Deep Learning at Scale for GPU poor

Practice Examination Questions

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Notes

- These are some rough practice questions designed to reflect the type of exam questions that you **may** face.
- Marks are rough and maybe scaled to fit exam-specific requirements.
- Solutions will not be provided; rather discussion on EdStem is encouraged.

Question 1: Estimating scale in Deep Learning

Consider the recently proposed MLP-Mixer model with the following specifications:

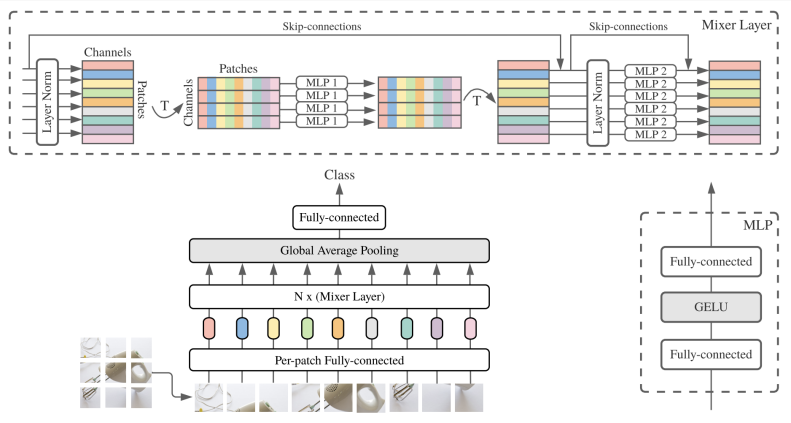


Figure 1: MLP-Mixer Architecture

Where:
$$\mathbf{U}_{*,i} = \mathbf{X}_{*,i} + \mathbf{W}_2\sigma\left(\mathbf{W}_1\,\text{LayerNorm}(\mathbf{X})_{*,i}\right), \quad \text{for } i = 1\ldots C, (MLP1)$$
$$\mathbf{Y}_{j,*} = \mathbf{U}_{j,*} + \mathbf{W}_4\sigma\left(\mathbf{W}_3\,\text{LayerNorm}(\mathbf{U})_{j,*}\right), \quad \text{for } j = 1\ldots S. (MLP2)$$

- $\mathbf{X} \in \mathbb{R}^{s\times c}$
- Patches, $s = 128$
- Hidden dimension, $c = 1024$
- MLP1:$\mathbf{W}_1 \in \mathbb{R}^{d_s\times s}$, $\mathbf{W}_2 \in \mathbb{R}^{s\times d_s}$
- MLP2:$\mathbf{W}_3 \in \mathbb{R}^{d_c\times c}$, $\mathbf{W}_4 \in \mathbb{R}^{c\times d_c}$
- Channel-mixing MLP hidden dimension: $d_c = 4096$
- Patch-mixing MLP hidden dimension: $d_s = 512$
- Number of Mixer layers: 24
- Batch size: 1024

(a) Calculate the number of FLOPs required to complete a forward and backward pass. You can ignore the embedding layer, pooling, and final fully connected layer. This is a rough calculation, so you can neglect certain operations! You will be marked based on a log scale (be within one order of magnitude of the correct answer). Please show your workings. **[10 marks]**

(b) Calculate the total memory requirements (in MB) for storing all **activations** during the forward pass of the entire MLP-Mixer model. Assume all values/parameters are stored in 32-bit floating-point format and no gradient checkpointing is applied. Please only consider the activations in the Mixer Layer (you can ignore the embedding layer and global average pooling). **[10 marks]**

(c) Why do the MLP-Mixer authors claim that this architecture has linear complexity with respect to the number of input patches. **[1 marks]**

Question 2: Memory Optimisation Techniques

(a) Explain the concept of gradient accumulation in detail. Specifically, what problem does it solve and how. **[6 marks]**

(b) The following PyTorch code attempts to implement gradient accumulation. Please fill in the required code.

