Kernel Tuner Tutorial – Advanced Topics

netherlands eScience center

Advanced topics session outline

- Performance portable applications
- Optimization strategies
- Observers
- Fourth hands-on session
- Closing

Performance portable applications

Performance portability

- The property that an application performance similarly on different hardware
- Auto-tuning may be used to achieve performance portability, if an application has been tuned on different hardware and we can select the right kernel based on the hardware at hand
- Kernel configuration selection can be done compile-time or run-time, based on earlier obtained tuning results

store_results

- The `store_results` function can be used to store information about the best performing configurations of a tunable kernel

```
from kernel_tuner.integration import store_results

store_results("vector_add_results.json", "vector_add", "vector_add.cu",
              tune_params, size, results, env, top=3)
```

- Stores the (e.g.) top 3% of tuning results for the specified combination of `problem_size` and GPU (retrieved from `env`) to the JSON file
  - The new results are appended to the JSON file
  - Results for the same `problem_size` and GPU are updated

Compile-time kernel selection

- Performs kernel selection at compile time
- Main advantage:
  - Can be done with very limited changes to the host application
- Limitation:
  - Limited to only selecting kernels based on properties known at compile-time, e.g. the target GPU

Compile-time kernel selection example

```python
from kernel_tuner.integration import store_results, create_device_targets

store_results("results.json", "vector_add", "vector_add.cu", tune_params, size, results, env)
create_device_targets("vector_add.h", "results.json")
```

vector_add.h

```c
/* header file generated by Kernel Tuner, do not modify by hand */
#pragma once
#ifndef kernel_tuner /* only use these when not tuning */

#ifdef TARGET_A100_PCIE_40GB
#define block_size_x 672

#elif TARGET_RTX_A6000
#define block_size_x 160

#else /* default configuration */
#define block_size_x 352
#endif /* GPU TARGETS */

#endif /* kernel_tuner */
```

Compile-time kernel selection example

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create_device_targets("vector_add.h", "results.json")
```

Kernel Tuner always inserts
#define kernel_tuner
When compiling kernels for
benchmarking

vector_add.h

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```

This `block_size_x` value showed best performance on the A100

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#endif /* GPU TARGETS */

#endif /* kernel_tuner */
```

This `block_size_x` value showed best performance on the A6000

Compile-time kernel selection example

```python
from kernel_tuner.integration import store_results, create_device_targets

store_results("results.json", "vector_add", "vector_add.cu", tune_params, size, results, env)
create_device_targets("vector_add.h", "results.json")
```

vector_add.h

```c
/* header file generated by Kernel Tuner, do not modify by hand */
#pragma once
#ifndef kernel_tuner /* only use these when not tuning */

#ifdef TARGET_A100_PCIE_40GB
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#elif TARGET_RTX_A6000
#define block_size_x 160

#else /* default configuration */
#define block_size_x 352
#endif /* GPU TARGETS */

#endif /* kernel_tuner */
```

This `block_size_x` value showed best performance overall, on all GPUs

Compile-time kernel selection example

In vector_add.cu:

```
#include "vector_add.h"
```

In Makefile:

```
TARGET_GPU = `nvidia-smi --query-gpu="gpu_name" --format=csv,noheader | sed -E 's/[^[:alnum:]]+/_/g'`
CU_FLAGS = -DTARGET_${TARGET_GPU}

vector_add.o: vector_add.cu
	nvcc ${CU_FLAGS} -c $< -o $@
```

Typing ‘make’ will now use different `block_size_x` values on A100, A6000, and on other GPUs

Run-time kernel selection

- More flexible, allows also to select kernels based on data size or other properties
- Requires more significant modification of the host application
- Depends on the programming language of the host application

Run-time kernel selection Python

In Python:

```python
from kernel_tuner.integration import store_results

store_results("vector_add_results.json", "vector_add", "vector_add.cu", tune_params, size, results, env)
```

In the Python host application:

```python
from kernel_tuner import kernelbuilder

# create a kernel using the stored results
vector_add = kernelbuilder.PythonKernel(kernel_name, kernel_string, n, args,
                                        results_file=test_results_file)

# call the kernel
vector_add(c, a, b, n)
```

