The Kokkos Lectures

The Fundamentals: A Condensed Short Tutorial

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A Condensed Short Tutorial

This lecture covers fundamental concepts of Kokkos with Hands-On Exercises as homework.

Slides: https://github.com/kokkos/kokkos-tutorials/ blob/main/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

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

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

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Software Cost Switching Vendors

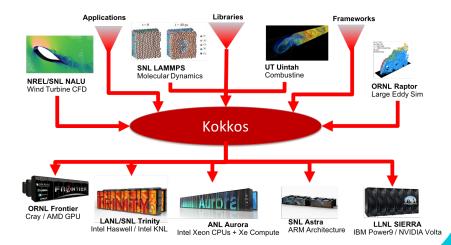
Just switching Programming Models costs multiple person-years per app!

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
- It 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

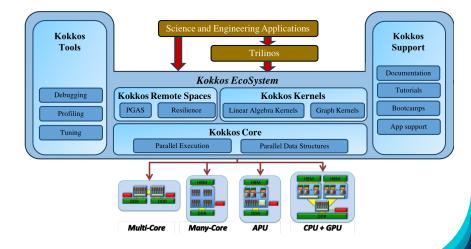


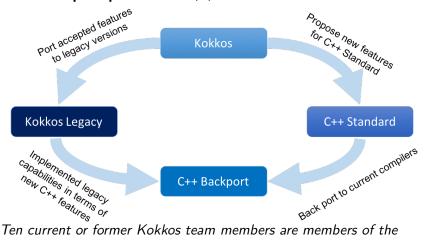
Image: Stripsy of Strips

| Kokkos Core: | C. Trott, D. Lebrun-Grandié, D. Arndt, J. Ciesko, C. Clevenger, N. | | |
|-----------------|---|--|--|
| | Ellingwood, R. Gayatri, D. Ibanez, D. Lee, S. Lee, N. Liber, P. Miller, | | |
| | N. Morales, A. Powell, F. Rizzi, M. Simberg, C. Skrzyński, B. Turcksin | | |
| Kokkos Kernels: | S. Rajamanickam, L. Berger-Vergiat, V. Dang, N. Ellingwood, J. | | |
| | Foucar, E. Harvey, B. Kelley, K. Liegeois, C. Pearson, E. Prudencio | | |
| Kokkos Support | C. Trott, G. Shipmann, G. Womeldorff, and all of the above | | |

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://kokkos.github.io/kokkos-core-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>
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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

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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?

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

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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);
```

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struct Functor {
   void operator()(const int64_t index) const {...}
}
```

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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

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data already exists
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```

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

Using Kokkos for data parallel patterns (7)

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    }
):
```

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 */
}
```

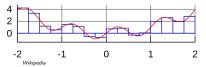
```
parallel_for(N, [=] (const int64_t i) {
    /* loop body */
});
```

Important concept

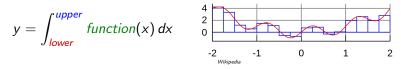
Simple Kokkos usage is **no more conceptually difficult** than OpenMP, the annotations just go in different places.

Riemann-sum-style numerical integration:



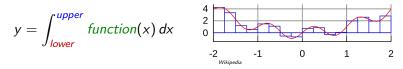


Riemann-sum-style numerical integration:



```
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;
```

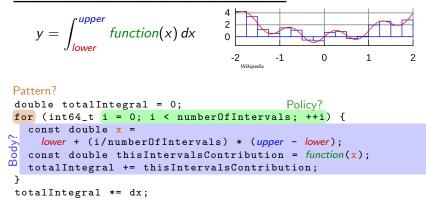
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How do we parallelize it? Correctly?

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);},
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      *totalIntegralPointer += function(x);},
   );
totalIntegral *= dx;
```

Second problem: race condition

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

Important concept: Reduction

Reductions combine the results contributed by parallel work.

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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>
```

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!

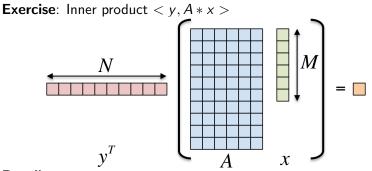
Giving unique names to each kernel is immensely helpful for debugging and profiling. You will regret it if you don't!

- 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

Using your own \${HOME}

Git

► GCC 8.2 (or newer) OR Intel 19.0.5 (or newer) OR Clang 8.0 (or newer)

- CUDA nvcc 11.0 (or newer) AND NVIDIA compute capability 6.0 (or newer)
- git clone https://github.com/kokkos/kokkos into \${HOME}/Kokkos/kokkos
- git clone https://github.com/kokkos/kokkos-tutorials into \${HOME}/Kokkos/kokkos-tutorials

Slides are in \${HOME}/Kokkos/kokkos-tutorials/LectureSeries

Exercises are in
\${HOME}/Kokkos/kokkos-tutorials/Exercises

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

Exercise #1: include, initialize, finalize Kokkos

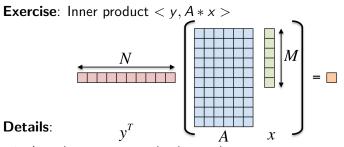
The first step in using Kokkos is to include, initialize, and finalize:

```
#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=...

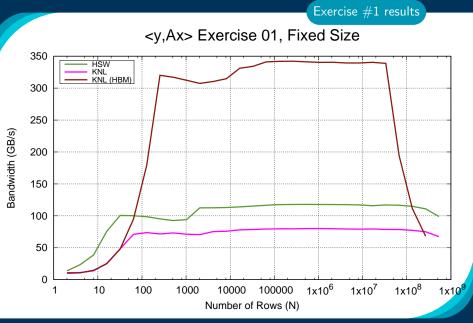
Running on CPU with OpenMP back-end

Set OpenMP affinity
export OMP_NUM_THREADS=8
export OMP_PROC_BIND=spread OMP_PLACES=threads
Print example command line options:
./O1_Exercise.host -h
Run with defaults on CPU
./O1_Exercise.host
Run larger problem
./O1_Exercise.host -S 26

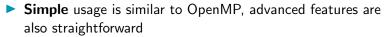
Things to try:

- 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 = $2^s = 2^{n+m}$

August 3, 2023



August 3, 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];
});
```

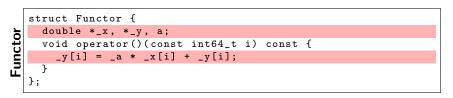
```
struct Functor {
   double *_x, *_y, a;
   void operator()(const int64_t i) const {
    _y[i] = _a * _x[i] + _y[i];
   }
};
```



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double * x = new double[N]; // also y
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Problem: x and y reside in CPU memory.

