Kokkos Tutorial

H. Carter Edwards ¹, Christian R. Trott ¹, and Fernanda Foertter ²

¹Sandia National Laboratories

²Oak Ridge National Laboratory

Supercomputing, Nov 12-17, 2017

Sandia National Laboratories is a multi-mission laboratory managed and operated by National Technology and Engineering Solutions of Sandia, LLC., a wholly owned subsidiary of Honeywell International, Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

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SOFTWARE FOR LAB

Remote Desktop Software:

- Download NoMachine now for best performance from www.nomachine.com/download
- Alternatively you may use a VNC client or the provided browser-based VNC option

SSH Access Software (optional):

- PuTTy for Windows can be downloaded from www.putty.org
- Alternatively you may use a provided browser-based SSH option

CONNECTION INSTRUCTIONS

- Navigate to nvlabs.qwiklab.com
- Login or create a new account
- Select the Instructor-Led Hands-on Labs Class
- Find the lab called Kokkos, ..., select it, click Select, and finally click Start
- After a short wait, lab instance Connection information will be shown
- Please ask Lab Assistants for help!

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This research was supported by the Exascale Computing Project (17-SC-20-SC), a joint project of the U.S. Department of Energy's Office of Science and National Nuclear Security Administration, responsible for delivering a capable exascale ecosystem, including software, applications, and hardware technology, to support the nation's exascale computing imperative.

Prerequisites for Tutorial Exercises

Knowledge of C++: class constructors, member variables, member functions, member operators, template arguments

Using NVIDIA's NVLABS

- Kokkos pre installed in \${HOME}/kokkos
- Exercises pre installed in \${HOME}/SC2017

Using your own \${HOME}

- Git
- ► GCC 4.8.4 (or newer) *OR* Intel 15 (or newer) *OR* Clang 3.5.2 (or newer)
- ► CUDA nvcc 7.5 (or newer) AND NVIDIA compute capability 3.0 (or newer)
- clone github.com/kokkos/kokkos into \${HOME}/kokkos
- clone github.com/kokkos/kokkos-tutorials into \${HOME}/kokkos-tutorials Exercises are in \${HOME}/kokkos-tutorials/Intro-Short/SC2017

Exercises' makefiles look for \${HOME}/kokkos

Understand Kokkos Programming Model Abstractions

- What, how and why of performance portability
- Productivity and hope for future-proofing

Kokkos' basic capabilities covered today:

- Simple data parallel computational patterns
- Deciding where code is run and where data is placed
- Managing data access pattens for performance portability

Kokkos' advanced capabilities not covered today:

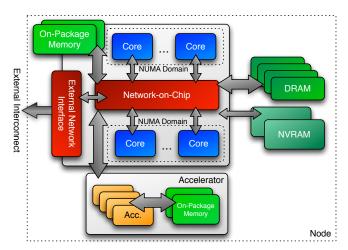
- Thread safety, thread scalability, and atomic operations
- Hierarchical patterns for maximizing parallelism
- Dynamic directed acyclic graph of tasks pattern
- Numerous pluggin points for extensibility

- ► For **portability**: OpenMP, OpenACC, ... or Kokkos.
- Only Kokkos obtains performant memory access patterns via architecture-aware arrays and work mapping. i.e., not just portable, performance portable.
- With Kokkos, simple things stay simple (parallel-for, etc.). i.e., it's no more difficult than OpenMP.
- ► Advanced performance-optimizing patterns are simpler with Kokkos than with native versions.
 - i.e., you're not missing out on advanced features.
 - full day tutorial only

Assume you are here because:

- ▶ Want to use **all** HPC node architectures; including GPUs
- ► Are familiar with C++
- Are familiar with data parallelism
- A little familiar with OpenMP
- A little familiar with NVIDIA GPU architecture Spoiler alert: memory access patterns are important
- Want GPU programming to be easier
- ▶ Would like **portability**, as long as it doesn't hurt performance

Target machine:



Important Point: Performance Portability

Important Point

There's a difference between *portability* and *performance portability*.

Example: implementations may target particular architectures and may not be *thread scalable*.

(e.g., locks on CPU won't scale to 100,000 threads on GPU)

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Goal: write one implementation which:

- compiles and runs on multiple architectures,
- obtains performant memory access patterns across architectures,
- can leverage architecture-specific features where possible.

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(e.g., locks on CPU won't scale to 100,000 threads on GPU)

Goal: write one implementation which:

- compiles and runs on multiple architectures,
- obtains performant memory access patterns across architectures,
- can leverage architecture-specific features where possible.

Kokkos: performance portability across manycore architectures.

Concepts for threaded data parallelism

Learning objectives:

- Terminology of pattern, policy, and body.
- ► The data layout problem.

Concepts: Patterns, Policies, and Bodies

```
for (element = 0; element < numElements; ++element) {
  total = 0;
  for (qp = 0; qp < numQPs; ++qp) {
    total += dot(left[element][qp], right[element][qp]);
  }
  elementValues[element] = total;
}</pre>
```

Terminology:

- ▶ **Pattern**: structure of the computations for, reduction, scan, task-graph, ...
- ► Execution Policy: how computations are executed static scheduling, dynamic scheduling, thread teams, ...
- Computational Body: code which performs each unit of work; e.g., the loop body
- ⇒ The **pattern** and **policy** drive the computational **body**.

What if we want to thread the loop?

```
for (element = 0; element < numElements; ++element) {
  total = 0;
  for (qp = 0; qp < numQPs; ++qp) {
    total += dot(left[element][qp], right[element][qp]);
  }
  elementValues[element] = total;
}</pre>
```

What if we want to **thread** the loop?

```
#pragma omp parallel for
for (element = 0; element < numElements; ++element) {
  total = 0;
  for (qp = 0; qp < numQPs; ++qp) {
    total += dot(left[element][qp], right[element][qp]);
  }
  elementValues[element] = total;
}</pre>
```

(Change the execution policy from "serial" to "parallel.")

What if we want to **thread** the loop?

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#pragma omp parallel for
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    total += dot(left[element][qp], right[element][qp]);
  }
  elementValues[element] = total;
}</pre>
```

(Change the execution policy from "serial" to "parallel.")

OpenMP is simple for parallelizing loops on multi-core CPUs, but what if we then want to do this on **other architectures**?

Intel MIC and NVIDIA GPU and AMD Fusion and ...

Option 1: OpenMP 4.0

```
#pragma omp target data map(...)
#pragma omp teams num_teams(...) num_threads(...) private(...)
#pragma omp distribute
for (element = 0; element < numElements; ++element) {
   total = 0

#pragma omp parallel for
   for (qp = 0; qp < numQPs; ++qp)
       total += dot(left[element][qp], right[element][qp]);
   elementValues[element] = total;
}</pre>
```

Option 1: OpenMP 4.0

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#pragma omp target data map(...)
#pragma omp teams num_teams(...) num_threads(...)
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for (element = 0; element < numElements; ++element) {
   total = 0

#pragma omp parallel for
   for (qp = 0; qp < numQPs; ++qp)
        total += dot(left[element][qp], right[element][qp]);
   elementValues[element] = total;
}</pre>
```

Option 2: OpenACC

```
#pragma acc parallel copy(...) num_gangs(...) vector_length(...)
#pragma acc loop gang vector

for (element = 0; element < numElements; ++element) {
   total = 0;
   for (qp = 0; qp < numQPs; ++qp)
      total += dot(left[element][qp], right[element][qp]);
   elementValues[element] = total;
}</pre>
```

A standard thread parallel programming model may give you portable parallel execution if it is supported on the target architecture.

