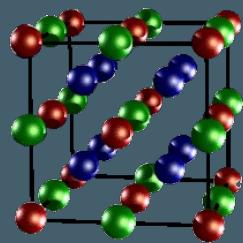


Up-scale Python Functions for High-Performance Computing with Executorlib

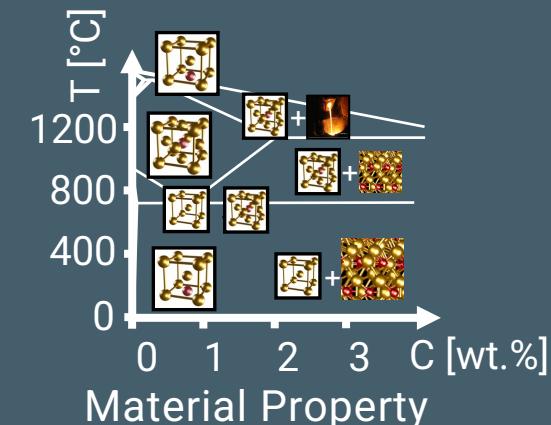
Jan Janssen – Group Leader for Materials Informatics



Atomistic Simulation



High-Performance Computing

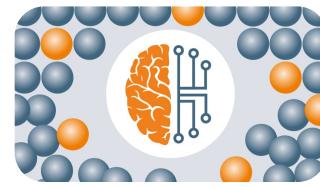


Material Property

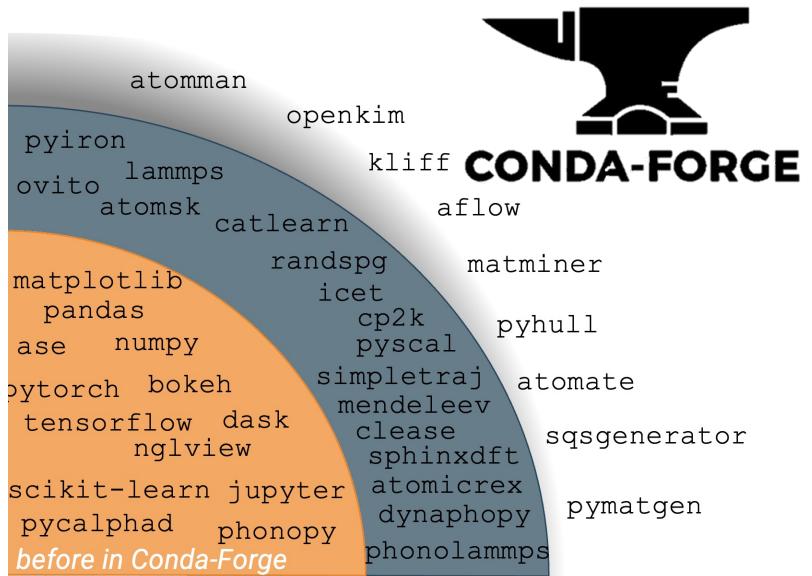
2026/01/14 – Workflow Community Talk

Materials Informatics Group

Our Expertise: Simulation Workflows to Predict Sustainable Materials



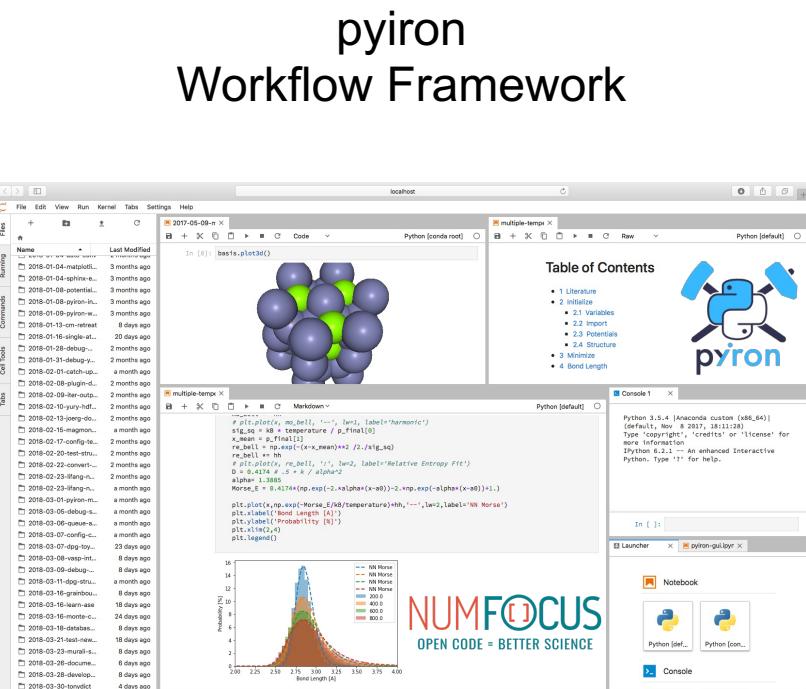
Conda-Forge Installation of Scientific Software



Maintaining over 1000 materials informatics packages on conda-forge with over 500 million downloads so far.

<https://github.com/jan-janssen/conda-forge-contribution>

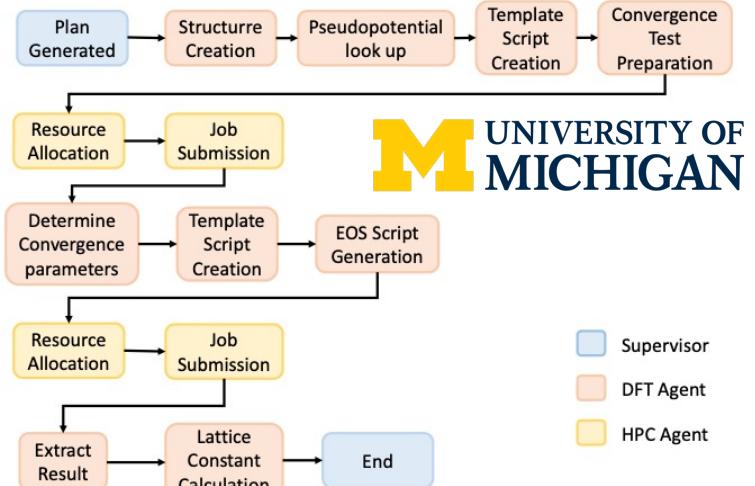
pyiron Workflow Framework



Jupyter Lab based interface for data-driven materials informatics to enable rapid prototyping and up-scaling.

<https://github.com/pyiron> - <https://pyiron.org>

Large Language Model Agents for atomistic simulations



UNIVERSITY OF MICHIGAN

Reduce hallucination by restricting the large language model to use pre-defined workflows developed by experts.

