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Parallel
Programming

Validating the Performance of GPU-Offloading with Differential Performance Models

Motivation

- When offloading computation to the GPU we expect
  - Things to get faster
  - More energy efficient

- Are these expectations for a specific code fulfilled?
- What about individual application parts?
- What happens when scaling up?

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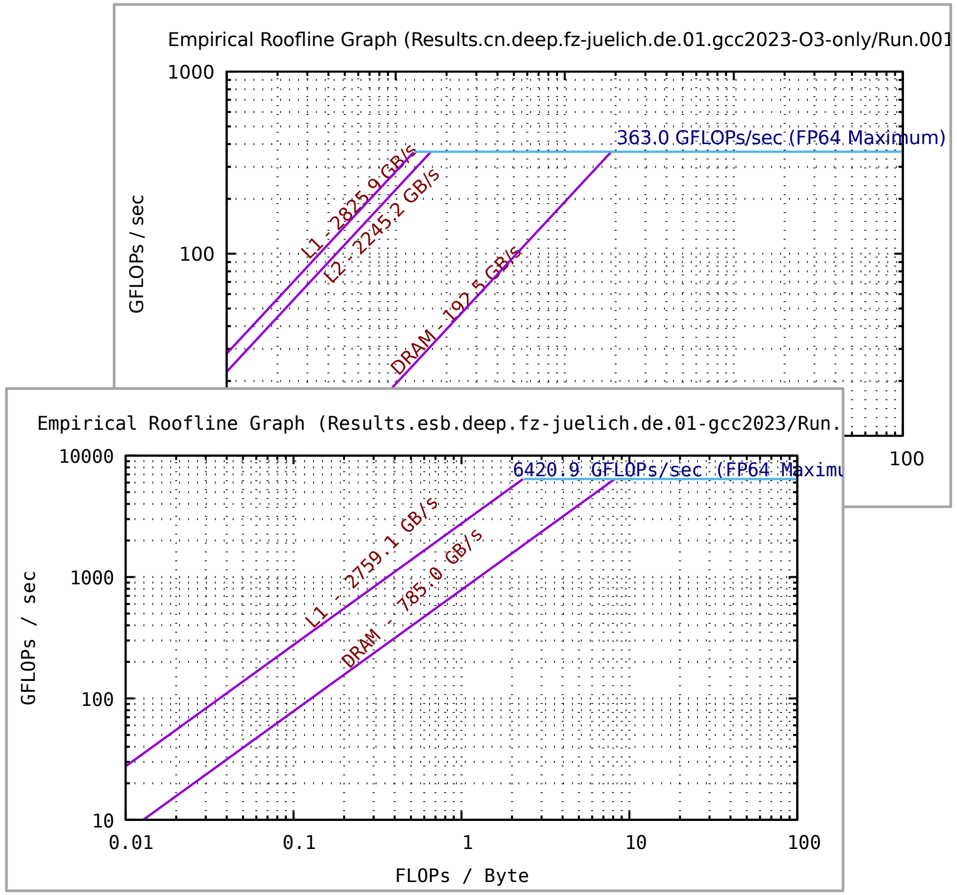
Parallel Programming

Workflow

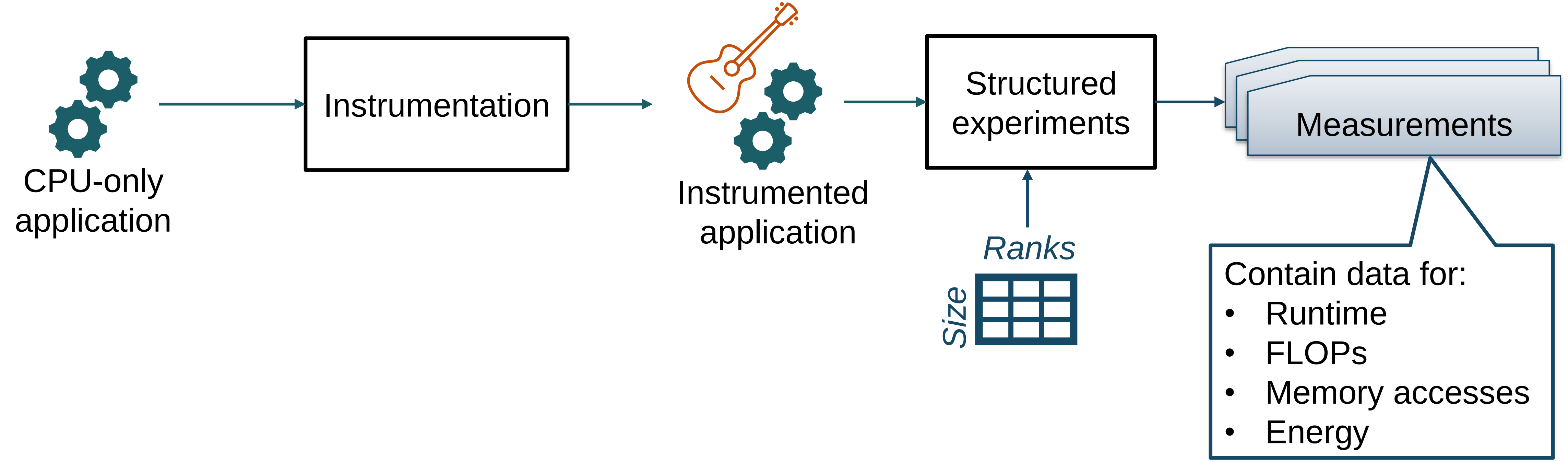
1. Obtain hardware capabilities
2. Collect baseline for the CPU-only version
3. Benchmark the GPU port
4. Generate performance models and explore them

1. Obtaining Hardware Capabilities

- Once per system/hardware
- Determining hardware capabilities
  - We use roofline models
    - Easy to create & understand
  - Generated with empirical roofline toolkit



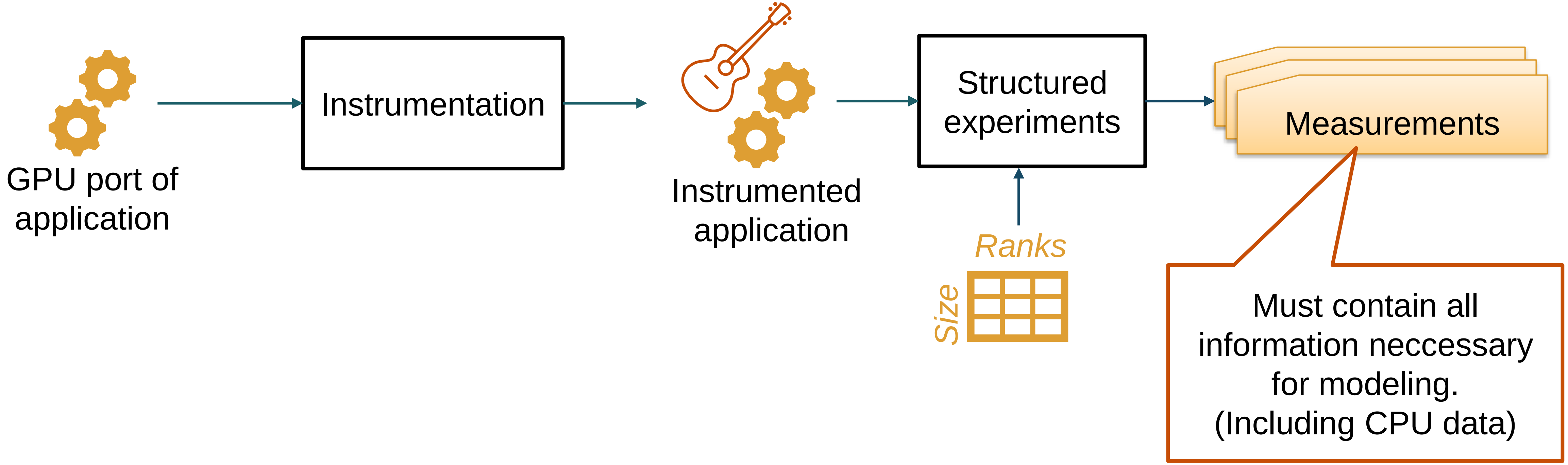
2. Baseline Measurements



Contain data for:

