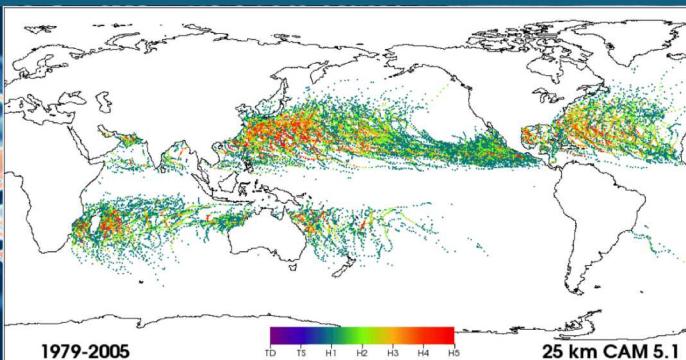


In-Situ Machine Learning for Intelligent Data Capture on Exascale Platforms



PRESENTED BY

Warren L. Davis IV

Collaborators: Tim Shead, Hemanth Kolla, Kevin Reed, Philip Kegelmeyer, Gabriel Popoola

Artificial Intelligence for Robust Engineering & Science Workshop (AIRES), January 22-24, 2023



DOE Base CS Research with Academic Collaboration



**U.S. DEPARTMENT OF
ENERGY**

Office of
Science



- DOE Office of Science - ASCR funded research (PM: Robinson Pino)
- Collaborative research with Stony Brook University
- Three-year research (\$500K) – leftover funding for wrap-up publications and conferences

SNL:

Warren Davis (PI), Tim Shead, Hemanth Kolla, Philip Kegelmeyer

Stony Brook:

Kevin Reed (PI)

North Carolina A&T:

Gabriel Popoola

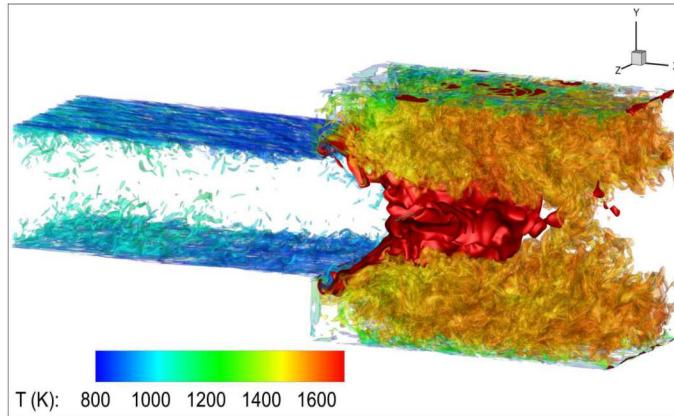
Past Members:

Danny Dunlavy (SNL), Julia Ling (Citrine Informatics), Aditya Konduri (Indian Institute of Science)

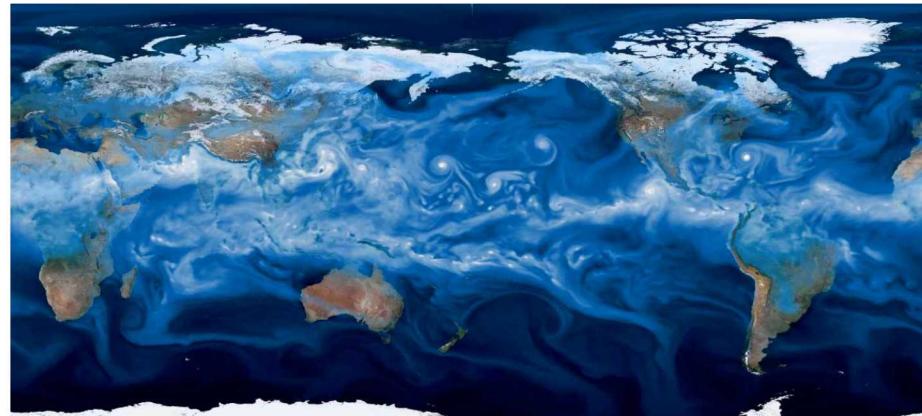
Motivation and Context



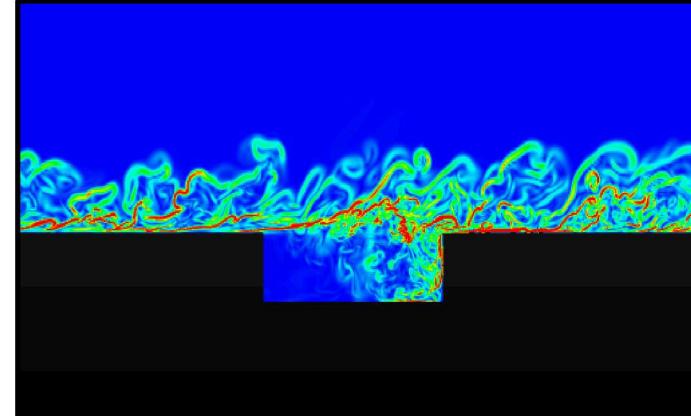
- DOE is interested in many problems that require high-fidelity physics-based HPC simulations