Z. Wang, H. Huang, H. Zhao, C. Xu, J. Janssen and V. Viswanathan – arXiv 2507.14267 (2025).

Three Levels of Workflow Interoperability in Materials Science



Simplify the exchange of workflows between the different workflow frameworks

Shared Python Functions

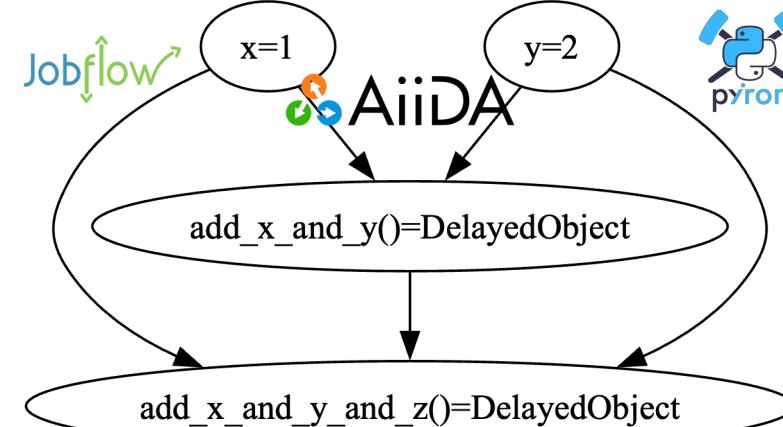
```
def add_x_and_y(x, y):    AiiDA
    z = x + y
    return z
    Jobflow
    Jobflow
    AiiDA
    pyron

def add_x_and_y_and_z(x, y, z): pyron
    w = x + y + z
    return w
```

Python functions are defined once and can be reused with different Workflow Managers.

- Easy to implement
- Dependencies are lost

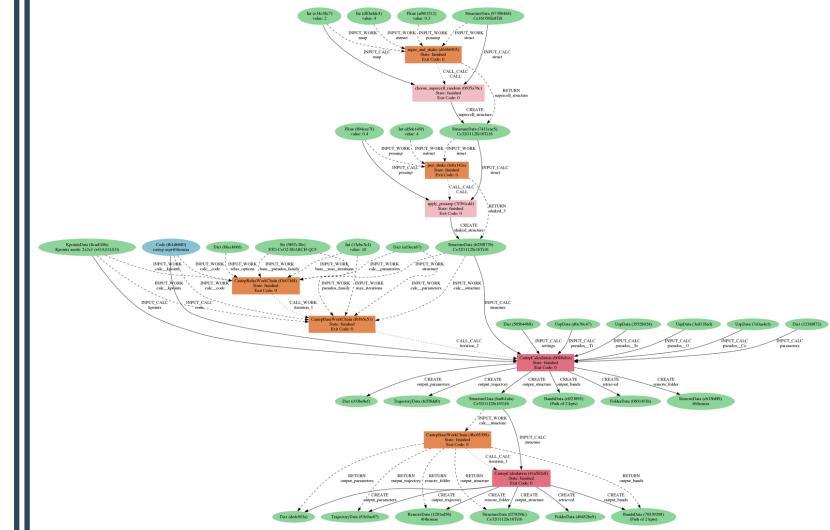
Python Workflow Definition



Export workflow in the Python Workflow Definition to share with different Workflow Frameworks.

- Reproducibility
- Repeated Calculation

Workflow Graph with Data



Sharing the provenances between different Workflow Frameworks enables efficient collaboration.

Python Standard Library

High-level Interface for Asynchronously Executing Callables

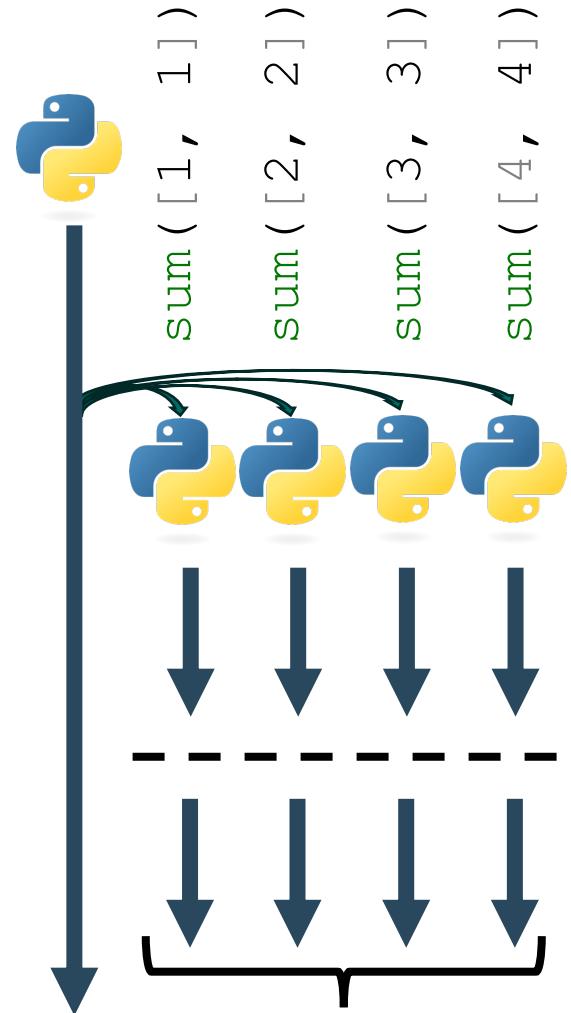


```
from concurrent.futures import ProcessPoolExecutor

with ProcessPoolExecutor() as exe:
    future_lst = []
    for i in range(1, 5):
        future_lst.append(exe.submit(sum, [i, i]))

    # check status
    print([f.done() for f in future_lst])

    # wait for computations to complete
    print([f.result() for f in future_lst])
```



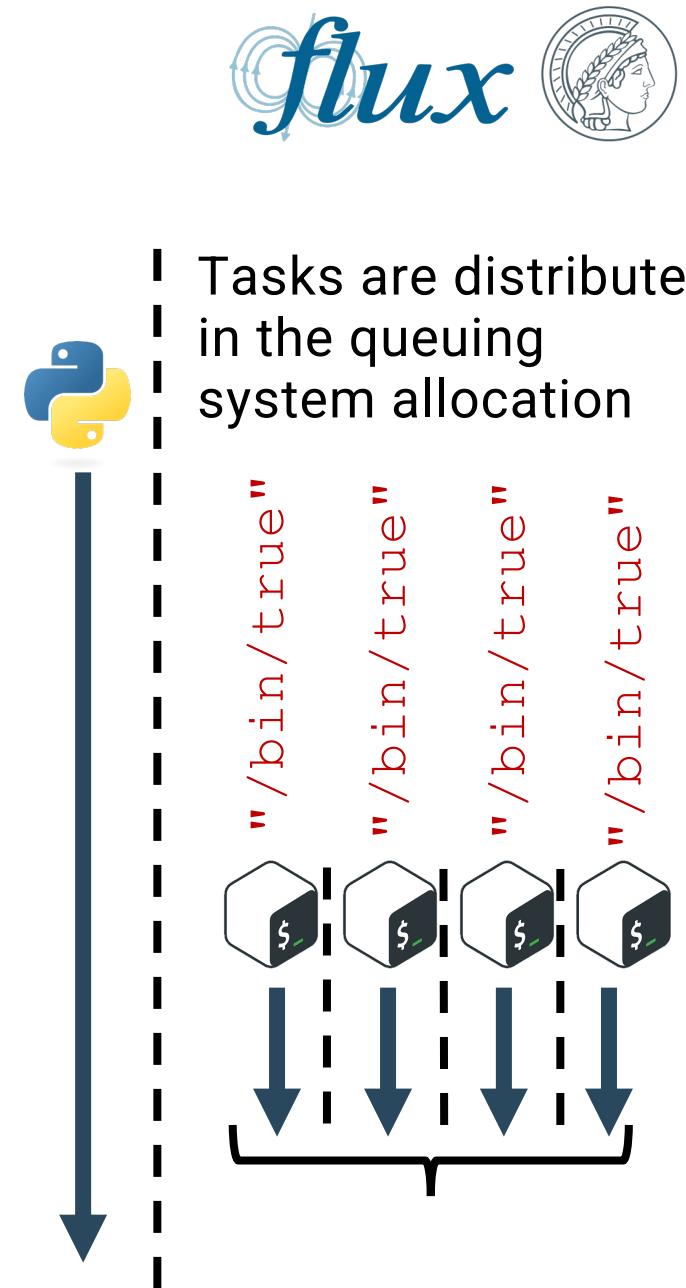
Flux Framework

Hierarchical Job Scheduler

```
import concurrent.futures
import flux.job

jobspec = flux.job.JobspecV1.from_command(
    ['/bin/true']
)
with flux.job.FluxExecutor() as exe:
    future_lst = []
    for i in range(1, 5):
        future_lst.append(exe.submit(jobspec))

    # wait for computations to complete
    print([f.result() for f in future_lst])
```

