EPSRC Centre for Doctoral Training in
Pervasive Parallelism

# Dynamic Autotuning of Algorithmic Skeletons

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informatics

EPSRC
Pioneering research and skills

# Objectives

Demonstrate **dynamic autotuning** of algorithmic skeletons.

Using the **SkelCL** data-parallel skeleton library.

Targeting heterogeneous parallelism with **OpenCL**.

# The problem



Program performance is **not portable** across architectures.

Heterogeneous parallelism targets **numerous architectures**.

Algorithmic skeletons target **numerous problems**.

To achieve portable performance, we **need** autotuning.

# Progress so far

- ✓ Identify a set of one or more **tunable parameters** in SkelCL.
- ✓ Modify SkelCL so that these tunable parameters can be set at **runtime**.
- ✓ Create a set of representative skeleton program **benchmarks**.
- ✓ **Enumerate** the optimisation space of tunable parameters and benchmarks.
- **Search** the optimisation space for optimal parameter values.
- Use **machine learning** to predict optimal parameter values for unseen programs.

# SkelCL: Overview



OpenCL implementations of data parallel skeletons:

Map, Reduce, Scan, Zip, Stencil, AllPairs.

Each skeleton is a C++ class template, parameterised with OpenCL muscle functions.

Vector and Matrix containers implement lazy copying between host and device memories.

# SkelCL: how it works



```
; Initialise SkelCL.
skelcl_init(dev_type)

; Instantiate skeletons with user kernels.
Zip mult("int f(int x, int y) {return x*y}")
Reduce sum("int f(int x, int y) {return x+y}", 0)

; Call skeletons.
Vector result = sum(mult(vector_a, vector_b))

; Read result.
print result.first()
```

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Initialise OpenCL devices

Prepare & compile device programs

Allocate space for data on hosts
Copy data to hosts

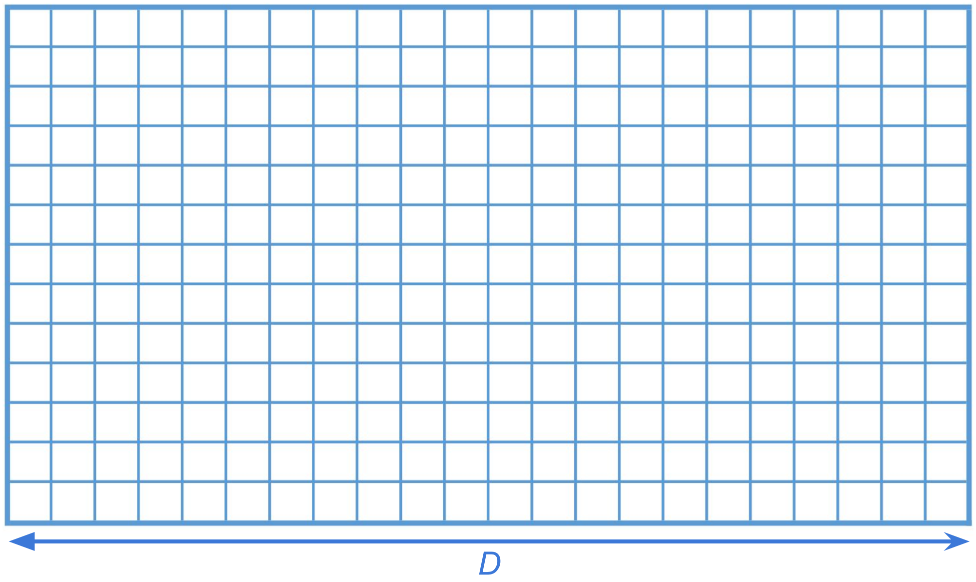
Enqueue jobs with devices

Wait until jobs have completed
Copy data from devices to host

# Stencil codes



Stencils operate on grids of **D**ata.

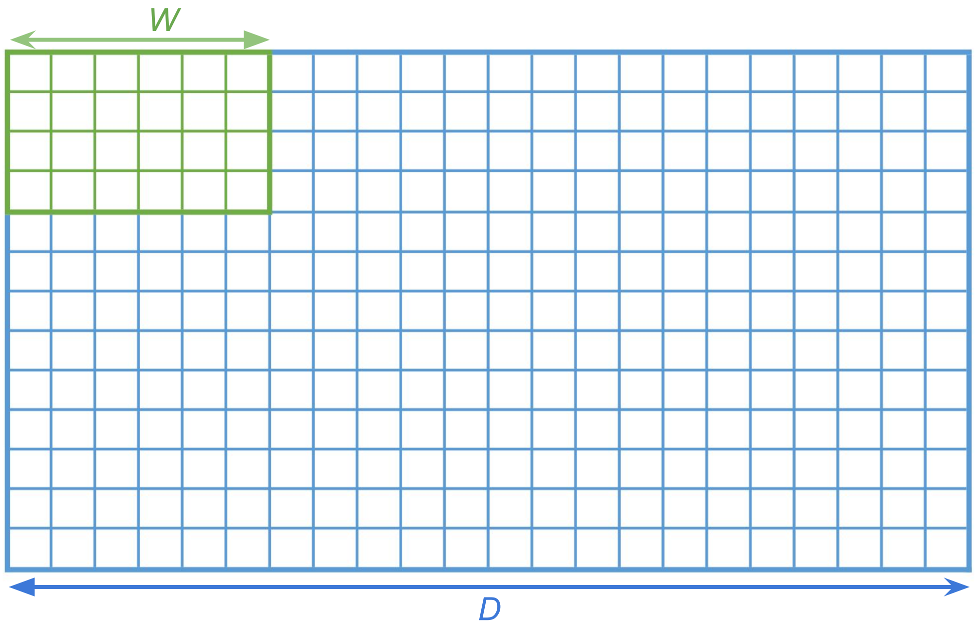


# Stencil codes



Stencils operate on grids of **D**ata.

Grids are decomposed into **Work groups**.



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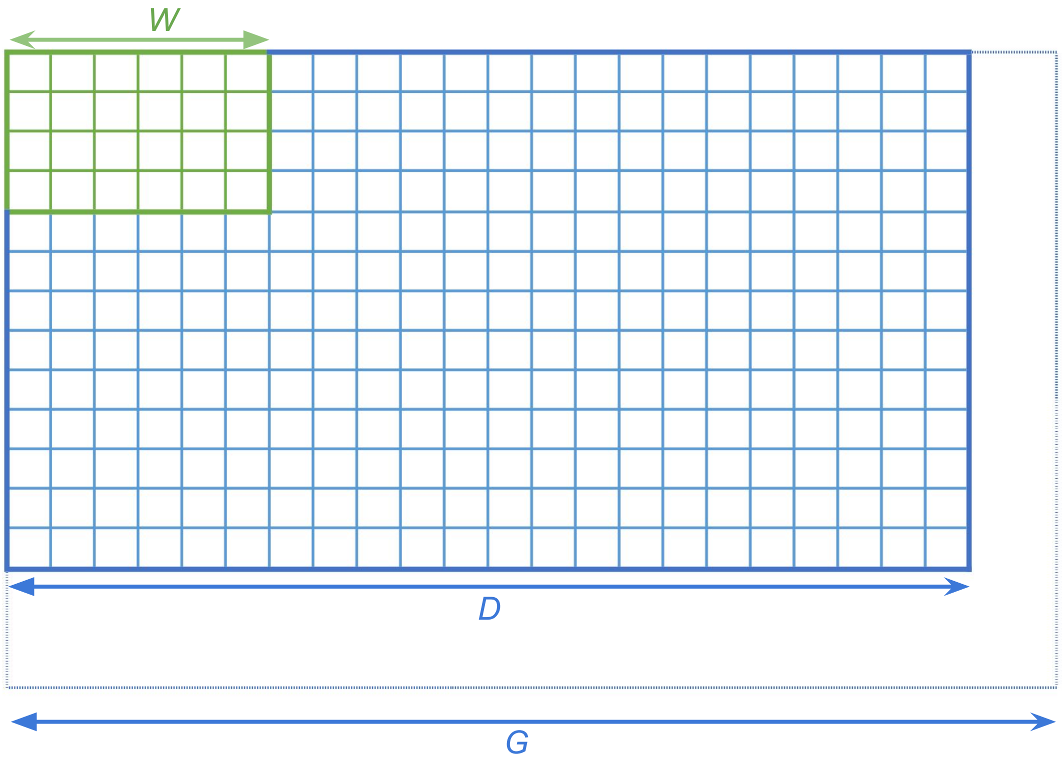
The size of the grid and work groups determine the **Global size**.



