

SYCL GPU Best Practices

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Occupancy

Give the GPU enough work!

GPU != CPU

- CPUs: Optimized for latency
 - Fewer fancier processors
- GPUs: Optimized for throughput
 - Many simpler processors

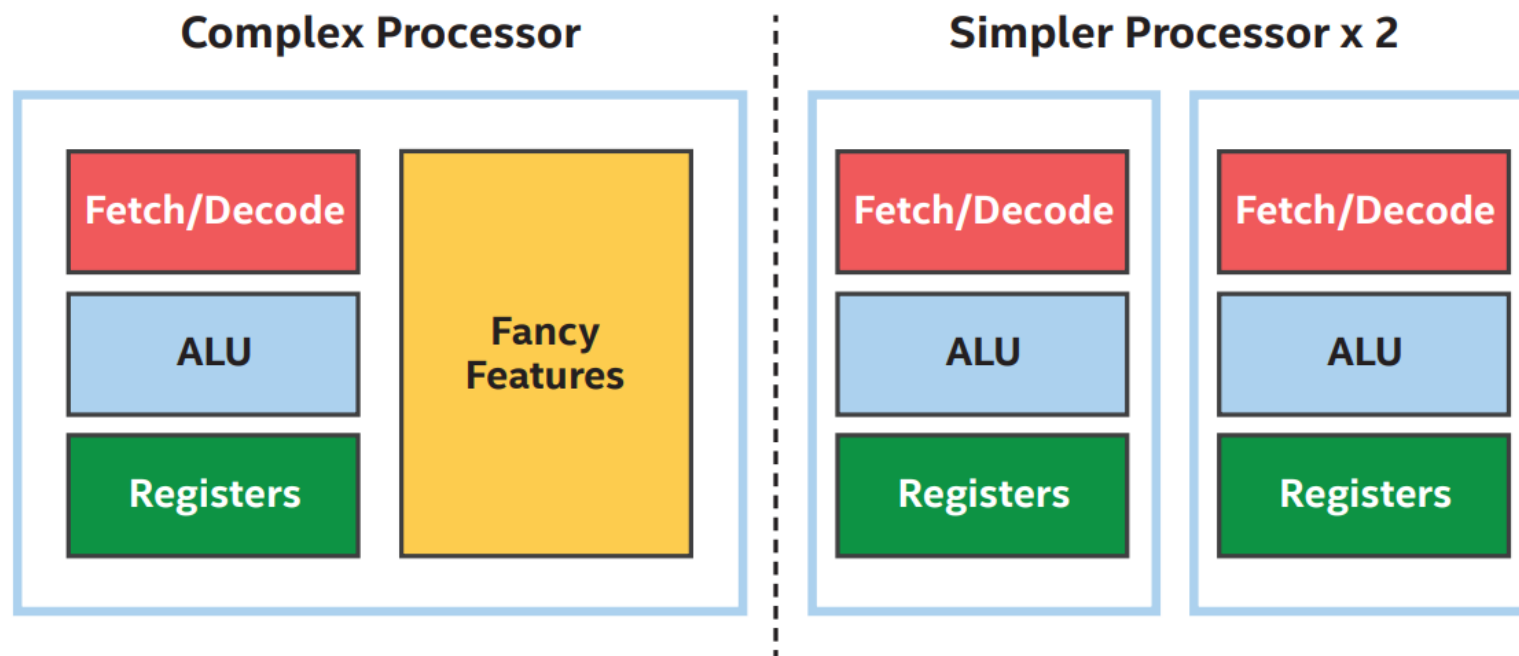


Figure 15-2. GPU processors are simpler, but there are more of them

GPUs need lots of data!

- Graphics and games requires processing millions of pixels per second
- GPUs prefer many work-items for general-purpose computation
- Many work-items keeps GPU execution resources busy (occupied)!



