

# Efficient Digital Twin Training using Uncertainty-Guided Data Generation

Ana Gainaru

MS323, Neural Acceleration, Surrogate Models, and Learning Techniques for HPC Kernels  
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# Interactions between HPC and AI frameworks

- Research on HPC I/O focused on **modeling and simulation applications**
  - Handling large output and checkpointing the results
  - Write operation bursts commonly dominate traditional workloads
  - Analysis and viz typically access large portions of the data
- ML workloads perform **small I/O reads spread across a large number of random files**
  - Usually read-intensive and use many small files
- There is **no well-established consensus** on the preferred I/O stack for ML workloads
  - Many developers resort to developing their own custom solution

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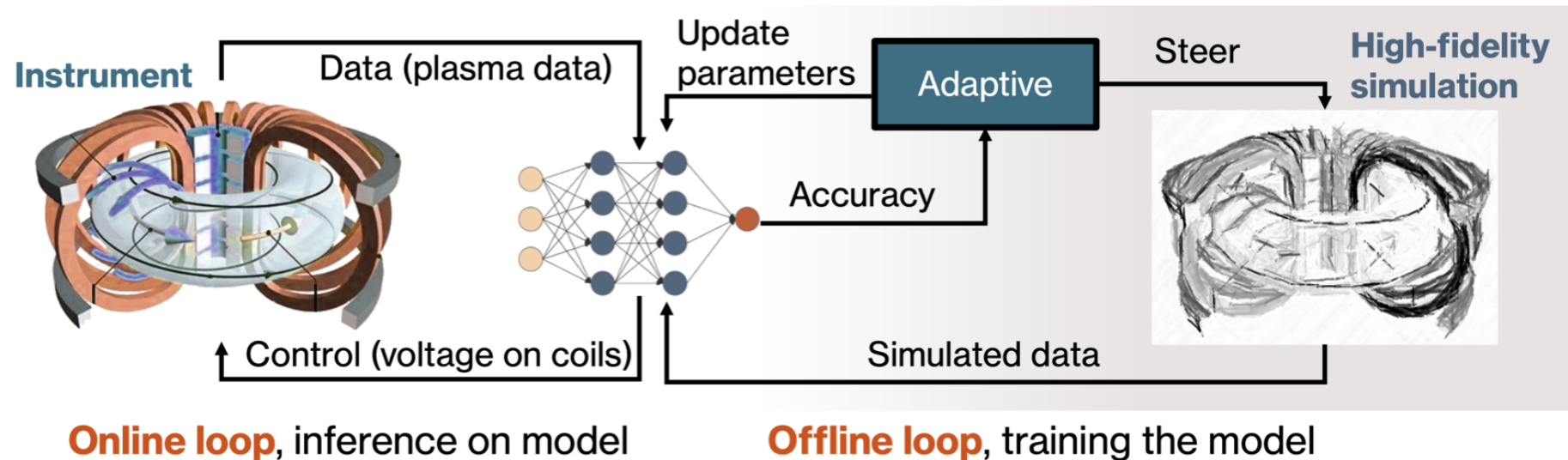
1. What are the types of workflows that combine HPC and AI ?

