oneAPI SYCL Essentials

Ben Odom

oneAPI's implementation of SYCL



Introduction to oneAPI

Agenda

- Introduction & Overview to oneAPI
- Introduction to the Intel® DevCloud for Hands On Section
- Introduction to Jupyter notebooks used for training
- Introduction to SYCL
- SYCL Program Structure
- Graphs and Dependences

Hands On

- Introduction to SYCL Simple
- Complex multiplication
- Vtune & Advisor

Learning Objectives

Explain how oneAPI can solve the challenges of programming in a heterogeneous world

Use oneAPI solutions to enable your workflows

Experiment with oneAPI tools and libraries on the Intel® DevCloud

Understand the SYCL language and programming model

Use device selection to offload kernel workloads

Build a sample SYCL application through hands-on lab exercises

Cross-Architecture Programming for Accelerated Compute, Freedom of Choice for Hardware

oneAPI: Industry Initiative & Intel Products

One Intel Software & Architecture group Intel Architecture, Graphics & Software November 2020





Programming Challenges

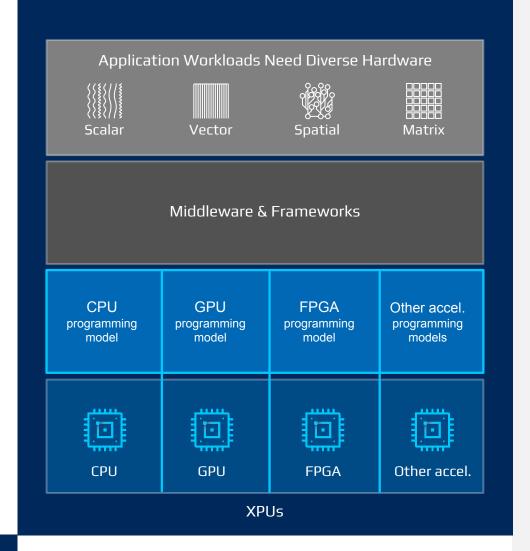
for Multiple Architectures

Growth in specialized workloads

Variety of data-centric hardware required

Separate programming models and toolchains for each architecture are required today

Software development complexity limits freedom of architectural choice



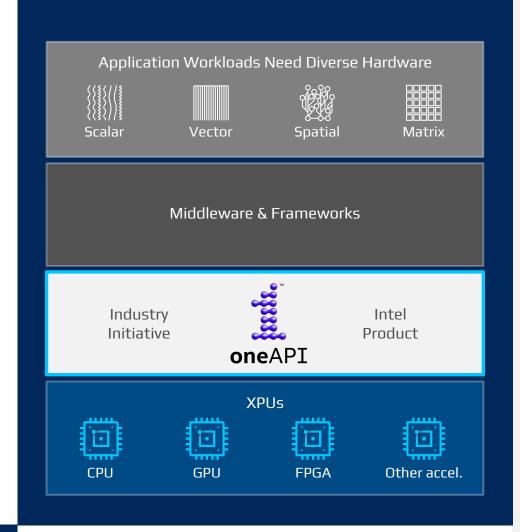
Introducing oneAPI

Cross-architecture programming that delivers freedom to choose the best hardware

Based on industry standards and open specifications

Exposes cutting-edge performance features of latest hardware

Compatible with existing high-performance languages and programming models including C++, OpenMP, Fortran, and MPI



Intel[®] oneAPI Toolkits

A complete set of proven developer tools expanded from CPU to XPU



Intel® oneAPI Base Toolkit

Native Code Developers



A core set of high-performance tools for building C++, SYCL applications & oneAPI library-based applications

Add-on Domain-specifi c Toolkits

Specialized Workloads



Intel® oneAPI Tools for HPC

Deliver fast Fortran, OpenMP & MPI applications that scale



Intel® oneAPI Tools for IoT

Build efficient, reliable solutions that run at network's edge



Intel® oneAPI Rendering Toolkit

Create performant, high-fidelity visualization applications

Toolkits powered by oneAPI

Data Scientists & Al Developers



Intel® Al Analytics Toolkit

Accelerate machine learning & data science pipelines with optimized DL frameworks & high-performing Python libraries



Intel® Distribution of OpenVINO™ Toolkit

Deploy high performance inference & applications from edge to cloud

*Other names and brands may be claimed as the property of others.

Intel® oneAPI Base Toolkit

Accelerate Data-centric Workloads

A core set of core tools and libraries for developing high-performance applications on Intel® CPUs, GPUs, and FPGAs.

Who Uses It?