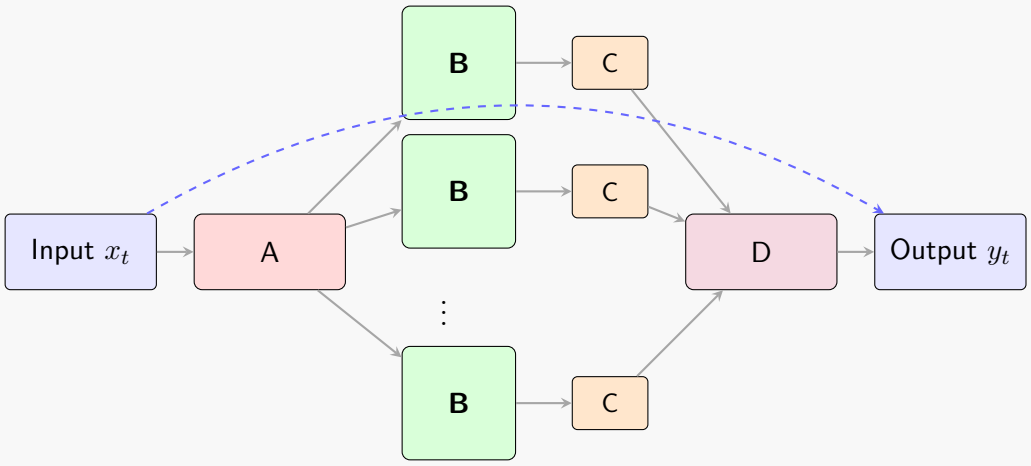
```
1
2  def train_with_gradient_accumulation(
3      model, dataloader, criterion, optimizer, accumulation_steps=4
4      ):
5      model.train()
6      optimizer.zero_grad()
7      for batch_idx, (data, target) in enumerate(dataloader):
8          data, target = data.to(device), target.to(device)
9          output = model(data)
10         loss = criterion(output, target)
11
12         ###start of code###
13
14
15         ###end of code###
16
17         if (batch_idx + 1) % accumulation_steps == 0:
18             ###start of code###
19
20
21             ###end of code###
```

[4 marks]

(c) Describe gradient checkpointing in detail. How does it trade off computation for memory, and in what circumstances should it be used? **[4 marks]**

Question 3: Mixture of Experts

(a) Briefly describe the Mixture of Experts (MoE) architecture, including its key components and how it differs from standard Transformer models. The following diagram represents a simplified Mixture of Experts layer. As part of your explanation, label each component and explain their functions. Finally detail the motivation behind MoE in the context of scale. **[8 marks]**



(b) Explain the phenomenon of "routing collapse" in Mixture of Experts models, what causes it and detail 2 strategies which can be employed to reduce this issue? **[4 marks]**

Question 4: Parameter-Efficient Fine-Tuning

(a) Consider a pre-trained Transformer block with a hidden dimension of 1024 and 1 attention head. If you apply LoRA with rank $r = 8$ to the query and value projection matrices:

(i) Calculate the number of trainable parameters in the original transformer block projection matrices (k, v, q, o). **[3 marks]**

(ii) Calculate the number of trainable parameters with the above LoRA setting. **[3 marks]**

(iii) Does LoRA increase or decrease the FLOP count for a forward pass? Explain your answer. **[2 marks]**

(b) The following PyTorch code attempts to implement LoRA for a linear layer. Identify 2 issues with the implementation. Noting that there are 4 issues in total. +2 points for each identified issue and -2 points for incorrect suggestions. Identifying all 4 issues gets you no more marks, just some kudos! The minimum mark for this question is 0.

```python
class LoRALayer(nn.Module):
    def __init__(self, base_layer, rank=4, alpha=1.0):
        super().__init__()
        self.base_layer = base_layer
        self.rank = rank
        self.alpha = alpha

        # Get input and output dimensions from the base layer
        in_features = base_layer.in_features
        out_features = base_layer.out_features

        # Initialise LoRA matrices
        self.lora_A = nn.Parameter(torch.zeros(in_features, rank))
        self.lora_B = nn.Parameter(torch.zeros(rank, out_features)
            )

        # Initialise with random values
        nn.init.normal_(self.lora_A, std=0.02)
        nn.init.normal_(self.lora_B)

    def forward(self, x):
        # Original output
        base_output = self.base_layer(x)


        lora_output = (x @ self.lora_A) @ self.lora_B

        return base_output + lora_output
```

[4 marks]

(c) Why for BFloat16 do we need to store a full precision copy of the model weights but in QLoRa we only need one copy of the pretrained weights in NFloat4? **[6 marks]**