2. What are the limitations integrating AI and HPC?

3. What are the benefits of unifying the AI and HPC solutions ?

# Interactions between HPC and AI frameworks

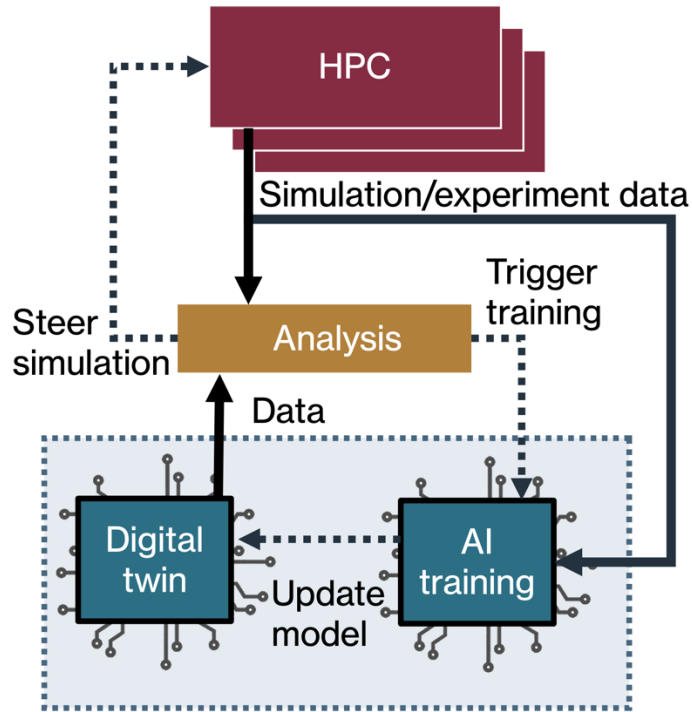
- **AI-in-HPC:** The AI system is introduced instead of a component or a whole HPC simulation.
  - e.g. medical pipelines
- **AI-out-HPC:** the outside AI system dynamically controls the progression of the HPC workflow
  - e.g. control of computational campaigns via reinforcement learning
- **AI-about-HPC:** the AI systems are concurrent and coupled to the main HPC tasks
  - e.g., AI-based analysis and viz use the output of the HPC simulation to provide further insights



1. What are the types of workflows that combine HPC and AI ?

# Types of AI+HPC workflows

Breakdown of the main characteristics used to define the different behavioral motifs



AI/HPC Workflows	Interaction	Coupling	Scope
	Data flow Control flow Human interaction	Concurrency Dynamism Federation	
	MOTIF		
	Implementation		
Performance characteristics			

- **AI-based steering ensembles of simulations**
  - HPC workflows, e.g. ensemble of simulations are “steered” by an AI system
- **Multistage pipeline**
  - Pipeline of HPCs with AI-based functions between stages
- **Inverse design**
  - AI-driven optimizations are used to iteratively identify causal factors from observational data
- **Digital replica**
  - HPC concurrent with AI digital replicas predictions and health monitoring

1. What are the types of workflows that combine HPC and AI ?

# Limitations of current solutions

- Testcases 3 types of AI/HPC workflows
  - Digital twin training for plasma physics simulation
  - Workflow pipelines in cancer research
  - Inverse design for plasma simulation\*
- A data-centric approach to integrating AI in HPC
  - **Throughput limitations of the filesystem (in memory)**
  - **Code coupling (strong/loose coupling)**
  - **Large data space for training (steering the experiment)**
- No consensus on the preferred I/O stack for ML workloads
  - **No schema**
  - **Not a consistent way of handling models and data**
  - **Custom solutions**

2. What are the limitations integrating AI and HPC?



# Limitation: Raw formats are common in AI

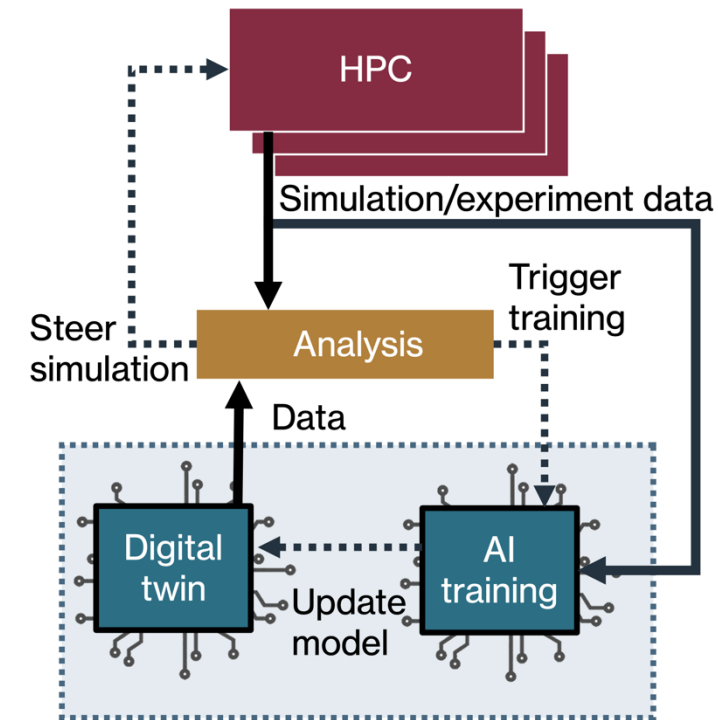
- Each solution uses different formats
  - Each with diverse properties that can affect performance when storing and retrieving ML datasets
  - Many applications still rely on unoptimized solutions (raw text and image formats)
  - Once a model is trained, the input data format is lost

