#### **HPC Libraries and Frameworks**

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### Overview

- Benefits of libraries and frameworks
- Exemplary libraries
- Open vs. proprietary/commercial
- State-of-the-art library technologies
- Trade-offs, costs, and limitations of libraries and frameworks
- Library usage do's and don'ts



## Major Types and Uses of Libraries and Frameworks

- Avoid "reinventing the wheel":
  - Mathematical functions
  - Data structures, containers, serialization and I/O
  - Algorithms
- Hardware-optimized: abstract hardware-specific implementation
- Callable from C, C++, Fortran, Python, etc.



# Role of HPC Libraries and Frameworks in Software Dev. Cycle

- Use libraries/frameworks to fill **software "gap"**
- Profiling to identify performance bottlenecks
- Find HPC libraries or algorithm frameworks covering gaps



# Benefits from Using Libraries and Frameworks

- Reduce application devel / maint cost
- Use a validated implementation of tricky algorithms, e.g., solvers, RNGs
- · Hardware-specific optimizations, abstraction
- Standardized or compatibility APIs allow libraries to be dropped in, swapped, compared



## Library Examples

- Mathematical functions:
  - Cephes, SVML, GSL
- Linear algebra kernels and solvers:
  - BLAS, LAPACK, MAGMA, MKL, cuBLAS, cuSPARSE, SCALAPACK, ...
- Random, quasi-random number generation:
  - SPRNG, cuRAND, GSL
- Fast Fourier Transform:
  - FFTW, cuFFT, MKL

The list goes on and on...



## Example: Dense Linear Algebra

- Due to the maturity and importance of linear algebra software, a thriving ecosystem of compatible and interoperable libraries and frameworks exist
- Libraries available for fundamental algorithms, higher level solvers, special hardware platforms, parallel solvers...
- Compatible and interoperable APIs



### Dense Linear Algebra

- BLAS Fundamental dense linear algebra
  - Level 1: Vector-Vector
  - Level 2: Matrix-Vector
  - Level 3: Matrix-Matrix
- LAPACK Matrix solvers based on BLAS
  - Linear equations, eigenvalue problems, ...
  - Matrix factorization: LU, QR, SVD, Cholesky, ...
- SCALAPACK Parallel LAPACK
  - Extended distributed memory message passing APIs



### **Evaluating Libraries**

- Accuracy, correctness, robustness against failure(s)
- Performance
- Standard or compatible APIs
- Language bindings
- Portability, Composability, and Hardware Support
  - Thread-safe? Interferes with MPI\_COMM\_WORLD?
  - Compatible with OpenMP, OpenACC, CUDA, etc?
- Built-in parallelization?:
  - Intra-node (multi-core CPUs, GPUs)
  - Distributed memory



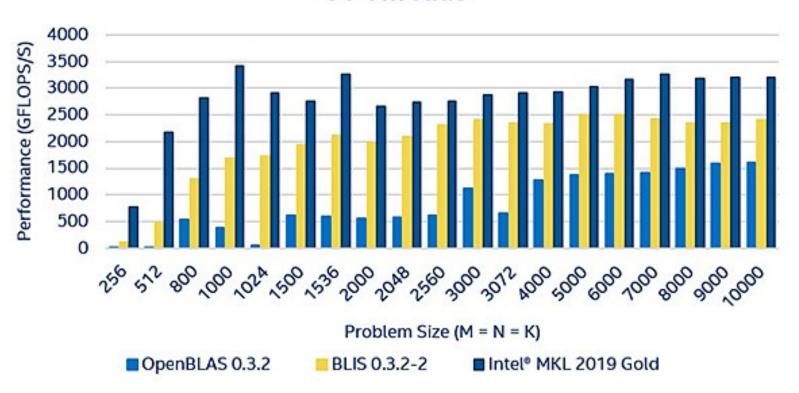
## Open vs. Proprietary, Free vs. Commercial

- Open libs ideal for gaining deep understanding of performance limitations imposed by APIs, application usage
- Hardware vendor libs try to provide optimal performance, approaching "speed of light" for their own platform
- Commercially licensed libs may present application distribution challenges in terms of price, ultimate scalability, etc.



