

# Beginner's guide to etal kernels



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# Preamble

- Laptop those slides are stream from is a pretty powerful machine
  - 110 Gflop of CPU perf vs 7 Tflop of GPU perf
  - Alas GPU is not CUDA capable, so it could not be used by existing ML frameworks
- MPS backend was first released in PyTorch-1.12 to expose more HW features to PyTorch users
  - It doesn't cover all the operations that one might need
  - On the MPS(which stands for Metal Performance Shaders) interoperates nicely with Metal, so it must be fun learning some
- GPU programming languages are all a bit alike
  - So if you can write CUDA, you can do Metal as well

# History of GPGPU

- OpenGL 1.0 was released in 1992, but it only had fixed pipelines



# History of GPGPU

- OpenGL 1.4 GLSLang ARB/ OpenGL 2.0 (2004) introduced programmable shaders
- Around the same time people noticed that fragment shaders could also be used for scientific computations (see [Ian Buck's PHD thesis](#) )
- And so in 2007 CUDA was born
- And OpenCL (Authored by Apple) two years later
- In 2014/2015 Metal replaced OpenGL and OpenCL and became the standard for Apple devices

# Prerequisites

- To write Metal shaders (either for Mac, iPhone or VisionPro) a MacOS device with developer tools installed is necessary
- One should also be familiar a little bit with ObjectiveC/Swift
  - Though Metal C++ interface technically exists
- And of course with [Metal Shading Language Spec](#)

```
id<MTLCommandBuffer> cmdBuffer = [queue commandBufferWithDescriptor:desc];
id<MTLComputeCommandEncoder> encoder = [cmdBuffer computeCommandEncoder];
[encoder setComputePipelineState:cpl];
[encoder setBuffer:rc offset:0 atIndex:0];
[encoder setBytes:&triu_size length:sizeof(uint64_t) atIndex:5];
[encoder dispatchThreads:MTLSizeMake(triu_size, 1, 1)
  threadsPerThreadgroup:MTLSizeMake(32, 1, 1)];
[encoder endEncoding];
[cmdBuffer commit];
[cmdBuffer waitUntilCompleted];
```

```
template <typename scalar_t>
kernel void triu_indices(device scalar_t * tensor,
  constant int64_t& rectangle_size,
  constant int64_t& triu_size,
  uint linear_index [[thread_position_in_grid]]) {
  int64_t r, c;
  if (linear_index < rectangle_size) {
    // the coordinate is within the top rectangle
    r = linear_index / col;
    c = linear_index % col;
```

# Terminology

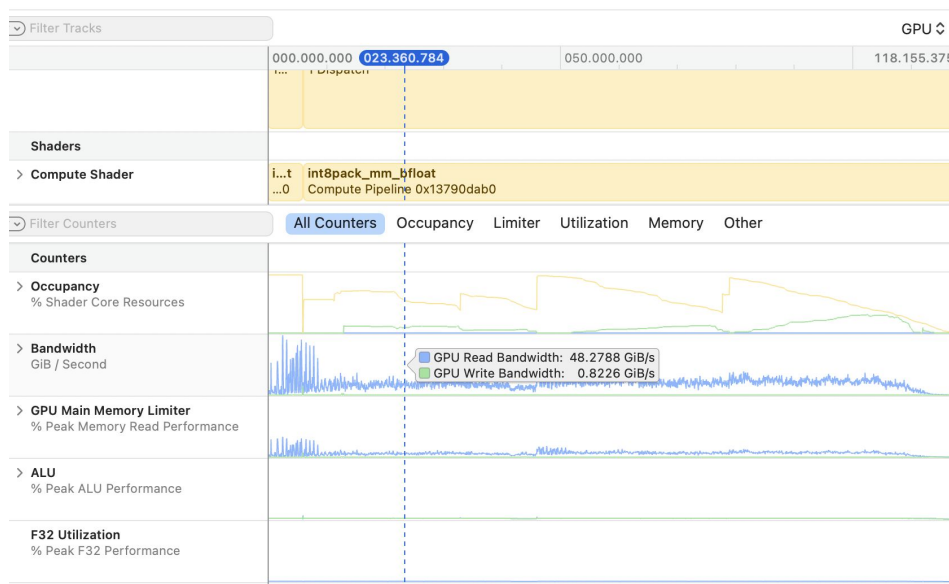
- Metal Shader - code to run on GPU
- MTLBuffer - GPU memory, can be shared with CPU
- Command Buffer - more or less command stream
- Metal Performance Shaders (hence name MPS) - collection of optimized shaders for popular operations (aka CUBLAS/cuDNN), for example see [LU factorization on MPS](#)
- Metal Performance Shaders Graph (MPSGraph) is a graph-like compiler that fuses multiple shaders together, default interface to access GPU

