CSC290/420 Machine Learning Systems for Efficient AI
Memory and Storage in ML Programs

Sreepathi Pai

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URCS

Outline

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Memory Management Basics

Memory Management in ML Programs

Optimizations for ML Programs

Recommended Reading

Memory Management in Programs

- Static (compile-time) management
  - Done by the compiler for fixed-size data structures
- Dynamic memory management
  - `malloc`, `free`, in languages like C
  - In garbage-collected languages, these are done under the hood by the runtime
- `malloc` returns a pointer to an area of memory on success
  - Usually from the "heap"
- `free` returns the allocation to the heap

Multi-device Memory Management

- Implicit in `malloc` is that it allocates memory on the CPU
- However, other devices, in particular GPUs have their own memory allocators
  - e.g., CUDA has `cudaMalloc` and `cudaFree`
  - can call `cudaMalloc` on both the CPU and GPU (but don't!)
- These allocators must be used even in GC languages
- GPUs have multiple memory "regions" (constant memory, local memory, shared memory)
  - (note: CUDA nomenclature)
  - Not all of them have allocators (compiler+runtime allocated)
  - a *memory mapping* problem
- Some accelerators have no dynamic memory allocation ability
  - E.g., Google's TPU, Pixel 6 TPU

Address Spaces

- On 64-bit machines, all addresses lie in a single address space
- The pointer from `malloc` isn't any different from `cudaMalloc`
- However, dereferencing a pointer on the wrong device can cause problems
  - segmentation fault
- Even CUDA's different memory regions use a unified pointer space
- May not be the case with accelerators
  - but C++ rules require unified address space

Characteristics of a Memory Allocation

- Size in bytes
- Scope
  - Local, Global
- Lifetime (or Lifespan, or Live Range)
  - from allocation to free
  - or from first user to last
- Type of accesses to data
  - Read/Write
  - Mostly read
- Source of data
  - from computation
  - from file

How Modern Dynamic Memory Allocators Work

- Allocate a global pool of memory from the system
- Divide the global pool in to per-thread pools
  - Leave some memory in the global pool
- Divide the per-thread pool into “buckets”
  - Each bucket satisfies one size of request (usually rounded up to power of 2)
  - Limited number of sizes supported
- Satisfy allocation requests from per-thread pools
  - Borrow from the global pool if running out
  - Or, for very large sizes, directly obtain memory from operating system
- Examples: hoard, jemalloc, tcmalloc

Large Allocations

- If the heap is full, the heap size can be increased using
  - `sbrk` (traditional)
  - `mmap` with anonymous pages
- Both ask the operating system for more memory
  - Involve a relatively slow system call
- Used by memory allocators for very large size allocations

Trying Out New Memory Allocators

- On Linux, the standard memory allocator is the one in `libc`
  - The C runtime library
- However, it is possible to override `malloc` and `free` at runtime
  - Use `LD_PRELOAD` environment variable on Linux
  - `LD_PRELOAD=mymalloc.so ./program`
- This only works if the C library is dynamically linked
  - Look for build options that allow changing the allocator

Garbage Collected Languages

- Garbage-collected languages also perform memory management
  - under the hood
- Garbage collectors can be tuned
  - out of scope for this class
- Remember, Python is a garbage-collected language

When is a Memory Allocation a Performance Issue?

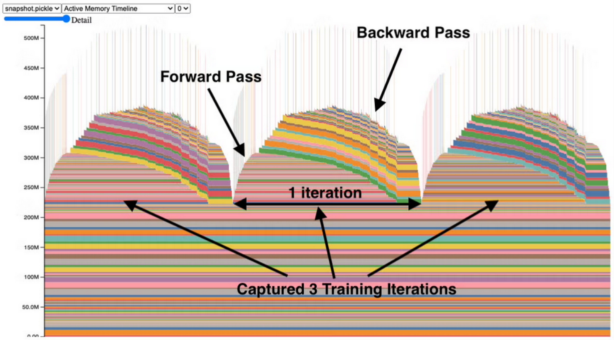
- Never
- Only under memory pressure
  - when the amount of free memory in the pool is low
  - or in the system or device
- At high rates of allocation/deallocation
  - book-keeping might consume all time
  - queueing might take up all time (e.g. `cudaMalloc` on the GPU)
- At high rates of system call invocation
- Due to poor synchronizing implementations
  - notoriously, on the GPU

Memory Allocator Debugging

- Production memory allocators can dump statistics about memory allocation
  - glibc: Allocator Debugging
  - Mostly useful for leaks and other statistics
- Valgrind also has tools for debugging memory
- Neither handles GPU memory very well

Memory Profiling

- Understanding GPU Memory 1: Visualizing All Allocations over Time



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Memory Usage

- Inputs, Outputs
- Weights (also an input, but usually read only and associated with an operator)
    - Plus biases
- Activations (also an output, but usually write only and associated with an operator)
- Temporaries (usually operator-specific)

Typical Sizes

- Usually referred to as parameters
  - Weights + Biases only
- AlexNet: 60M parameters (possibly fp32)
- GPT-3: 175B parameters (fp16)
- Deepseek-V3: 671B MoE parameters / 37B “activated parameters”

How do Memory Allocations Scale?

