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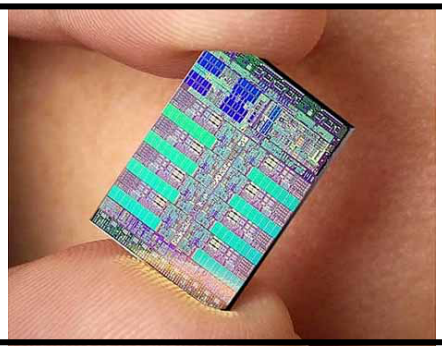
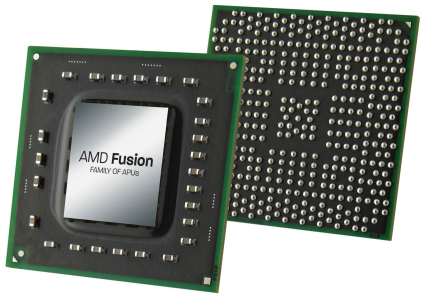

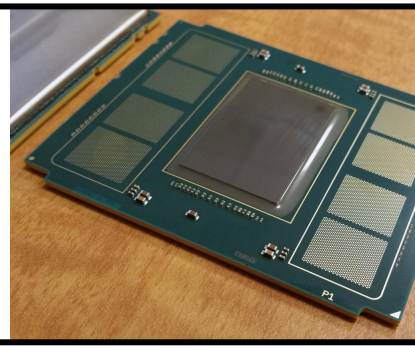

KokkosKernels Overview

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Center for Computing Research

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Unclassified Unlimited Release

SAND2020-6470 TR

U.S. DEPARTMENT OF ENERGY

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Presentation outline

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1. Introduction
2. Dense linear algebra: BLAS capabilities
3. Team level linear algebra: BatchedBLAS
4. Sparse linear algebra, preconditioners and graph kernels
5. Build system using Cmake

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Goal of the Project

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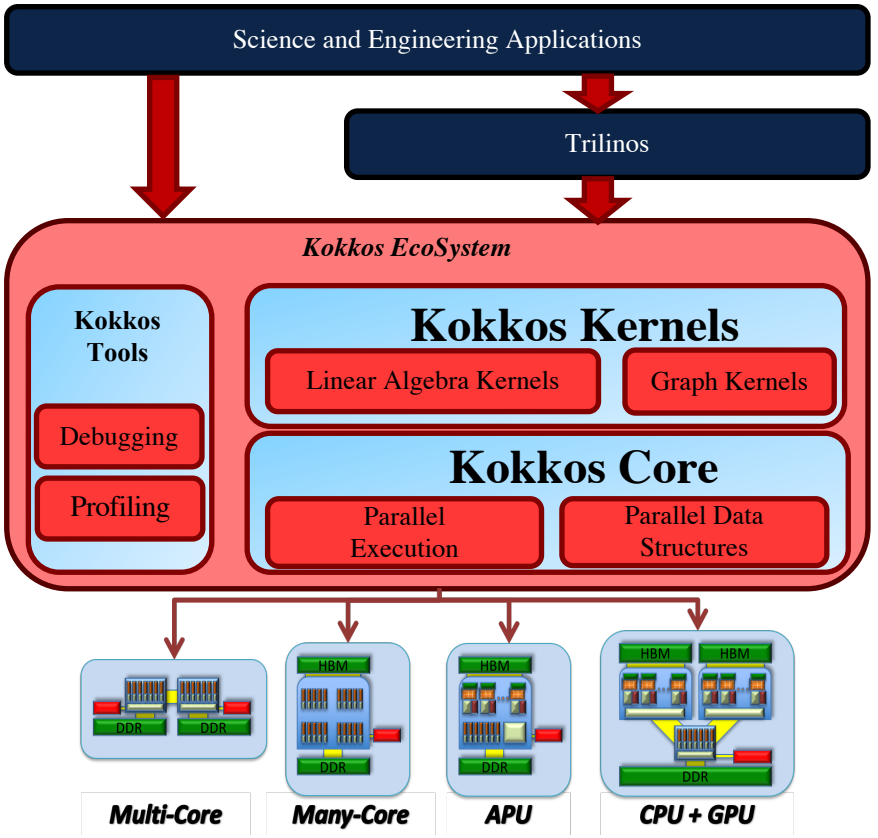
KokkosKernels provides math kernels for dense and sparse linear algebra as well as graph computations. It has multiple aims:

- Portable BLAS, Sparse and Graph kernels
- Generic implementations for various scalar types and data layouts
- Access to major vendor optimized math libraries.
- Expand the scope of BLAS to hierarchical implementations.