- Runtime
- FLOPs
- Memory accesses
- Energy

3. Benchmark the GPU port



GPU port of application

Instrumentation

Instrumented application

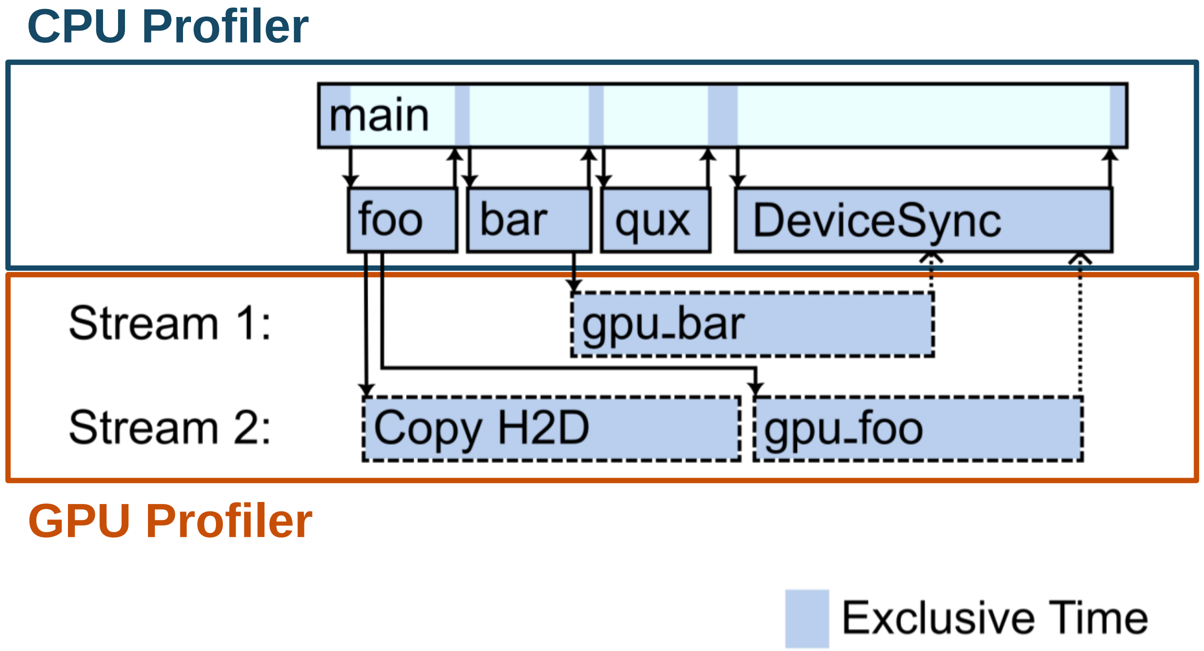
Structured experiments

Measurements

Must contain all information neccessary for modeling. (Including CPU data)

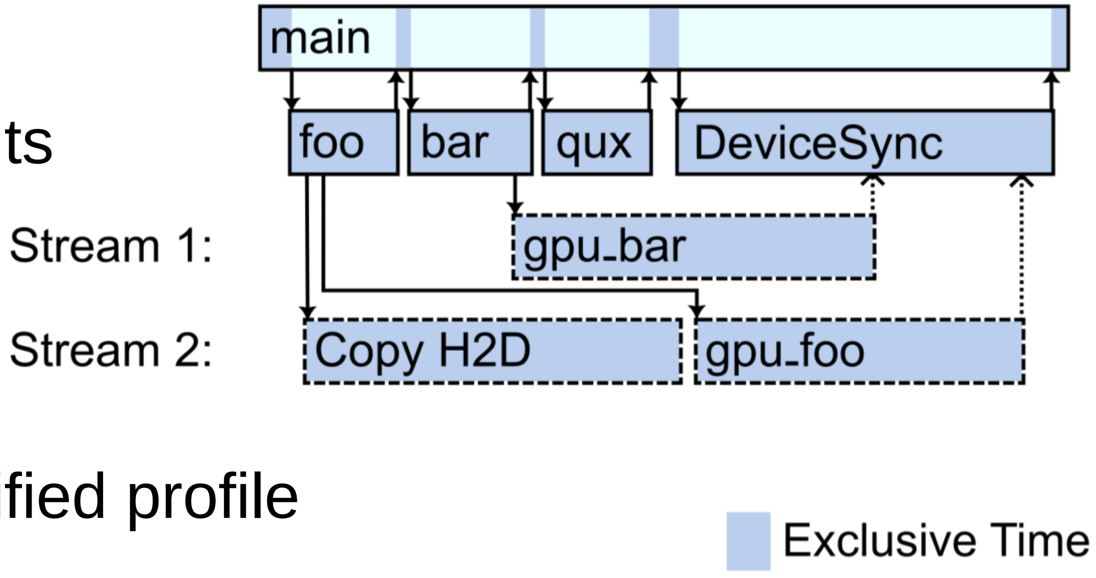
Joint CPU–GPU-Profiling

```
cudaStream_t stream1, stream2;
void foo(double* a_gpu, ...) { ...
  cudaMemcpyAsync(a_gpu, ..., H2D, stream2);
  gpu_foo<<<..., stream2>>>(a_gpu, ...); ...
}

void bar(...) { ...
  gpu_bar<<<..., stream1>>>(...); ...
}

int main() { ...
  foo(a_gpu, ...); ...
  bar(...); ...
  qux(...); ...
  cudaDeviceSynchronize(); ...
}
```