## Example of Proprietary Lib Perf.

#### Intel® MKL 2019 Gold vs Competitors DGEMM on 56 Threads



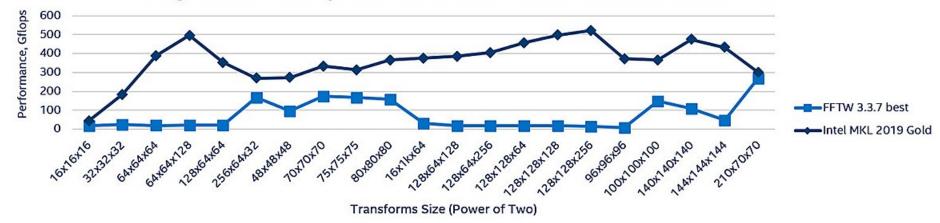
https://software.intel.com/en-us/mkl/features/benchmarks



## Example of Proprietary Lib Perf.

#### 3D FFT Performance Boost

3D FFT Performance Boost using Intel® Math Kernel Library 2019 Gold vs FFTW Single Precision Complex 3D FFT on Intel® Xeon® Platinum Processor 8180



https://software.intel.com/en-us/mkl/features/benchmarks



### Libraries vs. Frameworks

- Libraries typically "canned", not much caller-specialization possible
  - Example: Matrix Multiply
  - Caller runs the code
- Frameworks combine some existing code with caller-provided code to achieve application-specific functionality
  - Example: PETsc, AI stacks, OptiX Ray Tracing
  - Framework typically runs the code



## C++ Template Libraries

- Potential for generality across many types/classes
- Performance opportunities:
  - Template specialization, template metaprogramming
  - Compile-time optimization of per-thread ops by constant folding, loop unrolling, etc.
- Eigen linear algebra template library
- NVIDIA GPU accelerated template libraries:
  - Thrust: STL-like vector ops on GPUs (incl sort/scan)
  - CUB: per-block, device-wide sort/scan/reductions/etc
  - CUTLASS: matrix linear algebra ops

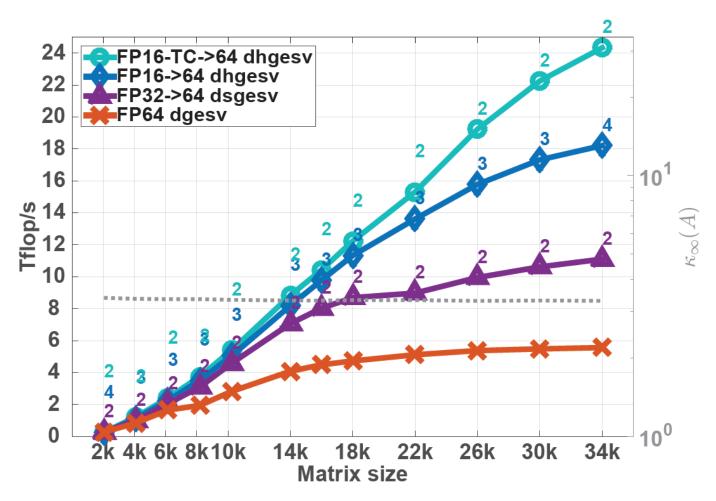


# Exploit New Hardware and Algorithmic Advances

- Library abstraction allows replacement of conventional solver with iterative refinement
- Mixed precision solvers, e.g. half-, single-, double-precision
- Example: Make use of special purpose hardware such as NVIDIA Tensor cores for higher performance dense linear algebra...



#### "Harnessing GPU Tensor Cores for Fast FP16 Arithmetic to Speed up Mixed-Precision Iterative Refinement Solvers", Haidar et al., SC2018



(a) Matrix of type 1: diagonally dominant.