KokkosKernels Tutorial and Exercises

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The hands-on exercises that follow demonstrate representative examples from the following categories of capabilities:

- BLAS and Team-based BLAS kernels
- Batched BLAS kernels
- Sparse linear-algebra kernels
- Sparse graph kernels
- Conjugate Gradient examples (Sparse matrix CG and Preconditioned CG)

Exercise location:
https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels

Preliminary step: run the **run_installlibs_cmake.sh** script

- This will install kokkos, kokkos-kernels, and run CMake to generate a Makefile

The KokkosKernels Wiki will be a useful API reference for the exercises:
https://github.com/kokkos/kokkos-kernels/wiki/APIReference

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Capabilities I: BLAS

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BLAS

BLAS-1 functions are available as multi-vector variants.

– abs(y,x)	y[i] = |x[i]|
– axpy(alpha,x,y)	y[i] += alpha * x[i]
– axpby(alpha,x,beta,y)	y[i] = beta * y + alpha * x[i]
– dot(x,y)	dot = SUM_i (x[i] * y[i])
– fill(x,alpha)	x[i] = alpha
– iamax(x)	i = min{i of MAX_i(x[i]) }
– mult(gamma,y,alpha,A,x)	y[i] = gamma * y[i] + alpha * A[i] * x[i]
– nrm1(x)	nrm1 = SUM_i(|x[i]|)
– nrm2(x)	nrm2 = sqrt (SUM_i(|x[i]| * |x[i]|))
– nrm2w(x,w)	nrm2w = sqrt (SUM_i((|x[i]|/|w[i]|)^2))
– nrminf(x)	nrminf = MAX_i(|x[i]|)
– reciprocal(r,x)	r[i] = 1 / x[i]
– scal(y,alpha,x)	y[i] = alpha * x[i]
– sum(x)	sum = SUM_i(x[i])
– update(a,x,b,y,g,z)	y[i] = g * z[i] + b * y[i] + a * x[i]
– gemv(t,alph,A,x,bet,y)	y[i] = bet*y[i] + alph*SUM_j(A[i,j]*x[j])
– gemm(tA,tB,alph,A,B,bet,C)	C[i,j]=bet*C[i,j]+alph*SUM_k(A[i,k]*B[k,j])
– trmm(s,uplo,t,d,alpha,A,B)	B = alpha*op(A)*B or alpha*B*op(A)
– trsm(s,uplo,t,d,alpha,A,B)	X = op(A)\alpha*B or alpha*B/op(A)

Capabilities II: LAPACK and TeamBLAS

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BLAS/LAPACK

- GESV
- TRTRI

TEAM

- abs
- axpby
- dot
- mult
- norm2
- scal
- update

Capabilities I: BLAS

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BLAS

BLAS-1 functions are available as multi-vector variants.

```
- abs(y,x)                    y[i]   = |x[i]|
- axpy(alpha,x,y)             y[i]  += alpha * x[i]
- axpby(alpha,x,beta,y)       y[i]   = beta * y + alpha * x[i]
- dot(x,y)                    dot    = SUM_i ( x[i] * y[i] )
- fill(x,alpha)               x[i]   = alpha
- iamax(x)                    i      = min{i of MAX_i(x[i]) }
- mult(gamma,y,alpha,A,x)     y[i]   = gamma * y[i] + alpha * A[i] * x[i]
- nrm1(x)                     nrm1   = SUM_i( |x[i]| )
- nrm2(x)                     nrm2   = sqrt ( SUM_i(  |x[i]| * |x[i]| ))
- nrm2w(x,w)                  nrm2w  = sqrt ( SUM_i( (|x[i]|/|w[i]|)^2 ))
- nrminf(x)                   nrminf = MAX_i( |x[i]| )
- reciprocal(r,x)             r[i]   = 1 / x[i]
- scal(y,alpha,x)             y[i]   = alpha * x[i]
- sum(x)                      sum    = SUM_i( x[i] )
- update(a,x,b,y,g,z)         y[i]   = g * z[i] + b * y[i] + a * x[i]
- gemv(t,alph,A,x,bet,y)      y[i]   = bet*y[i] + alph*SUM_j(A[i,j]*x[j])
- gemm(tA,tB,alph,A,B,bet,C)  C[i,j]=bet*C[i,j]+alph*SUM_k(A[i,k]*B[k,j])
- trmm(s,uplo,t,d,alpha,A,B)  B      = alpha*op(A)*B or alpha*B*op(A)
- trsm(s,uplo,t,d,alpha,A,B)  X      = op(A)\alpha*B or alpha*B/op(A)
```

