

A Short Introduction to Kokkos

Damien Lebrun-Grandié

ORNL is managed by UT-Battelle LLC for the US Department of Energy



A Condensed Short Tutorial

This lecture covers fundamental concepts of Kokkos with Hands-On Exercises as homework. Slides: https://github.com/kokkos/kokkos-tutorials/ Intro-Short/KokkosTutorial_Short.pdf

For the full lectures, with more capabilities covered, and more in-depth explanations visit: https://github.com/kokkos/kokkos-tutorials/wiki/ Kokkos-Lecture-Series Current Generation: Programming Models OpenMP 3, CUDA and OpenACC depending on machine





LANL/SNL Trinity Intel Haswell / Intel KNL OpenMP 3



LLNL SIERRA IBM Power9 / NVIDIA Volta CUDA / OpenMP^(a)



ORNL Summit IBM Power9 / NVIDIA Volta CUDA / OpenACC / OpenMP (9)



SNL Astra ARM CPUs OpenMP 3



Riken Fugaku ARM CPUs with SVE OpenMP 3 / OpenACC ^(b)

Upcoming Generation: Programming Models OpenMP 5, CUDA, HIP and DPC++ depending on machine



NERSC Perimutter AMD CPU / NVIDIA GPU CUDA / OpenMP 5^(c)



ORNL Frontier AMD CPU / AMD GPU HIP / OpenMP 5^(d)



ANL Aurora Xeon CPUs / Intel GPUs DPC++ / OpenMP 5 (*)



LLNL EI Capitan AMD CPU / AMD GPU HIP / OpenMP 5^(d)

(a) Initially not working. Now more robust for Fortran than C++, but getting better.

- (b) Research effort.
- (c) OpenMP 5 by NVIDIA.
- (d) OpenMP 5 by HPE.

(e) OpenMP 5 by Intel.

Industry Estimate

A full time software engineer writes 10 lines of production code per hour: 20k LOC/year.

Typical HPC production app: 300k-600k lines

- Sandia alone maintains a few dozen
- Large Scientific Libraries:
 - E3SM: 1,000k lines
 - Trilinos: 4,000k lines

Conservative estimate: need to rewrite 10% of an app to switch Programming Model

Cost of Coding

Industry Estimate

A full time software engineer writes 10 lines of production code per hour: 20k LOC/year.

Typical HPC production app: 300k-600k lines

- Sandia alone maintains a few dozen
- Large Scientific Libraries:
 - E3SM: 1,000k lines
 - Trilinos: 4,000k lines

Conservative estimate: need to rewrite 10% of an app to switch Programming Model

Software Cost Switching Vendors

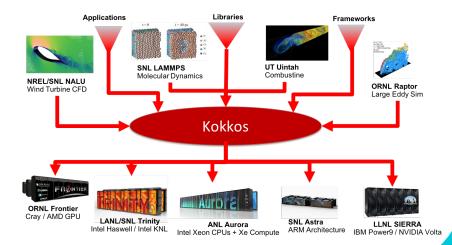
Just switching Programming Models costs multiple person-years per app!

Cost of Coding

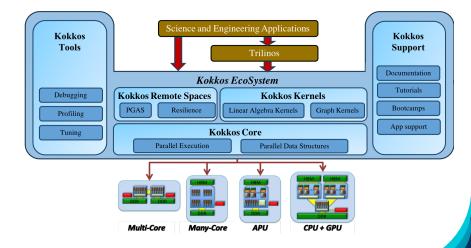
► A C++ Programming Model for Performance Portability

- Implemented as a template library on top CUDA, HIP, OpenMP, ...
- Aims to be descriptive not prescriptive
- Aligns with developments in the C++ standard
- Expanding solution for common needs of modern science and engineering codes
 - Math libraries based on Kokkos
 - Tools for debugging, profiling and tuning
 - Utilities for integration with Fortran and Python
- Is is an Open Source project with a growing community
 - Maintained and developed at https://github.com/kokkos
 - Hundreds of users at many large institutions

