DRESDEN concept

HZDR HELMHOLTZ ZENTRUM DRESDEN ROSSENDORF

DAG Optimizations for Feynman Diagrams of High-Multiplicity Scattering Processes in Julia

Anton Reinhard[1,2], Simeon Ehrig[1,2], Uwe Hernandez Acosta[1,2], René Widera[1]

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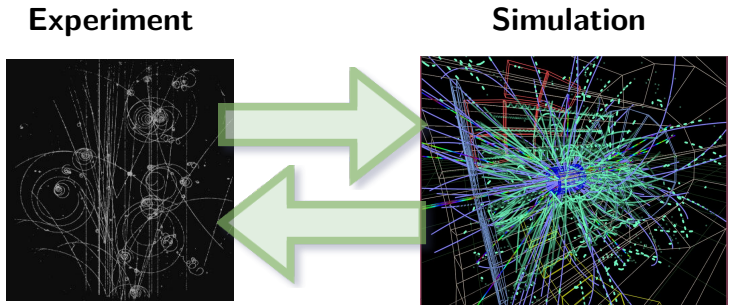
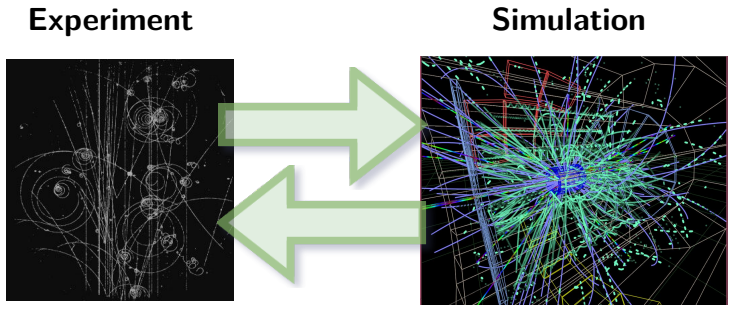
Goal

- Evaluate large QED-processes (superfactorial scaling)



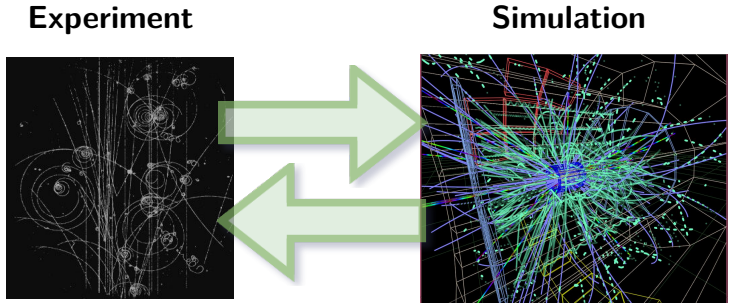
Goal

- Evaluate large QED-processes (superfactorial scaling)
- For this, generate optimized code for a specific machine

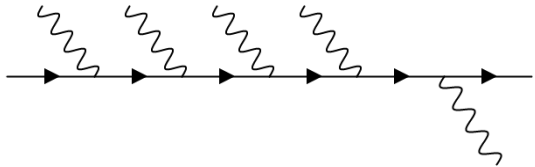


Goal

- Evaluate large QED-processes (superfactorial scaling)
- For this, generate optimized code for a specific machine
- Use high-level knowledge about the problem



Motivation



State of the art implementations fail to

- employ strategies from computer science

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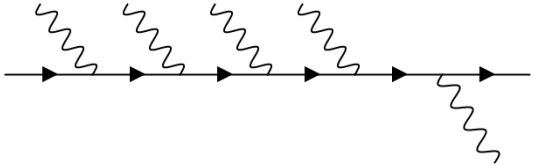

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We try to instead

$\Rightarrow$ use graph representation for high-level optimizations

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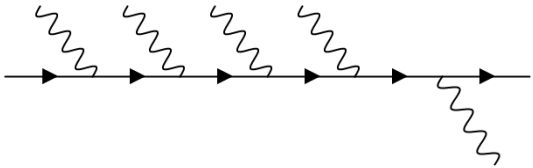