# How to call Metal kernels from PyTorch

- Use `MetalShaderLibrary` class to JIT-compile your kernel
- Kernel invocation from ATEN looks as follows:

```
dispatch_sync_with_rethrow(mpsStream->queue(), ^() {  
    @autoreleasepool {  
        id<MTLComputeCommandEncoder> computeEncoder = mpsStream->commandEncoder();  
        auto crossPSO = lib.getPipelineStateForFunc("cross " + scalarToMetalTypeString(out));  
        [computeEncoder setComputePipelineState:crossPSO];  
        mtl_setBuffer(computeEncoder, input, 0);  
        mtl_setBuffer(computeEncoder, other, 1);  
        mtl_setBuffer(computeEncoder, out, 2);  
        [computeEncoder setBuffer:kernelDataOffsets offset:0 atIndex:3];  
        [computeEncoder setBytes:&out_dim_stride length:sizeof(int64_t) atIndex:4];  
        [computeEncoder setBytes:&input_dim_stride length:sizeof(int64_t) atIndex:5];  
        [computeEncoder setBytes:&other_dim_stride length:sizeof(int64_t) atIndex:6];  
        mtl_dispatch1DJob(computeEncoder, crossPSO, numThreads);  
    }  
});
```

# How to profile/debug Metal Kernels



- On Mac there are no better tool that Xcode :)
- Use `MTL_CAPTURE_ENABLED` environment variable to enable capture
- Then open `.gputrace`



# How to profile Metal from command line

- Short answer: you can not
- But you can measure CPU wall clock time to estimate your kernel perf (but make sure to sync your pipeline at the end)
- See [benchmark\\_unary](#) for example

```
def bench_unary(m, n, unary_func, dtype=torch.float32, device="cpu"):
    if device == "mps":
        sync_cmd = "torch.mps.synchronize()"
    elif device == "cuda":
        sync_cmd = "torch.cuda.synchronize()"
    else:
        sync_cmd = ""
    t = Timer(
        stmt=f"f(x);{sync_cmd}",
        setup=f"x=torch.rand(({m}, {n}), dtype={dtype}, device='{device}'))",
        globals = {'f': unary_func},
        language="python", timer=default_timer
    )
    return t.blocked_autorange()
```

# How to debug Metal from command line

From Apple's [Validating your app Metal API usage](#) / [man MetalValidation](#):

```
(base) malfet@Nikitas-MacBook-Pro benchmarks %  
(base) malfet@Nikitas-MacBook-Pro benchmarks % git diff mps_sum_sincos.mm  
diff --git a/benchmarks/mps_sum_sincos.mm b/benchmarks/mps_sum_sincos.mm  
index 252f107..e646dad 100644  
--- a/benchmarks/mps_sum_sincos.mm  
+++ b/benchmarks/mps_sum_sincos.mm  
@@ -9,7 +9,7 @@ kernel void sum_sincos(constant T* x,  
                        device T* out,  
                        uint index [[thread_position_in_grid]])  
{  
-    out[index] = static_cast<T>(sin(x[index]) + cos(x[index]));  
+    out[index + 1] = static_cast<T>(sin(x[index]) + cos(x[index]));  
}  
  
template [[host_name("sum_sincos_float")]] kernel void sum_sincos(constant float*, device float*, uint);  
(base) malfet@Nikitas-MacBook-Pro benchmarks % MTL_SHADER_VALIDATION_REPORT_TO_STDERR=1 MTL_SHADER_VALIDATION=1 \  
> python benchmark_torch_trig.py  
2024-10-12 10:11:39.065 python[39102:1314087] Metal GPU Validation Enabled  
Invalid device store at offset 92432171008, executing kernel function: "sum_sincos_float"  
buffer: <unnamed>, length:536870912, resident:Read Write  
pipeline: "(null)", UID: "B40D46B1D6AF128BEE8071FBAB2E3F50822CFAD15AB54497A963B2A393A452D7" encoder: "0", dispatch: 0  
* frame #0: sum_sincos<float>() - /program_source:9:20
```

# Case study 1: Accelerating GemV

# (Intermission) Is AI ready to replace us? (by seeking Llama2 help)

> Write fast matrix vector multiplication metal kernel

GPU acceleration of matrix vector multiplication using OpenCL

This is an example of a GPU-accelerated matrix vector multiplication kernel written in OpenCL. It demonstrates how to implement a simple matrix vector multiplication operation using OpenCL.

// Matrix vector multiplication kernel

```
kernel void MatrixVectorMul(  
    global float *A, // Input matrix A  
    global float *x, // Input vector x  
    global float *y, // Output vector y  
    int M, int N, int K // Matrix dimensions  
) {  
    int idx = get_global_id(0); // Get global ID  
    // Calculate the result  
    float sum = 0.0f;  
    for (int i = 0; i < K; i++) {  
        sum += A[idx * K + i] * x[i];  
    }  
    y[idx] = sum;  
}
```