- A broad range of developers across industries
- Add-on toolkit users since this is the base for all toolkits

Top Features/Benefits

- Data Parallel C++ compiler, library and analysis tools
- DPC++ Compatibility tool helps migrate existing code written in CUDA
- Python distribution includes accelerated scikit-learn, NumPy, SciPy libraries
- Optimized performance libraries for threading, math, data analytics, deep learning, and video/image/signal processing

Intel® oneAPI Base Toolkit

Direct Programming

Intel® oneAPI DPC++/C++ Compiler

Intel® DPC++ Compatibility
Tool

Intel® Distribution for Python

Intel® FPGA Add-on for oneAPI Base Toolkit

API-Based Programming

Intel® oneAPI DPC++ Library oneDPL

Intel® oneAPI Math Kernel Library - oneMKL

Intel® oneAPI Data Analytics Library - oneDAL

Intel® oneAPI Threading Building Blocks - oneTBB

Intel® oneAPI Video Processing Library - oneVPL

Intel® oneAPI Collective Communications Library oneCCL

Intel® oneAPI Deep Neural Network Library - oneDNN

Intel® Integrated Performance Primitives - Intel® IPP

Analysis & debug Tools

Intel® VTune™ Profiler

Intel® Advisor

Intel® Distribution for GDB



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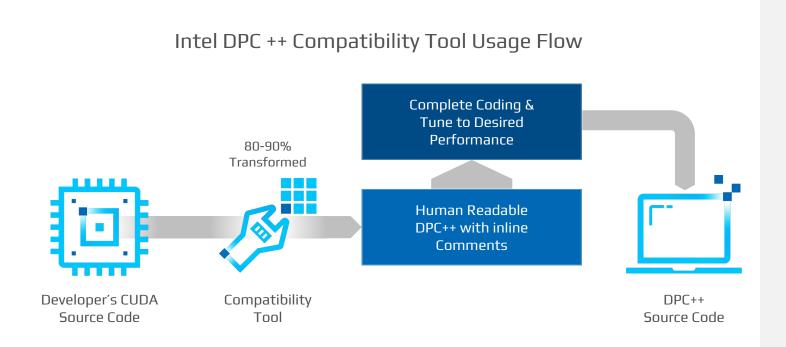
Intel® DPC++ Compatibility Tool

Minimizes Code Migration Time

Assists developers migrating code written in CUDA to DPC++ once, generating **human readable** code wherever possible

~80-90% of code typically migrates automatically

Inline comments are provided to help developers finish porting the application



Intel[®] VTune[™] Profiler

SYCL Profiling-Tune for CPU, GPU & FPGA

Analyze SYCL

See the lines of SYCL that consume the most time

Tune for Intel CPUs, GPUs & FPGAs

Optimize for any supported hardware accelerator

Optimize Offload

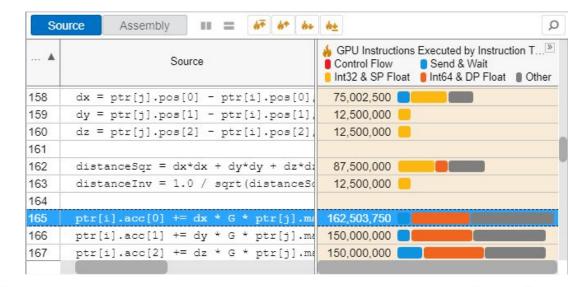
Tune OpenMP offload performance

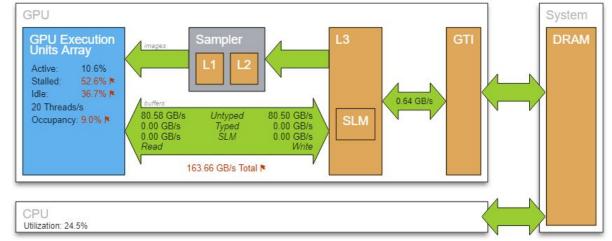
Wide Range of Performance Profiles

CPU, GPU, FPGA, threading, memory, cache, storage...

Supports Popular Languages

SYCL, C, C++, Fortran, Python, Go, Java, or a mix





There will still be a need to tune for each architecture.

