

# Dynamic OpenCL

DISTRIBUTED COMPUTING ON CLOUD SCALE

FLORIAN ROESLER

# OUTLINE

1. Motivation
2. Related Work
3. Basics
4. Contributions
5. Evaluation
6. Future Work
7. Conclusion

**MOTIVATION**

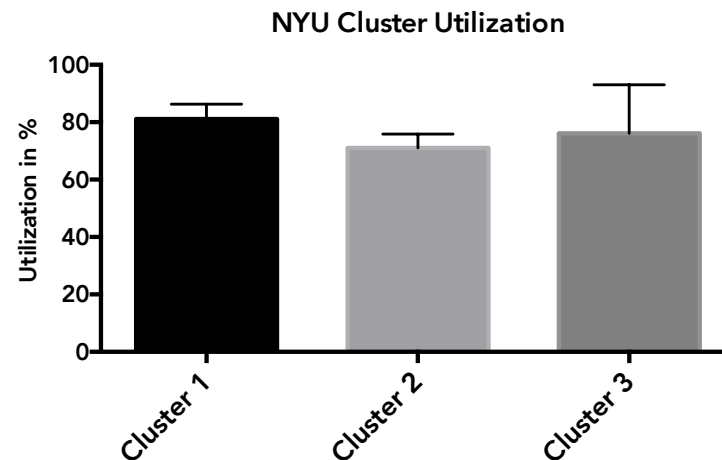
# COMPUTATIONAL COMPLEXITY

- Certain computations can not be efficiently computed on a single machine
- Single-threaded code → Multi-threaded code → Distributed code
- Code complexity increases drastically

Related Technologies: MapReduce, OpenMP, MPI, CUDA, OpenCL

# COST EFFICIENT CLUSTERS

- Shared clusters face trade off scenario:
  - Underutilization → high total costs of ownership
  - Overutilization → job queues and increased waiting time
- Solution: dynamic resource adjustments



# RESEARCH GOALS

Build a framework that provides ...

- Cluster execution of jobs on CPUs and GPUs of various vendors
- Dynamic scaling of cluster resources through cloud services
- Handling multiple simultaneous jobs efficiently by employing suitable scheduling algorithms
- Easy-to-use API in high-level language

# RELATED WORK

# RELATED WORK

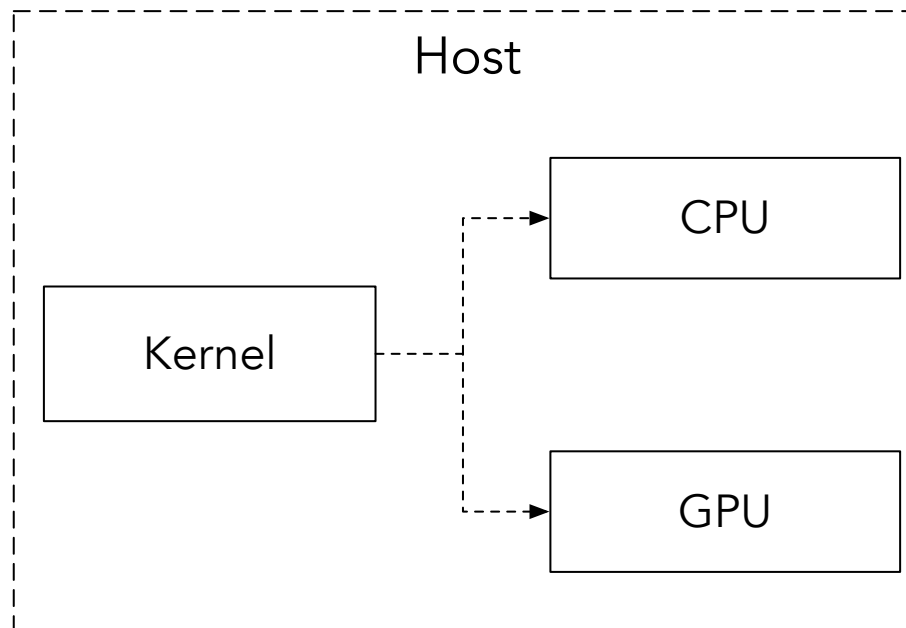
- rCUDA
- Virtualizing CUDA Enabled GPGPUs on ARM Clusters
- DistCL
- Hadoop+Aparapi



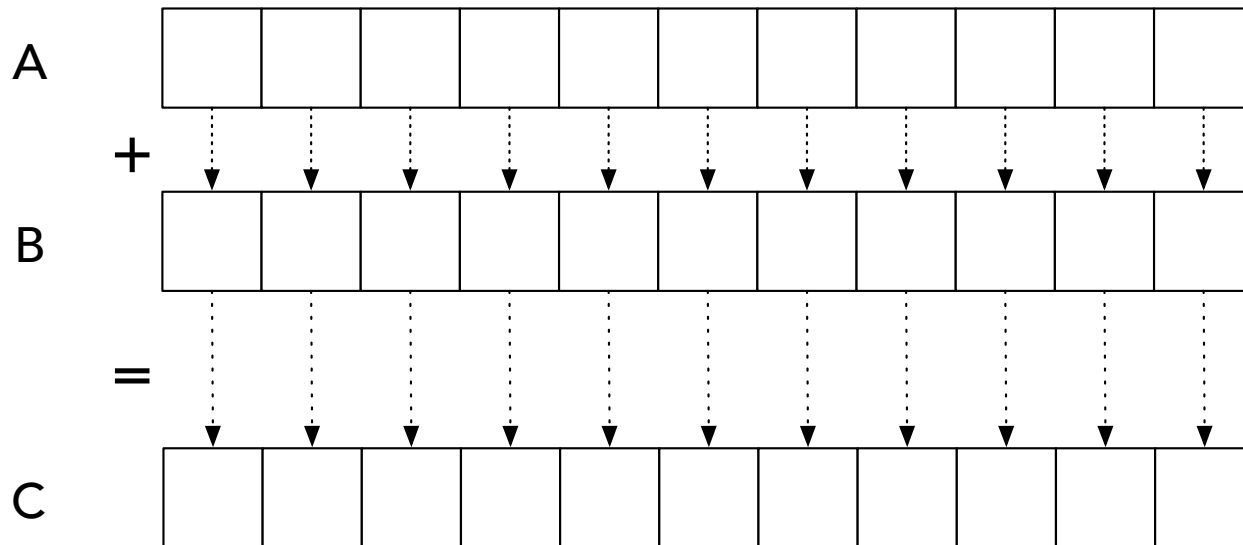
# BASICS

# OpenCL

- Execute parallel programs (Kernels) on heterogeneous hardware (CPU, GPU, FPGA and more)
- Kernels written in OpenCL C
- Kernels are started on host from C or C++ programs



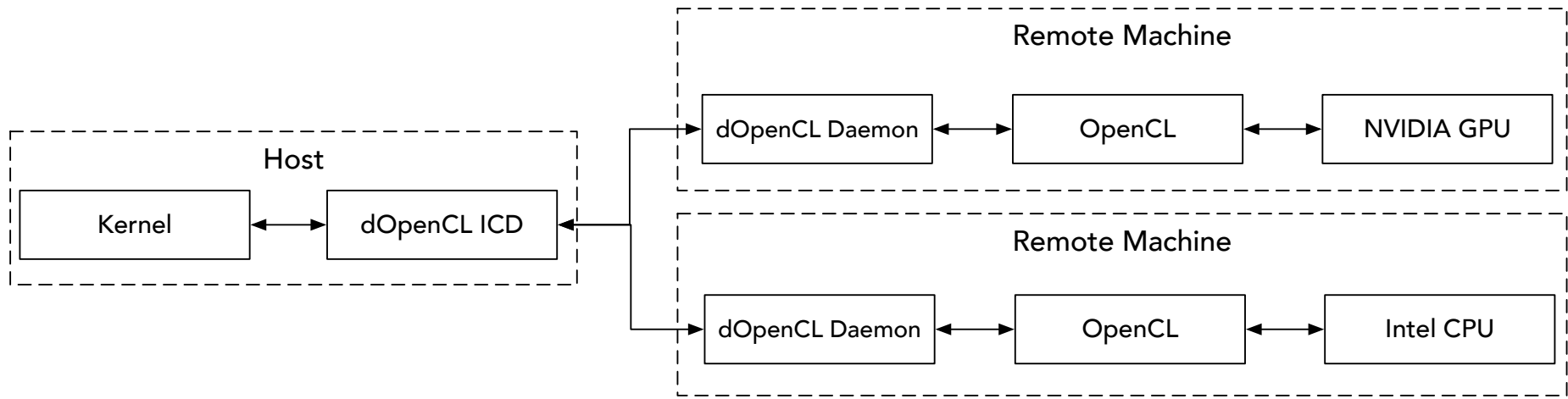
# OpenCL Vector Addition Example



```
__kernel void run(__global double *a, __global double *b, __global double *c)
{
    int i = get_global_id(0);
    c[i] = a[i] + b[i];
}
```

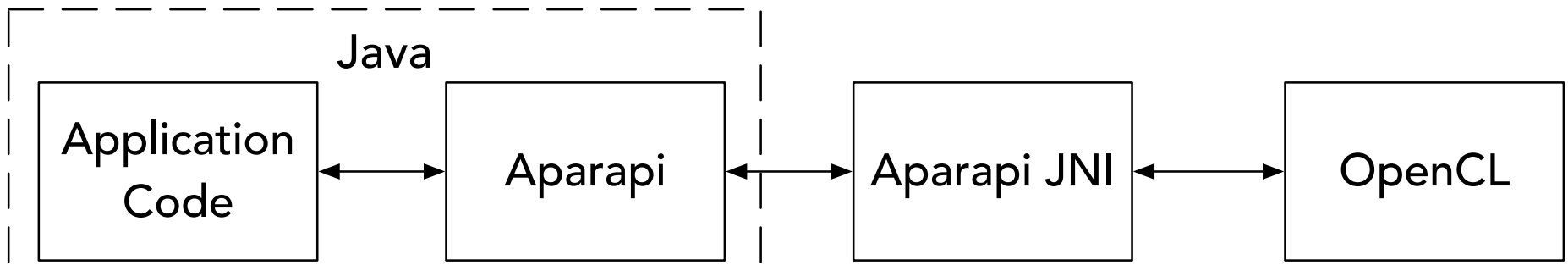
# OpenCL API Forwarding (dOpenCL)

- Access OpenCL devices on remote host
- No code changes necessary
- Reduces distribution complexity



# Aparapi

- Translates Java code to OpenCL Kernels
- Kernels are started from Java
- Reduces programming complexity
- Minimizes auxiliary code



