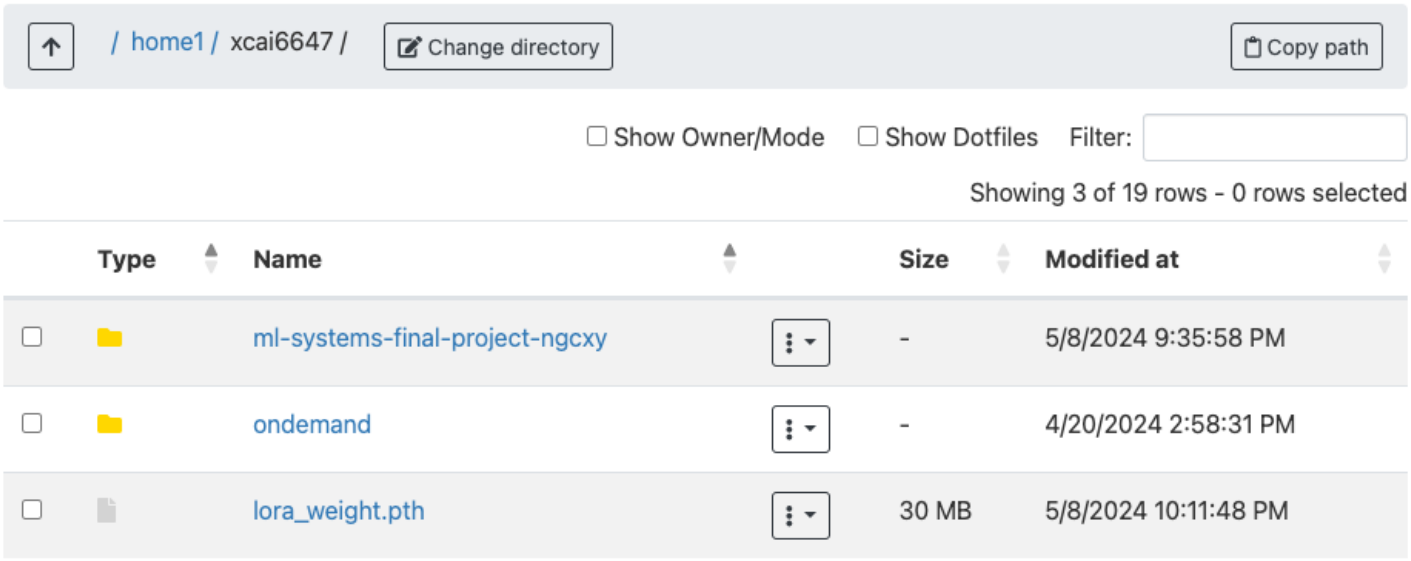
Inference Evaluation

Some modifications were made to store the LoRA weights and load the weights before inference.

In `finetuning.py`:

```python
def train():
    ...
    # store the LoRA weights
    model_weights = model.state_dict()
    lora_weights = {k: v for k, v in model_weights.items() if "lora_" in k}
    torch.save(lora_weights, "/home1/xcai6647/lora_weight.pth")
```

Now the weights are store under the repository:



We then add the code in `inference.py` to retrieve the weight along with the pre-trained weights:

```python
def inference():
    ...
    tokenizer_path = "/project/saifhash_1190/llama2-7b/tokenizer.model"
    model_path = "/project/saifhash_1190/llama2-7b/consolidated.00.pth"
    lora_path = "/home1/xcai6647/lora_weight.pth"   # path for lora weights

    tokenizer = Tokenizer(tokenizer_path)

    checkpoint = torch.load(model_path, map_location="cpu")
    lora = torch.load(lora_path, map_location="cpu")    # load lora weights

    model_args = ModelArgs()
    torch.set_default_tensor_type(torch.cuda.HalfTensor) # load model in fp16
    model = Llama(model_args)
    model.load_state_dict(checkpoint, strict=False)
    model.load_state_dict(lora, strict=False)   # load into the model
    model.to("cuda")
```

