

Request-level GPU Sharing on vLLM

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Planning and Tracking List

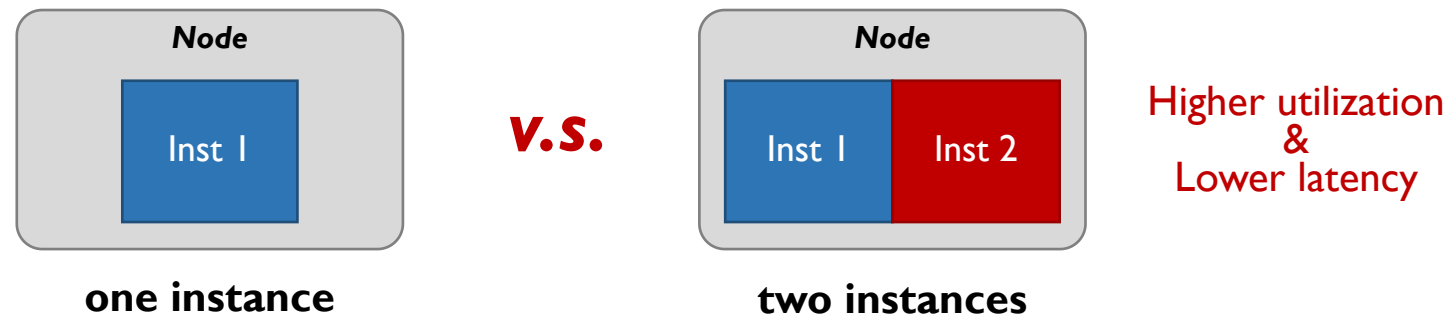
		Task	Schedule	Task Owner	11.12 Status	Last Week Status	Current Status
Model level		Deploy serverlessLLM on k8s	11.4-8	Tao&Zhuoyuan	Complete	Complete	Complete
		Profile key metrics of LLMs under different configurations	11.4-8	Chuanyi	Complete	Complete	Complete
		Implement MPS on serverlessLLM	11.8-15	Chuanyi	On track	Complete	Complete
		Dynamic resource allocation based on model popularity	11.15-20	Tao&Zhuoyuan	On track	Complete	Complete
Request level		Independent scheduling for prefill and decode phases	11.19-26	Chuanyi Liu	-	-	On track
		Parameter-sharing for multiple requests of the same model	11.19-26	Tao&Zhuoyuan	-	-	Complete (vLLM)

**Part I: Parameter-sharing for
multiple requests of the same model**

**Part I.1: GPU memory sharing
among processes**

Why Sharing Parameters?

- Instances of one model reside on the same GPU
 - Scenario 1: Multiple instances can utilize GPU better than single one
 - Scenario 2: Disaggregate prefill and decode phases (*Part 2*)



- Multiple replicas of parameters bring about memory waste
 - Each redundant replica wastes space of ~GB

Underlying support: CUDA Runtime



➤ Mechanism

- *IpcMemHandle* from CUDA Runtime
- Allows different processes to access the same memory

➤ Usage

- Owner: Expose an address as a handle

```
handle = cudart.cudaIpcGetMemHandle(data_ptr1)
```

- User: Read the handle and restore it to memory address

```
data_ptr2 = cudart.cudaIpcOpenMemHandle(handle)
```

Underlying support: CUDA Runtime



➤ An example

- Owner

```
data_ptr1 = tensor.data_ptr()

status, handle = cudart.cudalpcGetMemHandle(data_ptr1)

memory_handle_str1 =
base64.b64encode(handle.reserved).decode('utf-8')

with open(memory_handle_file, 'w') as f:
    f.write(memory_handle_str)
```

```
# llm @ gpu-node in ~/sharemem [11:17:09]
$ python create_handler.py
tensor: tensor([[ 0.9282, -0.1506, -0.9697],
               [ 1.7256,  0.4512, -0.2925],
               [-0.7432,  0.9395,  0.0214]], device='cuda:0', dtype=torch.float16)
data ptr: 0x7f885e200000
```