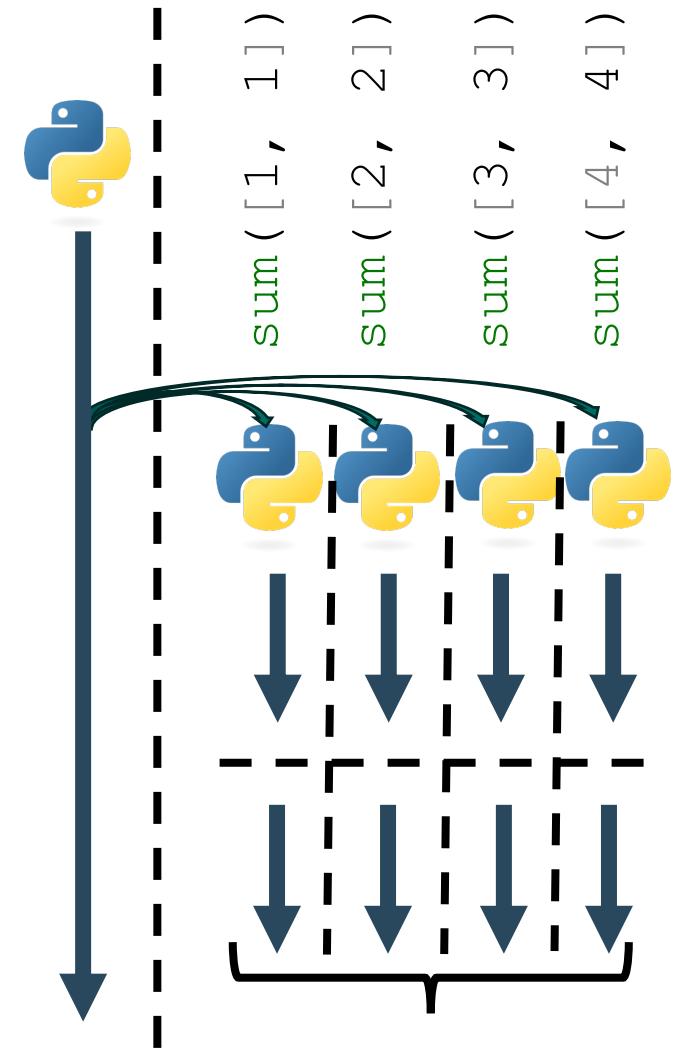


```
from executorlib import FluxJobExecutor

with FluxJobExecutor() as exe:
    future_lst = []
    for i in range(1, 5):
        future_lst.append(exe.submit(sum, [i, i]))

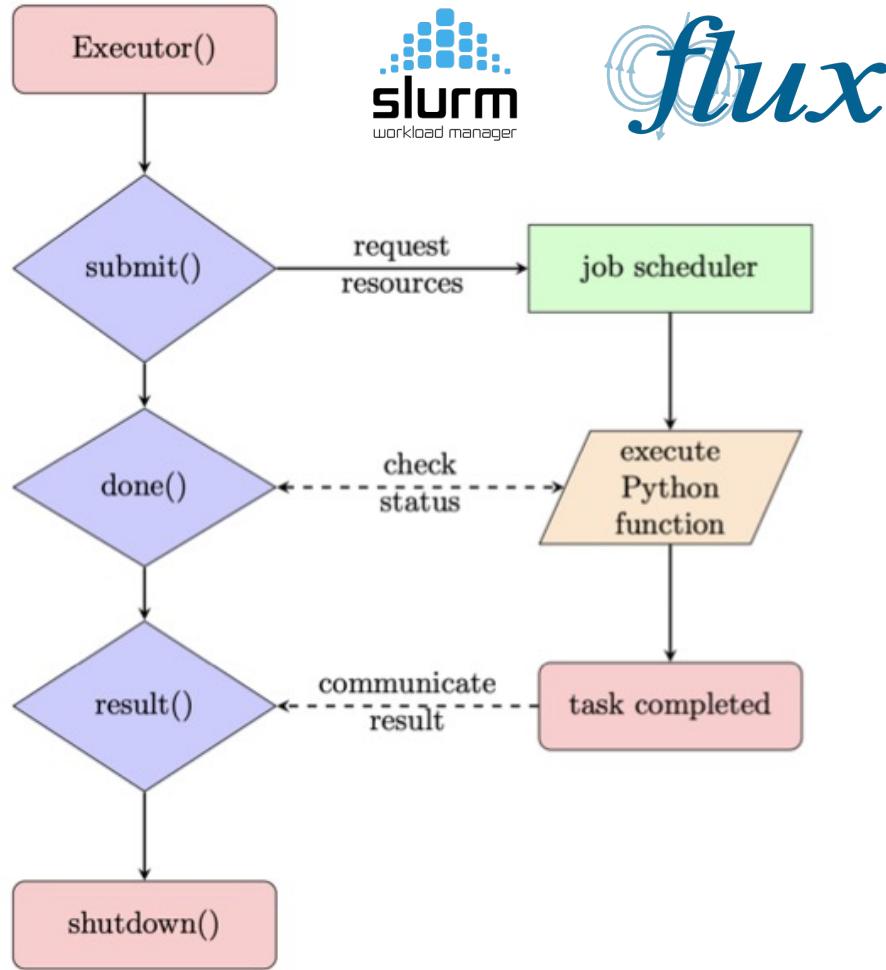
    # check status
    print([f.done() for f in future_lst])

    # wait for computations to complete
    print([f.result() for f in future_lst])
```



Up-scale your Python Functions with Executorlib

No Database, No Daemon Process, Just Job Schedulers



Executor	Communication	Scheduler
SingleNodeExecutor	Socket	
SlurmClusterExecutor	File	 SLURM
SlurmJobExecutor	Socket	 SLURM
FluxClusterExecutor	File	 Flux
FluxJobExecutor	Socket	 Flux

Message Passing Interface in Python



Assignment of Computational Resources

```
from executorlib import FluxJobExecutor

def calc_mpi(i):
    from mpi4py import MPI
    size = MPI.COMM_WORLD.Get_size()
    rank = MPI.COMM_WORLD.Get_rank()
    return i, size, rank

with FluxJobExecutor() as exe:
    fs = exe.submit(calc_mpi, 3, resource_dict={
        "cores": 2,
        "threads_per_core": 1,
        "gpus_per_core": 1,
        "cwd": "/a/b/c",
    })
```