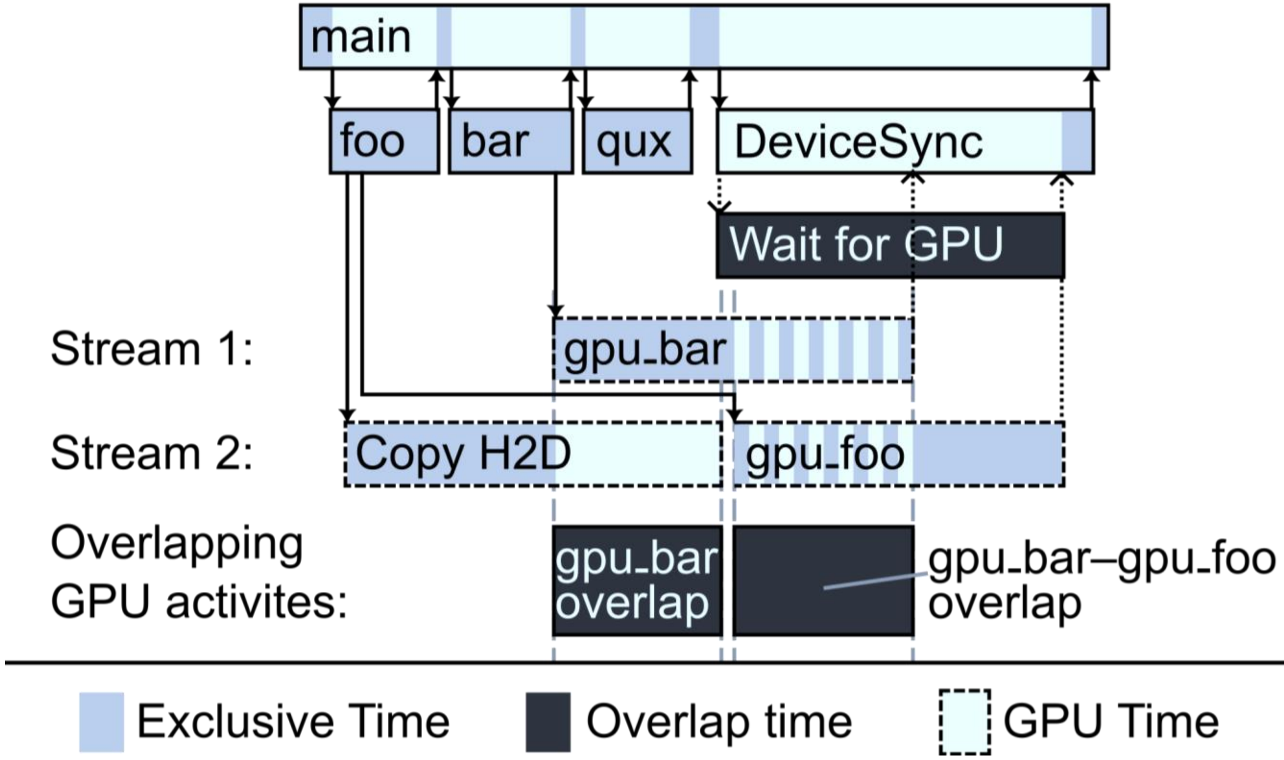
Joint CPU–GPU-Profiling II

- We collect timestamps on start and end of each function and kernel
  - Using compiler instrumentation on CPU
  - CUPTI Callback API for GPU
- We profile the CPU and trace the GPU events
  - We store only limited trace data
  - Calling context is tracked
  - During post-processing we convert to a unified profile

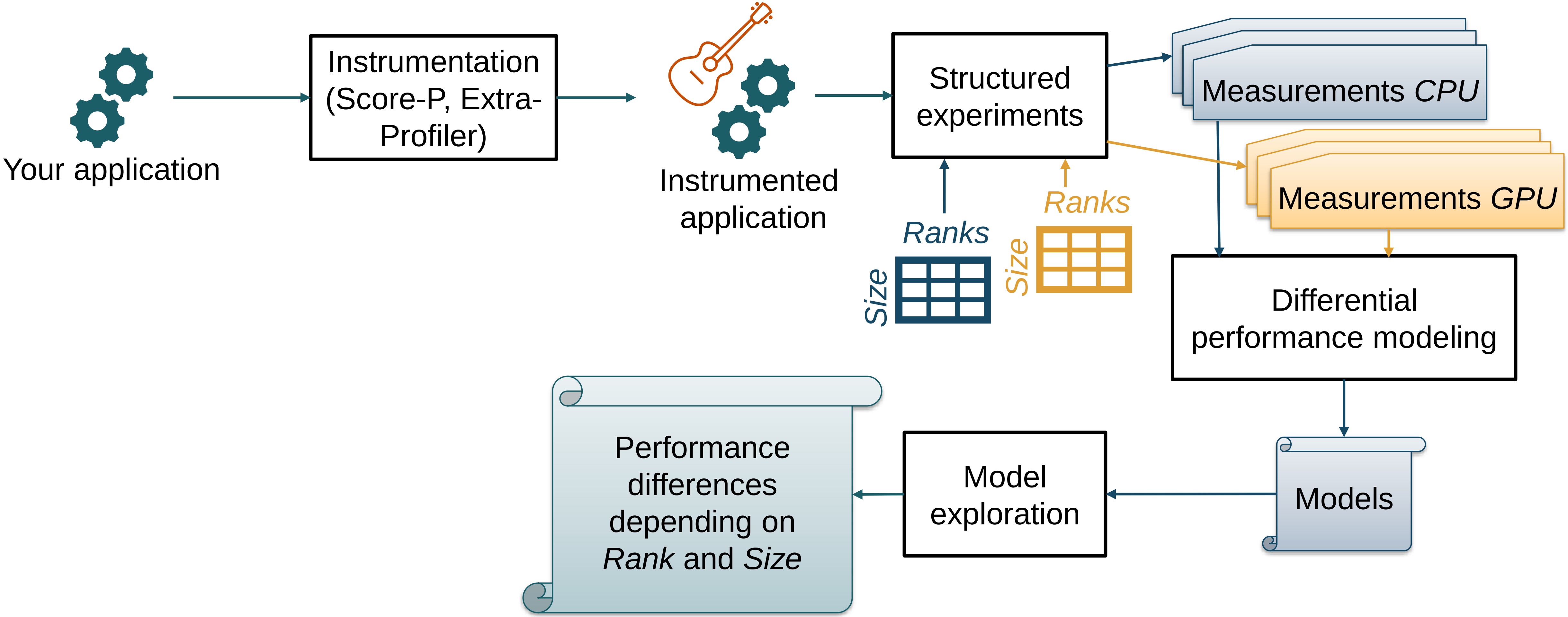


Joint CPU–GPU-Profiling III

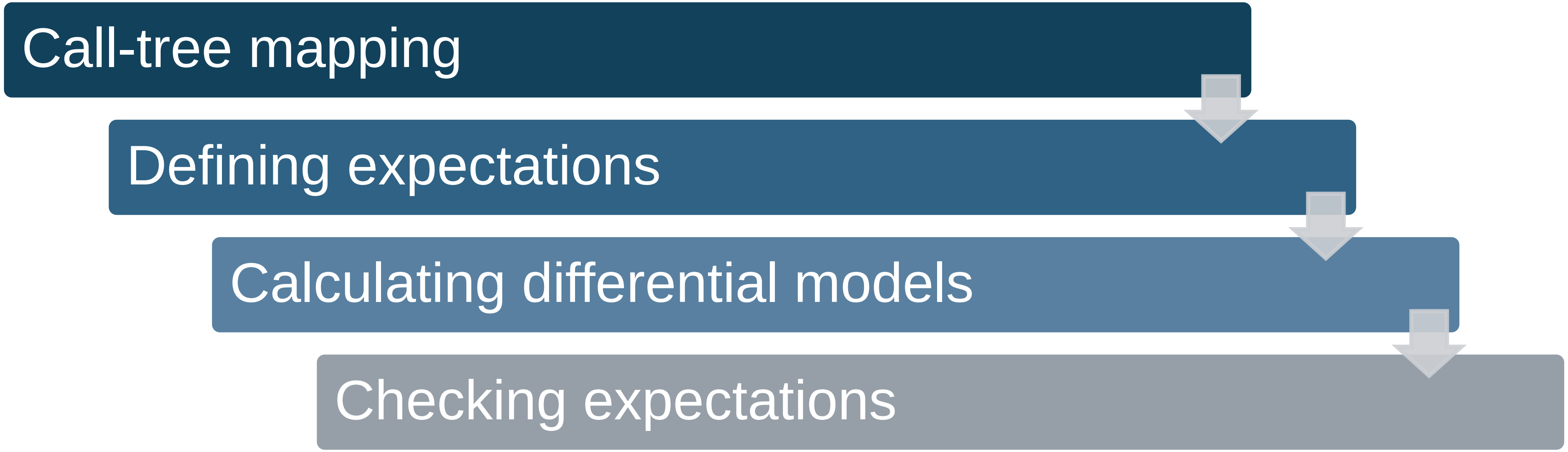
- This allows recording of
  - Synchronization of GPU actions with CPU functions
  - Overlap of concurrent GPU activities
- Small result files with data necessary for modeling
- Full call path up to kernel



