

Alexandru Calotoiu

Slides courtesy of Tal Ben-Nun, Johannes de Fine Licht, Alexandros-Nikolaos Ziogas, Timo Schneider, Torsten Hoefler, Jan Kleine, Philipp Schaad and others at SPCL

# Stateful Dataflow Multigraphs: A Data-Centric Model for Performance Portability on Heterogeneous Architectures



This project has received funding from the European Research Council (ERC) under grant agreement "DAPP (PI: T. Hoefler)".





# Motivation

Cray-1 Vector Processor



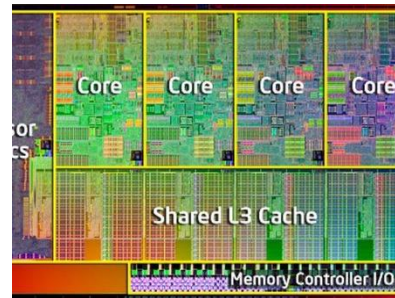
1976

CPU



1992

Multi-Core



2002

GPU Computing  
Heterogeneous Systems



2007



OpenCL



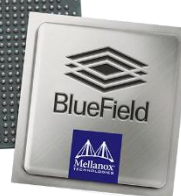
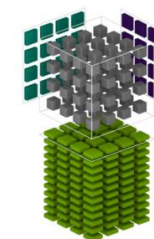
2012

Specialization



2016

FPGAs and beyond



2017

Today

# Motivation

Cray-1 Vector  
Processor

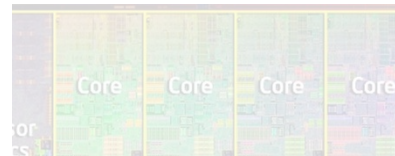
CPU

Multi-Core

GPU Computing  
Heterogeneous Systems

Specialization

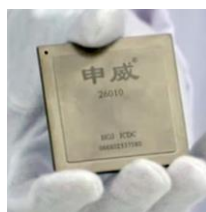
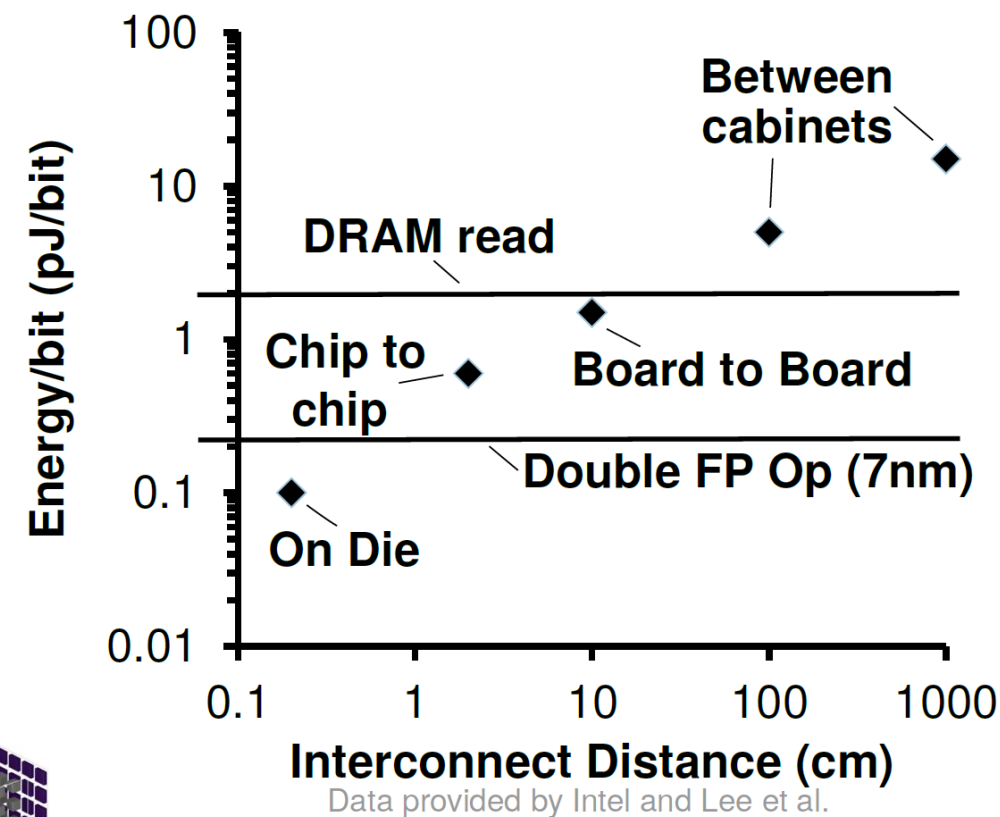
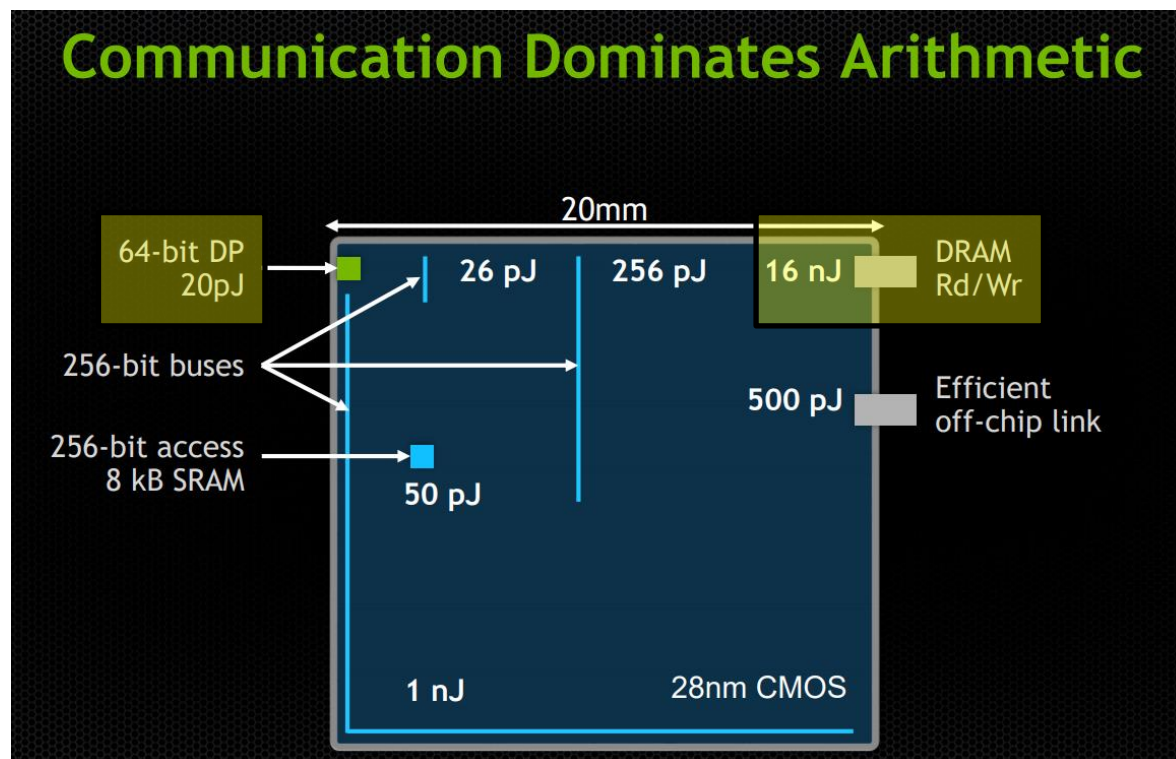
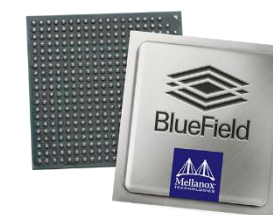
FPGAs and  
beyond