Kokkos at the Center



The Kokkos EcoSystem



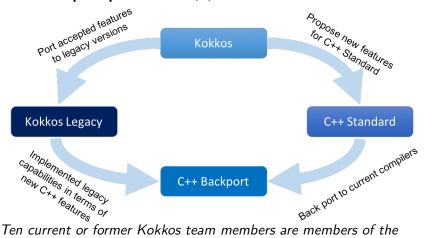


Kokkos Core:	C. Trott, D. Lebrun-Grandié, D. Arndt, J. Bludau, J. Ciesko, V. Dang,
	N. Ellingwood, R. Gayatri, D. Ibanez, V. Kale, N. Liber, P. Miller, N.
	Morales, A. Powell, F. Rizzi, C. Skrzyński, B. Turcksin
	former: H.C. Edwards, D. Labreche, G. Mackey, S. Bova, D. Sun-
	derland, D.S. Hollman, J. Miles, J. Wilke, J. Madsen, D. Poliakoff, C.
	Lewis, H. Finkel
Kokkos Kernels:	S. Rajamanickam, L. Berger-Vergiat, V. Dang, N. Ellingwood, J.
	Foucar, E. Harvey, B. Kelley, K. Kim, J. Loe, C. Pearson
	former: J. Wilke, S. Acer

The Kokkos Team

Kokkos and the C++ Standard

Kokkos helps improve ISO C++



ISO C++ standard committee.



Kokkos has a growing OpenSource Community

20 ECP projects list Kokkos as Critical Dependency

- 41 list C++ as critical
- 25 list Lapack as critical
- 21 list Fortran as critical

Slack Channel: 900 members from 90+ institutions

- 15% Sandia Nat. Lab.
- 24% other US Labs
- 22% universities
- 39% other
- GitHub: 1.1k stars



Weekly active members
 Members who posted

Online Resources:

- https://github.com/kokkos:
 - Primary Kokkos GitHub Organization
- https://github.com/kokkos/kokkos-tutorials/wiki/ Kokkos-Lecture-Series:
 - Slides, recording and Q&A for the Full Lectures
- https://github.com/kokkos/kokkos/wiki:
 - Wiki including API reference
- https://kokkosteam.slack.com:
 - Slack channel for Kokkos.
 - Please join: fastest way to get your questions answered.
 - Can whitelist domains, or invite individual people.

Data parallel patterns

Learning objectives:

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

Data parallel patterns and work

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

Kokkos maps work to execution resources

Data parallel patterns and work

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

Kokkos maps work to execution resources

- 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.

Data parallel patterns and work

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

Kokkos maps work to execution resources

- 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, and Kokkos decides how to map that work to execution resources.

How are computational bodies given to Kokkos?

How are computational bodies given to Kokkos?

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

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 ... */
        ...
};
```

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

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

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 int64_t index) const {...}
}
```

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 int64_t index) const {...}
}
```

Warning: concurrency and order

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

The complete picture (using functors):

1. Defining the functor (operator+data):

```
struct AtomForceFunctor {
  ForceType _atomForces;
  AtomDataType _atomData;
  AtomForceFunctor(ForceType atomForces, AtomDataType data) :
    _atomForces(atomForces), _atomData(data) {}
  void operator()(const int64_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 int64_t atomIndex) {
    atomForces[atomIndex] = calculateForce(data);
  }
);
```

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 int64_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

```
atomForces already exists
data already exists
Kokkos::parallel_for(numberOfAtoms,
    [=] (const int64_t atomIndex) {
    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 (int64_t i = 0; i < N; ++i) {
    /* loop body */
}</pre>
```

```
#pragma omp parallel for
for (int64_t i = 0; i < N; ++i) {
    /* loop body */
}
```

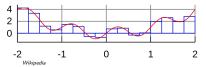
```
parallel_for(N, [=] (const int64_t i) {
    /* loop body */
});
```

Important concept

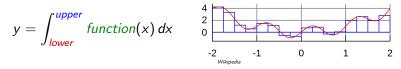
Simple Kokkos usage is **no more conceptually difficult** than OpenMP, the annotations just go in different places.

Riemann-sum-style numerical integration:



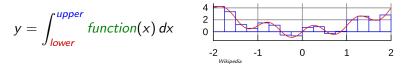


Riemann-sum-style numerical integration:



```
double totalIntegral = 0;
for (int64_t i = 0; i < numberOfIntervals; ++i) {
   const double x =
        lower + (i/numberOfIntervals) * (upper - lower);
   const double thisIntervalsContribution = function(x);
   totalIntegral += thisIntervalsContribution;
}
totalIntegral *= dx;
```

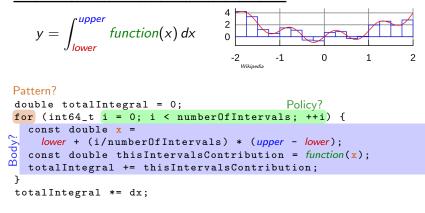
Riemann-sum-style numerical integration:



```
double totalIntegral = 0;
for (int64_t i = 0; i < numberOfIntervals; ++i) {
   const double x =
        lower + (i/numberOfIntervals) * (upper - lower);
   const double thisIntervalsContribution = function(x);
   totalIntegral += thisIntervalsContribution;
}
totalIntegral *= dx;
```

How do we parallelize it? Correctly?

Riemann-sum-style numerical integration:



How do we parallelize it? Correctly?

An (incorrect) attempt:

```
double totalIntegral = 0;
Kokkos::parallel_for(numberOfIntervals,
  [=] (const int64_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 int64_t index) {
    const double x =
        lower + (index/numberOfIntervals) * (upper - lower);
    *totalIntegralPointer += function(x);},
 );
totalIntegral *= dx;
```

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

```
double totalIntegral = 0;
double * totalIntegralPointer = &totalIntegral;
Kokkos::parallel_for(numberOfIntervals,
   [=] (const int64_t index) {
      const double x =
        lower + (index/numberOfIntervals) * (upper - lower);
      *totalIntegralPointer += function(x);},
   );
totalIntegral *= dx;
```

Second problem: race condition

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

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

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

Important concept: Reduction

Reductions combine the results contributed by parallel work.

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 (int64_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 (int64_t i = 0; i < N; ++i) {
   finalReducedValue += ...
}
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 (int64_t i = 0; i < numberOfIntervals; ++i) {
  totalIntegral += function(...);
}
```

```
double totalIntegral = 0;
parallel_reduce(numberOfIntervals,
  [=] (const int64_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.

Always name your kernels!

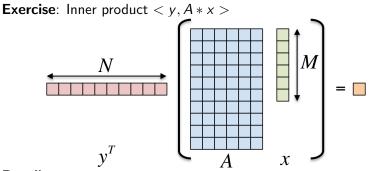
Giving unique names to each kernel is immensely helpful for debugging and profiling. You will regret it if you don't!

- Non-nested parallel patterns can take an optional string argument.
- The label doesn't need to be unique, but it is helpful.
- Anything convertible to "std::string"
- Used by profiling and debugging tools (see Profiling Tutorial)

Example:

```
double totalIntegral = 0;
parallel_reduce("Reduction",numberOfIntervals,
  [=] (const int64_t i, double & valueToUpdate) {
    valueToUpdate += function(...);
    },
    totalIntegral);
```

Recurring Exercise: Inner Product



Details:

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

Exercise #1: include, initialize, finalize Kokkos

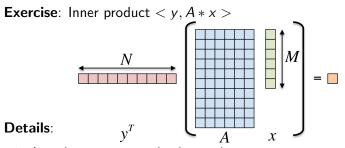
The **first step** in using Kokkos is to include, initialize, and finalize:

```
#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 or environment variables:

kokkos-num-threads=INT	or	total number of threads
KOKKOS_NUM_THREADS		
kokkos-device-id=INT	or	device (GPU) ID to use
KOKKOS_DEVICE_ID		

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



- Location: 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.