4. Differential Performance Modeling



4. Differential performance modeling



Call-tree mapping

Defining expectations

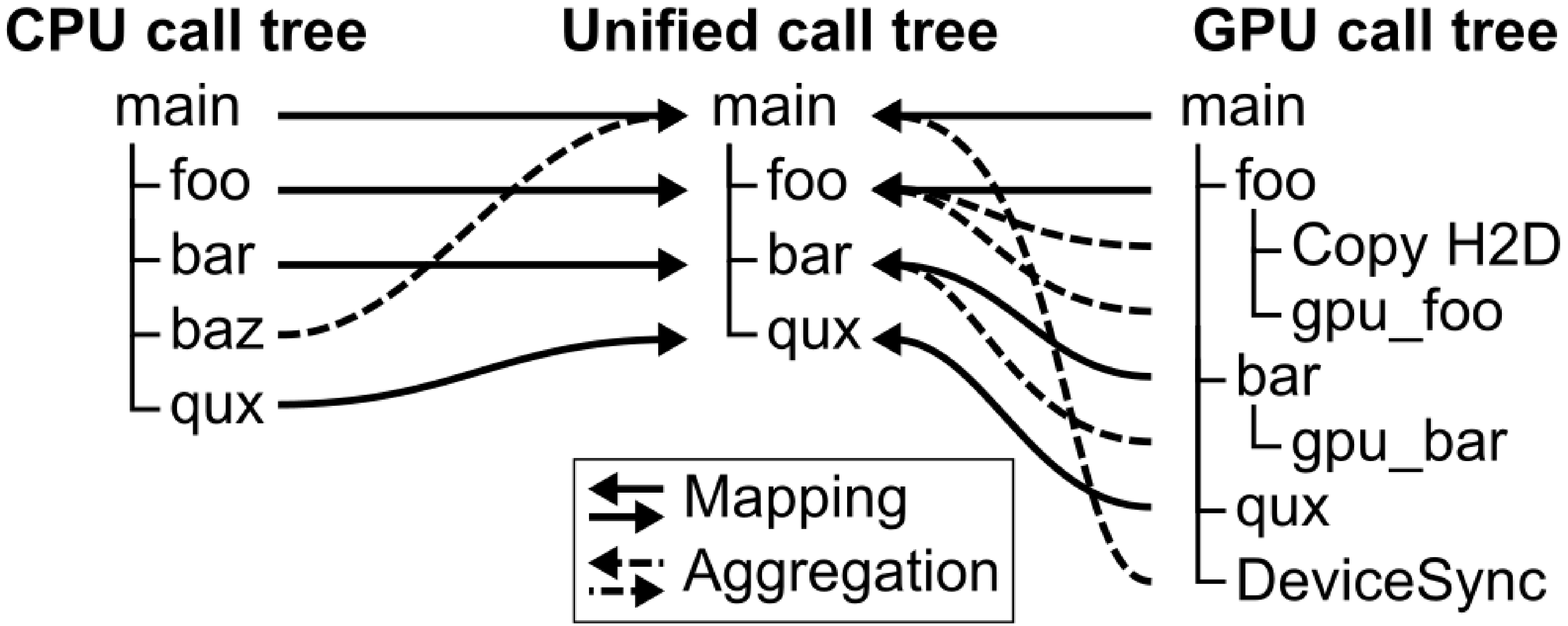
Calculating differential models

Checking expectations

Call-Tree Mapping

- Prefix matching with aggregation

Remember we are using exclusive values

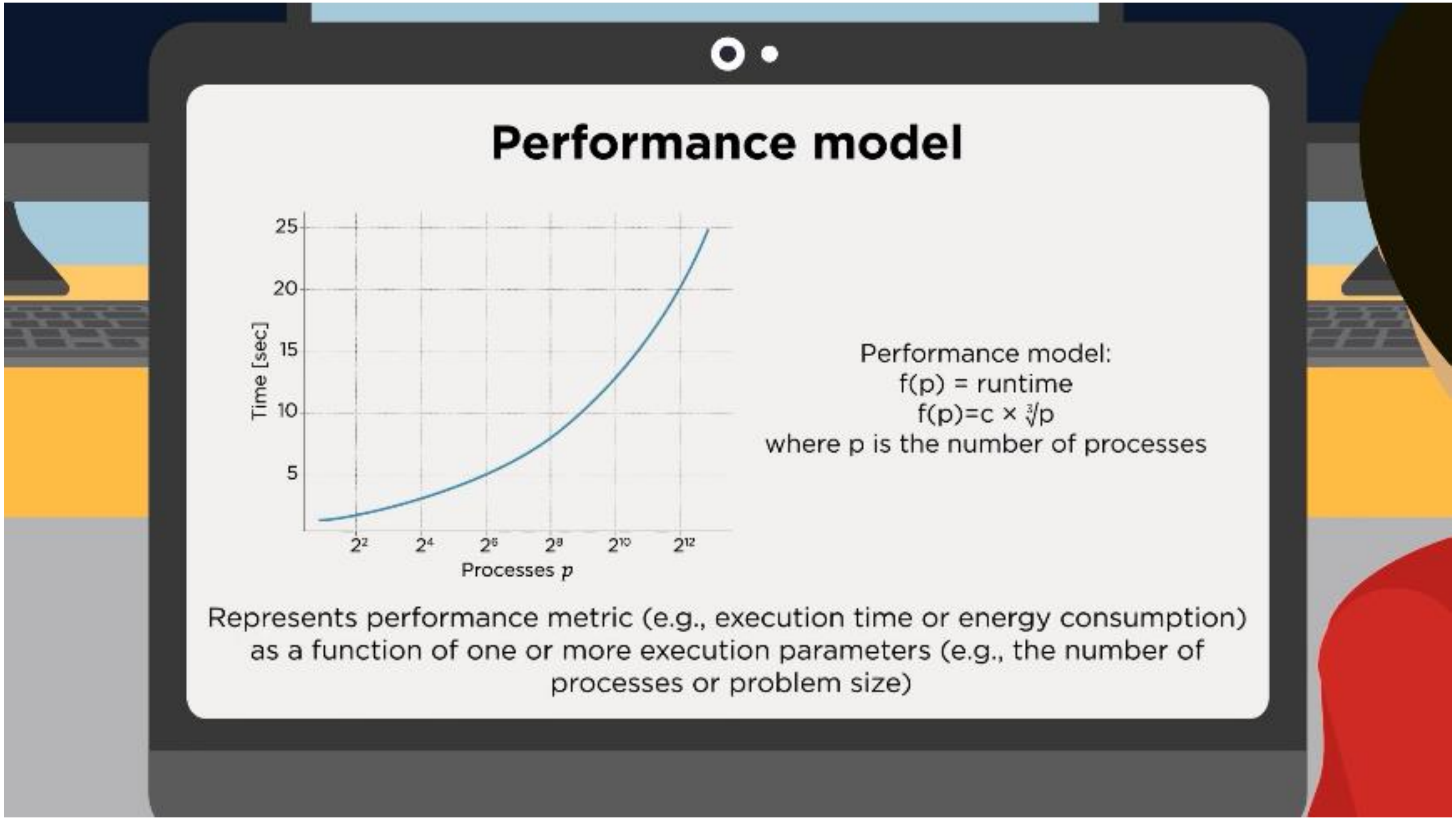


Defining Expectations

Faster than CPU-only implementation	• Runtime of GPU port is lower than runtime of CPU-only version
Uses less energy	• Energy usage of GPU port is lower than runtime of CPU-only version
Uses the hardware well	• Achieves same or higher hardware efficiency