KokkosKernels Interface: Inner Product Exercise

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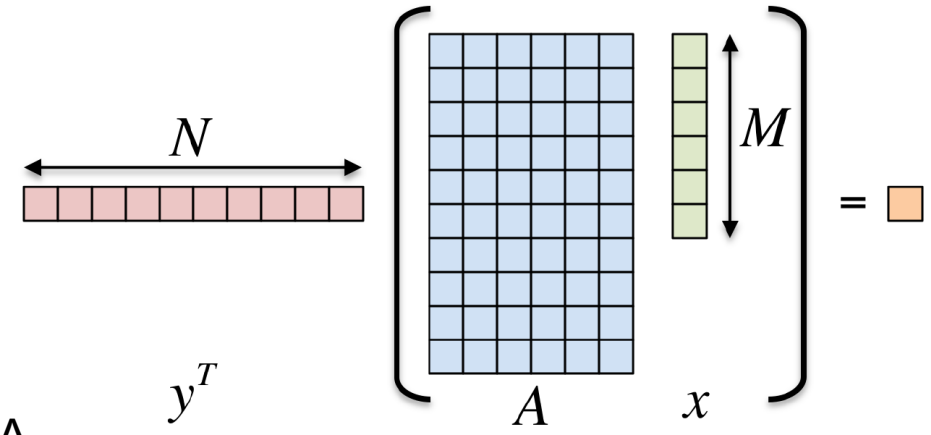
BLAS and Team-based BLAS interface

- Goal: Re-implement the inner product exercise using
  1. KokkosKernels BLAS functions
  2. KokkosKernels team-based BLAS function
- Details: <**y**,**A*****x**>
  - **y** is *N*x1, **A** is *N*x*M,* **x** is *M*x1
  - Look for comments labeled with "EXERCISE"
  - Compile and run on OpenMP, CUDA backends
  - Compare performance of these two implementations
  - Try LayoutLeft and LayoutRight



KokkosKernels Interface: Inner Product Exercise

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- Exercise location:

  https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/InnerProduct/Begin

- Details:
  1. KokkosKernels BLAS functions
     - Convert from hierarchical parallel execution to using BLAS functions
     - **tmp** = **A*x** (tmp for **gemv** results)
     - result = <**y**,**tmp**>
  2. KokkosKernels team-based BLAS
     - Same as hierarchical parallel execution
     - Call team-based **dot** within each team to perform <A[teamId,:],x>

Hint: KokkosKernels Functions

```
result = KokkosBlas::dot(x,y)
```

performs `result = SUM_i(y[i]*x[i])`

```
KokkosBlas::gemv("N",alpha,A,x,beta,y)
```

performs matrix-vector multiplication
`y[i] = beta*y[i] + alpha*SUM_j(A[i,j]*x[j])`

```
KokkosBlas::Experimental::dot(teamId,x,y)
```

performs `result = SUM_i(y[i]*x[i])` within each thread team

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Capabilities III: Batched BLAS/LAPACK

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Batched BLAS

```
parallel_for(TeamPolicy(N), KOKKOS_LAMBDA(member_type &member) {
  parallel_for(TeamThreadRange(member, nRows), [&](int &i) {
    parallel_for(ThreadVectorRange(member, nCols),[&](cint &j) {
      for (int k=0;k<len;++k)
        C(i,j) += A(i,k) * B(k,j);
}); }); });
```

SerialDot ← TeamVectorGemm

- Parallel batched operations are composed of using parallel-for with hierarchical interface of BLAS/LAPACK.
- Provides hierarchical interface matching to Kokkos hierarchical parallelism.
  - Serial – a single thread can invoke this layer of functions
  - Team – a single level of nested parallelism is used
  - TeamVector
    - Two nested parallel-for's are used TeamThread, ThreadVector, or
    - A single flattened nested parallel-for is used with TeamVectorRange.
- Function list
  - [S] Givens rotation, [S,TV] Householder transformation, [S] Hessenberg transformation, [S,T] LU, [S,T] Gemm, [S,T] Gemv, [S,T] Trsm, [S,T] Trsv, [S] Trmm, [S] Trtri, etc.
  - Implement new functions upon requests.