# Aparapi Example

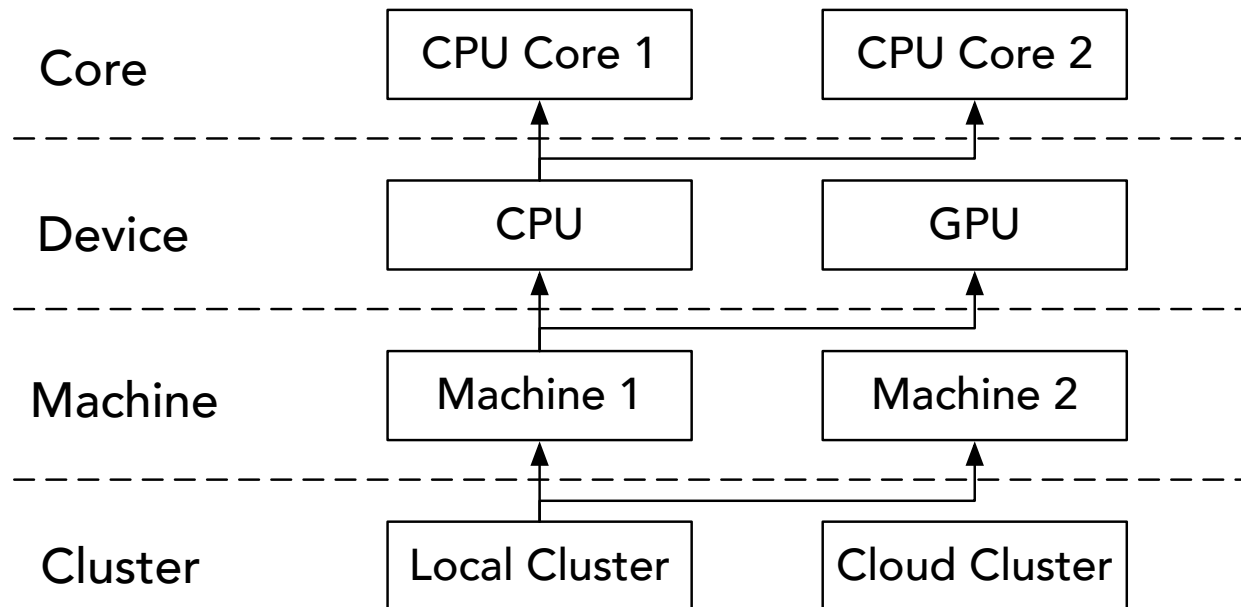
```
final double[] a = new double[]{0, 1, 2, 3, 4, 5, 6, 7, 8, 9};
final double[] b = new double[]{0, 1, 2, 3, 4, 5, 6, 7, 8, 9};
final double[] c = new double[10];

Kernel kernel = new Kernel() {
    @Override
    public void run() {
        int i = getGlobalId();
        c[i] = a[i] + b[i];
    }
};

kernel.execute(10);
```

# CONTRIBUTIONS

# LEVELS OF PARALLELIZATION





# CORE & DEVICE LEVEL

## Choosing OpenCL:

- Code utilizes all cores of CPUs and GPUs
- Programs are portable and follow a fixed programming model

## Alternatives:

- Low-level technologies like OpenMP and MPI provide complex APIs without a fixed programming model
- Targeting GPUs requires additional solutions like OpenACC

# MACHINE & CLUSTER LEVEL

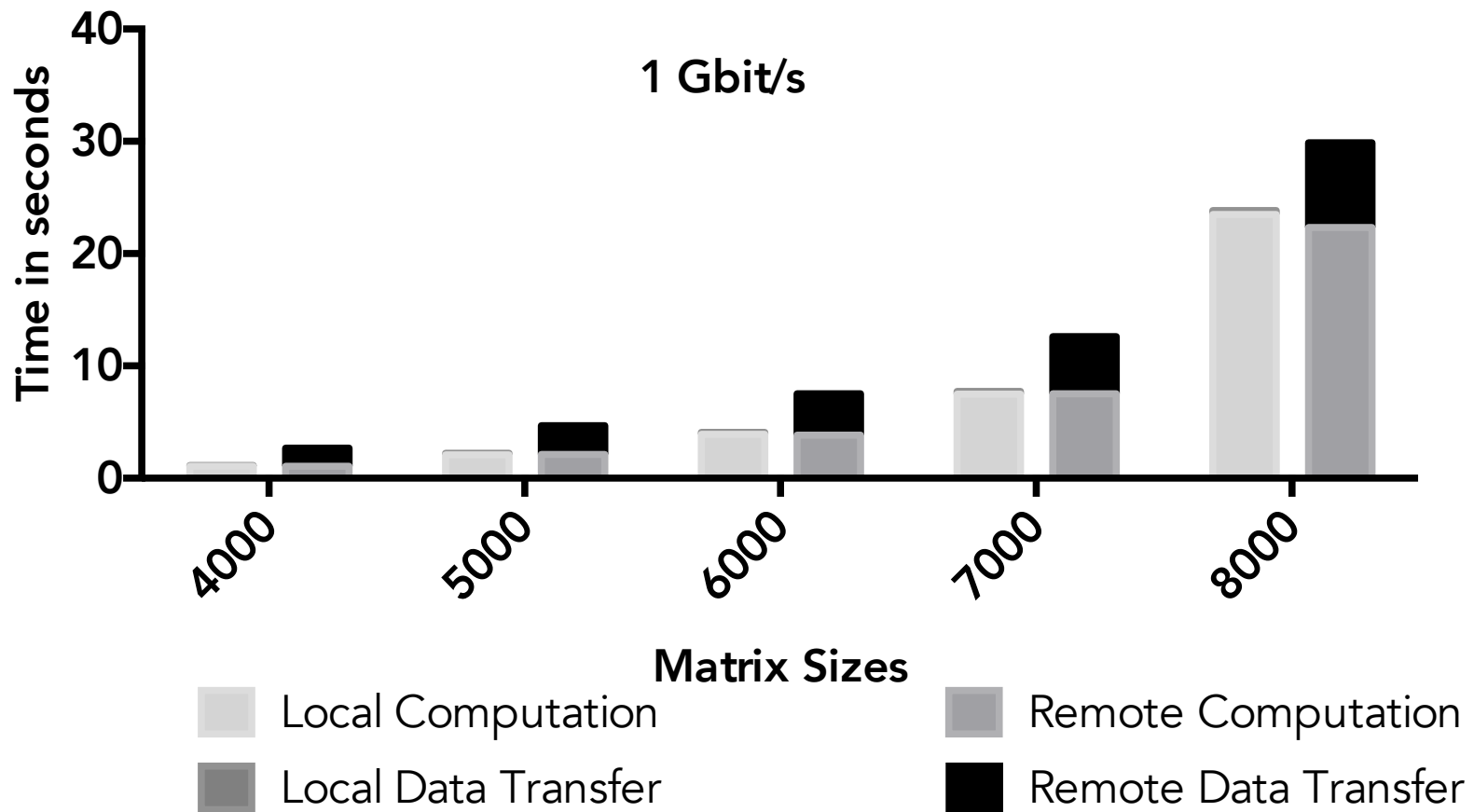
## Choosing dOpenCL:

- API forwarding requires no code changes
- Minimal overhead and cluster management
- Similar libraries like SnuCL and VirtualCL could not be operated without errors

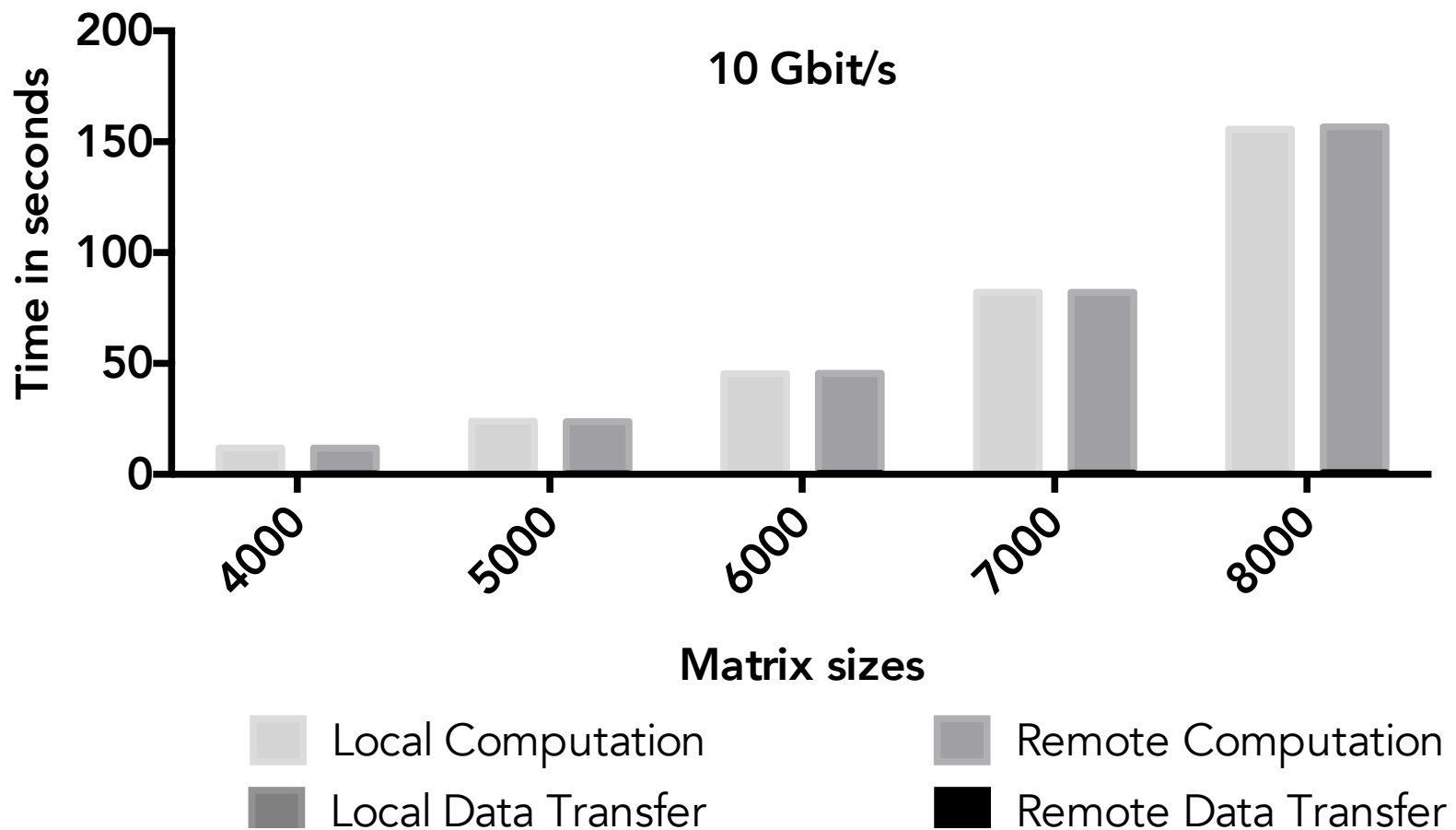
## Alternatives:

- MPI increases code complexity
- MapReduce requires cluster management and adds startup/memory overhead due to JVM