Cache Results



Beyond the Execution

```
from executorlib import SingleNodeExecutor, get_cache_data

def calc_add(a, b):
    return a + b

with SingleNodeExecutor(cache_directory=".cache") as exe:
    future = 0
    for i in range(1, 4):
        future = exe.submit(calc_add, i, future)
    print(future.result())
```

Cache Results



Beyond the Execution

```
withSingleNodeExecutor(cache_directory=".cache") as exe:  
    future = 0  
    for i in range(1, 4):  
        future = exe.submit(calc_add, i, future)  
    print(future.result())
```

```
pandas.DataFrame(get_cache_data(cache_directory=".cache"))
```

	function	input_args	input_kwargs	output	runtime
0	<built-in function sum>	[[1, 1]]	{}	2	0.180522
1	<built-in function sum>	[[2, 2]]	{}	4	0.179688
2	<built-in function sum>	[[3, 3]]	{}	6	0.132677

From Python Functions to Workflows – Dependency Management



Link Python Functions with Different Resource Requirements

```
from executorlib import SingleNodeExecutor

def calc_add(a, b):
    return a + b

with SingleNodeExecutor() as exe:
    future = 0
    for i in range(1, 4):
        future = exe.submit(calc_add, i, future)
    print(future.result())
```



From Python Functions to Workflows – Dependency Management

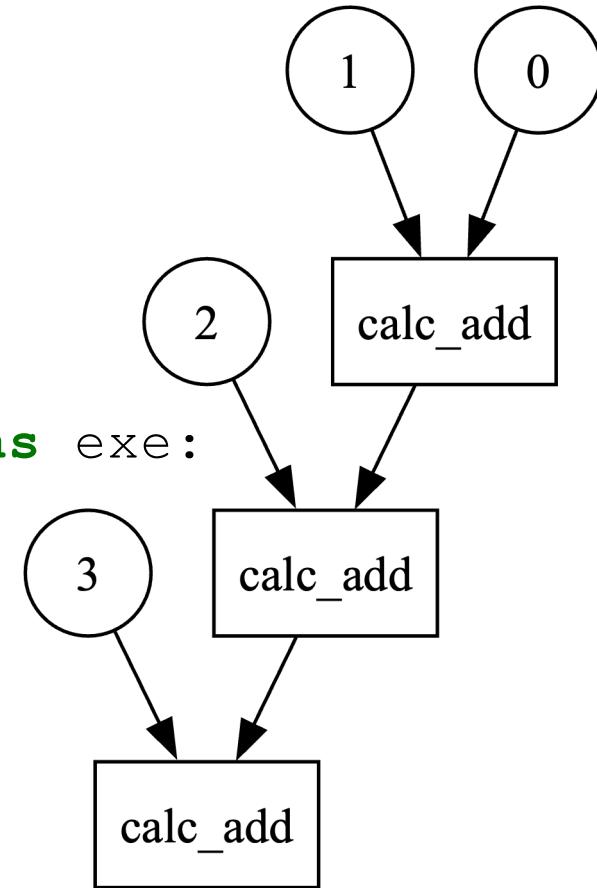


Link Python Functions with Different Resource Requirements

```
from executorlib import SingleNodeExecutor

def calc_add(a, b):
    return a + b

with SingleNodeExecutor(plot_dependency_graph=True) as exe:
    future = 0
    for i in range(1, 4):
        future = exe.submit(calc_add, i, future)
    print(future.result())
```



From Python Functions to Workflows – Dependency Management

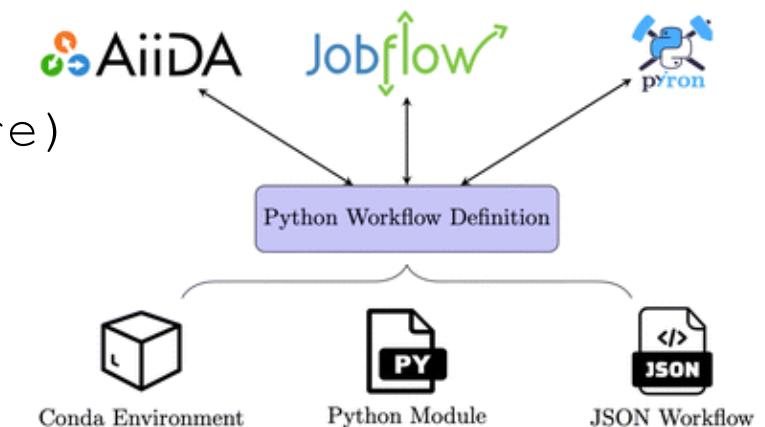


Link Python Functions with Different Resource Requirements

```
from executorlib import SingleNodeExecutor
```

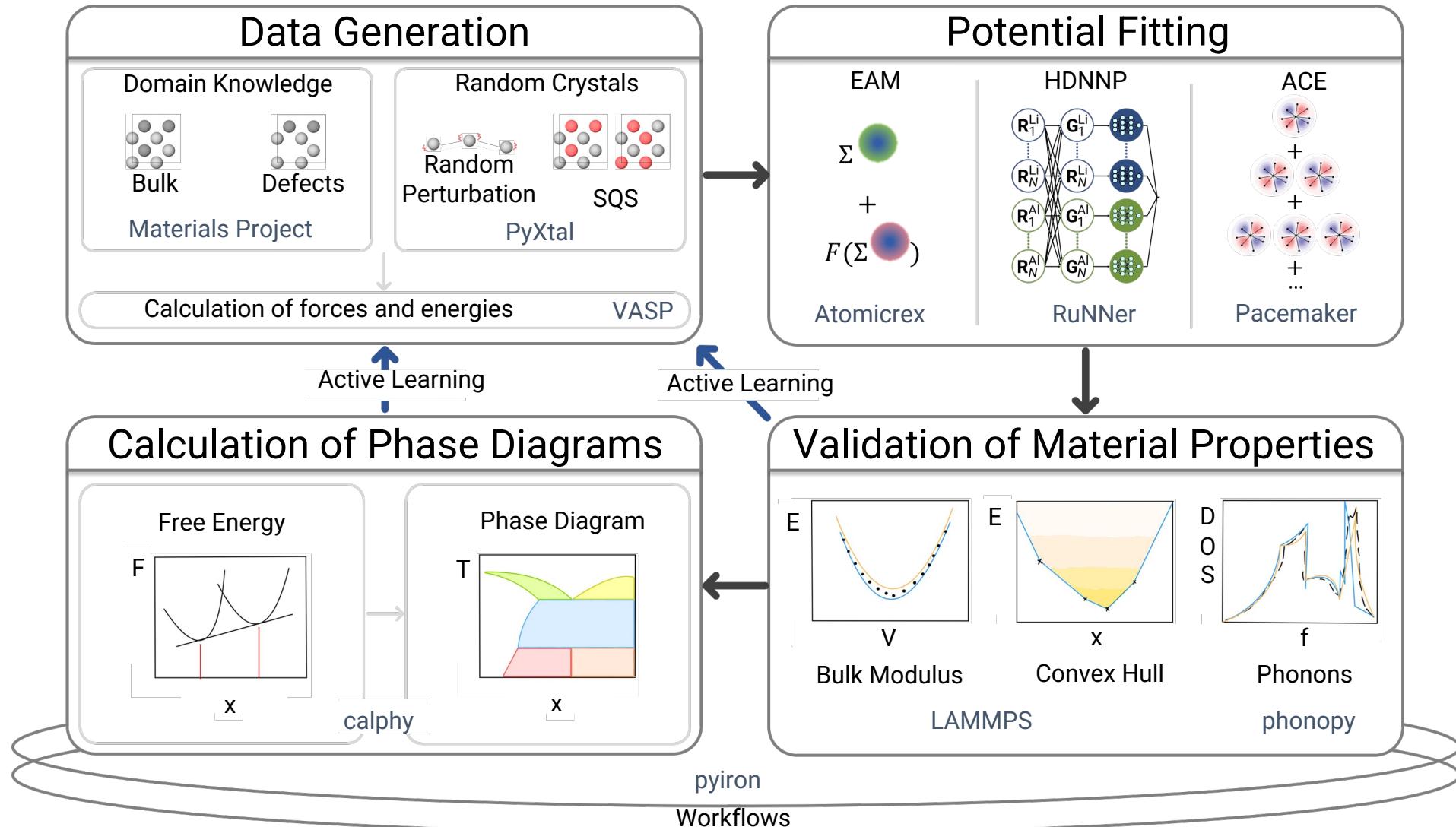
```
def calc_add(a, b):  
    return a + b
```

```
with SingleNodeExecutor(export_workflow_filename="flow.json") as exe:  
    future = 0  
    for i in range(1, 4):  
        future = exe.submit(calc_add, i, future)  
    print(future.result())
```