Refresher

Performance Modeling with Extra-P



Performance model

Performance model:
$f(p)$ = runtime
$f(p)=c \times \sqrt[3]{p}$
where p is the number of processes

Represents performance metric (e.g., execution time or energy consumption) as a function of one or more execution parameters (e.g., the number of processes or problem size)

Watch Extra-P overview video

https://www.youtube.com/watch?v=Cv2YRCMWqBM

Refresher

Automatic Performance Modeling

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Parallel Programming

```
main() {
    foo()
    bar()
    compute()
}
```

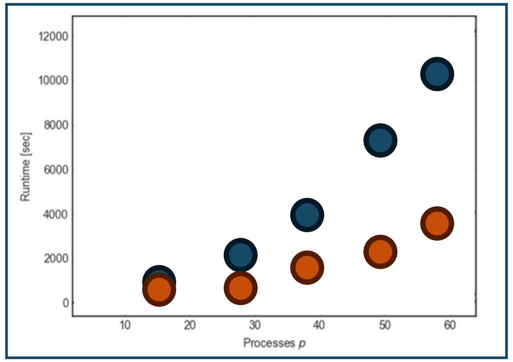
Input

Instrumentation

- All functions

Performance measurements

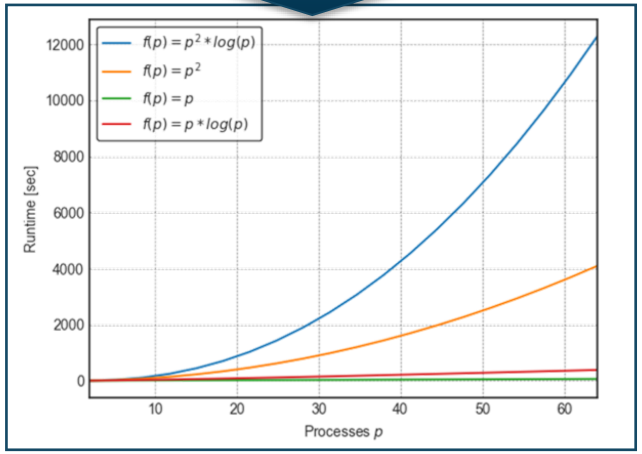
M_i M_j



Extra-P

Output

Human-readable performance models of all functions (e.g., $t(p) = c_1 \cdot \log(p) + c_2$)



Performance Model Normal Form

$$f(x) = \sum_{k=1}^{n} c_k \cdot x^{i_k} \cdot log_2^{j_k}(x)$$

$n \in \mathbb{N}$
$i_k \in I$
$j_k \in J$
$I, J \subset \mathbb{Q}$

$n = 1$
$I = \{0, 1, 2\}$
$J = \{0, 1\}$

c_1	$c_1 \cdot \log x$
$c_1 \cdot x$	$c_1 \cdot x \cdot \log x$
$c_1 \cdot x^2$	$c_1 \cdot x^2 \cdot \log x$

Calculating Differential Models

- All models f_c^{GPU} and f_c^{CPU} are mathematical expressions
  - We can calculate with them

Differential models express the difference

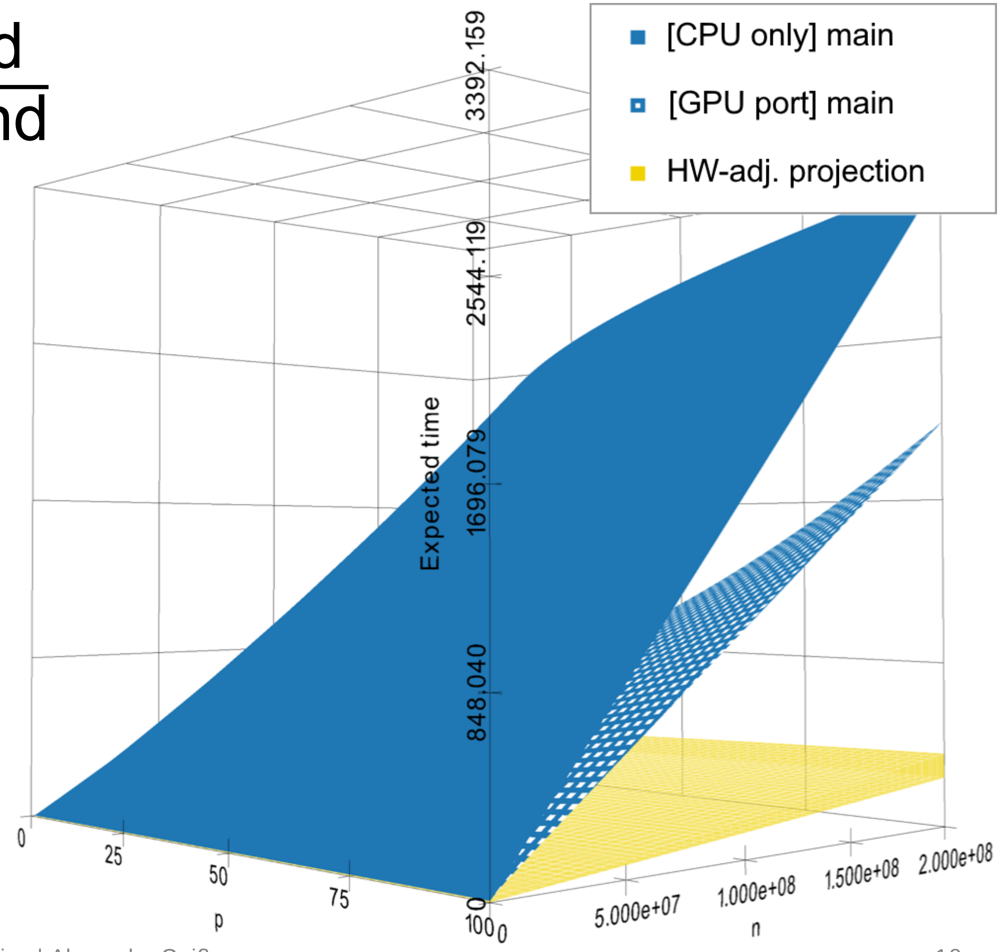
- $\Delta_c(p_1, \dots) = f_c^{\mathrm{GPU}}(p_1, \dots) - f_c^{\mathrm{CPU}}(p_1, \dots)$
  - For a specific call tree entry c