## State-of-the-Art Library Runtime Technologies

- Runtime dispatch of hardware-optimized code paths: MKL, CUDA Libraries
- Autotuners: FFTW "Plan"
- Built-in runtime systems for scheduling work in complex multi-phase parallel algorithms, heterogeneous platforms: MAGMA (UTK)



### Library Performance Considerations

- How does library perform with varying problem size?
- Libraries may provide special APIs for batching of large numbers of "small problems
- May have significant startup cost:
  - Autotuners
  - JIT code generators
  - GPUs or other accelerators



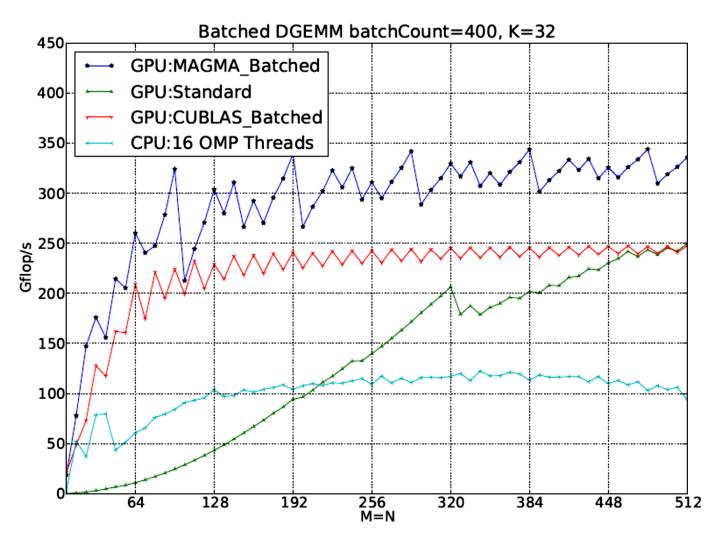
### Improving Performance with Batching APIs

- Trivial example:
  - Replace separate sin() and cos() calls with sincos() (C99 math lib standard)
  - Input angle domain checking logic is amortized, approach
     2x speedup
- Mainstream examples:
  - FFTW, MKL, cuFFT batched FFTs
  - MAGMA:

"MAGMA Batched: A Batched BLAS Approach for Small Matrix Factorizations and Applications on GPUs", Dong et al., ICL Tech Rep. 2016

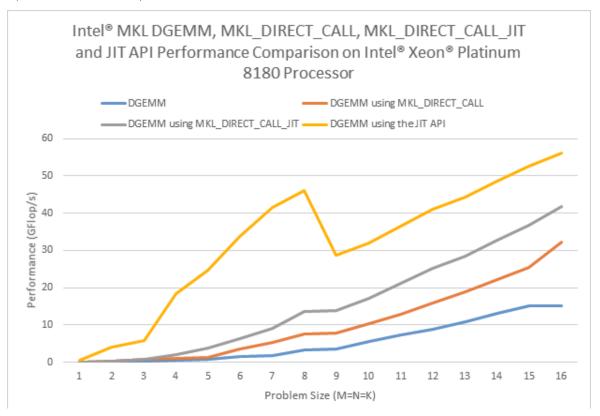


#### MAGMA: GPU Batched DGEMM



"MAGMA Batched: A Batched BLAS Approach for Small Matrix Factorizations and Applications on GPUs", Dong et al., ICL Tech Rep. 2016

## JIT Code Generation for Large Repetitions (1000x) of Small Problem Sizes



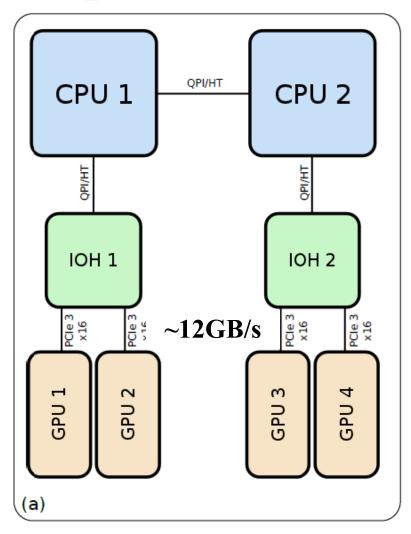
https://software.intel.com/en-us/articles/intel-math-kernel-library-improved-small-matrix-performance-using-just-in-time-jit-code