File Format	Parallel I/O	Compression	Schema
TFRecords	✗	✗	✓
Apache Parquet	✓	✓	✓
RecordIO	✗	✓	✗
NPZ	✗	✗	✗
HDF5	✓	✓	✓
ADIOS2	✓	✓	✓
Raw formats (e.g. images, video, text)	✗	✗	✗

2. What are the limitations integrating AI and HPC?

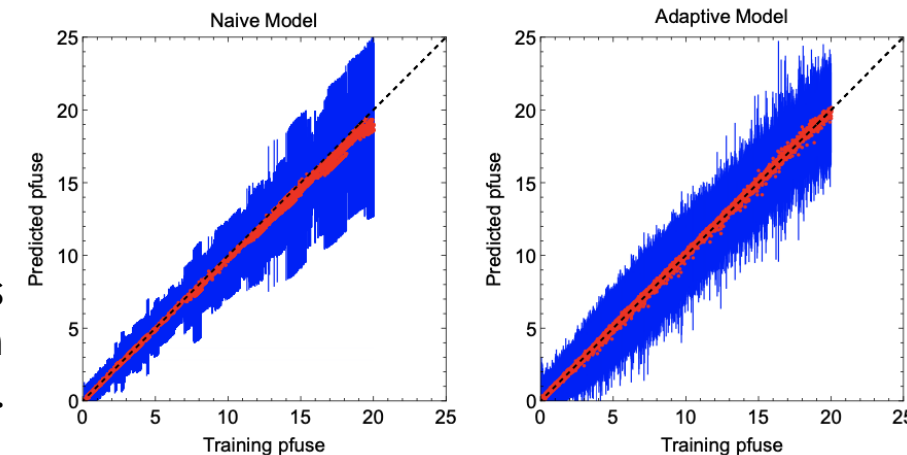
# Limitation: Massive training datasets

- Naive uniform sampling of the input space
  - Imbalance data coverage
    - Some areas unnecessary over-sampled while others have sparse data coverage
  - Identifying deficit regions is a challenging task
    - Current solutions are increasing the amount of training data to eventually fill the coverage gaps -> **Massive datasets**
- Choosing the location of data samples
  - Bayesian approach to capture uncertainty in a deep neural network
- Steer an ensemble of simulations



3. What are the benefits of unifying the AI and HPC solutions ?

An adaptively trained model provides more accurate prediction at high electron fusion power output.