Bad: Not Enough Parallelism

```
h.single_task([=]() {  
    for (int m = 0; m < M; m++) {  
        for (int n = 0; n < N; n++) {  
            T sum = 0;  
            for (int k = 0; k < K; k++)  
                sum += matrixA[m * K + k] * matrixB[k * N + n];  
            matrixC[m * N + n] = sum;  
        }  
    }  
});
```

Figure 15-3. A single task matrix multiplication looks a lot like CPU host code

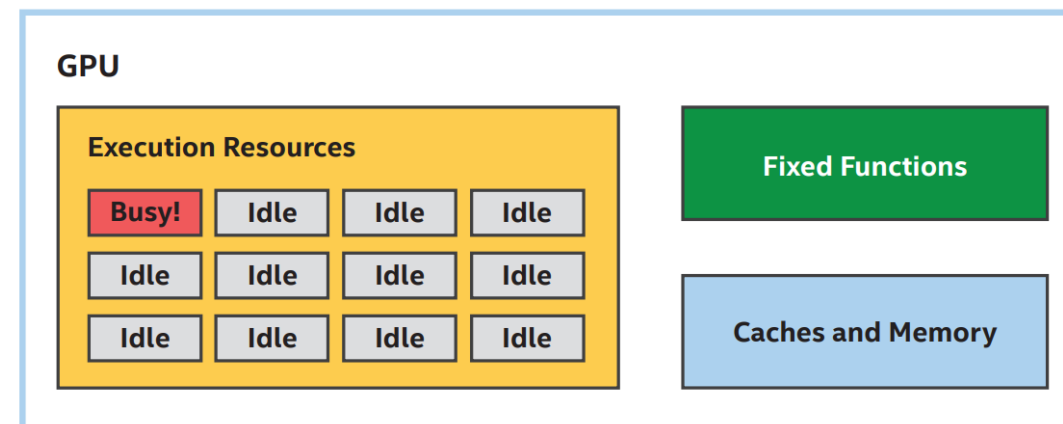


Figure 15-4. A single task kernel on a GPU leaves many execution resources idle



Better: More Parallelism

```
h.parallel_for(range{M}, [=] (id<1> idx) {  
    int m = idx[0];
```

```
    for (int n = 0; n < N; n++) {  
        T sum = 0;  
        for (int k = 0; k < K; k++)  
            sum += matrixA[m * K + k] * matrixB[k * N + n];  
        matrixC[m * N + n] = sum;  
    }  
});
```

Figure 15-5. *Somewhat-parallel matrix multiplication*

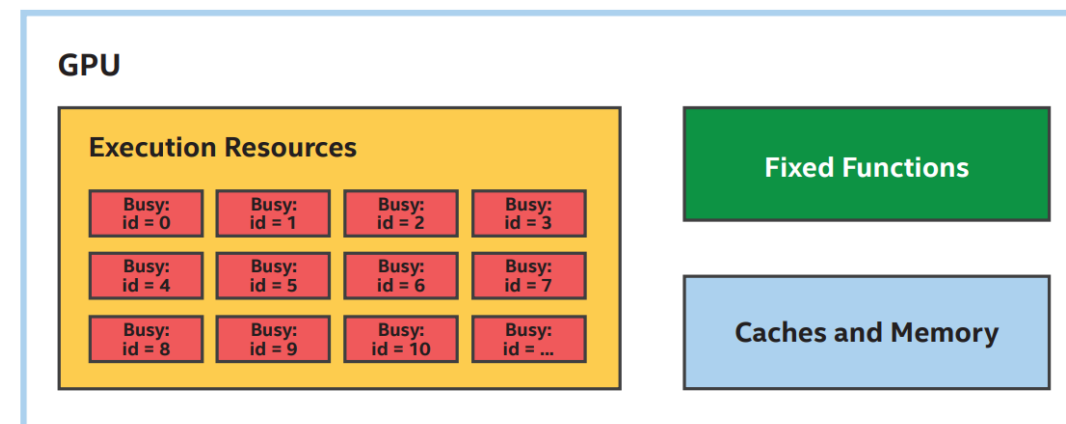


Figure 15-6. *Somewhat-parallel kernel keeps more processor resources busy*



More Parallelism is Even Better!

```
h.parallel_for(range{M, N}, [=](id<2> idx) {  
    int m = idx[0];  
    int n = idx[1];  
    T sum = 0;  
    for (int k = 0; k < K; k++)  
        sum += matrixA[m * K + k] * matrixB[k * N + n];  
    matrixC[m * N + n] = sum;  
});
```

Figure 15-7. Even more parallel matrix multiplication



Why is so much parallelism important?

