Triolet C++/Python – productive programming in heterogeneous parallel systems

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Agenda

- Performance portability of imperative parallel programming
  - OpenCL
- Algorithm selection, scalability, and efficiency of intentional parallel programming
  - Triolet C++
  - Triolet Python

Essential work in writing efficient parallel code.

Planning how to execute an algorithm

- Distribute computation across
  - cores,
  - hardware threads, and
  - vector processing elements
- Distribute data across
  - discrete GPUs or
  - clusters
- Orchestrate communication for
  - reductions,
  - variable-size list creation,
  - stencils, etc.

Implementing the plan

- Rearrange data for locality
- Fuse or split loops
- Map loop iterations onto hardware

- Allocate memory
- Partition data
- Insert data movement code

- Reduction trees
- Array packing
- Boundary cell communication

Current State of Programming Heterogeneous Systems

CPU | Multicore | Xeon Phi | GPU | FPGA

Current State of Programming Heterogeneous Systems

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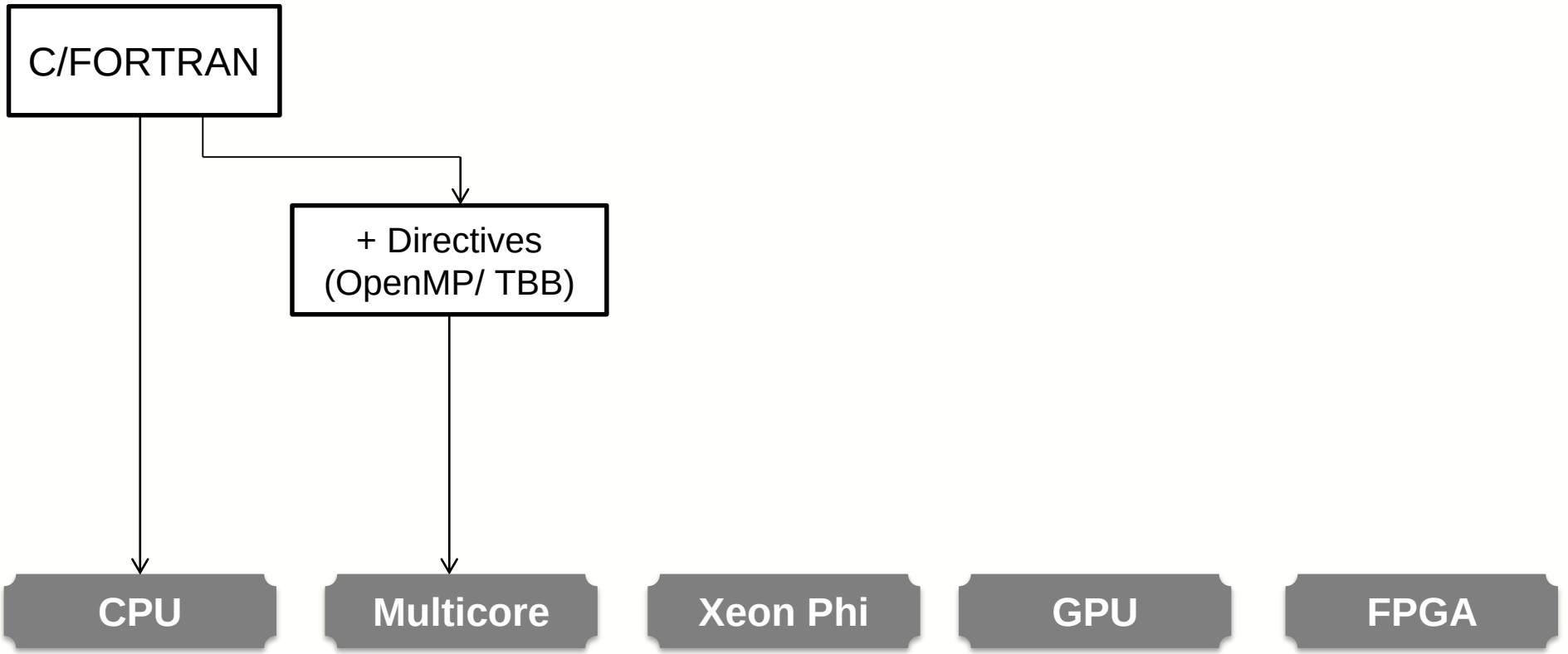

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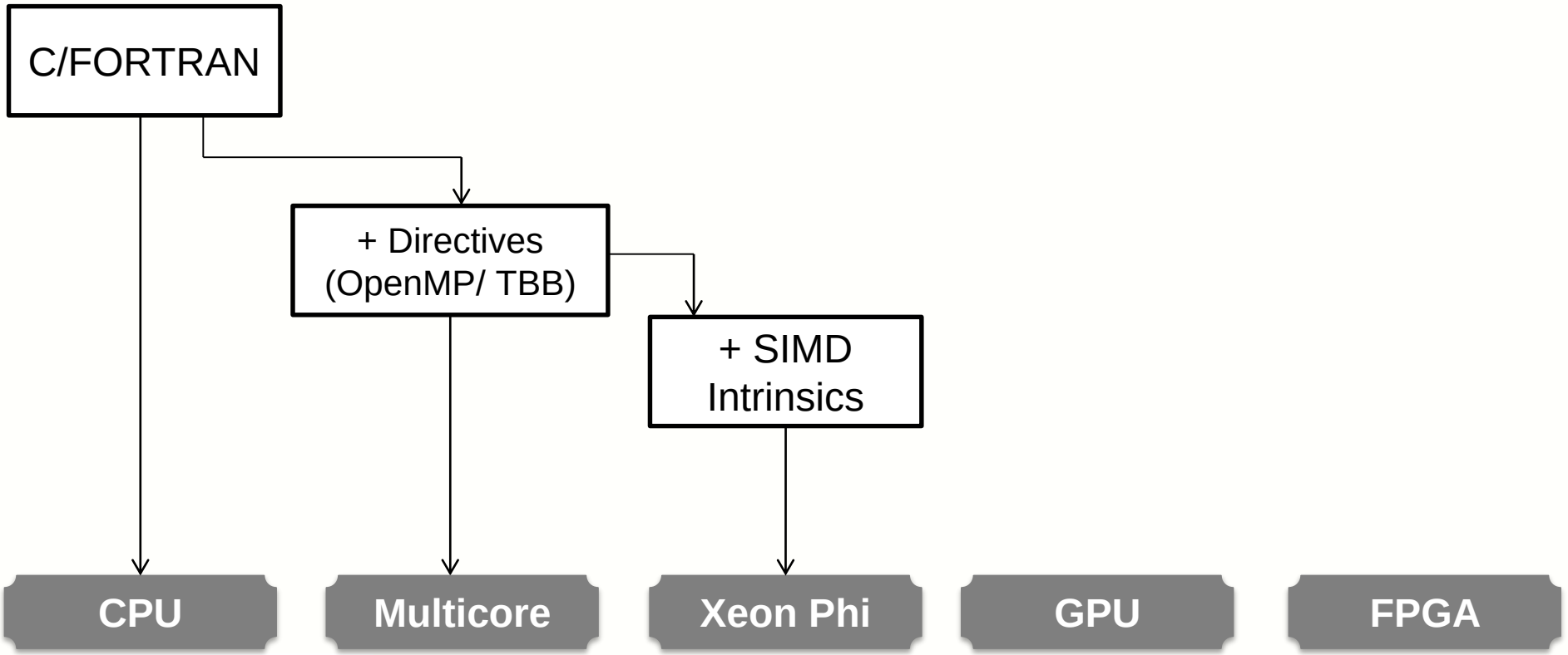