# EVALUATING DOPENCL



# EVALUATING DOPENCL

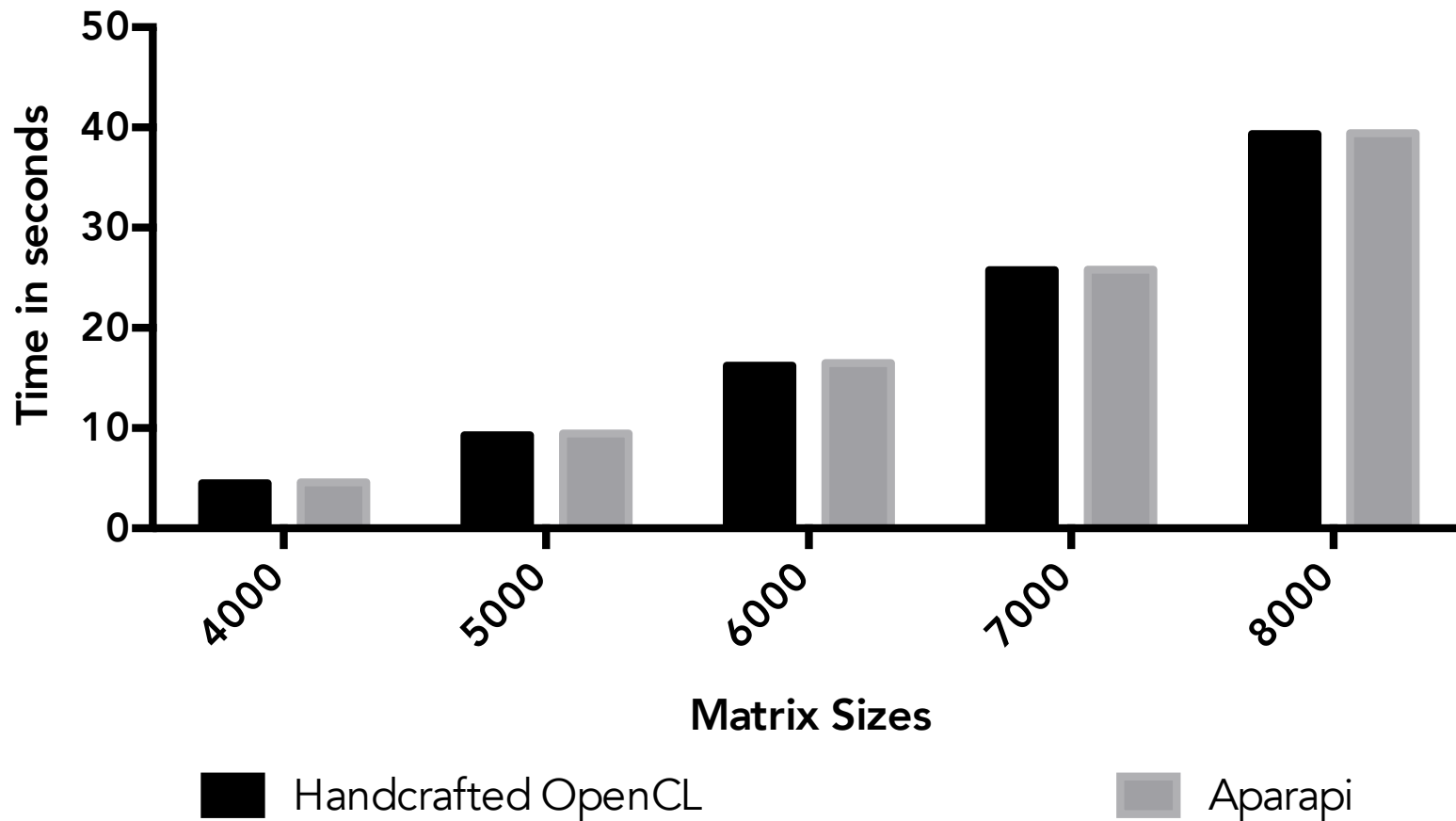


# HIGH-LEVEL ABSTRACTION

- OpenCL requires much auxiliary code for data initialization and device selection
- Aparapi allows to write OpenCL in Java
  - Flatten learning curve
  - Reduce auxiliary code

But is it fast enough?

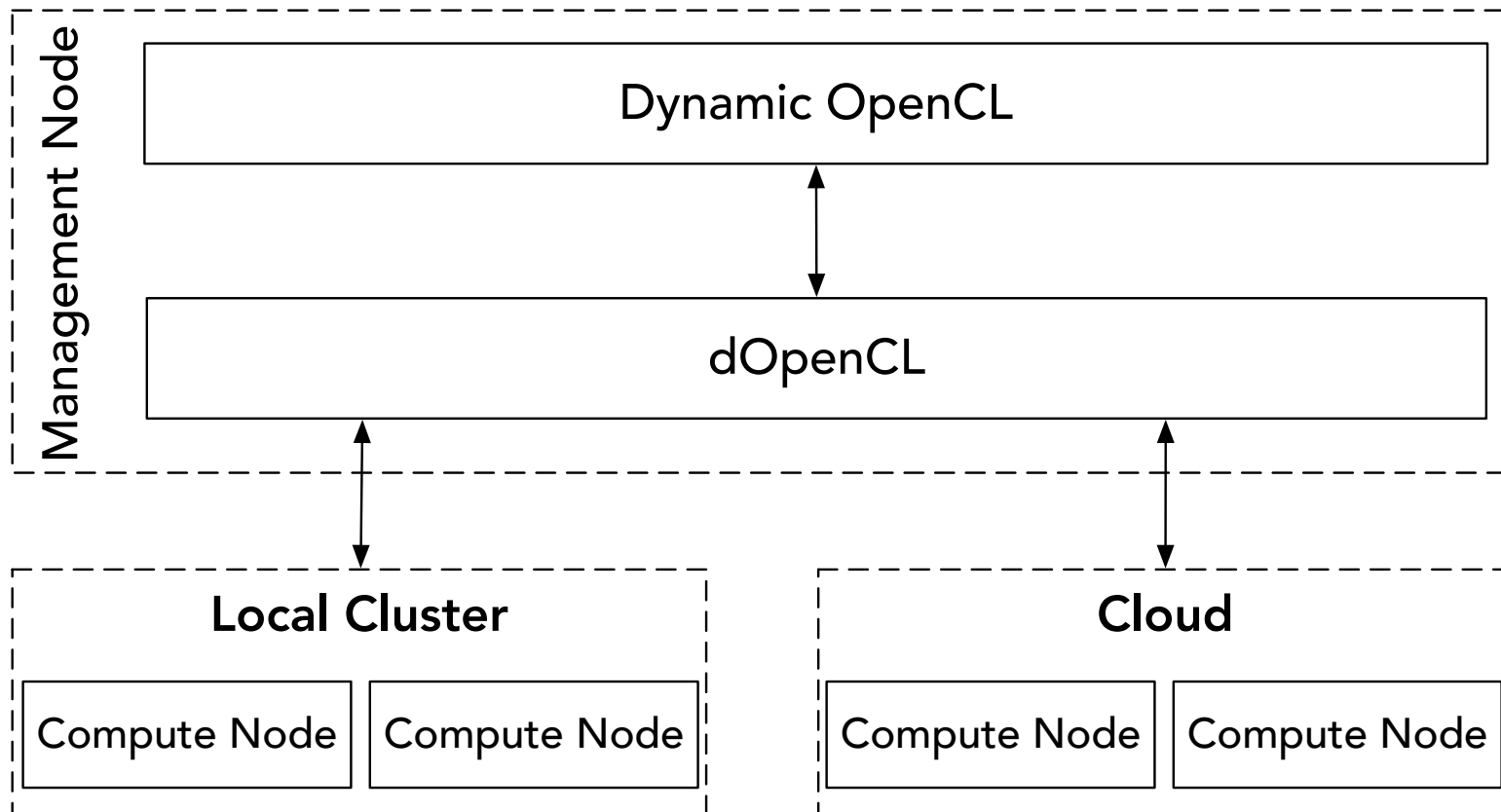
# EVALUATING APARAPI



# Connecting Aparapi and dOpenCL

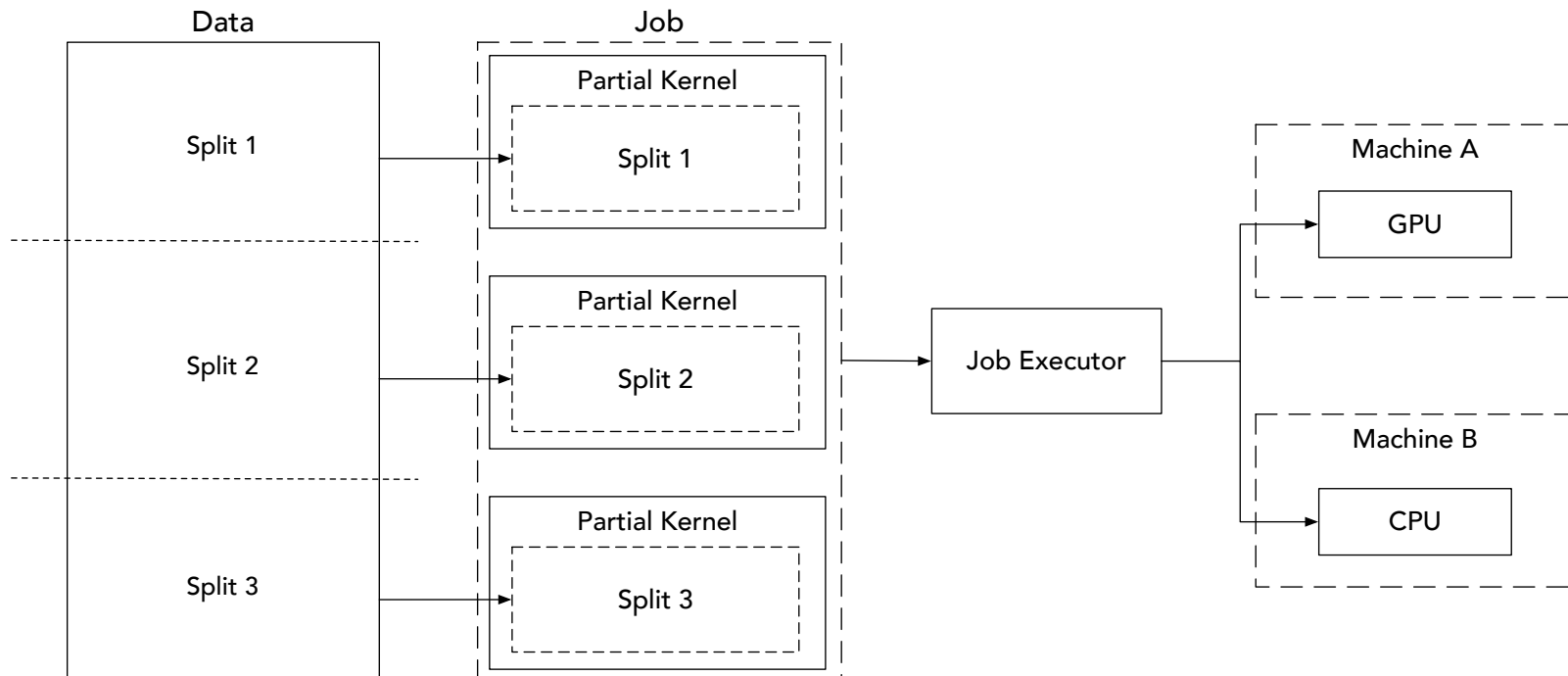
- Both include incompatible design decisions
- Forked both libraries
- Fixed several bugs and design decisions
  - Dynamic resource adjustments
  - Device selection