- In addition to keeping processing elements busy...
- Many GPU processors operate on multiple data elements simultaneously:
- Many GPU processors use multiple threads to hide latency:

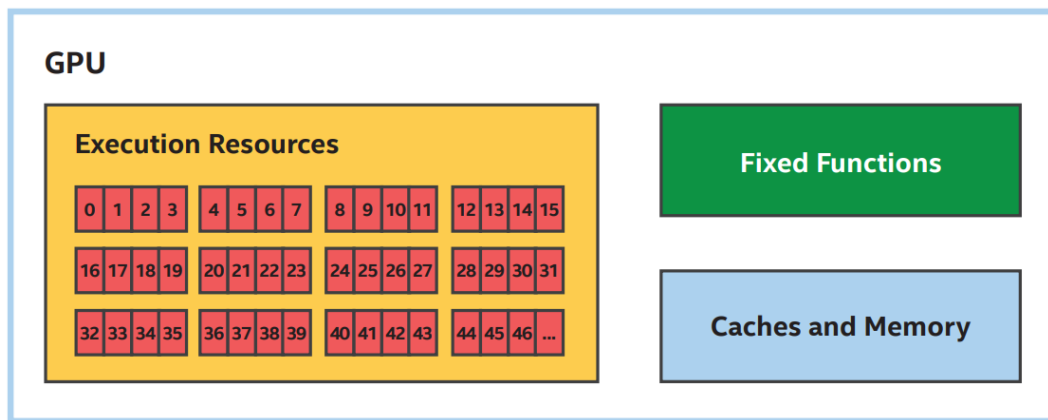


Figure 15-9. Executing a somewhat-parallel kernel on SIMD processors

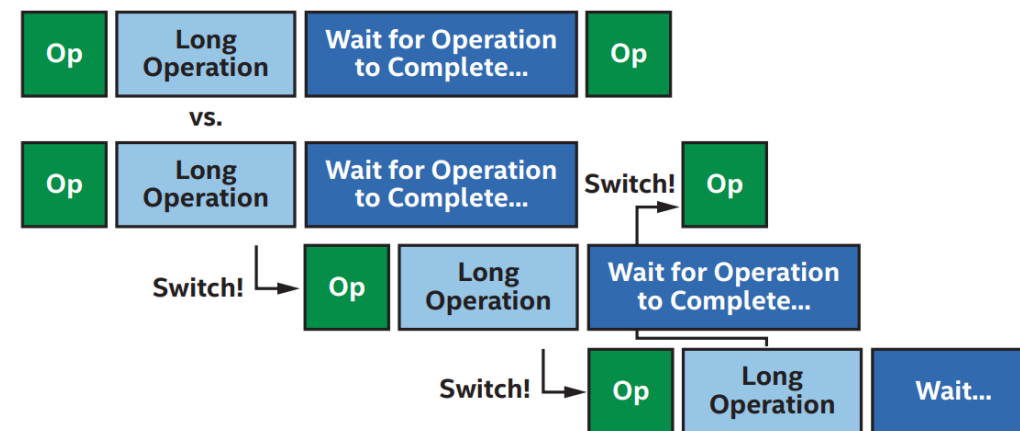


Figure 15-13. Switching instruction streams to hide latency

Memory

Keep the GPU fed and happy!

Beware the Costs of Offload

- Moving data to or from a GPU is not free
- Moving an algorithm to or from a GPU is not always profitable