State of the art implementations fail to

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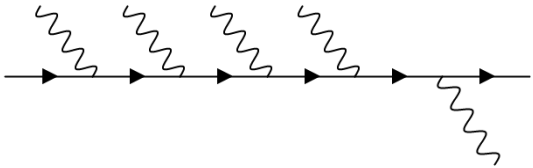

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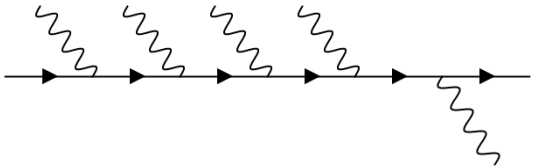

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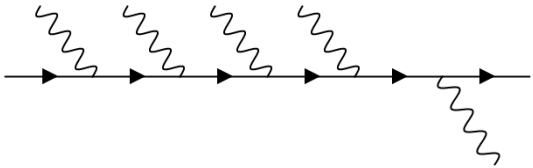

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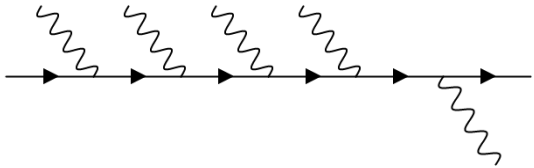

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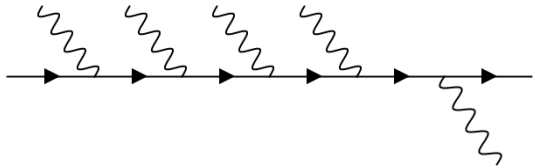

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⇒ support multiple platforms (CPU, GPU) with generic code

⇒ benefit from all available hardware

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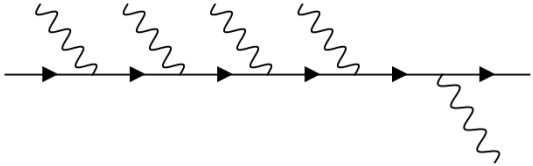
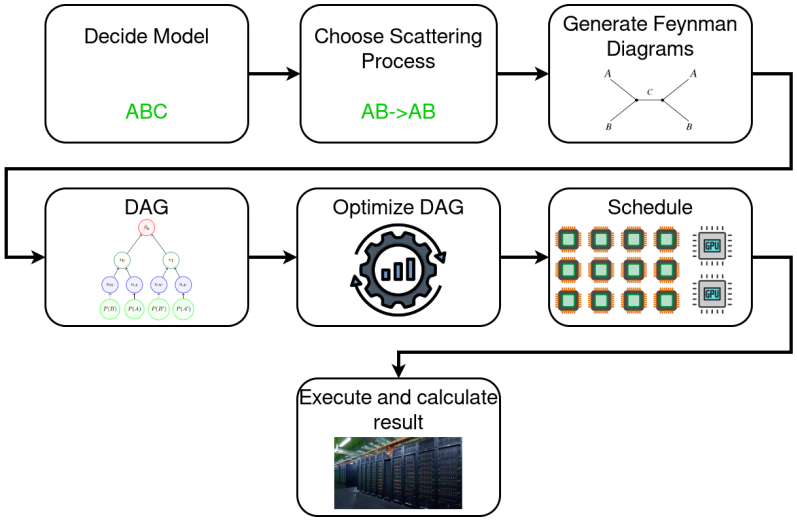