- User

```
with open(memory_handle_file, 'r') as f:
    cuda_memory_handle_b64 = f.read()

handle = cudart.cudalpcMemHandle_t()

handle.reserved = base64.b64decode(cuda_memory_handle_b64)

data_ptr2 =
cudart.cudalpcOpenMemHandle(handle, cudart.cudalpcMemLazyEn
ablePeerAccess)

tensor = torch_tensor_module.create_gpu_tensor
(data_ptr2, dims, dtype)
```

```
# llm @ gpu-node in ~/sharemem [11:19:01]
$ python get_handler.py
tensor: tensor([[ 0.9282, -0.1506, -0.9697],
               [ 1.7256,  0.4512, -0.2925],
               [-0.7432,  0.9395,  0.0214]], device='cuda:0', dtype=torch.float16)
data ptr: 0x7fe7c2200000
```

Underlying support: CUDA Runtime



➤ An example

- Owner

```
data_ptr1 = tensor.data_ptr()

status, handle = cudart.cudalpcGetMemHandle(data_ptr1)

memory_handle_str1 =
base64.b64encode(handle.reserved).decode('utf-8')

with open(memory_handle_file, 'w') as f:
    f.write(memory_handle_str)
```

➤ Python tensor is not fit for pointer

- Create tensor with C++ and integrate into python as **torch_tensor_module**

- User

```
with open(memory_handle_file, 'r') as f:
    cuda_memory_handle_b64 = f.read()

handle = cudart.cudalpcMemHandle_t()

handle.reserved = base64.b64decode(cuda_memory_handle_b64)

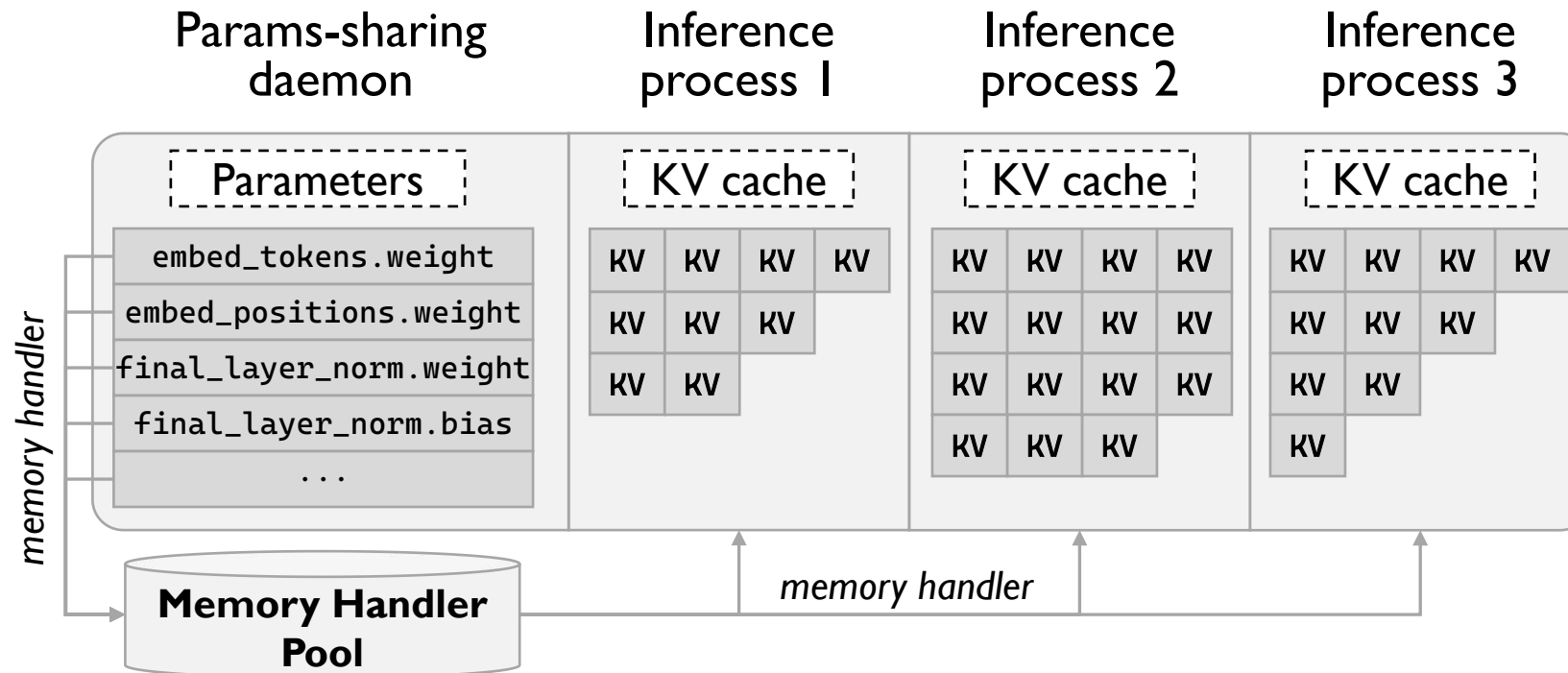
data_ptr2 =
cudart.cudalpcOpenMemHandle(handle, cudart.cudalpcMemLazyEn
ablePeerAccess)

tensor = torch_tensor_module.create_gpu_tensor
(data_ptr2, dims, dtype)
```