Temperature Concentration Phase Diagram

Ab-initio Thermodynamics



Temperature Concentration Phase Diagram

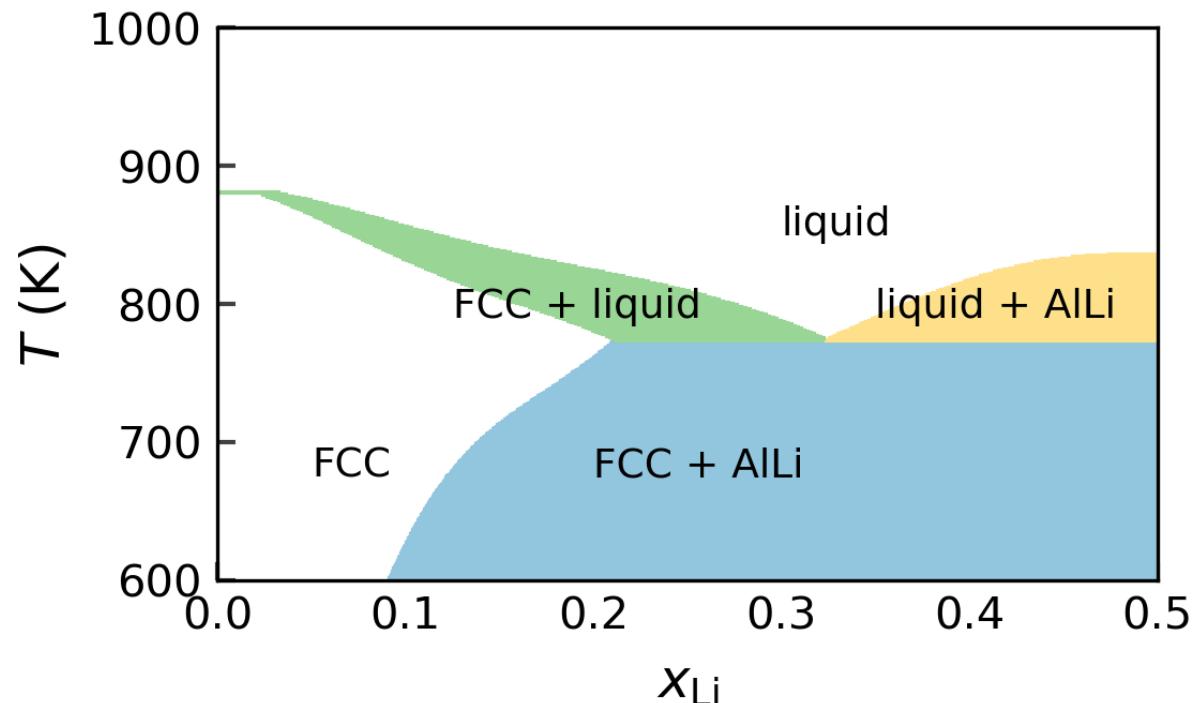
Ab-initio Thermodynamics



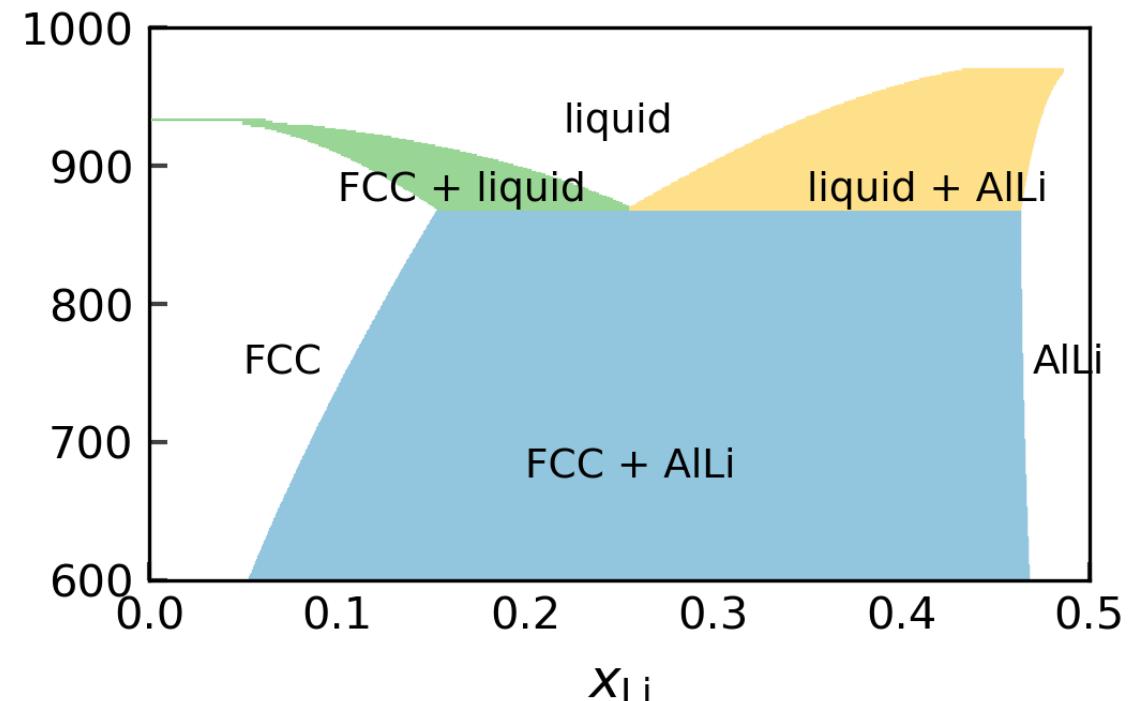
Data Generation

Potential Fitting