The Pipeline - Top Down



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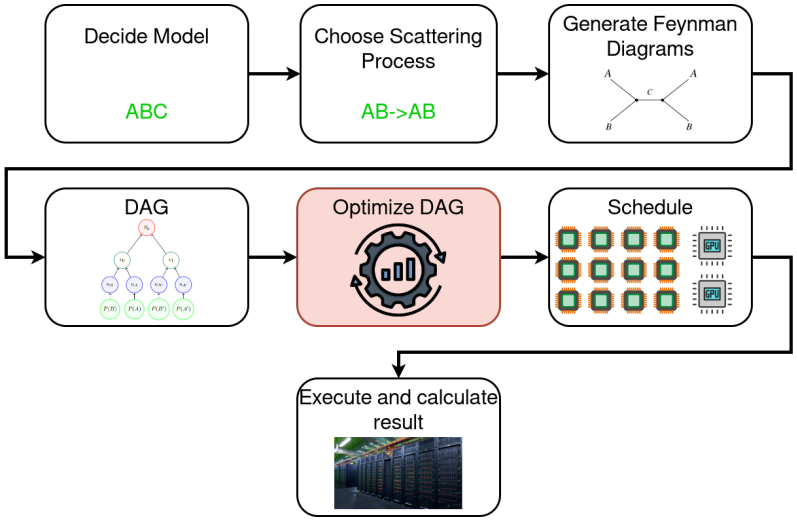
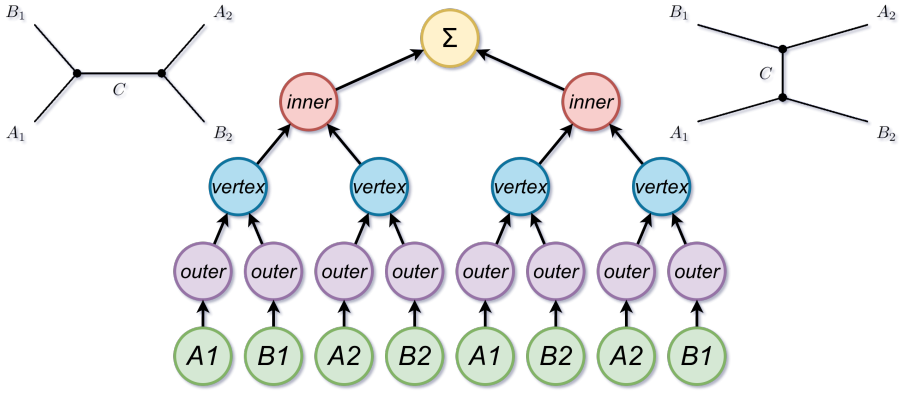
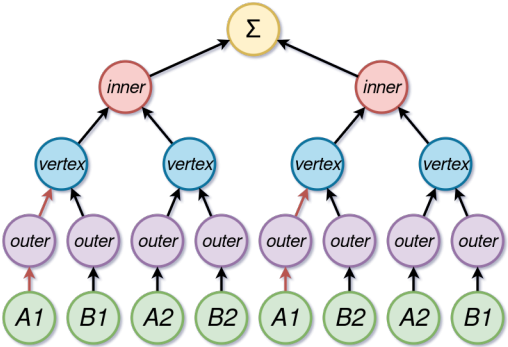
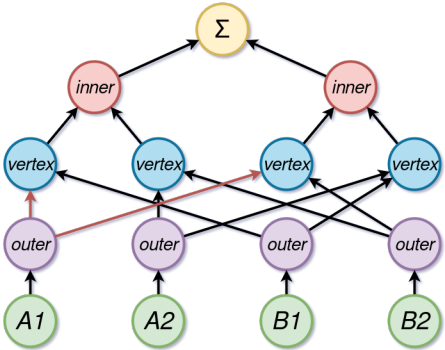


The Pipeline - The (Naive) Directed Acyclic Graph (DAG)



