

PROGRAMMING MODERN GPU SUPERCOMPUTERS

JEFF HAMMOND INTEL

US-DOE EXASCALE SYSTEMS (2021+)

Neither of these systems is has a many-core CPU or an NVIDIA GPU...



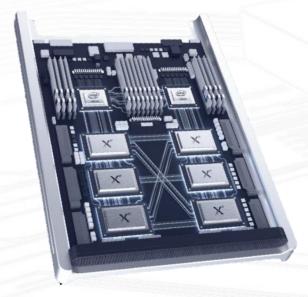


What programming model(s) take a developer from 2012 to 2022?

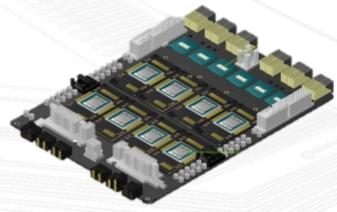


GPU Supercomputers are Multi-GPU Systems

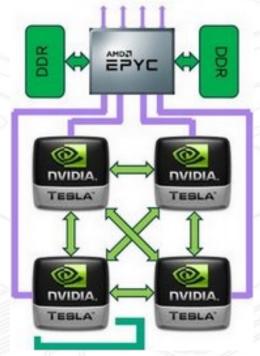
Argonne Aurora: 2 CPU & 6 GPU

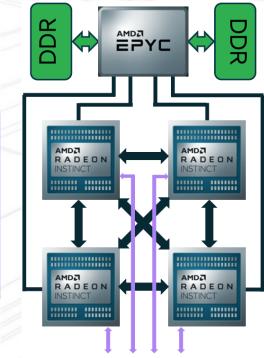


NVIDIA HGX A100: 2 CPU & 8 GPU



NERSC Perlmutter and ORNL Frontier: 1 CPU & 4 GPU





https://www.servethehome.com/wp-content/uploads/2019/11/SC19-Intel-DoE-Aurora.jpg



OUTLINE

- 1. Brief overview of SYCL ecosystem for GPUs.
- 2. SYCL w/ one device per process
 - MPI+X where X=SYCL
 - All of the good and bad of distributed-memory...
- 3. SYCL w/ multiple devices per process
 - More PGAS-like
 - All of the good and bad of shared-memory...

MPI = Message Passing Interface
PGAS = Partitioned Global Address Space
e.g. UPC and Fortran coarrays.