# First step towards better perf: classic SIMD

```
constant float *A_ptr = A + m * lda;
```

```
constant float *B_ptr = B + n * lda;
```

```
float rc = 0.0;
```

```
for (uint k = 0; k < sizes.y; k++) {
```

```
    const auto a_val = A_ptr[k];
```

```
    const auto b_val = B_ptr[k];
```

```
    rc += a_val * b_val;
```

```
}
```

```
outputData[m * ldc + n] = rc;
```

```
constant float4 *A_ptr = reinterpret_cast<constant  
float4 *>(A + m * lda);
```

```
constant float4 *B_ptr = reinterpret_cast<constant  
float4 *>(B + n * lda);
```

```
float rc = 0.0;
```

```
for (uint k = 0; k < sizes.y / 4; k++) {
```

```
    const auto a_val = A_ptr[k];
```

```
    const auto b_val = B_ptr[k];
```

```
    rc += dot(a_val, b_val);
```

```
}
```

```
outputData[m * ldc + n] = rc;
```

## 2nd step: using mat4 SIMD

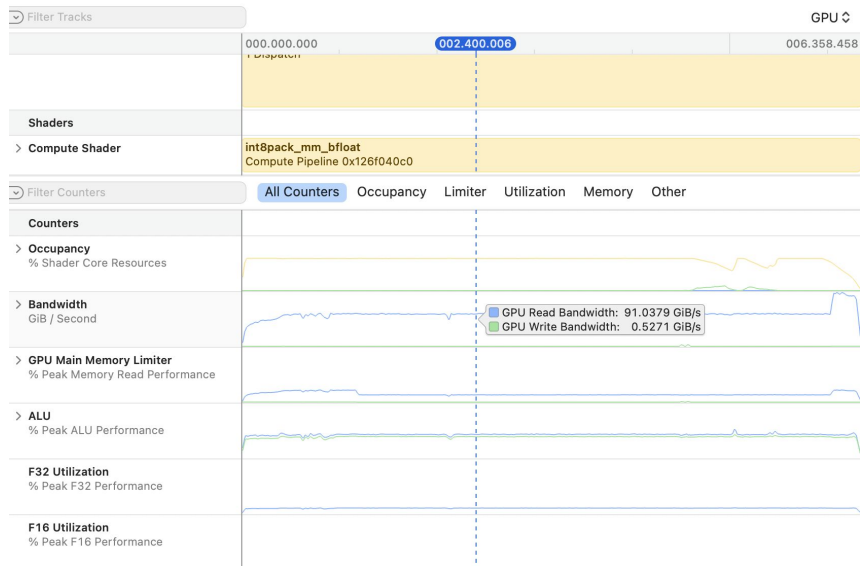
```
float rc = 0.0;
for (uint k = 0; k < sizes.y / 4; k++) {
    const auto a_val = A_ptr[k];
    const auto b_val = B_ptr[k];
    rc += dot(a_val, b_val);
}
outputData[m * ldc + n] = rc;
```

```
float4 rc = 0.0;
for (uint k = 0; k < sizes.y / 4; k++) {
    float4x4 b_mat;
    for(int j = 0; j < 4; ++j) {
        b_mat[j] = B_ptr[k + j * lda / 4];
    }
    const auto a_vec = A_ptr[k];
    rc += transpose(b_mat) * a_vec;
}
```

## 3<sup>rd</sup> step: optimize memory access pattern

- GPU threads are organized in threadgroups
- Threads further organized into simd groups (something like CUDA warps)
- Scheduling threads from single threadgroups to access memory concurrently can significantly improve perf
- See MLX GEMVT kernel's nice comment explaining the idea in a bit more details

# Progress so far...



```
Using device Apple M1 Pro
Perf of naive_int8mm type bfloat dim 32x4128x4096 is 8.9569 GFLOPs
Perf of reduce_vec4_int8mm type bfloat dim 32x4128x4096 is 35.5667 GFLOPs
Perf of reduce_mat4_int8mm type bfloat dim 32x4128x4096 is 147.826 GFLOPs
Perf of reduce_group_int8mm type bfloat dim 32x4128x4096 is 231.306 GFLOPs
```



# Links

- <https://pytorch.org/get-started/locally/>
- <https://github.com/pytorch/pytorch/blob/main/aten/src/ATen/native/mps/operations/CrossKernel.mm>
- <https://github.com/ml-explore/mlx/blob/main/mlx/backend/metal/kernels/gemv.metal>
- [https://github.com/malfet/llm\\_experiments/blob/main/metal-perf/gemm\\_perf\\_studies.mm](https://github.com/malfet/llm_experiments/blob/main/metal-perf/gemm_perf_studies.mm)
- [Metal Shading Language Specification - Apple Developer](#)
- [MPS missing ops issue](#)
- [Metal Puzzles](#)

# Interactive part: let's try to implement $I_0$

Defined [torch.special — PyTorch 2.4 documentation](https://pytorch.org/docs/stable/special.html) as

$$\text{out}_i = I_0(\text{input}_i) = \sum_{k=0}^{\infty} \frac{(\text{input}_i^2/4)^k}{(k!)^2}$$

Implemented in <https://github.com/pytorch/pytorch/pull/137849>