Part 1.2: Parameter-sharing on vLLM

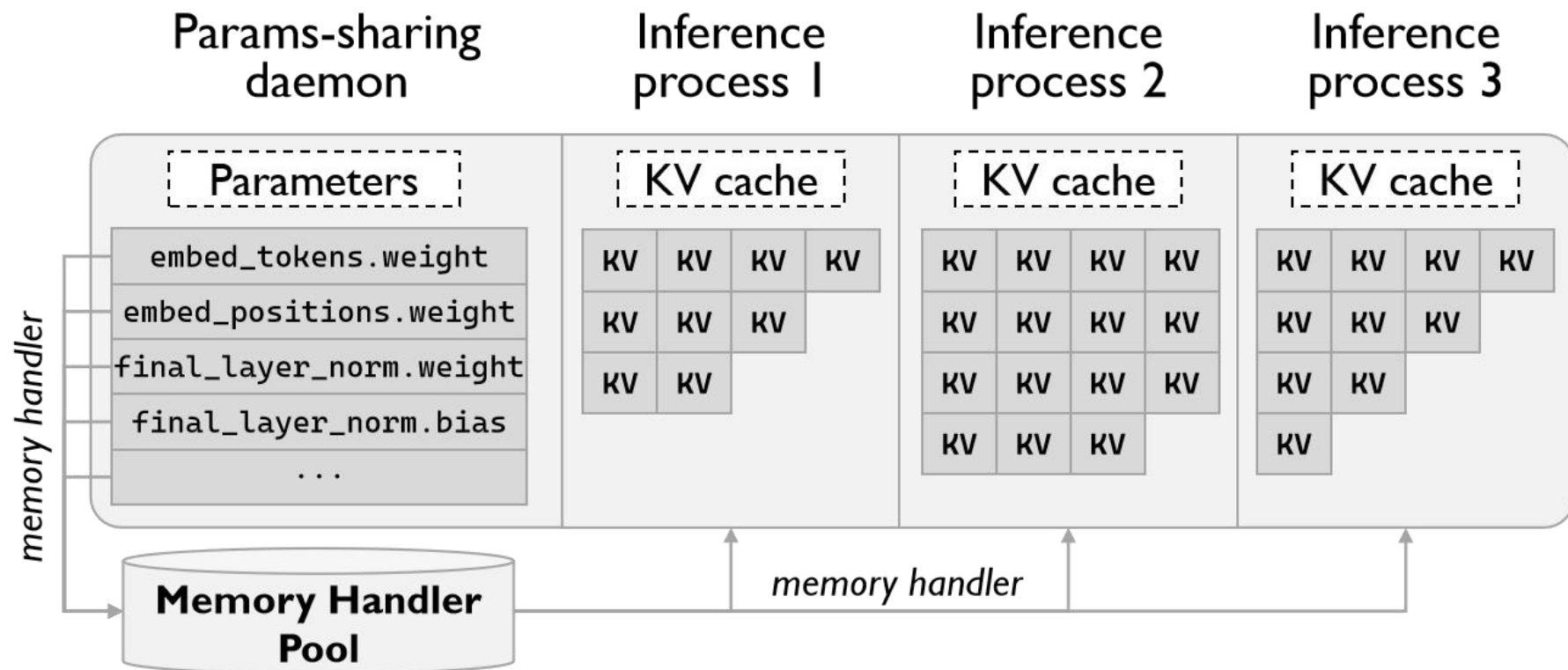
Overview

- Params-sharing daemon and Inference processes
- Inference processes share parameters but have a separate kv cache address space