Capabilities III: Batched BLAS/LAPACK

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Batched BLAS

```
parallel_for(TeamPolicy(N), KOKKOS_LAMBDA(member_type &member) {
  parallel_for(TeamThreadRange(member, nRows), [&](int &i) {
    parallel_for(ThreadVectorRange(member, nCols),[&](cint &j) {
      for (int k=0;k<len;++k)
        C(i,j) += A(i,k) * B(k,j);
});  });  });
```

SerialDot ← TeamVectorGemm

- Parallel batched operations are composed of using parallel-for with hierarchical interface of BLAS/LAPACK.
- Provides hierarchical interface matching to Kokkos hierarchical parallelism.
  - Serial – a single thread can invoke this layer of functions
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  - Implement new functions upon requests.

Team-level Batched BLAS: Gemm

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- Objective
  - Learn how to use the Team-level interface for Gemm.
- Exercise location:

  https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/TeamGemm/Begin
- Details:
  1. Perform general matrix multiplies in parallel on a batch of matrices using the team-level Gemm function.
  2. Tune the team size on Cuda (via –A.m) and see how it impacts the performance.

KokkosBatched BLAS/LAPACK

Construction & Apply BlockJacobi

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- Objective
  - Compose a batched LU factorization on diagonal blocks and compute the inverse of the blocks.
  - Compare different parallelization strategies: a sequence of parallel_for calls vs a single parallel_for interface.

- Exercise location:

  https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/BlockJacobi/Begin

- Details:
  1. Simulate the standard batch functions running a sequence of parallel_for with LU, Lower Trsm, Upper Trsm to invert diagonal blocks.
  2. Compose a batched block matrix inversion using the so-called batched BLAS/LAPACK interface and a parallel_for with functor-level functions.
  3. On GPUs,
     1. Test the code with different team size with the run-different-teamsize.sh script.
     2. Run nvprof and see the difference (run-nvprof.sh script) and tune the team size for the problem size.

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Capabilities IV: Sparse Kernels

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Sparse

- CSR-Sparse Matrix Class providing fundamental capabilities
- SPMV: Sparse Matrix Vector Multiply
- SPADD: Sparse Matrix Matrix Addition
- SPGEMM: Sparse Matrix Matrix Multiply; separate symbolic and numeric phase
- SPGEMM_Jacobi: Fused Sparse Matrix Matrix Multiply + Jacobi
- GS: Gauss-Seidel Method using graph coloring: symbolic, numeric, solve phases]
- SPILU(K): Incomplete LU Factorization
- SPTRSV: Sparse triangular solve; super-nodal variant

Graph

- Distance-1 and Distance-2 graph coloring
- Triangle enumeration for graph analytics
  - Using SpGEMM + Visitor Pattern: can be used to represent large problems

SPARSE: CrsMatrix

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- Example location:
- https://github.com/kokkos/kokkos-kernels/blob/develop/example/wiki/sparse/KokkosSparse_wiki_crsmatrix.cpp

- Container for compressed row sparse matrix (CrsMatrix)
  - API available in our wiki: https://github.com/kokkos/kokkos-kernels/wiki/CrsMatrix
  - Currently no deep_copy constructor or operator
  - Row pointers is const, you cannot re-order in place or increase storage space

- Interfaced with the following kernels:
  - SpMV
  - SpADD
  - SpGEMM

SPARSE: SPMV

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- Exercise location:
- https://github.com/kokkos/kokkos-kernels/blob/develop/example/wiki/sparse/KokkosSparse_wiki_spmv.cpp
- Usage:
  - `KokkosSparse::spmv(mode, alpha, A, x, beta, y);`
- Performs:
  - `y = beta*y + alpha*op(A)*x`
- Parameters:
  - `mode`: input "`N`" (non-transpose), "`T`" (transpose), "`C`" (conjugate-transpose)
  - `alpha, beta`: input scalars
  - `A`: input sparse matrix (KokkosSparse::CrsMatrix) of size n x m
  - `x`: input vector (rank-1 or rank-2 Kokkos::View) of length m
  - `y`: input/output vector (rank-1 or rank-2 Kokkos::View) of length n