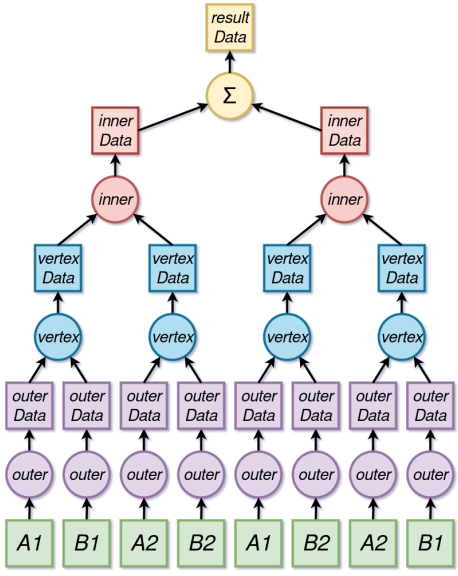
The Pipeline - The (Naive) DAG, Reduced





Optimize the DAG

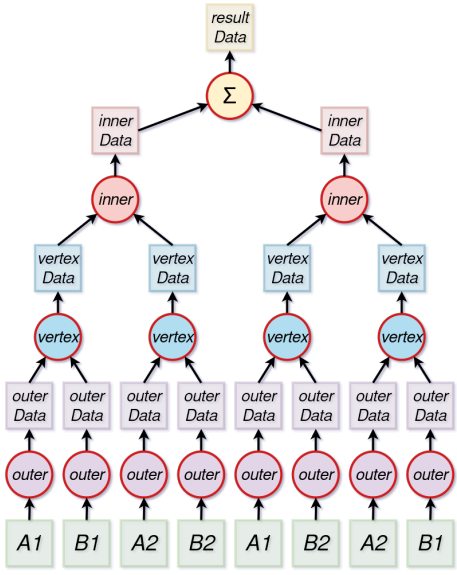
What are we optimizing?



Optimize the DAG

What are we optimizing?

- Compute Effort



Optimize the DAG

What are we optimizing?

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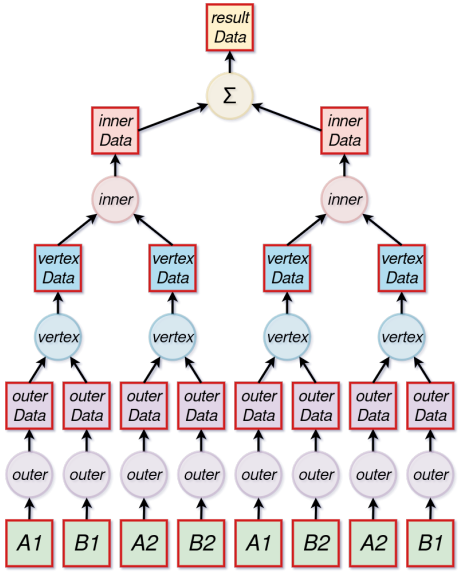

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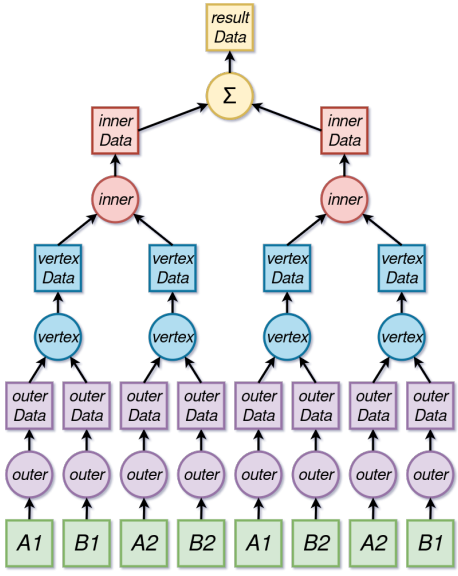
- Compute Intensity $= \frac{\text{Compute Effort}}{\text{Data Transfer}}$



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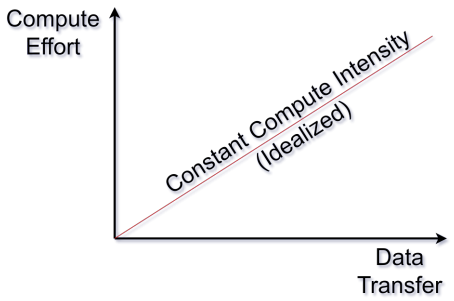

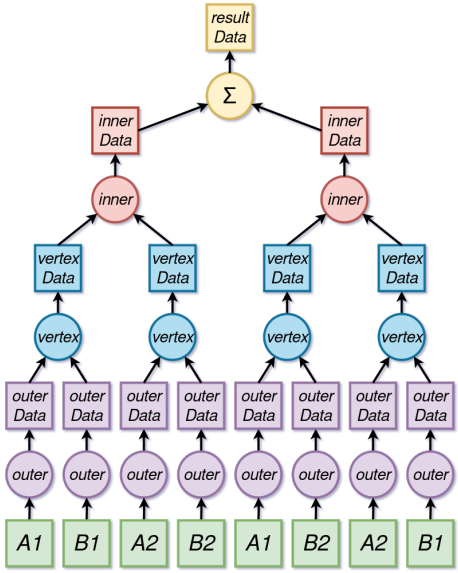

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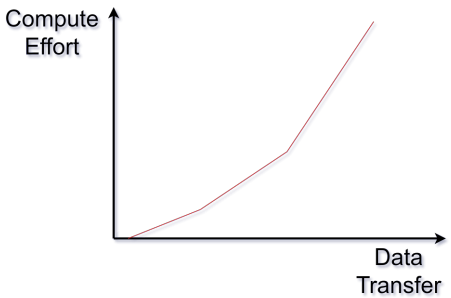