But what about performance?

A standard thread parallel programming model may give you portable parallel execution if it is supported on the target architecture.

But what about performance?

Performance depends upon the computation's **memory access pattern**.

Problem: memory access pattern

Memory access pattern problem: CPU data layout reduces GPU performance by more than 10X.

Memory access pattern problem: CPU data layout reduces GPU performance by more than 10X.

Important Point

For performance the memory access pattern *must* depend on the architecture.

How does Kokkos address performance portability?

Kokkos is a *productive*, *portable*, *performant*, shared-memory programming model.

- ▶ is a C++ **library**, not a new language or language extension.
- supports clear, concise, thread-scalable parallel patterns.
- ▶ lets you write algorithms once and run on **many architectures** e.g. multi-core CPU, NVidia GPU, Xeon Phi, ...
- minimizes the amount of architecture-specific implementation details users must know.
- solves the data layout problem by using multi-dimensional arrays with architecture-dependent layouts

Data parallel patterns

Learning objectives:

- How computational bodies are passed to the Kokkos runtime.
- How work is mapped to cores.
- The difference between parallel_for and parallel_reduce.
- Start parallelizing a simple example.

Using Kokkos for data parallel patterns (0)

Data parallel patterns and work

```
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex) {
  atomForces[atomIndex] = calculateForce(...data...);
}</pre>
```

Kokkos maps work to cores

Using Kokkos for data parallel patterns (0)

Data parallel patterns and work

```
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex) {
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Kokkos maps work to cores

- each iteration of a computational body is a unit of work.
- an iteration index identifies a particular unit of work.
- an iteration range identifies a total amount of work.

Using Kokkos for data parallel patterns (0)

Data parallel patterns and work

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for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex) {
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Kokkos maps work to cores

- each iteration of a computational body is a unit of work.
- an iteration index identifies a particular unit of work.
- an iteration range identifies a total amount of work.

Important concept: Work mapping

You give an **iteration range** and **computational body** (kernel) to Kokkos, Kokkos maps iteration indices to cores and then runs the computational body on those cores.

Using Kokkos for data parallel patterns (2)

How are computational bodies given to Kokkos?

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As **functors** or *function objects*, a common pattern in C++.

Using Kokkos for data parallel patterns (2)

How are computational bodies given to Kokkos?

As **functors** or *function objects*, a common pattern in C++.

Quick review, a functor is a function with data. Example:

```
struct ParallelFunctor {
    ...
    void operator()( a work assignment ) const {
        /* ... computational body ... */
    ...
};
```

Using Kokkos for data parallel patterns (3)

How is work assigned to functor operators?

Using Kokkos for data parallel patterns (3)

How is work assigned to functor operators?

A total amount of work items is given to a Kokkos pattern,

```
ParallelFunctor functor;
Kokkos::parallel_for(numberOfIterations, functor);
```

Using Kokkos for data parallel patterns (3)

How is work assigned to functor operators?

A total amount of work items is given to a Kokkos pattern,

```
ParallelFunctor functor;
Kokkos::parallel_for(numberOfIterations, functor);
```

and work items are assigned to functors one-by-one:

```
struct Functor {
  void operator()(const size_t index) const {...}
}
```

Using Kokkos for data parallel patterns (3)

How is work assigned to functor operators?

A total amount of work items is given to a Kokkos pattern,

```
ParallelFunctor functor;
Kokkos::parallel_for(numberOfIterations, functor);
```

and work items are assigned to functors one-by-one:

```
struct Functor {
  void operator()(const size_t index) const {...}
}
```

Warning: concurrency and order

Concurrency and ordering of parallel iterations is *not* guaranteed by the Kokkos runtime.

Using Kokkos for data parallel patterns (4)

How is data passed to computational bodies?

```
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex) {
   atomForces[atomIndex] = calculateForce(...data...);
}

struct AtomForceFunctor {
   ...
   void operator()(const size_t atomIndex) const {
      atomForces[atomIndex] = calculateForce(...data...);
   }
   ...
}</pre>
```

How is data passed to computational bodies?

```
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex) {
   atomForces[atomIndex] = calculateForce(...data...);
}

struct AtomForceFunctor {
   ...
   void operator()(const size_t atomIndex) const {
      atomForces[atomIndex] = calculateForce(...data...);
   }
   ...
}</pre>
```

How does the body access the data?

Important concept

A parallel functor body must have access to all the data it needs through the functor's **data members**.

Using Kokkos for data parallel patterns (5)

Putting it all together: the complete functor:

```
struct AtomForceFunctor {
   ForceType _atomForces;
   AtomDataType _atomData;
   void operator()(const size_t atomIndex) const {
    _atomForces[atomIndex] = calculateForce(_atomData);
   }
}
```

Putting it all together: the complete functor:

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struct AtomForceFunctor {
  ForceType _atomForces;
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  void operator()(const size_t atomIndex) const {
    _atomForces[atomIndex] = calculateForce(_atomData);
  }
}
```

Q/ How would we reproduce serial execution with this functor?

```
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex){
   atomForces[atomIndex] = calculateForce(data);
}</pre>
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Putting it all together: the complete functor:

```
struct AtomForceFunctor {
   ForceType _atomForces;
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```

Q/ How would we reproduce serial execution with this functor?

```
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex){
   atomForces[atomIndex] = calculateForce(data);
}</pre>
```

```
AtomForceFunctor functor(atomForces, data);
for (atomIndex = 0; atomIndex < numberOfAtoms; ++atomIndex){
  functor(atomIndex);
}</pre>
```

The complete picture (using functors):

1. Defining the functor (operator+data):

```
struct AtomForceFunctor {
   ForceType _atomForces;
   AtomDataType _atomData;

AtomForceFunctor(atomForces, data) :
   _atomForces(atomForces) _atomData(data) {}

   void operator()(const size_t atomIndex) const {
    _atomForces[atomIndex] = calculateForce(_atomData);
   }
}
```

2. Executing in parallel with Kokkos pattern:

```
AtomForceFunctor functor(atomForces, data);
Kokkos::parallel_for(numberOfAtoms, functor);
```

Using Kokkos for data parallel patterns (7)

Functors are tedious \Rightarrow C++11 Lambdas are concise

```
atomForces already exists
data already exists
Kokkos::parallel_for(numberOfAtoms,
    [=] (const size_t atomIndex) {
    atomForces[atomIndex] = calculateForce(data);
}
);
```

Using Kokkos for data parallel patterns (7)

Functors are tedious \Rightarrow C++11 Lambdas are concise

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atomForces already exists
data already exists
Kokkos::parallel_for(numberOfAtoms,
    [=] (const size_t atomIndex) {
    atomForces[atomIndex] = calculateForce(data);
}
);
```

A lambda is not *magic*, it is the compiler **auto-generating** a **functor** for you.

Using Kokkos for data parallel patterns (7)

Functors are tedious \Rightarrow C++11 Lambdas are concise

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    atomForces[atomIndex] = calculateForce(data);
}
);
```

A lambda is not *magic*, it is the compiler **auto-generating** a **functor** for you.