Inference Results

1. Origin Prompt

Prompt list:

```
prompts = [
    # For these prompts, the expected answer is the natural continuation of the prompt
    "I believe the meaning of life is",
    "Simply put, the theory of relativity states that ",
    """A brief message congratulating the team on the launch:

    Hi everyone,

    I just """,
    # Few shot prompt (providing a few examples before asking model to complete more);
    """Translate English to French:

    sea otter => loutre de mer
    peppermint => menthe poivrée
    plush girafe => girafe peluche
    cheese =>""",
]
```

Outputs:

```
I believe the meaning of life is
> to find your own meaning in life.
I believe that you are here on this earth to fulfill your own destiny.
I believe that we are all here to learn.
I believe that we are all here to grow.
I believe that we are all here to share.
I believe that we

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Simply put, the theory of relativity states that
> 1) the speed of light is the same for all observers and 2) the laws of physics are the same for all observers.
Einstein’s theory of special relativity, which was first published in 1905, states that the laws of physics are the s
ame for all obser

==================================

A brief message congratulating the team on the launch:

        Hi everyone,

        I just
>
        <a href="https://github.com/hackathon/hackathon-2019/blob/master/docs/project/README.md" target="_blank">read
</a>
        the project README, and I think it looks really good!

==================================

Translate English to French:

        sea otter => loutre de mer
        peppermint => menthe poivrée
        plush girafe => girafe peluche
        cheese =>
> fromage
        egg => oeuf
        beef => viande bovine
        apples => pommes
        beef => viande bovine
        pizza => pizza
        hamburger => hamburger
        coffee => café
        chicken

==================================
```

2. Custom prompts from Alpaca

Prompt list:

```
def Alpaca_prompt(instruction, input):
    return f"""Below is an instruction that describes a task, paired with an input that provides further context.
    Write a response that appropriately completes the request.
    ### Instruction:{instruction}
    ### Input:{input}
    ### Response:"""

prompts = [
    Alpaca_prompt("Convert the following sentence into the present continuous tense",
                  "He reads books"),
    Alpaca_prompt("Give an example of a metaphor that uses the following object",
                  "Stars"),
    Alpaca_prompt("Describe the following person",
                  "John"),
    Alpaca_prompt("Construct an argument to defend the following statement",
                  "Alternative energy sources are critical to solving the climate crisis"),
]
```

Outputs:

```
Below is an instruction that describes a task, paired with an input that provides further context.
        Write a response that appropriately completes the request.
        ### Instruction:Convert the following sentence into the present continuous tense
        ### Input:He reads books
        ### Response:
> He is reading books
        ```
        <p>
        He reads books.
        </p>
        <p>
        He is reading books.
        </p>
        ```


==================================

Below is an instruction that describes a task, paired with an input that provides further context.
        Write a response that appropriately completes the request.
        ### Instruction:Give an example of a metaphor that uses the following object
        ### Input:Stars
        ### Response:
>
        #### "The stars were like diamonds in the sky"
        #### "The stars were like jewels in the sky"
        #### "The stars were like gems in the sky"
        #### "The stars were like rubies in the sky"
        #### "The stars were

==================================

Below is an instruction that describes a task, paired with an input that provides further context.
        Write a response that appropriately completes the request.
        ### Instruction:Describe the following person
        ### Input:John
        ### Response:
>
        John is a great guy!
        He is a programmer and has been for 10 years.
        He is the best programmer I know.
        He is a very friendly person.
        He is very helpful and kind.
        He is very smart.
        He is a

==================================

Below is an instruction that describes a task, paired with an input that provides further context.
        Write a response that appropriately completes the request.
        ### Instruction:Construct an argument to defend the following statement.
        ### Input:Alternative energy sources are critical to solving the climate crisis
        ### Response:
>
        ### 1. The climate crisis is not the only problem that alternative energy sources can solve.
        ### 2. Alternative energy sources are not a practical solution to the climate crisis.
        ### 3. The climate crisis is not a problem that can be solved by alternative energy sources.


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```

Comments:

Despite some weird behaviors like writing the HTML code in the first task, the model can provide an overall satisfying performance. It not only outputs the contexts that are closely related to the instructions, but also creates the contents beyond the database of Alpaca.