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```

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});
```

| | struct Functor { |
|---|---|
| ٦ | double *_x, *_y, a; |
| Ĕ | <pre>void operator()(const int64_t i) const {</pre> |
| Ĕ | y[i] = a * x[i] + y[i]; |
| Ы | } |
| _ | }; |

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

August 3, 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);
});
```



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});
```

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)

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- 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:

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- 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.
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a(0,2) = 1;
b(0,2) = 2;
c(0,2) = 3;
print_value( a(0,2) );
What gets printed?
```

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

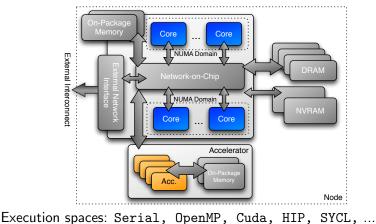
- Location: Exercises/02/Begin/
- Assignment: Change data storage from arrays to Views.
- Compile and run on CPU, and then on GPU with UVM

```
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
```

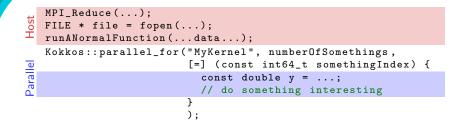
- Vary problem size: -S #
- Vary number of rows: -N #
- Vary repeats: -nrepeat #
- Compare performance of CPU vs GPU

Execution Space

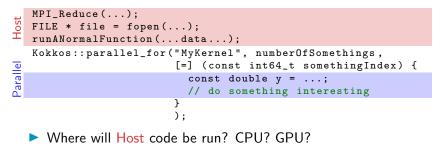
a homogeneous set of cores and an execution mechanism (i.e., "place to run code")





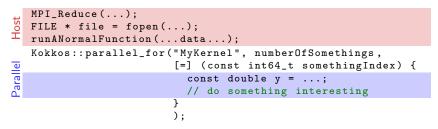






 \Rightarrow Always in the **host process**





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



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

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

| | <pre>parallel_for("Label",</pre> | |
|-----|---|---|
| Ħ | <pre>numberOfIntervals, // => RangePolicy<>(0,numberOfIntervals)</pre> | Ĺ |
| J | [=] (const int64_t i) { | ĺ |
| efa | /* body */ | |
| | }); | |

Changing the parallel execution space:

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

| | <pre>parallel_for("Label",</pre> | |
|---------|--|--|
| Default | <pre>numberOfIntervals, // => RangePolicy <>(0,numberOfIntervals)</pre> | |
| Ja | <pre>[=] (const int64_t i) {</pre> | |
| 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.

August 3, 2023

Kokkos function and lambda portability annotation macros:

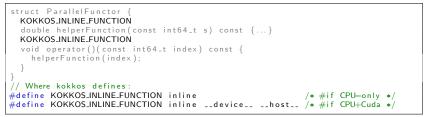
Function annotation with KOKKOS_INLINE_FUNCTION macro



Execution spaces (4)

Kokkos function and lambda portability annotation macros:

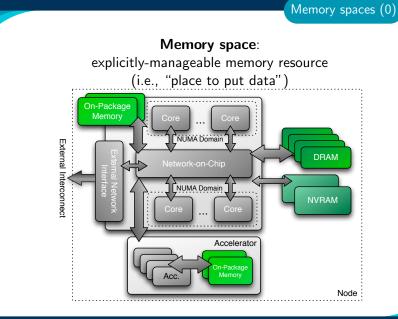
Function annotation with KOKKOS_INLINE_FUNCTION macro



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 (4)





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

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

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- Available **memory spaces**:

HostSpace, CudaSpace, CudaUVMSpace, ... more

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- 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.

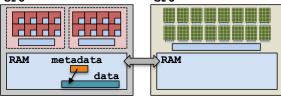
Every view stores its data in a memory space set at compile time.

- 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



Example: HostSpace

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

Example: CudaSpace

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

Example (redux): summing an array with the GPU

(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);

Execution and Memory spaces (3) Example (redux): summing an array with the GPU (failed) Attempt 1: View lives in CudaSpace View<double*, CudaSpace> array("array", size); for (int64_t i = 0; i < size; ++i) {</pre> 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);
```

Example (redux): summing an array with the GPU

(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);
  },
  sum):
```

Execution and Memory spaces (4)

Example (redux): summing an array with the GPU

(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):
```

Example (redux): summing an array with the GPU

(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

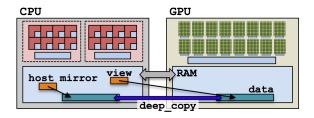
Mirrors are views of equivalent arrays residing in possibly different memory spaces.

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);
```





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

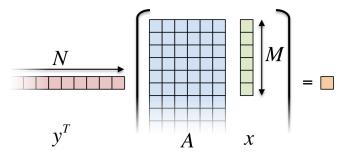
- Data is stored in Views that are "pointers" to multi-dimensional arrays residing in memory spaces.
- Views abstract away platform-dependent allocation, (automatic) deallocation, and access.
- Heterogeneous nodes have one or more memory spaces.
- Mirroring is used for performant access to views in host 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

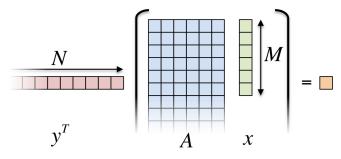
Learning objectives:

- 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) {
        thisRowsSum += A(row, entry) * x(entry);
    }
    valueToUpdate += y(row) * thisRowsSum;
}, result);
```



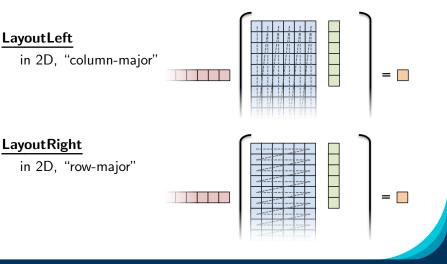
```
Kokkos::parallel_reduce("Label",
RangePolicy<ExecutionSpace>(0, N),
KOKKOS_LAMBDA (const size_t row, double & valueToUpdate) {
    double thisRowsSum = 0;
    for (size_t entry = 0; entry < M; ++entry) {
        thisRowsSum += A(row, entry) * x(entry);
    }
    valueToUpdate += y(row) * thisRowsSum;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



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

August 3, 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:

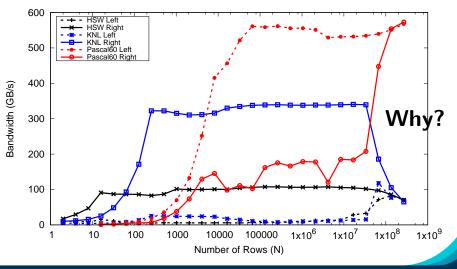
- Location: Exercises/04/Begin/
- Replace 'N'' in parallel dispatch with RangePolicy<ExecSpace>
- Add MemSpace to all Views and Layout to A
- Experiment with the combinations of ExecSpace, Layout to view performance

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

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



August 3, 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.