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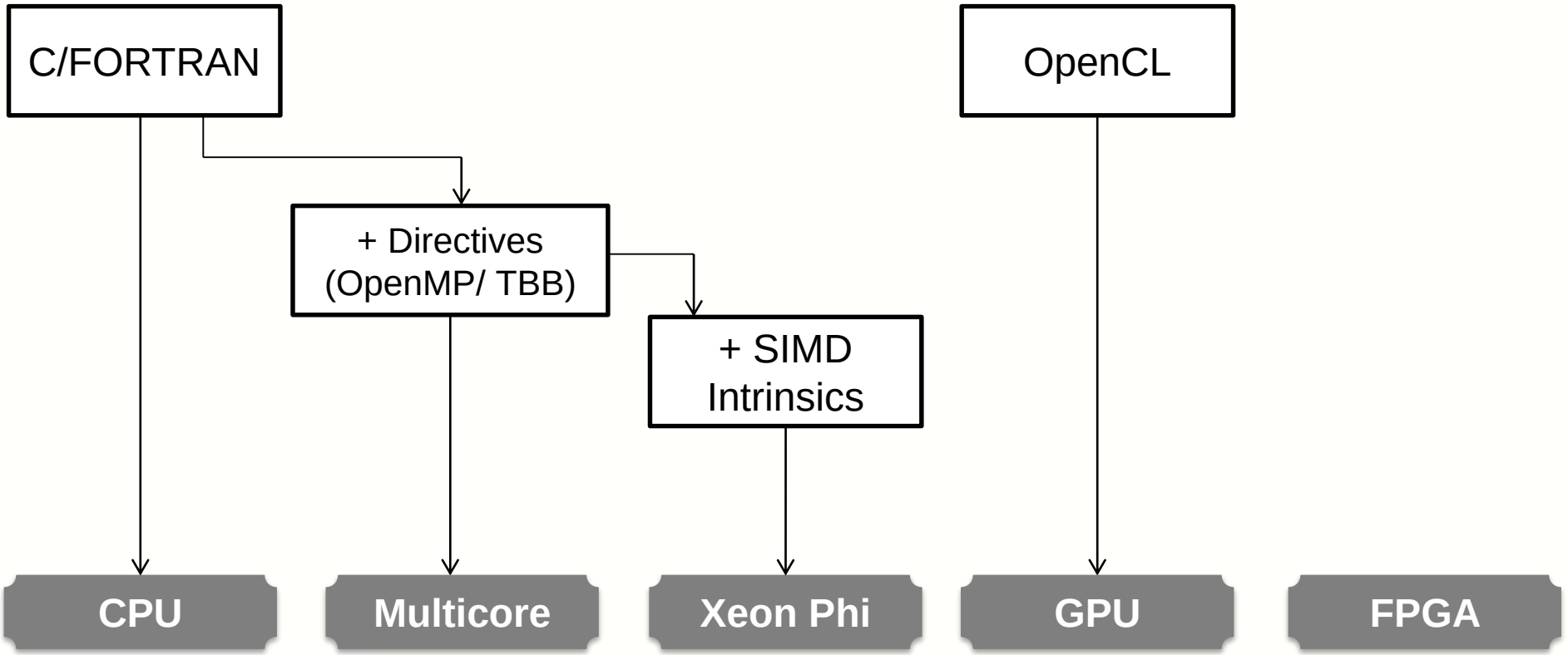
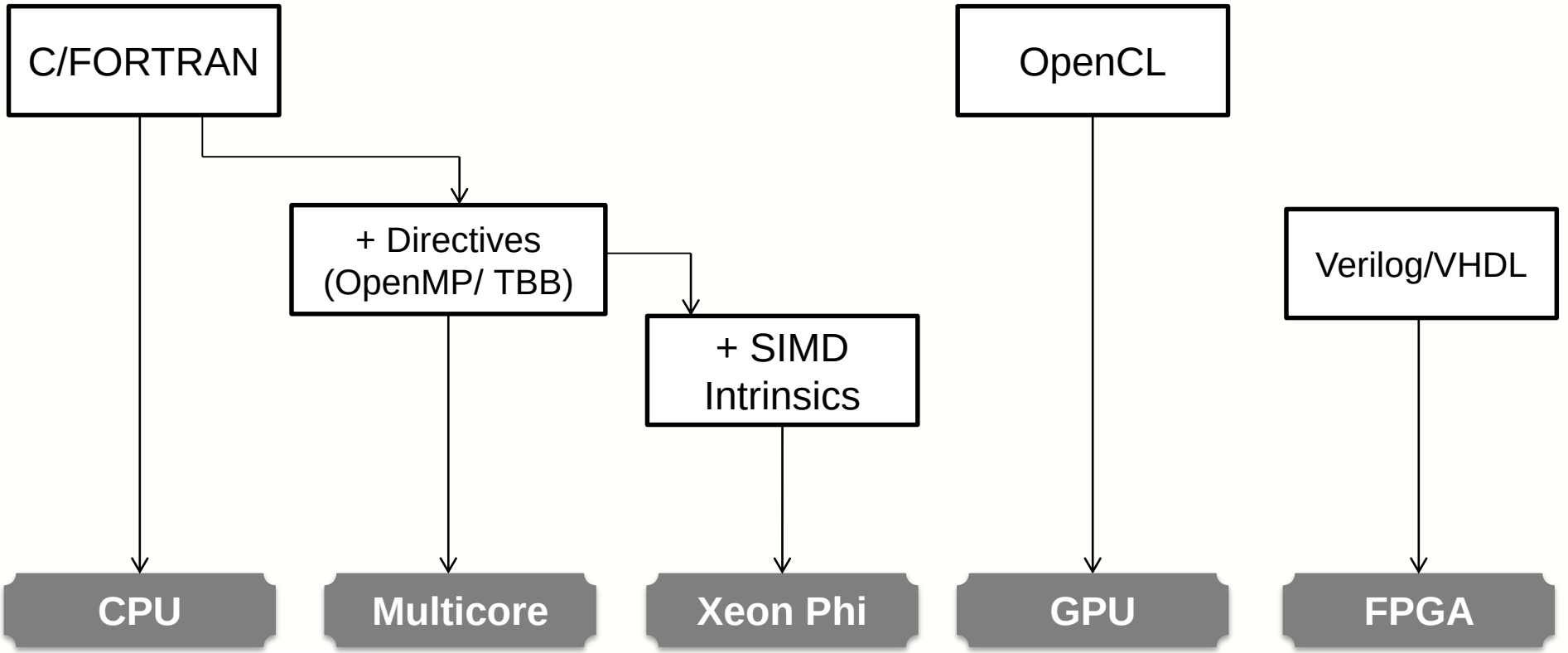
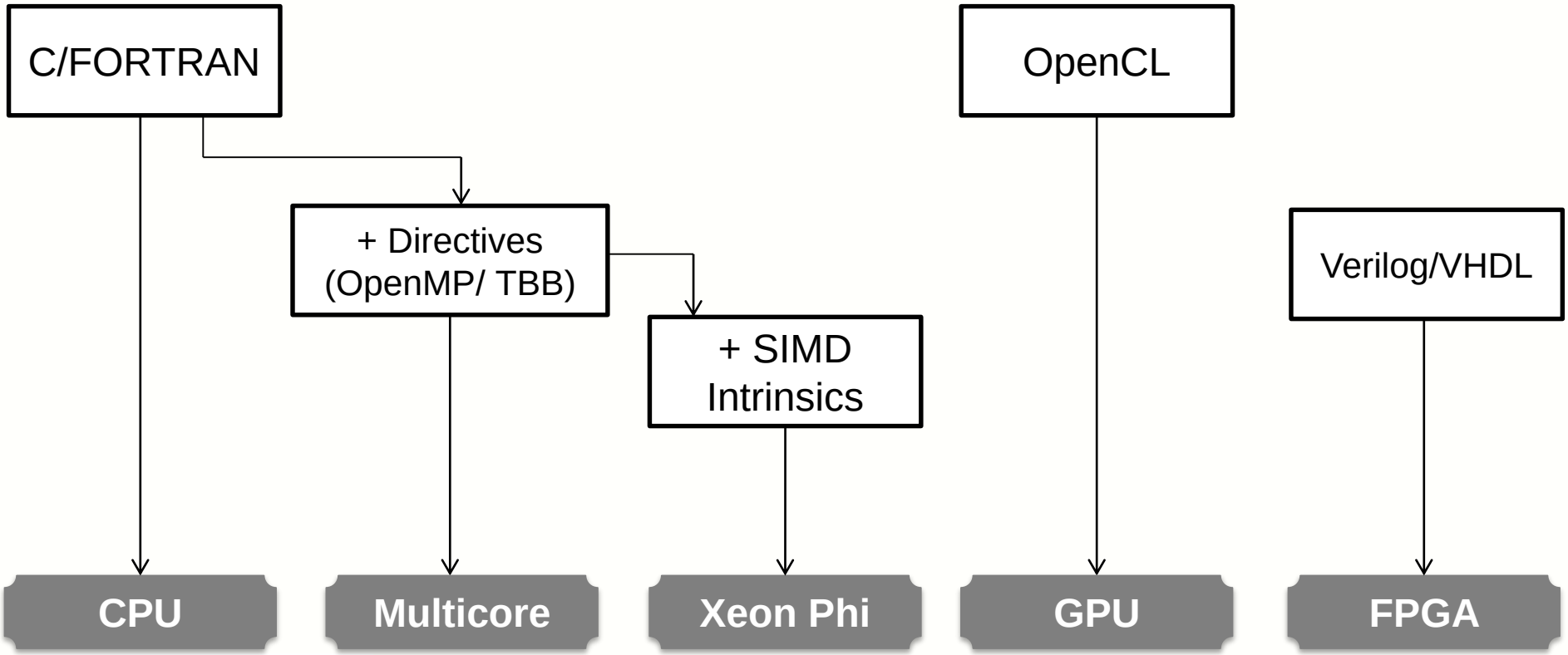