Warning: Lambda capture and C++ containers

For portability to GPU a lambda must capture by value [=]. Don't capture containers (e.g., std::vector) by value because it will copy the container's entire contents.

How does this compare to OpenMP?

```
for (size_t i = 0; i < N; ++i) {
    /* loop body */
}
```

```
#pragma omp parallel for
for (size_t i = 0; i < N; ++i) {
    /* loop body */
}</pre>
```

```
parallel_for(N, [=] (const size_t i) {
   /* loop body */
});
```

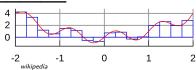
Important concept

Simple Kokkos usage is **no more conceptually difficult** than OpenMP, the annotations just go in different places.

Scalar integration (0)

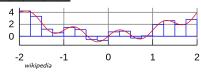
Riemann-sum-style numerical integration:

$$y = \int_{lower}^{upper} function(x) dx$$



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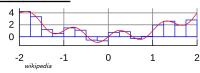
$$y = \int_{lower}^{upper} function(x) dx$$



```
double totalIntegral = 0;
for (size_t i = 0; i < numberOfIntervals; ++i) {
  const double x =
    lower + (i/numberOfIntervals) * (upper - lower);
  const double thisIntervalsContribution = function(x);
  totalIntegral += thisIntervalsContribution;
}
totalIntegral *= dx;</pre>
```

Riemann-sum-style numerical integration:

$$y = \int_{lower}^{upper} function(x) dx$$



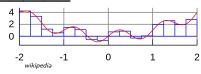
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}
totalIntegral *= dx;</pre>
```

How would we parallelize it?

Riemann-sum-style numerical integration:

$$y = \int_{lower}^{upper} function(x) dx$$

$$\begin{cases} 4 \\ 2 \\ 0 \end{cases}$$



How would we parallelize it?

An (incorrect) attempt:

```
double totalIntegral = 0;
Kokkos::parallel_for(numberOfIntervals,
   [=] (const size_t index) {
   const double x =
     lower + (index/numberOfIntervals) * (upper - lower);
   totalIntegral += function(x);},
   );
totalIntegral *= dx;
```

First problem: compiler error; cannot increment totalIntegral (lambdas capture by value and are treated as const!)

An (incorrect) solution to the (incorrect) attempt:

```
double totalIntegral = 0;
double * totalIntegralPointer = &totalIntegral;
Kokkos::parallel_for(numberOfIntervals,
   [=] (const size_t index) {
    const double x =
       lower + (index/numberOfIntervals) * (upper - lower);
   *totalIntegralPointer += function(x);},
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    const double x =
       lower + (index/numberOfIntervals) * (upper - lower);
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   );
totalIntegral *= dx;
```

Second problem: race condition

step	thread 0	thread 1
0	load	
1	increment	load
2	write	increment
3		write

Scalar integration (3)

Root problem: we're using the **wrong pattern**, *for* instead of *reduction*

Scalar integration (3)

Root problem: we're using the **wrong pattern**, for instead of reduction

Important concept: Reduction

Reductions combine the results contributed by parallel work.

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Important concept: Reduction

Reductions combine the results contributed by parallel work.

How would we do this with **OpenMP**?

```
double finalReducedValue = 0;
#pragma omp parallel for reduction(+:finalReducedValue)
for (size_t i = 0; i < N; ++i) {
  finalReducedValue += ...
}</pre>
```

Root problem: we're using the **wrong pattern**, for instead of reduction

Important concept: Reduction

Reductions combine the results contributed by parallel work.

```
How would we do this with OpenMP?
double finalReducedValue = 0;
#pragma omp parallel for reduction(+:finalReducedValue)
for (size_t i = 0; i < N; ++i) {
   finalReducedValue += ...
}</pre>
```

How will we do this with Kokkos?

```
double finalReducedValue = 0;
parallel_reduce(N, functor, finalReducedValue);
```

Example: Scalar integration

```
double totalIntegral = 0;
#pragma omp parallel for reduction(+:totalIntegral)
for (size_t i = 0; i < numberOfIntervals; ++i) {
   totalIntegral += function(...);
}</pre>
```

```
double totalIntegral = 0;
parallel_reduce(numberOfIntervals,
  [=] (const size_t i, double & valueToUpdate) {
   valueToUpdate += function(...);
},
totalIntegral);
```

- ► The operator takes **two arguments**: a work index and a value to update.
- ► The second argument is a **thread-private value** that is managed by Kokkos; it is not the final reduced value.

Scalar integration (5)

Warning: Parallelism is NOT free

Dispatching (launching) parallel work has non-negligible cost.

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Dispatching (launching) parallel work has non-negligible cost.

Simplistic data-parallel performance model: Time = $\alpha + \frac{\beta * N}{P}$

- $ightharpoonup \alpha = dispatch overhead$
- $\triangleright \beta = time for a unit of work$
- N = number of units of work
- ightharpoonup P = available concurrency

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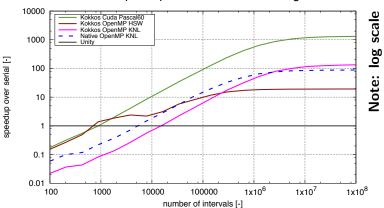
Speedup =
$$P \div \left(1 + \frac{\alpha * P}{\beta * N}\right)$$

- ▶ Should have $\alpha * P \ll \beta * N$
- ightharpoonup All runtimes strive to minimize launch overhead lpha
- Find more parallelism to increase N
- ▶ Merge (fuse) parallel operations to increase β

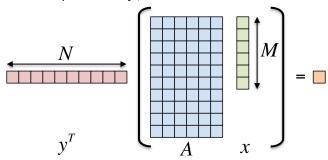
Scalar integration (6)

Results: illustrates simple speedup model = $P \div \left(1 + \frac{\alpha * P}{\beta * N}\right)$

Kokkos speedup over serial: Scalar Integration



Exercise: Inner product $\langle y, A * x \rangle$



Details:

- \triangleright y is Nx1, A is NxM, x is Mx1
- ▶ We'll use this exercise throughout the tutorial

The **first step** in using Kokkos is to include, initialize, and finalize:

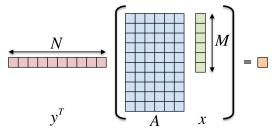
```
#include <Kokkos_Core.hpp>
int main(int argc, char** argv) {
   /* ... do any necessary setup (e.g., initialize MPI) ... */
   Kokkos::initialize(argc, argv);
   /* ... do computations ... */
   Kokkos::finalize();
   return 0;
}
```

(Optional) Command-line arguments:

kokkos-threads=INT	total number of threads
kokkos-threads=INI	(or threads within NUMA region)
kokkos-numa=INT	number of NUMA regions
kokkos-device=INT	device (GPU) ID to use

Exercise #1: Inner Product, Flat Parallelism on the CPU

Exercise: Inner product $\langle y, A * x \rangle$



- Location: SC2017/Exercises/01/Begin/
- Look for comments labeled with "EXERCISE"
- ▶ Need to include, initialize, and finalize Kokkos library
- Parallelize loops with parallel_for or parallel_reduce
- Use lambdas instead of functors for computational bodies.
- For now, this will only use the CPU.

Details:

Compiling for CPU

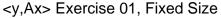
gcc using OpenMP (default) and Serial back-ends
make -j [KOKKOS_DEVICES=OpenMP, Serial]

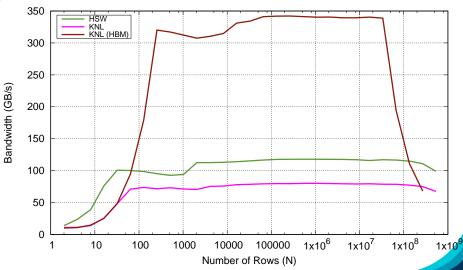
Running on CPU with OpenMP back-end