SPARSE: SPADD

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- Exercise location:
- https://github.com/kokkos/kokkos-kernels/blob/develop/example/wiki/sparse/KokkosSparse_wiki_spadd.cpp
- Usage:
  - `KokkosSparse::spadd_symbolic(handle, A, B, C);`
  - `KokkosSparse::spadd_numeric(handle, alpha, A, beta, B, C);`
- Performs:
  - `C = beta*C + alpha*(A+B)`
- Parameters:
  - `alpha, beta`: input scalars
  - `A, B`: input sparse matrices (KokkosSparse::CrsMatrix) of size n x m
  - `C`: input/output sparse matrix (KokkosSparse::CrsMatrix) of size n x m

SPARSE: SpGEMM

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- Exercise location:
- https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/SpGEMM/Begin
- Usage:
  - `KokkosSparse::spgemm_symbolic(handle, A, isTransposed, B, isTransposed, C);`
  - `KokkosSparse::spgemm_numeric(handle, A, isTransposed, B, isTransposed, C);`
- Performs:
  - `C = op(A)*op(B)`
- Notes:
  - Create an SpGEMM handle: `handle.create_spgemm_handle(spgemm_algorithm);`
  - Create an empty matrix for output: `KokkosSparse::CrsMatrix<…> C;`
  - Use the same handle for both symbolic and numeric calls

SPARSE: Gauss-Seidel

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Given: **A**, a CrsMatrix that is numRows x numCols

x: unknown vector. **b**: right-hand side vector.

First, create `KokkosKernelsHandle` and call `create_gs_handle()`.

Structural (symbolic) setup.

- `KokkosSparse::Experimental::gauss_seidel_symbolic(&handle, numRows, numCols, A.graph.row_map, A.graph.entries, graphIsSymmetric);`

Numeric setup: anything depending on matrix values.

- `KokkosSparse::Experimental::gauss_seidel_numeric(&handle, numRows, numCols, A.graph.row_map, A.graph.entries, A.values, graphIsSymmetric);`

Forward apply (symmetric and backward have same interface):

- `KokkosSparse::Experimental::forward_sweep_gauss_seidel_apply(&handle, numRows, numCols, A.graph.row_map, A.graph.entries, A.values, x, b, initZeroX, updateCachedB, omega, numSweeps);`

SPARSE: Gauss-Seidel Exercise

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- Why both numRows and numCols?
  - For distributed Tpetra::CrsMatrix, numRows is number of locally owned rows, and numCols is locally owned + remote columns (column map). Matrix should still be globally square.
- `initZeroX`: whether to zero out x before apply. Only set to true on first apply on a given system.
- `updateCachedB`: if first apply with this b, or b has changed for any reason since last apply.

Exercise: https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/GaussSeidel/Begin

- First, fill in the code after `//EXERCISE` comments. Check that the solve converges in ~7 iterations.
- Then: try other algorithms when creating the GS sub-handle:

```
handle.create_gs_handle(KokkosSparse::GS_CLUSTER, 10);
```

or:

```
handle.create_gs_handle(KokkosSparse::GS_TWOSTAGE);
```

- In apply, try increasing number of sweeps from 1, or omega (damping factor) to something other than 1.0
- Try using `symmetric_gauss_seidel_apply` instead of `forward`

GRAPH: Coloring

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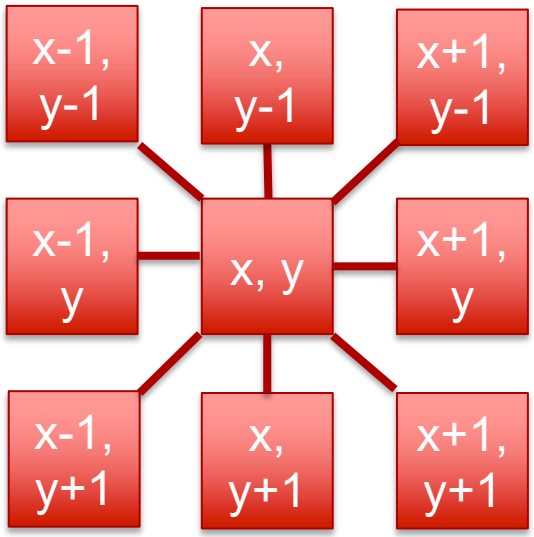
Given: **rowmap**, **entries** (forming a sparse CRS graph)