Intel® Advisor

Design Assistant - Design for Modern Hardware

Offload Advisor

Estimate performance of offloading to an accelerator

Roofline Analysis

Optimize CPU/GPU code for memory and compute

Vectorization Advisor

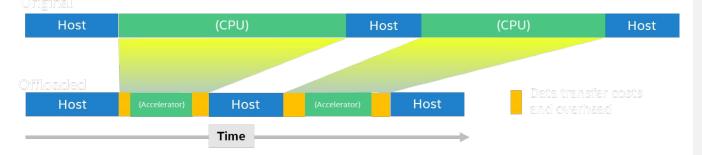
Add and optimize vectorization

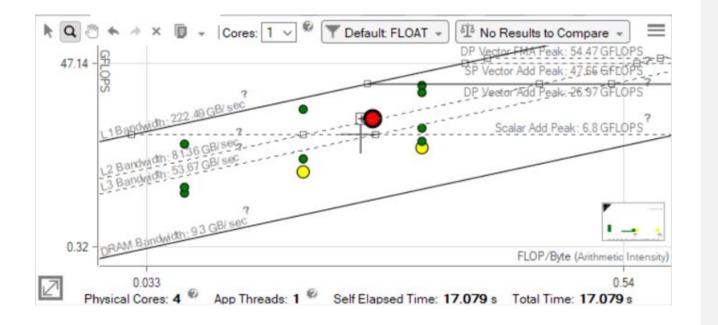
Threading Advisor

Add effective threading to unthreaded applications

Flow Graph Analyzer

Create and analyze efficient flow graphs

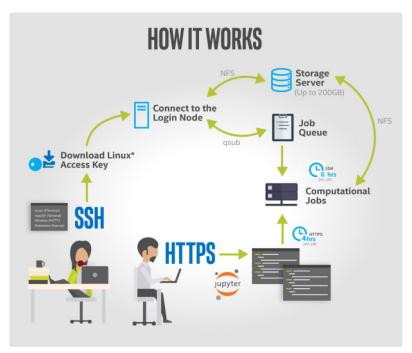


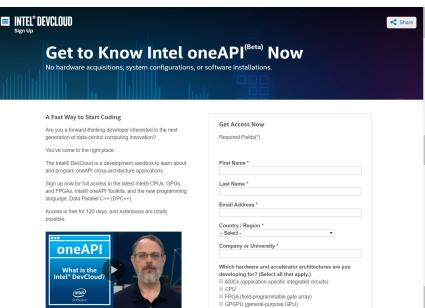


Setup Intel® DevCloud and Jupyter Environment

Intel® Devcloud for oneAPI

- A development sandbox to develop, test and run workloads across a range of Intel CPUs, GPUs, and FPGAs using Intel® oneAPI beta software
- A fast way to start coding
- Try the oneAPI toolkits, compilers, performance libraries, and tools
- Get 120 days of free access to the latest Intel® hardware and oneAPI software
- No downloads; No hardware acquisition; No installation





Register to Intel® Devcloud for oneAPI

 Step 1: Register or Sign into Intel Developer Zone

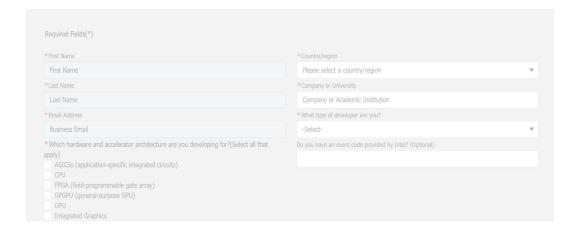




 Step 2: Activate Intel Devcloud Account

Step 2: Activate Intel® DevCloud for oneAPI

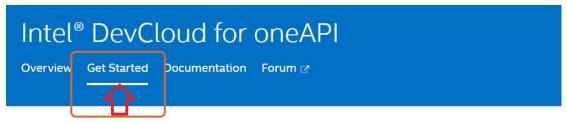
To get free access, tell us a bit more about yourself and how you would like to use the Intel DevCloud.



https://www.intel.com/content/www/us/en/developer/tools/devcloud/overview.html

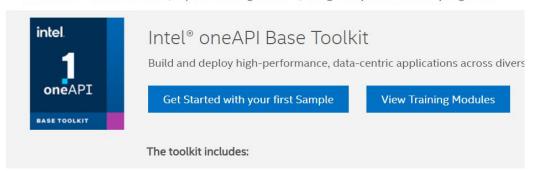
Get Started with Intel® Devcloud for oneAPI

Step 3: Click on Get Started button



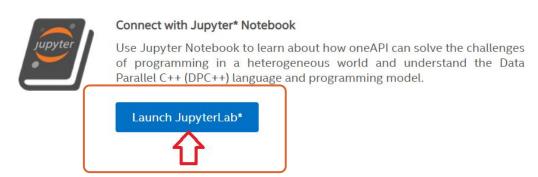
Explore Intel oneAPI Toolkits in the DevCloud

These toolkits are for performance-driven applications—HPC, IoT, advanced rendering, deep learn toolkit to see what it includes, explore training modules, and go deeper with developer guides.