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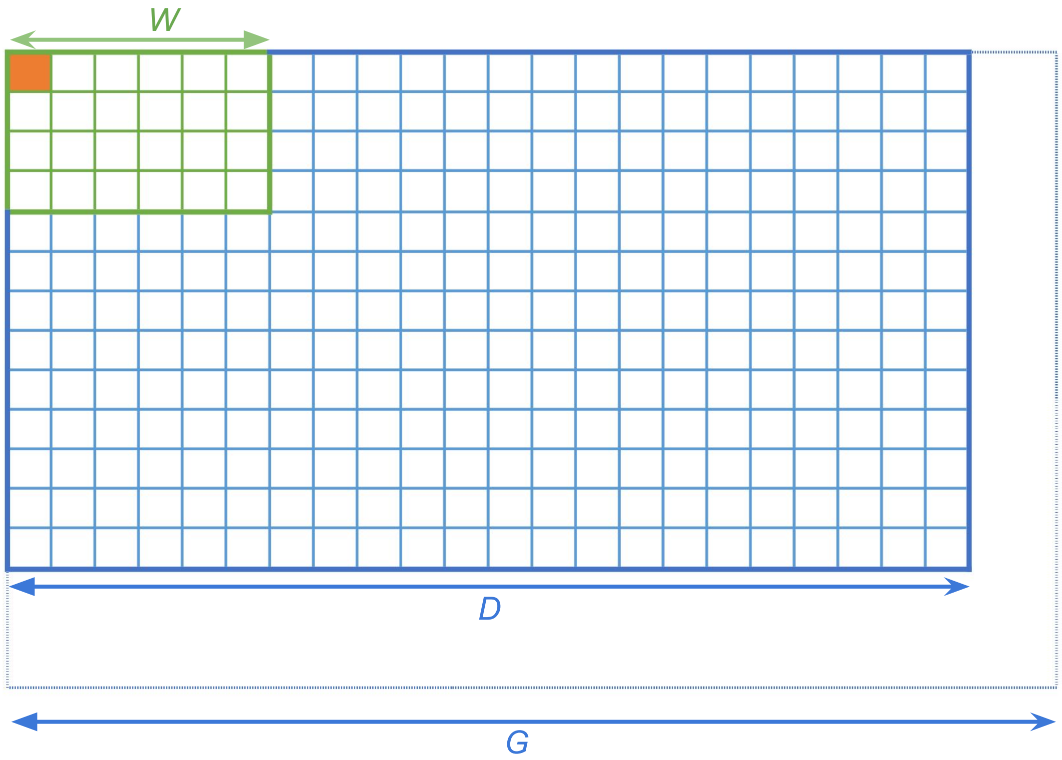

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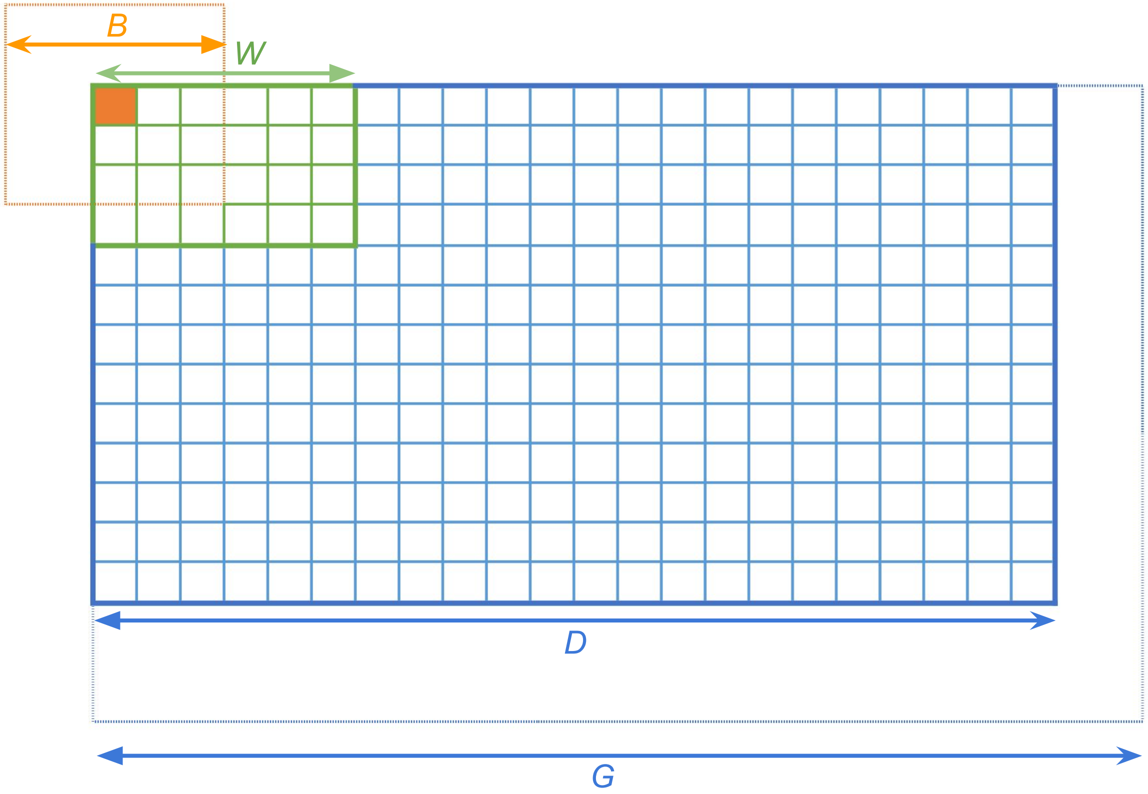

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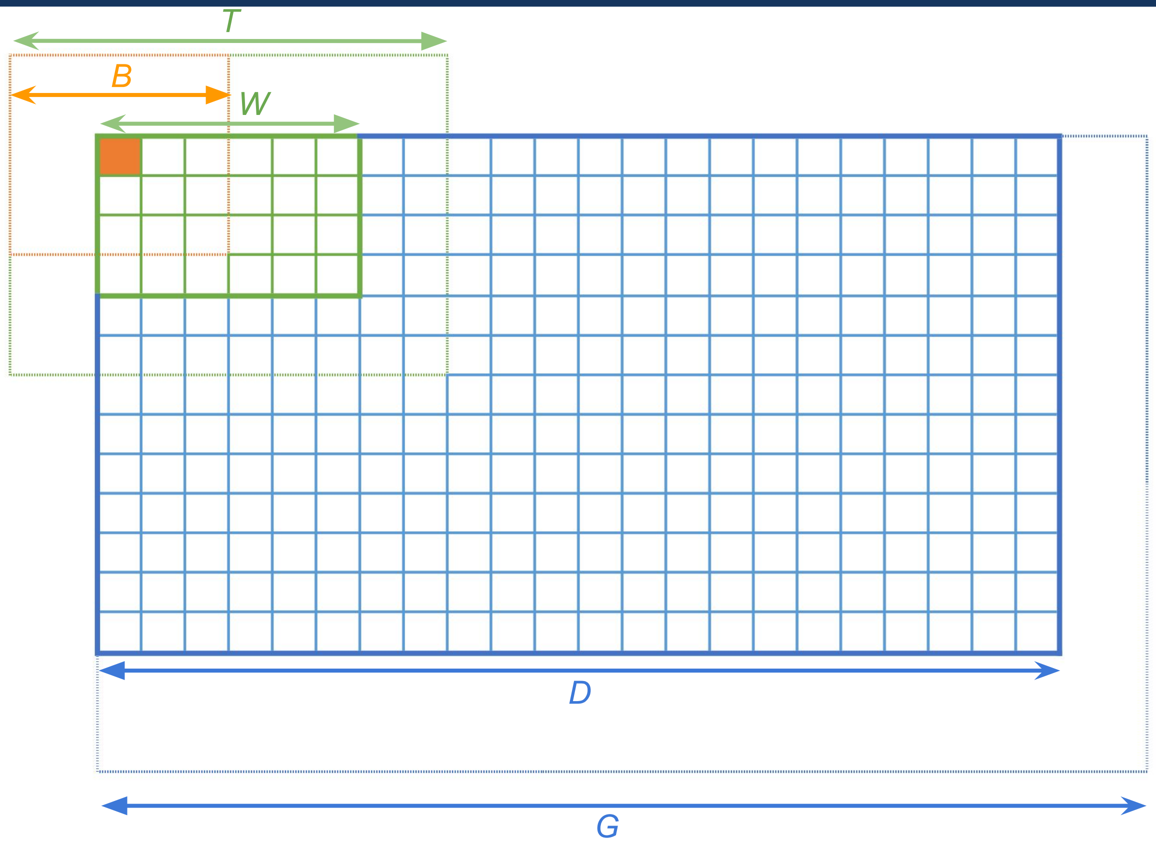
Grids are decomposed into **Work groups**.

The size of the grid and work groups determine the **Global size**.

A **work item** operates on a single data element.

The **B**order region is the number of neighbouring elements accessed by a **work item**.

The size of the work group and border region determines the **Tile size**.