## Heterogeneous Compute Node

- NUMA CPU architecture
- Dense PCIe-based multi-GPU compute node
- Application would ideally exploit all of the CPU, GPU, and I/O resources concurrently...

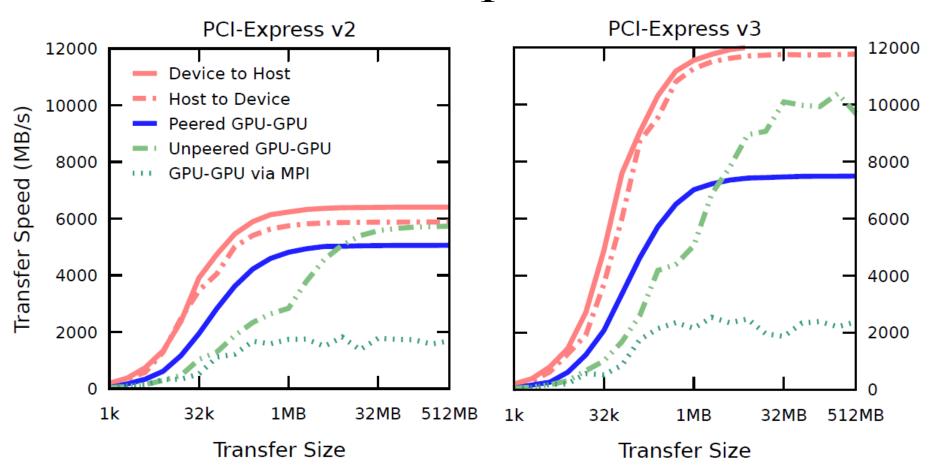
(I/O devs not shown)



Simulation of reaction diffusion processes over biologically relevant size and time scales using multi-GPU workstations Michael J. Hallock, John E. Stone, Elijah Roberts, Corey Fry, and Zaida Luthey-Schulten.

Journal of Parallel Computing, 40:86-99, 2014.

### GPU PCI-Express DMA



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Journal of Parallel Computing, 2014. (In press)

http://dx.doi.org/10.1016/j.parco.2014.03.009



## Exemplary Heterogeneous Computing Challenges

- Tuning, adapting, or developing software for multiple processor types
- Decomposition of problem(s) and load balancing work across heterogeneous resources for best overall performance and work-efficiency
- Managing data placement in disjoint memory systems with varying performance attributes
- Transferring data between processors, memory systems, interconnect, and I/O devices





## Using Libraries for Programming Heterogeneous Computing Architectures

- Use drop-in libraries in place of CPU libs
  - Little or no code development
  - Examples: MAGMA, cuBLAS, cuSPARSE, cuSOLVER, cuFFT libraries, many more...
  - Speedups limited by Amdahl's Law and overheads associated with data movement between CPUs and GPUs

https://developer.nvidia.com/gpu-accelerated-libraries



# Costs, Limitations, Arising from Using Libraries and Frameworks

- Lib API may require inconvenient data layout
- Lib API boundaries inhibit inlining of small functions, and prevent "kernel fusion"
- Lib implementation may sacrifice some performance to ensure generality
- Too many library dependencies create challenge for source compilation, e.g., for MPI codes



# Libraries May Sacrifice Performance to Ensure Generality

- Math lib functions do significant preprocessing and validation on input parameters for allowed function domain
- Caller may know that that input param may fall within a very limited subrange, but there's no way to exploit this in a conventional library
- Bespoke math functions can outrun general math lib function by significant margin for limited input domain or reduced precision