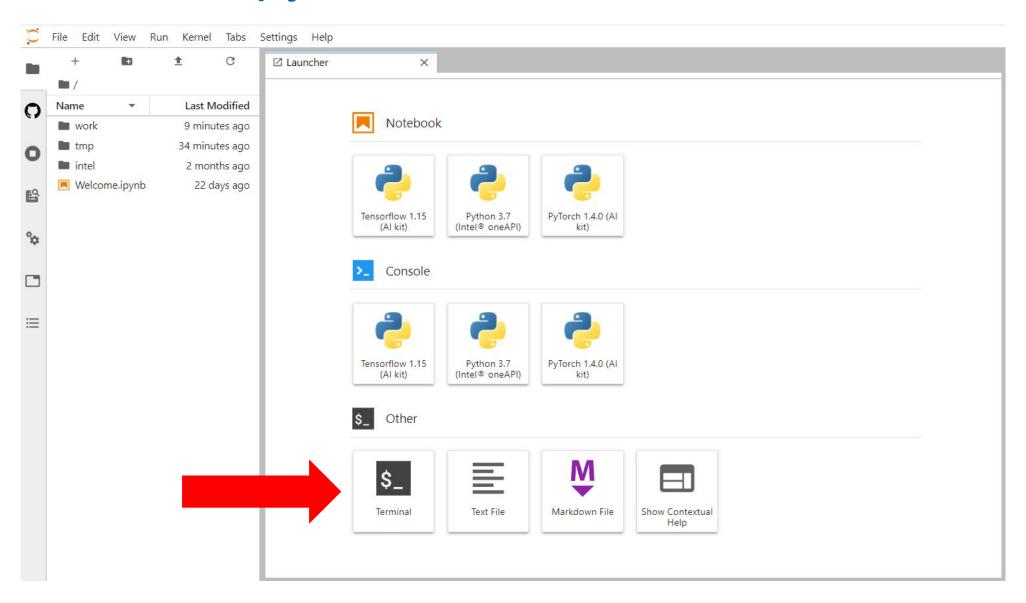
 Step 4: Scroll Down to the bottom of the page and click on Launch JupyterLab

Connect with Jupyter* Lab



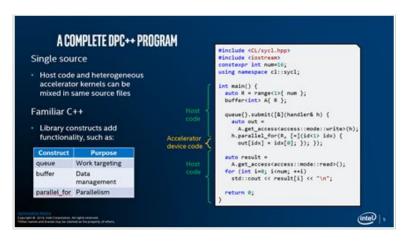
Setup Intel® DevCloud and Jupyter Environment

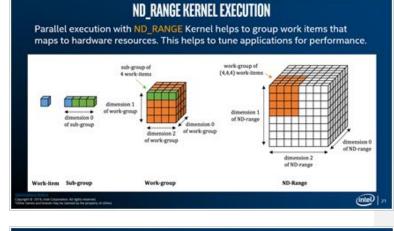
Launch Jupyter and select Terminal



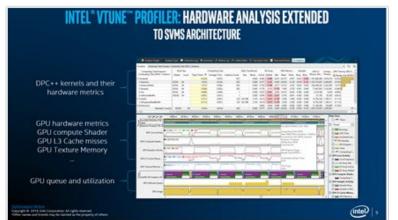
SYCL essentials Course

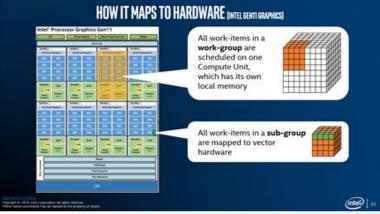












SYCL Essentials Course Curriculum provides 20 hours of training and exercises using Jupyter Notebooks integrated with Intel® DevCloud

oneAPI's implementation of SYCL

Standards-based, Cross-architecture Language ISO C++ and Khronos SYCL

Parallelism, productivity and performance for CPUs and **Accelerators**

- Delivers accelerated computing by exposing hardware features
- Allows code reuse across hardware targets, while permitting custom tuning for specific accelerators
- Provides an open, cross-industry solution to single architecture proprietary lock-in

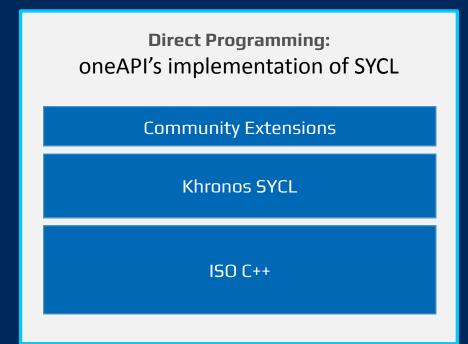
Based on C++ and SYCL

- Delivers C++ productivity benefits, using common, familiar C and C++ constructs
- Incorporates SYCL from the Khronos Group to support data parallelism and heterogeneous programming

Community Project to drive language enhancements

- Provides extensions to simplify data parallel programming
- Continues evolution through open and cooperative development

Apply your skills to the next innovation, not rewriting software for the next hardware platform



What is oneAPI's implementation of SYCL

oneAPI's implementation of SYCL

C++ and SYCL* standard and extensions

Based on modern C++

C++ productivity benefits and familiar constructs

Standards-based, cross-architecture

Incorporates the SYCL standard for data parallelism and heterogeneous programming

Extends SYCL* standard

Enhance Productivity

- Simple things should be simple to express
- Reduce verbosity and programmer burden

Enhance Performance

- Give programmers control over program execution
- Enable hardware-specific features

Fast-moving open collaboration feeding into the SYCL* standard

- Open source implementation with goal of upstream LLVM
- DPC++ extensions aim to become core SYCL*, or Khronos* extensions