# Autotuning stencil codes

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The aim of autotuning is to generate a function which maps a set of feature vectors to optimal parameter values.

For stencil operations:

$$f : \boldsymbol{a}, \boldsymbol{k}, \boldsymbol{h}, \boldsymbol{d} \rightarrow \boldsymbol{p}$$

To explore this space, compare the performance of different ***p*** values for combinations of ***a***, ***k***, ***h***, ***d***.

| | |
|---|---|
| ***a*** | Architecture features |
| ***k*** | Kernel features |
| ***h*** | Border sizes (NESW) |
| ***d*** | Input data features |
| ***p*** | Parameter values |

# Autotuning stencil codes



Example ***p***arameters: work group size.

Changing work group size affects:

- Local memory allocation per workgroup.
- The number of  simultaneously active threads.
- Vectorisation for CPUs.

**BUT** values cannot be set arbitrarily:

- Hardware constraints limit maximum size.

| | |
|---|---|
| ***a*** | Architecture features |
| ***k*** | Kernel features |
| ***h*** | Border sizes (NESW) |
| ***d*** | Input data features |
| ***p*** | Parameter values |

# Exploring optimisation space



Defining an optimisation space for Stencil operations:

| | **Type** | **Variables** | **Values** |
|---|---|---|---|
| ***a*** | Architecture features | Host, execution device(s) | 10 device combinations |
| ***k*** | Kernel features | Simple or complex | 2 kernels |
| ***h*** | Border sizes (NESW) | North, East, South, West | 7 border sizes |
| ***d*** | Input data features | Grid size | 2 data sizes |
| ***p*** | Parameter values | Work group size | 9 combinations |

2520 unique configurations.

With hardware constraints: 1792 unique configurations.

# Exploring optimisation space



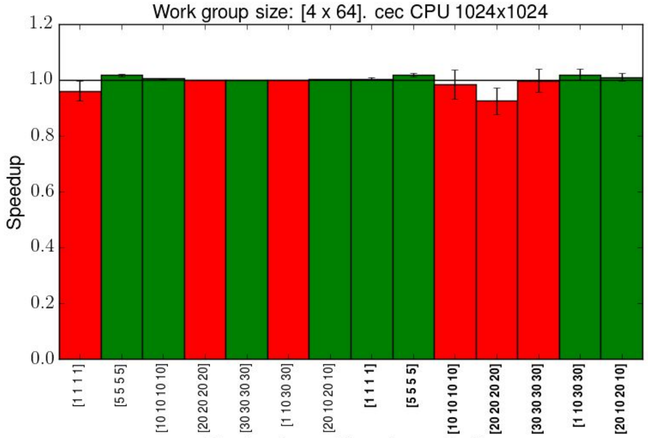
Using scripting to collect sound and reproducible results.

Experiment descriptor file: lists architectures, benchmarks, arguments, parameter values.

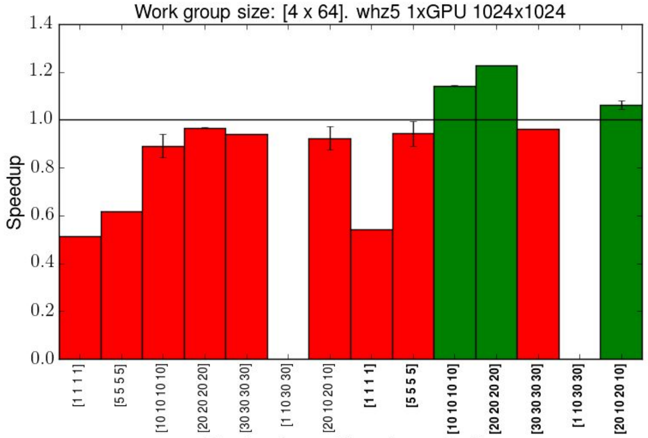
Script enumerates test cases, using fixed or dynamic sampling plans for statistical soundness.

```
{
  hosts: ["foo", "bar" ...],
  benchmarks: {
    GaussianBlur: {args: {...}},
    Mandelbrot: {args: {...}},
  },
  params: {
    LocalSizeR: [4, 8, 16],
    LocalSizeC: [32, 64]
  }
}
```

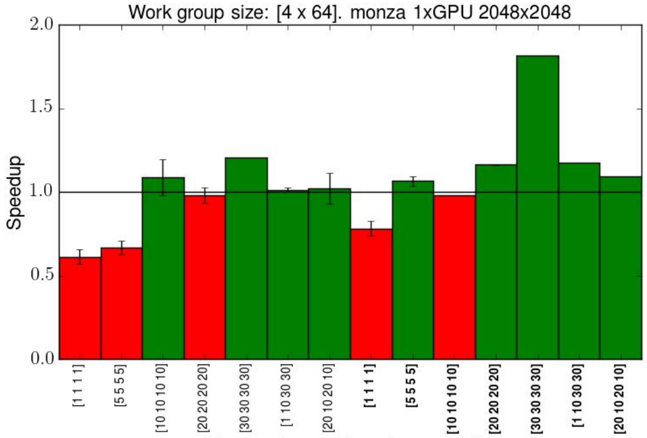
From the 1792 test cases, 252 are for this device, and 14 require samples...




Average 10.0 iterations.




Average 8.0 iterations.

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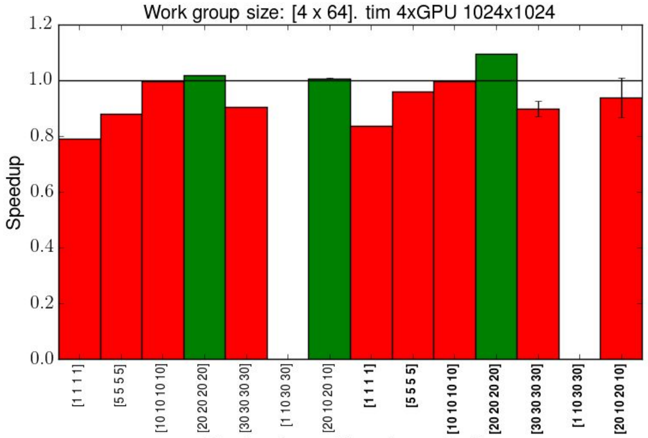


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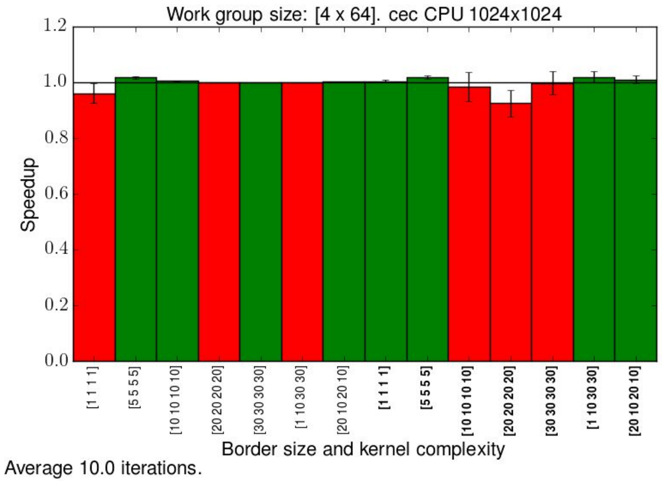
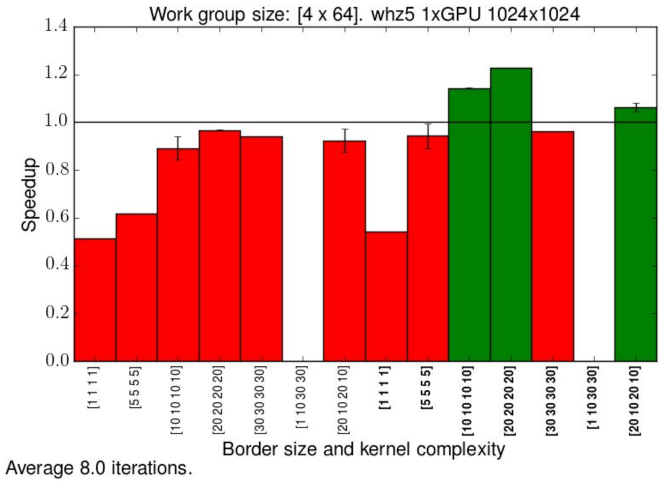
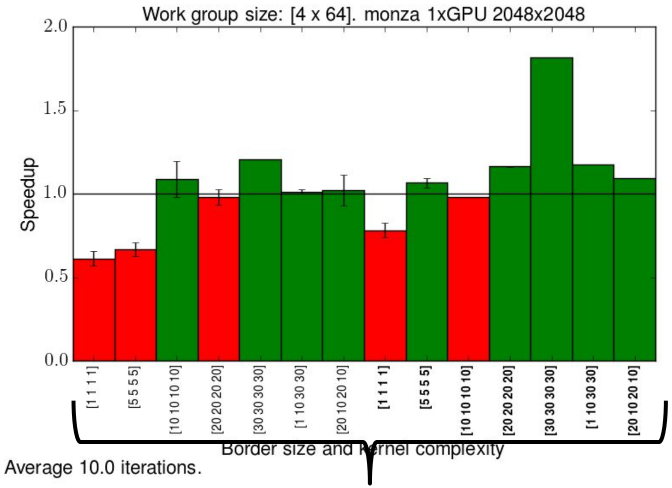
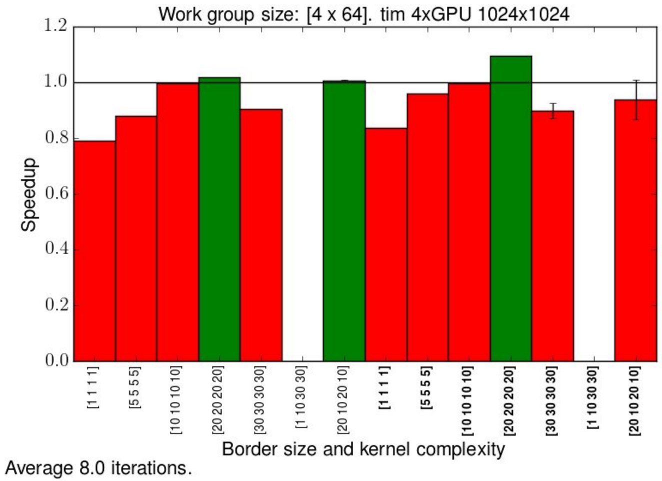
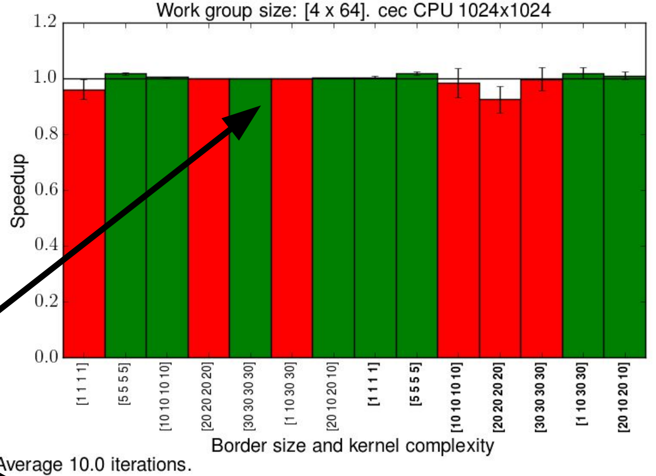