Compiling for CPU

- # gcc using OpenMP (default) and Serial back-ends,
- # (optional) change non-default arch with KOKKOS_ARCH make -j KOKKOS_DEVICES=OpenMP,Serial KOKKOS_ARCH=...

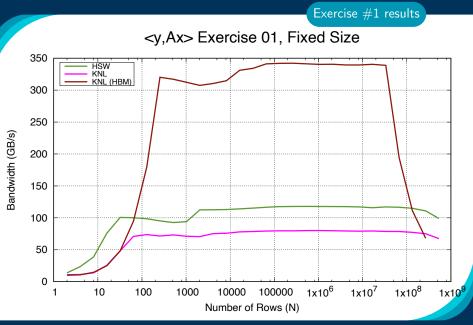
Running on CPU with OpenMP back-end

Set OpenMP affinity
export OMP_NUM_THREADS=8
export OMP_PROC_BIND=spread OMP_PLACES=threads
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

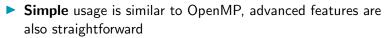
Things to try:

- Vary problem size with cline arg -S s
- Vary number of rows with cline arg -N n
- Num rows = 2^n , num cols = 2^m , total size = $2^s = 2^{n+m}$

GATech Spring 2023



GATech Spring 2023



- 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.

Section Summary

Views

Learning objectives:

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



Example: running daxpy on the GPU:

```
double * x = new double[N]; // also y
parallel_for("DAXPY",N, [=] (const int64_t i) {
    y[i] = a * x[i] + y[i];
});
```

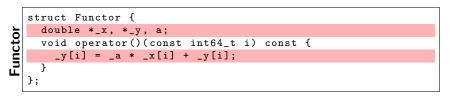
```
struct Functor {
    double *_x, *_y, a;
    void operator()(const int64_t i) const {
        _y[i] = _a * _x[i] + _y[i];
    }
};
```



Example: running daxpy on the GPU:

ъ	
9	
2	
J J	

double * x = new double[N]; // also y
parallel_for("DAXPY",N, [=] (const int64_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("DAXPY",N, [=] (const int64_t i) {
    y[i] = a * x[i] + y[i];
});
```

Ictor	struct Functor {
	double *_x, *_y, a;
	<pre>void operator()(const int64_t i) const {</pre>
ĕ	y[i] = a * x[i] + y[i];
Ш	}
_	};

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).

$$\Rightarrow$$
 Views

GATech Spring 2023



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("DAXPY",N, [=] (const int64_t i) {
    // Views x and y are captured by value (shallow 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:

```
View<double*, ...> x(...), y(...);
...populate x, y...
parallel_for("DAXPY",N, [=] (const int64_t i) {
    // Views x and y are captured by value (shallow 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.
- Access elements via "(...)" operator.

Views (1)

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.
- Access elements via "(...)" operator.

Example:

```
View<double***> data("label", N0, N1, N2); //3 run, 0 compile
View<double**[N2]> data("label", N0, N1); //2 run, 1 compile
View<double*[N1][N2]> data("label", N0); //1 run, 2 compile
View<double[N0][N1][N2]> data("label"); //0 run, 3 compile
//Access
data(i,j,k) = 5.3;
Note: runtime-sized dimensions must come first.
```

Views (1)

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 std::shared_ptr

Views (2)

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 std::shared_ptr

Example:

```
View<double*[5]> a("a", N), b("b", K);
a = b;
View<double**> c(b);
a(0,2) = 1;
b(0,2) = 2;
c(0,2) = 3;
print_value( a(0,2) );
```

Views (2)

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 std::shared_ptr

Example:

```
View<double*[5]> a("a", N), b("b", K);
a = b;
View<double**> c(b);
a(0,2) = 1;
b(0,2) = 2;
c(0,2) = 3;
print_value( a(0,2) );
```

Views (2)

View Properties:

- Accessing a View's sizes is done via its extent(dim) function.
 - Static extents can additionally be accessed via static_extent(dim).
- You can retrieve a raw pointer via its data() function.
- The label can be accessed via label().

