

Proxy Apps for X (Co-design, Real life and Fun!)



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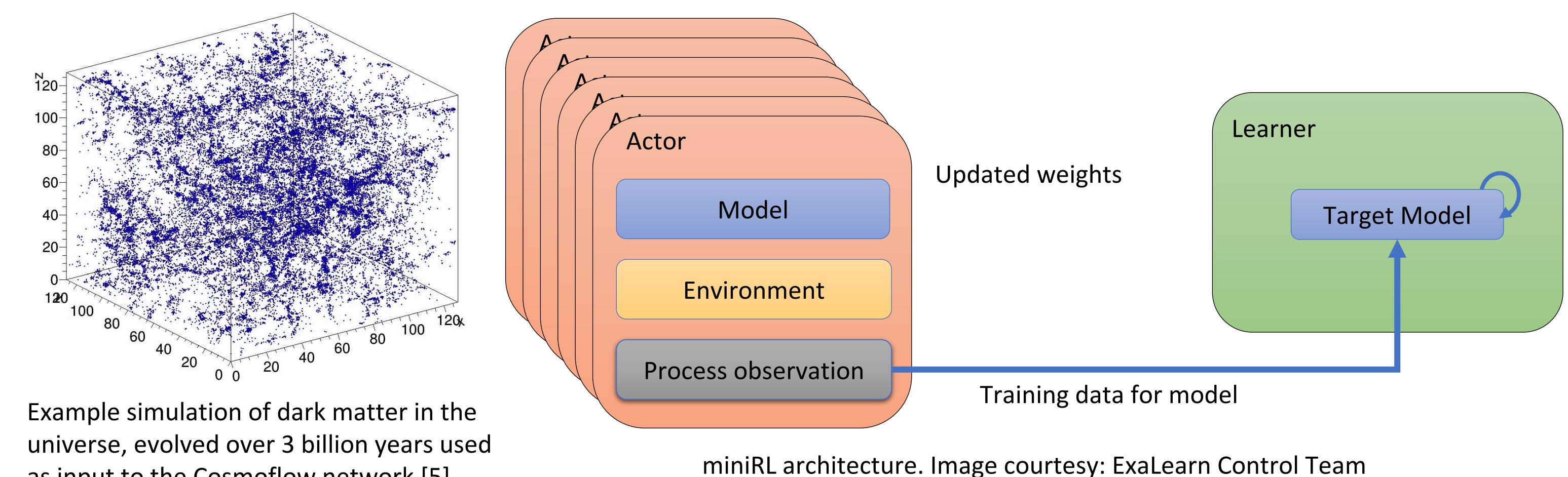
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Mission

To curate a suite of proxy applications that are representative of the intended characteristics of their respective parent applications and are easy to obtain and use. Characteristics include hardware bottlenecks (e.g., memory, computation, communication) and programming models.

Machine Learning Proxy Suite

- Proxies for ML applications require a somewhat different approach
 - ML problems frequently present a data centric approach rather than an algorithmic one
 - May be necessary to simplify the dataset instead of the algorithm
- ML proxies are different from traditional proxies in other important ways
 - ML workloads often rely on a complex set of third-party dependencies such as PyTorch or TensorFlow
 - Contrary to the usual principles of simple-to-build proxies by avoiding dependencies
 - ML space is fortunate to have tools such as Spack to manage dependencies
 - Rapid pace of development requires ML proxies to be nimble enough to adapt to changes



Principles of Machine Learning Proxies

With the above-mentioned differences in mind, ML proxies are selected based on two sets of criteria:

1. The suite must embody the core purposes and uses of proxy apps: Hardware and software co-design, programming model exploration and innovation, development of numerical methods and algorithms, optimization and benchmarking, and education
2. The suite must cover the breadth of the ML application space. The ML suite will encompass different ML proxy apps chosen to represent the basic learning paradigms associated with ML.

Machine Learning Proxies

The following proxies are included in the current version of the ML proxy suite:

- **miniGAN** - A Generative Adversarial Network (GAN) proxy for related ML applications in cosmology, such as CosmoFlow and ExaGAN, and in wind energy, such as ExaWind.
- **miniRL** - A reinforcement learning (RL) proxy application derived from the Easily extensible Architecture for Reinforcement Learning (EXARL) framework, used for control and optimization of applications or experiments.
- **CRADL** - Concurrent Relaxation through Accelerated Deep Learning (CRADL) performs inference, with a trained machine learning algorithm, on mesh geometry data from hydrodynamics simulations.
- **Cosmoflow-Benchmark** - Cosmoflow-Benchmark is an implementation of CosmoFlow 3D convolutional neural network for benchmarking.
- **MLperf-DeepCam** - MLperf-DeepCam is a PyTorch implementation for the climate segmentation benchmark, based on the Exascale Deep Learning for Climate Analytics codebase.