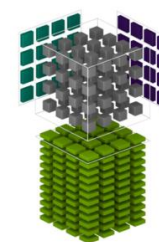
## Newer computer $\neq$ faster application



# Motivation



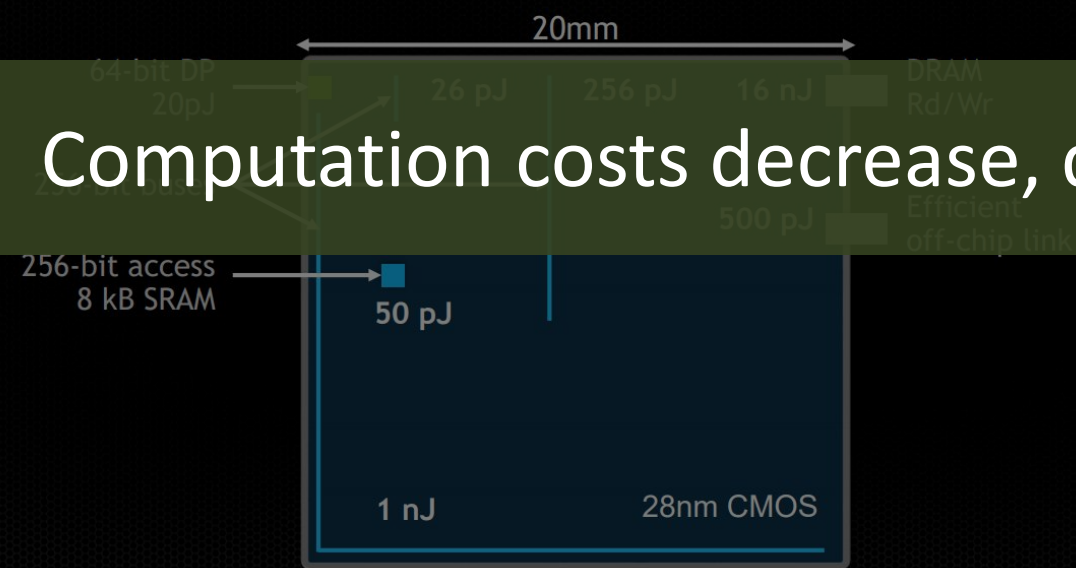
Slide courtesy of NVIDIA



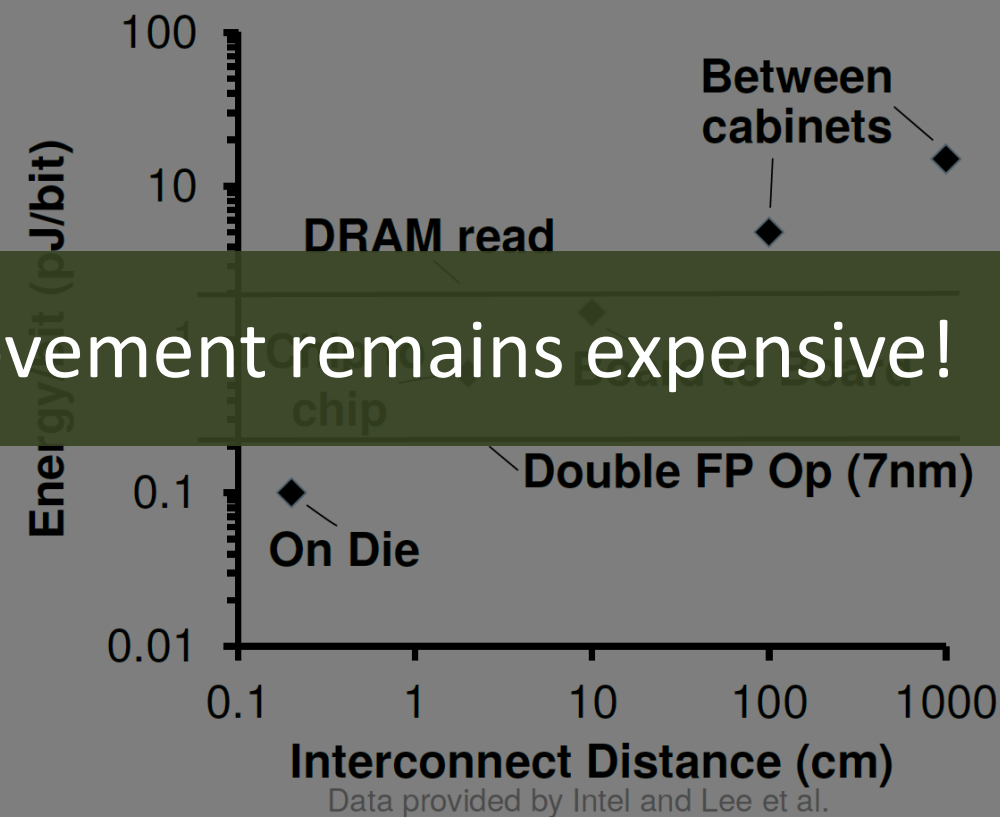


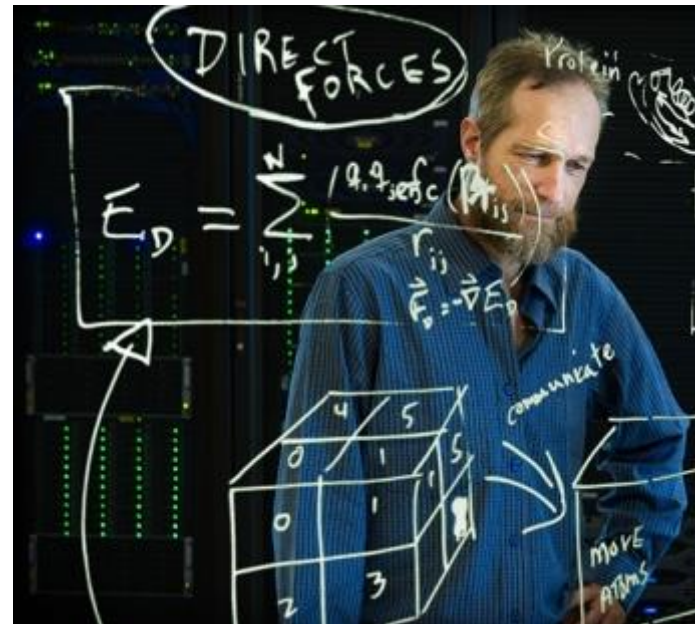
# Motivation

## Communication Dominates Arithmetic



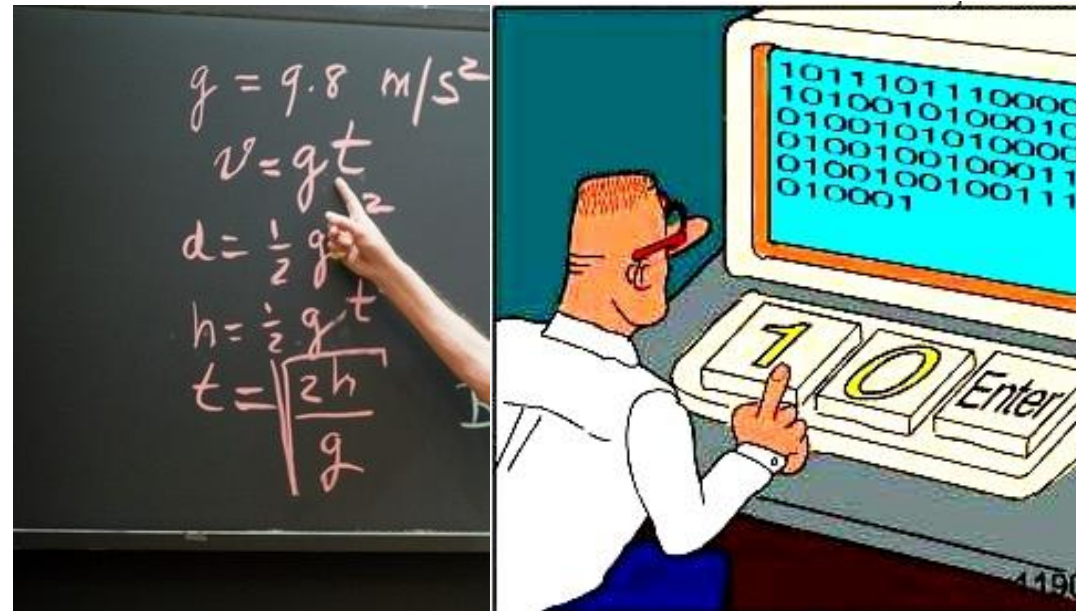
Slide courtesy of NVIDIA





Source: US DoE

## Computational Scientist



**Domain Scientist**

**Performance Engineer**

# Optimization Techniques

## ■ Multi-core CPU

- Tiling for complex cache hierarchies
- Register optimizations
- Vectorization



## ■ Many-core GPU

- High-performance optimization = data movement reduction
- Warp divergence minimization, register tiling
- Task fusion



NVIDIA®



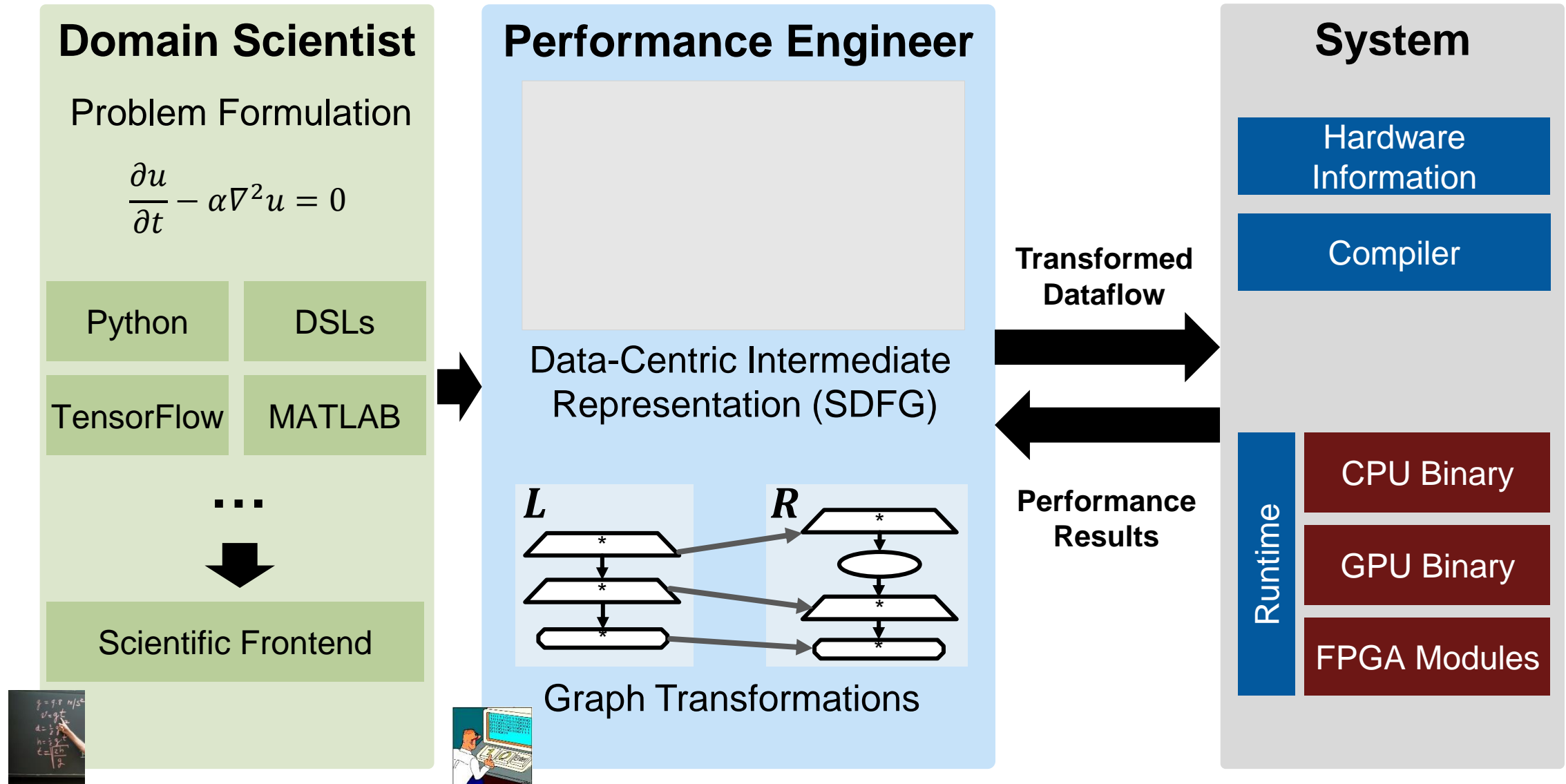
## ■ FPGA

- Maximize resource utilization (logic units, DSPs)
- Streaming optimizations, pipelining
- Explicit buffering (FIFO) and wiring





# aCe Overview



# Data-centric Parallel Programming for Python

- **Programs** are integrated within existing codes

In Python, integrated functions in existing code

In MATLAB, separate .m files

In TensorFlow, takes existing graph

- **In Python: Implicit and Explicit Dataflow**

**Implicit:** numpy syntax

**Explicit:** Enforce **memory access** decoupling from **computation**

- **Output compatible with existing programs**

C-compatible SO/DLL file with autogenerated include file

```
@dace.program
def program_numpy(A, B):
    B[:] = np.transpose(A)
```

```
@dace.program
def program_explicit(A, B):

    @dace.map
    def transpose(i: _[0:N],
                  j: _[0:M]):
        a << A[i,j]
        b >> B[j,i]

    b = a
```