```
# Set OpenMP affinity
export OMP_NUM_THREADS=8
export GOMP_CPU_AFFINITY=0-8
# Print example command line options:
./01_Exercise.host -h
# Run with defaults on CPU
./01_Exercise.host
# Run larger problem
./01_Exercise.host -S 26
```

Things to try:

- Vary number of threads
- Vary problem size
- Vary number of rows (-N ...)





Basic capabilities we haven't covered

- Customizing parallel_reduce data type and reduction operator
 - e.g., minimum, maximum, ...
- parallel_scan pattern for exclusive and inclusive prefix sum
- Using tag dispatch interface to allow non-trivial functors to have multiple "operator()" functions.
 - very useful in large, complex applications

- ► **Simple** usage is similar to OpenMP, advanced features are also straightforward
- Three common data-parallel patterns are parallel_for, parallel_reduce, and parallel_scan.
- A parallel computation is characterized by its pattern, policy, and body.
- User provides computational bodies as functors or lambdas which handle a single work item.

Views

Learning objectives:

- Motivation behind the View abstraction.
- Key View concepts and template parameters.
- ► The View life cycle.

Example: running daxpy on the GPU:

```
Lambda
```

```
double * x = new double[N]; // also y
parallel_for(N, [=] (const size_t i) {
   y[i] = a * x[i] + y[i];
});
```

```
Functor
```

```
struct Functor {
  double *_x, *_y, a;
  void operator()(const size_t i) {
    _y[i] = _a * _x[i] + _y[i];
  }
};
```

Example: running daxpy on the GPU:

```
double * x = new double[N]; // also y
parallel_for(N, [=] (const size_t i) {
   y[i] = a * x[i] + y[i];
 });
```

```
struct Functor {
  double *_x, *_y, a;
  void operator()(const size_t i) {
    _{y}[i] = _{a} * _{x}[i] + _{y}[i];
```

Problem: x and y reside in CPU memory.

Example: running daxpy on the GPU:

```
ambda-
```

```
double * x = new double[N]; // also y
parallel_for(N, [=] (const size_t i) {
    y[i] = a * x[i] + y[i];
});
```

```
struct Functor {
  double *_x, *_y, a;
  void operator()(const size_t i) {
    _y[i] = _a * _x[i] + _y[i];
  }
};
```

Problem: x and y reside in CPU memory.

Solution: We need a way of storing data (multidimensional arrays) which can be communicated to an accelerator (GPU).

⇒ Views

View abstraction

- ► A *lightweight* C++ class with a pointer to array data and a little meta-data,
- ▶ that is *templated* on the data type (and other things).

High-level example of Views for daxpy using lambda:

```
View < double *, ... > x(...), y(...);
...populate x, y...

parallel_for(N, [=] (const size_t i) {
    // Views x and y are captured by value (copy)
    y(i) = a * x(i) + y(i);
});
```

View abstraction

- ► A *lightweight* C++ class with a pointer to array data and a little meta-data,
- ▶ that is *templated* on the data type (and other things).

High-level example of Views for daxpy using lambda:

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parallel_for(N, [=] (const size_t i) {
    // Views x and y are captured by value (copy)
    y(i) = a * x(i) + y(i);
});
```

Important point

Views are like pointers, so copy them in your functors.

View overview:

- ► **Multi-dimensional array** of 0 or more dimensions scalar (0), vector (1), matrix (2), etc.
- ▶ Number of dimensions (rank) is fixed at compile-time.
- Arrays are rectangular, not ragged.
- ➤ **Sizes of dimensions** set at compile-time or runtime. e.g., 2x20, 50x50, etc.

View overview:

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- ▶ Number of dimensions (rank) is fixed at compile-time.
- Arrays are rectangular, not ragged.
- ➤ **Sizes of dimensions** set at compile-time or runtime. e.g., 2x20, 50x50, etc.

Example:

```
View < double *** > data("label", NO, N1, N2); 3 run, 0 compile
View < double ** [N2] > data("label", NO, N1); 2 run, 1 compile
View < double * [N1] [N2] > data("label", NO); 1 run, 2 compile
View < double [NO] [N1] [N2] > data("label"); 0 run, 3 compile
```

Note: runtime-sized dimensions must come first.