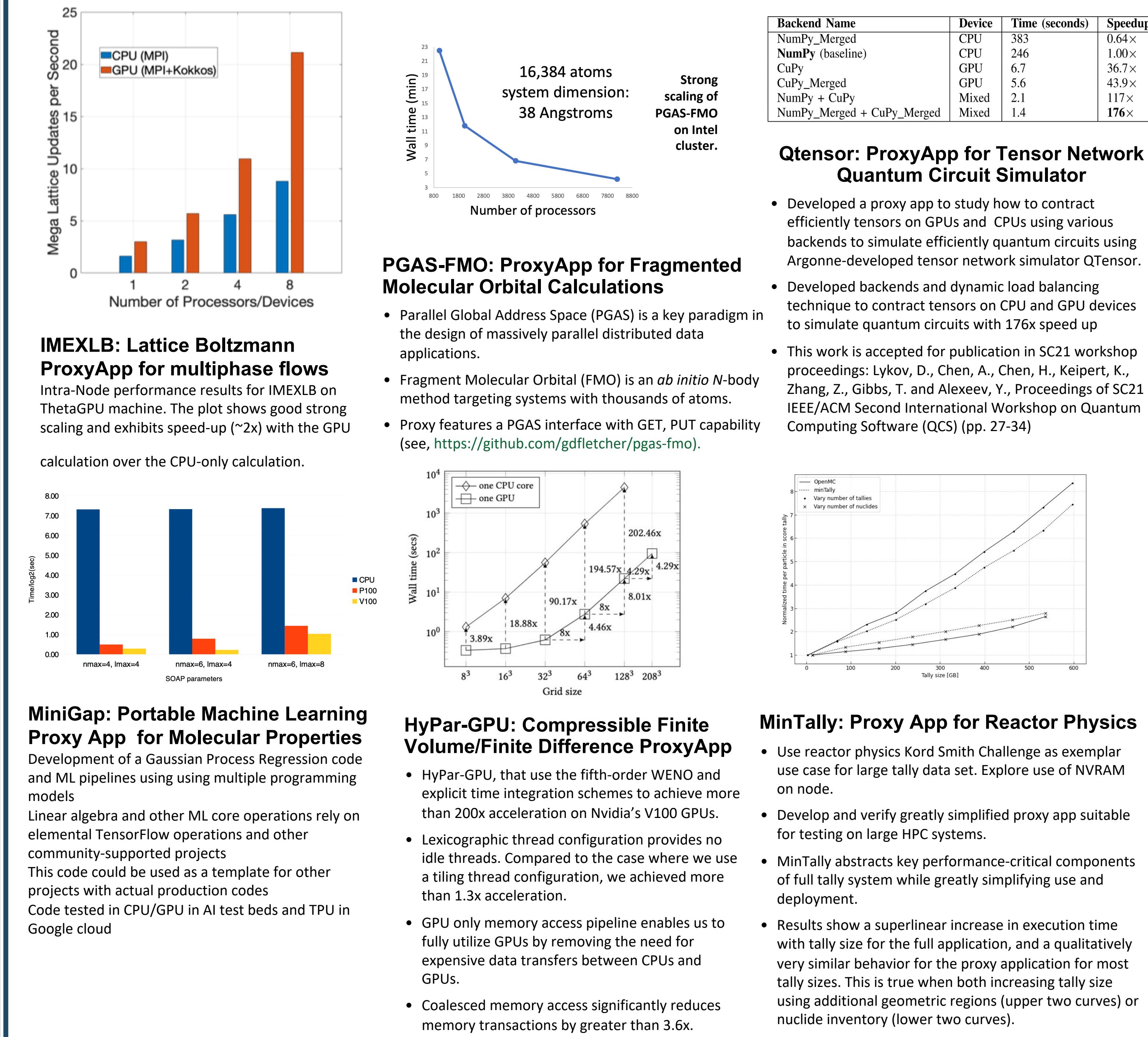
Proxy Apps in FFTX

ECP-funded FFTX is an exascale follow-on to the 1990s FFTW package for executing the Fast Fourier Transform, as well as compositions of FFTs with linear operations. FFTX optimizes algorithms over high-performance kernels for specific environments, and generates code for CPU & GPU platforms. Four proxy applications representative of HPC applications space using FFTs:

1. Hockney free-space convolution
2. WarpX Pseudo-Spectral Maxwell solver
3. NWChemEx planewave solver
4. Poisson solver

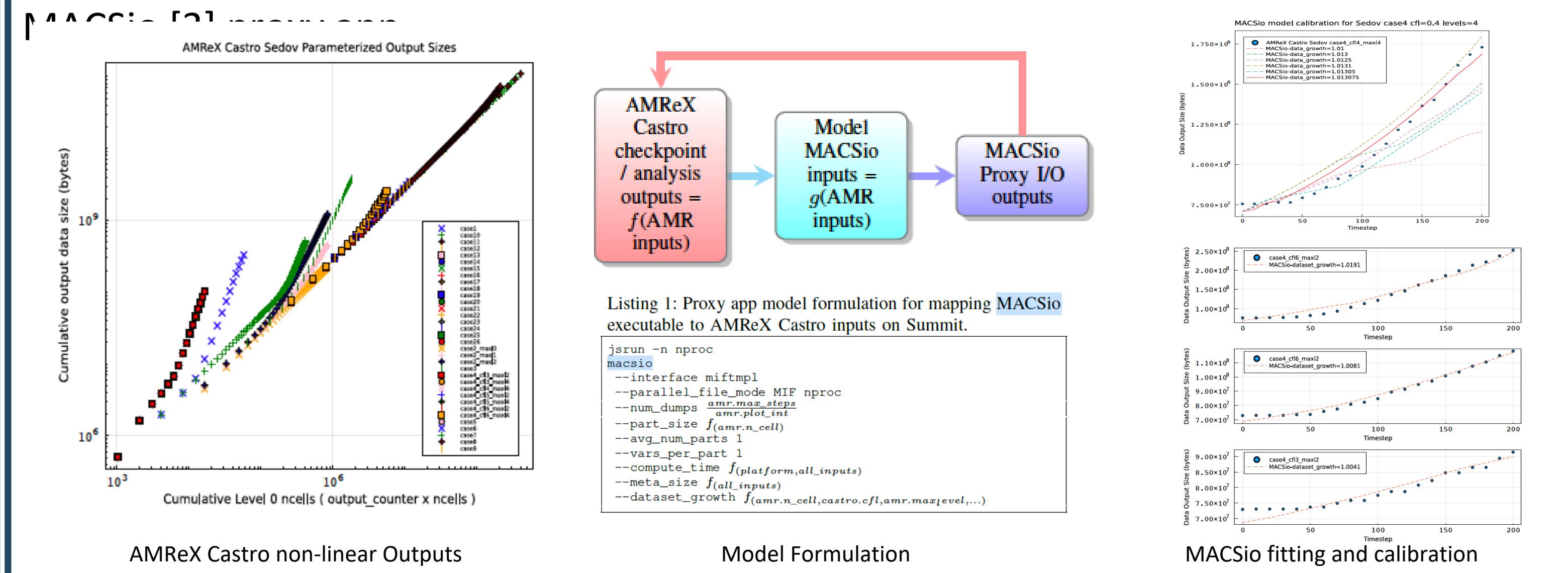
FFTX and CUDA library cuFFT on cori @ NERSC.
FFTX and HIP library rocFFT on spock and crusher @ OLCF.

Argonne ProxyApps



Assessing AMReX I/O Behavior

Goal: provide understanding to AMReX Castro [1,2] I/O workloads via modeling using the MACSio [3] proxy app.



MACSio provides <step, rank> and non-linear growth capabilities to model N-to-N data. AMReX N-to-N outputs at every <step, level, rank>. Our model is from a parameterized and calibration study identifying the problems size, number of levels, CFL condition at a "step" level from 40 Summit runs of the Sedov hydrodynamic problem. Work accepted at the iWAPT workshop, IPDPS 2022 [4].

Generating I/O Proxy Apps

- Skel-IO allows application behavior to be modeled, and supports generation of benchmark codes based on those models
- Current work involves extending Skel-IO to support combining multi-faceted models into unified, application-specific proxies