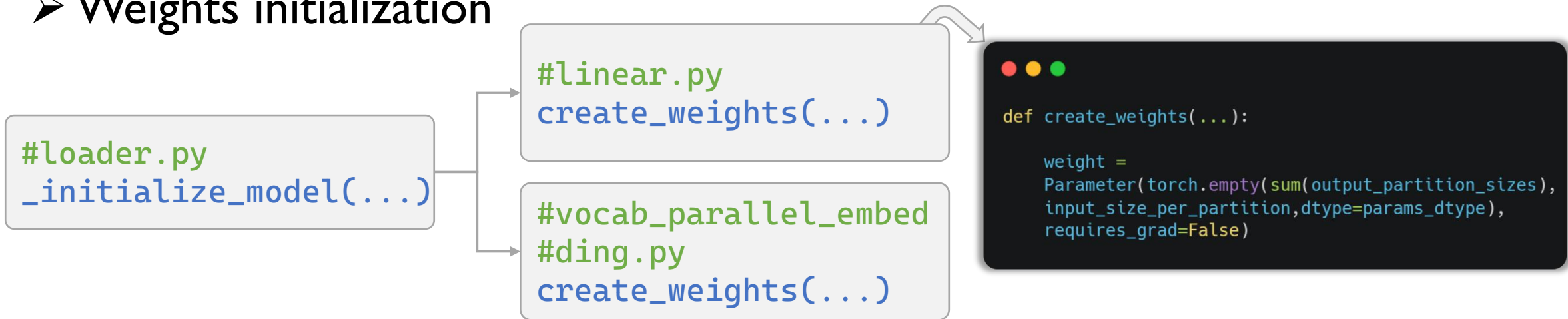
Overview

- Params-sharing daemon and Inference processes
- Inference processes share parameters but have a separate kv cache address space