Current State of Programming Heterogeneous Systems



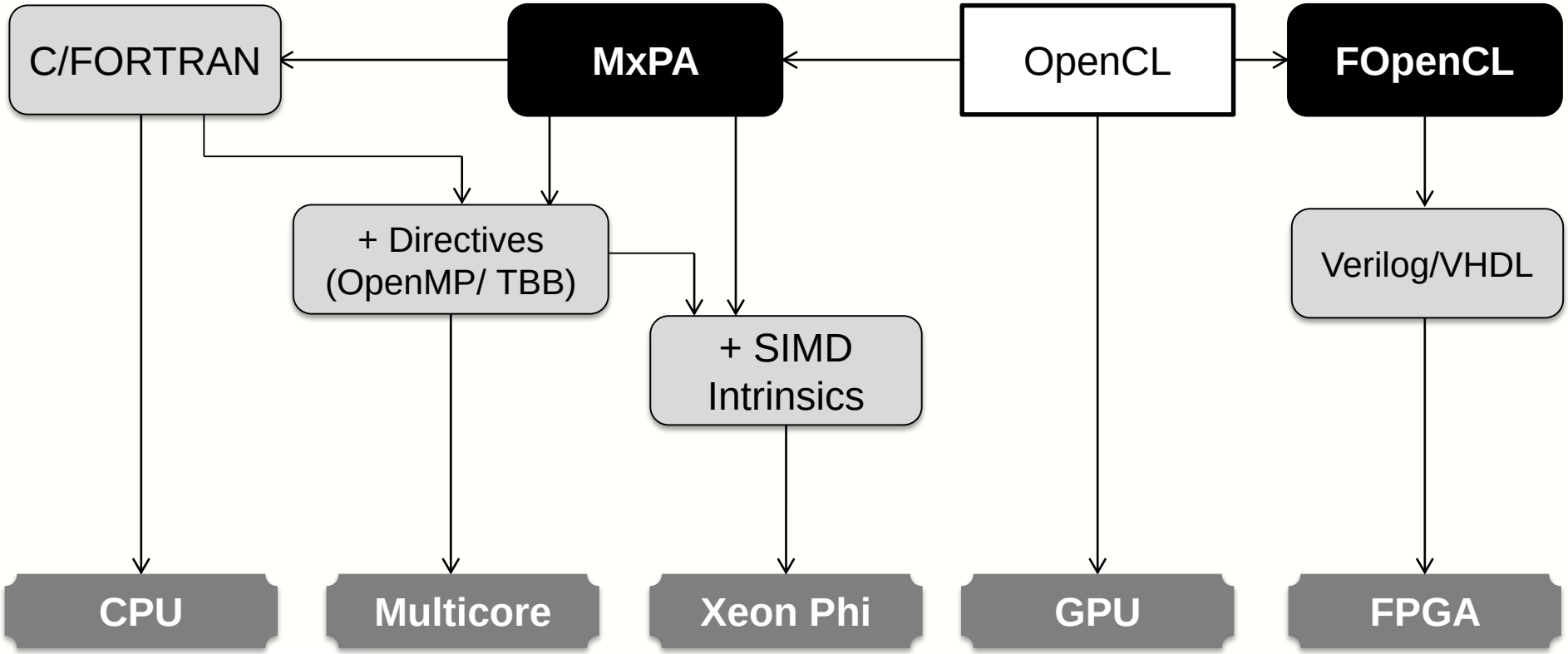
Current State of Programming Heterogeneous Systems

Programming heterogeneous systems requires too many versions of code!



Productivity in Programming Heterogeneous Systems

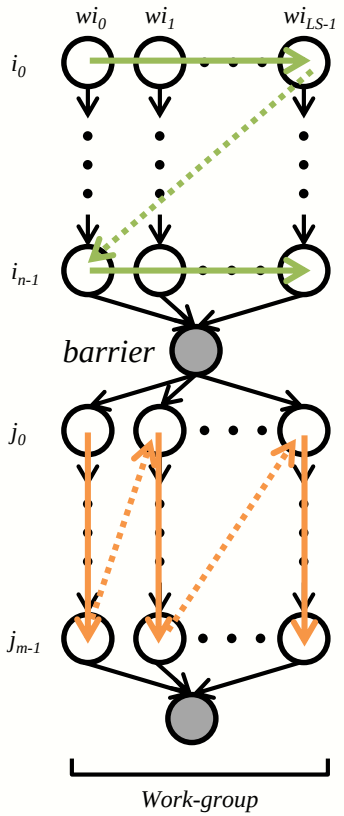
<u>Step #1:</u> Keep only one of the versions and use portability tools to generate the others.



MxPA: Overview

- Optimizes scheduling of work-item execution for **locality** and **vectorization** for the hardware
- Locality-centric compile-time scheduling selects between:
  - *BFO (Breadth-First Order):* issue each memory access for all work-items first
  - *DFO (Depth-First Order):* issue all memory accesses for a single work-item first
- Kernel fusion run-time scheduling reduces memory traffic for common data flow between kernels
- Dynamic vectorization maintains vector execution in spite of apparent control flow divergence

MxPA: Locality-centric Scheduling



Dependency in executing OpenCL kernels

```
CLKernel() {
  // e.g. SOA
  for (i = 0..N) {
    .. = A[c0*i + wid];
  }
  barrier();
  // e.g. AOS
  for (j = 0..M) {
    .. = B[c1*wid + j];
  }
}
```

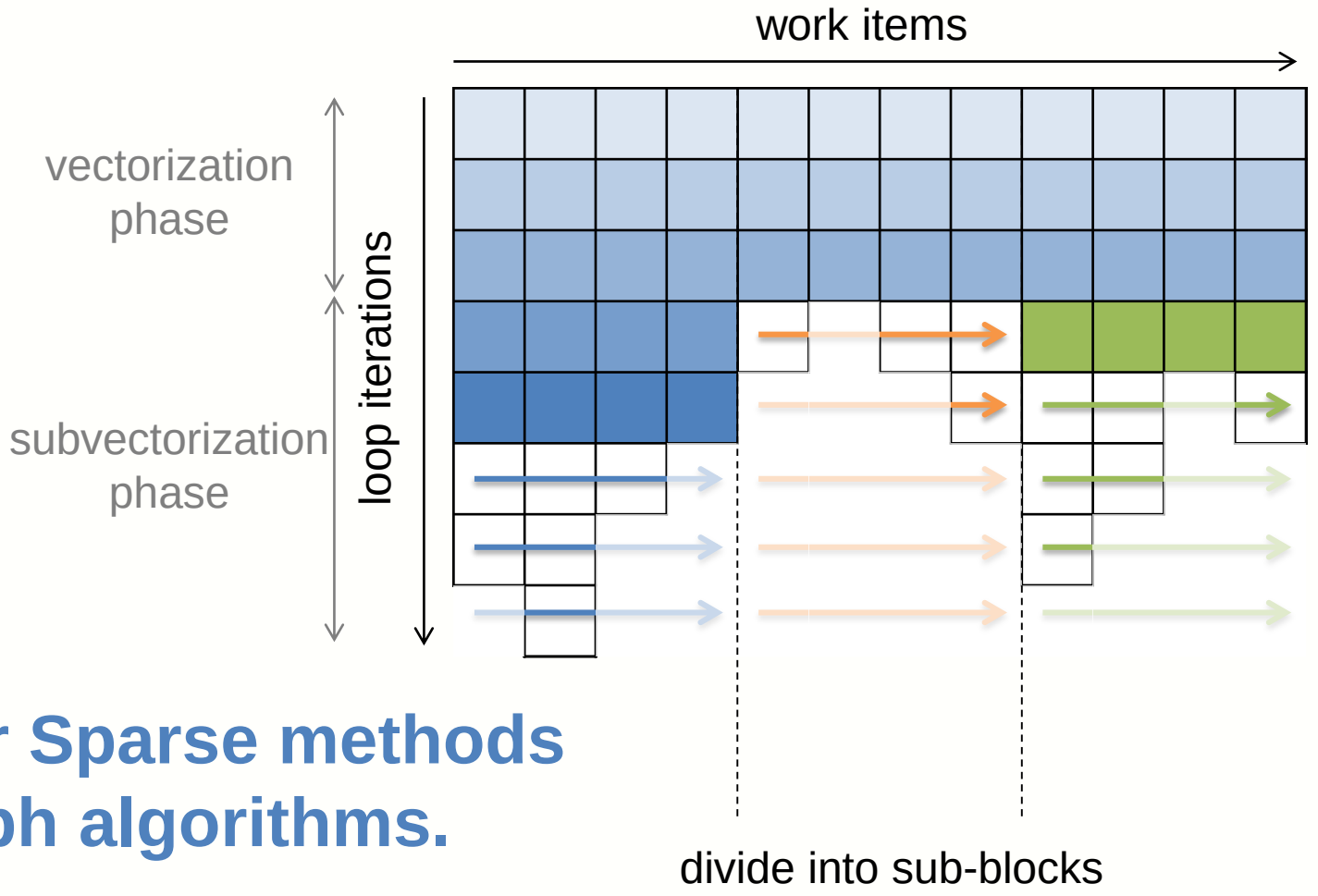
An example OpenCL code

```
CLKernel_MXPA() {
  // BFO
  for (i = 0..N) {
    for (wid = 0..LS) {
      .. = A[c0*i + wid];
    }
  }

  // DFO
  for (wid = 0..LS) {
    for (j = 0..M) {
      .. = B[c1*wid + j];
    }
  }
}
```