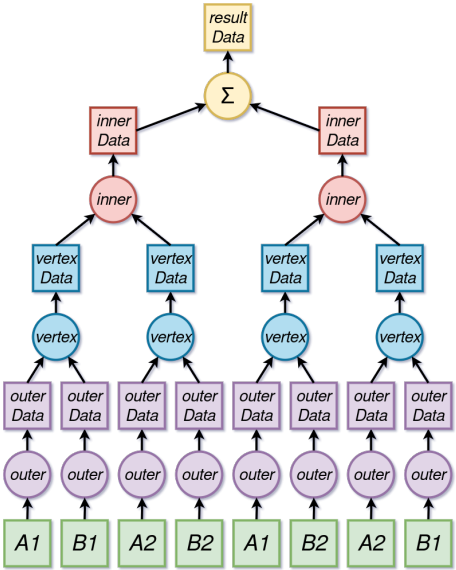

Implementation - Structure

Several Components:

Graph and Operations

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Optimizer

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Devices

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- ☐ Greedy optimizer

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Implementation - Code Generation

DAG

- Get graph, a scheduler, and machine information

Implementation - Code Generation

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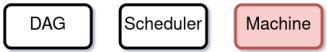
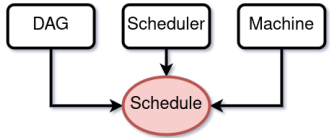


- Get graph, a scheduler, and machine information

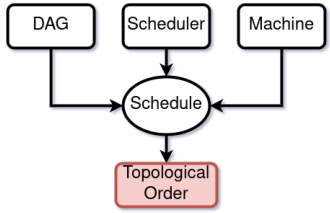
Implementation - Code Generation

- Get graph, a scheduler, and machine information
- Use scheduler interface



Implementation - Code Generation

- Get graph, a scheduler, and machine information
- Use scheduler interface to create a topological ordering of tasks for each device



Implementation - Code Generation

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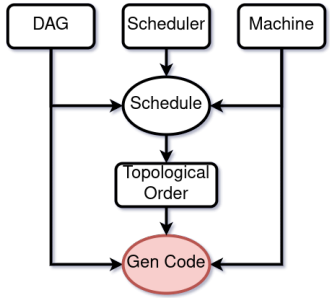
- Use scheduler interface to create a topological ordering of tasks for each device
- For each task in the ordering, generate code using the scheduled device



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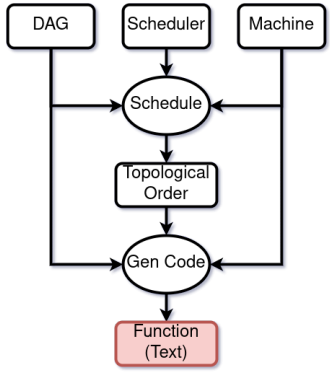
- Evaluate the function code



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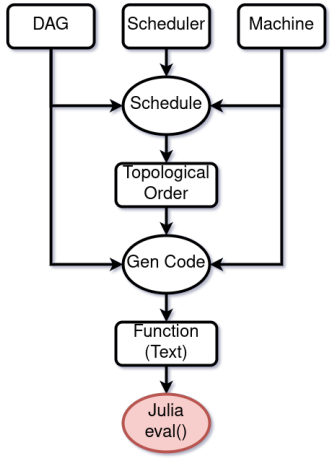
- Evaluate the function code into a function



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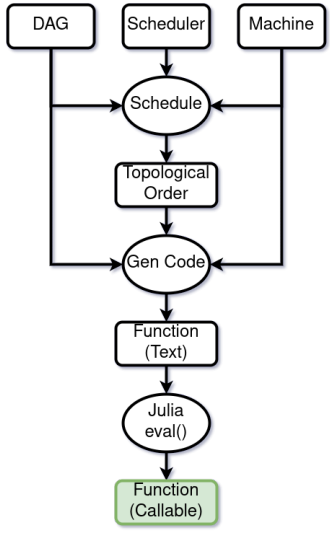