Example:

```
View<double*[5]> a("A",NO);
assert(a.extent(0) == NO);
assert(a.extent(1) == 5);
static_assert(a.static_extent(1) == 5);
assert(a.data() != nullptr);
assert(a.label() == "A");
```

Views (3)

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

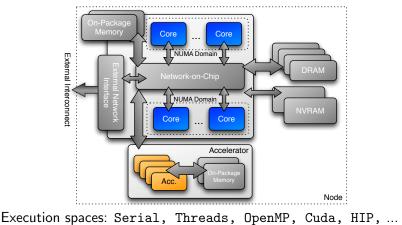
- Location: Exercises/02/Begin/
- Assignment: Change data storage from arrays to Views.
- Compile and run on CPU, and then on GPU with UVM

```
make -j KOKKOS_DEVICES=OpenMP # CPU-only using OpenMP
make -j KOKKOS_DEVICES=Cuda # GPU - note UVM in Makefile
# 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

Execution Space

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



GATech Spring 2023

Changing the parallel execution space:

```
parallel_for("Label",
RangePolicy < ExecutionSpace >(0,numberOfIntervals),
[=] (const int64_t i) {
    /* ... body ... */
  });
```

	<pre>parallel_for("Label",</pre>	
늭	<pre>numberOfIntervals, // => RangePolicy <>(0, numberOfIntervals)</pre>	
efau	[=] (const int64_t i) {	
ef	/* body */	
	});	

Changing the parallel execution space:

```
parallel_for("Label",
RangePolicy < ExecutionSpace >(0,numberOfIntervals),
[=] (const int64_t i) {
    /* ... body ... */
  });
```

	<pre>parallel_for("Label",</pre>	
)efault	<pre>numberOfIntervals, // => RangePolicy<>(0,numberOfIntervals)</pre>	
a	[=] (const int64_t i) {	
e	/* 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:

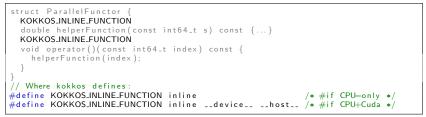
Function annotation with KOKKOS_INLINE_FUNCTION macro

```
struct ParallelFunctor {
    KOKKOS_INLINE_FUNCTION
    double helperFunction(const int64_t s) const {...}
    KOKKOS_INLINE_FUNCTION
    void operator()(const int64_t index) const {
        helperFunction(index);
    }
}
// Where kokkos defines:
#define KOKKOS_INLINE_FUNCTION inline /* #if CPU—only */
#define KOKKOS_INLINE_FUNCTION inline ...device....host... /* #if CPU+Cuda */
```

Execution spaces (5)

Kokkos function and lambda portability annotation macros:

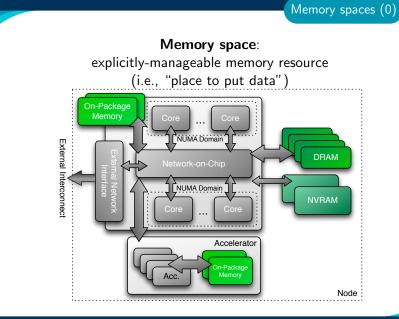
Function annotation with KOKKOS_INLINE_FUNCTION macro



Lambda annotation with KOKKOS_LAMBDA macro

```
Kokkos::parallel_for("Label",numberOfIterations,
KOKKOSLAMBDA (const int64_t index) {...});
// Where Kokkos defines:
#define KOKKOSLAMBDA [=] /* #if CPU-only */
#define KOKKOSLAMBDA [=] __device__ __host__ /* #if CPU+Cuda */
```

Execution spaces (5)





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***, MemorySpace> data(...);
- Available **memory spaces**:

HostSpace, CudaSpace, CudaUVMSpace, ... more

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

- View<double***, MemorySpace> 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***, MemorySpace> 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.

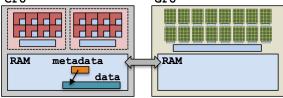
Every view stores its data in a memory space set at compile time.

- View<double***, MemorySpace> 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.