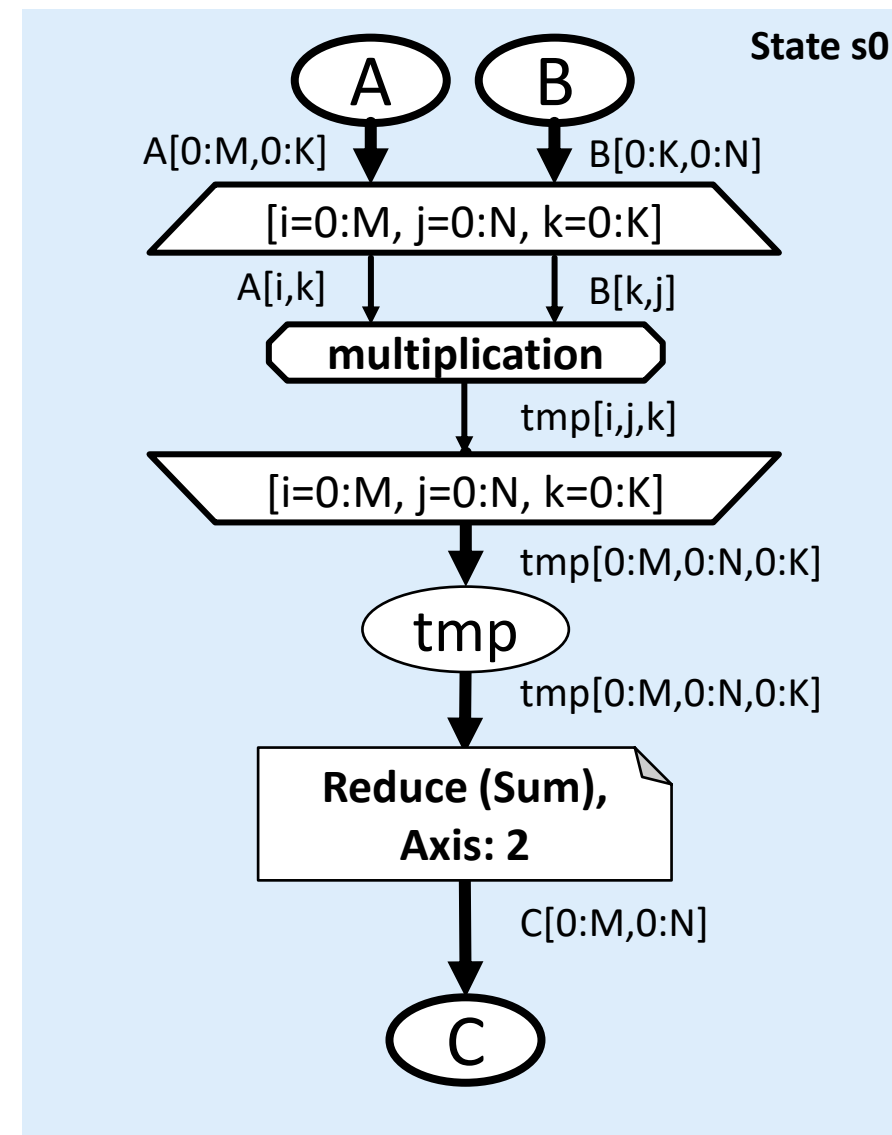
# Matrix Multiplication SDFG

```
@dace.program
def gemm(A: dace.float64[M, K], B: dace.float64[K, N],
        C: dace.float64[M, N]):
    # Transient variable
    tmp = np.ndarray([M, N, K], dtype=A.dtype)

    @dace.map
    def multiplication(i: _[0:M], j: _[0:N], k: _[0:K]):
        in_A << A[i,k]
        in_B << B[k,j]
        out >> tmp[i,j,k]

        out = in_A * in_B

    dace.reduce(lambda a, b: a + b, tmp, C, axis=2)
```