View life cycle:

- ► Allocations only happen when *explicitly* specified. i.e., there are **no hidden allocations**.
- Copy construction and assignment are shallow (like pointers). so, you pass Views by value, not by reference
- ▶ Reference counting is used for **automatic deallocation**.
- They behave like shared_ptr

View life cycle:

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- ▶ Reference counting is used for **automatic deallocation**.
- ► They behave like shared_ptr

Example:

```
View < double *> a("a", N0), b("b", N0);
a = b;
View < double *> c(b);
a(0) = 1;
b(0) = 2;
c(0) = 3;
print a(0)
What gets printed?
```

View life cycle:

- Allocations only happen when explicitly specified. i.e., there are no hidden allocations.
- Copy construction and assignment are shallow (like pointers). so, you pass Views by value, not by reference
- ▶ Reference counting is used for **automatic deallocation**.
- ▶ They behave like shared_ptr

Example:

```
View < double *> a("a", N0), b("b", N0);
a = b;
View < double *> c(b);
a(0) = 1;
b(0) = 2;
c(0) = 3;
print a(0)
What gets printed?
3.0
```

Exercise #2: Inner Product, Flat Parallelism on the CPU, with Views

- Location: SC2017/Exercises/03/Begin/
- Assignment: Change data storage from arrays to Views.
- Compile and run on CPU, and then on GPU with UVM

```
make -j KOKKOS_DEVICES=OpenMP # CPU-only using OpenMP
make -j KOKKOS_DEVICES=Cuda \
   KOKKOS_CUDA_OPTIONS=force_uvm,enable_lambda
# Run exercise
./02_Exercise.host -S 26
./02_Exercise.cuda -S 26
# Note the warnings, set appropriate environment variables
```

- Vary problem size: -S #
- Vary number of rows: -N #
- Vary repeats: -nrepeat #
- Compare performance of CPU vs GPU

Advanced features we haven't covered

- ▶ Memory space in which view's data resides; covered next.
- deep_copy view's data; covered later.
 Note: Kokkos never hides a deep_copy of data.
- Layout of multidimensional array; covered later.
- Memory traits; covered later.
- Subview: Generating a view that is a "slice" of other multidimensional array view; will not be covered today.

Execution and Memory Spaces

Learning objectives:

- Heterogeneous nodes and the space abstractions.
- How to control where parallel bodies are run, execution space.
- ▶ How to control where view data resides, **memory space**.
- How to avoid illegal memory accesses and manage data movement.
- ▶ The need for Kokkos::initialize and finalize.
- Where to use Kokkos annotation macros for portability.

Thought experiment: Consider this code:

Thought experiment: Consider this code:

- ▶ Where will section 1 be run? CPU? GPU?
- Where will section 2 be run? CPU? GPU?
- How do I control where code is executed?

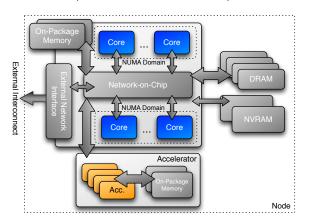
Thought experiment: Consider this code:

- ▶ Where will section 1 be run? CPU? GPU?
- Where will section 2 be run? CPU? GPU?
- How do I control where code is executed?

⇒ Execution spaces

Execution Space

a homogeneous set of cores and an execution mechanism (i.e., "place to run code")



Execution spaces: Serial, Threads, OpenMP, Cuda, ...

```
MPI_Reduce(...);
FILE * file = fopen(...);
runANormalFunction(...data...);
Kokkos::parallel_for(numberOfSomethings,
                      [=] (const size_t somethingIndex) {
                        const double y = ...;
                       // do something interesting
```

```
Parallel
```

```
MPI_Reduce(...);
FILE * file = fopen(...);
runANormalFunction(...data...);
Kokkos::parallel_for(numberOfSomethings,
                      [=] (const size_t somethingIndex) {
                        const double y = ...;
                       // do something interesting
```

- Where will Host code be run? CPU? GPU?
 - ⇒ Always in the **host process**

```
MPI_Reduce(...);
FILE * file = fopen(...);
runANormalFunction(...data...);
Kokkos::parallel_for(numberOfSomethings,
                     [=] (const size_t somethingIndex) {
                       const double y = ...;
                       // do something interesting
```

- Where will Host code be run? CPU? GPU?
 - ⇒ Always in the **host process**
- ▶ Where will Parallel code be run? CPU? GPU?
 - ⇒ The default execution space

```
MPI_Reduce(...);
FILE * file = fopen(...);
runANormalFunction(...data...);
Kokkos::parallel_for(numberOfSomethings,
                      [=] (const size_t somethingIndex) {
                        const double y = ...;
                       // do something interesting
```

- Where will Host code be run? CPU? GPU?
 - ⇒ Always in the **host process**
- ▶ Where will Parallel code be run? CPU? GPU?
 - ⇒ The default execution space
- ▶ How do I **control** where the Parallel body is executed? Changing the default execution space (at compilation), or specifying an execution space in the **policy**.

Changing the parallel execution space:

```
parallel_for(
   RangePolicy < ExecutionSpace > (0, numberOfIntervals),
   [=] (const size_t i) {
        /* ... body ... */
   });
```

```
parallel_for(
  numberOfIntervals, // == RangePolicy <> (0, numberOfIntervals)
[=] (const size_t i) {
    /* ... body ... */
});
```

Changing the parallel execution space:

```
parallel_for(
  RangePolicy < ExecutionSpace > (0, numberOfIntervals),
  [=] (const size_t i) {
    /* ... body ... */
});
```

```
parallel_for(
  numberOfIntervals, // == RangePolicy <> (0, numberOfIntervals)
  [=] (const size_t i) {
    /* ... body ... */
  });
```

Requirements for enabling execution spaces:

- ► Kokkos must be **compiled** with the execution spaces enabled.
- Execution spaces must be initialized (and finalized).
- ► **Functions** must be marked with a **macro** for non-CPU spaces.
- Lambdas must be marked with a macro for non-CPU spaces.

Kokkos function and lambda portability annotation macros:

Function annotation with KOKKOS_INLINE_FUNCTION macro

```
struct ParallelFunctor {
   KOKKOS_INLINE_FUNCTION
   double helperFunction(const size_t s) const {...}
   KOKKOS_INLINE_FUNCTION
   void operator()(const size_t index) const {
      helperFunction(index);
   }
}
// Where kokkos defines:
#define KOKKOS_INLINE_FUNCTION inline
#define KOKKOS_INLINE_FUNCTION inline __device__ __host__ /* #if CPU+Cuda */
```

Kokkos function and lambda portability annotation macros:

Function annotation with KOKKOS_INLINE_FUNCTION macro

```
struct ParallelFunctor {
  KOKKOS_INLINE_FUNCTION
  double helperFunction(const size_t s) const {...}
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    helperFunction(index);
  }
}
// Where kokkos defines:
#define KOKKOS_INLINE_FUNCTION inline
#define KOKKOS_INLINE_FUNCTION inline -_device_- __host_- /* #if CPU+Cuda */
```

Lambda annotation with KOKKOS_LAMBDA macro (requires CUDA 8.0)

```
View < double *> data("data", size);
for (size_t i = 0; i < size; ++i) {
   data(i) = ...read from file...
}

double sum = 0;
Kokkos::parallel_reduce(
   RangePolicy < SomeExampleExecutionSpace > (0, size),
   KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += data(index);
   },
   sum);
```

```
View < double *> data("data", size);
for (size_t i = 0; i < size; ++i) {
   data(i) = ...read from file...
}

double sum = 0;
Kokkos::parallel_reduce(
   RangePolicy < SomeExampleExecutionSpace > (0, size),
   KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += data(index);
},
sum);
```