Hardware Efficiency

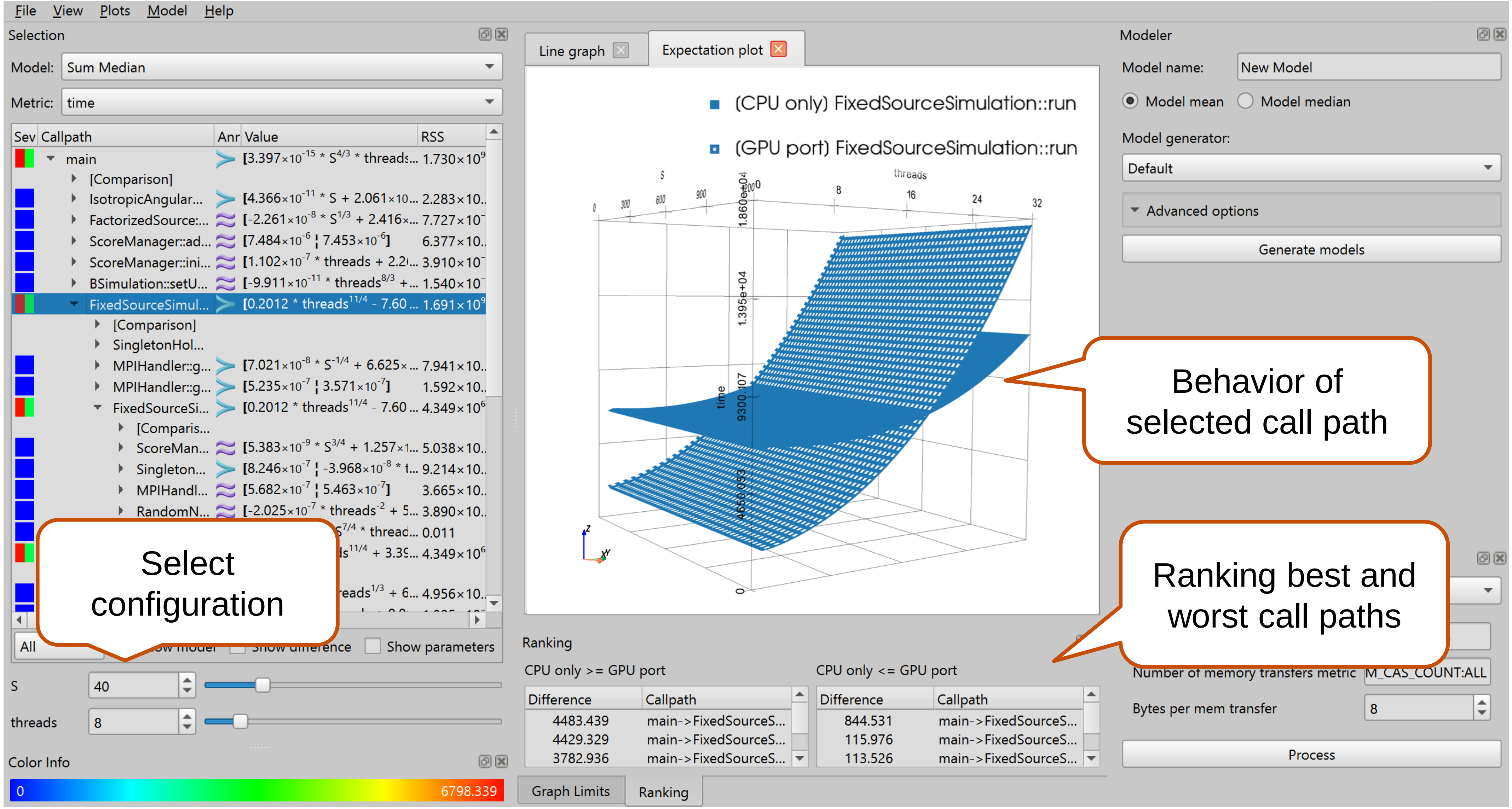
$$\text{Hardware efficiency} = \frac{\text{achieved FLOPs per second}}{\text{achievable FLOPs per second}}$$

- Modeled with Extra-P
  - We build models for FLOPs, time, and memory accesses from measurements
    - All models are mathematical expressions

- We present this as a hardware adjusted runtime model to the user



Interactive Exploration



Model: Sum Median

Metric: time

Sev	Callpath	Anr	Value	RSS
🟥🟩	main	≻	[3.397×10^{-15} * S$^{4/3}$ * threads...	1.730×10^{9}
	[Comparison]			
🟦	IsotropicAngular...	≻	[4.366×10^{-11} * S + 2.061×10...	2.283×10...
🟦	FactorizedSource:...	≈	[-2.261×10^{-8} * S$^{1/3}$ + 2.416×...	7.727×10
🟦	ScoreManager::ad...	≈	[7.484×10^{-6} ¦ 7.453×10^{-6}]	6.377×10...
🟦	ScoreManager::ini...	≈	[1.102×10^{-7} * threads + 2.2...	3.910×10
🟦	BSimulation::setU...	≈	[-9.911×10^{-11} * threads$^{8/3}$ +...	1.540×10
🟥🟩	FixedSourceSimul...	≻	[0.2012 * threads$^{11/4}$ - 7.60...	1.691×10^{9}
	[Comparison]			
	SingletonHol...			
🟦	MPIHandler::g...	≻	[7.021×10^{-8} * S$^{-1/4}$ + 6.625×...	7.941×10...
🟦	MPIHandler::g...	≻	[5.235×10^{-7} ¦ 3.571×10^{-7}]	1.592×10...
🟥🟩	FixedSourceSi...	≻	[0.2012 * threads$^{11/4}$ - 7.60...	4.349×10^{6}
	[Comparis...			
🟦	ScoreMan...	≈	[5.383×10^{-9} * S$^{3/4}$ + 1.257×1...	5.038×10...
🟦	Singleton...	≻	[8.246×10^{-7} ¦ -3.968×10^{-8} * t...	9.214×10...
🟦	MPIHandl...	≈	[5.682×10^{-7} ¦ 5.463×10^{-7}]	3.665×10...
🟦	RandomN...	≈	[-2.025×10^{-7} * threads^{-2} + 5...	3.890×10...
🟦			S$^{7/4}$ * thread...	0.011
🟥🟩			ds$^{11/4}$ + 3.39...	4.349×10^{6}
🟦			reads$^{1/3}$ + 6...	4.956×10...

All □ Show difference □ Show parameters

S 40

threads 8

■ (CPU only) FixedSourceSimulation::run

■ (GPU port) FixedSourceSimulation::run

Model name: New Model

● Model mean ○ Model median

Model generator: Default

Advanced options

Generate models

Number of memory transfers metric M_CAS_COUNT:ALL

Bytes per mem transfer 8

Process

Ranking

CPU only >= GPU port

Difference	Callpath
4483.439	main->FixedSourceS...
4429.329	main->FixedSourceS...
3782.936	main->FixedSourceS...