Run-time kernel selection C++ example

In Python:

```python
from kernel_tuner.integration import store_results

store_results("vector_add_results.json", "vector_add", "vector_add.cu", tune_params, size, results, env)
```

In vector_add.cpp:

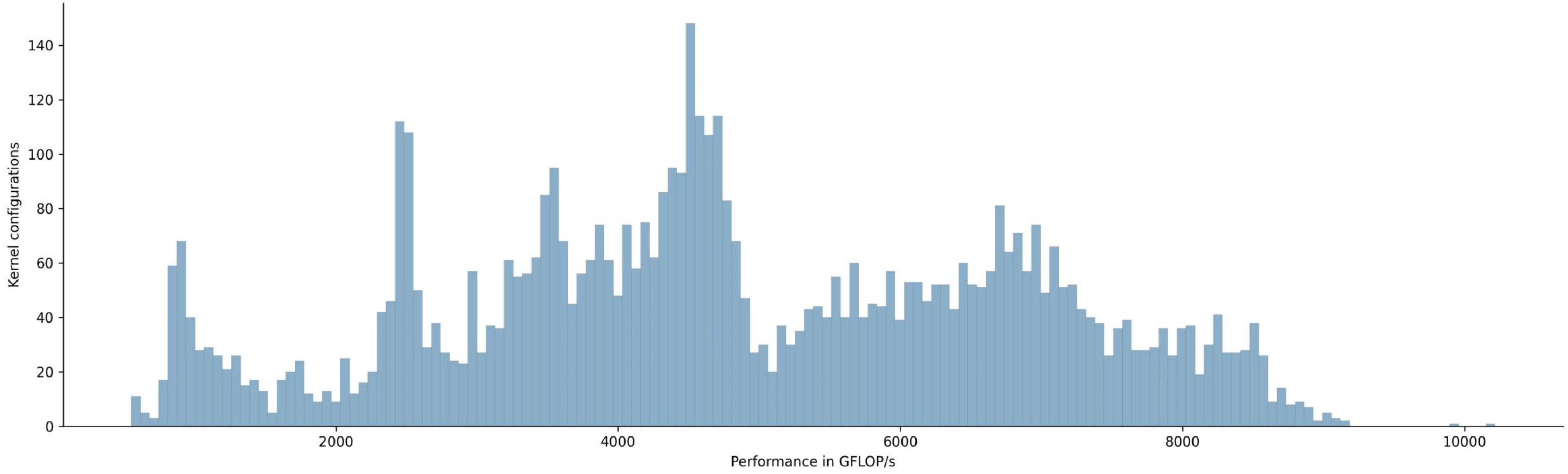
```cpp
#include "kernel_launcher.h"
using namespace kernel_launcher;


auto vector_add = CudaKernel<float*, float*, float*, int>::compile_best_for_current_device(
            "vector_add_results.json", 800000000, "vector_add.cu", {"-std=c++11"});

int grid_size = (n + vector_add.get_block_dim().x - 1) / vector_add.get_block_dim().x;

vector_add(grid_size)(dev_C, dev_A, dev_B, n);
```

Uses Kernel Launcher header-only C++ library: https://github.com/stijnh/kernel_launcher

Optimization strategies

Large search space of kernel configurations

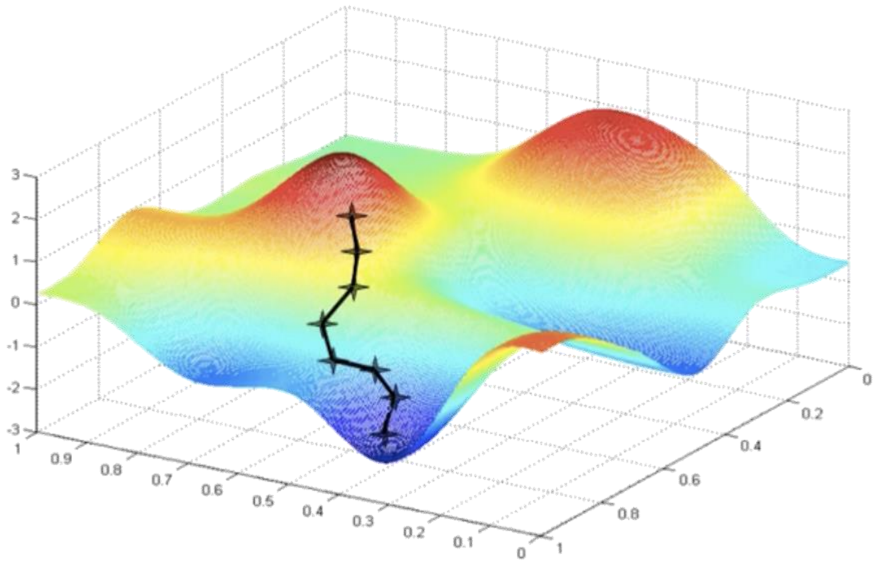
Auto-tuning a Convolution kernel on Nvidia A100