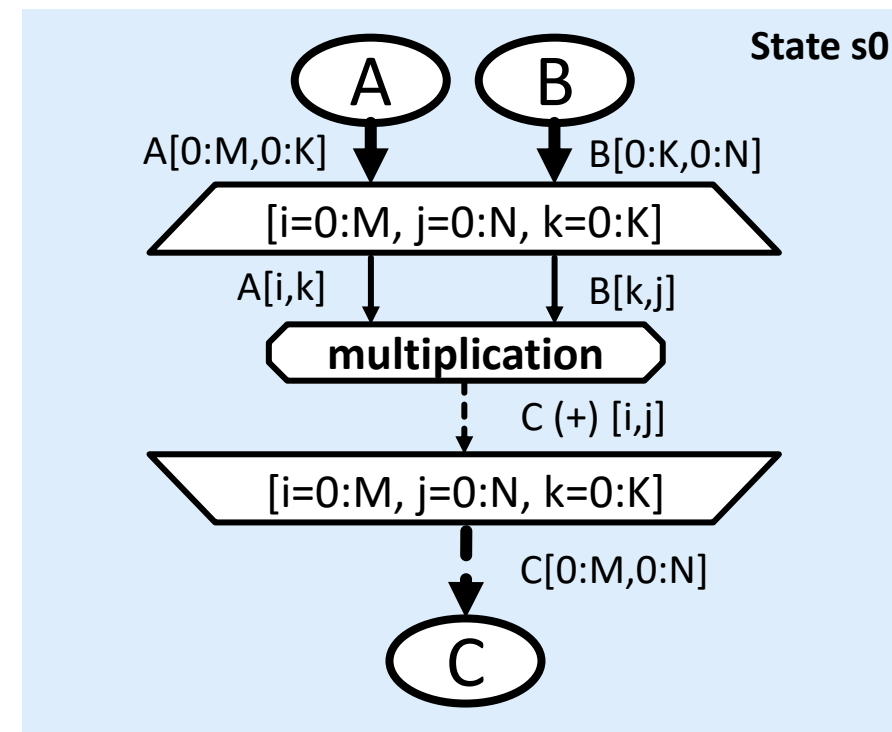
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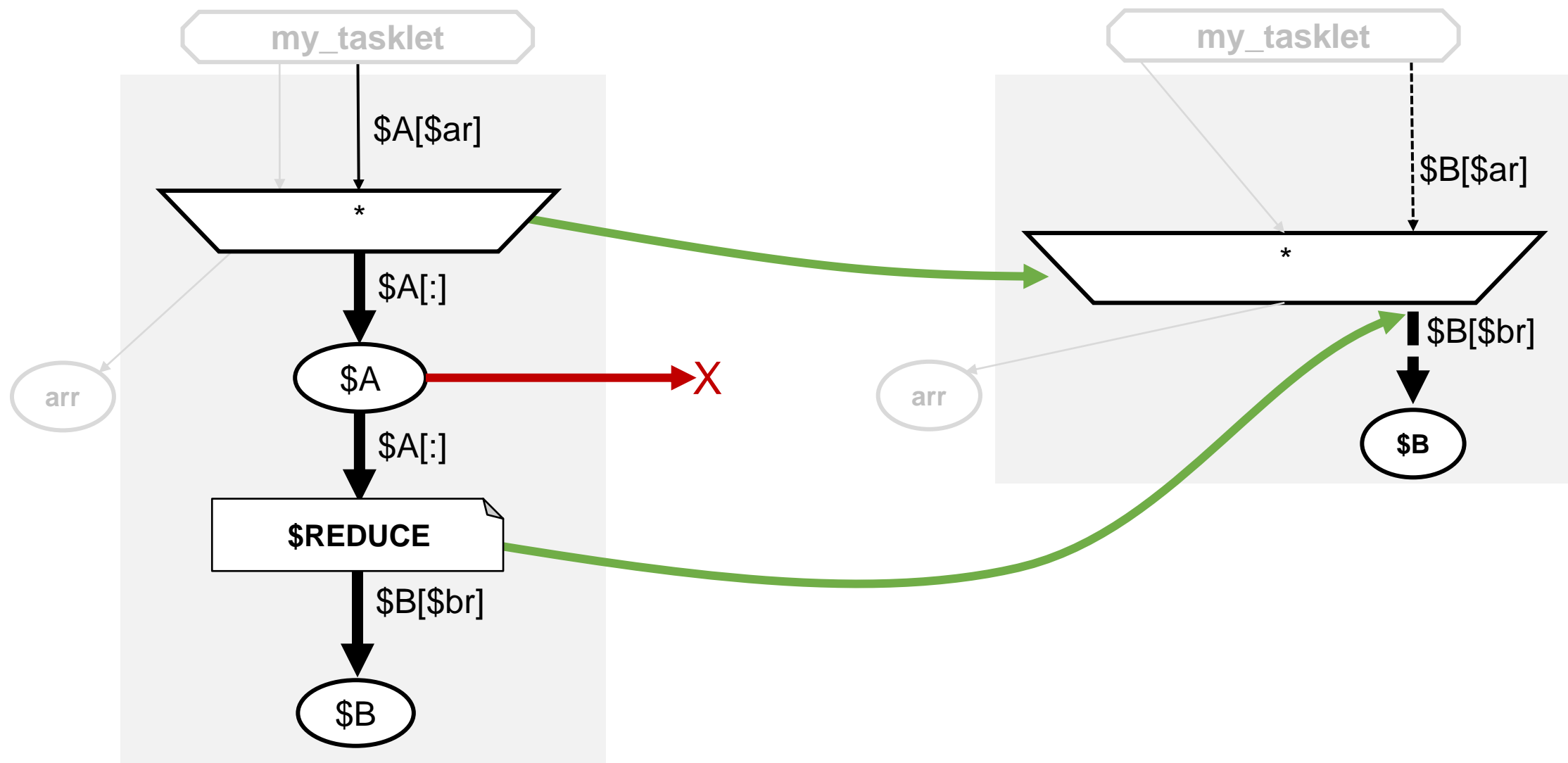
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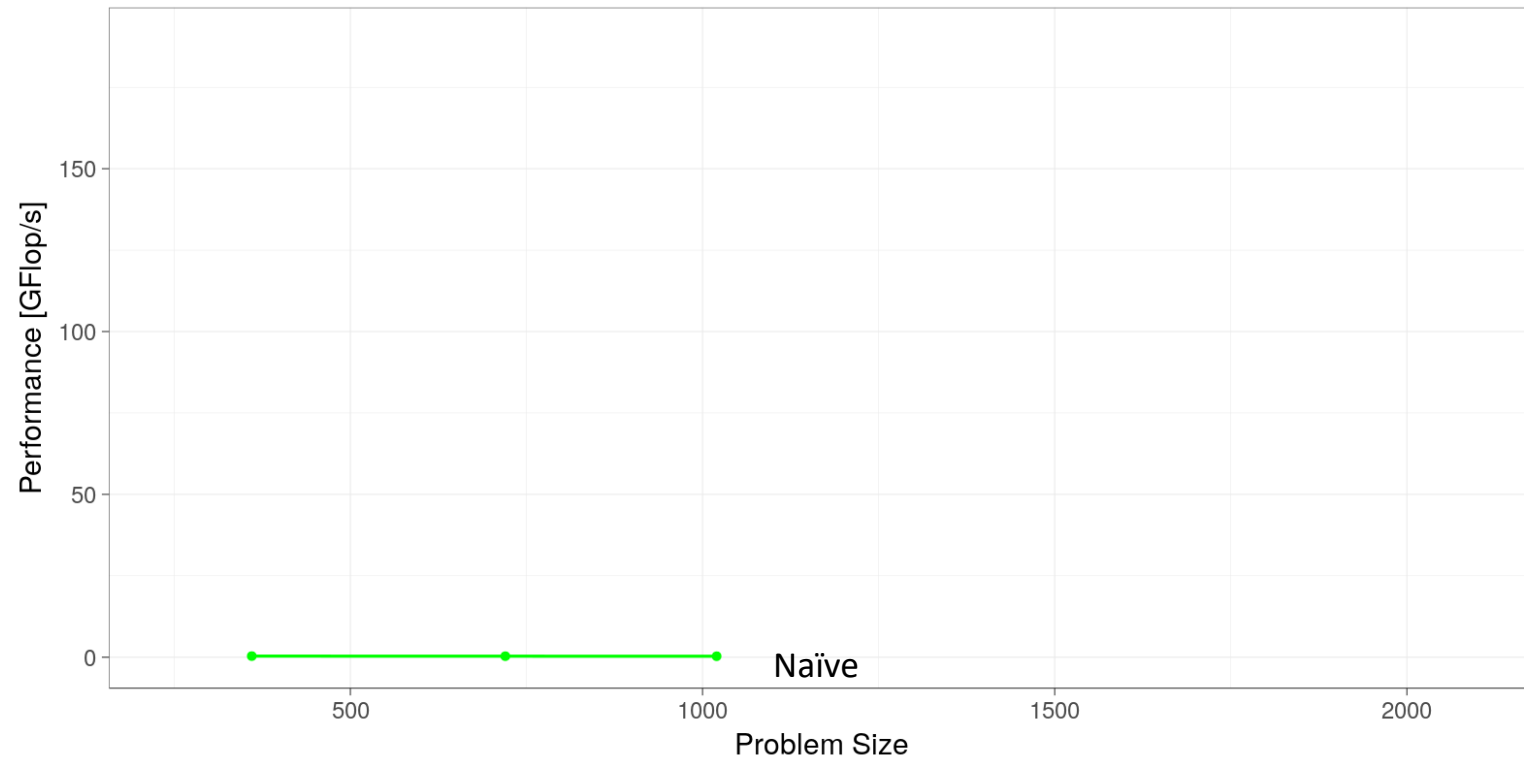
    dace.reduce(lambda a, b: a + b, tmp, C, axis=2)