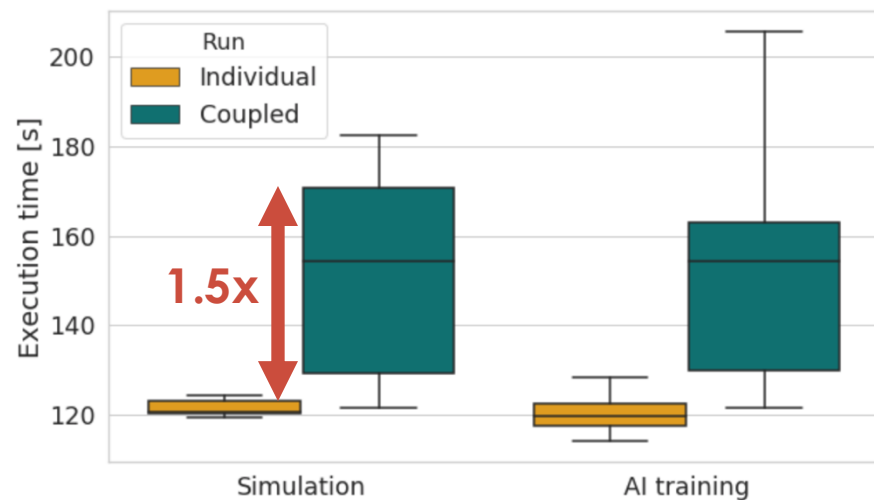




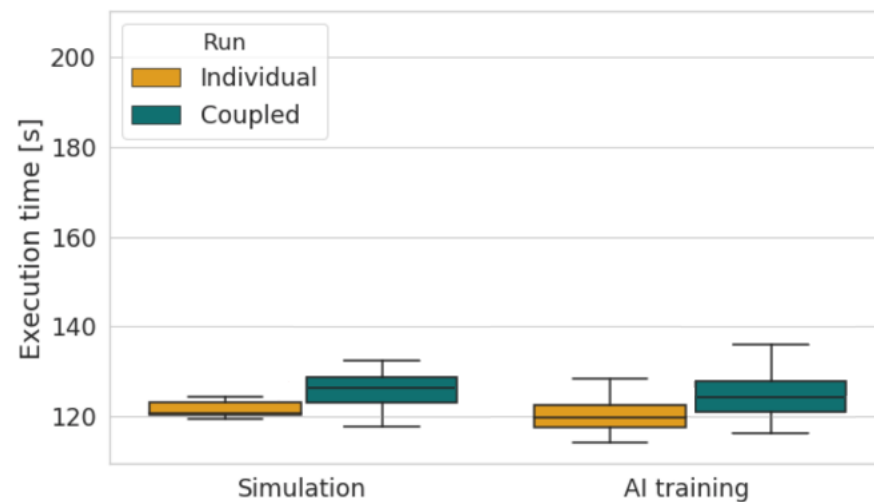
# Limitation: Filesystem throughput

- Separate runs
  - Less than 3% performance degradation compared to separate runs
  - Less variation
  - If more models are needed
    - Overhead stays below 5% for 3 models
    - Variation increases with the number of nodes
- Throughput of **40 TFlops**
  - On Frontier

3. What are the benefits of unifying the AI and HPC solutions ?



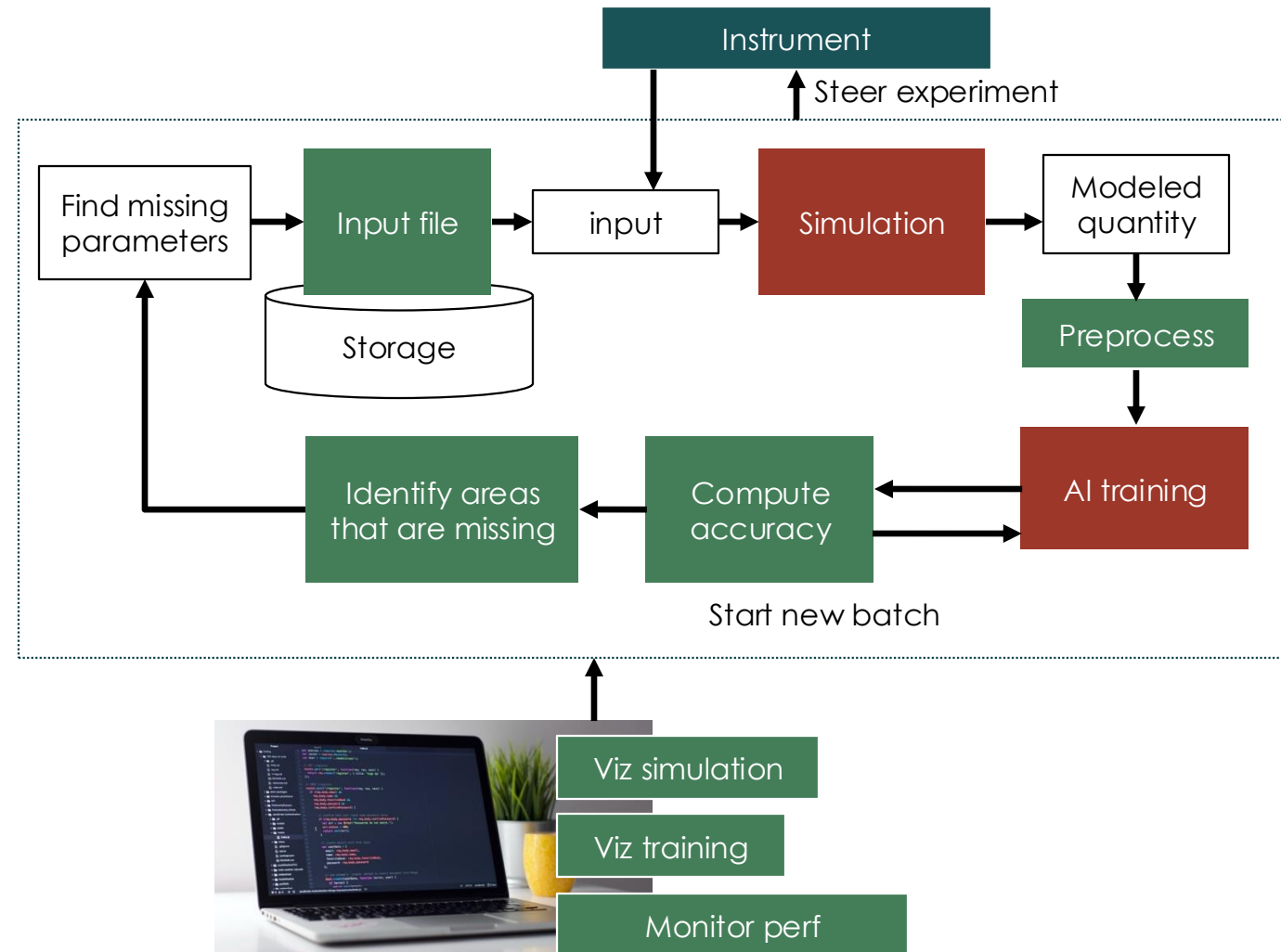
Simulation and analysis execution time if ran separately or coupled