Thread independence:

```
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

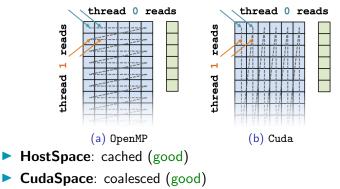
Kokkos index mapping and default layouts provide efficient access if **iteration indices** correspond to the **first index** of array.

Example:

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

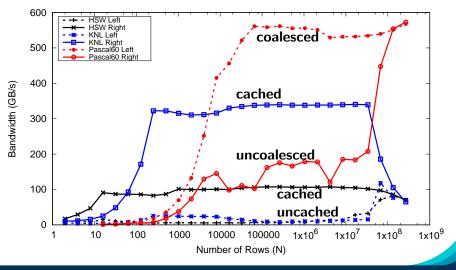
Analysis: Kokkos architecture-dependent

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



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

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



August 3, 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 SYCL to manage layouts.

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



Tightly Nested Loops with MDRangePolicy

Learning objectives:

- Demonstrate usage of the MDRangePolicy with tightly nested loops.
- Syntax Required and optional settings
- Code demo and example

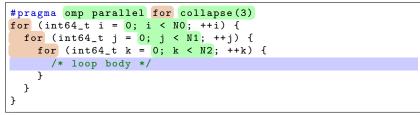
Motivating example: Consider the nested for loops:

```
for ( int i = 0; i < N0; ++i )
for ( int j = 0; j < N1; ++j )
for ( int k = 0; k < N2; ++k )
   some_init_fcn(i, j, k);</pre>
```

Based on Kokkos lessons thus far, you might parallelize this as

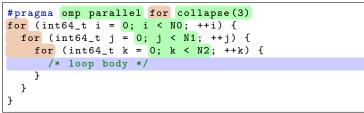
- This only parallelizes along one dimension, leaving potential parallelism unexploited.
- What if Ni is too small to amortize the cost of constructing a parallel region, but Ni*Nj*Nk makes it worthwhile?

OpenMP has a solution: the collapse clause



MDRangePolicy (1)

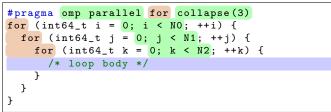
OpenMP has a solution: the collapse clause



Note this changed the policy by adding a 'collapse' clause.

MDRangePolicy (1)

OpenMP has a solution: the collapse clause



Note this changed the policy by adding a 'collapse' clause.

With Kokkos you also change the policy:

MDRangePolicy (1)

MDRangePolicy can parallelize tightly nested loops of 1 to 6 dimensions.

▶ Specify the dimensionality of the loop with *Rank* < *DIM* >.

- ▶ Specify the dimensionality of the loop with *Rank* < *DIM* >.
- As with Kokkos Views: only rectangular iteration spaces.

- ▶ Specify the dimensionality of the loop with *Rank* < *DIM* >.
- ► As with Kokkos Views: only rectangular iteration spaces.
- Provide initializer lists for begin and end values.

- ▶ Specify the dimensionality of the loop with *Rank* < *DIM* >.
- ► As with Kokkos Views: only rectangular iteration spaces.
- Provide initializer lists for begin and end values.
- The functor/lambda takes matching number of indicies.



```
double result;
parallel_reduce("Label",
    MDRangePolicy <Rank <3>>({0,0,0}, {N0,N1,N2}),
    KOKKOS_LAMBDA(int i, int j, int k, double& lsum) {
        /* loop body */
    lsum += something;
}, result);
```



The Policy doesn't change the rules for 'parallel_reduce'.



- The Policy doesn't change the rules for 'parallel_reduce'.
- Additional Thread Local Argument.



```
double result;
parallel_reduce("Label",
    MDRangePolicy <Rank <3>>({0,0,0}, {N0,N1,N2}),
    KOKKOS_LAMBDA(int i, int j, int k, double& lsum) {
        /* loop body */
    lsum += something;
}, result);
```

- The Policy doesn't change the rules for 'parallel_reduce'.
- Additional Thread Local Argument.
- Can do other reductions with reducers.



```
double result;
parallel_reduce("Label",
    MDRangePolicy<Rank<3>>({0,0,0},{N0,N1,N2}),
    KOKKOS_LAMBDA(int i, int j, int k, double& lsum) {
        /* loop body */
        lsum += something;
}, result);
```

- The Policy doesn't change the rules for 'parallel_reduce'.
- Additional Thread Local Argument.
- Can do other reductions with reducers.
- Can use 'View's as reduction argument.



```
double result;
parallel_reduce("Label",
    MDRangePolicy<Rank<3>>({0,0,0},{N0,N1,N2}),
    KOKKOS_LAMBDA(int i, int j, int k, double& lsum) {
        /* loop body */
        lsum += something;
}, result);
```

- The Policy doesn't change the rules for 'parallel_reduce'.
- Additional Thread Local Argument.
- Can do other reductions with reducers.
- Can use 'View's as reduction argument.
- Multiple reducers not yet implemented though.

In structured grid applications a **tiling** strategy is often used to help with caching.

Tiling

MDRangePolicy uses a tiling strategy for the iteration space.

Specified as a third initializer list.

For GPUs a tile is handled by a single thread block.

If you provide too large a tile size this will fail!

In Kokkos 3.3 we will add auto tuning for tile sizes.

```
double result;
parallel_reduce("Label",
    MDRangePolicy<Rank<3>>({0,0,0},{N0,N1,N2},{T0,T1,T2}),
    KOKKOS_LAMBDA(int i, int j, int k, double& lsum) {
        /* loop body */
        lsum += something;
}, result);
```

Initializing a Matrix:

```
View<double**,LayoutLeft> A("A",N0,N1);
parallel_for("Label",
    MDRangePolicy<Rank<2>>({0,0},{N0,N1}),
    KOKKOS_LAMBDA(int i, int j) {
        A(i,j) = 1000.0 * i + 1.0*j;
});
View<double**,LayoutRight> B("B",N0,N1);
parallel_for("Label",
        MDRangePolicy<Rank<2>>({0,0},{N0,N1}),
        KOKKOS_LAMBDA(int i, int j) {
        B(i,j) = 1000.0 * i + 1.0*j;
});
```

MDRangePolicy (5)

Initializing a Matrix:

```
View<double**,LayoutLeft> A("A",N0,N1);
parallel_for("Label",
    MDRangePolicy<Rank<2>>({0,0},{N0,N1}),
    KOKKOS_LAMBDA(int i, int j) {
        A(i,j) = 1000.0 * i + 1.0*j;
});
View<double**,LayoutRight> B("B",N0,N1);
parallel_for("Label",
    MDRangePolicy<Rank<2>>({0,0},{N0,N1}),
    KOKKOS_LAMBDA(int i, int j) {
        B(i,j) = 1000.0 * i + 1.0*j;
});
```

How do I make sure that I get the right access pattern?

MDRangePolicy (5)

Iteration Pattern

MDRangePolicy provides compile time control over iteration patterns.

Kokkos::Rank
 N, IterateOuter, IterateInner >

- ▶ N: (Required) the rank of the index space (limited from 2 to 6)
- IterateOuter (Optional) iteration pattern between tiles
 - Options: Iterate::Left, Iterate::Right, Iterate::Default
- IterateInner (Optional) iteration pattern within tiles
 - **Options:** Iterate::Left, Iterate::Right, Iterate::Default

Initializing a Matrix fast:

```
View<double**,LayoutLeft> A("A",N0,N1);
parallel for ("Label".
  MDRangePolicy <Rank <2, Iterate::Left, Iterate::Left>>(
        \{0,0\},\{N0,N1\}\},\
  KOKKOS_LAMBDA(int i, int j) {
    A(i,j) = 1000.0 * i + 1.0*j;
});
View<double**,LayoutRight> B("B",N0,N1);
parallel_for("Label",
  MDRangePolicy <Rank <2, Iterate :: Right, Iterate :: Right >> (
        \{0.0\},\{N0,N1\}\},\
  KOKKOS_LAMBDA(int i, int j) {
    B(i,j) = 1000.0 * i + 1.0*j;
});
```

MDRangePolicy (7)

Initializing a Matrix fast:

```
View<double**,LayoutLeft> A("A",N0,N1);
parallel_for("Label",
  MDRangePolicy <Rank <2, Iterate::Left, Iterate::Left>>(
        \{0,0\},\{N0,N1\}\},\
  KOKKOS_LAMBDA(int i, int j) {
    A(i,j) = 1000.0 * i + 1.0*j;
});
View<double**,LayoutRight> B("B",N0,N1);
parallel_for("Label",
  MDRangePolicy <Rank <2, Iterate::Right, Iterate::Right>>(
        {0.0}, {N0, N1}),
  KOKKOS_LAMBDA(int i, int j) {
    B(i,j) = 1000.0 * i + 1.0*j;
});
```

Default Patterns Match

Default iteration patterns match the default memory layouts!

MDRangePolicy (7)

Exercise - mdrange: Initialize multi-dim views with MDRangePolicy

Details:

- Location: Exercises/mdrange/Begin/
- This begins with the Solution of 02
- Initialize the device Views x and y directly on the device using a parallel for and RangePolicy
- Initialize the device View matrix A directly on the device using a parallel for and MDRangePolicy

```
# 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
./mdrange_exercise.cuda -S 26
```

Template Parameters common to ALL policies.

ExecutionSpace: control where code executes

Options: Serial, OpenMP, Threads, Cuda, HIP, ...

Schedule<Options>: set scheduling policy.

Options: Static, Dynamic

IndexType<Options>: control internal indexing type

Options: int, long, etc

WorkTag: enables multiple operators in one functor

```
struct Foo {
   struct Tag1{}; struct Tag2{};
   KOKKOS_FUNCTION void operator(Tag1, int i) const {...}
   KOKKOS_FUNCTION void operator(Tag2, int i) const {...}
   void run_both(int N) {
      parallel_for(RangePolicy<Tag1>(0,N),*this);
      parallel_for(RangePolicy<Tag2>(0,N),*this);
   }
});
```

- allows for tightly nested loops similar to OpenMP's collapse clause.
- requires functors/lambdas with as many parameters as its rank is.
- works with parallel_for and parallel_reduce.
- uses a tiling strategy for the iteration space.
- provides compile time control over iteration patterns.

Hierarchical parallelism

Finding and exploiting more parallelism in your computations.

Learning objectives:

- Similarities and differences between outer and inner levels of parallelism
- Thread teams (league of teams of threads)
- Performance improvement with well-coordinated teams

thread

(Flat parallel) Kernel:

```
Kokkos::parallel_reduce("yAx",N,
KOKKOS_LAMBDA (const int row, double & valueToUpdate) {
    double thisRowsSum = 0;
    for (int col = 0; col < M; ++col) {
        thisRowsSum += A(row,col) * x(col);
    }
    valueToUpdate += y(row) * thisRowsSum;
}, result);
</pre>
```



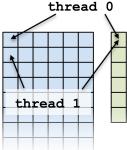
August 3, 2023

(Flat parallel) Kernel:

```
Kokkos::parallel_reduce("yAx",N,
KOKKOS_LAMBDA (const int row, double & valueToUpdate) {
    double thisRowsSum = 0;
    for (int col = 0; col < M; ++col) {
        thisRowsSum += A(row,col) * x(col);
    }
    valueToUpdate += y(row) * thisRowsSum;
}, result);
    thread 0</pre>
```

Problem: What if we don't have enough rows to saturate the GPU?





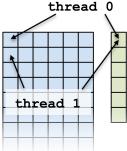
(Flat parallel) Kernel:

```
Kokkos::parallel_reduce("yAx",N,
KOKKOS_LAMBDA (const int row, double & valueToUpdate) {
    double thisRowsSum = 0;
    for (int col = 0; col < M; ++col) {
        thisRowsSum += A(row,col) * x(col);
    }
    valueToUpdate += y(row) * thisRowsSum;
}, result);
    thread 0</pre>
```

Problem: What if we don't have enough rows to saturate the GPU?

Solutions?





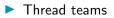
(Flat parallel) Kernel:

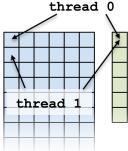
```
Kokkos::parallel_reduce("yAx",N,
KOKKOS_LAMBDA (const int row, double & valueToUpdate) {
    double thisRowsSum = 0;
    for (int col = 0; col < M; ++col) {
        thisRowsSum += A(row,col) * x(col);
    }
    valueToUpdate += y(row) * thisRowsSum;
}, result);
    thread 0</pre>
```

Problem: What if we don't have enough rows to saturate the GPU?

Solutions? Atomics

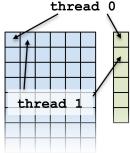






Atomics kernel:

```
Kokkos::parallel_for("yAx", N*M,
KOKKOS_LAMBDA (const size_t index) {
    const int row = extractRow(index);
    const int col = extractCol(index);
    atomic_add(&result, y(row) * A(row,col) * x(col));
});
thread 0
```

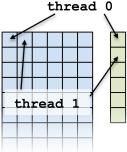


Atomics kernel:

```
Kokkos::parallel_for("yAx", N*M,
KOKKOS_LAMBDA (const size_t index) {
    const int row = extractRow(index);
    const int col = extractCol(index);
    atomic_add(&result, y(row) * A(row,col) * x(col));
});
    thread 0
```

Problem: Poor performance





Using an atomic with every element is doing scalar integration with atomics. (See module 3)

Instead, you could envision doing a large number of parallel_reduce kernels.

```
for each row
  Functor functor(row, ...);
  parallel_reduce(M, functor);
}
```

Using an atomic with every element is doing scalar integration with atomics. (See module 3)

Instead, you could envision doing a large number of parallel_reduce kernels.

```
for each row
  Functor functor(row, ...);
  parallel_reduce(M, functor);
}
```

This is an example of *hierarchical work*.

Important concept: Hierarchical parallelism

Algorithms that exhibit hierarchical structure can exploit hierarchical parallelism with **thread teams**.

Important concept: Thread team

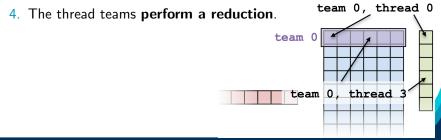
A collection of threads which are guaranteed to be executing **concurrently** and **can synchronize**.

Important concept: Thread team

A collection of threads which are guaranteed to be executing **concurrently** and **can synchronize**.

High-level strategy:

- 1. Do one parallel launch of N teams.
- 2. Each team handles a row.
- 3. The threads within teams perform a reduction.



The final hierarchical parallel kernel:

```
parallel_reduce("vAx",
 team_policy(N, Kokkos::AUTO),
  KOKKOS_LAMBDA (const member_type & teamMember, double & update)
    int row = teamMember.league_rank();
    double thisRowsSum = 0:
    parallel_reduce(TeamThreadRange(teamMember, M),
      [=] (int col, double & innerUpdate) {
        innerUpdate += A(row, col) * x(col);
      }, thisRowsSum);
    if (teamMember.team rank() == 0) {
      update += y(row) * thisRowsSum;
   }
 }, result);
```

Important point

Using teams is changing the execution policy.