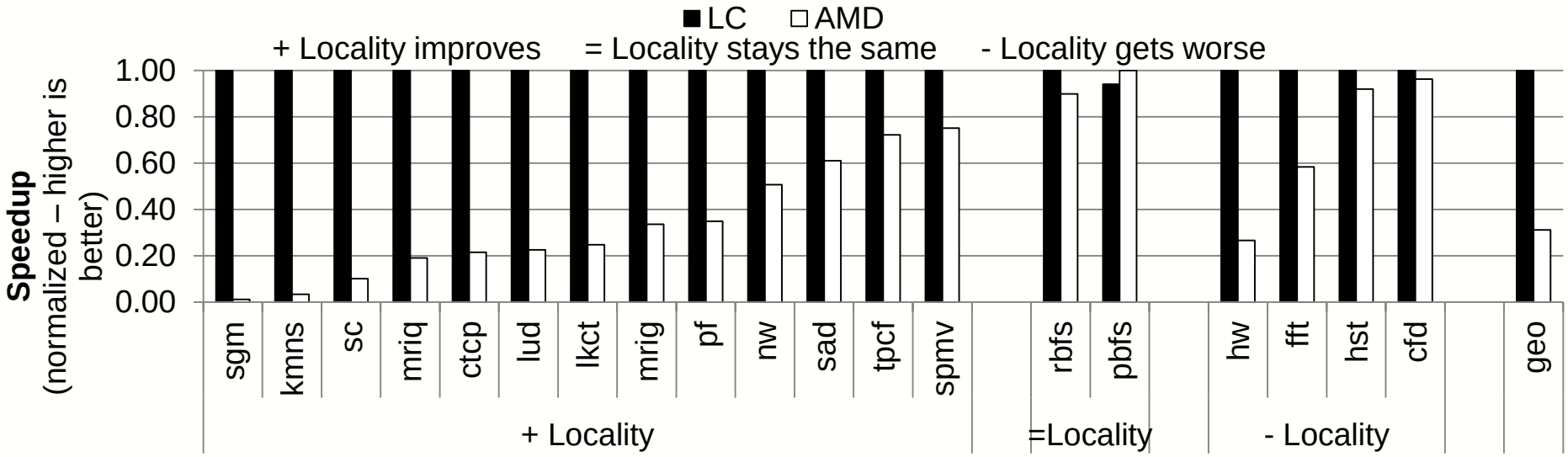
MXPA-translated code

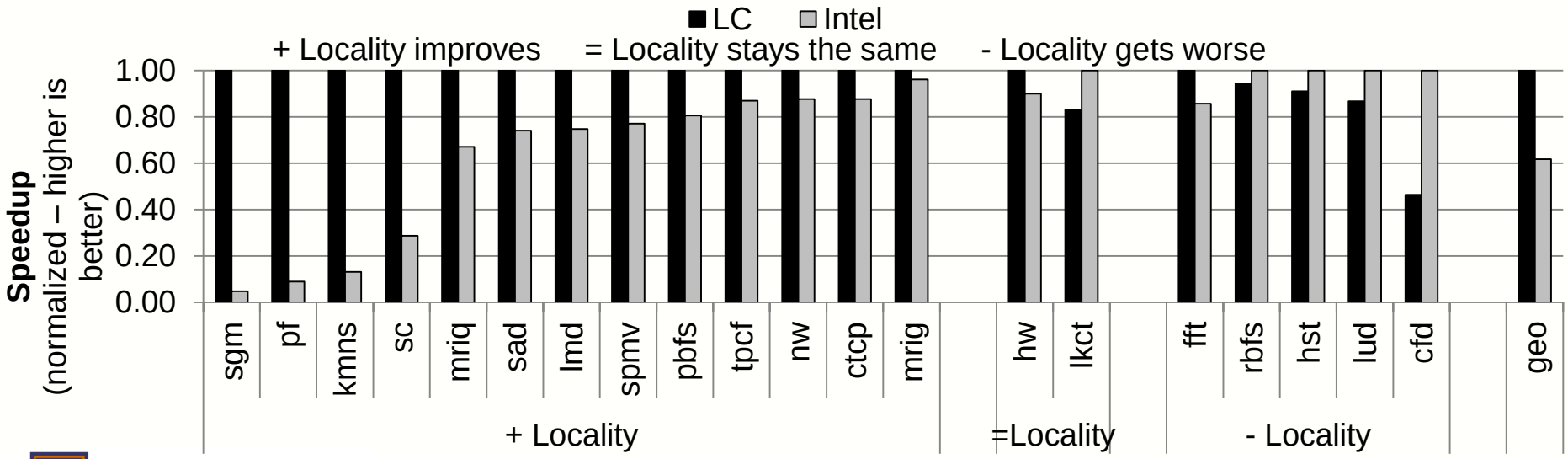
MxPA: Dynamic Vectorization of Control Divergent Loops



Effective for Sparse methods and graph algorithms.

MxPA Results: Comparison to Industry





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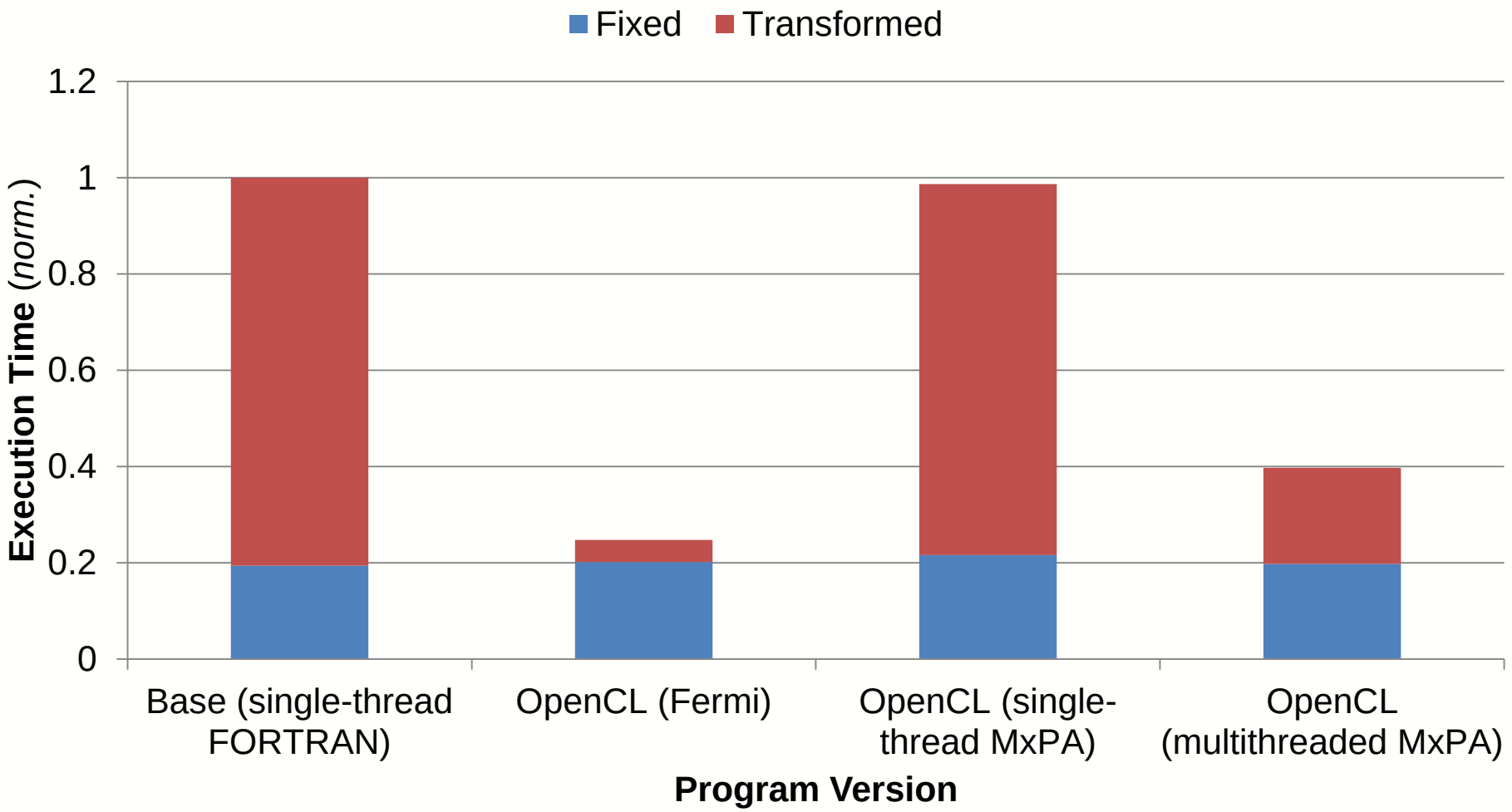
MxPA Results: Comparison to Industry

Metric	LC/AMD	LC/Intel
Speedup	3.20x	1.62x
L1 Data Cache Misses	0.12x	0.36x
Data TLB Misses	0.23x	0.33x
LLC Misses	0.91x	0.97x