A Complete SYCL Program

Single source

 Host code and heterogeneous accelerator kernels can be mixed in same source files

Familiar C++

 Library constructs add functionality, such as:

Construct	Purpose
queue	Work targeting
malloc_shared	Data management
parallel_for	Parallelism



```
#include <CL/sycl.hpp>
constexpr int N=16;
using namespace sycl;
int main() {
  queue q;
  int *data = malloc shared<int>(N, q);
  q.parallel_for(N, [=](auto i) {
      data[i] = i;
  }).wait();
  for (int i=0; i<N; i++) std::cout << data[i] << "\n"</pre>
  free(data, q);
  return 0;
```

SYCL Program Structure

Agenda

- · Deciding where code is run
- Data transfers and synchronization
- SYCL execution model and memory model

Hands On

Complex Multiplication

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Buffer Memory Model

Buffers encapsulate data shared between host and device.

Accessors provide access to data stored in buffers and create data dependences in the graph.

Unified Shared Memory (USM) provides an alternative pointer-based mechanism for managing memory;

```
queue q;
std::vector<int> v(N, 10);
  buffer buf(v);
  q.submit([&](handler& h) {
    accessor a(buf, h , write_only);
    h.parallel_for(N, [=](auto i) { a[i] = i; });
  });
for (int i = 0; i < N; i++) std::cout << v[i] <<</pre>
```

Submitting to a Device

- A device represents a specific accelerator in the system.
- Work is not submitted to devices directly, but to a queue associated with the device.
- Creating a queue for a specific device requires a device_selector.

```
default_selector selector;
// host_selector selector;
// cpu_selector selector;
// gpu_selector selector;
queue q(selector);
std::cout << "Device: " << q.get_device().get_info<info::device::name>() << std::endl;</pre>
```

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Important Classes in SYCL

Class	Functionality
sycl::device	Represents a specific CPU, GPU, FPGA or other device that can execute SYCL kernels.
sycl::queue	Represents a queue to which kernels can be submitted (enqueued). Multiple queues may map to the same sycl::device.
sycl::buffer	Encapsulates an allocation that the runtime can transfer between host and device.
sycl::handler	Used to define a command-group scope that connects buffers to kernels.
sycl::accessor	Used to define the access requirements of specific kernels (e.g. read, write, read-write).
<pre>sycl::range, sycl::nd_range sycl::id, sycl::item, sycl::nd_item</pre>	Representations of execution ranges and individual execution agents in the range.

Accessor Modes

Access Mode	Description
read_only	Read only Access
write_only	Write-only access. Previous contents not discarded
read_write	Read and Write access

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Parallel Kernels

- Parallel Kernel allows multiple instances of an operation to execute in parallel.
- Useful to offload parallel execution of a basic for-loop in which each iteration is completely independent and in any order.
- Parallel kernels are expressed using the parallel_for function

for-loop in CPU application

```
for(int i=0; i < 1024; i++){
    a[i] = b[i] + c[i];</pre>
```

Offload to accelerator using parallel_for

```
h.parallel_for(range<1>(1024), [=](id<1> i){
    A[i] = B[i] + C[i];
});
```

});

Basic Parallel Kernels

The functionality of basic parallel kernels is exposed via range, id and item classes

- range class is used to describe the iteration space of parallel execution
- id class is used to index an individual instance of a kernel in a parallel execution
- item class represents an individual instance of a kernel function, exposes additional functions to query properties of the execution range

```
h.parallel_for(range<1>(1024), [=](id<1> idx){
    // CODE THAT RUNS ON DEVICE
});
```

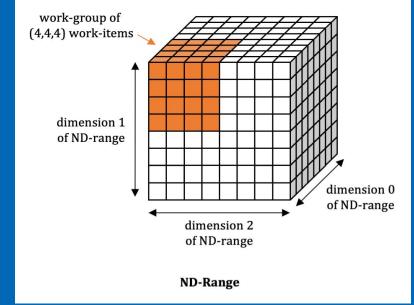
```
h.parallel_for(range<1>(1024), [=](item<1> item){
    auto idx = item.get_id();
    auto R = item.get_range();
    // CODE THAT RUNS ON DEVICE
});
```

ND-Range Kernels

Basic Parallel Kernels are easy way to parallelize a for-loop but does not allow performance optimization at hardware level.

ND-Range kernel is another way to expresses parallelism which enable low level performance tuning by providing access to local memory and mapping executions to compute units on hardware.

- The entire iteration space is divided into smaller groups called work-groups, work-items within a work-group are scheduled on a single compute unit on hardware.
- The grouping of kernel executions into work-groups will allow control of resource usage and load balance work distribution.



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ND-Range Kernels

The functionality of nd_range kernels is exposed via nd_range and nd_item classes

- nd_range class represents a grouped execution range using global execution range and the local execution range of each work-group.
- nd_item class represents an individual instance of a kernel function and allows to query for work-group range and index.