```
"Flat parallelism" uses RangePolicy:
    We specify a total amount of work.
// total work = N
parallel_for("Label",
    RangePolicy<ExecutionSpace>(0,N), functor);
```

TeamPolicy (0)

Important point

Using teams is changing the execution *policy*.

```
"Flat parallelism" uses RangePolicy:
    We specify a total amount of work.
// total work = N
parallel_for("Label",
    RangePolicy<ExecutionSpace>(0,N), functor);
```

"Hierarchical parallelism" uses TeamPolicy:

We specify a *team size* and a *number of teams*.

```
// total work = numberOfTeams * teamSize
parallel_for("Label",
   TeamPolicy<ExecutionSpace>(numberOfTeams, teamSize), functor);
```

TeamPolicy (0)

Important point

When using teams, functor operators receive a team member.

```
using member_type = typename TeamPolicy <ExecSpace >::member_type;
```

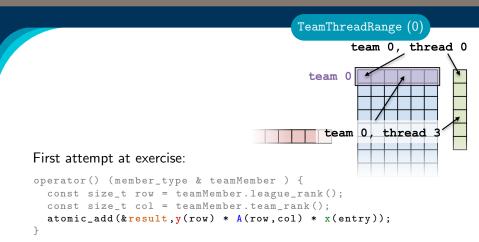
void operator()(const member_type & teamMember) {
 // How many teams are there?
 const unsigned int league_size = teamMember.league_size();

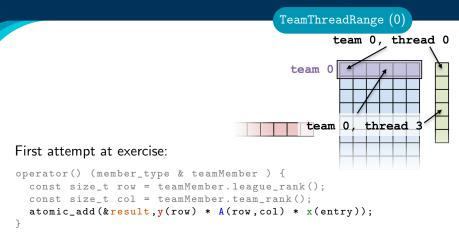
// Which team am I on?
const unsigned int league_rank = teamMember.league_rank();

// How many threads are in the team?
const unsigned int team_size = teamMember.team_size();

// Which thread am I on this team?
const unsigned int team_rank = teamMember.team_rank();

// Make threads in a team wait on each other: teamMember.team_barrier(); TeamPolicy (1)





When team size ≠ number of columns, how are units of work mapped to team's member threads? Is the mapping architecture-dependent? Second attempt at exercise:

Divide row length among team members.

```
operator() (member_type & teamMember ) {
  const size_t row = teamMember.league_rank();
  int begin = teamMember.team_rank();
  for(int col = begin; col < M; col += teamMember.team_size()) {
    atomic_add(&result, y(row) * A(row,col) * x(entry));
  }
}</pre>
```

Second attempt at exercise:

Divide row length among team members.

```
operator() (member_type & teamMember ) {
  const size_t row = teamMember.league_rank();
  int begin = teamMember.team_rank();
  for(int col = begin; col < M; col += teamMember.team_size()) {
    atomic_add(&result, y(row) * A(row,col) * x(entry));
  }
}</pre>
```

- Still bad because atomic_add performs badly under high contention, how can team's member threads performantly cooperate for a nested reduction?
- On CPUs you get a bad data access pattern: this hardcodes coalesced access, but not caching.

```
operator() (member_type & teamMember, double & update) {
  const int row = teamMember.league_rank();
  double thisRowsSum;
  ''do a reduction''(''over M columns''),
  [=] (const int col) {
    thisRowsSum += A(row,col) * x(col);
  });
  if (teamMember.team_rank() == 0) {
    update += (row) * thisRowsSum;
  }
}
```

```
operator() (member_type & teamMember, double & update) {
  const int row = teamMember.league_rank();
  double thisRowsSum;
  ''do a reduction')(''over M columns''),
  [=] (const int col) {
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    });
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  }
}
```

If this were a parallel execution, we'd use Kokkos::parallel_reduce.

```
operator() (member_type & teamMember, double & update) {
  const int row = teamMember.league rank();
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    update += (row) * thisRowsSum;
  }
}
If this were a parallel execution,
    we'd use Kokkos::parallel_reduce.
Key idea: this is a parallel execution.
```

```
operator() (member_type & teamMember, double & update) {
  const int row = teamMember.league_rank();
  double thisRowsSum;
  ''do a reduction''(''over M columns'',
    [=] (const int col) {
     thisRowsSum += A(row,col) * x(col);
    });
  if (teamMember.team_rank() == 0) {
     update += (row) * thisRowsSum;
  }
}
```

If this were a parallel execution,

we'd use Kokkos::parallel_reduce.

Key idea: this is a parallel execution.

```
\Rightarrow Nested parallel patterns
```

TeamThreadRange:

```
operator() (const member_type & teamMember, double & update ) {
  const int row = teamMember.league_rank();
  double thisRowsSum;
  parallel_reduce(TeamThreadRange(teamMember, M),
    [=] (const int col, double & thisRowsPartialSum ) {
    thisRowsPartialSum += A(row, col) * x(col);
    }, thisRowsSum );
    if (teamMember.team_rank() == 0) {
        update += y(row) * thisRowsSum;
    }
}
```

TeamThreadRange:

```
operator() (const member_type & teamMember, double & update ) {
  const int row = teamMember.league_rank();
  double thisRowsSum;
  parallel_reduce(TeamThreadRange(teamMember, M),
    [=] (const int col, double & thisRowsPartialSum ) {
    thisRowsPartialSum += A(row, col) * x(col);
    }, thisRowsSum );
    if (teamMember.team_rank() == 0) {
        update += y(row) * thisRowsSum;
    }
}
```

- The mapping of work indices to threads is architecture-dependent.
- The amount of work given to the TeamThreadRange need not be a multiple of the team_size.
- Intrateam reduction handled by Kokkos.

Anatomy of nested parallelism:

```
parallel_outer("Label",
  TeamPolicy<ExecutionSpace>(numberOfTeams, teamSize),
  KOKKOS_LAMBDA (const member_type & teamMember[, ...]) {
    /* beginning of outer body */
    parallel_inner(
       TeamThreadRange(teamMember, thisTeamsRangeSize),
       [=] (const unsigned int indexWithinBatch[, ...]) {
        /* inner body */
        }[, ...]);
        /* end of outer body */
        }[, ...]);
        /* end of outer body */
        }[, ...]);
```

- parallel_outer and parallel_inner may be any combination of for and/or reduce.
- The inner lambda may capture by reference, but capture-by-value is recommended.
- The policy of the inner lambda is always a TeamThreadRange.
- TeamThreadRange cannot be nested.

In practice, you can let Kokkos decide:

```
parallel_something(
   TeamPolicy<ExecutionSpace>(numberOfTeams, Kokkos::AUTO),
   /* functor */);
```

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```
parallel_something(
   TeamPolicy<ExecutionSpace>(numberOfTeams, Kokkos::AUTO),
   /* functor */);
```

GPUs

- Special hardware available for coordination within a team.
- Within a team 32 (NVIDIA) or 64 (AMD) threads execute "lock step."
- Maximum team size: 1024; Recommended team size: 128/256