CPU only <= GPU port

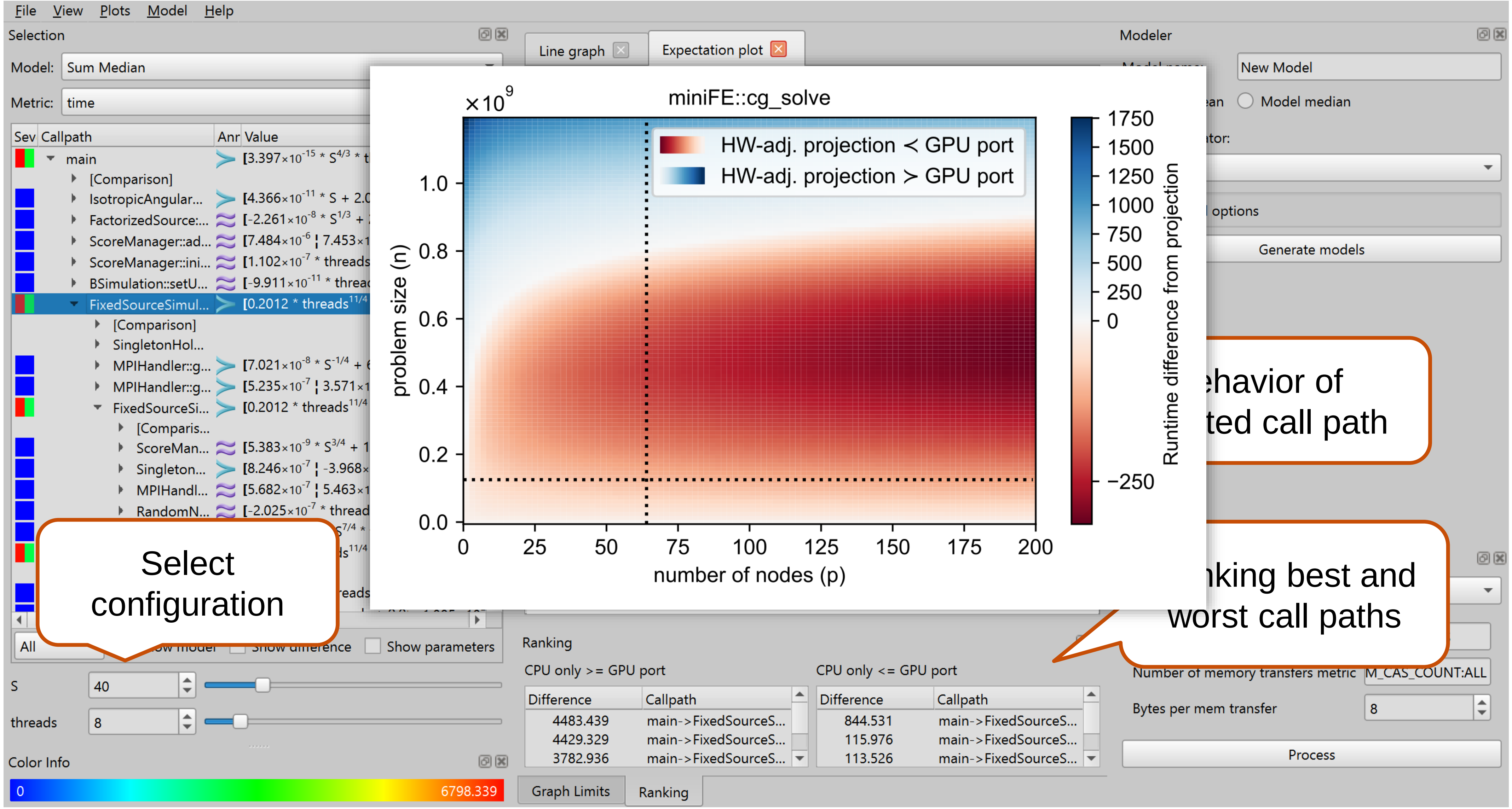
Difference	Callpath
844.531	main->FixedSourceS...
115.976	main->FixedSourceS...
113.526	main->FixedSourceS...

Behavior of selected call path

Select configuration

Ranking best and worst call paths

Interactive Exploration



Model: Sum Median

Metric: time

Sev Callpath Anr Value

- main [$3.397{\times}10^{-15}$ * $S^{4/3}$ * t
  - [Comparison]
  - IsotropicAngular... [$4.366{\times}10^{-11}$ * S + 2.0
  - FactorizedSource:... [$-2.261{\times}10^{-8}$ * $S^{1/3}$ +
  - ScoreManager::ad... [$7.484{\times}10^{-6}$ ¦ 7.453×1
  - ScoreManager::ini... [$1.102{\times}10^{-7}$ * threads
  - BSimulation::setU... [$-9.911{\times}10^{-11}$ * threac
  - FixedSourceSimul... [0.2012 * $\text{threads}^{11/4}$
    - [Comparison]
    - SingletonHol...
    - MPIHandler::g... [$7.021{\times}10^{-8}$ * $S^{-1/4}$ + 6
    - MPIHandler::g... [$5.235{\times}10^{-7}$ ¦ 3.571×1
    - FixedSourceSi... [0.2012 * $\text{threads}^{11/4}$
      - [Comparis...
      - ScoreMan... [$5.383{\times}10^{-9}$ * $S^{3/4}$ + 1
      - Singleton... [$8.246{\times}10^{-7}$ ¦ -3.968×
      - MPIHandl... [$5.682{\times}10^{-7}$ ¦ 5.463×1
      - RandomN... [$-2.025{\times}10^{-7}$ * thread

All ☐ Show difference ☐ Show parameters

S 40

threads 8

Model name: New Model

○ Model median

options

Number of memory transfers metric M_CAS_COUNT:ALL

Bytes per mem transfer 8

Ranking

CPU only >= GPU port

Difference	Callpath
4483.439	main->FixedSourceS...
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CPU only <= GPU port

Difference	Callpath
844.531	main->FixedSourceS...
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113.526	main->FixedSourceS...

Select configuration

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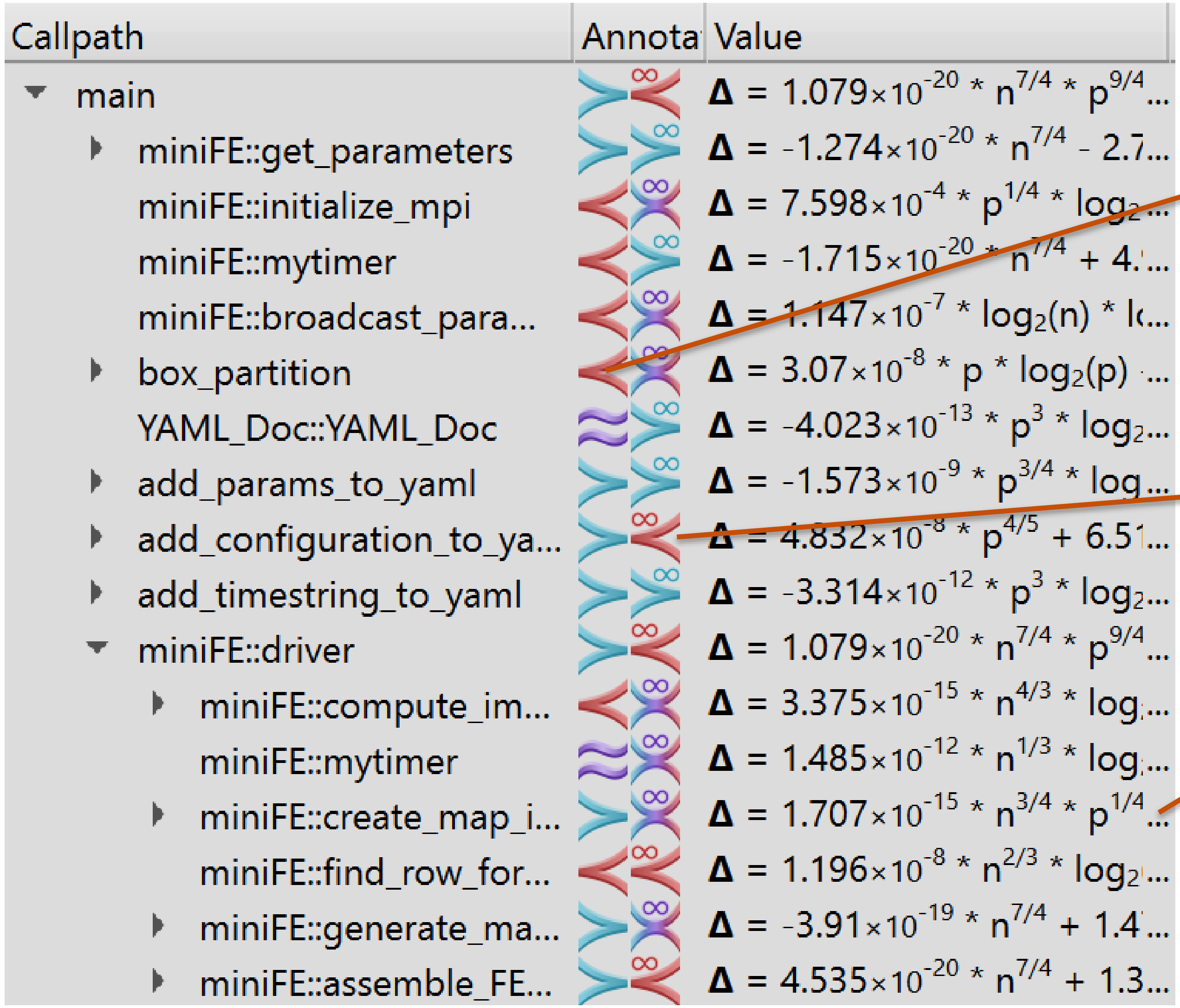
nking best and worst call paths