Question: Where is the data stored? GPU memory? CPU memory? Both?

```
View < double *> data("data", size);
for (size_t i = 0; i < size; ++i) {
   data(i) = ...read from file...
}

double sum = 0;
Kokkos::parallel_reduce(
   RangePolicy < SomeExampleExecutionSpace > (0, size),
   KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += data(index);
   },
   sum);
```

Question: Where is the data stored? GPU memory? CPU memory? Both?

```
View < double *> data("data", size);
for (size_t i = 0; i < size; ++i) {
   data(i) = ...read from file...
}

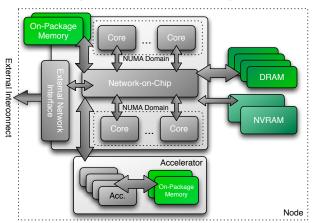
double sum = 0;
Kokkos::parallel_reduce(
   RangePolicy < SomeExampleExecutionSpace > (0, size),
   KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
   valueToUpdate += data(index);
   },
   sum);
```

Question: Where is the data stored? GPU memory? CPU memory? Both?

⇒ Memory Spaces

Memory space:

explicitly-manageable memory resource (i.e., "place to put data")



Every view stores its data in a **memory space** set at compile time.

Every view stores its data in a memory space set at compile time.

View<double***, Memory Space> data(...);

Every view stores its data in a memory space set at compile time.

- View<double***, Memory Space> data(...);
- Available memory spaces:

HostSpace, CudaSpace, CudaUVMSpace, ... more

Every view stores its data in a memory space set at compile time.

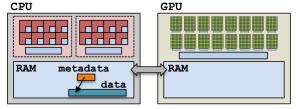
- View<double***, Memory Space> data(...);
- Available memory spaces: HostSpace, CudaSpace, CudaUVMSpace, ... more
- ► Each **execution space** has a default memory space, which is used if **Space** provided is actually an execution space

Every view stores its data in a memory space set at compile time.

- View<double***, Memory Space> data(...);
- Available memory spaces: HostSpace, CudaSpace, CudaUVMSpace, ... more
- ► Each **execution space** has a default memory space, which is used if **Space** provided is actually an execution space
- ▶ If no Space is provided, the view's data resides in the **default** memory space of the **default execution space**.

Example: HostSpace

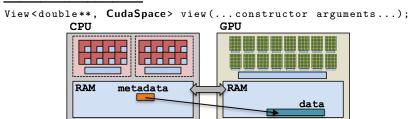
View < double ***, HostSpace > hostView (...constructor arguments...);



Example: HostSpace

View<double**, HostSpace> hostView(...constructor arguments...);
CPU
GPU
RAM metadata
RAM

Example: CudaSpace



data

View < int *, Cuda > dev (...

parallel_for(N,

[=] (int i) {

dev(i) = ...;

Anatomy of a kernel launch:

- 1. User declares views, allocating.
- User instantiates a functor with views.
- 3. User launches parallel_something:
 - Functor is copied to the device.

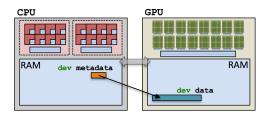
 - Copy of functor on the device is released.

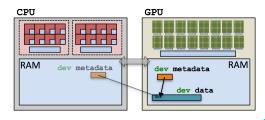
```
}):
Kernel is run.
```

Note: **no deep copies** of array data are performed; views are like pointers.

Example: one view

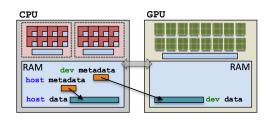
```
View < int*, Cuda > dev;
parallel_for(N,
    [=] (int i) {
      dev(i) = ...;
});
```

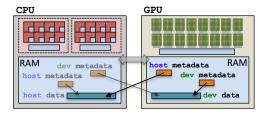




Example: two views

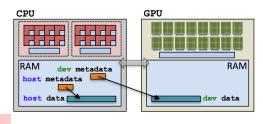
```
View < int*, Cuda > dev;
View < int*, Host > host;
parallel_for(N,
    [=] (int i) {
    dev(i) = ...;
    host(i) = ...;
});
```

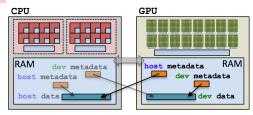




Example: two views

```
View < int *, Cuda > dev;
View < int *, Host > host;
parallel_for(N,
    [=] (int i) {
    dev(i) = ...;
    host(i) = ...;
});
```





(failed) Attempt 1: View lives in CudaSpace

```
View < double *, CudaSpace > array("array", size);
for (size_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}

double sum = 0;
Kokkos::parallel_reduce(
    RangePolicy < Cuda > (0, size),
    KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += array(index);
},
    sum);
```

(failed) Attempt 1: View lives in CudaSpace

```
View < double *, Cuda Space > array("array", size);
for (size_t i = 0; i < size; ++i) {
    array(i) = ...read from file... fault
}

double sum = 0;
Kokkos::parallel_reduce(
    Range Policy < Cuda > (0, size),
    KOKKOS_LAMBDA (const size_t index, double & value To Update) {
    value To Update += array(index);
},
    sum);
```

(failed) Attempt 2: View lives in HostSpace

```
View < double *, HostSpace > array("array", size);
for (size_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}

double sum = 0;
Kokkos::parallel_reduce(
    RangePolicy < Cuda > (0, size),
    KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += array(index);
    },
    sum);
```

(failed) Attempt 2: View lives in HostSpace

```
View < double *, HostSpace > array("array", size);
for (size_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}

double sum = 0;
Kokkos::parallel_reduce(
    RangePolicy < Cuda > (0, size),
    KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += array(index); illegal access
    },
    sum);
```

(failed) Attempt 2: View lives in HostSpace

```
View < double *, HostSpace > array("array", size);
for (size_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}

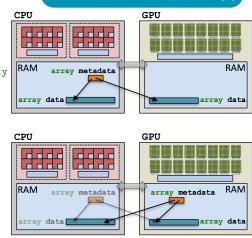
double sum = 0;
Kokkos::parallel_reduce(
    RangePolicy < Cuda > (0, size),
    KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += array(index); illegal access
    },
    sum);
```

What's the solution?

- CudaUVMSpace
- CudaHostPinnedSpace (skipping)
- Mirroring

Execution and Memory spaces (5)

CudaUVMSpace



Cuda runtime automatically handles data movement, at a **performance hit**.

Important concept: Mirrors

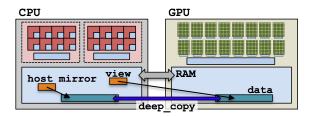
Mirrors are views of equivalent arrays residing in possibly different memory spaces.

Important concept: Mirrors

Mirrors are views of equivalent arrays residing in possibly different memory spaces.