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```
parallel_something(
   TeamPolicy<ExecutionSpace>(numberOfTeams, Kokkos::AUTO),
   /* functor */);
```

GPUs

- Special hardware available for coordination within a team.
- Within a team 32 (NVIDIA) or 64 (AMD) threads execute "lock step."
- Maximum team size: 1024; Recommended team size: 128/256

Intel Xeon Phi:

- Recommended team size: # hyperthreads per core
- Hyperthreads share entire cache hierarchy a well-coordinated team avoids cache-thrashing

Details:

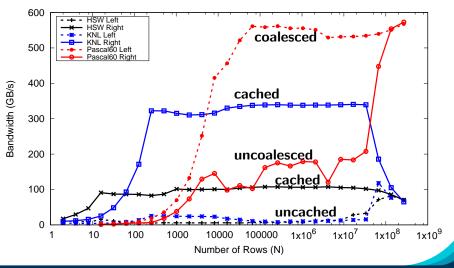
- Location: Exercises/team_policy/
- Replace RangePolicy<Space> with TeamPolicy<Space>
- Use AUTO for team_size
- Make the inner loop a parallel_reduce with TeamThreadRange policy
- Experiment with the combinations of Layout, Space, N to view performance
- Hint: what should the layout of A be?

Things to try:

- Vary problem size and number of rows (-S ...; -N ...)
- Compare behavior with Exercise 4 for very non-square matrices
- Compare behavior of CPU vs GPU

Reminder, Exercise #4 with Flat Parallelism <y|Ax> Exercise 04 (Layout) Fixed Size

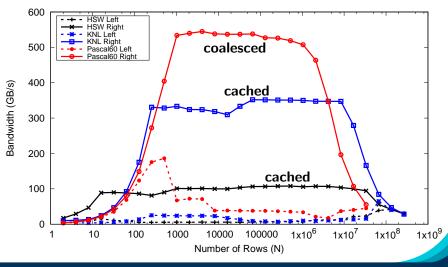
KNL: Xeon Phi 68c HSW: Dual Xeon Haswell 2x16c Pascal60: Nvidia GPU



August 3, 2023

<y|Ax> Exercise 05 (Layout/Teams) Fixed Size

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



August 3, 2023

Exposing Vector Level Parallelism

- Optional third level in the hierarchy: ThreadVectorRange
 - Can be used for parallel_for, parallel_reduce, or parallel_scan.
- Maps to vectorizable loop on CPUs or (sub-)warp level parallelism on GPUs.
- Enabled with a runtime vector length argument to TeamPolicy
- There is no explicit access to a vector lane ID.
- Depending on the backend the full global parallel region has active vector lanes.
- TeamVectorRange uses both thread and vector parallelism.

Anatomy of nested parallelism:

```
parallel_outer("Label",
   TeamPolicy <> (numberOfTeams, teamSize, vectorLength),
   KOKKOS_LAMBDA (const member_type & teamMember [, ...]) {
     /* beginning of outer body */
     parallel_middle(
       TeamThreadRange(teamMember, thisTeamsRangeSize),
        [=] (const int indexWithinBatch [, ...]) {
         /* begin middle body */
         parallel_inner(
             ThreadVectorRange(teamMember, thisVectorRangeSize),
             [=] (const int indexVectorRange[, ...]) {
              /* inner body */
            }[, ....);
         /* end middle body */
       \{[, \ldots]\}
     parallel_middle(
      TeamVectorRange(teamMember, someSize),
       [=] (const int indexTeamVector[, ...]) {
         /* nested body */
       \{[, \ldots]\};
     /* end of outer body */
   <u>}[, ..</u>]):
August 3, 2023
                                                               96/126
```

```
int totalSum = 0;
parallel_reduce("Sum", RangePolicy<>(0, numberOfThreads),
   KOKKOS_LAMBDA (size_t& index, int& partialSum) {
      int thisThreadsSum = 0;
      for (int i = 0; i < 10; ++i) {
         ++thisThreadsSum;
      }
      partialSum += thisThreadsSum;
}, totalSum);
```

```
int totalSum = 0;
parallel_reduce("Sum", RangePolicy<>(0, numberOfThreads),
   KOKKOS_LAMBDA (size_t& index, int& partialSum) {
     int thisThreadsSum = 0;
     for (int i = 0; i < 10; ++i) {
        ++thisThreadsSum;
     }
     partialSum += thisThreadsSum;
}, totalSum);
```

totalSum = numberOfThreads * 10

```
int totalSum = 0;
parallel_reduce("Sum", TeamPolicy<>(numberOfTeams, team_size),
    KOKKOS_LAMBDA (member_type& teamMember, int& partialSum) {
    int thisThreadsSum = 0;
    for (int i = 0; i < 10; ++i) {
        ++thisThreadsSum;
    }
    partialSum += thisThreadsSum;
}, totalSum);
```

```
int totalSum = 0;
parallel_reduce("Sum", TeamPolicy<>(numberOfTeams, team_size),
    KOKKOS_LAMBDA (member_type& teamMember, int& partialSum) {
    int thisThreadsSum = 0;
    for (int i = 0; i < 10; ++i) {
        ++thisThreadsSum;
    }
    partialSum += thisThreadsSum;
}, totalSum);
```

totalSum = numberOfTeams * team_size * 10

```
int totalSum = 0;
parallel_reduce("Sum", TeamPolicy<>(numberOfTeams, team_size),
   KOKKOS_LAMBDA (member_type& teamMember, int& partialSum) {
    int thisTeamsSum = 0;
    parallel_reduce(TeamThreadRange(teamMember, team_size),
      [=] (const int index, int& thisTeamsPartialSum) {
      int thisThreadsSum = 0;
      for (int i = 0; i < 10; ++i) {
        ++thisThreadsSum;
      }
      thisTeamsPartialSum += thisThreadsSum;
    }, thisTeamsSum);
    partialSum += thisTeamsSum;
}, totalSum);
```