```



# MapReduceFusion Transformation

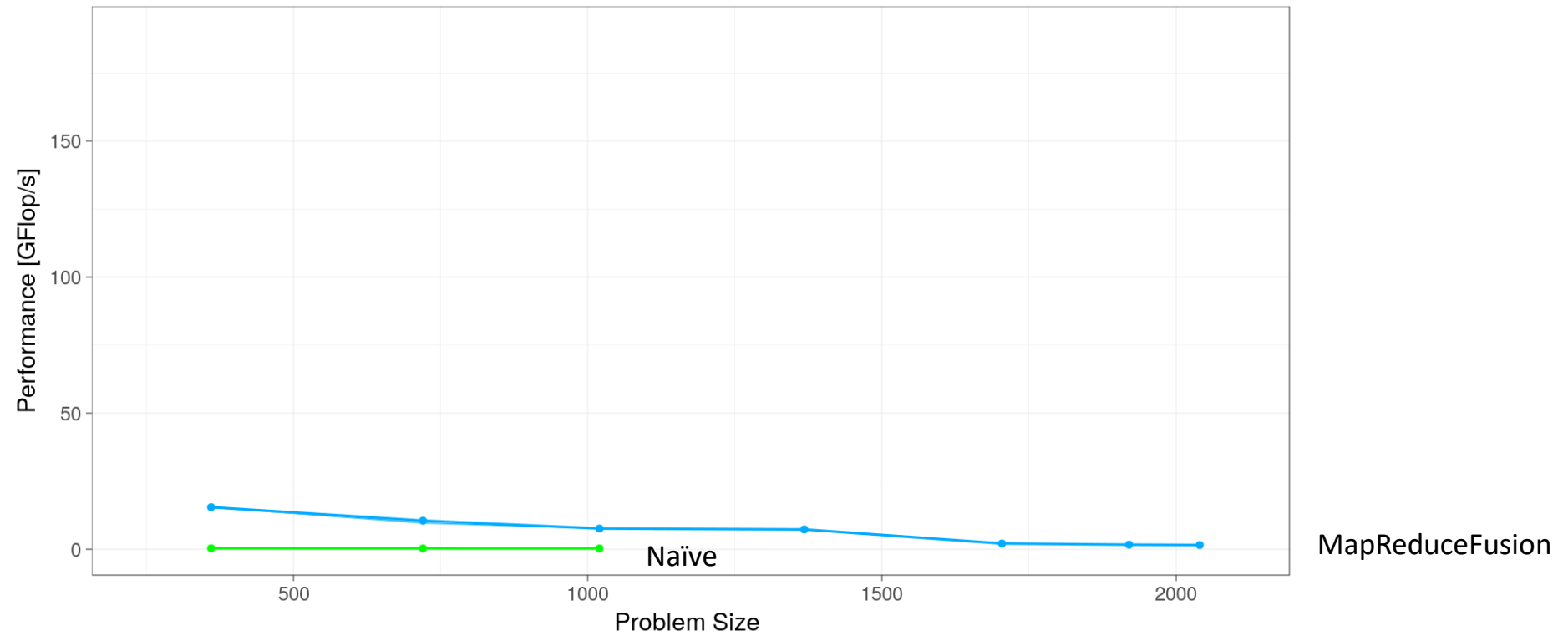


# Performance

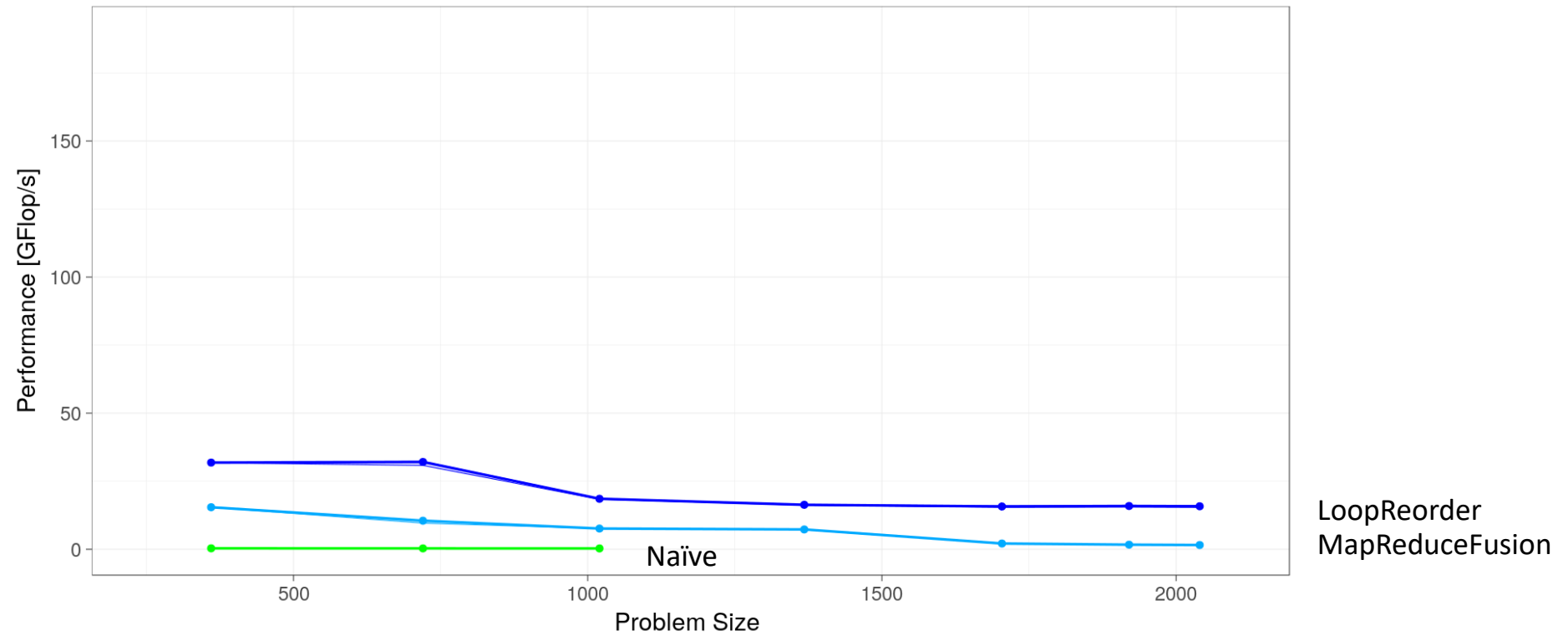




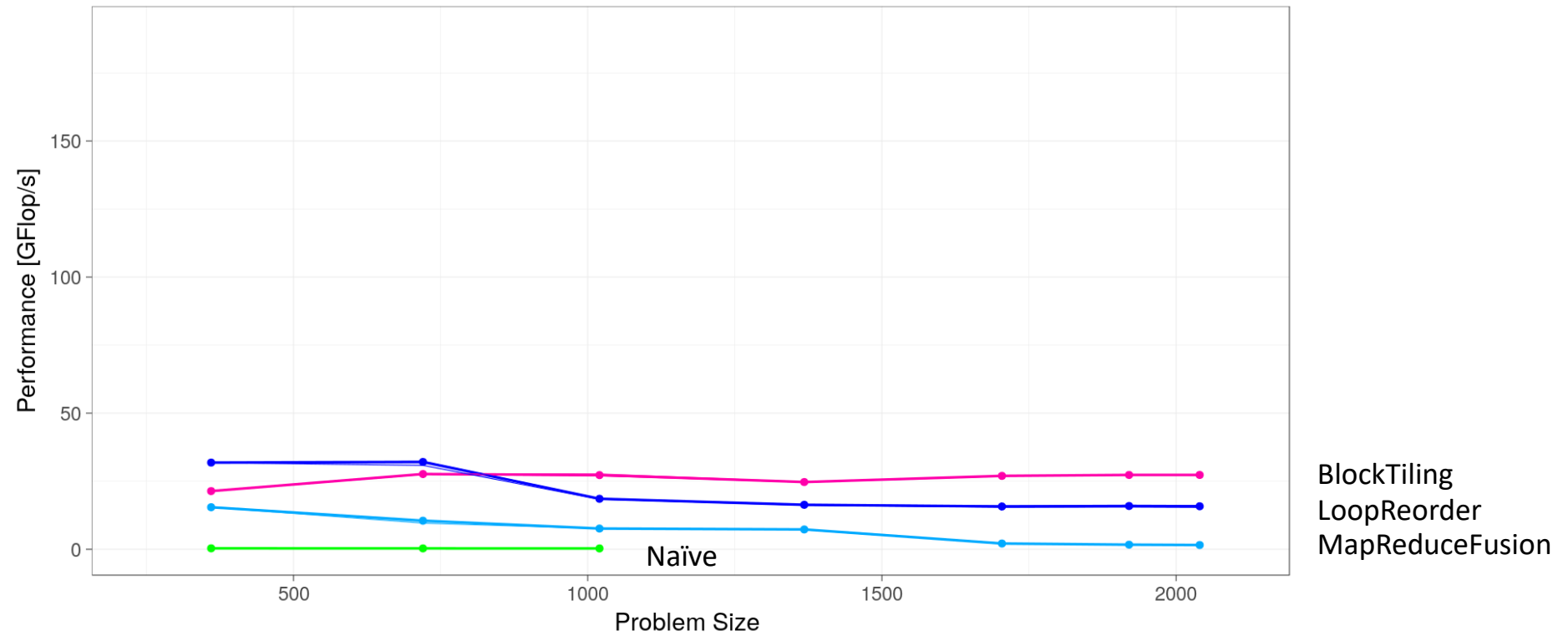
# Performance



# Performance

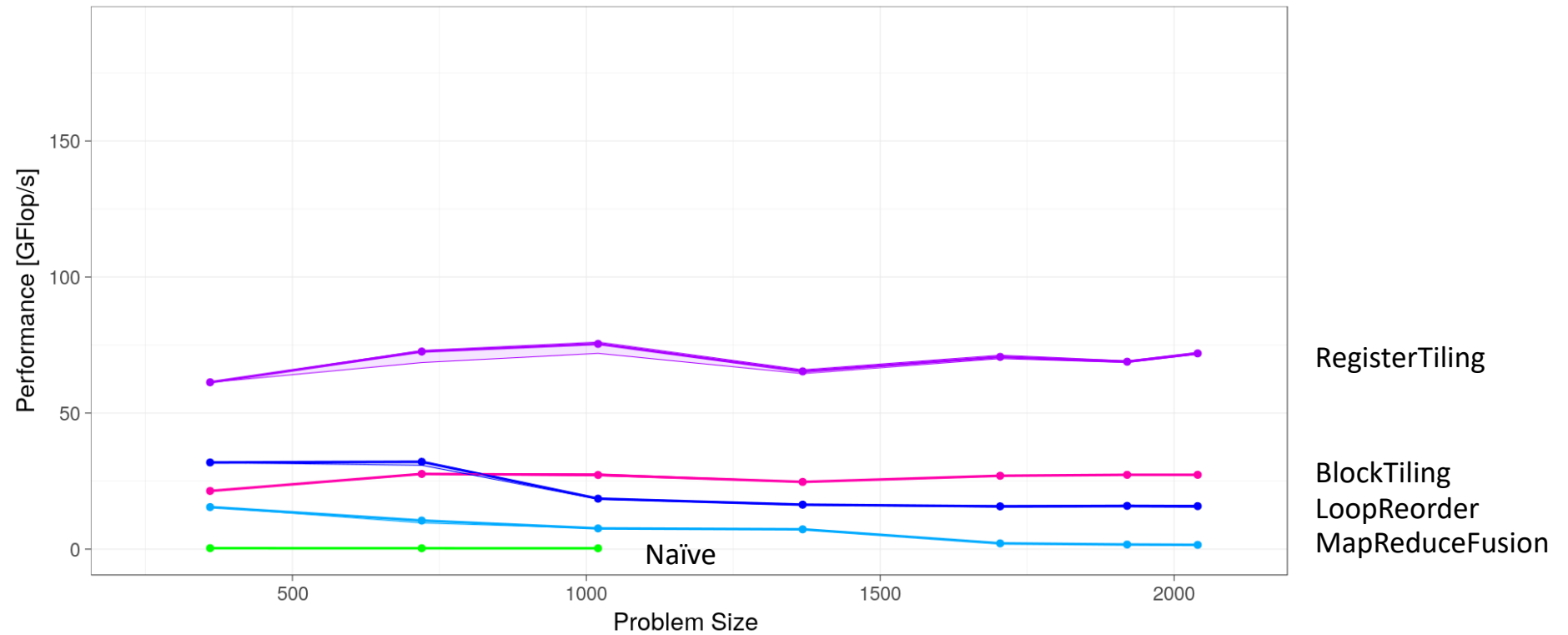