MxPA Case Study: MOCFE-Bone



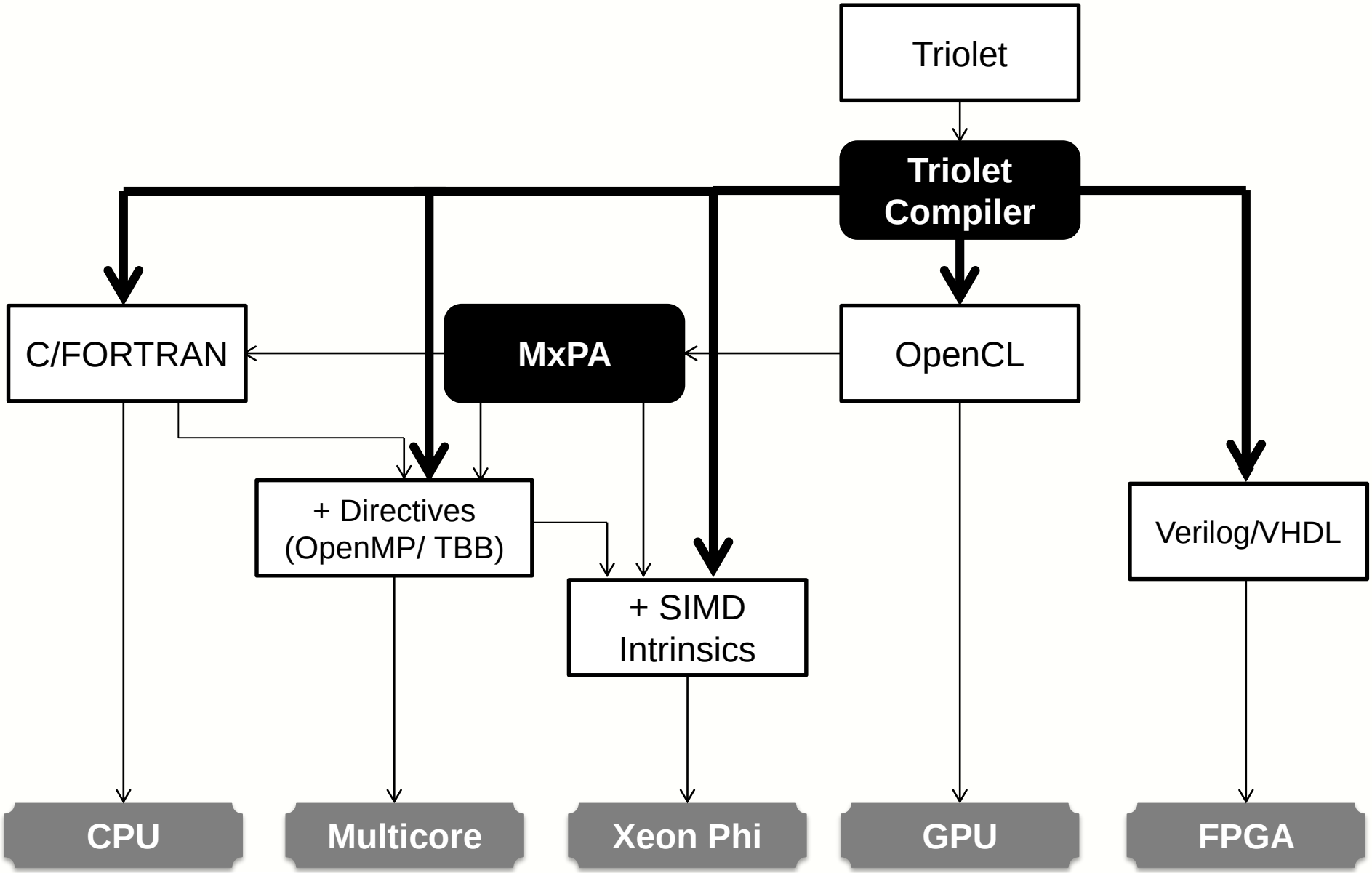
Input Configurations: Nodes = 1, Groups = 25, Angles = 128, MeshScale=10 (Elements=10^3)

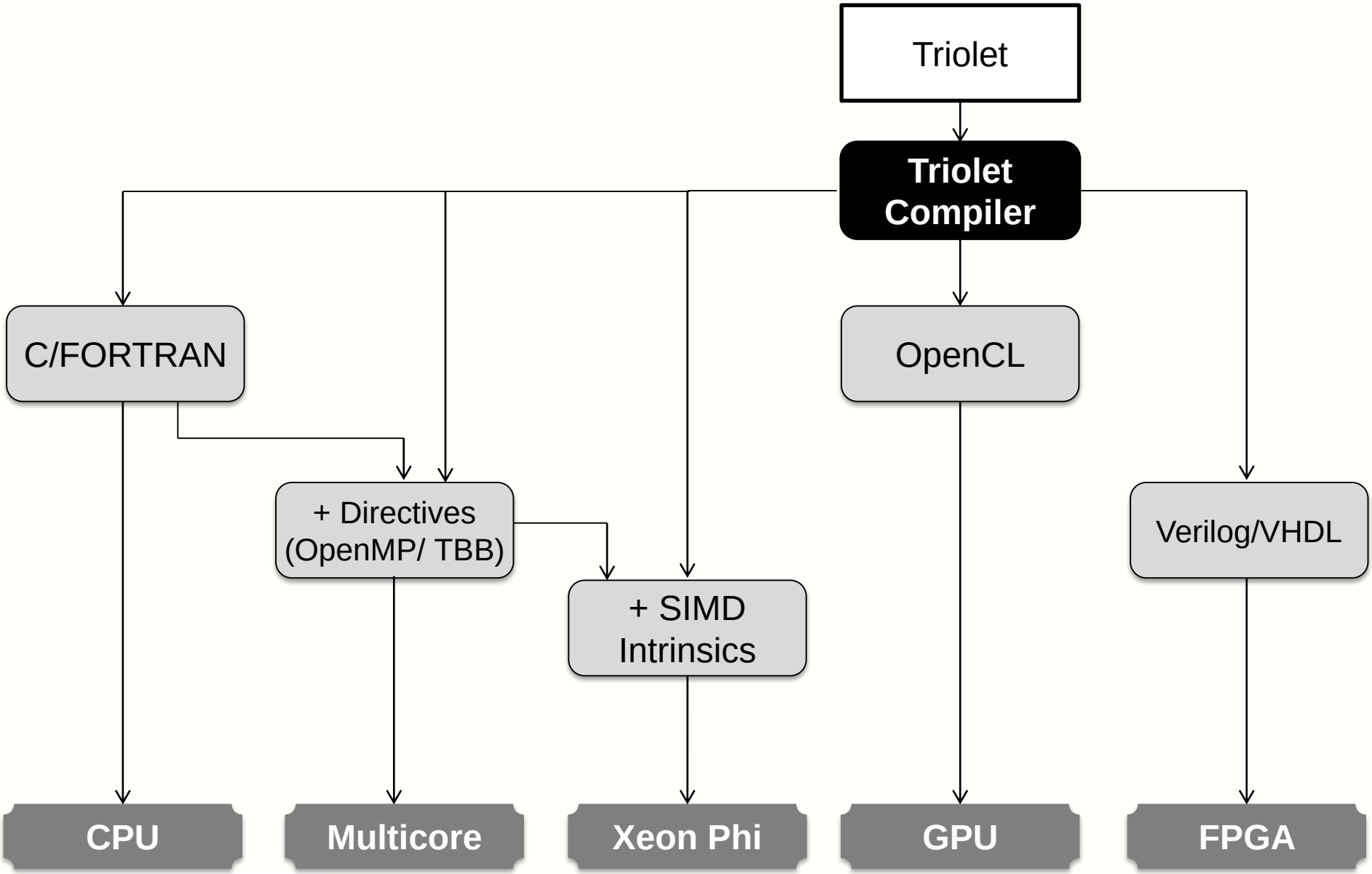
HIGH-LEVEL INTERFACE

Who does the hard work in parallelization?

- General-purpose language + parallelizing compiler
  - Requires a very intelligent compiler
  - Limited success outside of regular array algorithms
- Delite - Domain-specific language + domain-specific compiler
  - Simplify compiler's job with language restrictions and extensions
  - Requires customizing a compiler for each domain
- Triolet - Parallel library + optimizing compiler
  - Library makes parallelization decisions
  - Uses a rich transformation, library aware compiler
  - Extensible—just add library functions

Step #2: Use a higher-level algorithm representation.




Triolet
Triolet Compiler
C/FORTRAN
OpenCL
+ Directives (OpenMP/ TBB)
+ SIMD Intrinsics
Verilog/VHDL
CPU
Multicore
Xeon Phi
GPU
FPGA

Triolet C++

- Goal – design and implement a simple, user-friendly interface for communicating the intended data access and computation patterns to a library-aware C++ compiler
- Technical approach
  - Data objects allow changes to logical data organization and content without touching storage
  - Computations based on map and reduce
  - Aggressive algorithm selection and auto-tuning through hardware specific library implementation
  - Compiler code synthesis technology for target hardware built on MxPA

Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
        const std::vector<float>& kernel)
{
    auto input_co = make_matrix<int, 2>(input, x_size, y_size);
}
```

Ask the compiler to treat the C++ **input** array as a 2D matrix object whose dimensions are given by arguments x_size and y_size.

Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
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{
    auto input_co = make_matrix<int, 2>(input, x_size, y_size);
    auto kernel_co = make_small_vector<int>(kernel);
```

Treat the C++ **kernel** array as a small 1D vector in preparation for dot product .

Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
        const std::vector<float>& kernel)
{
    auto input_co = make_matrix<int, 2>(input, x_size, y_size);
    auto kernel_co = make_small_vector<int>(kernel);
    auto stencil_co = make_stencil_transform<9,9>(input_co);
}
```

Conceptually form a 2D x_size by y_size matrix whose elements are the 9x9 neighbor stencils around the original **input_co** elements.

Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
        const std::vector<float>& kernel)
{
    auto input_co = make_matrix<int, 2>(input, x_size, y_size);
    auto kernel_co = make_small_vector<int>(kernel);
    auto stencil_co = make_stencil_transform<9,9>(input_co);
    auto const_co = make_const_transform(kernel_co, x_size*y_size);
}
```