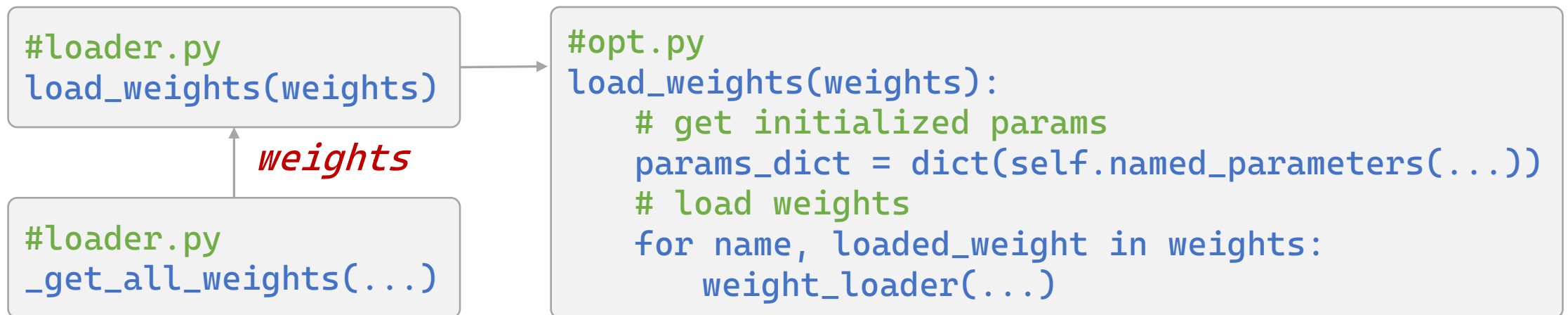


Weights loader of vLLM

➤ Weights initialization



➤ Weights loading



Weights loader of params-sharing daemon

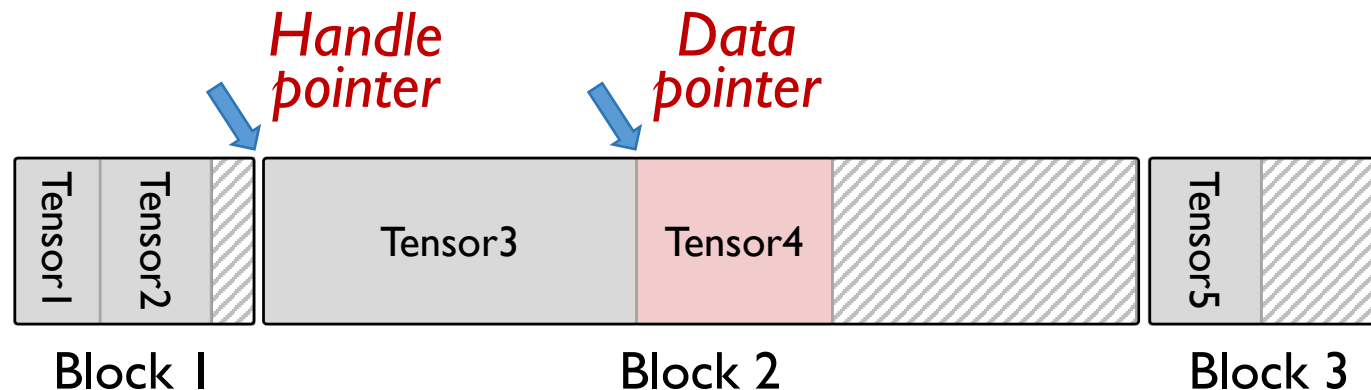
- Save memory handles when loading the weights

```
#opt.py
load_weights(weights):
    # get initialized params
    params_dict = dict(self.named_parameters(...))
    # load weights
    for name, loaded_weight in weights:
        weight_loader(...)

        device_buffer_ptr = params_dict[name].data_ptr()
        err, ipc_mem_handle =
            cudart.cudaIpcGetMemHandle(device_buffer_ptr)
            handler_dict[name] = {
                "handler": ipc_mem_handle,
                "offset": offset,
                "dims": dims,
                "dtype": "float16"
            }
```

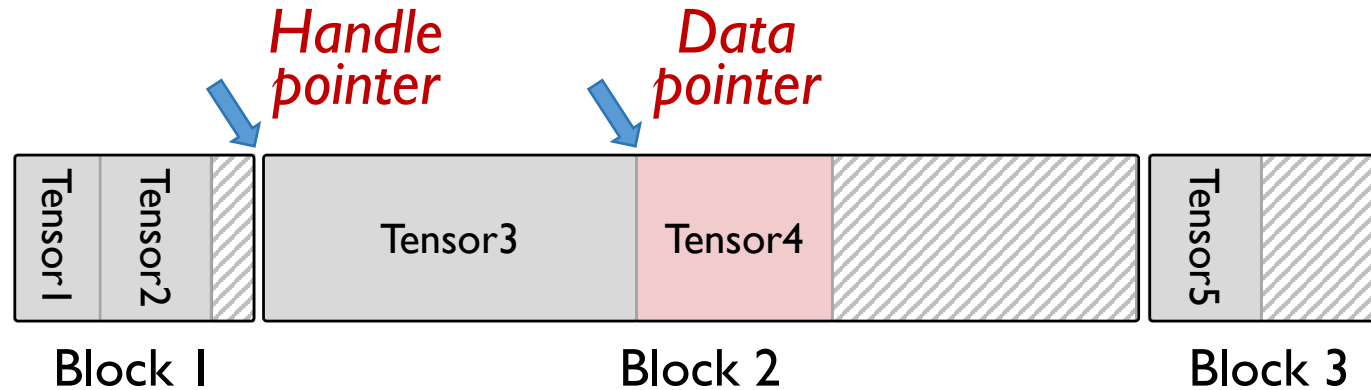
PyTorch memory management and allocation

- PyTorch memory management
 - At block granularity
 - `cudaIpcGetMemHandle(data_ptr)` returns block base address, not data address
- PyTorch memory allocation
 - Allocate 2MB for size less than 1MB;
 - Allocate 20MB for size 1MB ~ 10MB;
 - Allocate { size rounded up to a multiple of 2MB } MB for size ≥ 10 MB



Record offset

- Record the address of the handle: $addr(handle)$
- $offset = addr(data) - addr(handle)$



Weights loader of inference processes

➤ Weights initialization

- **weight = empty()**

```
#loader.py  
_initialize_model(...)
```

```
#linear.py  
create_weights(...)
```

```
#vocab_parallel_embed  
#ding.py  
create_weights(...)
```

```
def create_weights(...):  
  
    weight =  
        Parameter(torch.empty(sum(output_partition_sizes),  
                                input_size_per_partition, dtype=params_dtype),  
                  requires_grad=False)
```

weight <= empty()

```
#loader.py  
_initialize_model(...)
```

```
#linear.py  
create_weights(...)
```

```
#vocab_parallel_embed  
#ding.py  
create_weights(...)
```

```
def create_weights(...):  
  
    weight =Parameter()
```