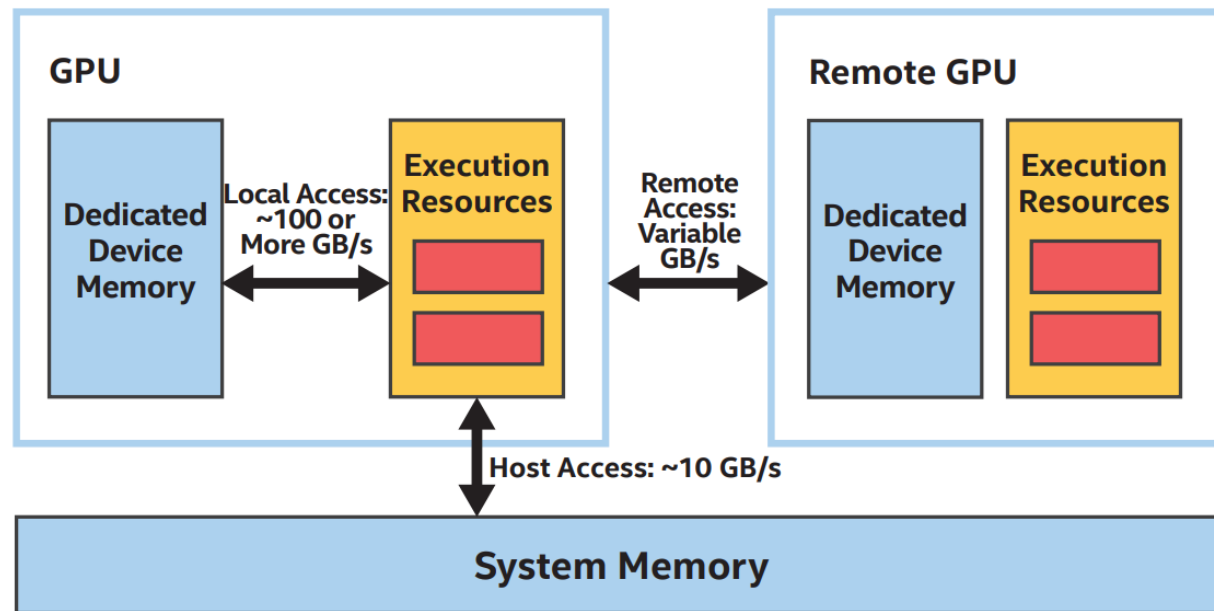


Figure 15-16. Typical differences between device memory, remote memory, and host memory

Accessing Memory in Kernels

- Maximize performance by maximizing locality
- Typically means organizing data structures efficiently
- Or, choosing the right dimension to parallelize
- Not sure which dimension is best? Try both and profile!



Bad: Strided Memory Accesses

```
h.parallel_for(range{M}, [=](id<1> idx) {  
    int m = idx[0];  
  
    for (int n = 0; n < N; n++) {  
        T sum = 0;  
        for (int k = 0; k < K; k++)  
            sum += matrixA[m * K + k] * matrixB[k * N + n];  
        matrixC[m * N + n] = sum;  
    }  
});
```

Figure 15-5. *Somewhat-parallel matrix multiplication*

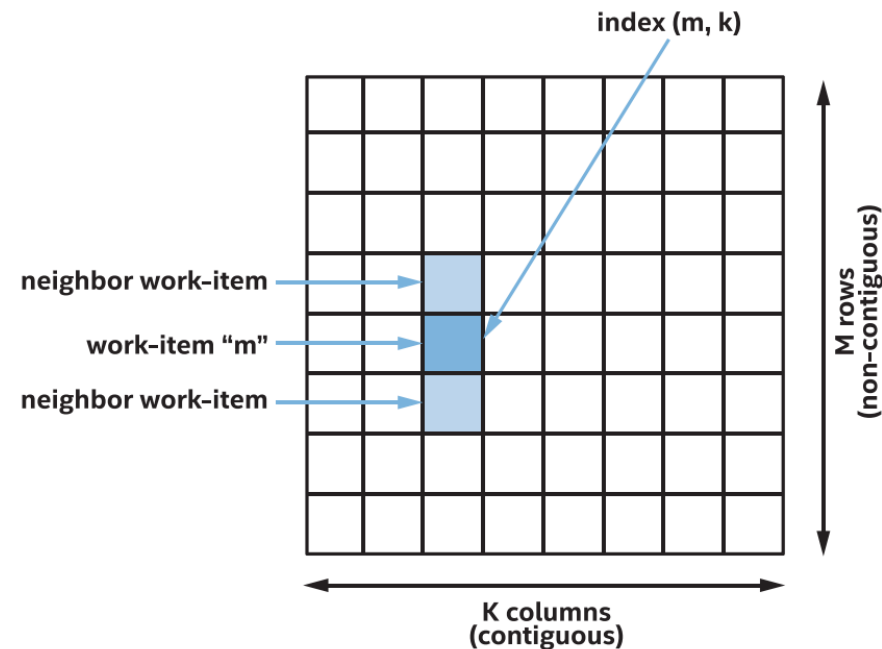


Figure 15-17. *Accesses to matrixA are highly strided and inefficient*



Good: Contiguous Memory Accesses

```
// This kernel processes columns of the result matrix in parallel.  
h.parallel_for(N, [=](item<1> idx) {  
    int n = idx[0]  
  
    for (int m = 0; m < M; m++) {  
        T sum = 0;  
        for (int k = 0; k < K; k++)  
            sum += matrixA[m * K + k] * matrixB[k * N + n];  
        matrixC[m * N + n] = sum;  
    }  
});
```