Mirroring schematic

```
typedef Kokkos::View<double**, Space> ViewType;
ViewType view(...);
ViewType::HostMirror hostView =
   Kokkos::create_mirror_view(view);
```



```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view(...);
```

```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view(...);
```

2. **Create** hostView, a *mirror* of the view's array residing in the host memory space.

```
ViewType::HostMirror hostView =
   Kokkos::create_mirror_view(view);
```

```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view(...);
```

2. **Create** hostView, a *mirror* of the view's array residing in the host memory space.

```
ViewType::HostMirror hostView =
  Kokkos::create_mirror_view(view);
```

3. Populate hostView on the host (from file, etc.).

```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view(...);
```

2. **Create** hostView, a mirror of the view's array residing in the host memory space.

```
ViewType::HostMirror hostView =
  Kokkos::create_mirror_view(view);
```

- 3. **Populate hostView** on the host (from file, etc.).
- 4. **Deep copy** hostView's array to view's array.

```
Kokkos::deep_copy(view, hostView);
```

```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view(...);
```

2. **Create** hostView, a mirror of the view's array residing in the host memory space.

```
ViewType::HostMirror hostView =
  Kokkos::create_mirror_view(view);
```

- 3. **Populate hostView** on the host (from file, etc.).
- 4. Deep copy hostView's array to view's array. Kokkos::deep_copy(view, hostView);
- 5. Launch a kernel processing the view's array.

```
Kokkos::parallel_for(
  RangePolicy < Space > (0, size),
  KOKKOS_LAMBDA (...) { use and change view });
```

```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view(...);
```

2. **Create** hostView, a mirror of the view's array residing in the host memory space.

```
ViewType::HostMirror hostView =
  Kokkos::create_mirror_view(view);
```

- 3. Populate hostView on the host (from file, etc.).
- 4. **Deep copy** hostView's array to view's array.

```
\texttt{Kokkos}:: \textbf{deep\_copy}(\texttt{view}, \ \textbf{hostView});
```

5. **Launch** a kernel processing the view's array.

```
Kokkos::parallel_for(
  RangePolicy < Space > (0, size),
  KOKKOS_LAMBDA (...) { use and change view });
```

If needed, deep copy the view's updated array back to the hostView's array to write file, etc.

```
Kokkos::deep_copy(hostView, view);
```

What if the View is in HostSpace too? Does it make a copy?

```
typedef Kokkos::View<double*, Space> ViewType;
ViewType view("test", 10);
ViewType::HostMirror hostView =
   Kokkos::create_mirror_view(view);
```

- create_mirror_view allocates data only if the host process cannot access view's data, otherwise hostView references the same data.
- create_mirror always allocates data.
- Reminder: Kokkos never performs a hidden deep copy.

Exercise #3: Flat Parallelism on the GPU, Views and Host Mirrors

Details:

- Location: SC2017/Exercises/03/Begin/
- Add HostMirror Views and deep copy
- ▶ Make sure you use the correct view in initialization and Kernel

```
# Compile for CPU
make -j KOKKOS_DEVICES=OpenMP
# Compile for GPU (we do not need UVM anymore)
make -j KOKKOS_DEVICES=Cuda
# Run on GPU
./03_Exercise.cuda -S 26
```

Things to try:

- Vary problem size and number of rows (-S ...; -N ...)
- ► Change number of repeats (-nrepeat ...)
- Compare behavior of CPU vs GPU

- Data is stored in Views that are "pointers" to multi-dimensional arrays residing in memory spaces.
- Views abstract away platform-dependent allocation, (automatic) deallocation, and access.
- ▶ Heterogenous nodes have one or more memory spaces.
- Mirroring is used for performant access to views in host and device memory.
- ▶ Heterogenous nodes have one or more **execution spaces**.
- You control where parallel code is run by a template parameter on the execution policy, or by compile-time selection of the default execution space.

Managing memory access patterns for performance portability

Learning objectives:

- ▶ How the View's Layout parameter controls data layout.
- How memory access patterns result from Kokkos mapping parallel work indices and layout of multidimensional array data
- Why memory access patterns and layouts have such a performance impact (caching and coalescing).
- See a concrete example of the performance of various memory configurations.

Example: inner product (0)

```
Kokkos::parallel_reduce(
 RangePolicy < Execution Space > (0, N),
 KOKKOS_LAMBDA (const size_t row, double & valueToUpdate) {
    double thisRowsSum = 0:
    for (size_t entry = 0; entry < M; ++entry) {
      thisRowsSum += A(row, entry) * x(entry);
    valueToUpdate += y(row) * thisRowsSum;
 }, result);
```

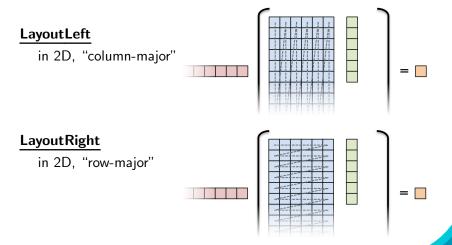
Example: inner product (0)

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Driving question: How should A be laid out in memory?

Example: inner product (1)

Layout is the mapping of multi-index to memory:



Important concept: Layout

Every View has a multidimensional array Layout set at compile-time.

```
View<double***, Layout, Space> name(...);
```

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- Most-common layouts are LayoutLeft and LayoutRight. LayoutLeft: left-most index is stride 1. LayoutRight: right-most index is stride 1.
- ▶ If no layout specified, default for that memory space is used.

 LayoutLeft for CudaSpace, LayoutRight for HostSpace.
- Layouts are extensible: ~50 lines
- Advanced layouts: LayoutStride, LayoutTiled, ...

Exercise #4: Inner Product, Flat Parallelism

Details:

- ▶ Location: SC2017/Exercises/04/Begin/
- ► Replace ''N'' in parallel dispatch with RangePolicy<ExecSpace>
- Add MemSpace to all Views and Layout to A
- Experiment with the combinations of ExecSpace, Layout to view performance

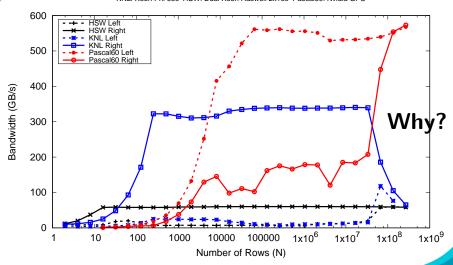
Things to try:

- Vary problem size and number of rows (-S ...; -N ...)
- Change number of repeats (-nrepeat ...)
- Compare behavior of CPU vs GPU
- Compare using UVM vs not using UVM on GPUs
- ► Check what happens if MemSpace and ExecSpace do not match.

Exercise #4: Inner Product, Flat Parallelism

<y|Ax> Exercise 04 (Layout) Fixed Size

KNL: Xeon Phi 68c HSW: Dual Xeon Haswell 2x16c Pascal60: Nvidia GPU



```
operator()(const size_t index, double & valueToUpdate) {
  const double d = _data(index);
  valueToUpdate += d;
}
```

Question: once a thread reads d, does it need to wait?