Weights loader of inference processes



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ADSLAB

- Weights loading: load weights from memory handles

```
#opt.py
load_weights(weights):
    # get initialized params
    params_dict = dict(self.named_parameters(...))
    # load weights

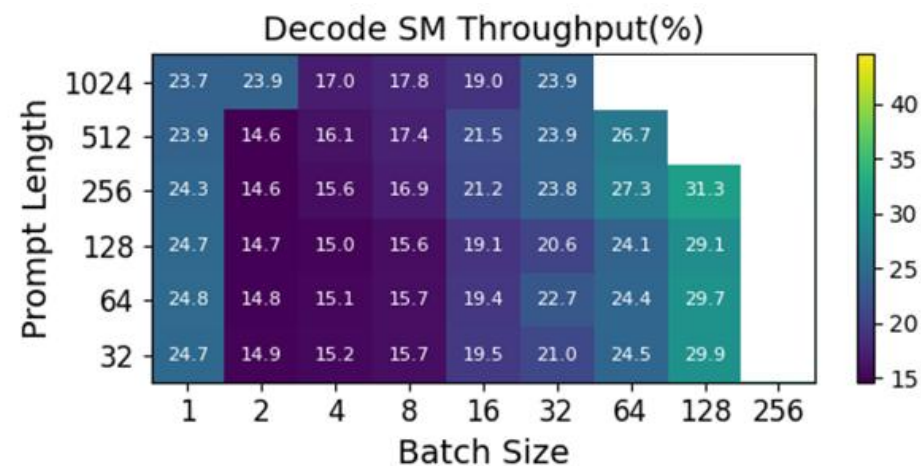
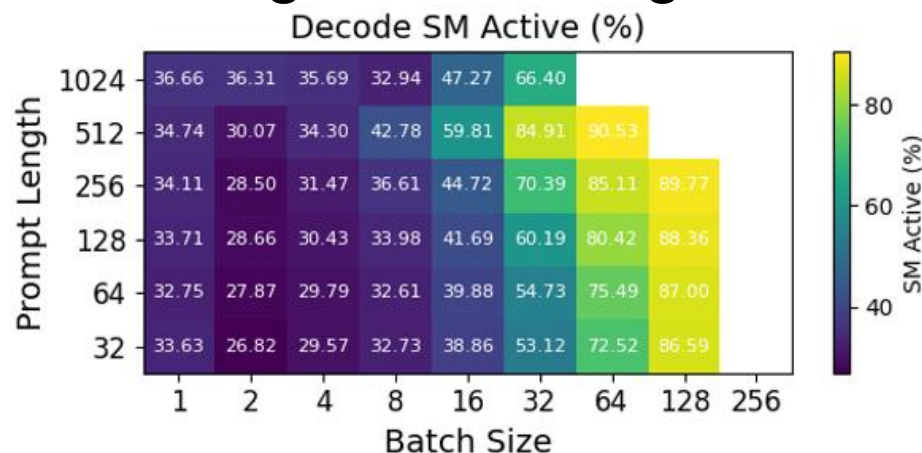
    for name, shared_weight in handles:
        # Gets memory pointers from handles
        err, devPtr = cudart.cudaIpcOpenMemHandle(
            shared_weight['handler'], cudart.cudaIpcMemLazyEnablePeerAccess)

        # Get weights by memory pointers
        params_dict[name].data =
            torch_tensor_module.create_gpu_tensor(devPtr +
                shared_weight["offset"], shared_weight['dims'],
                shared_weight['dtype'])
```

**Part2: Prefill and decode phases
disaggregating**

Overview

- Why do we need to disaggregate prefill and decode stages?
 - Address low GPU utilization caused by mismatched resource demands
 - Leverage GPU Sharing to further raise resource utilization