```
// Equivalent:
View<double*> a("A",N);
View<double*,DefaultExecutionSpace::memory_space> b("B",N);
```

Example: HostSpace

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



Memory spaces (2)

Example: HostSpace

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

RAM

Example: CudaSpace

RAM

metadata

data

View<double**, CudaSpace> view(...constructor arguments...); CPU RAM metadata RAM metadata data

GATech Spring 2023

Memory spaces (2)

(failed) Attempt 1: View lives in CudaSpace

```
View<double*, CudaSpace> array("array", size);
for (int64_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}
double sum = 0;
Kokkos::parallel_reduce("Label",
    RangePolicy < Cuda>(0, size),
    KOKKOS_LAMBDA (const int64_t index, double & valueToUpdate) {
    valueToUpdate += array(index);
    },
```

sum);

(failed) Attempt 1: View lives in CudaSpace

```
View<double*, CudaSpace> array("array", size);
for (int64_t i = 0; i < size; ++i) {
    array(i) = ...read from file... fault
}
double sum = 0;
Kokkos::parallel_reduce("Label",
```

```
RangePolicy< Cuda>(0, size),
```

```
KOKKOS_LAMBDA (const int64_t index, double & valueToUpdate) {
  valueToUpdate += array(index);
}.
```

```
sum):
```

(failed) Attempt 2: View lives in HostSpace

```
View<double*, HostSpace> array("array", size);
for (int64_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}
double sum = 0;
Kokkos::parallel_reduce("Label",
    RangePolicy < Cuda>(0, size),
    KOKKOS_LAMBDA (const int64_t index, double & valueToUpdate) {
      valueToUpdate += array(index);
    },
    sum):
```

(failed) Attempt 2: View lives in HostSpace

```
View<double*, HostSpace> array("array", size);
for (int64_t i = 0; i < size; ++i) {
    array(i) = ...read from file...
}
double sum = 0;
Kokkos::parallel_reduce("Label",
    RangePolicy< Cuda>(0, size),
    KOKKOS_LAMBDA (const int64_t index, double & valueToUpdate) {
    valueToUpdate += array(index); illegal access
    },
    sum):
```

(failed) Attempt 2: View lives in HostSpace

```
View<double*, HostSpace> array("array", size);
for (int64_t i = 0; i < size; ++i) {</pre>
  array(i) = ...read from file...
}
double sum = 0:
Kokkos::parallel_reduce("Label",
  RangePolicy < Cuda > (0, size),
  KOKKOS_LAMBDA (const int64_t index, double & valueToUpdate) {
    valueToUpdate += array(index);
                                             illegal access
  },
  sum):
                          CudaUVMSpace
What's the solution?
                          CudaHostPinnedSpace (skipping)
                          Mirroring
```

Important concept: Mirrors

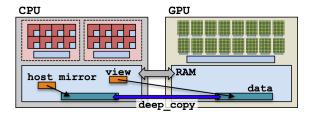
Mirrors are views of equivalent arrays residing in possibly different memory spaces.

Important concept: Mirrors

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

Mirroring schematic

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





1. **Create** a view's array in some memory space.

```
using view_type = Kokkos::View<double*, Space>;
view_type view(...);
```

2. Create hostView, a mirror of the view's array residing in the host memory space. view_type::HostMirror hostView =

```
Kokkos::create_mirror_view(view);
```

- 2. Create hostView, a mirror of the view's array residing in the host memory space. view_type::HostMirror hostView = Kokkos::create_mirror_view(view);
- 3. **Populate** hostView on the host (from file, etc.).

- 2. Create hostView, a mirror of the view's array residing in the host memory space. view_type::HostMirror hostView = Kokkos::create_mirror_view(view);
- 3. **Populate** hostView on the host (from file, etc.).
- Deep copy hostView's array to view's array. Kokkos::deep_copy(view, hostView);

- 2. Create hostView, a mirror of the view's array residing in the host memory space. view_type::HostMirror hostView = Kokkos::create_mirror_view(view);
- 3. **Populate** hostView on the host (from file, etc.).
- 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("Label", RangePolicy< Space>(0, size), KOKKOS_LAMBDA (...) { use and change view });

- 2. Create hostView, a mirror of the view's array residing in the host memory space. view_type::HostMirror hostView = Kokkos::create_mirror_view(view);
- 3. **Populate** hostView on the host (from file, etc.).
- 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("Label", RangePolicy< Space>(0, size), KOKKOS_LAMBDA (...) { use and change view });
- 6. 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?