SYCL Code Anatomy

```
void dpcpp code(int* a, int* b, int* c) {
 // Setting up a device queue
 queue q;
  // Setup buffers for input and output vectors
 buffer buf a(a, range<1>(N));
  buffer buf b(b, range<1>(N));
  buffer buf c(c, range<1>(N));
  //Submit command group function object to the queue
  q.submit([&](handler &h){
    //Create device accessors to buffers allocated in global memory
    accessor A(buf a, h, read only);
    accessor B(buf b, h, read only);
    accessor C(buf_c, h, write_only);
    //Specify the device kernel body as a lambda function
    h.parallel_for(range<1>(N), [=](auto i){
     C[i] = A[i] + B[i];
```

Step 1: create a device queue (developer can specify a device type via device selector or use default selector)

Step 2: create buffers (represent both host and device memory)

Step 3: submit a command group for (asynchronous) execution

Step 4: create accessors describing how buffer is used on the device

Step 5: specify kernel function and launch parameters (e.g. group size)

Step 6: specify code to run on the device

Kernel invocations are executed in parallel

Kernel is invoked for each element of the range

Kernel invocation has access to the invocation id

Done!

The results are copied to vector c at buf_c buffer destruction

Buffer: sub buffers

A sub-buffer requires three things, a reference to a parent buffer, a base index, and the range of the sub-buffer.

The main advantage of using the sub-buffers is different kernels can operate on different sub buffers concurrently.

Sub Buffer for one dimensional buffer

Sub buffer for a 2-dimensional buffer

```
buffer B(data, range(N));
buffer<int> B1(B, 0, range{ N / 2 });
buffer<int> B2(B, 32, range{ N / 2 });
```

```
buffer<int, 2> b10{range{2, 5}};

buffer b11{b10, id{0, 0}, range{1, 5}};

buffer b12{b10, id{1, 0}, range{1, 5}};
```

*Other names and brands may be claimed as the property of others.

Sub Buffers

Buffer for Vectors

Create sub buffers B1 and B2

Submit q1 using B1

Submit q2 using B2

Create Host accessors

```
int main() {
   const int N = 64; const int num1 = 2; const int num2 = 3;
   int data[N];
   for (int i = 0; i < N; i++) data[i] = i; for (int i = 0; i < N; i++) std::cout << data[i] << " ";
   buffer B(data, range(N));
   buffer<int> B1(B, 0, range{ N / 2 });
   buffer<int> B2(B, 32, range{ N / 2 });
   queue q1;
   q1.submit([&](handler& h) {
       accessor a1(B1, h);
       h.parallel for(N/2, [=](auto i) { a1[i] *= num1; });
   });
   queue q2;
   q2.submit([&](handler& h) {
       accessor a2(B2, h);
       h.parallel for(N/2, [=](auto i) { a2[i] *= num2; });
   });
   host_accessor b1(B1, read_only);
   host accessor b2(B2, read only);
   return 0;
```

Asynchronous Execution

<u>Host</u>

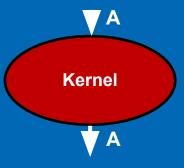
Host code execution

Enqueues kernel to graph, and keeps going

```
#include <CL/sycl.hpp>
constexpr int N=16;
using namespace sycl;
int main() {
  std::vector<int> data(N);
    buffer A(data);
    queue q;
    q.submit([&](handler& h) {
      accessor out(A, h, write_only);
      h.parallel_for(N, [=](auto i)
        out[i] = i;
      });
    });
  for (int i=0; i<N; ++i) std::cout << data[i];</pre>
```

<u>Graph</u>

Graph executes asynchronously to host program

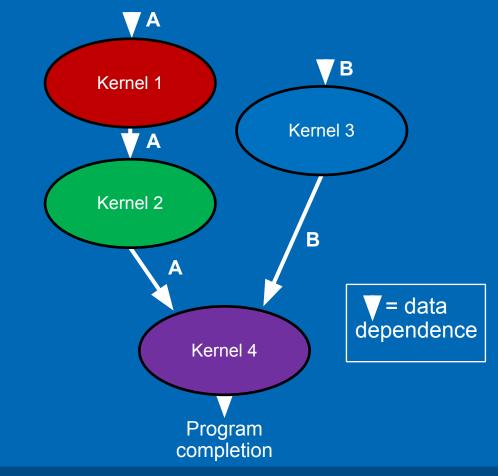


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Asynchronous Execution

```
int main() {
  auto R = range<1>{ num };
 buffer<int> A{ R }, B{ R };
 queue q;
 q.submit([&](handler& h) {
    accessor out(A, h, write only);
    h.parallel_for(R, [=](id<1> i) {
      out[i] = i; }); });
                                            Kernel 1
 q.submit([&](handler& h) {
    accessor out(A, h, write only);
    h.parallel for(R, [=](id<1> i) {
      out[i] = i; }); });
                                           Kernel 2
 q.submit([&](handler& h) {
    accessor out(B, h, write only);
    h.parallel_for(R, [=](id<1> i) {
      out[i] = i; }); });
                                           Kernel 3
 q.submit([&](handler& h) {
    accessor in(A, h, read only);
    accessor inout(B, h);
    h.parallel_for(R, [=](id<1> i) {
      inout[i] *= in[i]; }); });
                                           Kernel 4
```