Interactive Exploration



Callpath	Annota	Value
▾ main	≻ ∞≺	$\Delta = 1.079\times10^{-20} * n^{7/4} * p^{9/4}$...
▸ miniFE::get_parameters	≻ ≻∞	$\Delta = -1.274\times10^{-20} * n^{7/4} - 2.7$...
miniFE::initialize_mpi	≺ ≻≺∞	$\Delta = 7.598\times10^{-4} * p^{1/4} * \log_2$...
miniFE::mytimer	≺ ≻∞	$\Delta = -1.715\times10^{-20} * n^{7/4} + 4.$...
miniFE::broadcast_para...	≺ ≻≺∞	$\Delta = 1.147\times10^{-7} * \log_2(n) * l$...
▸ box_partition	≺ ≻≺∞	$\Delta = 3.07\times10^{-8} * p * \log_2(p)$ ...
YAML_Doc::YAML_Doc	≈ ≻∞	$\Delta = -4.023\times10^{-13} * p^{3} * \log_2$...
▸ add_params_to_yaml	≻ ≻∞	$\Delta = -1.573\times10^{-9} * p^{3/4} * \log$...
▸ add_configuration_to_ya...	≻ ∞≺	$\Delta = 4.832\times10^{-8} * p^{4/5} + 6.51$...
▸ add_timestring_to_yaml	≻ ≻∞	$\Delta = -3.314\times10^{-12} * p^{3} * \log_2$...
▾ miniFE::driver	≻ ∞≺	$\Delta = 1.079\times10^{-20} * n^{7/4} * p^{9/4}$...
▸ miniFE::compute_im...	≺ ≻≺∞	$\Delta = 3.375\times10^{-15} * n^{4/3} * \log$...
miniFE::mytimer	≈ ≻≺∞	$\Delta = 1.485\times10^{-12} * n^{1/3} * \log$...
▸ miniFE::create_map_i...	≻ ≻≺∞	$\Delta = 1.707\times10^{-15} * n^{3/4} * p^{1/4}$...
miniFE::find_row_for...	≺ ∞≺	$\Delta = 1.196\times10^{-8} * n^{2/3} * \log_2$...
▸ miniFE::generate_ma...	≻ ≻≺∞	$\Delta = -3.91\times10^{-19} * n^{7/4} + 1.4$...
▸ miniFE::assemble_FE...	≻ ∞≺	$\Delta = 4.535\times10^{-20} * n^{7/4} + 1.3$...

Result: GPU port...

≺ ... is slower than expected

≻ ... is faster than expected

≈ ... meets expectation

Result: GPU port is asymptotically...

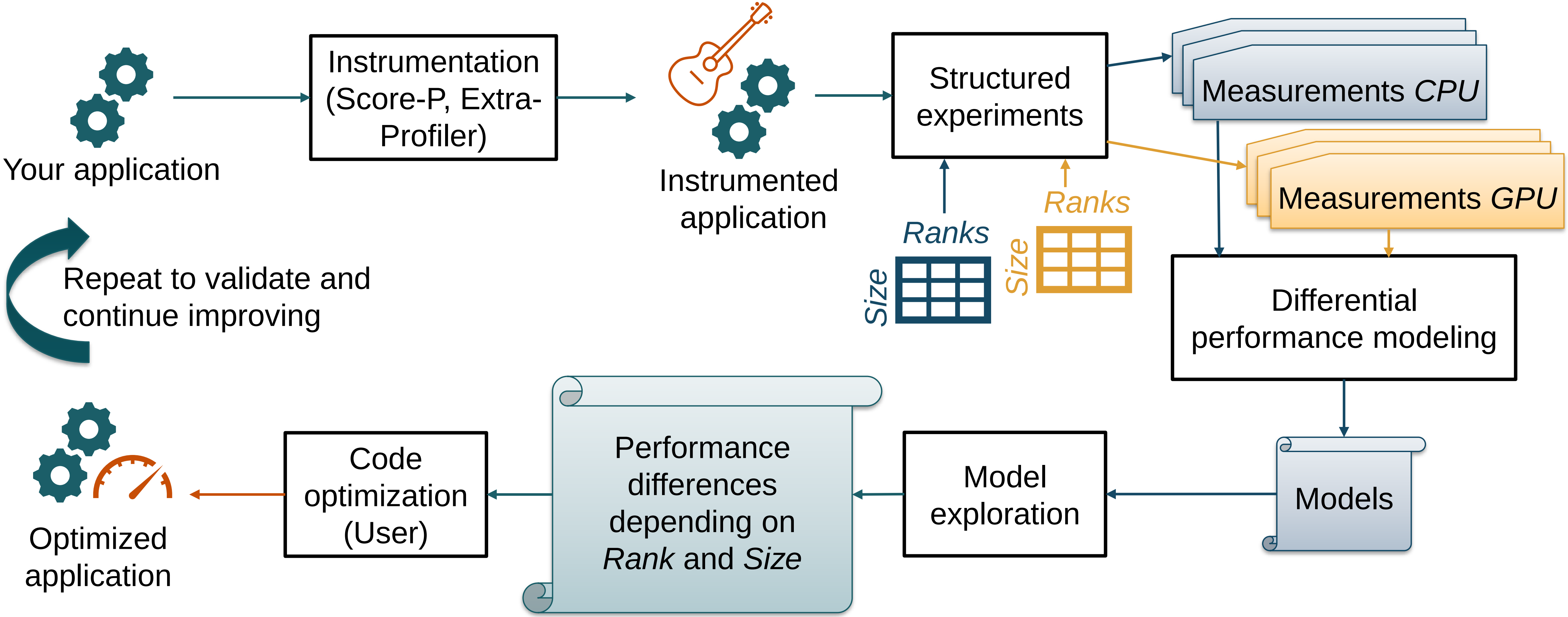
∞≺ ... slower than expected

≻∞ ... faster than expected

≻≺∞ ... faster and slower than expected depending on the parameter

Differential performance models

Summary



Your application
Instrumentation (Score-P, Extra-Profiler)
Instrumented application
Structured experiments
Ranks
Size
Ranks
Size
Measurements *CPU*
Measurements *GPU*
Differential performance modeling
Models
Model exploration
Performance differences depending on *Rank* and *Size*
Code optimization (User)
Optimized application
Repeat to validate and continue improving

Acknowledgement

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