Combustion



Climate Modeling



Fluid Dynamics

- Want to find “interesting” events, anomalies, state changes, etc.
 - Examples may include cyclones, onset of combustion, or other things that the scientists may not prescribe *a priori* and may be difficult to perform via rule-based detection
- Desired solution would be to take all the data and run the appropriate detection algorithms (e.g., LOF, isolation forests, clustering)
- These simulations produce massive amounts of data (problems for storage capacity, bandwidth)

Current state-of-the-art for HPC simulation analysis

- Take “snapshots” in space and time (1/1000th or 1/10000th)
- Post-process snapshot data with standard algorithms

Problems with the current methods:

- Interesting events may happen between or outside of these snapshots
- Important information leading up to the captured event could be lost
- Rerunning simulations to capture lost information is expensive

- This problem will only get worse as the amount of data and fidelity of the simulations increases

Is there a way to detect the anomalies *in-situ*,
thus facilitating more precisely targeted event capture?

Changing the Paradigm with *In-Situ* Event Detection

- Develop techniques to detect interesting spatial and temporal events *in-situ* for HPC physics simulations
- Scalable : Can't significantly hinder the runtime of the application
- Unsupervised : To enable discovery, should not require labeling of interesting events
- Generalizable : Not focused on one specific event or domain
- Online : Don't require having access to all the data from every time step (post-processing)

This is foundational research, with a focus on algorithms that can motivate changes to simulation code and facilitate more intelligent, focused data capture

Anomaly Detection Framework



Signatures

A condensed, information-rich, representation of the simulation data on a node

- E.g., descriptive statistics, embeddings

Measures

A representation of how close a signature is to other signatures in the simulation

- E.g., distances, densities, estimators

Decisions

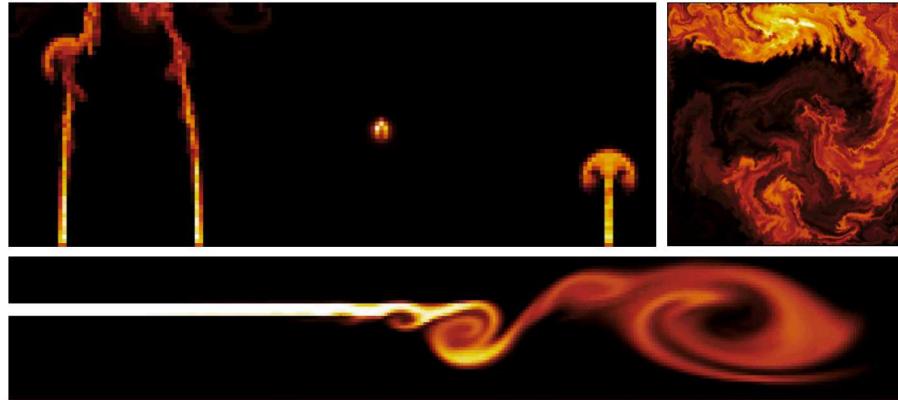
An arbitration of the measures to determine which nodes contain “interesting” data, given the signatures and measures