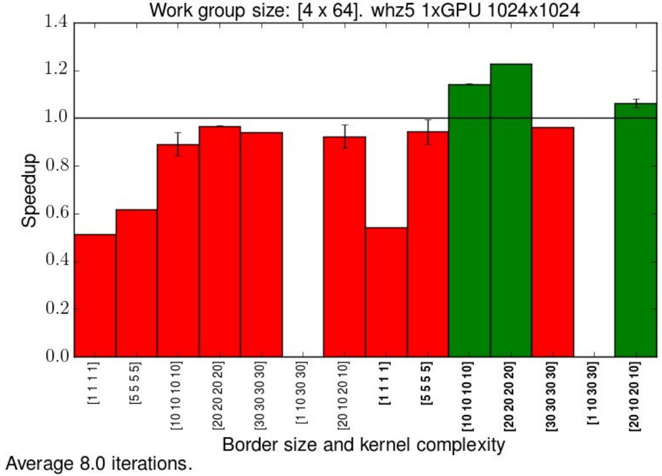




Performance across programs is non-uniform.

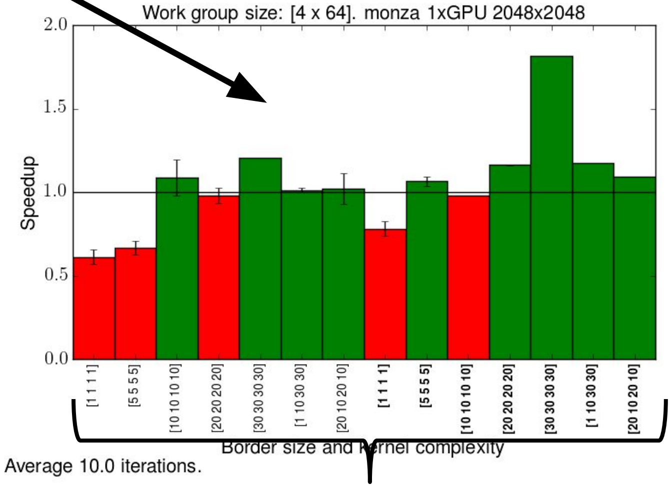


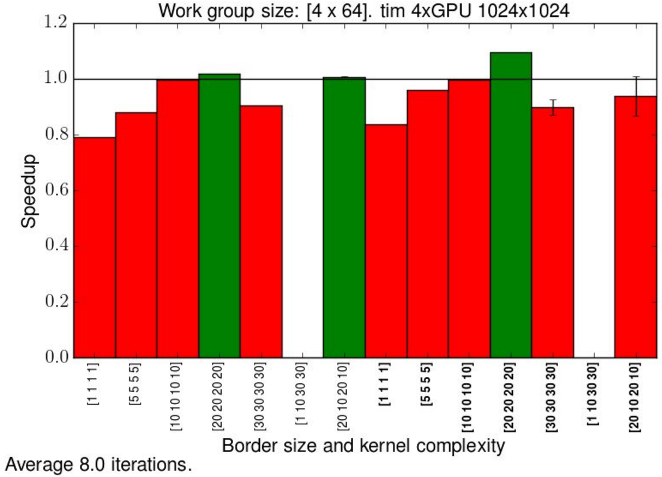






Performance across devices is non-uniform.

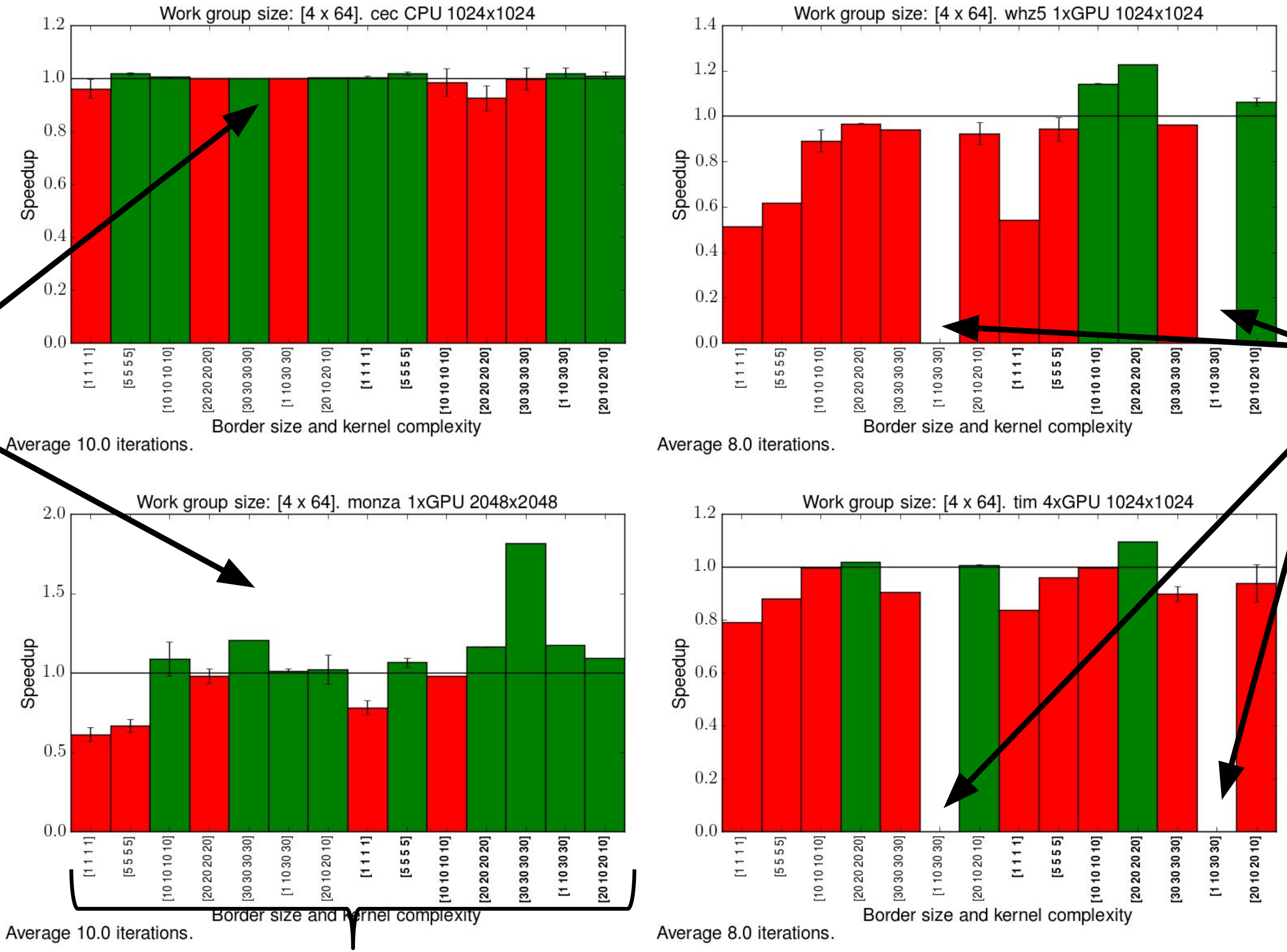



Performance across programs is non-uniform.