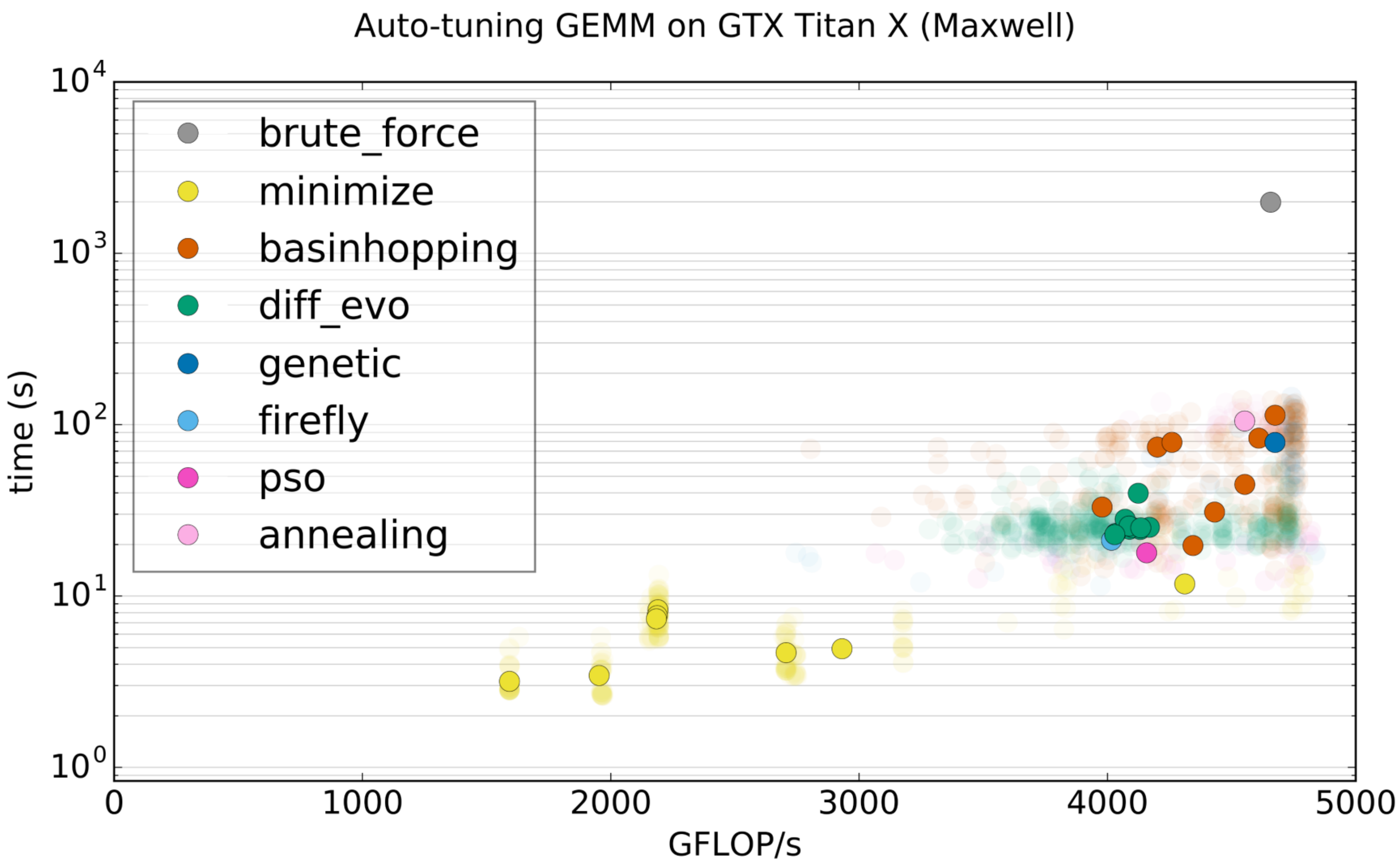
Optimization strategies in Kernel Tuner

- Local optimization
  - Nelder-Mead, Powell, CG, BFGS, L-BFGS-B, TNC, COBYLA, and SLSQP