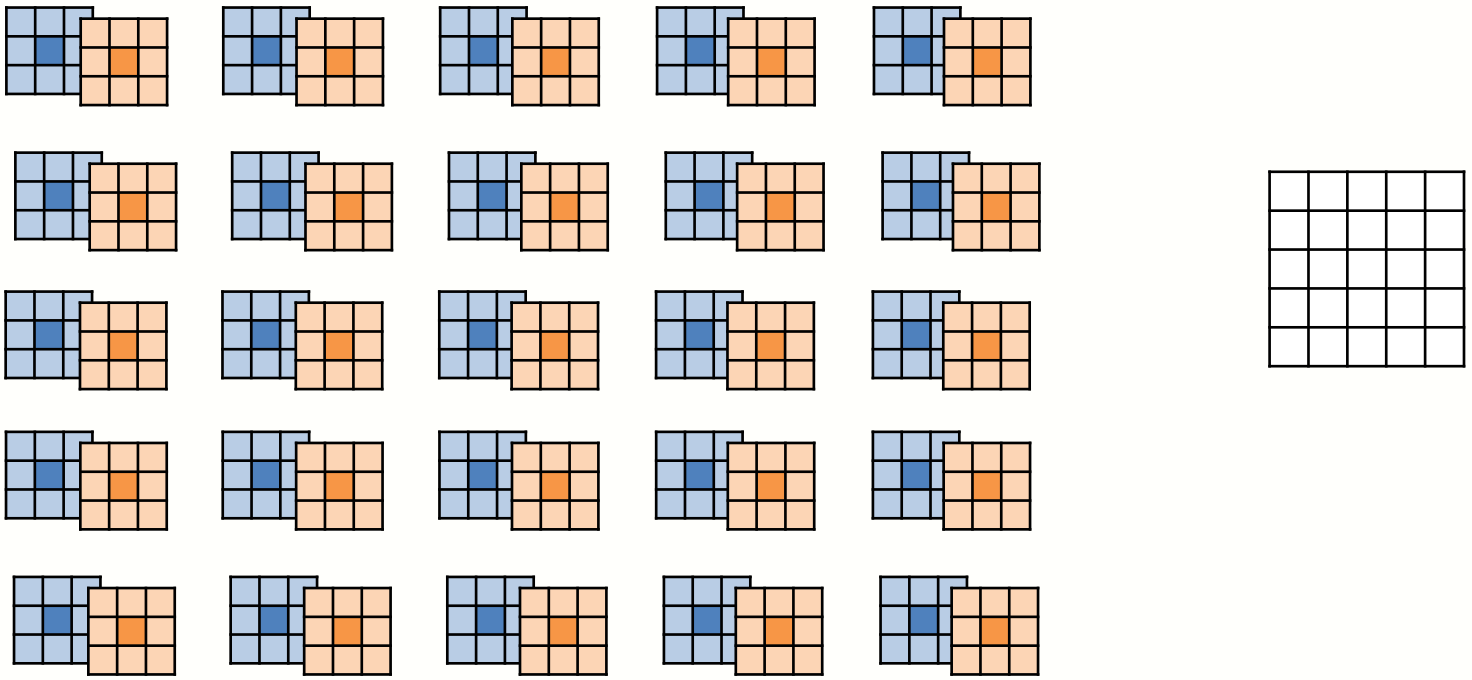
Conceptually replicate **kernel_co** into an x_size by y_size stencil matrix

Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
        const std::vector<float>& kernel)
{
    auto input_co = make_matrix<int, 2>(input, x_size, y_size);
    auto kernel_co = make_small_vector<int>(kernel);
    auto stencil_co = make_stencil_transform<9,9>(input_co);
    auto const_co = make_const_transform(kernel_co, x_size * y_size);
    auto zip_co = make_zip_transform(stencil_co, const_co);
}
```

Conceptually form an x_size by y_size matrix where each element is a tuple of one stencil_co element and one const_co element.

Convolution Example (5x5 Zipped Matrix)



zip(filters, stencils)

Triolet/C++ Convolution Code

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{
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    auto kernel_co = make_small_vector<int>(kernel);
    auto stencil_co = make_stencil_transform<9,9>(input_co);
    auto const_co = make_const_transform(kernel_co, x_size * y_size);
    auto zip_co = make_zip_transform(stencil_co, const_co);
    auto map_co = make_map_transform(zip_co,map_operation<mul_op>());
}
```

Perform pair-wise multiplication onto all zipped elements

Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
        const std::vector<float>& kernel)
{
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    auto kernel_co = make_small_vector<int>(kernel);
    auto stencil_co = make_stencil_transform<9,9>(input_co);
    auto const_co = make_const_transform(kernel_co, x_size * y_size);
    auto zip_co = make_zip_transform(stencil_co, const_co);
    auto map_co = make_map_transform(zip_co,map_operation<mul_op>());
    auto reduce_co =
       make_map_transform(map_co,reduce_operation<add_op>());
}
```

Perform vector reduction on all map_co elements, this finishes convolution

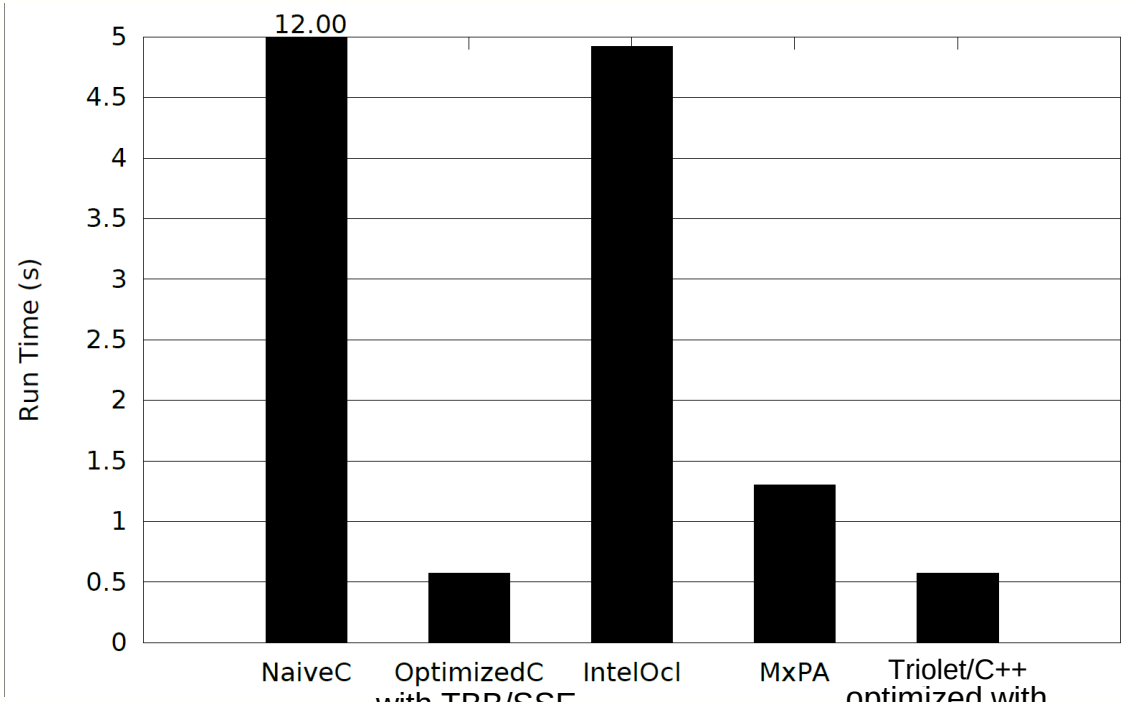
Triolet/C++ Convolution Code