THREADS: THE WRONG ABSTRACTION AND THE WRONG SEMANTIC

Jeff Hammond Parallel Computing Lab Intel Corporation

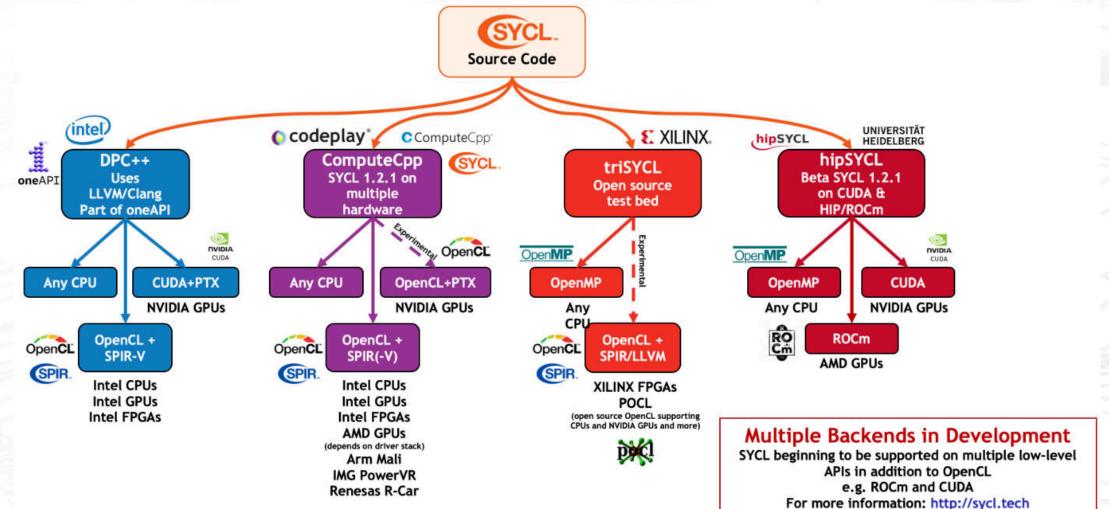


OVERVIEW OF THE SYCL™ ECOSYSTEM FOR GPUS

- Intel® Data Parallel C++ https://software.intel.com/en-us/oneapi/base-kit
 - oneAPI product compiler based on Clang/LLVM (open-source [1]).
 - Supports multiple HPC-oriented SYCL 2020 features including USM (pointers).
 - Supports Intel GPU, CPU, FPGA (by Intel) and NVIDIA (by CodePlay)
- CodePlay ComputeCpp https://developer.codeplay.com/home/
 - Product compiler (commercial support and free community edition).
 - Supports OpenCL™/SPIR-V devices (e.g. Intel GPU) and NVIDIA (via PTX).
- University of Heidelberg's hipSYCL https://github.com/illuhad/hipSYCL
 - Based on Clang/LLVM, i.e. CUDA Clang (open-source).
 - Recently implemented SYCL 2020 USM [2,3].
 - Supports CPU (OpenMP), NVIDIA (CUDA) and AMD GPU (HIP/ROCm).
 - [1] https://github.com/intel/llvm/
 - [2] https://github.com/illuhad/hipSYCL/pulls?q=USM
 - [3] https://www.urz.uni-heidelberg.de/en/2020-09-29-oneapi-coe-urz

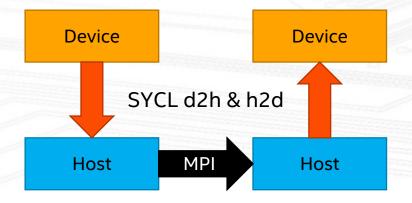


SYCL ECOSYSTEM AS OF JUNE 2020



PURE DISTRIBUTED MEMORY APPROACH

- Portable: MPI works within and between nodes, VMs, etc.
- Homogeneous: Treat all inter-device relationships as if different nodes.
- Standard: MPI doesn't know anything about GPUs (yet).
- Inefficient: Moves more data than necessary in multiple directions.
- Restrictive: process_per_node := device_per_node * proc_per_device.

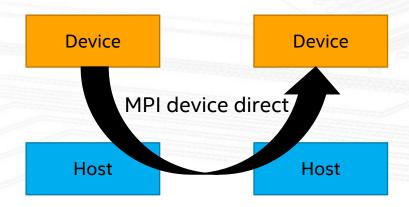


- 1. SYCL moves device data to host
- 2. MPI moves data between hosts
- 3. SYCL moves host data to device



IMPROVED DISTRIBUTED MEMORY APPROACH

- Portable: MPI works within and between nodes, VMs, etc.
- Homogeneous: Treat all inter-device relationships as if different nodes.
- Standard: MPI doesn't know anything about GPUs (yet).
- Inefficient: Moves more data than necessary in multiple directions.
- Restrictive: process_per_node := device_per_node * proc_per_device.
- Device support in MPI is non-standard and implementation-dependent.

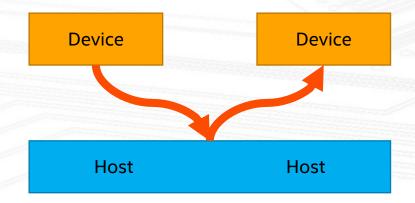


1. Hosts make MPI calls with USM pointers (SYCL 2020)

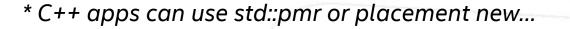


INTRANODE SHARED-MEMORY APPROACH WITH MPI

- Portable: MPI works within and between nodes, VMs, etc.
- Homogeneous: Treat all inter-device relationships as if different nodes.
- Standard: MPI doesn't know anything about GPUs (yet).
- Inefficient: Moves more data than necessary in multiple directions.
- Restrictive: process_per_node := device_per_node * proc_per_device.
- MPI-3 shared-memory requires a special allocator* and other "fun"...



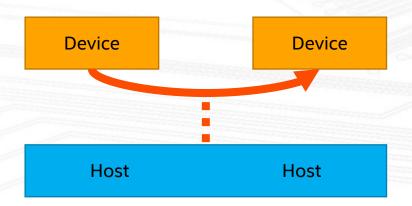
- 1. SYCL moves device data to host
- 2. SYCL moves host data to device





INTRANODE SHARED-MEMORY APPROACH WITH SYCL-NEXT?