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i.e., threads may execute at any rate.

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- **CPU** threads are independent.
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- ▶ **GPU** threads are synchronized in groups (of 32).
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In particular, all threads in a group (warp) must finished their loads before any thread can move on.

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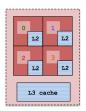
In particular, all threads in a group (warp) must finished their loads before any thread can move on.

So, **how many cache lines** must be fetched before threads can move on?

Caching and coalescing (1)

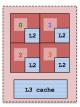
CPUs: few (independent) cores with separate caches:

0 +	0 H	0 H	0 +	
read	read	read	read	
00	H	N N	നന	
thread	thread	thread	thread	
]

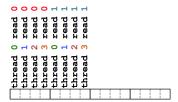


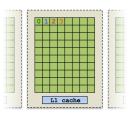
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read	read	read	read	
00	H	N N	ന ന	
thread	thread	thread	thread	



GPUs: many (synchronized) cores with a shared cache:





For performance, accesses to views in HostSpace must be **cached**, while access to views in CudaSpace must be **coalesced**.

Caching: if thread t's current access is at position i, thread t's next access should be at position i+1.

Coalescing: if thread t's current access is at position i, thread t+1's current access should be at position i+1.

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Warning

Uncoalesced access in CudaSpace *greatly* reduces performance (more than 10X)

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Warning

Uncoalesced access in CudaSpace *greatly* reduces performance (more than 10X)

Note: uncoalesced *read-only, random* access in CudaSpace is okay through Kokkos const RandomAccess views (more later).

Consider the array summation example:

```
View < double *, Space > data("data", size);
...populate data...

double sum = 0;
Kokkos::parallel_reduce(
  RangePolicy < Space > (0, size),
  KOKKOS_LAMBDA (const size_t index, double & valueToUpdate) {
    valueToUpdate += data(index);
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Question: is this cached (for OpenMP) and coalesced (for Cuda)?

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Given P threads, which indices do we want thread 0 to handle?

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Contiguous: Strided: 0, 1, 2, ..., N/P 0, N/P, 2*N/P, ...
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Contiguous: Strided:

0, 1, 2, ..., N/P 0, N/P, 2*N/P, ...

CPU GPU
```

Why?

Iterating for the execution space:

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operator()(const size_t index, double & valueToUpdate) {
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As users we don't control how indices are mapped to threads, so how do we achieve good memory access?

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Important point

Kokkos maps indices to cores in **contiguous chunks** on CPU execution spaces, and **strided** for Cuda.

Rule of Thumb

Kokkos index mapping and default layouts provide efficient access if **iteration indices** correspond to the **first index** of array.

Example:

```
View < double ***, ...> view (...);
...
Kokkos::parallel_for( ... ,
    KOKKOS_LAMBDA (const size_t workIndex) {
    ...
    view (..., ..., workIndex ) = ...;
    view (..., workIndex , ...) = ...;
    view (workIndex , ...) = ...;
});
...
```

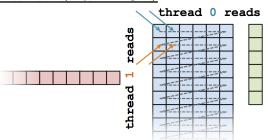
Example: inner product (2)

Important point

Performant memory access is achieved by Kokkos mapping parallel work indices **and** multidimensional array layout *appropriately for* the architecture.

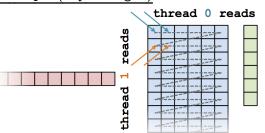
Performant memory access is achieved by Kokkos mapping parallel work indices **and** multidimensional array layout *appropriately for the architecture*.

Analysis: row-major (LayoutRight)



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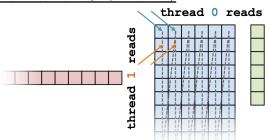
Analysis: row-major (LayoutRight)



- ► HostSpace: cached (good)
- ► CudaSpace: uncoalesced (bad)

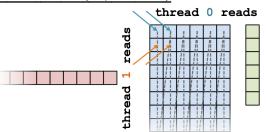
Performant memory access is achieved by Kokkos mapping parallel work indices **and** multidimensional array layout *optimally for the architecture*.

Analysis: column-major (LayoutLeft)



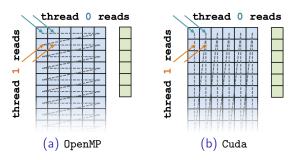
Performant memory access is achieved by Kokkos mapping parallel work indices **and** multidimensional array layout *optimally for the architecture*.

Analysis: column-major (LayoutLeft)



- HostSpace: uncached (bad)
- ► CudaSpace: coalesced (good)

Analysis: Kokkos architecture-dependent

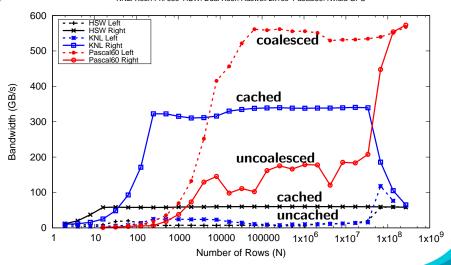


- ► HostSpace: cached (good)
- CudaSpace: coalesced (good)

Example: inner product (5)

<y|Ax> Exercise 04 (Layout) Fixed Size

KNL: Xeon Phi 68c HSW: Dual Xeon Haswell 2x16c Pascal60: Nvidia GPU



Memory Access Pattern Summary

- Every View has a Layout set at compile-time through a template parameter.
- LayoutRight and LayoutLeft are most common.
- Views in HostSpace default to LayoutRight and Views in CudaSpace default to LayoutLeft.
- Layouts are extensible and flexible.
- For performance, memory access patterns must result in caching on a CPU and coalescing on a GPU.
- Kokkos maps parallel work indices and multidimensional array layout for performance portable memory access patterns.
- ► There is **nothing in** OpenMP, OpenACC, or OpenCL to manage layouts.
 - ⇒ You'll need multiple versions of code or pay the performance penalty.

Kokkos capabilities NOT covered today, only 2 hours

- Atomic operations and their scalability
- Multidimensional range policy (heirarchical pattern)
- Thread-team policy (hierarchical pattern) with intra-team shared memory

CUDA grid-block parallelism, but easier and portable

- Dynamic directed acyclic graph (DAG) of tasks pattern
- Plugging in customized multdimensional array data layout e.g., arbitrarily strided, heirarchical tiling

- ► For **portability**: OpenMP, OpenACC, ... or Kokkos.
- Only Kokkos obtains performant memory access patterns via architecture-aware arrays and work mapping. i.e., not just portable, performance portable.
- ▶ With Kokkos, simple things stay simple (parallel-for, etc.).
 i.e., it's no more difficult than OpenMP.
- ► Advanced performance-optimizing patterns are simpler with Kokkos than with native versions.
 - i.e., you're not missing out on advanced features.
 - full day tutorial only