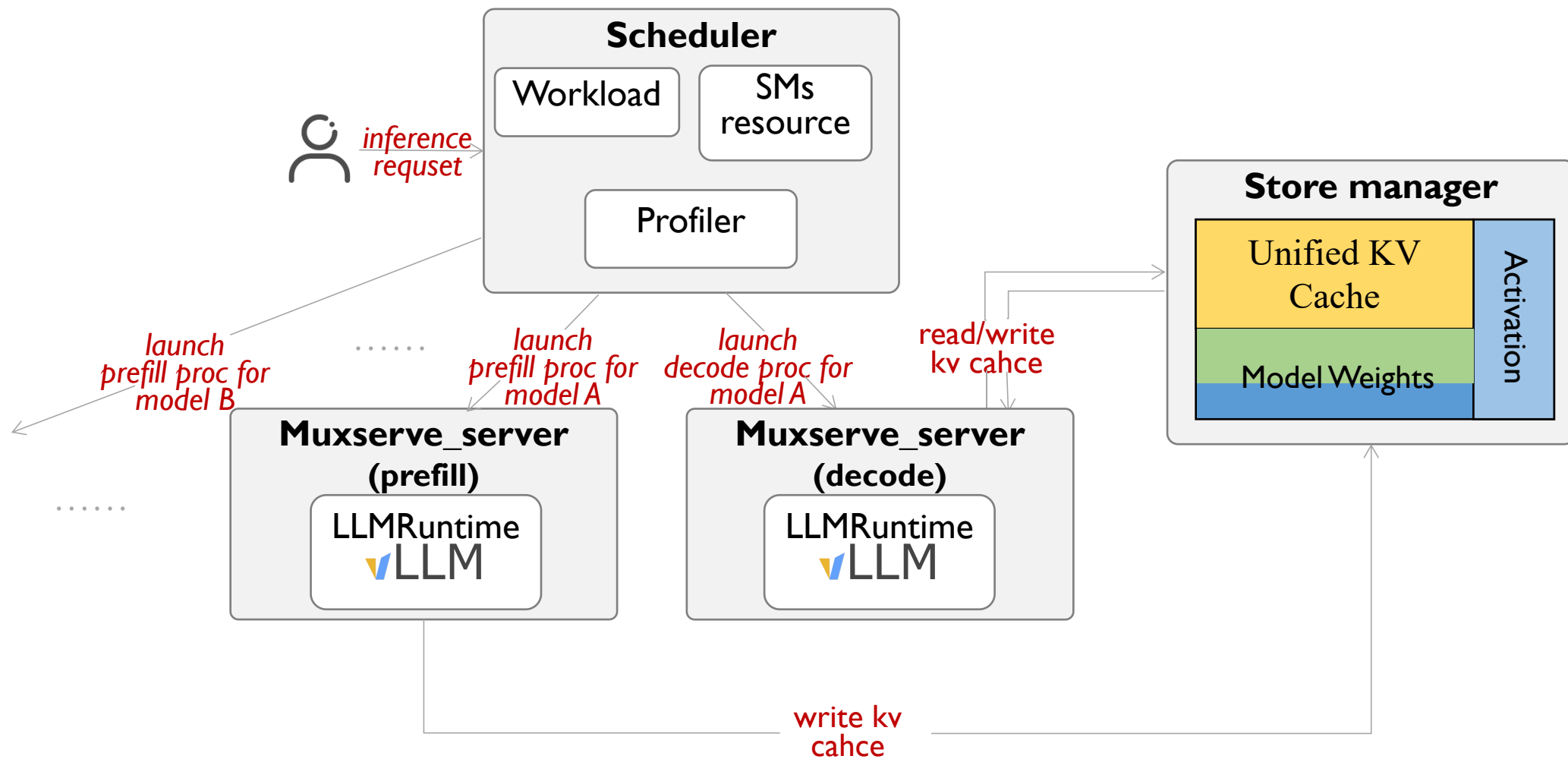


➤ Challenges

- How to combine prefill-decode disaggregation with MPS?
- How to disaggregate prefill and decode stages in vLLM?

Disaggregate prefill and decode




➤ Architecture of Muxserve^[1]



Disaggregate prefill and decode



➤ Current idea

- Launch two subprocesses for prefilling and decoding to utilize MPS for each request  **More flexible dynamic allocation**
- Do not maintain a unified KV cache, decoding process shares memory with prefilling process or deepcopy  **Fine-grained memory management**
- Write our own LLMEngine atop vLLM  **To combine with vLLM**

➤ TODO

- Implement the scheduling algorithm for prefill and decode stages
- Share KV cache between prefill and decode processes

Planning and Tracking List

Task	Schedule	Task Owner
Implement prefill-decode disaggregated instances	11.26-12.03	Chuanyi
Independent scheduling policy for prefill and decode phases	11.26-12.03	Tao
Implement parameter-sharing on serverlessLLM	11.26-12.03	Zhuoyuan

THANKS

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Thanks for your attention