# DYNAMIC OPENCL





# JOB DESIGN

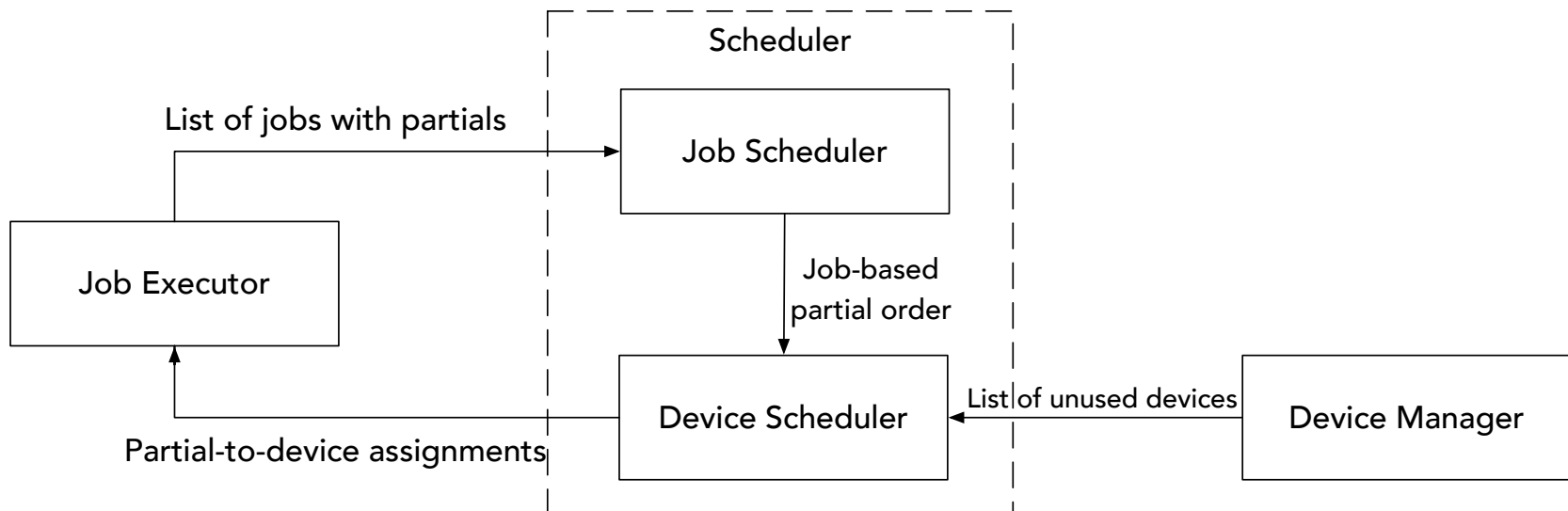


# HYBRID CLUSTER

- Created abstract class "*Machine Manager*"
- Handles dOpenCL cluster management
- One implementation per cloud service
  - Provides cloud service communication
  - Implementations required to fill 2 methods
  - Exemplary implementation for Amazon EC2

# SCHEDULING

- Fairness vs. Efficiency
- Heterogeneous hardware offers optimization potential



# SCHEDULING ALGORITHMS

## **JOB SCHEDULER**

Round-Robin

First-In-First-Out

## **DEVICE SCHEDULER**

Device Preference

Performance Based

Network Based

# USE CASES

- Job-based library
- Local cluster
- Hybrid cluster
- Cloud Cluster

**EVALUATION**

# BENCHMARK SETUP

- Local FSOC hardware
- EC2 CPUs and GPUs
- Local, hybrid and cloud cluster
- Various Computations
  - Matrix Multiplication (data-heavy)
  - Mandelbrot Set (computation-heavy)
  - Multiple jobs in parallel: Matrix Multiplication, Mandelbrot, K-means and N-body

# HARDWARE

Local Machine Type A:

144 logical cores and 1 Gbit/s Ethernet

Local Machine Type B:

8 logical cores and 10 Gbit/s Ethernet

EC2 c4.8xlarge:

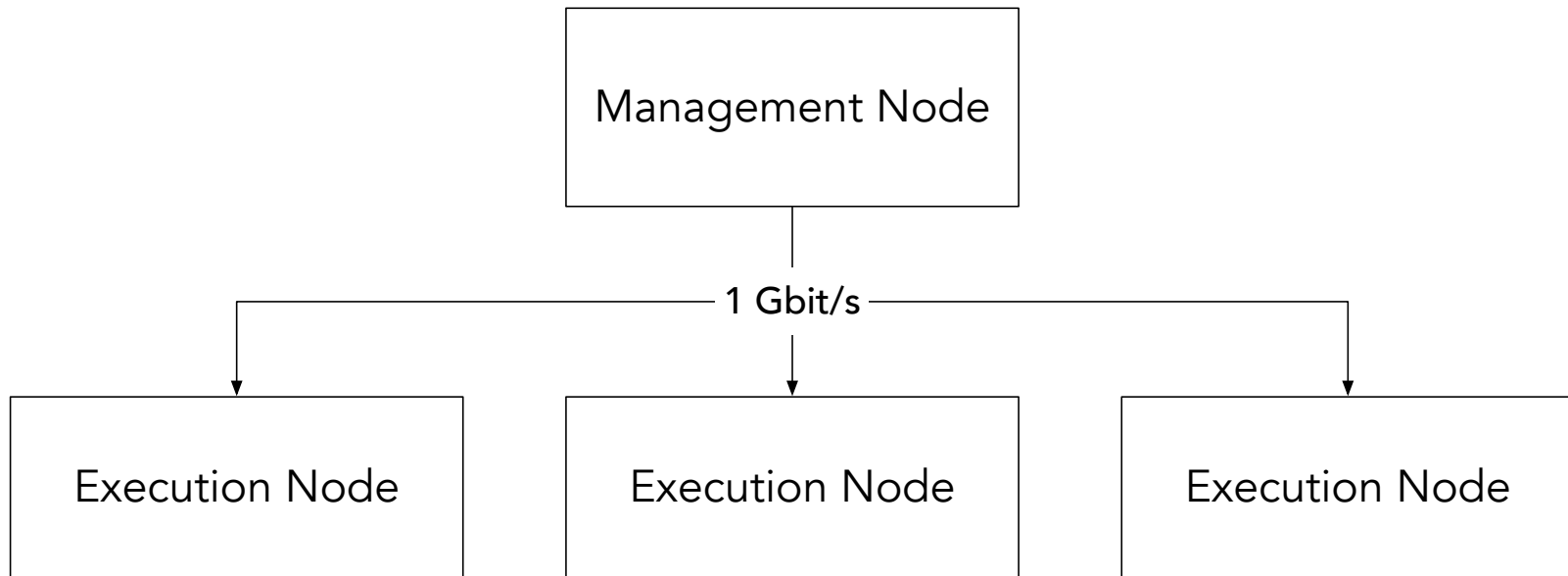
36 logical cores and 10 Gbit/s Ethernet

EC2 g2.2xlarge:

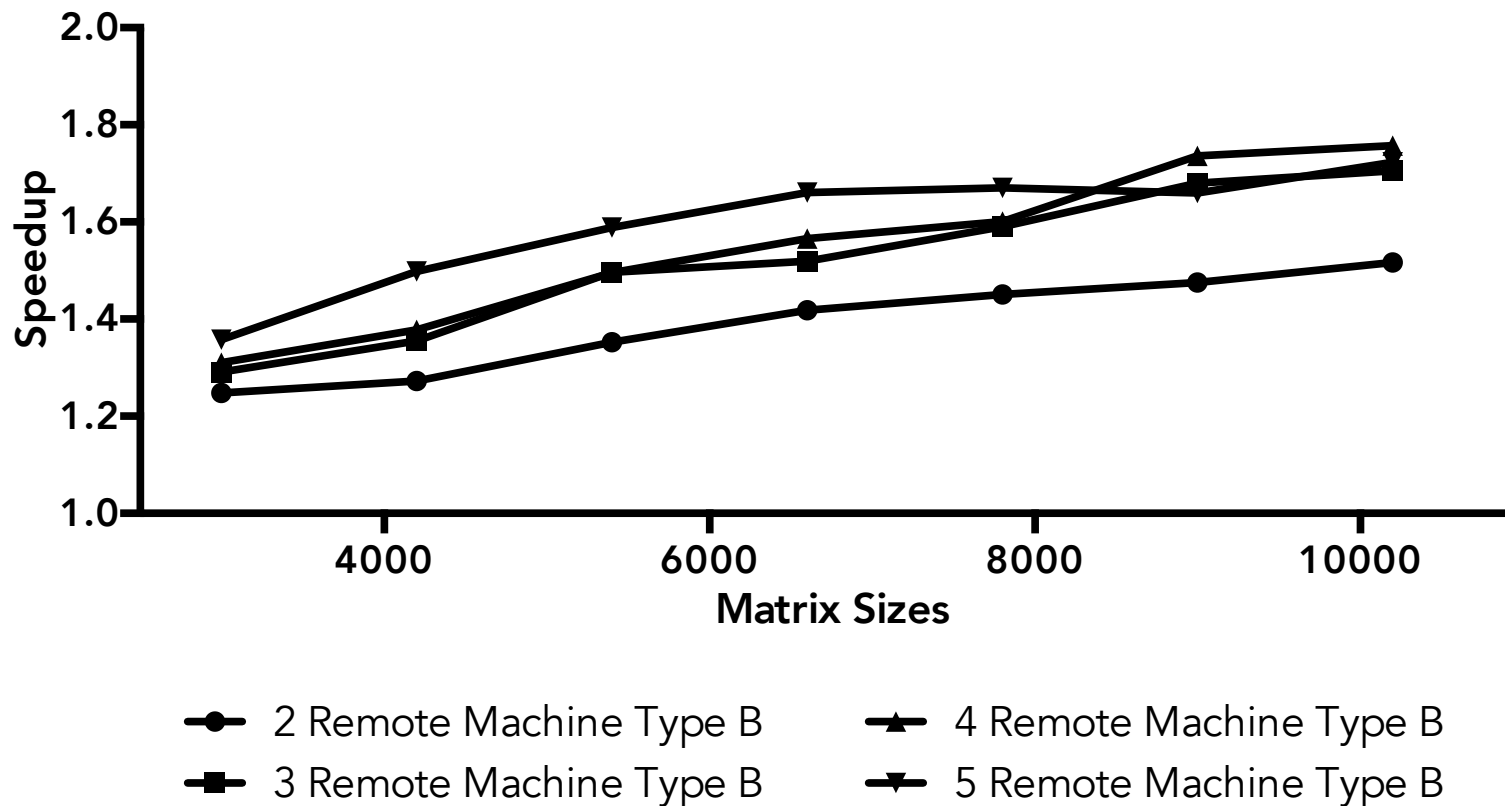
NVIDIA GRID K520 and 1 Gbit/s Ethernet



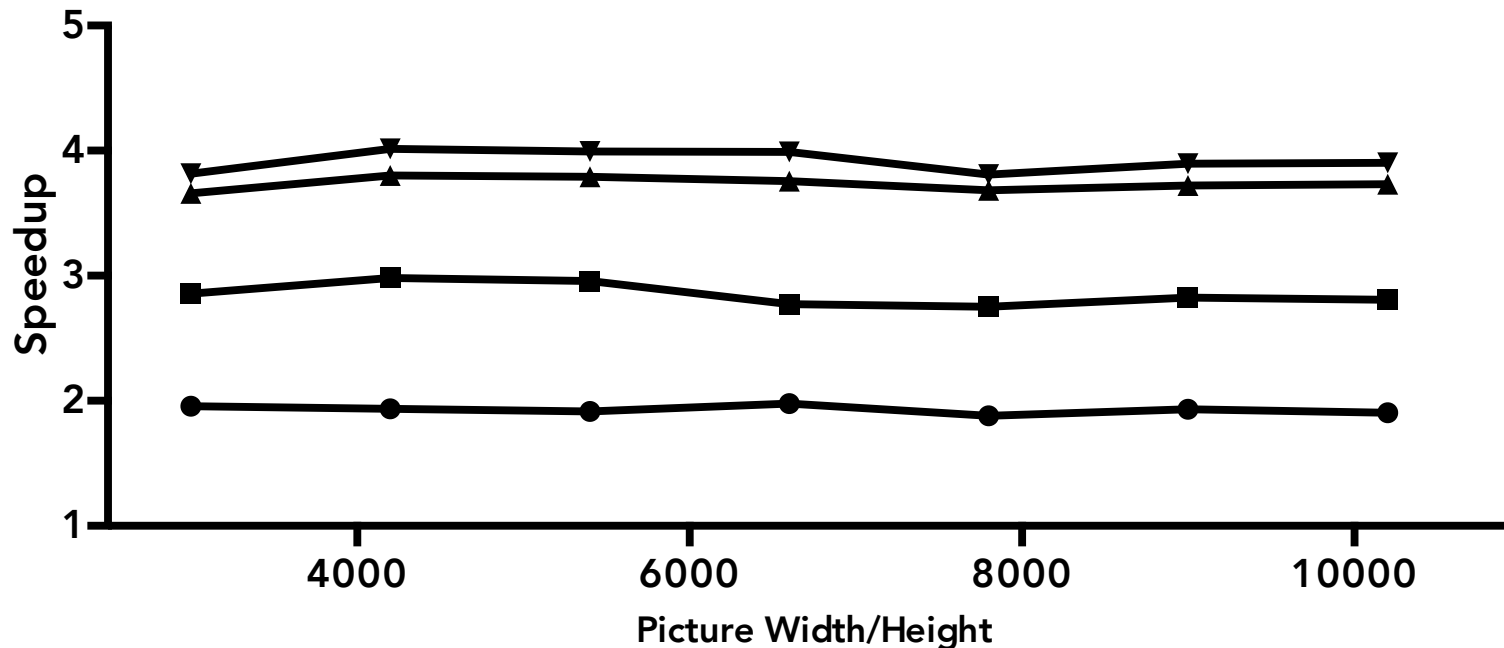
# LOCAL FULLY ASSISTED SETUP



# FULLY ASSISTED MATRIX MULT.



# FULLY ASSISTED MANDELBROT



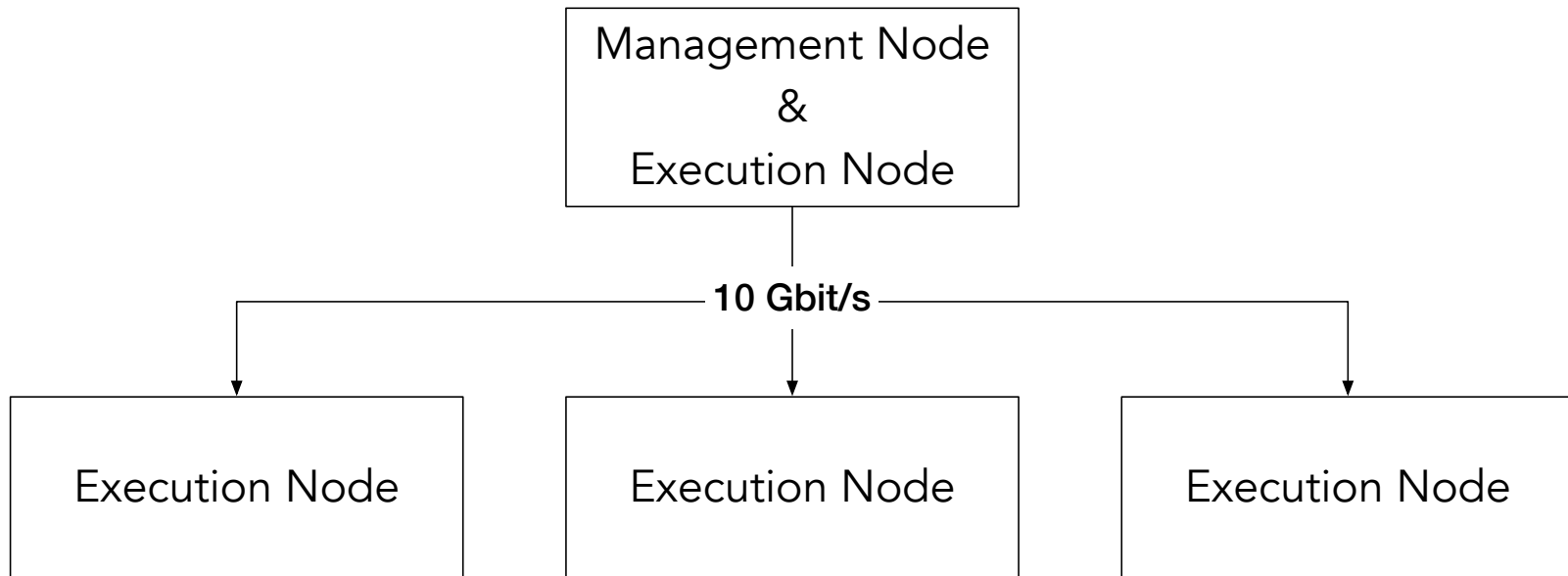
● 2 Remote Machine Type B

■ 3 Remote Machine Type B

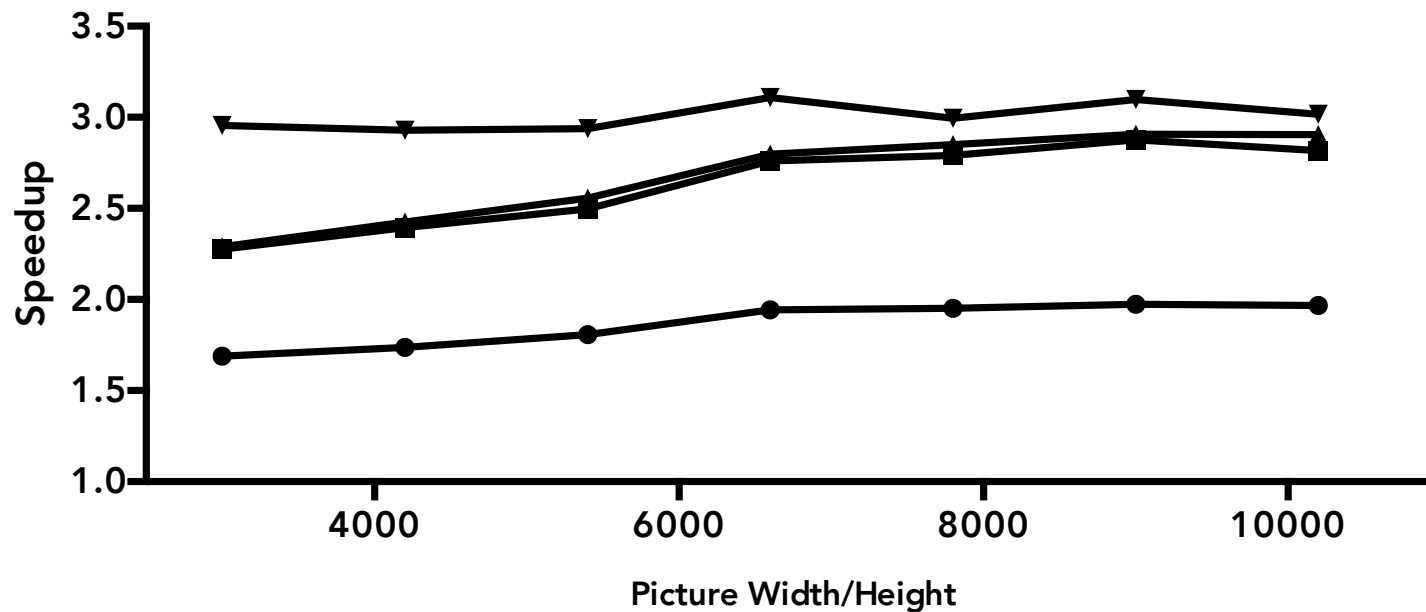
▲ 4 Remote Machine Type B

▼ 5 Remote Machine Type B

# LOCAL PARTLY ASSISTED SETUP

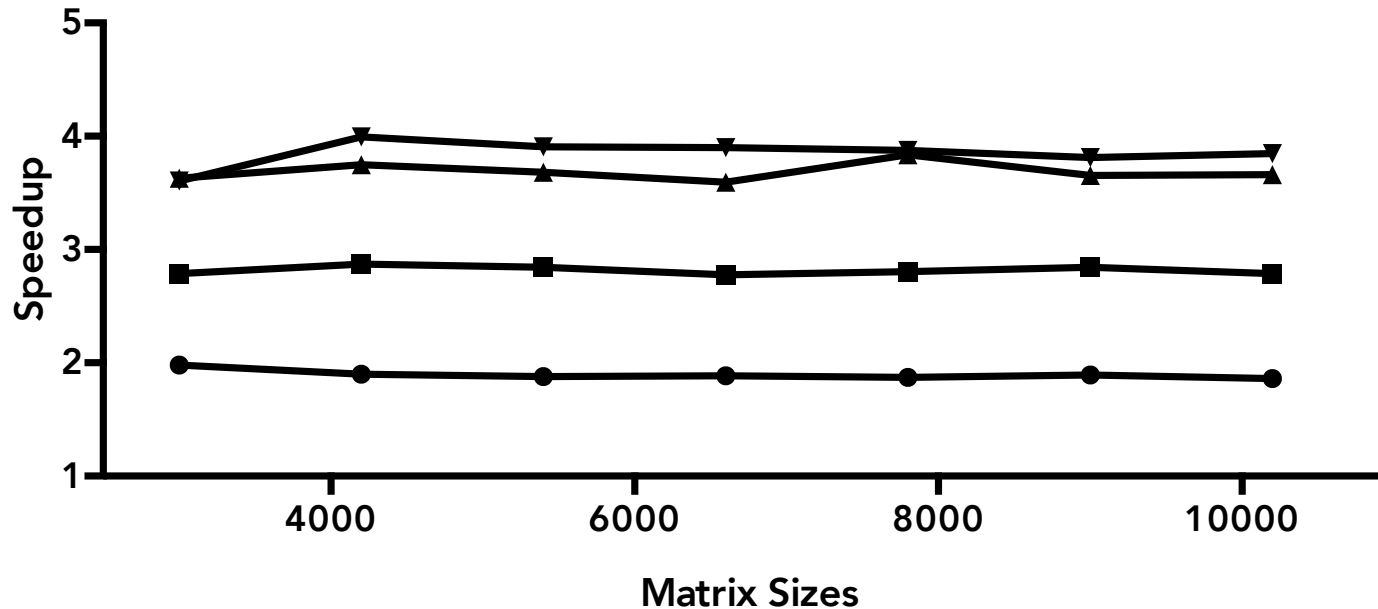


# PARTLY ASSISTED MATRIX MULT.



- 1 Local Machine Type B + 1 Remote Machine Type B
- 1 Local Machine Type B + 2 Remote Machine Type B
- ▲ 1 Local Machine Type B + 3 Remote Machine Type B
- ▼ 1 Local Machine Type B + 4 Remote Machine Type B