- Global optimization
  - Basin Hopping
  - Simulated Annealing
  - Differential Evolution
  - Genetic Algorithm
  - Particle Swarm Optimization
  - Firefly Algorithm
  - Bayesian Optimization
  - Multi-start local search
  - …



Speeding up auto-tuning



Your mileage may vary

- Active topic of research
- Different optimizers seem to perform differently for certain combinations of tunable kernel + GPU + input
- Nearly all methods are stochastic, meaning that they do not always return the global optimum or even the same result
- It is all a matter of how much time you have versus how strongly you want guarantees of finding an optimal configuration
- Experiment!

How to use a search strategy

- By passing `strategy="string_name"`, where `"string_name"` is any of:
    - `"brute_force"`: Brute force search
    - `"random_sample"`: random search
    - `"minimize"`: minimize using a local optimization method
    - `"basinhopping"`: basinhopping with a local optimization method
    - `"diff_evo"`: differential evolution
    - `"genetic_algorithm"`: genetic algorithm optimizer
    - `"mls"`: multi-start local search
    - `"pso"`: particle swarm optimization
    - `"simulated_annealing"`: simulated annealing optimizer
    - `"firefly_algorithm"`: firefly algorithm optimizer
    - `"bayes_opt"`: Bayesian Optimization
- Note that nearly all methods have specific options or hyperparameters that can be set using the `strategy_options` argument of `tune_kernel`

Observers

Observers introduction

- Observers allow to modify the behavior during benchmarking and measure quantities other than time
- It follows the ‘observer’ programming pattern, allowing an observer object to observe certain events
- Also used internally for measuring time in the various backends

Observer base class

```python
class BenchmarkObserver(ABC):
    """Base class for Benchmark Observers"""

    def register_device(self, dev):
        """Sets self.dev, for inspection by the observer at various points during benchmarking"""
        self.dev = dev

    def before_start(self):
        """before start is called every iteration before the kernel starts"""
        pass

    def after_start(self):
        """after start is called every iteration directly after the kernel was launched"""
        pass

    def during(self):
        """during is called as often as possible while the kernel is running"""
        pass

    def after_finish(self):
        """after finish is called once every iteration after the kernel has finished execution"""
        pass

    @abstractmethod
    def get_results(self):
        """ get_results should return a dict with results that adds to the benchmarking data
            get_results is called only once per benchmarking of a single kernel configuration and
            generally returns averaged values over multiple iterations.
        """
        pass
```

NVMLObserver

- NVML is the NVIDIA Management Library for monitoring and managing GPUs
- Kernel Tuner's NVMLObserver supports the following observable quantities: `"power_readings", "nvml_power", "nvml_energy", "core_freq", "mem_freq", "temperature"`
- If you pass an NVMLObserver, you can also use the following special tunable parameters to benchmark GPU kernels under certain conditions: `nvml_pwr_limit, nvml_gr_clock, nvml_mem_clock`
- Requires NVML, nvidia-ml-py3, and certain features may require root access

NVMLObserver example

```
...
tune_params["nvml_pwr_limit"] = [250, 225, 200, 175]

nvmlobserver = NVMLObserver(["nvml_energy", "temperature"])

metrics = OrderedDict()
metrics["GFLOPS/W"] = lambda p: (size/1e9) / p["nvml_energy"]

results, env = tune_kernel("vector_add", kernel_string, size, args,
                           tune_params, observers=[nvmlobserver],
                           metrics=metrics, iterations=32)
```