Machine-Learned Interatomic Potential



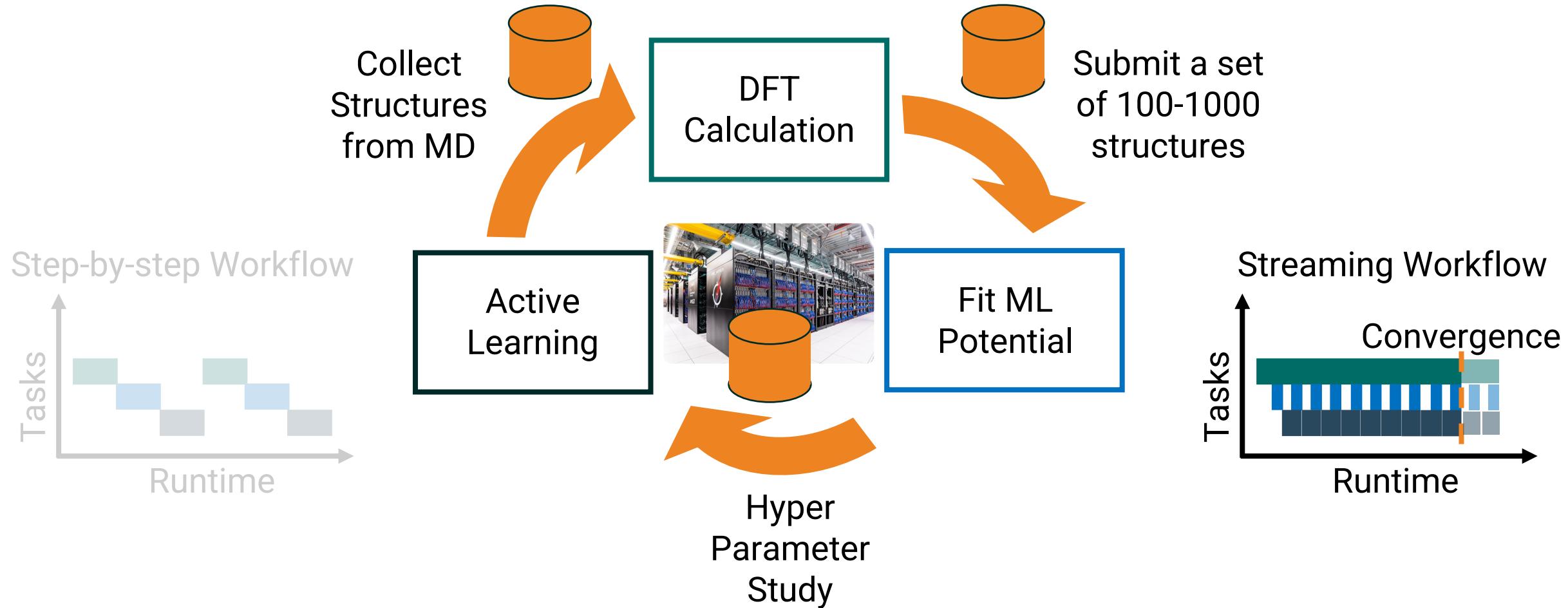
Experiment (CALPHAD)



pyiron
Workflows

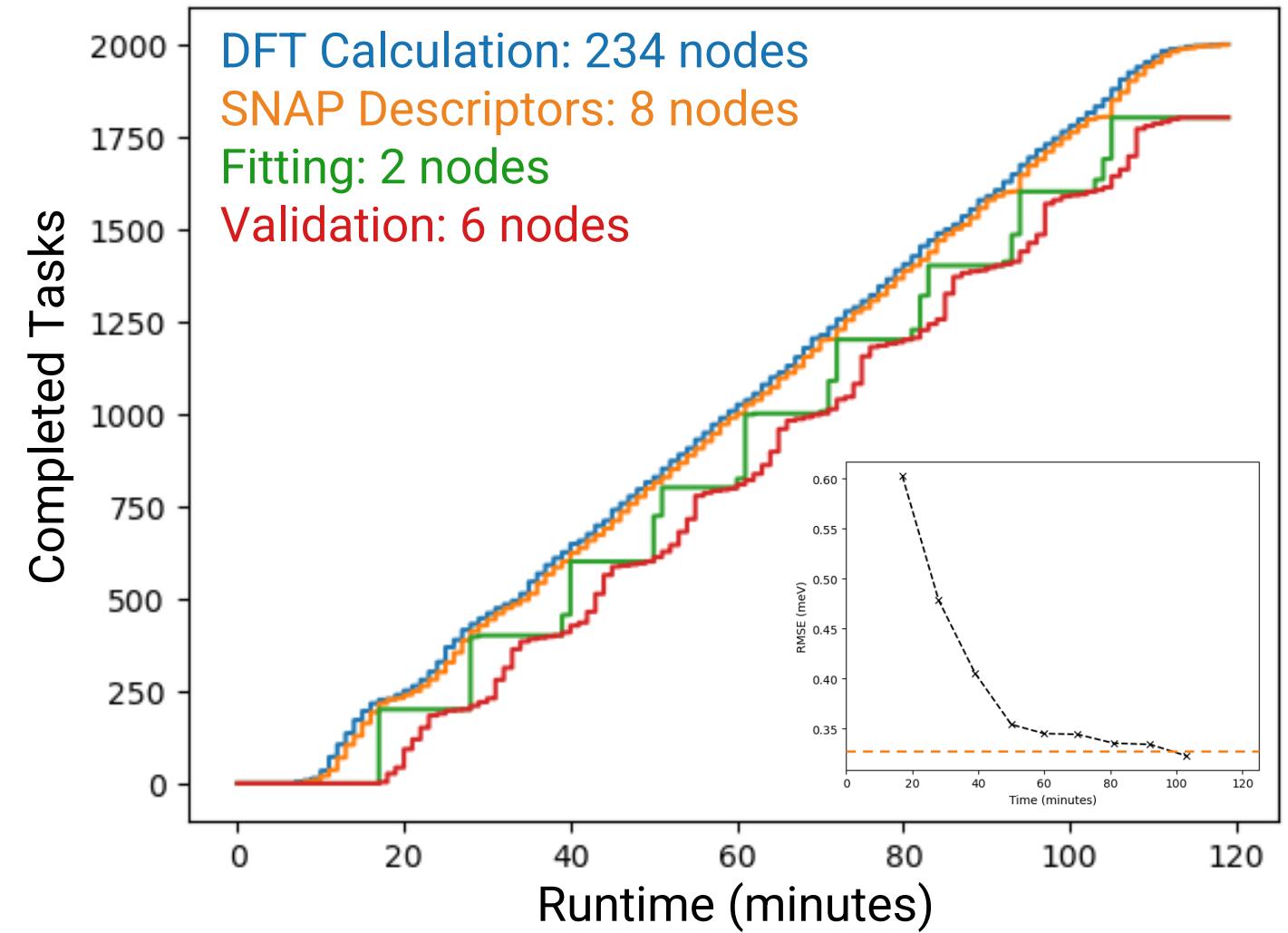
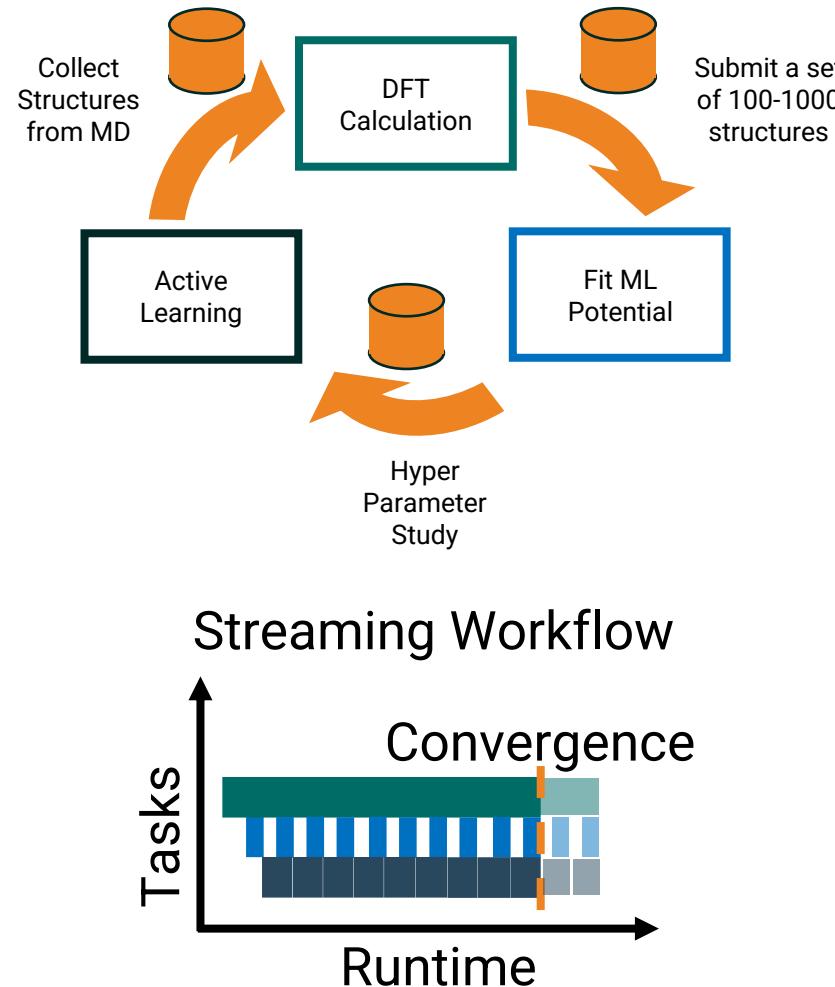
Fitting Interatomic Machine Learning Potentials