## Example of Lost Vectorization or Inlining Opportunities

- Traditional math libraries don't permit inlining of function calls into calling loop
- Significant function call overhead if the main content of loop is a library routine
- So-called "header-only" C++ template libraries can overcome some of this
- Special intrinsics and short-vector math libraries can be used to resolve cases where library calls would otherwise inhibit vectorization



#### MO Kernel for One Grid Point (Naive C)

```
for (at=0; at<numatoms; at++) {
                                                                                  Loop over atoms
  int prim counter = atom basis[at];
  calc distances to atom(&atompos[at], &xdist, &ydist, &zdist, &dist2, &xdiv);
  for (contracted gto=0.0f, shell=0; shell < num shells per atom[at]; shell++) {
                                                                                   Loop over shells
    int shell type = shell symmetry[shell counter];
   for (prim=0; prim < num prim per shell[shell counter]; prim++) {
                                                                                  Loop over primitives:
      float exponent
                       = basis array[prim counter
                                                                                   largest component of
      float contract coeff = basis array[prim counter + 1];
                                                                                  runtime, due to expf()
      contracted gto += contract coeff * expf(-exponent*dist2);
      prim counter += 2;
    for (tmpshell=0.0f, j=0, zdp=1.0f; j<=shell type; j++, zdp*=zdist) {
                                                                                     Loop over angular
     int imax = shell type - i;
                                                                                            momenta
     for (i=0, ydp=1.0f, xdp=pow(xdist, imax); i<=imax; i++, ydp*=ydist, xdp*=xdiv)
                                                                                   (unrolled in real code)
       tmpshell += wave f[ifunc++] * xdp * ydp * zdp;
   value += tmpshell * contracted gto;
    shell counter++;
```



### Value of Bespoke Math Functions

- Eliminate overheads from checking / preprocessing of general input domain
- Inlinable into loop body
- Only implement caller-required numerical precision / accuracy



#### I/O Libraries

- I/O is now and for all time a significant concern for HPC apps
- I/O performance has plateaued at many sites
- Meanwhile, compute capabilities are growing toward exascale by leaps and bounds
- App developers need easy-to-use and performant I/O mechanisms to avoid bottlenecking
- NetCDF and HDF5



### HDF5, NetCDF I/O Libraries

- Bindings for all major languages
- Lots of documentation and examples
- Easy to use for many HPC tools
  - Cross-platform portability, conversion of byte order to native endianism, etc.
  - HDF5 supports compression
  - User defined data blocks, organization
  - Makes it easy to author both the output code for a simulation tool and the matching input code for analysis and visualization usage
- Support integration with MPI-I/O for parallel I/O



## HPC Graphics and Visualization

- Visualization:
  - VTK, VTK-m
- Rasterization: EGL and Vulkan
- Ray tracing:
  - Intel OSPRay CPU Ray Tracing Framework
  - NVIDIA OptiX GPU Ray Tracing Framework
  - Research: NVIDIA VisRTX Framework



## Library "DOs"

- Do use standardized, interoperable library APIs
- Do use libraries to exploit GPU accelerators, new hardware features, new algorithms
- **Do use high level APIs**, abstractions, allow library freedom to use most efficient back-end solver
- Do use batched APIs for large numbers of small size problems
- Do use Autotuning and JIT when workload is repeated and overheads can be amortized



## Library "DON'Ts"

- **Don't** use a library without considering whether it creates an avoidable obstacle to software compilation, redistribution, or usages
- Don't use a library or framework that harms longterm portability for short-term gain, always leave yourself an "out" for future systems
- Don't continue using a library indefinitely -- periodically do a "bake-off" to see how it compares with other state-of-the-art choices



## Keep and Eye Out For

- New state-of-the-art libraries and frameworks arising from DOE Exascale Computing Project funding
- Ongoing advances by major library developers, hardware vendors
- Evolving and improving interoperability, compatibility APIs to ease porting



## Questions?