GPU Memory management

- Kernel Tuner reuses the same data on the GPU for benchmarking all kernel configurations
- When you use output verification, GPU data is refreshed from the host to the GPU right before calling the kernel once for output verification, before benchmarking
- This assumes the kernels are idempotent or at least that running the kernel multiple times on the same data does not significantly impact performance

Breadth First Search (BFS)

- For some kernels, like BFS, this assumption does not hold
- The BFS kernel in the Rodinia Benchmark Suite works as follows:
  - Threads are created for each node in the graph, each thread checks the `g_graph_mask` Boolean array to see if it is active in this computation
  - If so, it iterates over all edges of this node to set the `g_updating_graph_mask` for all neighbors to true and sets its own `g_graph_mask` to false
  - A separate kernel is used to update `g_graph_mask` based on the `g_updating_graph_mask`
- What happens when you call the first kernel multiple times?

Tuning BFS with Kernel Tuner

- Problem:
  - We cannot execute the first BFS kernels multiple times on the same data
- Not working solutions:
  - Use iterations=1, does not solve our problem because data is reused for multiple kernel configurations
  - Enable output verification and set iterations=1, does not work either because output verification calls the kernel once outside of benchmarking
- Real solution: Use an observer!

BFSObserver

```
class BFSObserver(BenchmarkObserver):

    def __init__(self, args):
        self.args = args

    def before_start(self):
        for i, arg in enumerate(self.args):
            if not arg is None:
                self.dev.memcpy_htod(self.dev.allocations[i], arg)

    def get_results(self):
        return {}
```

dev is set by Kernel Tuner to each observer to have access to the device functions interface of the backend

Tuning the BFS kernel

```
...

args = [starting, no_of_edges, graph_edges, g_graph_mask, g_updating_graph_mask,
        g_graph_visited, g_cost, num_of_nodes]

refresh_args = [None, None, None, g_graph_mask, g_updating_graph_mask, None, g_cost, None]

bfs_observer = BFSObserver(refresh_args)

results, env = tune_kernel("bfs_kernel", "kernels.cu",
                           problem_size, args, tune_params, metrics=metrics,
                           compiler_options=cp, answer=answer, grid_div_x=grid_div_x,
                           verbose=True, observers=[bfs_observer])
```

Fourth hands-on session

Advanced hands-on

- The fourth hands-on notebook is:
  - https://github.com/benvanwerkhoven/kernel_tuner_tutorial/blob/master/hands-on/cuda/03_Kernel_Tuner_Advanced.ipynb
- The goal of this hands-on is to experiment with search optimization strategies and custom observers
  - Copy the notebook to your Google Colab and work there
- Please follow the instructions in the Notebook
- Feel free to ask questions to instructors and mentors

Optional hands-on

- Done with the fourth hands-on already?
- Keep playing with this notebook
    - https://github.com/benvanwerkhoven/kernel_tuner_tutorial/blob/master/hands-on/cuda/Kernel_Tuner_Tutorial.ipynb
- Keep experimenting with your own code
- Feel free to ask questions to instructors and mentors

Closing remarks

Kernel Tuner – developed open source

- We are developing Kernel Tuner as an open source project
- GitHub repository:
  - https://github.com/benvanwerkhoven/kernel_tuner
- License: Apache 2.0
- If you use Kernel Tuner in a project, please cite the paper:
  - B. van Werkhoven, Kernel Tuner: A search-optimizing GPU code auto-tuner, *Future Generation Computer Systems,* 2019

Feature Roadmap

- Allow tuning objectives other than time
- Remote/parallel tuning
- Multi-objective optimization
- Further support for integrating kernels into applications
- API for plotting/analysis of tuning results
- Tuning compiler flags

Contributions are welcome!

- Contributions can come in many forms: tweets, blog posts, issues, pull requests
- Before making larger changes, please create an issue to discuss

- For the full contribution guide, please see: https://benvanwerkhoven.github.io/kernel_tuner/contributing.html

Thanks to all contributors!










And many more!

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- Collaborate with us:
  - Open calls
  - Partner in EU projects
  - Direct collaboration
  - See: https://www.esciencecenter.nl/collaborate-with-us/
- We are hiring:
  - Research Software Engineers (RSEs)
  - See: https://www.esciencecenter.nl/vacancies/

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Thanks!

If you have any further questions or would like to reach out, please feel free to contact me at:

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