Performance across devices is non-uniform.

Space is non-continuous.

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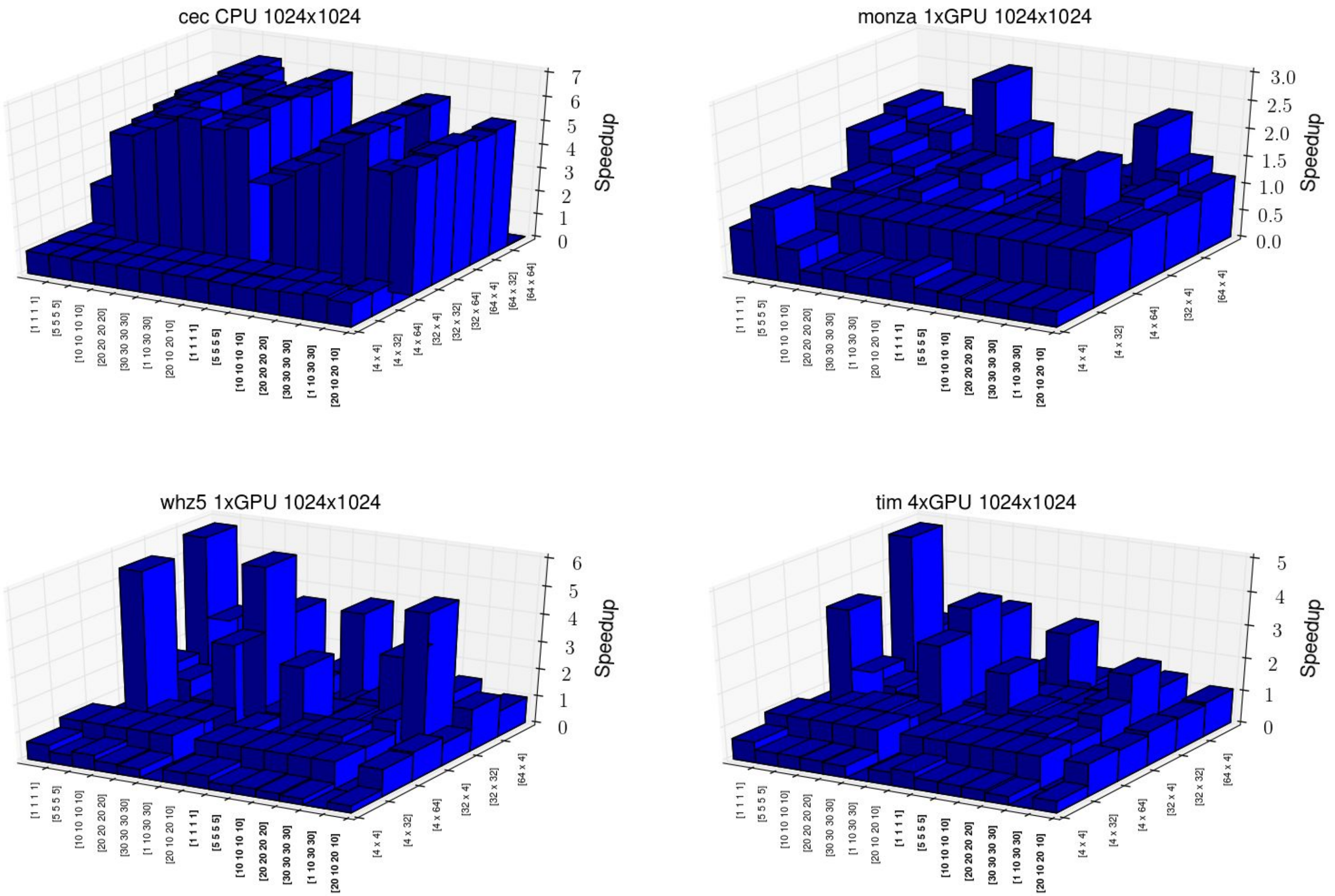
cec CPU 1024x1024
Speedup
0 1 2 3 4 5 6 7
[1 1 1 1] [5 5 5 5] [10 10 10 10] [20 20 20 20] [30 30 30 30] [1 10 30 30] [20 10 20 10]
**[1 1 1 1] [5 5 5 5] [10 10 10 10] [20 20 20 20] [30 30 30 30] [1 10 30 30] [20 10 20 10]**
[4 x 4] [4 x 32] [4 x 64] [32 x 4] [32 x 32] [32 x 64] [64 x 4] [64 x 32] [64 x 64]
monza 1xGPU 1024x1024
Speedup
0.0 0.5 1.0 1.5 2.0 2.5 3.0
[1 1 1 1] [5 5 5 5] [10 10 10 10] [20 20 20 20] [30 30 30 30] [1 10 30 30] [20 10 20 10]
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[4 x 4] [4 x 32] [4 x 64] [32 x 4] [64 x 4]
whz5 1xGPU 1024x1024
Speedup
0 1 2 3 4 5 6
[1 1 1 1] [5 5 5 5] [10 10 10 10] [20 20 20 20] [30 30 30 30] [1 10 30 30] [20 10 20 10]
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[4 x 4] [4 x 32] [4 x 64] [32 x 4] [32 x 32] [64 x 4]
tim 4xGPU 1024x1024
Speedup
0 1 2 3 4 5
[1 1 1 1] [5 5 5 5] [10 10 10 10] [20 20 20 20] [30 30 30 30] [1 10 30 30] [20 10 20 10]
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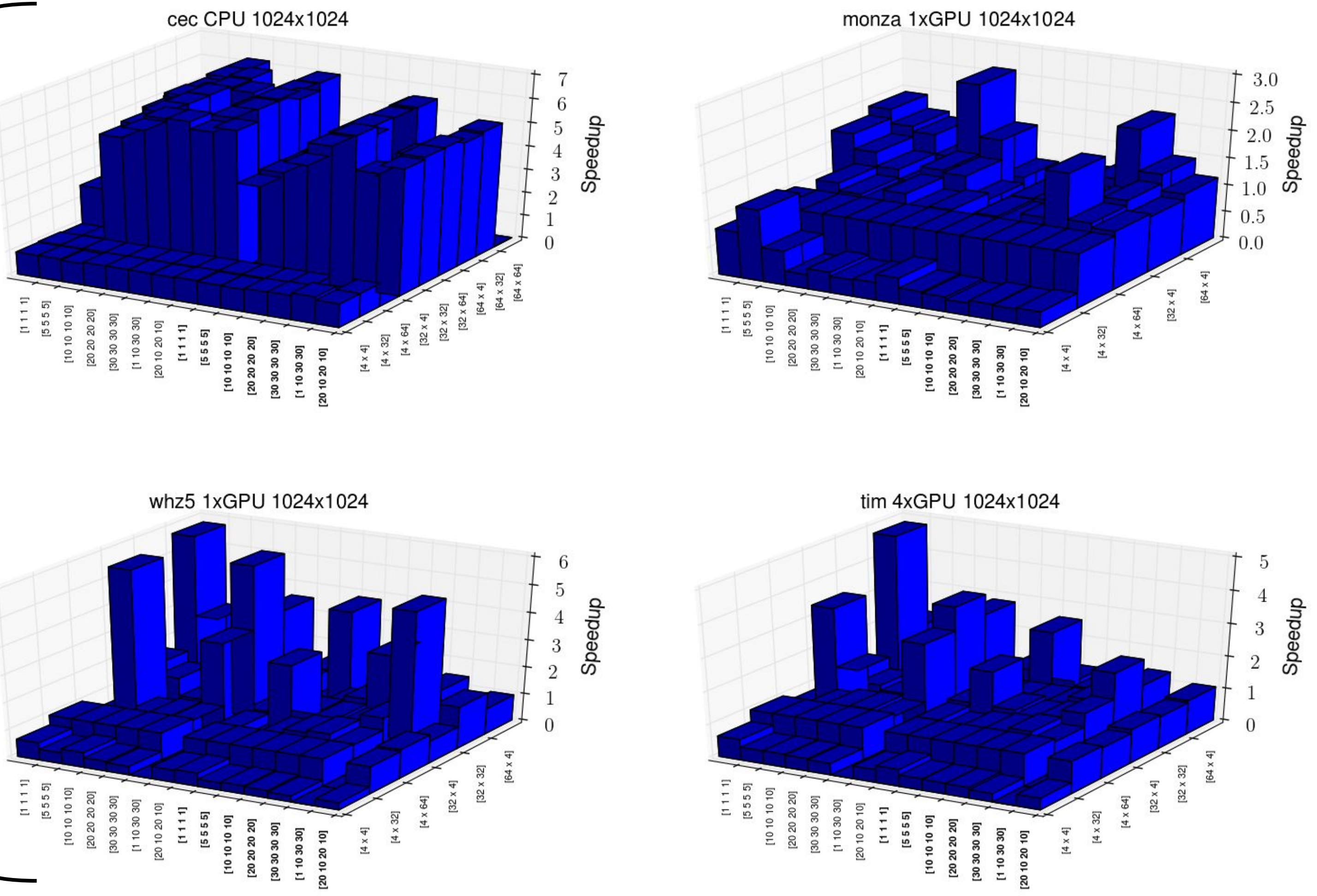
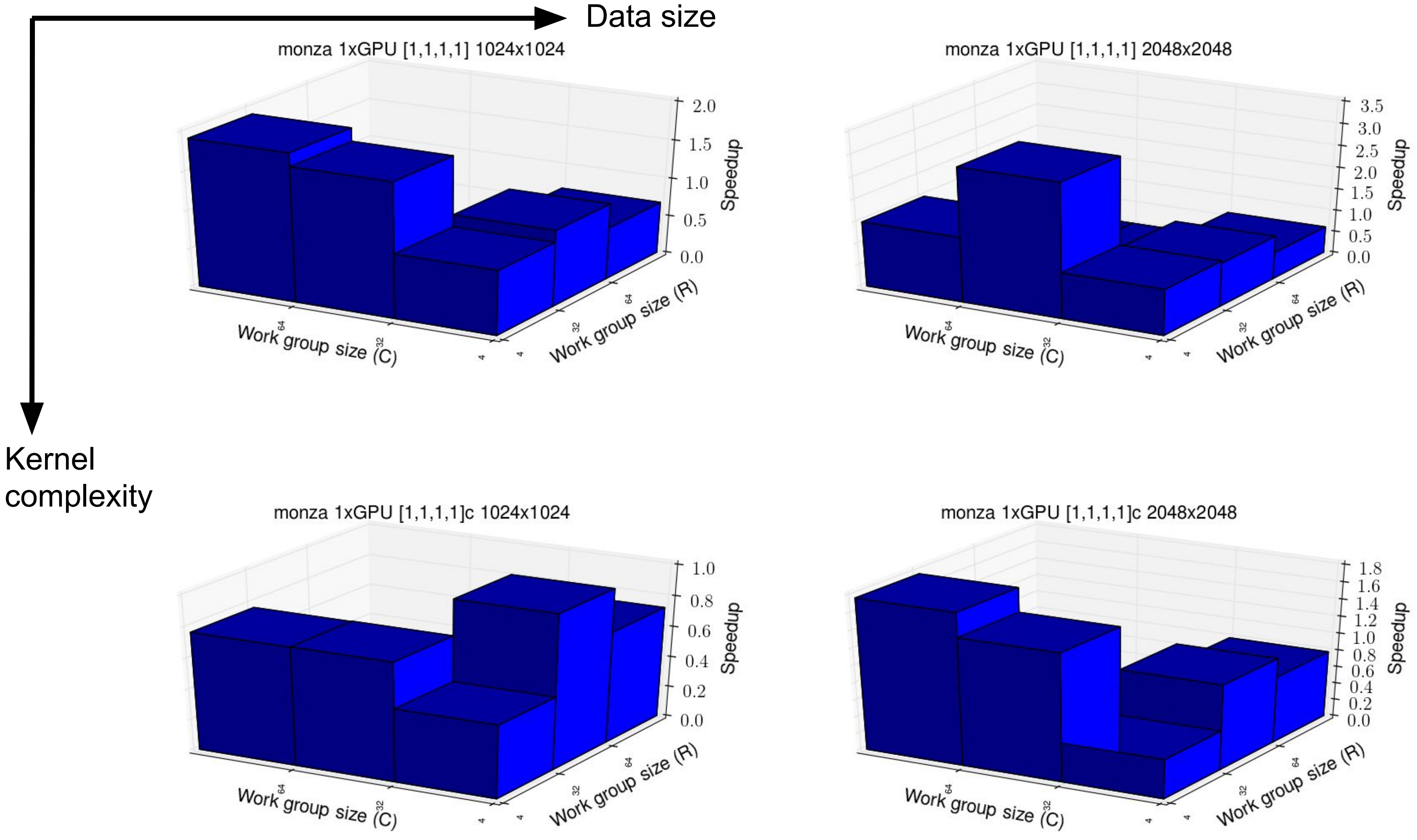
Performance across parameter values is non-uniform.