- Memory for inputs and outputs scale linearly with number of inputs and outputs
  - e.g., parallelism
- Weights occupy constant space (being read only)
  - but may need to be replicated across address spaces
- Activations scale linearly with parallel instances of an operator
- Temporaries also scale linearly with parallel instances of an operator
- Number of operators: size of neural network

Memory Allocation Strategy

- On demand: per-operator
  - just before operator begins execution
- Offline: per-graph
  - before execution of the graph
  - may be only option for accelerators
  - challenging for dynamic input sizes and changing parallelization

Orchestrating Memory Transfers Across Devices

- When an operator runs on a GPU, it must have space for its inputs and outputs
  - And all of its temporaries
- Then, its inputs must be transferred to it, and outputs transferred back
- In multi-device parallelism (e.g., data parallel), data shared across devices must be synchronized
  - data must be transferred across devices
  - later: Communication

Orchestrating Memory Transfers Across Machines

- When using a cluster of machines, data must be transferred across machines
- later: Communication

Micro-scale Memory Management: Placement (or Mapping)

- GPUs contain multiple memory spaces
    - constant memory: for read-only, broadcast data (e.g., convolution filters)
    - shared memory: on-chip data
- GPU compilers+runtimes will give a program a block of memory in these spaces
    - Must be populated by the CPU program (constant memory)
    - or by the GPU program/kernel (shared memory)
- Deciding *which* data resides *where* and *when* is a hard problem

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Data Layout

- Certain implementations of operators expect data in a particular format
  - e.g., tensor cores like NHWC vs NCHW
- Frameworks will translate behind the scenes!
  - Extra memory and extra work

Reducing Data Size: Quantization

- Change parameters from FP32 to FP16
  - halves memory usage
- Change parameters from FP32 to INT8
  - 1/4th the memory usage!
- Weight quantization (static)
- Activation quantization (dynamic)
- Many schemes for quantization exist

Reducing Data Size: Sparsification

- Weight and bias tensors mostly contain zeroes
- Different sparsification techniques exist
- Use sparse tensor formats (COO, etc.)
- Semi-structured Sparsity
  - Zeroes follow a predictable pattern

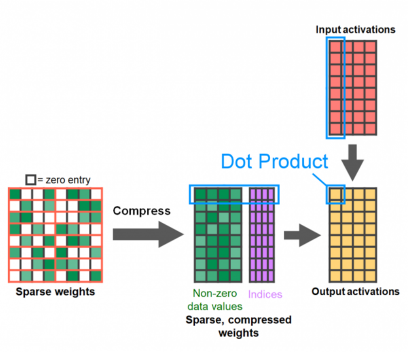

Image source: `https://developer.nvidia.com/blog/exploiting-ampere-structured-sparsity-with-cusparselt`

Reducing Data Size: Compression

- Lossless compression
  - Entropy-based schemes
- Lossy compression
  - e.g. quantization
- See, for example, QMoE: Sub-1-Bit Compression of Trillion-Parameter Models

Loading Weights Fast

- Loading weights from file is slow for large models
  - max tens of GB/s
- Example: PyTorch uses Pickle files for weights
  - also adds parsing overhead
- Best case would be equivalent to `mmap`-ing weights directly into memory

mmap-ing data

- On virtual memory systems, storage is part of memory address space
- Use the mmap system call to map a file into memory

```
// no error handling code!
FILE *f = fopen("/path/to/weights.file", "r")
fseek(f, 0, SEEK_END);
size_t sz = ftell(f)

unsigned char *contents = mmap(NULL, sz, PROT_READ,
                               MAP_SHARED, fileno(f), 0);
fclose(f);

// read contents as if it is an array
```

- What issues do you see with this scheme?

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Optional Recommended Reading

- MiMalloc: A Lightweight Memory Allocator for Hardware-Accelerated Machine Learning
  - Source: `https://github.com/google/minimalloc?tab=readme-ov-file`
- TelaMalloc: Efficient On-Chip Memory Allocation for Production Machine Learning Accelerators
- jemalloc Post-Mortem
  - a look at the life of a memory allocator