- Portable: Use SYCL to copy data between different processes.
- Homogeneous: Treat all inter-device relationships as if different nodes.
- Standard: SYCL needs to know about multi-process contexts.
- Efficient: Moves only the data necessary.
- Restrictive: process_per_node := device_per_node * proc_per_device.
- This feature does not currently exist... (it exists in proprietary models)



1. SYCL moves device data to device



SUMMARY #1

- Many HPC codes design for MPI first, and intranode parallelism second:
 - There is more MPI parallelism available than intranode:
 - MPI ~100K cores, OpenMP ~100 cores, SIMD ~10 lanes
 - MPI ~5K GPUs, GPUs ~10, GPU coarse ~100, GPU fine ~50
 - Intranode parallelism is growing; system size is not. Time to change priorities?
- MPI remains an extremely good parallel model but moves too much data within the node (CPU and GPU).
 - Upside of data privatization has historically outweighed downside of extra copies.
 - MPI routinely beats OpenMP for multicore execution, when both exist, in part because most applications do a terrible job MPI+OpenMP. (**#pragma omp parallel for** is an anti-pattern!)
 - GPUs change the relative costs of fork-join, intra/inter-device data movement, etc.
 - Newer HPC workloads, e.g. deep learning training, are communication-intensive.
- MPI isn't synonymous with HPC anymore.



CUDA EXAMPLE

nstream.h

nstream.cu

```
const int bytes = length * sizeof(double);

check( cudaMalloc((void**)&d_A, bytes) );
check( cudaMalloc((void**)&d_B, bytes) );
check( cudaMalloc((void**)&d_C, bytes) );

dim3 DB(blockSize, 1, 1);
dim3 DG(length/blockSize, 1, 1);

nstream<<<DG, DB>>>(length, scalar, d_A, d_B, d_C);
check( cudaDeviceSynchronize() );
```



OPENCL EXAMPLE

nstream.cl

```
__kernel void nstream(
    int length,
    double s,
    __global double * A,
    __global double * B,
    __global double * C)
{
    int i = get_global_id(0);
    A[i] += B[i] + s * C[i];
}
```

nstream.cpp

```
cl::Context gpu(CL DEVICE TYPE GPU, &err);
cl::CommandQueue queue(gpu);
cl::Program program(qpu,
    prk::opencl::loadProgram("nstream.cl"), true);
auto kernel = cl::make kernel<int, double, cl::Buffer,</pre>
    cl::Buffer, cl::Buffer>(program, "nstream", &err);
auto d a = cl::Buffer(gpu, begin(h a), end(h a));
auto d b = cl::Buffer(gpu, begin(h b), end(h b));
auto d c = cl::Buffer(gpu, begin(h c), end(h c));
kernel(cl::EnqueueArgs(queue, cl::NDRange(length)),
       length, scalar, d a, d b, d c);
queue.finish();
```



SYCL 1.2.1 EXAMPLE

```
Retains OpenCL's ability to easily target
sycl::gpu selector device selector;
                                                  different devices in the same thread.
sycl::queue q(device_selector);
sycl::buffer<double> d A { h A.data(), h A.size() };
sycl::buffer<double> d B { h B.data(), h B.size() };
                                                              Accessors create DAG to trigger data
sycl::buffer<double> d C { h C.data(), h C.size() };
                                                               movement and represent execution
                                                                       dependencies.
q.submit([&](sycl::handler& h)
    auto A = d A.get access<sycl::access::mode::read write>(h);
    auto B = d B.get access<sycl::access::mode::read>(h);
    auto C = d C.get access<sycl::access::mode::read>(h);
    h.parallel for<class nstream>(sycl::range<1>{n}, [=] (sycl::id<1> it) {
         int i = it[0];
        A[i] += B[i] + s * C[i];
    });
                                Parallel loops are explicit like C++ vs. implicit in OpenCL.
q.wait();
                           Kernel code does not need to live in a separate part of the program.
```

SYCL 2020 EXAMPLE

```
sycl::queue q(gpu selector{});
auto A = sycl::malloc shared<double>(n, q);
auto B = sycl::malloc shared<double>(n, q);
                                                      Pointers: everyone's favorite footgun!
auto C = sycl::malloc shared<double>(n, q);
q.submit([&](sycl::handler& h)
     h.parallel for(sycl::range<1>{n}, [=] (sycl::id<1> it) {
         int i = it[0];
         A[i] += B[i] + s * C[i];
     });
                                             Lambda names are optional, but
                                             potentially useful for debugging.
q.wait();
sycl::free(A, q);
sycl::free(B, q);
sycl::free(C, q);
```