Data and control dependences are resolved by the runtime



Synchronization – Host Accessors

```
#include <CL/sycl.hpp>
using namespace sycl;
constexpr int N = 16;
int main() {
  std::vector<double> v(N, 10);
  queue q;
  buffer buf(v);
  q.submit([&](handler& h) {
    accessor a(buf, h)
    h.parallel_for(N, [=](auto i) {
      a[i] -= 2;
   });
  });
 host_accessor b(buf, read_only);
 for (int i = 0; i < N; i++)
    std::cout << b[i] << "\n";</pre>
  return 0;
```

Buffer takes ownership of the data stored in vector.

Creating host accessor is a blocking call and will only return after all enqueued kernels that modify the same buffer in any queue completes execution and the data is available to the host via this host accessor.

Synchronization – Buffer Destruction

```
#include <CL/sycl.hpp>
using namespace sycl;
constexpr int N=16;
void dpcpp code(std::vector<double> &v, queue &q){
  buffer buf(v);
  q.submit([&](handler& h) {
    accessor a(buf, h);
    h.parallel_for(N, [=](auto i) {
      a[i] -= 2;
   });
int main() {
  std::vector<double> v(N, 10);
  queue q;
 dpcpp_code(v,q);
  for (int i = 0; i < N; i++)
      std::cout << v[i] << "\n";</pre>
  return 0;
```

Buffer creation happens within a separate function scope.

When execution advances beyond this function scope, buffer destructor is invoked which relinquishes the ownership of data and copies back the data to the host memory.

Custom Device Selector

The following code shows derived **device_selector** that employs a device selector heuristic. The selected device prioritizes a GPU device because the integer rating returned is higher than for CPU or other accelerator.

```
#include <CL/sycl.hpp>
using namespace cl::sycl;
class my device selector : public device selector {
public:
 int operator()(const device& dev) const override {
   int rating = 0;
   if (dev.is_gpu() & (dev.get_info<info::device::name>().find("Intel") != std::string::npos))
     rating = 3;
   else if (dev.is gpu()) rating = 2;
   else if (dev.is cpu()) rating = 1;
   return rating;
 };
int main() {
 my device selector selector;
 queue q(selector);
 std::cout << "Device: " << q.get device().get info<info::device::name>() << std::endl;</pre>
 return 0;
```

Execution Graph Scheduling

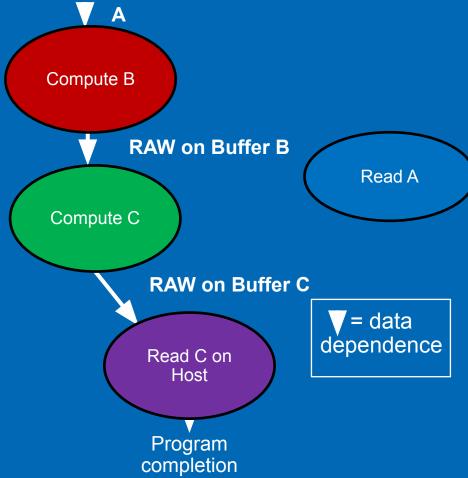
Mechanism to achieve proper sequencing of kernels, and data movement in a SYCL application.

- •Read-after-Write (RAW): Occurs when one task needs to read data produced by a different task.
- •Write-after-Read (WAR): Occurs when one task needs to update data after another task has read it.
- •Write-after-Write (WAW): Occurs when two tasks try to write the same data.

```
int main() {
  queue 0;
  //Create Buffers
  buffer A{a};
 buffer B{b};
  buffer C{c};
 Q.submit([&](handler &h) {
      accessor accA(A, h, read only);
      accessor accB(B, h, write_only);
      h.parallel for( // computeB
        N, [=](id<1>i) { accB[i] = accA[i] + 1; });
 Q.submit([&](handler &h) {
      accessor accA(A, h, read_only);
      h.parallel_for( // readA
        N, \lceil = \rceil (id < 1 > i) 
          // Useful only as an example
          int data = accA[i];
       });
 Q.submit([&](handler &h) {
     // RAW of buffer B
      accessor accB(B, h, read only);
                                              Kernel 3
      accessor accC(C, h, write_only);
      h.parallel for( // computeC
        N, [=](id<1>i) { accC[i] = accB[i] + 2; });
    });
 // read C on host
  host_accessor host_accC(C, read_only);
    std::cout << "\n";</pre>
  return 0;
```

Read after Write (RAW)

Automatic data and control dependence resolution!