```
int totalSum = 0;
parallel_reduce("Sum", TeamPolicy<>(numberOfTeams, team_size),
   KOKKOS_LAMBDA (member_type& teamMember, int& partialSum) {
    int thisTeamsSum = 0;
    parallel_reduce(TeamThreadRange(teamMember, team_size),
      [=] (const int index, int& thisTeamsPartialSum) {
      int thisThreadSSum = 0;
      for (int i = 0; i < 10; ++i) {
        ++thisThreadsSum;
      }
      thisTeamsPartialSum += thisThreadsSum;
    }, thisTeamsSum);
    partialSum += thisTeamsSum;
}, totalSum);
```

totalSum = numberOfTeams * team_size * team_size * 10

The single pattern can be used to restrict execution

- Like parallel patterns it takes a policy, a lambda, and optionally a broadcast argument.
- Two policies: PerTeam and PerThread.
- Equivalent to OpenMP single directive with nowait

The previous example was extended with an outer loop over "Elements" to expose a third natural layer of parallelism.

Details:

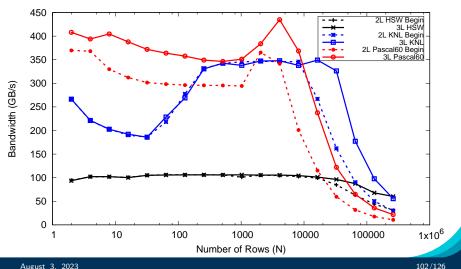
- Location: Exercises/team_vector_loop/
- Use the single policy instead of checking team rank
- Parallelize all three loop levels.

Things to try:

- Vary problem size and number of rows (-S ...; -N ...)
- Compare behavior with TeamPolicy Exercise for very non-square matrices
- Compare behavior of CPU vs GPU

<y|Ax> Exercise 06 (Three Level Parallelism) Fixed Size





- Hierarchical work can be parallelized via hierarchical parallelism.
- Hierarchical parallelism is leveraged using thread teams launched with a TeamPolicy.
- Team "worksets" are processed by a team in nested parallel_for (or reduce or scan) calls with a TeamThreadRange, ThreadVectorRange, and TeamVectorRange policy.
- Execution can be restricted to a subset of the team with the single pattern using either a PerTeam or PerThread policy.

Scratch memory

Learning objectives:

- Understand concept of team and thread private scratch pads
- Understand how scratch memory can reduce global memory accesses
- Recognize when to use scratch memory
- Understand how to use scratch memory and when barriers are necessary

Two Levels of Scratch Space

- Level 0 is limited in size but fast.
- Level 1 allows larger allocations but is equivalent to High Bandwidth Memory in latency and bandwidth.

Team or Thread private memory

- Typically used for per work-item temporary storage.
- Advantage over pre-allocated memory is aggregate size scales with number of threads, not number of work-items.

Manually Managed Cache

- Explicitly cache frequently used data.
- Exposes hardware specific on-core scratch space (e.g. NVIDIA GPU Shared Memory).

Two Levels of Scratch Space

- Level 0 is limited in size but fast.
- Level 1 allows larger allocations but is equivalent to High Bandwidth Memory in latency and bandwidth.

Team or Thread private memory

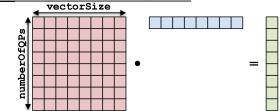
- Typically used for per work-item temporary storage.
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Manually Managed Cache

- Explicitly cache frequently used data.
- Exposes hardware specific on-core scratch space (e.g. NVIDIA GPU Shared Memory).

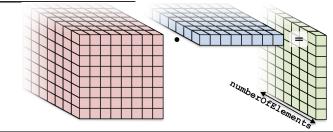
Now: Discuss Manually Managed Cache Usecase.

One slice of contractDataFieldScalar:



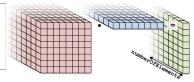
```
for (qp = 0; qp < numberOfQPs; ++qp) {
   total = 0;
   for (i = 0; i < vectorSize; ++i) {
      total += A(qp, i) * B(i);
   }
   result(qp) = total;
}</pre>
```

contractDataFieldScalar:



```
for (element = 0; element < numberOfElements; ++element) {
  for (qp = 0; qp < numberOfQPs; ++qp) {
    total = 0;
    for (i = 0; i < vectorSize; ++i) {
       total += A(element, qp, i) * B(element, i);
    }
    result(element, qp) = total;
}</pre>
```

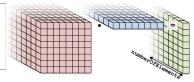
```
for (element = 0; element < numberOffElements; ++element) {
  for (ap = 0; ap < numberOfQPs; ++qp) {
    total = 0;
    for (i = 0; i < vectorSize; ++i) {
      total += A(element, qp, i) * B(element, i);
    }
    result(element, qp) = total;
  }
}</pre>
```



Parallelization approaches:

Each thread handles an element. Threads: numberOfElements

```
for (element = 0; element < numberOffElements; ++element) {
  for (qp = 0; qp < numberOfQPs; ++qp) {
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    }
    result(element, qp) = total;
  }
}</pre>
```

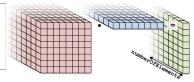


Parallelization approaches:

- Each thread handles an element. Threads: numberOfElements
- Each thread handles a qp.

Threads: numberOfElements * numberOfQPs

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    }
    result(element, qp) = total;
  }
}</pre>
```



Parallelization approaches:

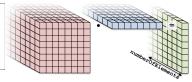
- Each thread handles an element. Threads: numberOfElements
- Each thread handles a qp.

Threads: numberOfElements * numberOfQPs

Each thread handles an i.

Threads: numElements * numQPs * vectorSize Requires a parallel_reduce.

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for (element = 0; element < numberOffElements; ++element) {
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    total = 0;
    for (i = 0; i < vectorSize; ++i) {
      total += A(element, qp, i) * B(element, i);
    }
    result(element, qp) = total;
    }
}</pre>
```



Parallelization approaches:

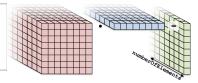
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 Threads: numberOfElements
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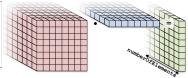
```
for (element = 0; element < numberOffElements; ++element) {
  for (qp = 0; qp < numberOfQPs; ++qp) {
    total = 0;
    for (i = 0; i < vectorSize; ++i) {
        total += A(element, qp, i) * B(element, i);
    }
    result(element, qp) = total;
}</pre>
```



Flat kernel: Each thread handles a quadrature point

```
parallel_for("L",MDRangePolicy<Rank<2>>({0,0},{numE,numQP}),
   KOKKOS_LAMBDA(int element, int qp) {
   double total = 0;
   for (int i = 0; i < vectorSize; ++i) {
      total += A(element, qp, i) * B(element, i);
   }
   result(element, qp) = total;
}
```

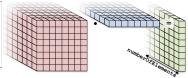
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for (element = 0; element < numberOffElements; ++element) {
  for (ap = 0; ap < numberOfQPs; ++ap) {
    total = 0;
    for (i = 0; i < vectorSize; ++i) {
      total += A(element, qp, i) * B(element, i);
    }
    result(element, qp) = total;
  }
}</pre>
```



Teams kernel: Each team handles an element

```
operator()(member_type teamMember) {
    int element = teamMember.league_rank();
    parallel_for(
        TeamThreadRange(teamMember, numberOfQPs),
        [=] (int qp) {
            double total = 0;
            for (int i = 0; i < vectorSize; ++i) {
                total += A(element, qp, i) * B(element, i);
            }
            result(element, qp) = total;
        });
}</pre>
```

```
for (element = 0; element < numberOffElements; ++element) {
  for (ap = 0; ap < numberOfQPs; ++ap) {
    total = 0;
    for (i = 0; i < vectorSize; ++i) {
      total += A(element, qp, i) * B(element, i);
    }
    result(element, qp) = total;
  }
}</pre>
```



Teams kernel: Each team handles an element

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    int element = teamMember.league_rank();
    parallel_for(
        TeamThreadRange(teamMember, numberOfQPs),
        [=] (int qp) {
            double total = 0;
            for (int i = 0; i < vectorSize; ++i) {
               total += A(element, qp, i) * B(element, i);
            }
            result(element, qp) = total;
        });
            No real advantage (yet)
</pre>
```

Scratch memory (0)

Each team has access to a "scratch pad".

global memory team shared memory "scratch pad"

August 3, 2023

Scratch memory (scratch pad) as manual cache:

- Accessing data in (level 0) scratch memory is (usually) much faster than global memory.
- GPUs have separate, dedicated, small, low-latency scratch memories (*NOT* subject to coalescing requirements).
- **CPUs** don't have special hardware, but programming with scratch memory results in cache-aware memory access patterns.
- Roughly, it's like a user-managed L1 cache.

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- **CPUs** don't have special hardware, but programming with scratch memory results in cache-aware memory access patterns.
- - Roughly, it's like a user-managed L1 cache.

Important concept

When members of a team read the same data multiple times, it's better to load the data into scratch memory and read from there.



Scratch memory for temporary per work-item storage:

- Scenario: Algorithm requires temporary workspace of size W.
- Without scratch memory: pre-allocate space for N work-items of size N x W.
- With scratch memory: Kokkos pre-allocates space for each Team or Thread of size T x W.
- PerThread and PerTeam scratch can be used concurrently.
- Level 0 and Level 1 scratch memory can be used concurrently.



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- Scenario: Algorithm requires temporary workspace of size W.
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- Level 0 and Level 1 scratch memory can be used concurrently.

Important concept

If an algorithm requires temporary workspace for each work-item, then use Kokkos' scratch memory.

To use scratch memory, you need to:

- 1. Tell Kokkos how much scratch memory you'll need.
- 2. Make scratch memory views inside your kernels.

Scratch memory (3)

To use scratch memory, you need to:

- 1. Tell Kokkos how much scratch memory you'll need.
- 2. Make scratch memory views inside your kernels.

TeamPolicy <ExecutionSpace > policy(numberOfTeams, teamSize);