SYCL 2020 EXAMPLE

```
sycl::queue q(gpu selector{});
auto A = sycl::malloc shared<double>(n, q);
auto B = sycl::malloc shared<double>(n, q);
auto C = sycl::malloc shared<double>(n, q);
q.parallel_for(sycl::range<1>{n}, [=] (sycl::id<1> it) {
     int i = it[0];
     A[i] += B[i] + s * C[i];
                                   Eliminate unnecessary syntax for expressing kernels.
});
q.wait();
sycl::free(A, q);
sycl::free(B, q);
sycl::free(C, q);
```



SYCL 2020 WITH EXPLICIT DATA MOVEMENT

```
auto H = sycl::malloc_host<double>(n, q);
// initialize H
auto D = sycl::malloc_device<double>(n, q);
q.memcpy(D, H, n*sizeof(double)).wait();
// do something with D on the device
q.memcpy(H, D, n*sizeof(double)).wait();
sycl::free(D, q);
// do something with H on the host
sycl::free(H, q);
```



MULTI-GPU SYCL PROGRAMMING CONCEPTS

Similar to MPI...

- SYCL has explicit state: devices, queues, contexts...
- SYCL is asynchronous and provides fine and coarse grain synchronization.
- Must solve domain decomposition and other application-specific problems.

Unlike MPI...

- "...all the member functions and special member functions of the SYCL classes are thread safe." [SYCL 1.2.1]
- Can choose between shared-memory (USM shared), PGAS (USM memcpy) and STL (buffer::copy) data management schemes.



DETECT ALL THE GPUS

```
private:
  std::vector<sycl::queue> list;
public:
  queues(void) {
    auto platforms = sycl::platform::get platforms();
    for (auto & p : platforms) {
       auto devices = p.get devices();
       for (auto & d : devices ) {
         if ( d.is gpu() ) {
           list.push back(sycl::queue(d));
                     Assumptions and logic to ensure devices are in the same context are hidden...
```



SYCL 2020 DATA MODELS

- Buffers are wonderfully opaque but makes reasoning about sharing hard.
- USM shared data moves between host and device (d2d is not portable).
- USM device data does not migrate start here.

Allocation Type	Initial Location	Accessible By		Migratable To	
device	device	host	No	host	No
		device	Yes	device	-
		Another device	Optional (P2P)	Another device	No
host	host	host	Yes	host	
		Any device	Yes (~PCle)	device	No
shared	host / device / Unspecified	host	Yes	host	Yes
		device	Yes	device	Yes
		Another device	Optional (P2P)	Another device	Optional



SUMMARY #2

- Like MPI, SYCL is explicit about providing a handle to state.
 - MPI communicators, groups, requests, windows, etc.
 - SYCL platforms, devices, queues, contexts, etc.
- Explicit device handles make the task of multi-GPU programming easier.
 - Contrast: CUDA runtime API hides the device id and CUBLAS contexts don't capture it...
- If GPU compute is tightly coupled, build a data-centric abstraction to manage allocation, data movement, synchronization, and collective compute.
 - PETSc, Elemental and Global Arrays are good examples of this in the MPI plane.
- Load-store is not a good abstraction for most interconnects...

```
for (int i=0; i<ngpus; ++i) {
  check( cudaSetDevice(i) );
  check( cublasCreate(&contexts[i]) );
}</pre>
for (int i=0; i<ngpus; ++i) {
  check( cudaSetDevice(i) );
  check( cudaDeviceSynchronize() );
}
```



WHERE SHOULD WE GO FROM HERE?*

- Independent of SYCL, we need to redesign applications for multi-GPU nodes.
 - A side-effect of this is that we should get very good single-node performance without a dependency on any form of multi-processing.
- Future versions of SYCL should support more device-to-device features.
 - Industry standards must capture the characteristics of multiple vendors' hardware.
 - All HPC-oriented GPU vendors are doing something to support this, but it will take a year or two to understand what is universal.
- Device-to-device should not be limited to a single node.
 - We want to support MPI within SYCL device code. Prototyping in progress.