Write After Read and Write after Write

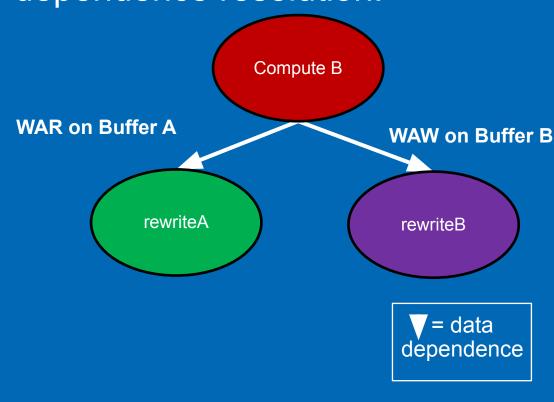
```
queue 0;
buffer A{a};
buffer B{b};
Q.submit([&](handler &h) {
    accessor accA(A, h, read_only);
    accessor accB(B, h, write_only);
    h.parallel for( // computeB
        N, [=](id<1>i) {
        accB[i] = accA[i] + 1;
        });
    }):
Q.submit([&](handler &h) {
    // WAR of buffer A
    accessor accA(A, h, write only);
    h.parallel_for( // rewriteA
        N, [=](id<1>i) {
        accA[i] = 21 + 21;
        });
    });
Q.submit([&](handler &h) {
    // WAW of buffer B
    accessor accB(B, h, write_only);
    h.parallel_for( // rewriteB
        N, [=](id<1>i) {
        accB[i] = 30 + 12;
        });
    });
host_accessor host_accA(A, read_only);
host accessor host accB(B, read only);
```

} Kernel 1

} Kernel 2

Kernel 3

Automatic data and control dependence resolution!



Linear dependency chain graphs and Y pattern Graphs Linear dependence chains where one task executes after another

- - First node represents the initialization of data.
 - Second node presents the reduction operation that will accumulate the data.
- "Y" pattern we independently initialize two different pieces of data.
 - An addition kernel will sum the two vectors together.
 - Finally, the last node in the graph accumulates the result into a single value.

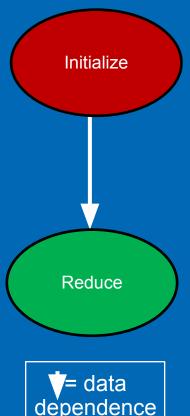
Linear Dependence Using In-order queue

Create In-order queue

Initialize the data in Kernel 1

Kernel 2 sums up the elements

```
constexpr int N = 42;
int main() {
  queue Q{property::queue::in_order()};
  int *data = malloc_shared<int>(N, Q);
 Q.parallel_for(N, [=](id<1> i) { data[i] = 1; });
 Q.single task([=]() {
      for (int i = 1; i < N; i++)
        data[0] += data[i];
    });
  Q.wait();
  assert(data[0] == N);
  return 0;
```





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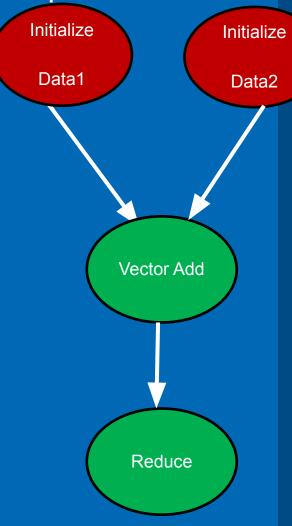
Y Pattern using in-order queues
We can see a "Y" pattern using in-order queues in the below example

In-Order Queue

Kernel 3 is dependent on Kernel1 and Kernel2

The final kernel sums up the elements of the first array

```
constexpr int N = 42;
int main() (
queue Q{property::queue::in order()};
 int *data1 = malloc shared<int>(N, Q);
 int *data2 = malloc shared<int>(N, 0);
 Q.parallel for(N, [=](id<1> i) { data1[i] = 1; });
 Q.parallel for(N, [=](id<1>i) { data2[i] = 2; });
 0.parallel for(N, [=](id<1> i) { data1[i] += data2[i]; });
 Q.single_task([=]() {
      for (int i = 1; i < N; i++)
        data1[0] += data1[i];
      data1[0] /= 3;
   });
 0.wait():
 assert(data1[0] == N);
 return 0;
```



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Recap

- oneAPI solves the challenges of programming in a heterogeneous world
- Take advantage of oneAPI solutions to enable your workflows
- Use the Intel® DevCloud to test-drive oneAPI tools and libraries
- Introduced to SYCL language and programming model
- Important Classes for SYCL application
- Device selection and offloading kernel workloads
- SYCL Buffers, Accessors, Command Group handler, lambda code as kernel
- Utilize different types of data dependences that are important for ensuring execution of graph scheduling

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