Figure 15-18. Computing columns of the result matrix in parallel, not rows

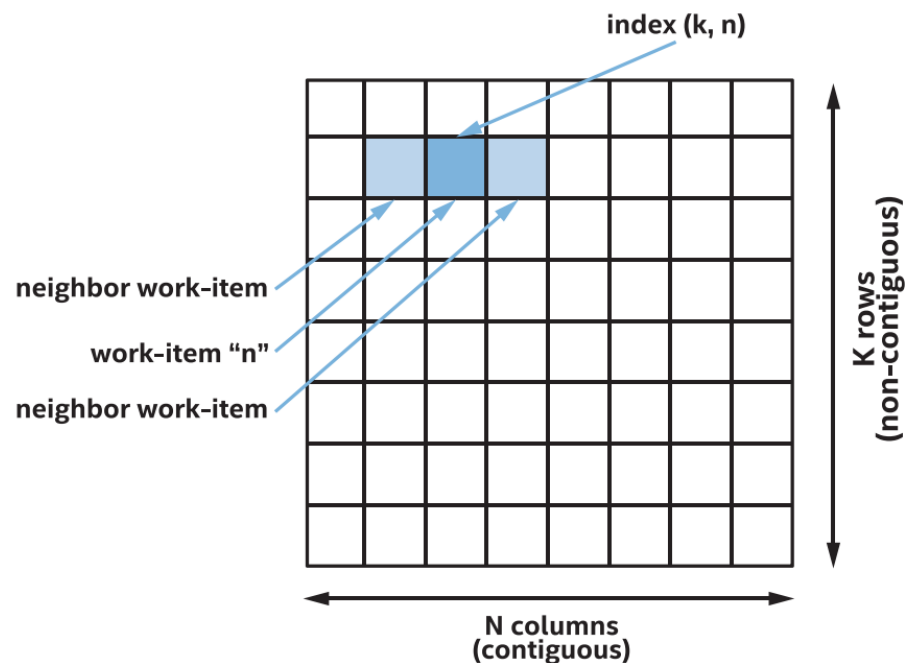


Figure 15-19. Accesses to matrixB are consecutive and efficient



Local Memory

- Beyond the scope of this talk
- Know that local memory supports more access patterns efficiently than global memory!

	Global Memory:	Local Memory:
<code>ptr[id]</code>	Full Performance!	Full Performance!
<code>ptr[id + 1]</code>	Lower Performance	Full Performance!
<code>ptr[id * 2]</code>	Lower Performance	Lower Performance
<code>ptr[id * N]</code>	Worst Performance	Worst Performance
<code>ptr[id * M]</code>	Worst Performance	Full Performance!

Figure 15-20. Possible performance for different access patterns, for global and local memory

Compute

Cater to GPU strengths!

Optimizing for GPU Compute


- GPUs are traditionally optimized for graphics tasks
- Typically, 32-bit floating-point math on vertices or pixels

GPU Compute Best Practices

- Prefer smaller data types, 32-bits or less
 - Some 64-bit data types may be slow or unsupported (e.g., double)
 - Watch for 64-bit address arithmetic, use of 64-bit `size_t`
 - 16-bit or smaller data types may be faster (e.g., half-precision fp16)
 - Use MAD or FMA, don't disable contractions
 - Trade precision for performance using `sycl::native` math functions
 - Trade portability for performance using vendor-specific extensions
-
- Special operations found in various devices, including GPUs: **MAD** = multiply-add; **FMA** = Fused multiply add
Their use can change the results slightly (typically more accurate, but also different);
they are generally much faster than using the individual instructions.

Summary and Recap

Summary

- GPUs are massively parallel throughput devices
 - Important to give a GPU lots of work, thousands or millions of work-items
- Optimize Memory First
 - Monitor and minimize data transfer costs to or from the GPU
 - Improve performance by rearrange data or computation for locality
- Optimize Compute Next
 - Prefer smaller data types, trade precision for performance
- Thank you!
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