Compute distance-1 coloring: no pair of adjacent vertices can have same color. Example usage of bitwise vertex-based (VBBIT) algorithm:

```
// Set up
KernelHandle handle;
handle.create_graph_coloring_handle(KokkosGraph::COLORING_VB);
// Compute the coloring
KokkosGraph::Experimental::graph_color(&handle, numVertices,
numVertices, rowmap, entries);
// Get the colors array and number of colors used
auto colorHandle = handle.get_graph_coloring_handle();
auto colors = colorHandle->get_vertex_colors();
auto numColors = colorHandle->get_num_colors();
// Clean up
handle.destroy_graph_coloring_handle();
```

GRAPH: Coloring Exercise

- **Exercise**: https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/GraphColoring/Begin
- Creates graph from 2D rectangular grid and a 9-point stencil



- Distance-2 coloring: vertices that are within 1 or 2 edges of each other can't have same color.
- Exercise runs both D-1 and D-2 coloring, and prints out the colors in a grid.
- (If building with OpenMP) Try changing the number of threads and see how the number of colors changes:
- `export OMP_NUM_THREADS=<n>`

- **Some D1 algorithms:**
  `COLORING_VB`, `COLORING_SERIAL`, `COLORING_EB`
- **Some D2 algorithms:**
  `COLORING_D2_VB`, `COLORING_D2_SERIAL`, `COLORING_D2_NB_BIT`

SPARSE: SpILUK

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- Goal: get familiar with Kokkos Kernels interfaces of ILU(k) for CRS matrices
- Exercise location:

  https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/SpILUK/Begin

- Kokkos Kernels interfaces:

```
handle.create_spiluk_handle(SPILUKAlgorithm, nrows, nnzL, nnzU);
KokkosSparse::Experimental::spiluk_symbolic(handle, fill_level,
                                            A_rowmap, A_entries,
                                            L_rowmap, L_entries,
                                            U_rowmap, U_entries);
KokkosSparse::Experimental::spiluk_numeric(handle, fill_level,
                                           A_rowmap, A_entries, A_values,
                                           L_rowmap, L_entries, L_values,
                                           U_rowmap, U_entries, U_values);
```

SPARSE: SpILUK

Sandia National Laboratories

- Exercise Instructions:
  - ❑ Generate a simple Laplacian matrix on a cartesian grid as a KokkosSparse::CrsMatrix
  - ❑ Create an SpILUK handle
  - ❑ Call `spiluk_symbolic(…)` in the symbolic phase to construct the nonzero patterns of L and U, and to do level scheduling
  - ❑ Call `spiluk_numeric(…)` in the numeric phase to perform an ILU factorization based on the nonzero patterns found in the symbolic phase
  - ❑ As fill-level *k* changes, observe the changes of
    - ➢ ILU(k) fill-factor, and
    - ➢ row-sum difference (A*ones-L*U*ones)

KokkosKernels Interface: Conjugate Gradient Solver

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- Goal: implement conjugate gradient solver for square, symmetric, positive-definite sparse matrix
- Details: **A*x=b**
  - **b** is *Nx*1
  - **A** is *NxN* symmetric, positive-definite sparse matrix
  - **x** is *Nx*1
  - Look for comments labeled with "EXERCISE"
  - Use KokkosKernels BLAS and KokkosKernels Sparse BLAS

- Algorithm:

$$\mathbf{r_0} = \mathbf{b} - \mathbf{A} * \mathbf{x_0}$$

$$\mathbf{p_0} = \mathbf{r_0}$$

$$k = 0$$

while $\|\mathbf{r}_k\| > \varepsilon$ and $k<N$

$$\alpha = \frac{\mathbf{r}_k^T * \mathbf{r}_k}{\mathbf{p}_k^T * \mathbf{A} * \mathbf{p}_k}$$

$$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha * \mathbf{p}_k$$

$$\mathbf{r}_{k+1} = \mathbf{r}_k - \alpha * \mathbf{A} * \mathbf{p}_k$$

$$\beta = \frac{\mathbf{r}_{k+1}^T * \mathbf{r}_{k+1}}{\mathbf{r}_k^T * \mathbf{r}_k}$$

$$\mathbf{p}_{k+1} = \mathbf{r}_{k+1} + \beta * \mathbf{p}_k$$

$$k = k + 1$$

KokkosKernels Interface: Conjugate Gradient Solver

Sandia National Laboratories

- Exercise location:

  https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/CGSolve/Begin

- Details:
  - Sparse matrix generation is provided
  - Compile and run on OpenMP, CUDA backends
  - Vary problem size: -N #
  - Compare performance of CPU vs GPU