Execution time when streaming between coupled codes

# Limitation: Code coupling

- Coupling plasma codes
  - Streaming data between
  - Pre-process / post-process as part of the workflow
  - EFFIS workflow management system
    - Overhead of 1-5%
    - Command and control capabilities
- Near real time
  - Visualization
  - Performance monitoring



3. What are the benefits of unifying the AI and HPC solutions ?

- Many DOE projects are developing AI / HPC workflows
  - The I/O solution for AI and HPC have evolved separately
  - There is no well-established consensus on the I/O stack for AI-HPC workflows
- Our experience at large scale
  - Use **self describing formats** for data management
    - Enables querying, model/data tracking, reproducibility
  - It's better to **avoid the filesystem**
  - Separate workflow into **units of work**
    - Offload data transfer to streaming libraries

## Conclusions



**Thank you !**

gainarua@ornl.gov



# Backup slides





# Relevant publications

Junqi Yin et al. **Evaluation of pre-training large language models on leadership-class supercomputers**  
The Journal of Supercomputing, June, 2023

Gainaru et al. **Understanding the Impact of Data Staging for Coupled Scientific Workflows**  
IEEE Transactions on Parallel and Distributed Systems, 2022

Gainaru et al. **Framework for Automating the I/O of Deep Learning Methods**  
In revision, Transactions on Computational Biology and Bioinformatics, 2022

Suchyta et al. **Hybrid Analysis of Fusion Data for Online Understanding of Complex Science on Extreme Scale Computers**, Cluster, 2022

Jean Luca Bez et al. **Access Patterns and Performance Behaviors of Multi-layer Supercomputer I/O Subsystems under Production Load**, HPDC 2022

Wang et al. **Improving I/O Performance for Exascale Applications through Online Data Layout Reorganization**, IEEE Transactions on Parallel and Distributed Systems, 2021

Gainaru et al. **Profiles of upcoming HPC Applications and their Impact on Reservation Strategies**, IEEE Transactions on Parallel and Distributed Systems, 2020

Gainaru et al. **Speculative scheduling for stochastic HPC applications**, Proceedings of the 48th International Conference on Parallel Processing, 2019

Raghul Gunasekaran et al. **Comparative I/O Workload Characterization of Two Leadership Class Storage Clusters**, PDSW 2015