Maximize the Resource Utilization



Develop a Machine Learning Potential in Two Hours

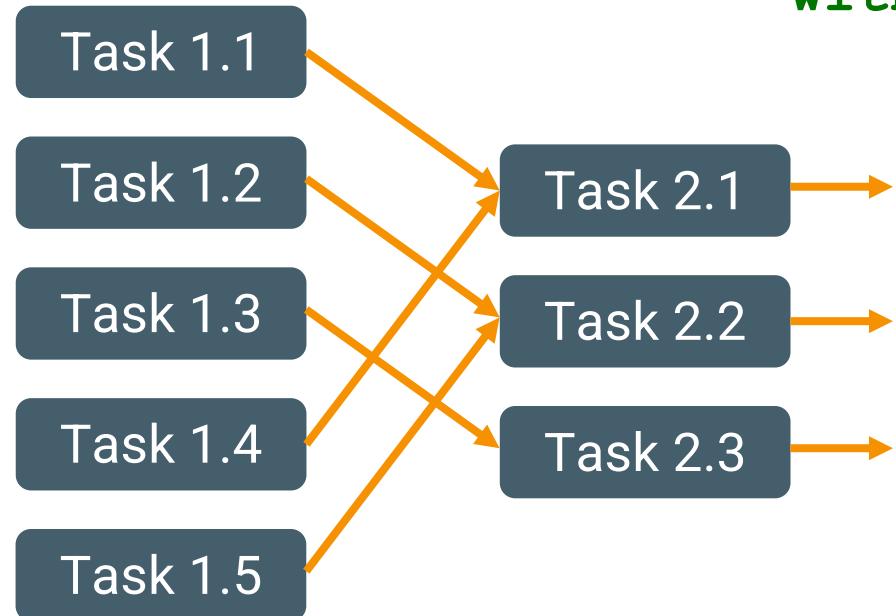
Testing on Frontier



Streaming Workflow in Executorlib



From a Group of Tasks Take the Batch of Tasks Which Finishes First



```
from executorlib import SingleNodeExecutor

with SingleNodeExecutor() as exe:
    task_one_lst = []
    for i in range(...):
        task_one_lst.append(
            exe.submit(task_one, ...))
    )

    task_two_lst = []
    for f in exe.batched(task_one_lst, n=2):
        task_two_lst.append(
            exe.submit(task_two, ...))
    )
```

Reusing Data in Memory



Block Allocation

```
from executorlib import FluxJobExecutor

def init_function():
    return {"j": 4, "k": 3, "l": 2}

def calc_with_preload(i, j, k):
    return i + j + k

with FluxJobExecutor(
    max_workers=2,
    resource_dict={"cores": 1},
    init_function=init_function,
    block_allocation=True,
) as exe:
    fs = exe.submit(calc_with_preload, 2, j=5)
```

Hierarchical Task Management

Based on Flux Hierarchical Job Scheduler



```
from executorlib import FluxJobExecutor

def calc_nested():
    from executorlib import FluxJobExecutor
    with FluxJobExecutor() as exe:
        fs = exe.submit(sum, [1, 1])
    return fs.result()

with FluxJobExecutor(flux_executor_nesting=True) as exe:
    future = exe.submit(calc_nested)
    print(future.result())
```

Open-Source Development

From Scientists for Scientists



pyiron / **executorlib** Public

Code Issues 26 Pull requests 4 Actions Security Insights

main 5 Branches 78 Tags Go to file Code

README BSD-3-Clause license

executorlib Continuous Integration with  

Pipeline passing codecov 97% launch binder JOSS 10.21105/joss.07782 Stars 36

pre-commit-ci[bot] [pre-commit.ci] pre-commit autoupdate (#766) 0d43ca3 · yesterday 1,747 Commits