Hint: KokkosKernels Functions

```
result = KokkosBlas::dot(x,y)
```

performs `result = SUM_i(y[i]*x[i])`

```
KokkosBlas::axpy(alpha,x,y)
```

performs `y[i] = y[i] + alpha*x[i]`

```
KokkosBlas::axpby(alpha,x,beta,y)
```

performs `y[i] = beta*y[i] + alpha*x[i]`

```
KokkosSparse::spmv("N",alpha,A,x,beta,y)
```

performs sparse matrix-vector multiplication
`y[i] = beta*y[i] + alpha*SUM_j(A[i,j]*x[j])`

ILU(k) Preconditioned Conjugate Gradient Solver with Kokkos Kernels

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- Goal: implement an ILU(k) preconditioned conjugate gradient solver for square, symmetric, positive-definite sparse matrix using Kokkos Kernels SpILUK and SpTRSV
- Exercise location:

  https://github.com/kokkos/kokkos-tutorials/tree/master/Intro-Full/Exercises/kokkoskernels/CGSolve_SpILUKprecond /Begin
- Kokkos Kernels interfaces:

```
handle.create_sptrsv_handle(SPTRSVAlgorithm, nrows, is_lower_tri);
KokkosSparse::Experimental::sptrsv_symbolic(handle,
                                            rowmap, entries);
KokkosSparse::Experimental::sptrsv_solve(handle,
                                         rowmap, entries, values,
                                         rhs, lhs);
```

ILU(k) Preconditioned Conjugate Gradient Solver with Kokkos Kernels

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- Exercise Instructions:
  - ❑ Generate a simple Laplacian matrix on a cartesian grid as a KokkosSparse::CrsMatrix
  - ❑ Create two SpTRSV handles (L and U)
  - ❑ Call `sptrsv_symbolic(…)` to do level scheduling
  - ❑ Call `sptrsv_solve(…)` to apply the preconditioner during the CGSolve

    ```
    1. tmp = L\r
    2. z = U\(tmp)
    ```

  - ❑ Observe the convergence behaviors:
    - ➢ without preconditioner
    - ➢ with preconditioner (as ILU(k) fill-level changes)

- Algorithm:

$\mathbf{r_0} = \mathbf{b} - \mathbf{A} * \mathbf{x_0}$

$\mathbf{z_0} = \mathbf{M}^{-1} * \mathbf{r_0}$

$\mathbf{p_0} = \mathbf{z_0}$

$k = 0$

while $\|\mathbf{r}_k\| > \varepsilon$ and $k < N$

$$\alpha = \frac{\mathbf{r}_k^T * z_k}{\mathbf{p}_k^T * \mathbf{A} * \mathbf{p}_k}$$

$\mathbf{x}_{k+1} = \mathbf{x}_k + \alpha * \mathbf{p}_k$

$\mathbf{r}_{k+1} = \mathbf{r}_k - \alpha * \mathbf{A} * \mathbf{p}_k$

$\mathbf{z}_{k+1} = \mathbf{M}^{-1} * \mathbf{r}_{k+1}$

$$\beta = \frac{\mathbf{r}_{k+1}^T * \mathbf{z}_{k+1}}{\mathbf{r}_k^T * \mathbf{z}_k}$$

$\mathbf{p}_{k+1} = \mathbf{z}_{k+1} + \beta * \mathbf{p}_k$

$k = k + 1$

Presentation outline

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1. Introduction
2. Dense linear algebra: BLAS capabilities
3. Team level linear algebra: BatchedBLAS
4. Sparse linear algebra, preconditioners and graph kernels
5. Build system using Cmake