# PARTLY ASSISTED MANDELBROT



- 1 Local Machine Type B + 1 Remote Machine Type B
- 1 Local Machine Type B + 2 Remote Machine Type B
- ▲ 1 Local Machine Type B + 3 Remote Machine Type B
- ▼ 1 Local Machine Type B + 4 Remote Machine Type B

# CLOUD

EC2

Management Node

10 Gbit/s

1 Gbit/s

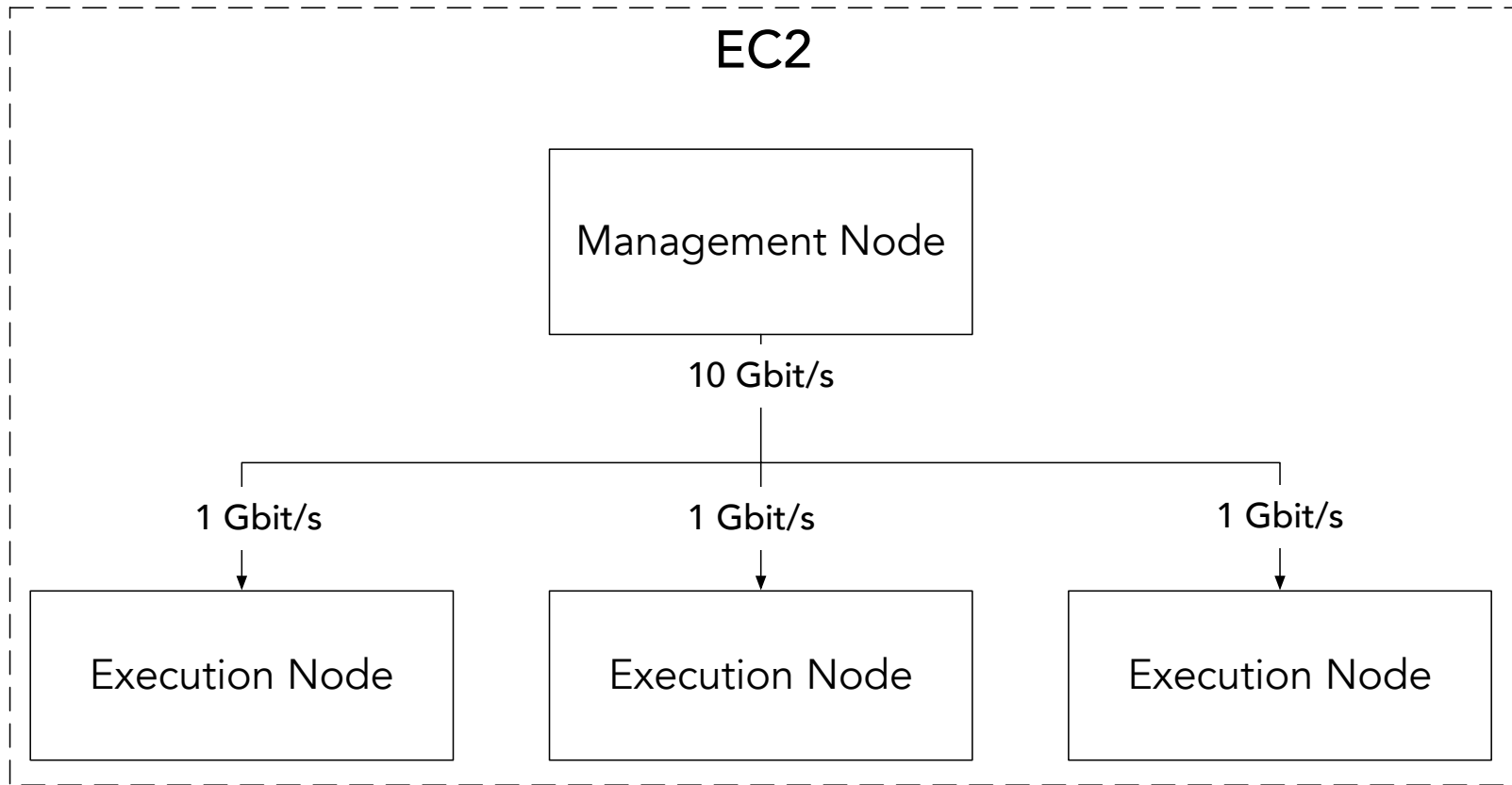
1 Gbit/s

1 Gbit/s

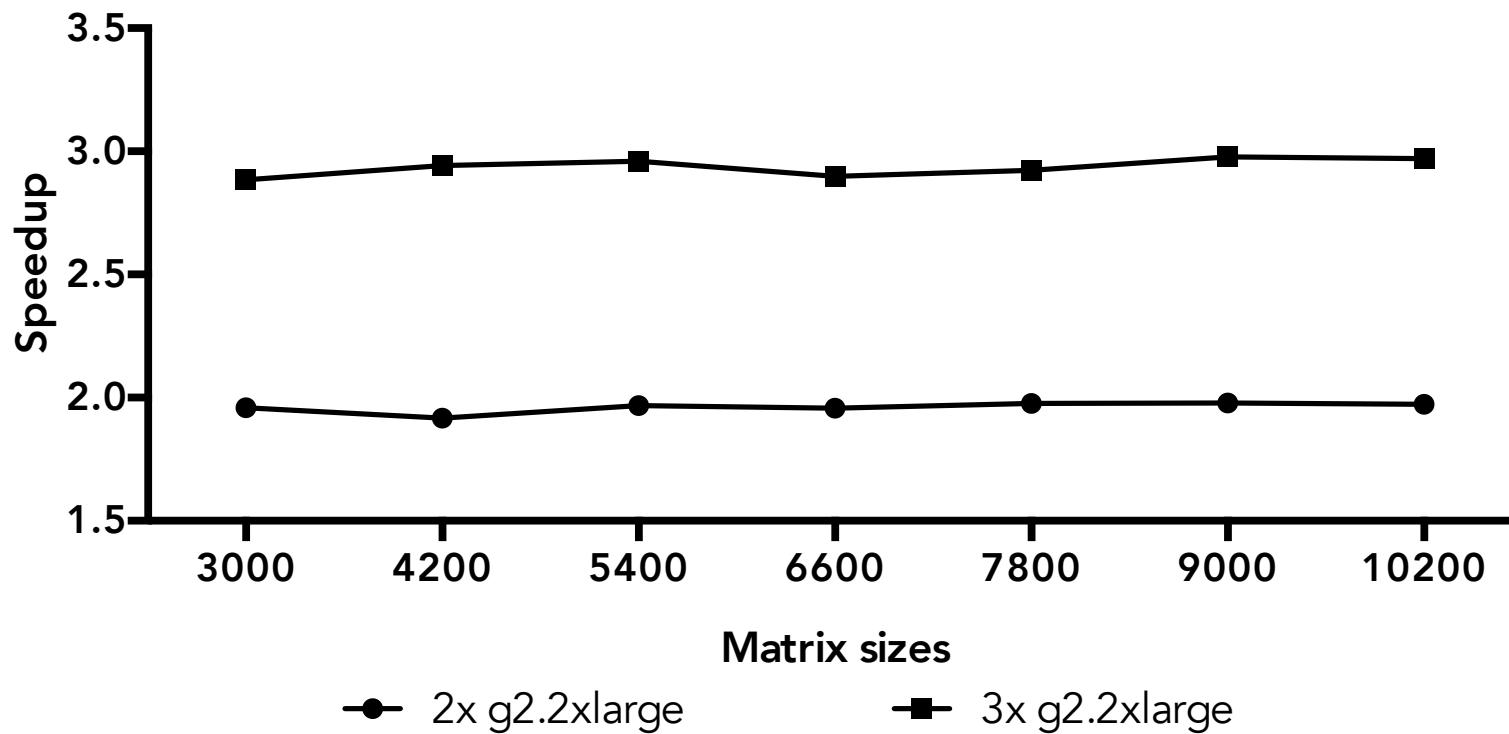
Execution Node

Execution Node

Execution Node

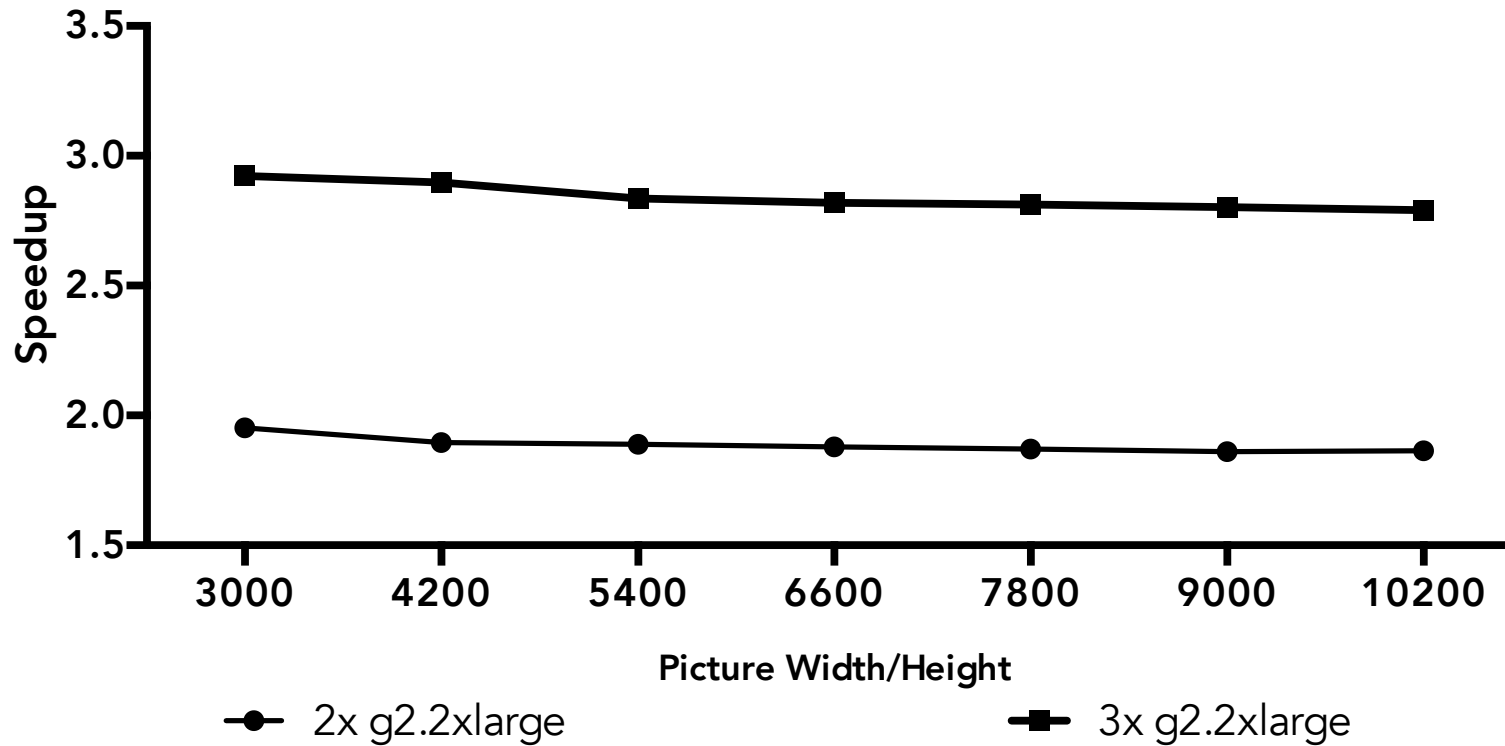


# CLOUD MATRIX MULT.

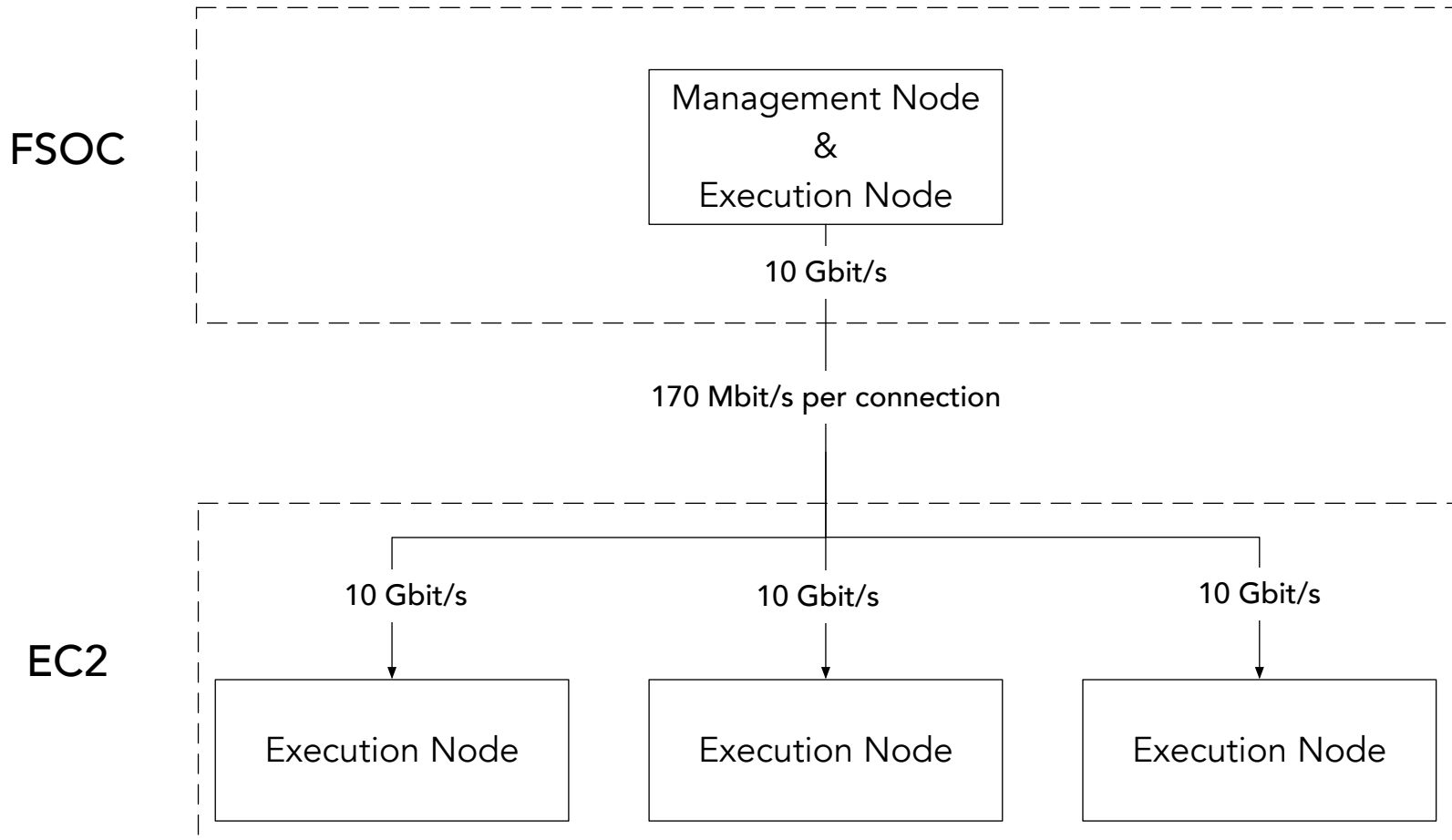




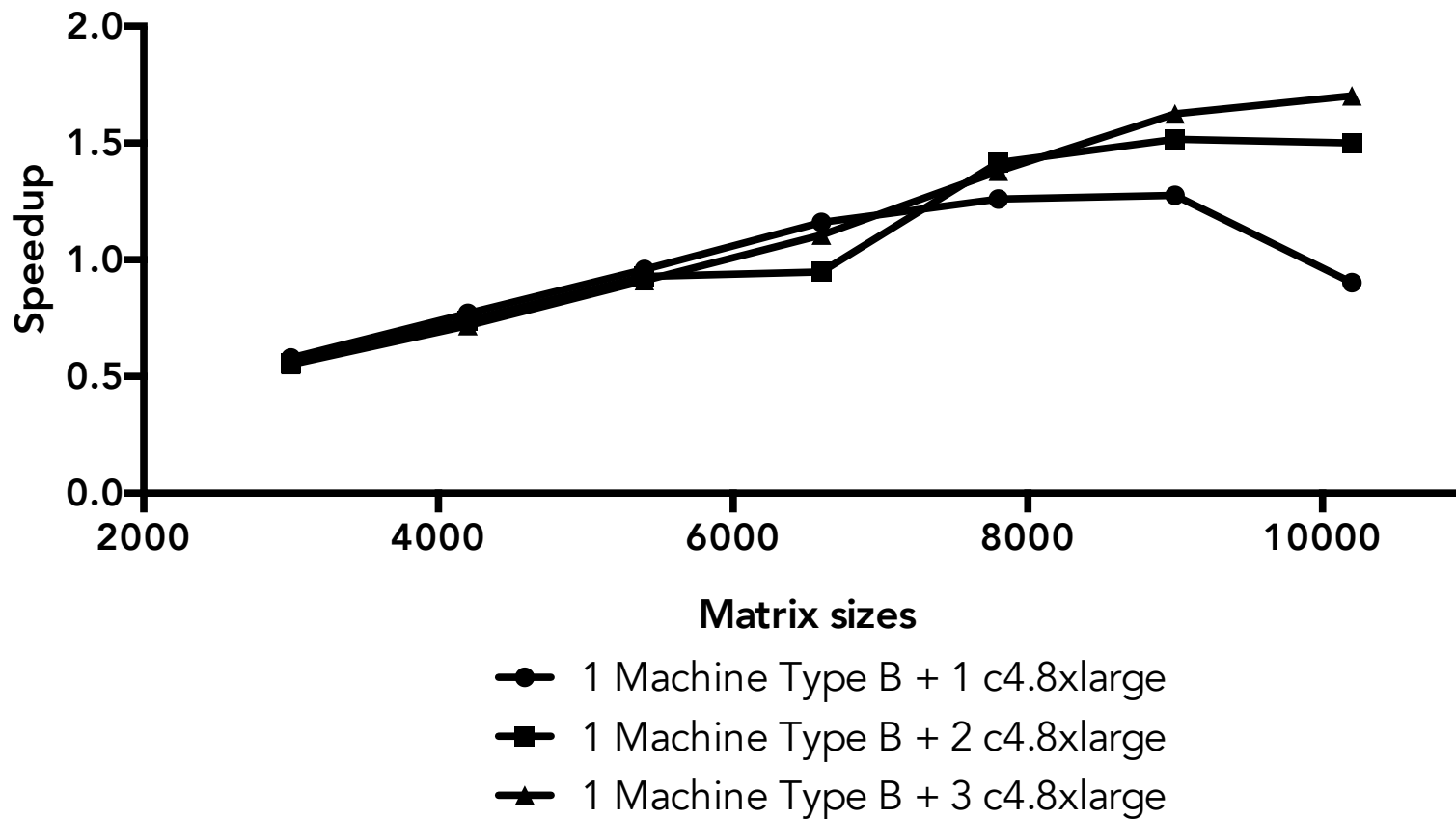