.ci_support Update integration test environment (#755) last week

.github Remove conda default channel (#765) yesterday

binder Bump pysqa from 0.2.6 to 0.2.7 (#702) 3 weeks ago

Notifications Fork 3 Star 36

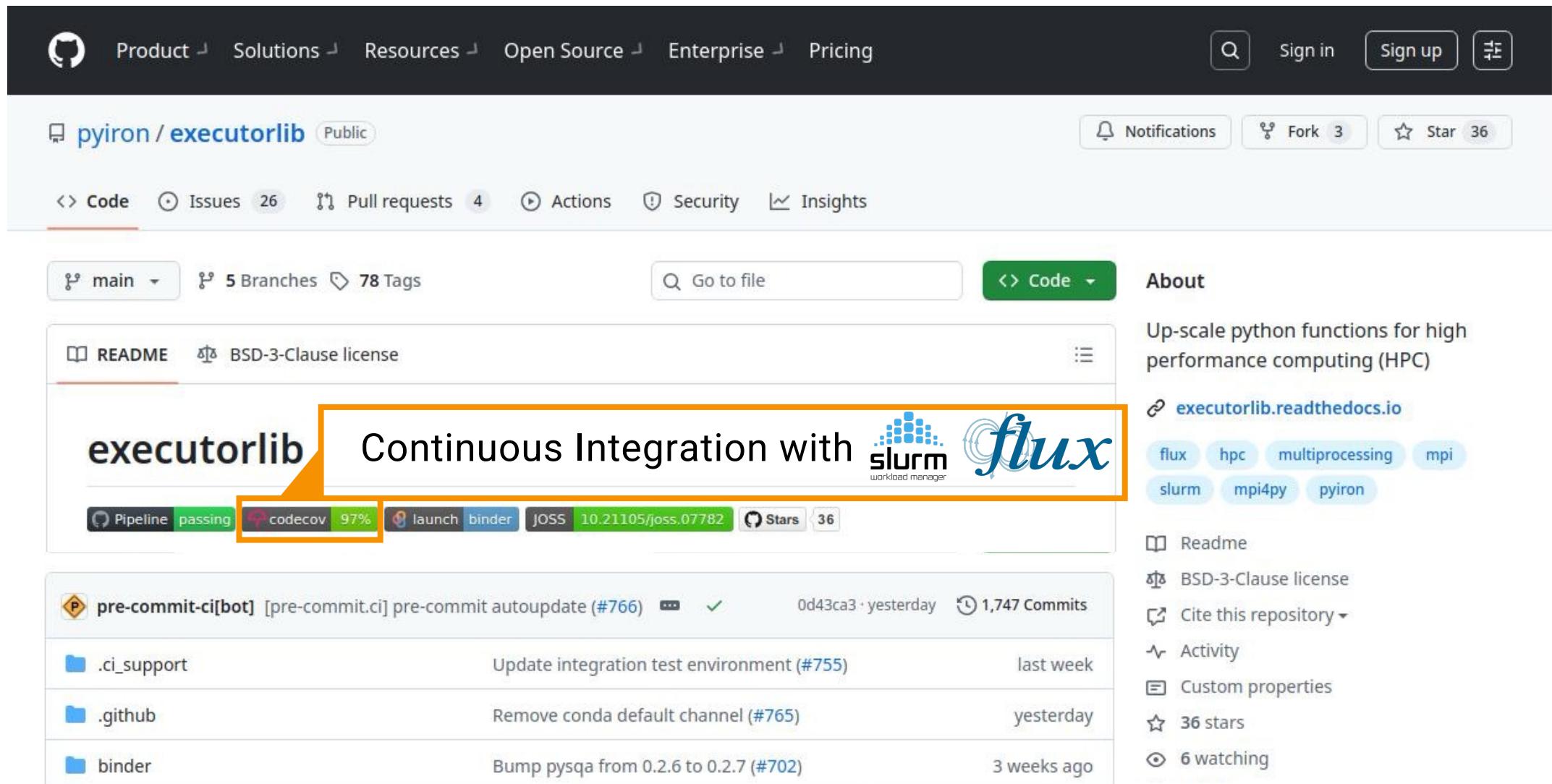
About

Up-scale python functions for high performance computing (HPC)

executorlib.readthedocs.io

flux hpc multiprocessing mpi
slurm mpi4py pyiron

Readme BSD-3-Clause license Cite this repository Activity Custom properties 36 stars 6 watching

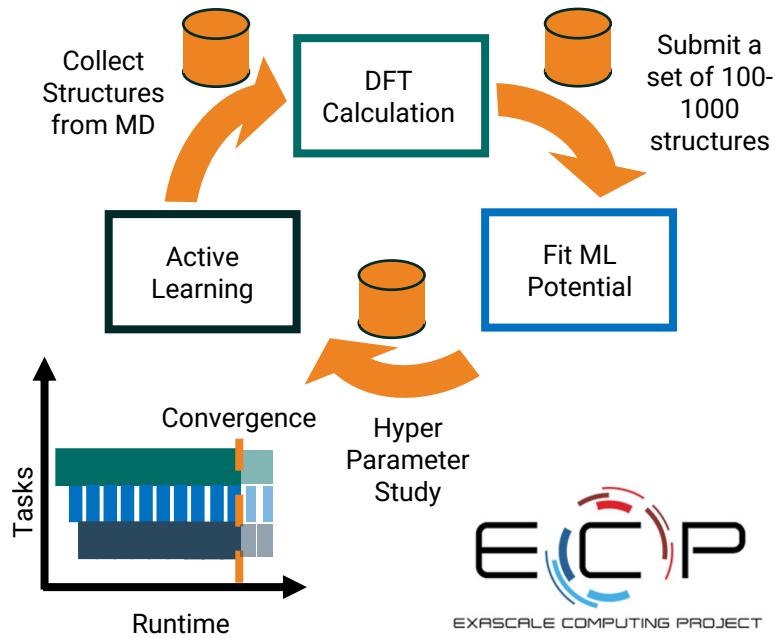


Summary: Up-scale Python Functions with Executorlib – Thank you

From your local workstation to high-performance computing and the Exascale

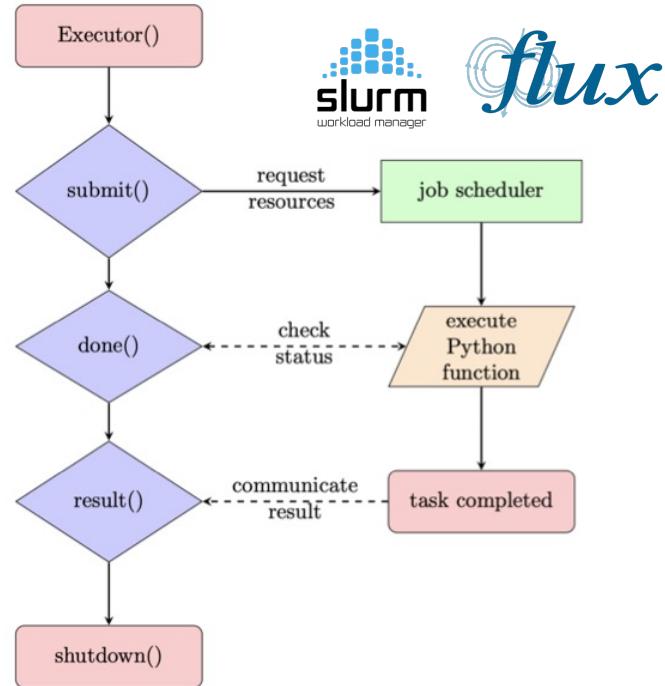


Streaming Workflows for Exascale Materials Science



Maximizing the utilization of available computational resources to gain scientific insights as fast as possible.

Executorlib For Up-Scaling Python Functions



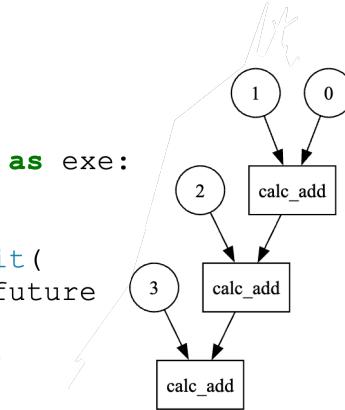
No database, no daemon process, just a Python interface to high-performance computing job schedulers.

Beyond Python Functions Towards Python Workflows

```
from executorlib import SingleNodeExecutor

def calc_add(a, b):
    return a + b

with SingleNodeExecutor() as exe:
    future = 0
    for i in range(1, 4):
        future = exe.submit(
            calc_add, i, future
        )
    print(future.result())
```



Follow the interface of the concurrent futures Executor class extended to address scientific computing challenges.