```
// Define a scratch memory view type
using ScratchPadView =
    View<double*,ExecutionSpace::scratch_memory_space>;
// Compute how much scratch memory (in bytes) is needed
size_t bytes = ScratchPadView::shmem_size(vectorSize);
// Tell the policy how much scratch memory is needed
int level = 0;
parallel_for(policy.set_scratch_size(level, PerTeam(bytes)),
    KOKKOS_LAMBDA (const member_type& teamMember) {
```

});

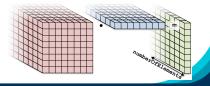
Scratch memory (3)

Kernel outline for teams with scratch memory:

```
operator()(member_type teamMember) {
  ScratchPadView scratch(teamMember.team_scratch(0),
                         vectorSize):
  // TODO: load slice of B into scratch
  parallel_for(
    TeamThreadRange(teamMember, numberOfQPs).
    [=] (int qp) {
      double total = 0:
      for (int i = 0; i < vectorSize; ++i) {</pre>
        // total += A(element, qp, i) * B(element, i);
        total += A(element, qp, i) * scratch(i);
     result(element, qp) = total;
   }):
```

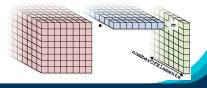
How to populate the scratch memory?

```
> One thread loads it all?
if (teamMember.team_rank() == 0) {
  for (int i = 0; i < vectorSize; ++i) {
    scratch(i) = B(element, i);
  }
}
```



August 3, 2023

How to populate the scratch memory?



August 3, 2023

How to populate the scratch memory?

> One thread loads it all? Serial if (teamMember.team_rank() == 0) { for (int i = 0; i < vectorSize; ++i) { scratch(i) = B(element, i); } } > Each thread loads one entry? teamSize ≠ vectorSize

```
scratch(team_rank) = B(element, team_rank);
```

TeamVectorRange

```
parallel_for(
  TeamVectorRange(teamMember, vectorSize),
  [=] (int i) {
    scratch(i) = B(element, i);
  });
```

How to populate the scratch memory?

```
> One thread loads it all? Serial
if (teamMember.team_rank() == 0) {
  for (int i = 0; i < vectorSize; ++i) {
    scratch(i) = B(element, i);
  }
}
> Each thread loads one entry? teamSize ≠ vectorSize
  scratch(team_rank) = B(element, team_rank);
```

TeamVectorRange

```
parallel_for(
  TeamVectorRange(teamMember, vectorSize),
  [=] (int i) {
    scratch(i) = B(element, i);
  });
```

(incomplete) Kernel for teams with scratch memory:

```
operator()(member_type teamMember) {
  ScratchPadView scratch(...);
  parallel_for(TeamVectorRange(teamMember, vectorSize),
    [=] (int i) {
      scratch(i) = B(element, i);
   }):
  // TODO: fix a problem at this location
  parallel_for(TeamThreadRange(teamMember, numberOfQPs),
    [=] (int qp) {
      double total = 0:
      for (int i = 0; i < vectorSize; ++i) {</pre>
        total += A(element, qp, i) * scratch(i);
      }
      result(element, qp) = total;
   });
}
```

(incomplete) Kernel for teams with scratch memory:

```
operator()(member_type teamMember) {
  ScratchPadView scratch(...);
  parallel_for(TeamVectorRange(teamMember, vectorSize),
    [=] (int i) {
      scratch(i) = B(element, i);
    }):
  // TODO: fix a problem at this location
  parallel_for(TeamThreadRange(teamMember, numberOfQPs),
    [=] (int qp) {
      double total = 0:
      for (int i = 0; i < vectorSize; ++i) {</pre>
        total += A(element, qp, i) * scratch(i);
      }
      result(element, qp) = total;
    });
7
Problem: threads may start to use scratch before all threads are
done loading.
```

August 3, 2023

Kernel for teams with scratch memory:

```
operator()(member_type teamMember) {
  ScratchPadView scratch(...);
  parallel_for(ThreadVectorRange(teamMember, vectorSize),
    [=] (int i) {
      scratch(i) = B(element, i);
    });
  teamMember.team_barrier();
```

```
parallel_for(TeamThreadRange(teamMember, numberOfQPs),
[=] (int qp) {
    double total = 0;
    for (int i = 0; i < vectorSize; ++i) {
        total += A(element, qp, i) * scratch(i);
    }
    result(element, qp) = total;
});</pre>
```

Use Scratch Memory to explicitly cache the x-vector for each element.

Details:

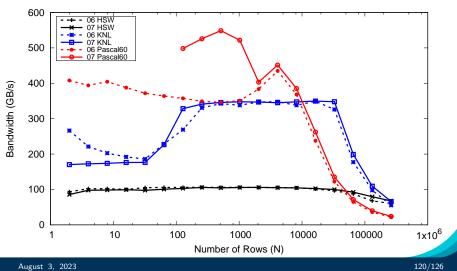
- Location: Exercises/team_scratch_memory/
- Create a scratch view
- Fill the scratch view in parallel using a TeamVectorRange

Things to try:

- ► Vary problem size and number of rows (-S ...; -N ...)
- Compare behavior with Exercise 6
- Compare behavior of CPU vs GPU

Exercise 07 (Scratch Memory) Fixed Size

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



Allocating scratch in different levels:

```
int level = 1; // valid values 0,1
policy.set_scratch_size(level,PerTeam(bytes));
```

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Using PerThread, PerTeam or both:

Allocating scratch in different levels:

```
int level = 1; // valid values 0,1
policy.set_scratch_size(level,PerTeam(bytes));
```

Using PerThread, PerTeam or both:

Using both levels of scratch:

```
policy.set_scratch_size(0,PerTeam(bytes0))
          .set_scratch_size(1,PerThread(bytes1));
```

Note: set_scratch_size() returns a new policy instance, it
doesn't modify the existing one.

- Scratch Memory can be use with the TeamPolicy to provide thread or team private memory.
- Usecase: per work-item temporary storage or manual caching.
- Scratch memory exposes on-chip user managed caches (e.g. on NVIDIA GPUs)
- The size must be determined before launching a kernel.
- ► Two levels are available: large/slow and small/fast.

Full BuildSystem integration.

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- ► Non-Sum reductions / multiple reductions.

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- Math Kernels (KokkosKernels).

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.

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