- E.g., threshold, momentum

Vehicles for Exploration and Experimentation

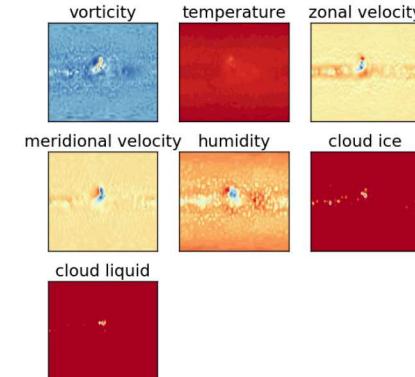


MantaFlow



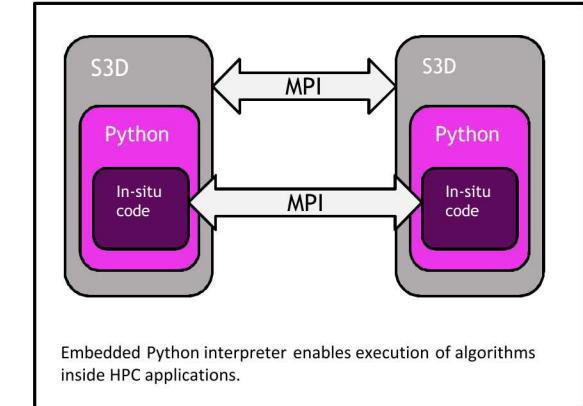
Fluid dynamics

CESM/CAM5



Climate

S3D



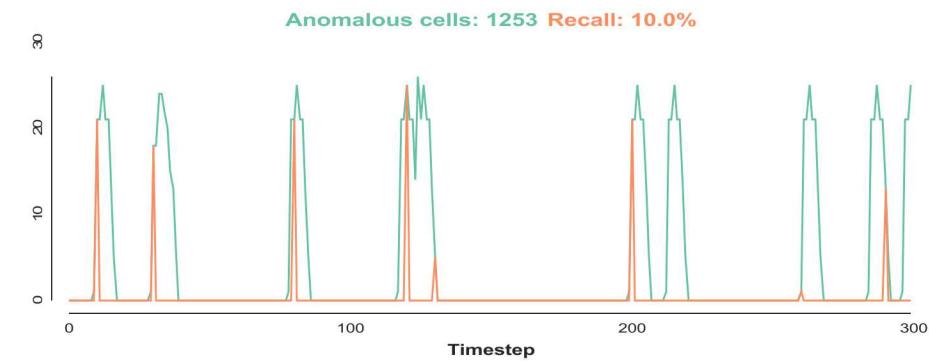
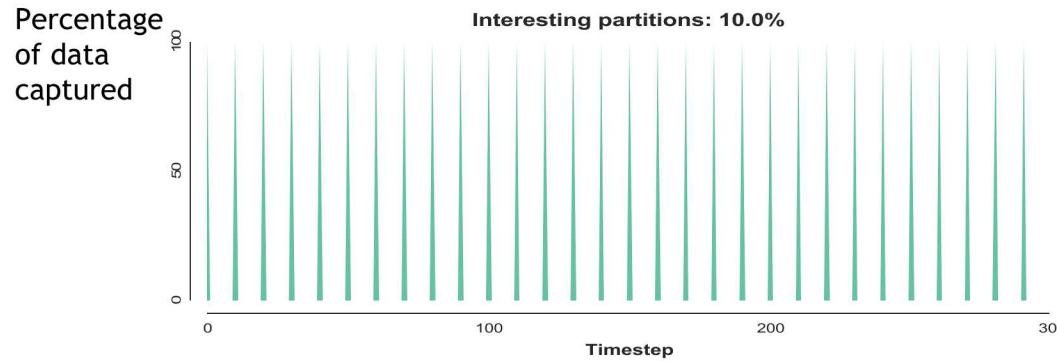
Combustion

Current research tools require ability to run Python from within the simulation code

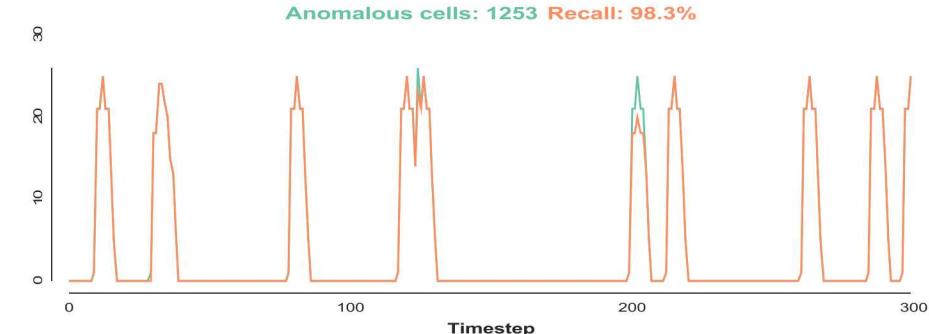
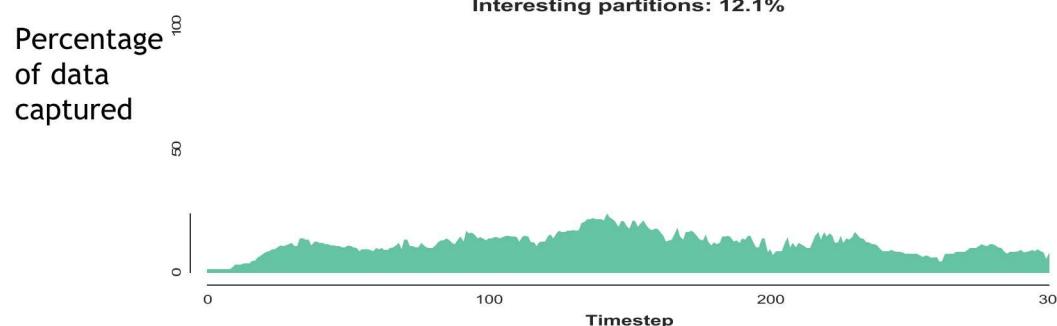
In-Situ Detection is More Accurate and Efficient