Results - Benchmark AB→ABBB - Proof of Concept

```
julia> bench_compute = @benchmark compute_function.(input_data)
BenchmarkTools.Trial: 960 samples with 1 evaluat
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 Range (min … max):  4.202 ms … 10.953 ms  ┊ GC (min … max):  0.00% … 55.28%
 Time  (median):     4.558 ms              ┊ GC (median):     0.00%
 Time  (mean ± σ):   5.212 ms ±  1.636 ms  ┊ GC (mean ± σ):  12.30% ± 17.24%

  4.2 ms         Histogram: frequency by time        9.52 ms <

 Memory estimate: 6.20 MiB, allocs estimate: 145010.

julia> bench_compute_reduced = @benchmark compute_function_reduced.(input_data)
BenchmarkTools.Trial: 1158 samples with 1 evaluation.
 Range (min … max):  3.466 ms … 9.212 ms  ┊ GC (min … max):  0.00% … 49.98%
 Time  (median):     3.749 ms             ┊ GC (median):     0.00%
 Time  (mean ± σ):   4.317 ms ± 1.510 ms  ┊ GC (mean ± σ):  12.68% ± 17.75%

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julia> judge(median(bench_compute_reduced), median(bench_compute))
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  3.47 ms        Histogram: frequency by time        8.67 ms <

 Memory estimate: 5.29 MiB, allocs estimate: 125010.

julia> judge(median(bench_compute_reduced), median(bench_compute))
BenchmarkTools.TrialJudgement:
  time:   -17.75% => improvement (5.00% tolerance)
  memory: -14.76% => improvement (1.00% tolerance)
```

Results - Benchmark AB→ABBB - Proof of Concept

```
julia> bench_compute = @benchmark compute_function.(input_data)
BenchmarkTools.Trial: 960 samples with 1 evaluat
ion.
 Range (min … max):   4.202 ms … 10.953 ms  ┊ GC (min … max):  0.00% … 55.28%
 Time  (median):      4.558 ms              ┊ GC (median):     0.00%
 Time  (mean ± σ):    5.212 ms ±  1.636 ms  ┊ GC (mean ± σ):  12.30% ± 17.24%

  4.2 ms         Histogram: frequency by time        9.52 ms <

 Memory estimate: 6.20 MiB, allocs estimate: 145010.

julia> bench_compute_reduced = @benchmark compute_function_reduced.(input_data)
BenchmarkTools.Trial: 1158 samples with 1 evaluation.
 Range (min … max):   3.466 ms … 9.212 ms  ┊ GC (min … max):  0.00% … 49.98%
 Time  (median):      3.749 ms              ┊ GC (median):     0.00%
 Time  (mean ± σ):    4.317 ms ± 1.510 ms   ┊ GC (mean ± σ):  12.68% ± 17.75%

  3.47 ms         Histogram: frequency by time        8.67 ms <

 Memory estimate: 5.29 MiB, allocs estimate: 125010.

julia> judge(median(bench_compute_reduced), median(bench_compute))
BenchmarkTools.TrialJudgement:
  time:   -17.75% => improvement (5.00% tolerance)
  memory: -14.76% => improvement (1.00% tolerance)
```

Outlook

The basic code structure is done, now:

- Add QED Model
- Compare different optimization algorithms and estimators
- Determine a machine's scaling functions and working point graph using microbenchmarks

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- **René Widera**[2]

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[2] Helmholtz-Zentrum Dresden-Rossendorf (HZDR)

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Backup

```julia
using MetagraphOptimization

# get our machine's info
machine = get_machine_info()

# create a model identifier
model = ABCModel()

# create a process in our model
process = parse_process("AB->ABBB", model)

# read the graph (of the same process) from a file
graph = parse_dag("../input/AB->ABBB.txt", model)

# generate some random input data for our process
input_data = gen_process_input(process)

# "compile" a compute function
compute = get_compute_function(graph, process, machine)

# compute a result using the generated function
result = compute(input_data)
```

```
Found 1 NUMA nodes
CUDA is non-functional
-2.5102328686552435e-14
```