```
using ViewType = Kokkos::View<double*, Space>;
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: 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.
- Heterogeneous nodes have one or more memory spaces.
- Mirroring is used for performant access to views in host and device memory.
- Heterogeneous 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.

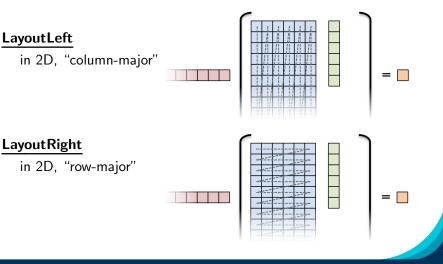
```
Kokkos::parallel_reduce("Label",
  RangePolicy < ExecutionSpace > (0, N),
  KOKKOS_LAMBDA (const size_t row, double & valueToUpdate) {
    double thisRowsSum = 0;
    for (size_t entry = 0; entry < M; ++entry) {</pre>
      thisRowsSum += A(row, entry) * x(entry);
    }
    valueToUpdate += y(row) * thisRowsSum;
  }. result).
            Ν
                                          х
```

```
Kokkos::parallel_reduce("Label",
  RangePolicy < ExecutionSpace > (0, N),
  KOKKOS_LAMBDA (const size_t row, double & valueToUpdate) {
    double thisRowsSum = 0:
    for (size_t entry = 0; entry < M; ++entry) {</pre>
      thisRowsSum += A(row, entry) * x(entry);
    }
    valueToUpdate += y(row) * thisRowsSum;
  }, result).
            N
                                          х
```

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

GATech Spring 2023

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(...);

Layout

Important concept: Layout

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

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

- 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, ...

Layout

Details:

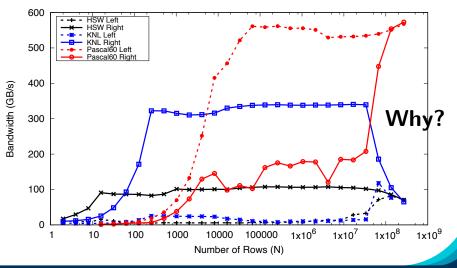
- Location: Exercises/04/Begin/
- Replace 'N'' in parallel dispatch with RangePolicy<ExecSpace>
- Add MemSpace to all Views and Layout to A
- Experiment with the combinations of ExecSpace, Layout to view performance

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 <ylAx> Exercise 04 (Layout) Fixed Size

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



GATech Spring 2023

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

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

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

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

CPU threads are independent.

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

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

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

CPU threads are independent.

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

GPU threads execute synchronized.

i.e., threads in groups can/must execute instructions together.

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

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

CPU threads are independent.

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

GPU threads execute synchronized.

▶ i.e., threads in groups can/must execute instructions together.

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

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

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

CPU threads are independent.

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

- **GPU** threads execute synchronized.
- i.e., threads in groups can/must execute instructions together. In particular, all threads in a group (*warp* or *wavefront*) must finished their loads before *any* thread can move on.

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

Important point

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.

Important point

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.

Warning

Uncoalesced access on GPUs and non-cached loads on CPUs *greatly* reduces performance (can be 10X)

Rule of Thumb

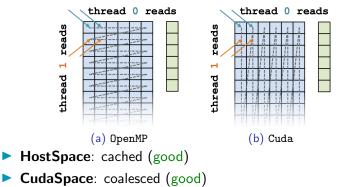
Kokkos index mapping and default layouts provide efficient access if **iteration indices** correspond to the **first index** of array.

