

# Homework 11

Anshul Sawant

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1 Q 1.1

2 A (coding)

3 B



The inference is faster with vLLM primarily because of PagedAttention and continuous batching.

4 Q 1.2

**Flash attention** makes sense as it improves the speed of forward pass.

**Data parallelism** Overall the technique is not applicable. Only the model replication aspect applies.

**Gradient checkpointing** No. No gradients are involved in the forward pass.

**DeepSpeed zero** No. Gradients and optimizer states are not required for inference.

## **5 Q 1.3**

### **5.1 A**

Allocating large chunk is not effective because:

1. Wasted memory as most inference requests will require less K-V cache memory leading to lower throughput.
2. Techniques that generate multiple output sequences (such as beam search) can potentially share parts (corresponding to the input sequence) of K-V cache. However, this cannot be done because of the separate pre-allocation for each sequence.

### **5.2 B**

The dynamic size of the KV cache during inference contrasts with static model components, demanding a different memory management approach. PagedAttention provides this by adapting operating system paging techniques. It uses fixed-size memory blocks and indirection tables to manage the KV cache efficiently, mirroring how an OS creates a contiguous virtual memory view over fragmented physical pages, thus enabling flexible allocation.

### **5.3 C**

One can possibly use the input/output of the unquantized model as the calibration dataset.

### **5.4 D**

Reduced range can lead to overflow and underflow leading to infinity/NaNs which can propagate throughout the computation.