Data size
Kernel complexity
monza 1xGPU [1,1,1,1] 1024x1024
monza 1xGPU [1,1,1,1] 2048x2048
monza 1xGPU [1,1,1,1]c 1024x1024
monza 1xGPU [1,1,1,1]c 2048x2048
Speedup
Work group size (C)
Work group size (R)
64
32
4
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
0.2
0.4
0.6
0.8
1.2
1.4
1.6
1.8

# Autotuning stencil codes



**172** oracle configurations. Default parameter values optimal for **2.29%** of cases.

Average oracle speedup **2.393x** (max **7.192x**).

Cannot statically tune: hardware constraints invalidate most optimal value for some cases.

Use **machine learning** to predict best values for new configurations.

Training data created from results of optimisation space exploration:

- **Features**: vectors of 11 explanatory variables.
- **Labels**: oracle workgroup size values.

# Autotuning stencil codes



**Decision tree** classifier:

- Simple to reason about and implement.
- Use Weka's J48 algorithm (default params).
- Script parses output and implements tree.

Results from 10 fold cross validation:

- Optimal parameter values **76.57%** of time.
- Average speedup of **2.309x**.
- Min **0.699x**, max **7.192x**.
- Performance is **95.83%** of oracle.

```
classify(x):
  if x.DevType == GPU:
    if x.BorderEast <= 10: return (64, 4)
    if x.BorderEast > 10:
      if x.Hostname == cec: return (32, 32)
      if x.Hostname == monza: return (64, 4)
      if x.Hostname == florence: return (32, 32)
      if x.Hostname == whz5: return (32, 32)
      if x.Hostname == tim:
        if x.Complexity == 0:
          if x.BorderNorth <= 20: return (64, 4)
          if x.BorderNorth > 20: return (32, 32)
        if x.Complexity == 1: return (32, 32)
  if x.DevType == CPU:
    if x.BorderNorth <= 20:
      if x.BorderSouth <= 10:
      ...
```

# Moving forward



Something I should improve upon: tackling “simple” cases first, then scaling up.

My approach was to complete one big block of work each for:

Developing benchmarks.

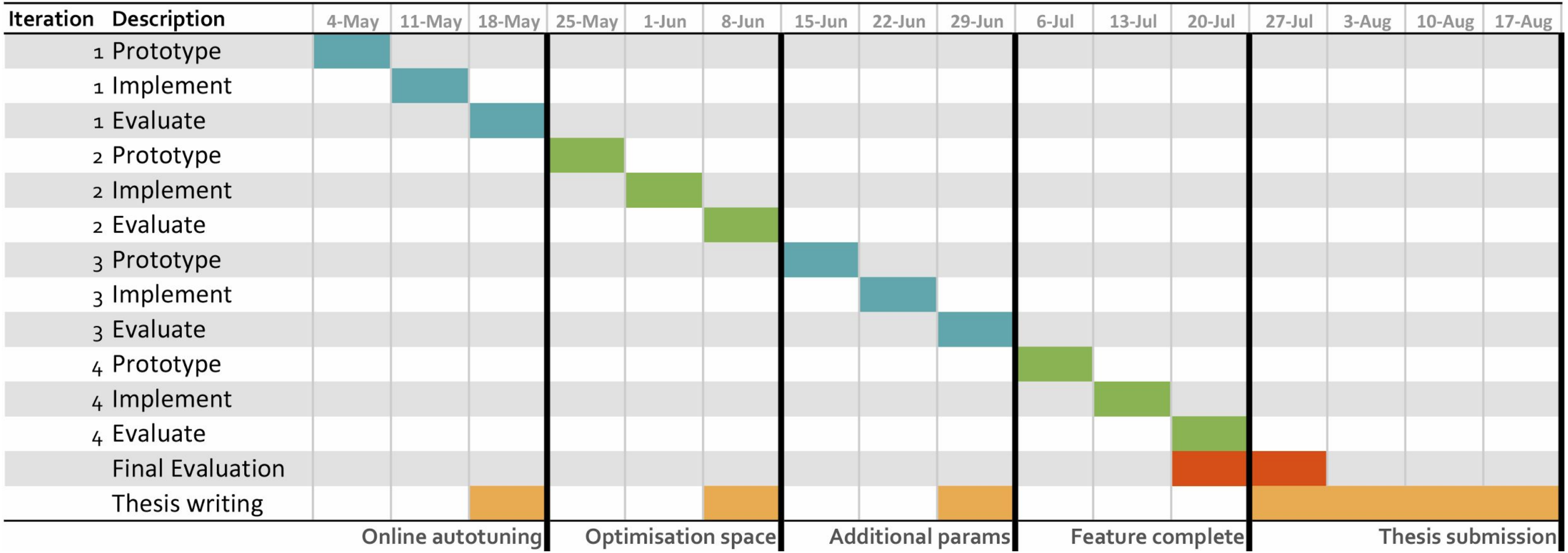
Creating tunable parameters.