Example:

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

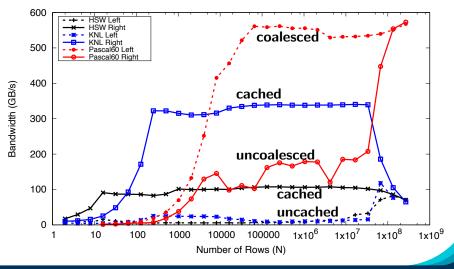
Analysis: Kokkos architecture-dependent

```
View<double**, ExecutionSpace> A(N, M);
parallel_for(RangePolicy< ExecutionSpace>(0, N),
    ... thisRowsSum += A(j, i) * x(i);
```



<ylAx> Exercise 04 (Layout) Fixed Size

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



GATech Spring 2023

- 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.

 \Rightarrow You'll need multiple versions of code or pay the performance penalty.

Exercise: Find x in b = A * xGetting set up in your home directory:

```
mkdir Kokkos
cd Kokkos
git clone https://github.com/kokkos/kokkos
git clone https://github.com/kokkos/kokkos-tutorials
```

Find the exercise in the kokkos-tutorials/Exercises/cg-solve-hp folder.

The Begin subdirectory contains the code. Only cg_solve.cpp needs modifications.

Look for EXERCISE comments to find places to modify. Note: this contains the same Exercise components as the first cg-solve. So you can just start with the solution of that and add the new things! To make it clearer they are marked as EXERCISE-HP.

Tasks:

- Use HostMirrors instead of Unified Memory for GPUs.
- Use a hierarchical parallelism SPMV.

Things to try:

- Compare with previous exercise on GPU with low iteration count.
- Compare performance for small problems.
- Compare performance dependent on Layout of col_idx and values.

This was a short introduction Didn't cover many things:

Didn't cover many things:

Full BuildSystem integration.

- Full BuildSystem integration.
- ▶ Non-Sum reductions / multiple reductions.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.
- Atomic operations and Scatter Contribute patterns.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.
- Atomic operations and Scatter Contribute patterns.
- Team Scratch memory (GPU shared memory).

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.
- Atomic operations and Scatter Contribute patterns.
- Team Scratch memory (GPU shared memory).
- SIMD vectorization.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.
- Atomic operations and Scatter Contribute patterns.
- Team Scratch memory (GPU shared memory).
- SIMD vectorization.
- MPI and PGAS integration.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.
- Atomic operations and Scatter Contribute patterns.
- Team Scratch memory (GPU shared memory).
- SIMD vectorization.
- MPI and PGAS integration.
- Tools for Profiling, Debugging and Tuning.

- Full BuildSystem integration.
- Non-Sum reductions / multiple reductions.
- Multidimensional loops.
- Advanced data structures.
- Subviews.
- Atomic operations and Scatter Contribute patterns.
- Team Scratch memory (GPU shared memory).
- SIMD vectorization.
- MPI and PGAS integration.
- Tools for Profiling, Debugging and Tuning.
- Math Kernels.

The Kokkos Lectures

Watch the Kokkos Lectures for all of those and more in-depth explanations or do them on your own.

- Module 1: Introduction, Building and Parallel Dispatch
- Module 2: Views and Spaces
- Module 3: Data Structures + MultiDimensional Loops
- Module 4: Hierarchical Parallelism
- Module 5: Tasking, Streams and SIMD
- Module 6: Internode: MPI and PGAS
- Module 7: Tools: Profiling, Tuning and Debugging
- Module 8: Kernels: Sparse and Dense Linear Algebra

https://kokkos.link/the-lectures

Online Resources:

- https://github.com/kokkos:
 - Primary Kokkos GitHub Organization
- https://kokkos.link/the-lectures:

Slides, recording and Q&A for the Full Lectures

- https://github.com/kokkos/kokkos/wiki:
 - Wiki including API reference
- https://kokkosteam.slack.com:
 - Slack channel for Kokkos.
 - Please join: fastest way to get your questions answered.
 - Can whitelist domains, or invite individual people.

Find More