```
std::vector<int> 2dconvolution(const std::vector<int>& input,
        int x_size, int y_size,
        const std::vector<float>& kernel)
{
    auto input_co = make_matrix<int, 2>(input, x_size, y_size);
    auto kernel_co = make_small_vector<int>(kernel);
    auto stencil_co = make_stencil_transform<9,9>(input_co);
    auto const_co = make_const_transform(kernel_co, x_size * y_size);
    auto zip_co = make_zip_transform(stencil_co, const_co);
    auto map_co = make_map_transform(zip_co,map_operation<mul_op>());
    auto reduce_co =
       make_map_transform(map_co,reduce_operation<add_op>());
    std::vector<int> output = Evaluate<std::vector, int>(reduce_co);
}
```

The compiler performs actual code synthesis

Convolution Performance

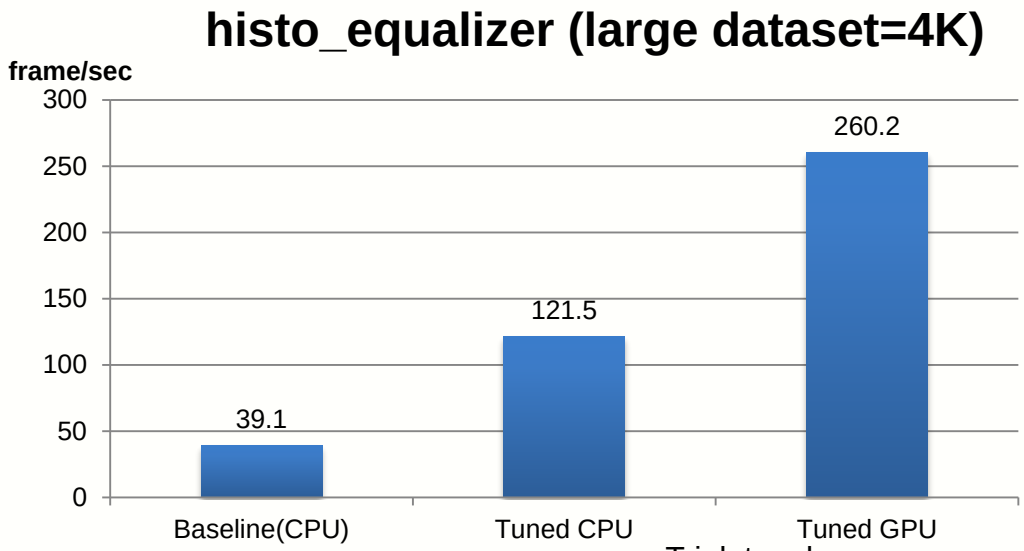
- All versions (except Naive) are multithreaded and vectorized
  - 8x performance difference (Intel vs. Ours)



Run time measured on Intel Core i7-3820 (4-core, hyperthreaded)

Triolet C++ equalize_frames Example

- Baseline is parallel code taken from DARPA PERFECT benchmark suite
- Tuned code outperforms baseline on both architectures

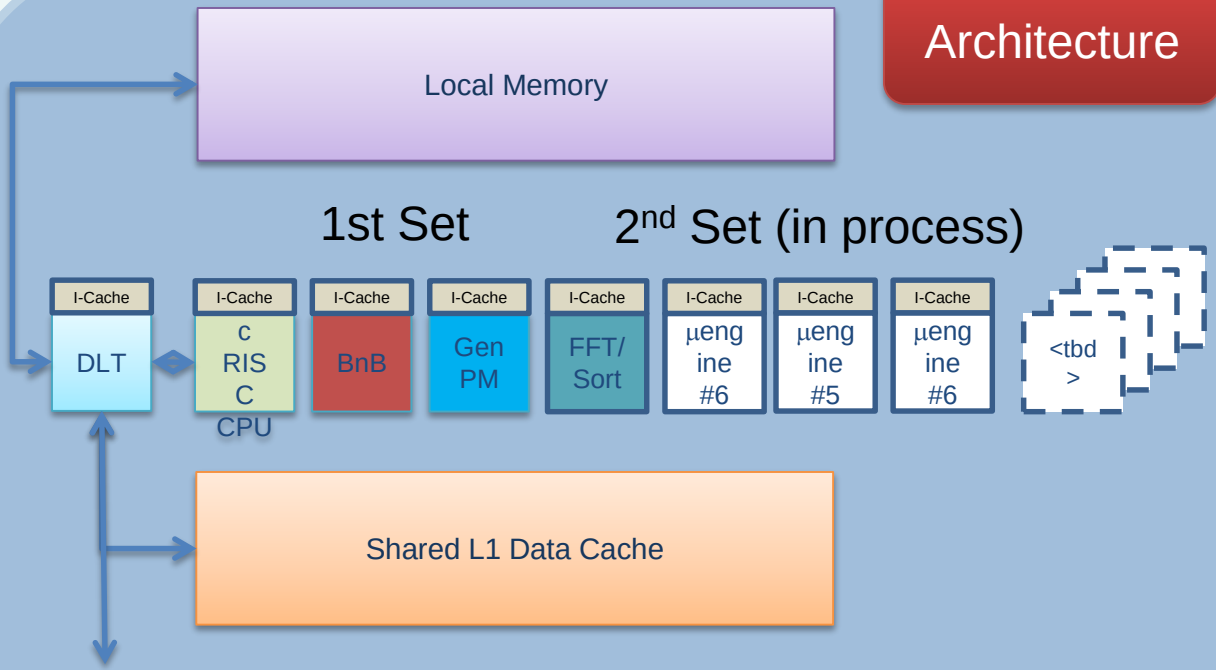


CPU time measured on Intel Xeon E5520 (4-core, hyperthreaded)

GPU time measured on Tesla C2050

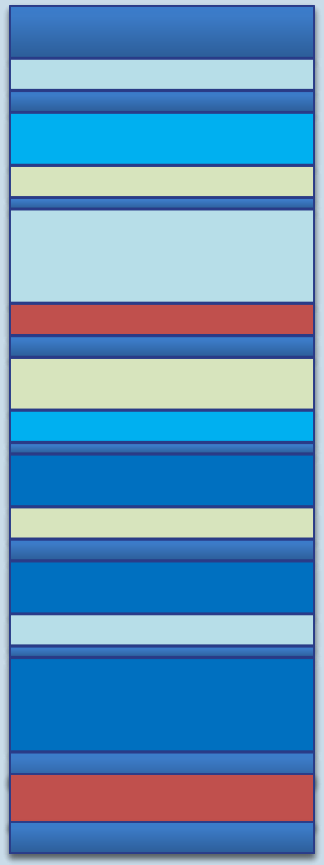
10x10 Heterogeneous Architecture

Architecture



- 1st set of micro-engines evaluation nearly complete
- Developing a set of complementary micro-engines
- Composite evaluation: 5x5

Application



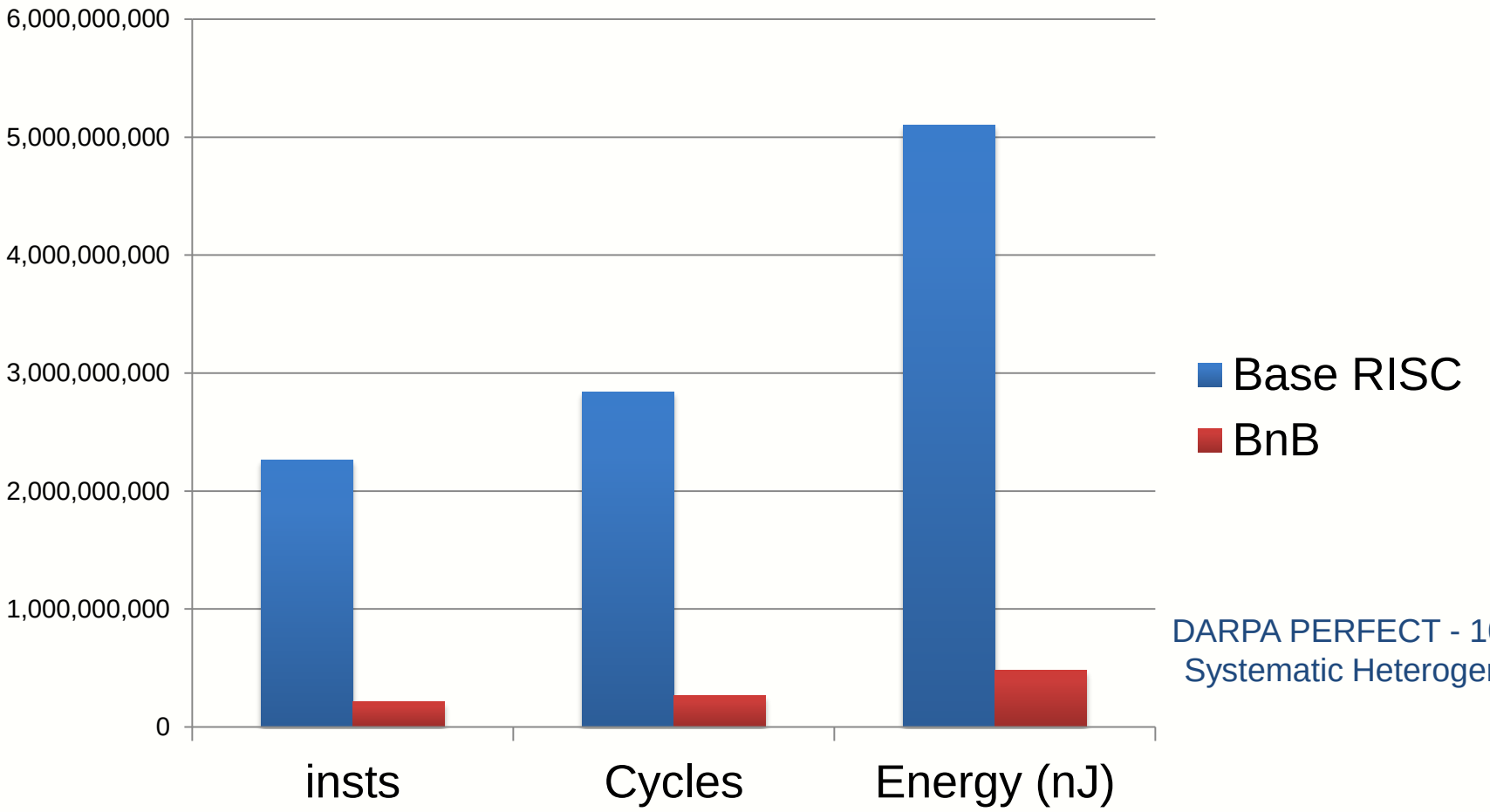
Compiler

- Compilation: Mapreduce, micro-engine, and robust vectorization and locality management

GPM

- Global Power Management: power & performance models for core and link frequency changes + opportunity assessment

Compiled Conv2D on BnB



DARPA PERFECT - 10x10: Systematic Heterogeneity

~10.5x improvement across the board
1024x1024 image, HMC memory system

Programming in Triolet Python

Nonuniform FT (real part)

$$y_i = \sum_{j=0}^{n-1} x_j \cos(r_i k_j) \qquad \text{for all } 0 \le i < m$$

Programming in Triolet Python

Nonuniform FT (real part)

Inner loop

$$y_i = \sum_{j=0}^{n-1} x_j \cos(r_i k_j) \qquad \text{for all } 0 \le i < m$$

Inner loop

```
sum(x * cos(r*k) for (x, k) in zip(xs, ks))
```

Programming in Triolet Python

Nonuniform FT (real part)

Inner loop

Outer loop

$$y_i = \sum_{j=0}^{n-1} x_j \cos(r_i k_j) \qquad \text{for all } 0 \le i < m$$

```
ys = [ sum(x * cos(r*k) for (x, k) in zip(xs, ks)) for r in par(rs)]
```

Inner loop

Outer loop

Programming in Triolet Python

Nonuniform FT (real part)

Inner loop

Outer loop

$$y_i = \sum_{j=0}^{n-1} x_j \cos(r_i k_j) \qquad \text{for all } 0 \le i < m$$