Building Kokkos Kernels with CMake

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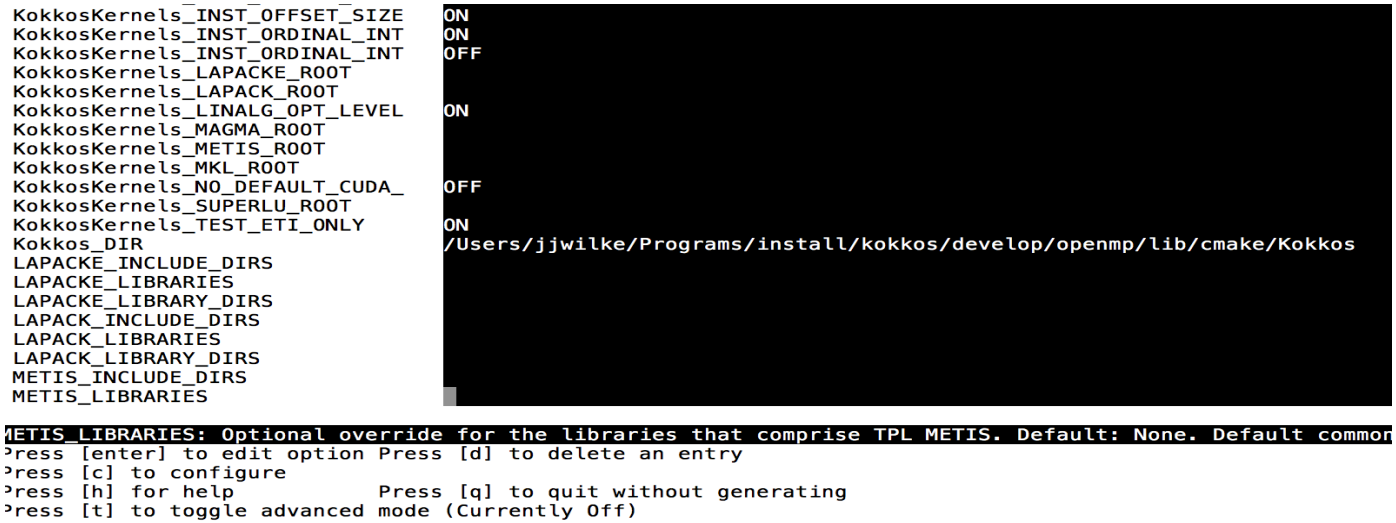
- cmake ${KERNELS_SOURCE} –D{OPTION}:BOOL=ON …
  Specify config variables on cmd line as –DOPT=Value
- To get a list of options in TUI, use ccmake:
  - ccmake ${KERNELS_SOURCE}
    –DCMAKE_CXX_COMPILER={}
    –DKokkos_ROOT=${PATH_TO_KOKKOS_INTALL}



  - Scroll over option and hit ‘h’ to see option details
  - Hit ‘enter’ to change option value

Most Important Build Options

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- -DKokkos_ROOT=${PATH_TO_KOKKOS}
  The underlying Kokkos. Many options (CUDA vs OpenMP, e.g.) automatically derived from Kokkos installation
- Template instantiation ahead of time to save compile-time
  - Scalars: e.g. –D KokkosKernels_INST_DOUBLE:BOOL=ON
  - Offsets: e.g. –D KokkosKernels_INST_OFFSET_SIZE_T:BOOL=ON
  - Mem/Exec Spaces: e.g.
    –D KokkosKernels_INST_EXECSPACE_OPENMP:BOOL=ON
- Third-party library (TPLs)
  - Enable: e.g. –D KokkosKernels_ENABLE_TPL_BLAS:BOOL=ON
    Kernels will look for BLAS in default locations
  - Customize paths:
    - e.g. –D BLAS_LIBRARIES="…"
    - e.g. –D BLAS_LIBRARY_DIRS="…"

A basic CMake project file creates a target and links to Kokkos

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Target linking in CMake automatically adds all include/link options.
Only need to link to KokkosKernels (Kokkos automatically comes with)

```
cmake_minimum_required(VERSION 3.12) #need >= 3.12
project(myProject CXX) #kokkos is always a C++ project

#must find installed kokkos kernels
find_package(KokkosKernels REQUIRED)

add_executable(myExe source.cpp) #add my program

#link to kokkos
target_link_libraries(myExe PRIVATE Kokkos::kokkoskernels)
```

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Exceptional service in the national interest

http://www.github.com/kokkos