# CLOUD MANDELBROT



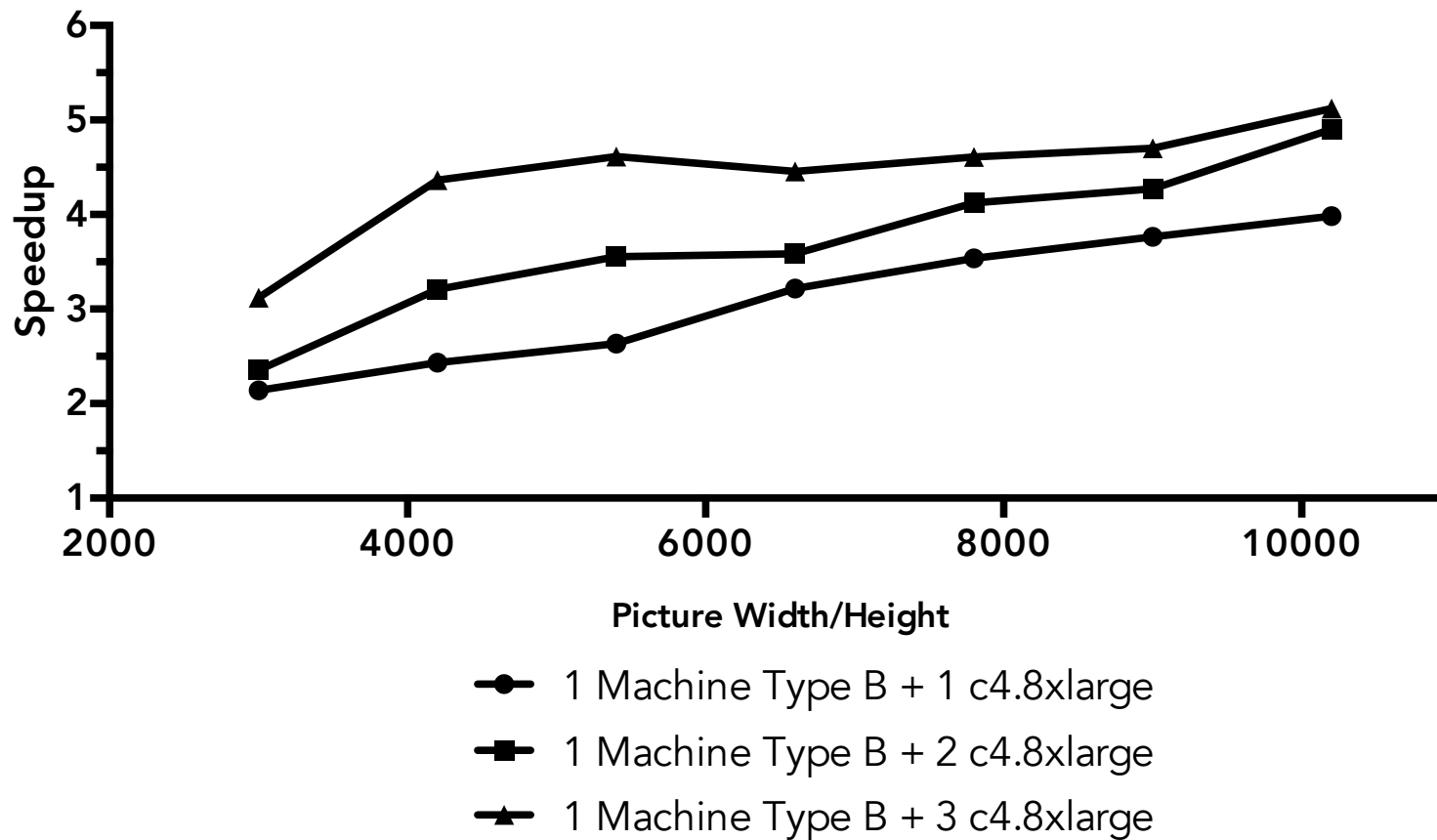
# HYBRID



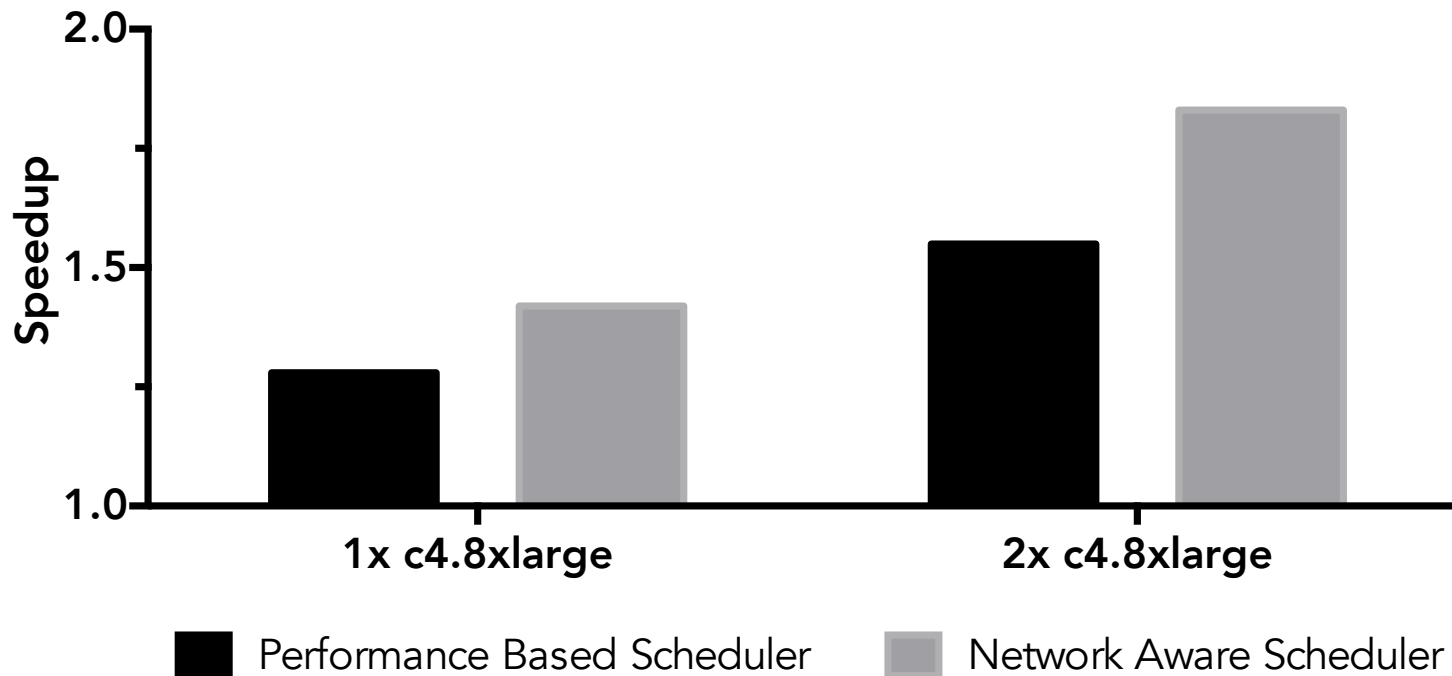
# HYBRID MATRIX MULT.



# HYBRID MANDELBROT

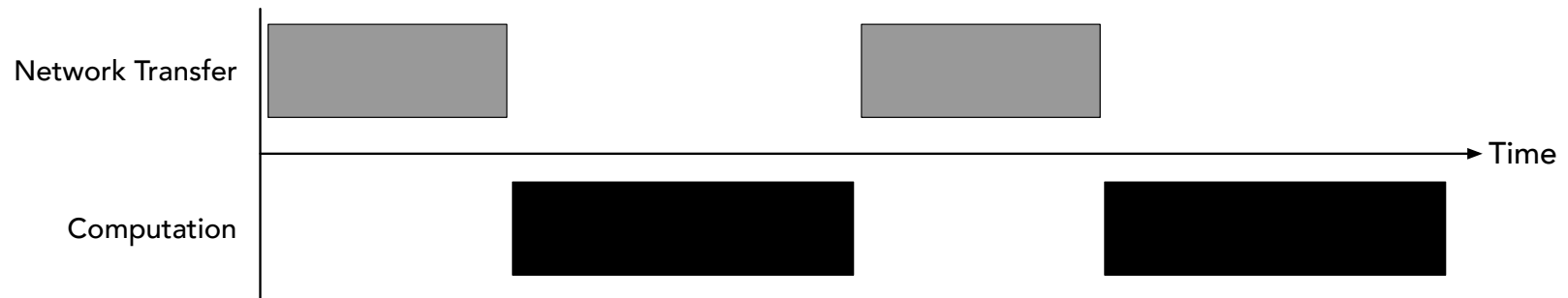


# HYBRID JOB SUITE SCHEDULING



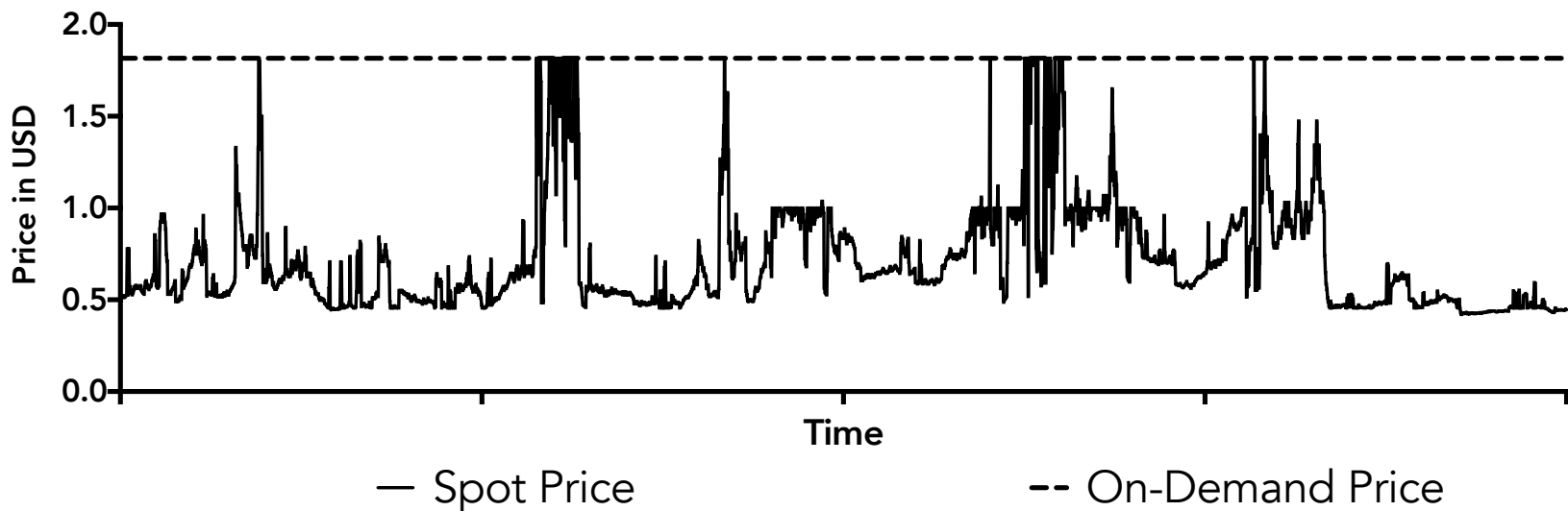
**FUTURE WORK**

# TASK QUEUE



# EC2 SPOT INSTANCES

- Optimize cloud resource costs
- Reserve cheap instances over time
- Automated process with upfront user input





**CONCLUSION**

# LIMITATIONS

- Network connection major bottleneck
- Limitations of Aparapi
  - Code translation
  - Device support
- Memory may become bottleneck when many jobs are executed in parallel

# ACHIEVEMENTS

- Distributed computations on heterogeneous clusters
- Flat learning curve and little code necessary
- Cluster size can be dynamically increased by cloud resources
- Scheduling architecture adaptable to various use cases
- Small code base (less than 1500 Java LOC)

# SOURCE CODES

<https://github.com/florianroesler/dopenc1>

<https://github.com/florianroesler/aparapi>

<https://github.com/florianroesler/dynamopenc1>

<https://github.com/florianroesler/dynamo-server>