```
ys = [ sum(x * cos(r*k) for (x, k) in zip(xs, ks)) for r in par(rs)]
```

Inner loop

Outer loop

- "map and reduce" style programming—no new paradigm to learn
- Parallel details are implicit—easy to use
- Automated data partitioning, MPI rank generation, MPI messaging, OpenMP, etc.
- Race-free, type-safe—no crashes or nondeterminism
  (with standard caveat about operator associativity)

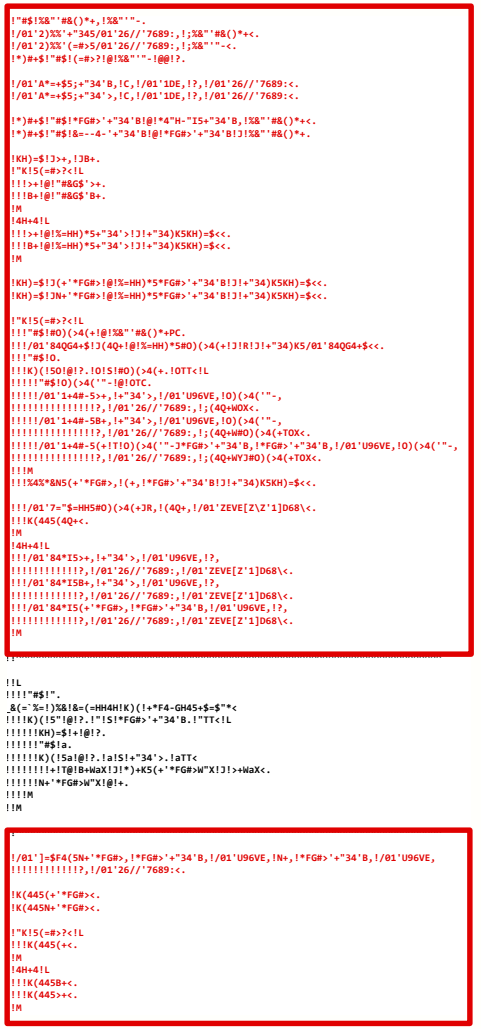
Productivity

Triolet

```
ys = [sum(x * cos(r*k) for (x, k) in zip(xs, ks))
      for r in par(rs)]
```

- Library functions factor out data decomposition, parallelism, and communication

C with MPI+OpenMP



Productivity and Performance

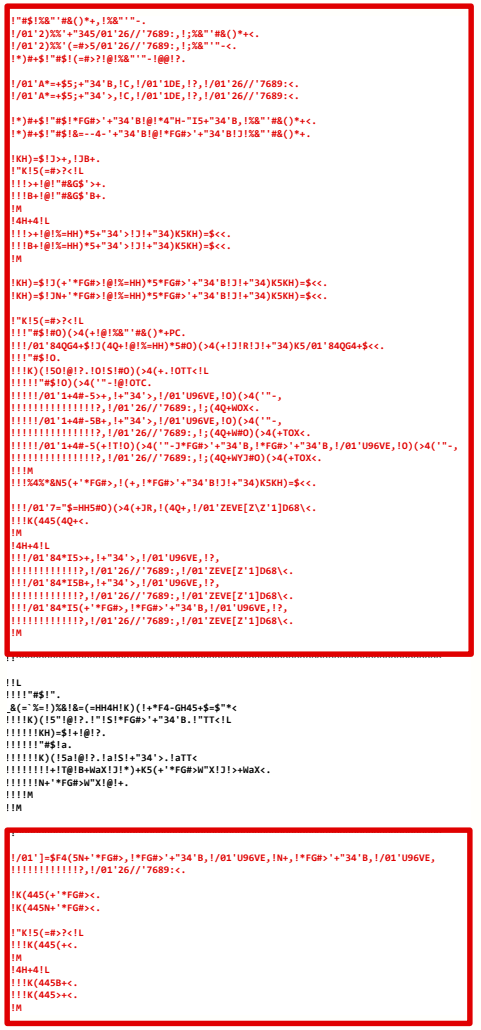
Triolet

```
ys = [sum(x * cos(r*k) for (x, k) in zip(xs, ks))
      for r in par(rs)]
```

- Library functions factor out data decomposition, parallelism, and communication

128-way Speedup (*16 cores × 8 nodes*)	**Triolet**	**C with MPI+OpenMP**
	99	115

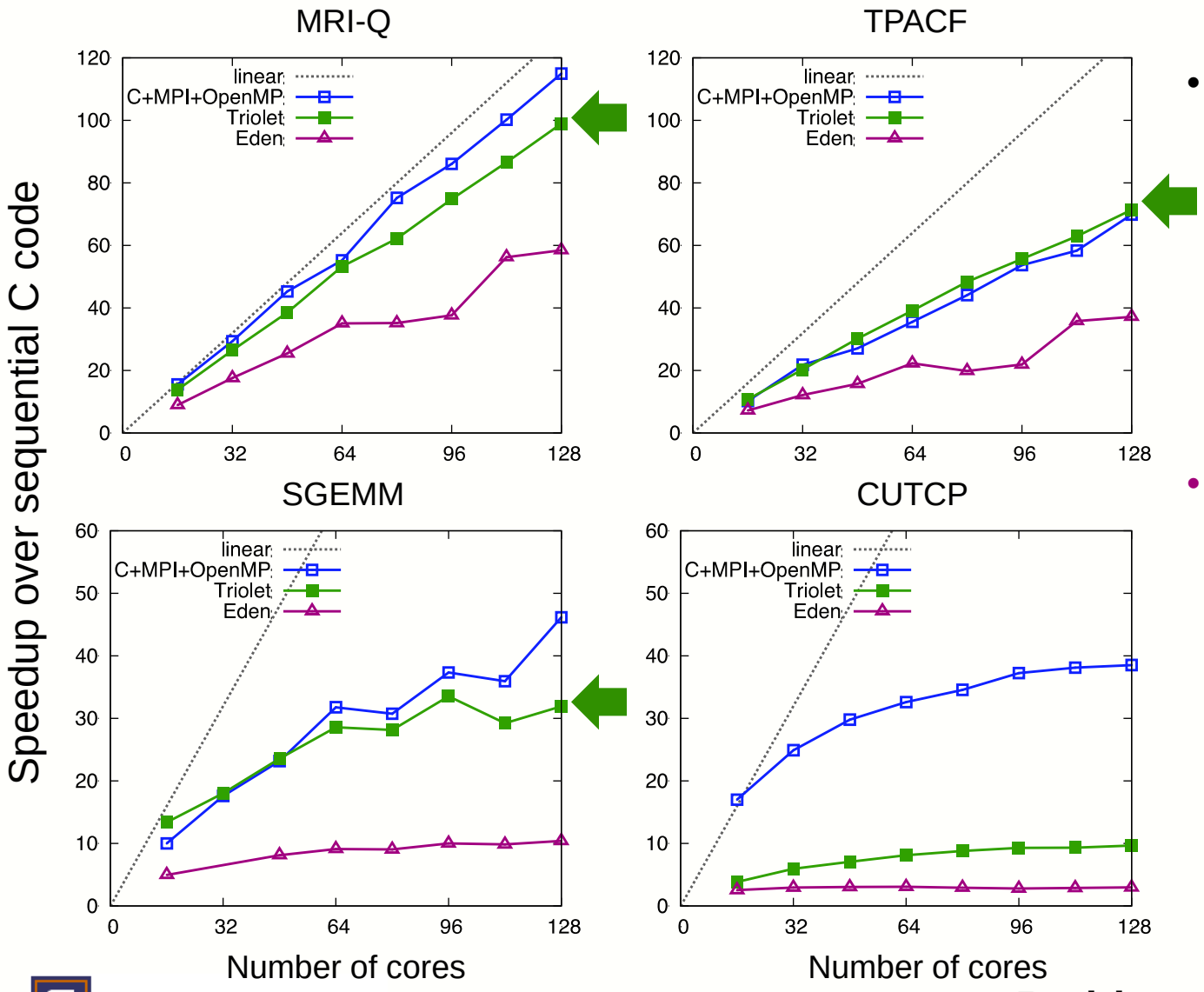
C with MPI+OpenMP



Setup

Cleanup

Cluster-Parallel Performance and Scalability



- Triolet delivers large speedup over sequential C
  - On par with manually parallelized C
  - Except in CUTCP; needs better GC policy for large arrays
- Similar high-level interfaces incur additional overhead
  - Message passing
  - Array split/merge
  - Run time variability

Rodrigues, et al PPoPP 2014

Triolet Pattern Domain Coverage Example

- Benchmarks suitable for HOF library
  - Each loop has one output
  - Outer parallelizable map in many benchmarks
  - Small set of computation patterns used repeatedly
    - Loops: map, reduce
    - Data merging: zip, outer product
    - array reshaping
- 8 of 15 benchmarks already ported to Triolet Python

Benchmark	Extra Patterns	Vectorizable
Discrete Wavelet Transform	deinterleave, regions	pixels
2 D Convolutions	regions	pixels
Histogram Equalization	histogram, scan, lut	pixels, bins
System Solver	triangular loop	matrix rows
Inner Product	-	channels
Outer Product	triangular loop	channels
Interpolation 1	-	range coords
Interpolation 2	lut	range coords
Back Projection	lut	
Debayer	interleave, regions	pixels
Image Registration	-	pixels
Change Detection	-	-
Sort	sort	array elements
FFT 1D	fft	
FFT 2D	fft	

Conclusion

- Near-term impact
  - MxPA locality-centric scheduling, kernel fusion scheduling, and dynamic vectorization make OpenCL kernel performance portability a reality – ready for industry impact
  - MulticoreWare MxPA product with several customers including Movidius and Samsung
- Medium term impact
  - Triolet C++ brings intentional programming into C++, giving CUDA/OpenCL/OpenMP/OpenACC developers a much more productive, maintainable, protable new option
  - Immediate commercial opportunity in mobile and server SOCs
- Long-term outlook
  - Triolet Python further brings intentional programming into heterogeneous computing server clusters and distributed computing
  - Triolet Java?