# Performance

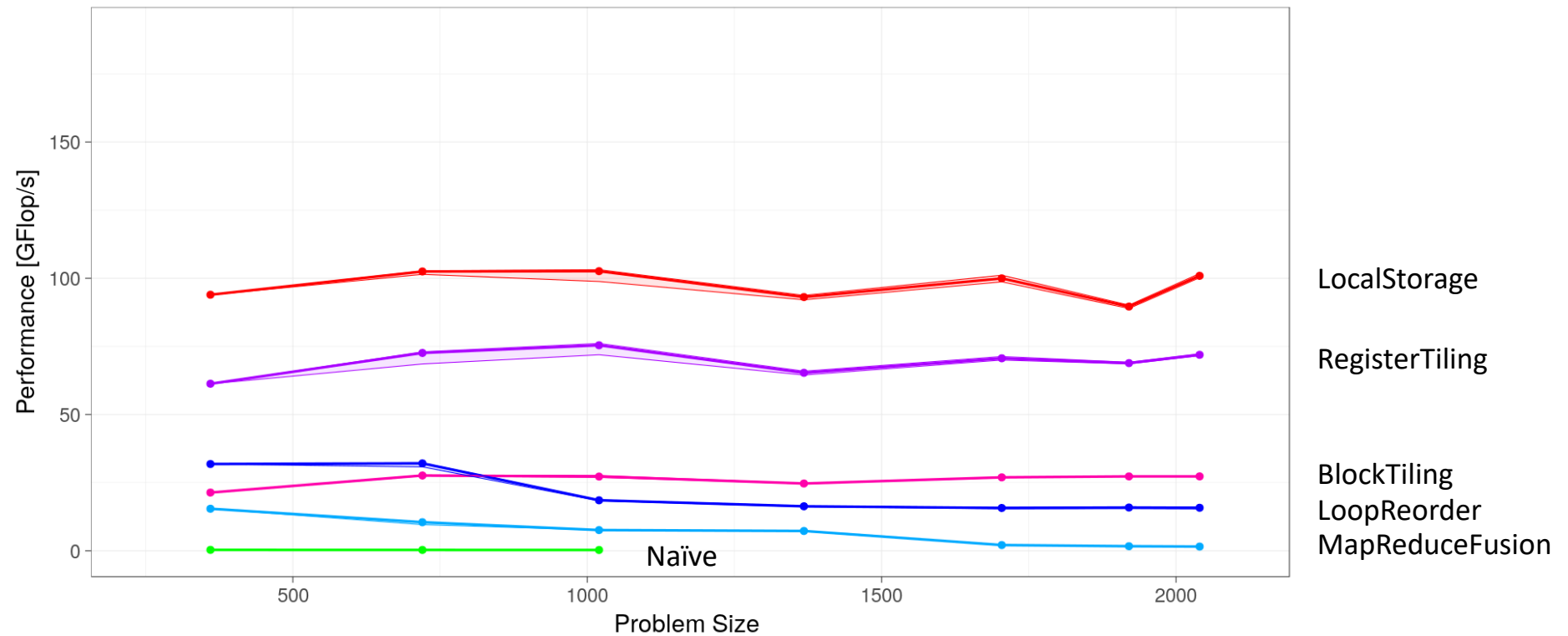




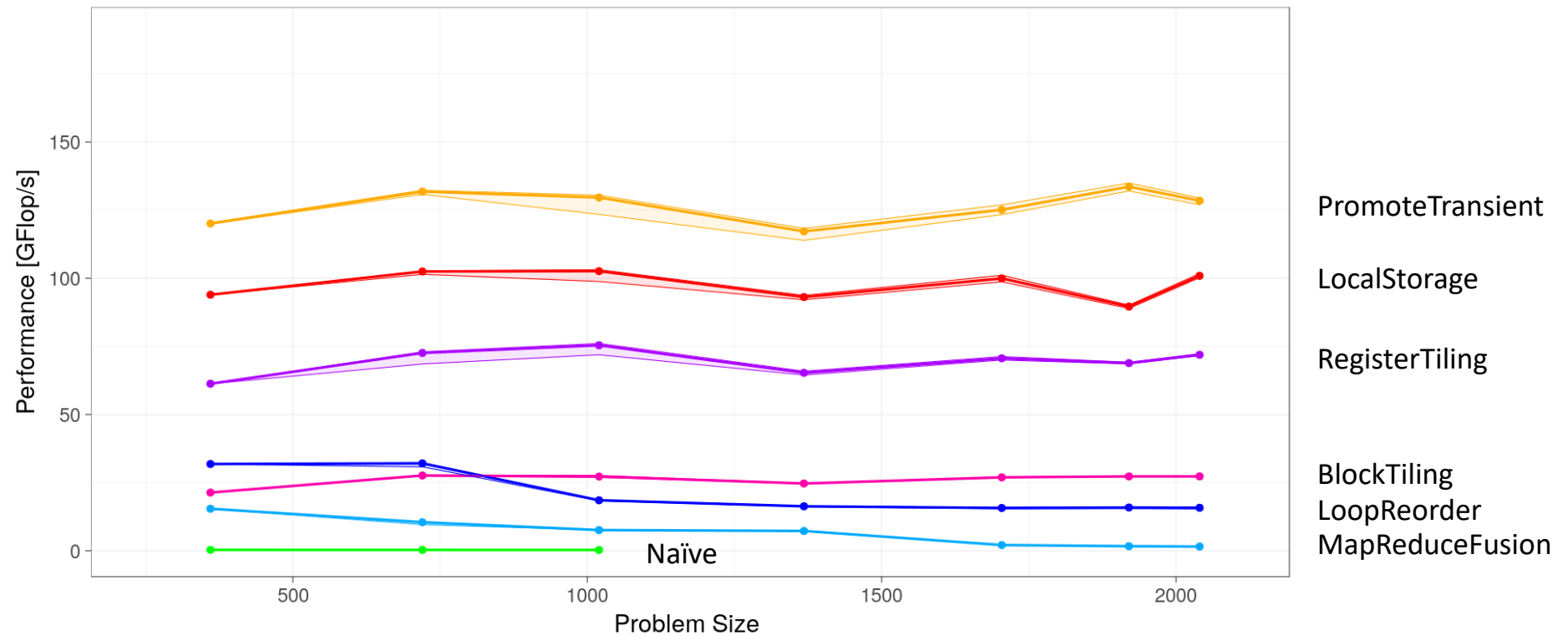
# Performance



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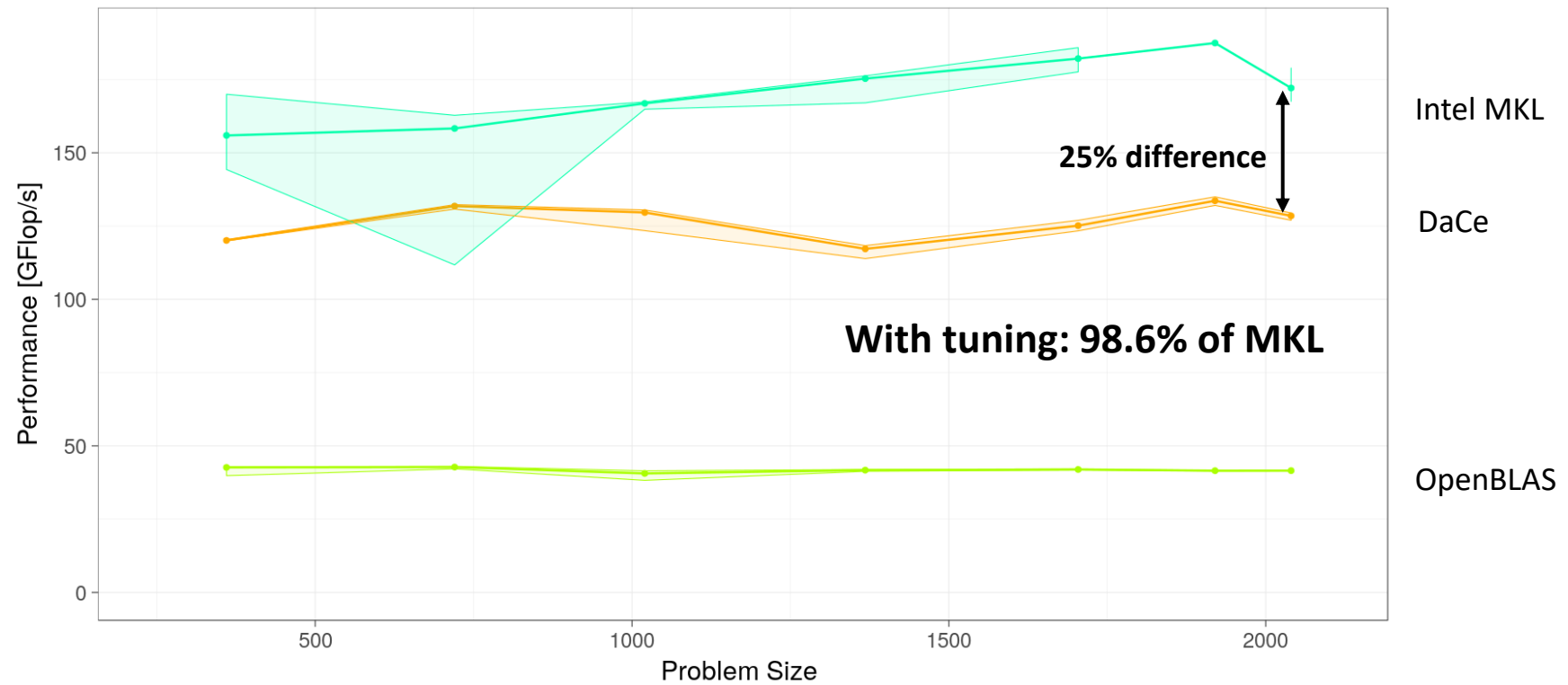


# Performance





# Performance





Intel Xeon E5-2650 v4



NVIDIA Tesla P100



Xilinx VU9P

**SDFG**

**General Compilers**

GCC 8, Clang 6, icc 18,  
NVCC 9.2, SDAccel

**Polyhedral Optimizers**

Polly 6, Pluto 0.11.4, PPCG 0.8

**Frameworks & Libraries**

HPX, Halide, Intel MKL, CUBLAS,  
CUSPARSE, CUTLASS, CUB

# Related work