Enumerating optimisation space.

Developing an autotuner.

For the remainder of the project (& PhD phase), use a workflow with small, incremental iterations.

# Moving forward



# Moving forward

**Iteration 1** - Online autotuning

- Runtime search
- Machine learning guided search
- Online machine learning

**Iteration 2** - Optimisation space

- Multi-label classification
- Auto-generated kernels
- Kernel feature extraction

**Iteration 3** - Additional params

- Stencil iterations between swaps
- MapOverlap vs Stencil
- Execution device and count

**Iteration 4** - Feature complete

- Integration & testing
- Evaluation

# Conclusions



There are a number of parameters which affect the performance of SkelCL. Performance depends on: muscle functions, input data, number of iterations, and architecture.

Experimental results for parameters. For a simple case, offline machine learning can achieve 96% of oracle performance for 2.3x speedup.

Remaining time spent on 4 short iterations targeting: online autotuning, increasing the number of parameters, and automatically generating benchmark programs.

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# End of presentation

# SkelCL: how it works



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; Call skeletons.
Vector result = sum(mult(vector_a, vector_b))

; Read result.
print result.first()
```

Initialise OpenCL devices

Prepare & compile
device programs

Allocate space for data on hosts
Copy data to hosts

Enqueue jobs with devices

Wait until jobs have completed
Copy data from devices to host

# Profiling SkelCL applications



Time types:

| | |
|---|---|
| ***c*** | Kernel compilation times |
| ***p*** | Skeleton prepare times |
| ***u*** | Host -> Device |
| ***k*** | Device execution times |
| ***d*** | Device -> Host |
| ***s*** | Devices <-> Host (sync) |

*Obtained from OpenCL events.*

Prepare & compile
device programs

Allocate space for data on hosts
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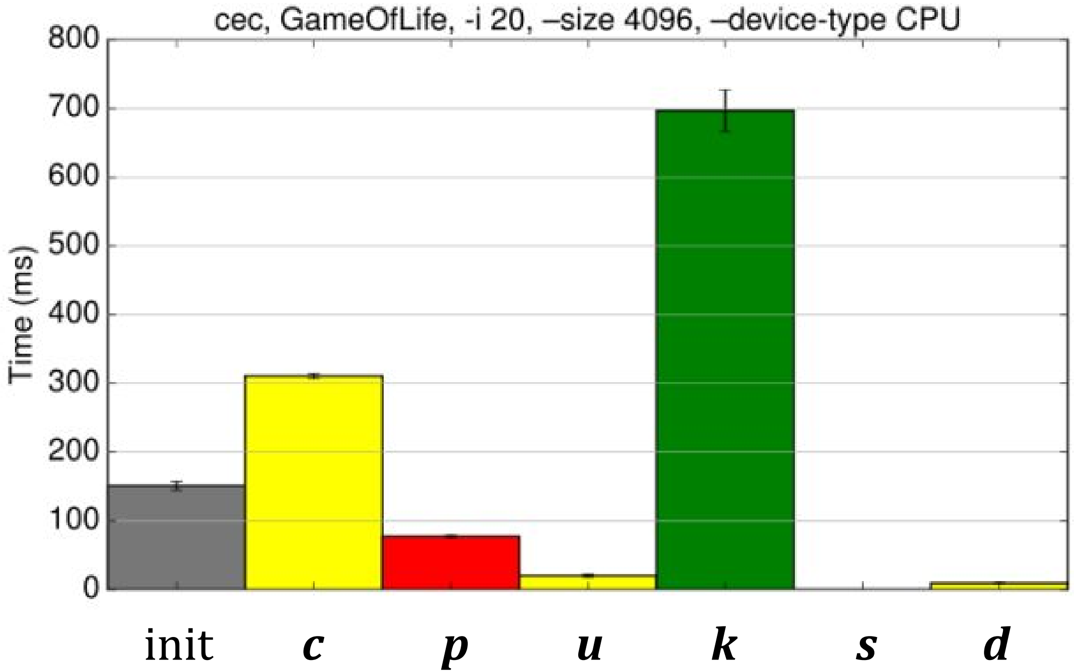


Times: no-init: **1115.25** ms, no-build: **804.25** ms. device: **726.55** ms.
ID: `c9b9bcf6c928d805a0730f1789fe205b2f39fc09`. 10 samples.

# Profiling SkelCL applications



Time types:

| | |
|---|---|
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| ***s*** | Devices <-> Host (sync) |

*Obtained from OpenCL events.*

Approximating end-to-end time (~95% accurate):

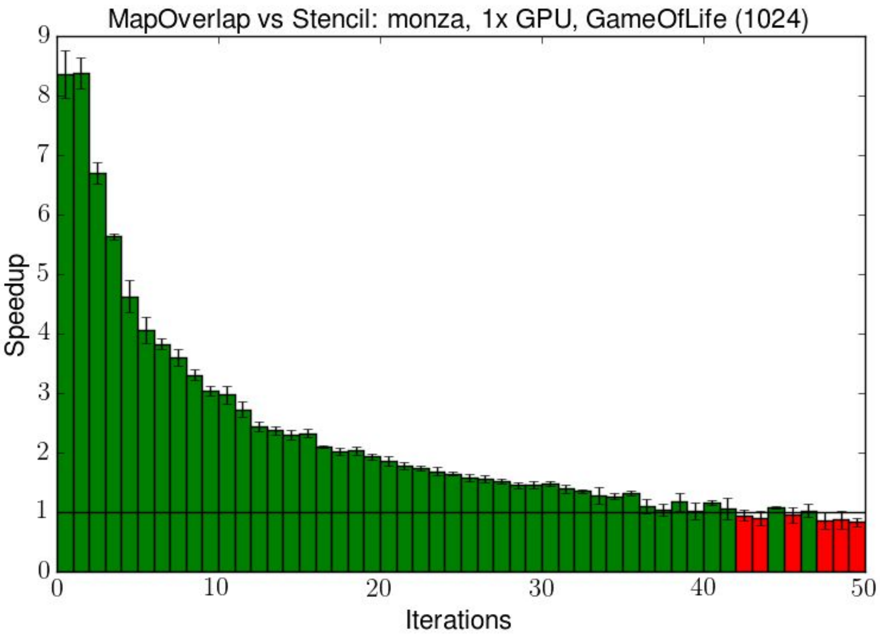
$$t \approx \underbrace{\sum_{i=1}^{n} \mathbf{1}\boldsymbol{c}_i + \mathbf{1}\boldsymbol{p} + \mathbf{1}\boldsymbol{s}}_{\text{Host}} + \underbrace{\frac{\sum_{i=1}^{n} \mathbf{1}\boldsymbol{u}_i + \mathbf{1}\boldsymbol{k}_i + \mathbf{1}\boldsymbol{d}_i}{n}}_{\text{Devices}}$$

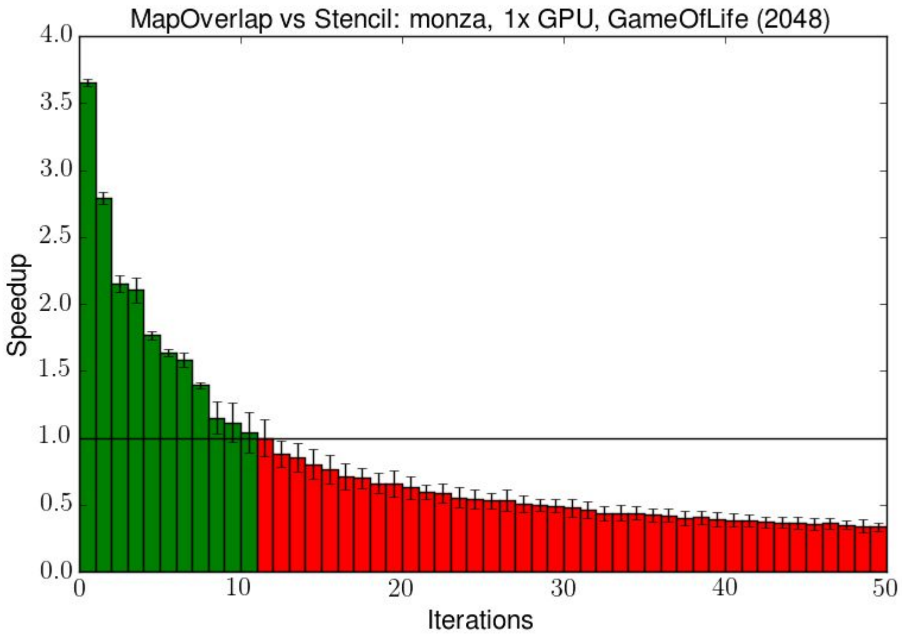
Measuring end-to-end time:

```
start timer
; Returns instantly:
result = skeleton(input)
; Force copy:
copy result to host
stop timer
```

# Tuning iterative stencil

Trading device memory bandwidth against kernel complexity.



# The need for generated kernels

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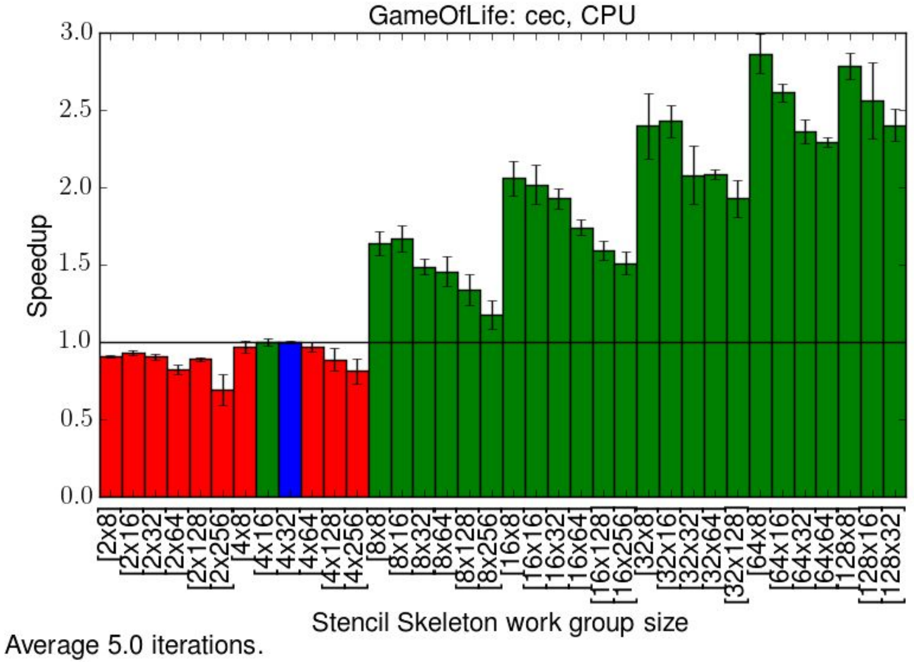
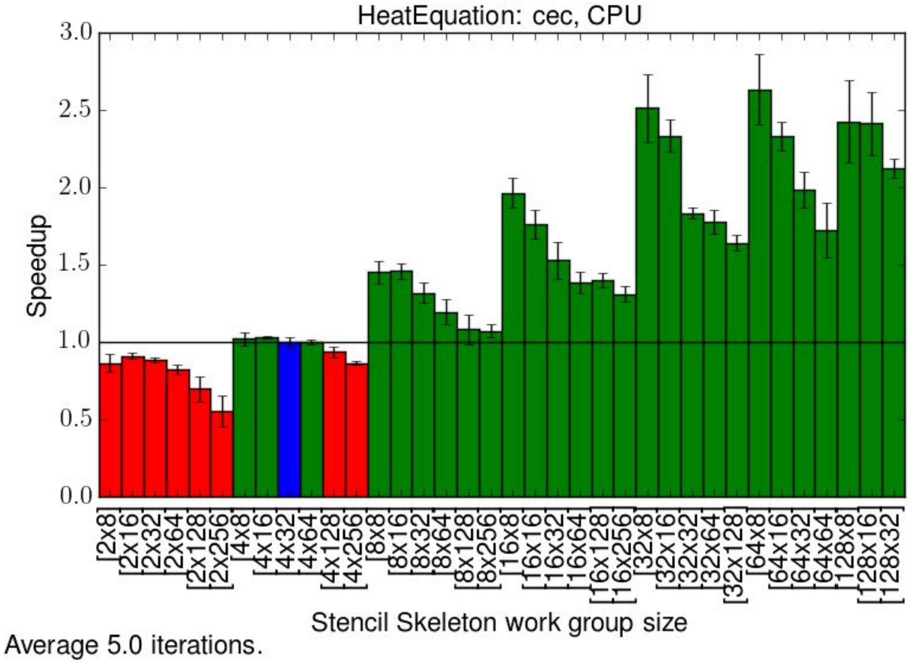
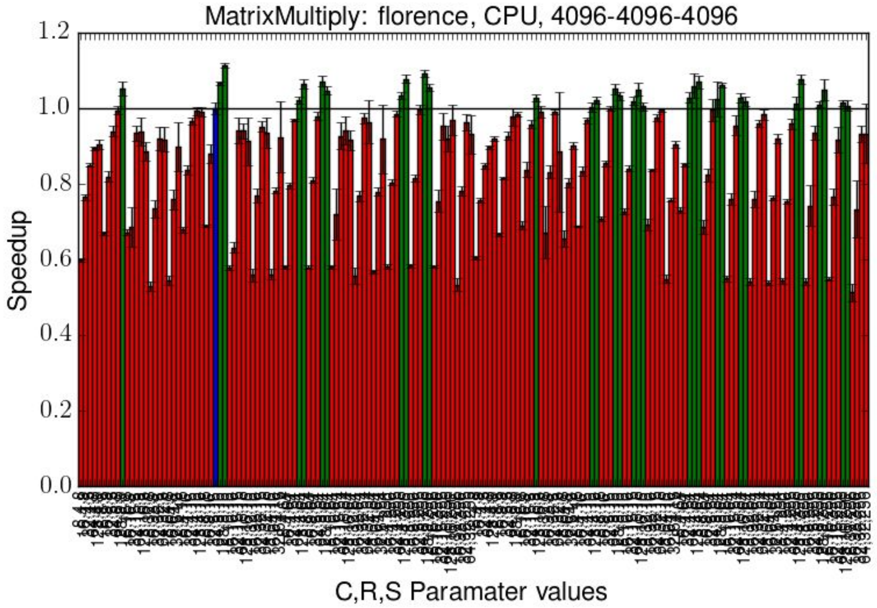
Benchmarks are too similar, no inter-program tuning necessary:



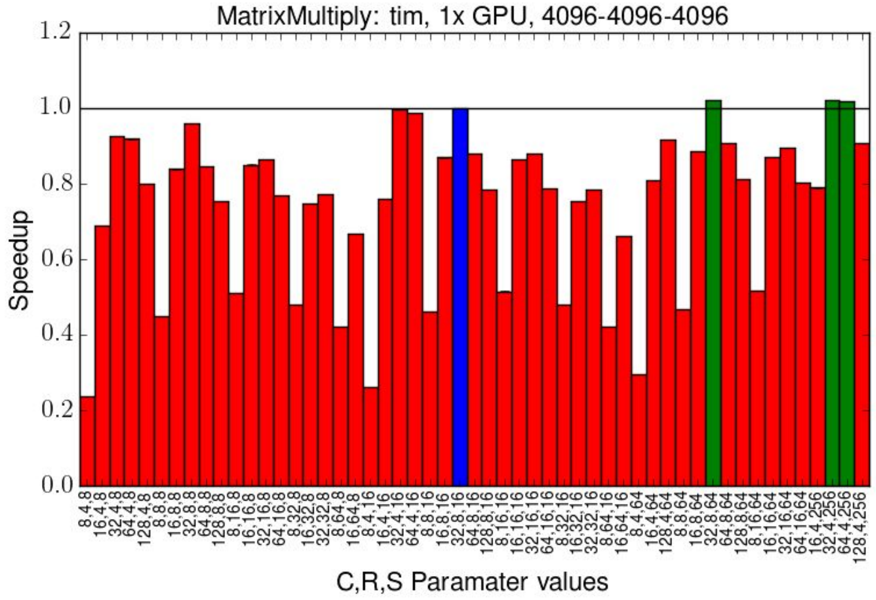



# Tuning AllPairs

Too little room for improvement, no tuning necessary:




Average 5.0 iterations.




Average 4.0 iterations.