Turbulent Flow anomaly detection in Mantaflow

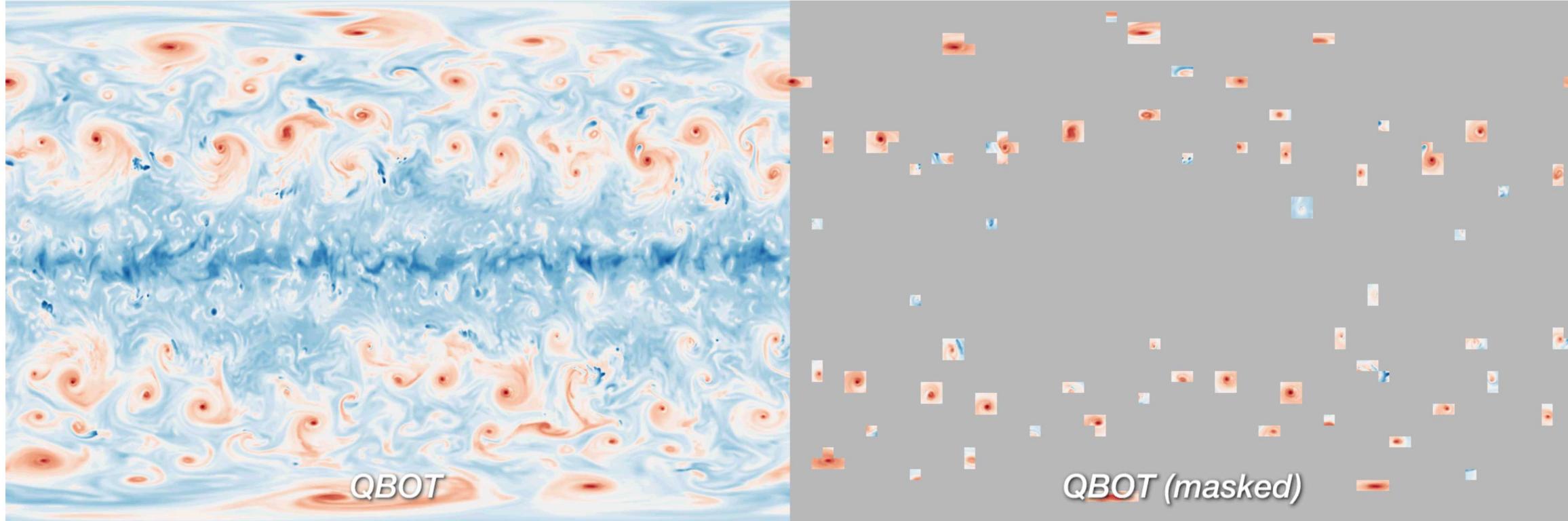
Snapshot (Conventional)



In-Situ Detection



9 Anomaly Detection in Climate Modeling



Climate Modeling

QBOT

QBOT (masked)

Towards Exascale

- Formally integrate *in-situ* capability to S3D
- Integration into CAM5
- Categorization of signatures, measures, and decisions
 - What signature works best for this type of data?
 - What measures best capture this particular type of change?
- Exploration of new domains / Increased scaling
- Finite-element simulations

More Information

- Publications/Presentations

- Ling, Julia, W. Philip Kegelmeyer, Aditya Konduri, Hemanth Kolla, Kevin A. Reed, Timothy M. Shead and Warren L. Davis IV. "Using feature importance metrics to detect events of interest in scientific computing applications." *2017 IEEE 7th Symposium on Large Data Analysis and Visualization (LDAV)* (2017): 55-63.
- Kolla, Hemanth, Aditya Konduri, Prashant Rai, Tamara G. Kolda, Warren Leon Davis. "Tensor Decomposition to Perform Change of Basis in Multi-Variate HPC Data to Preserve Higher Order Statistical Moments," *Presentation*, SIAM Parallel Processing 2018, March 2018.
- Konduri, Aditya, Hemanth Kolla, Julia Ling, W. Philip Kegelmeyer, Timothy Shead, Daniel Dunlavy, Warren Leon Davis. Event Detection in Multi-Variate Scientific Simulations Using Feature Anomaly Metrics," *Presentation*, SIAM Parallel Processing 2018, March 2018.
- Aditya K, Kolla H, Kegelmeyer WP, Shead TM, Ling J, Davis IV, Warren L. "Anomaly detection in scientific data using joint statistical moments", *Journal of Computational Physics*, Vol 387.
- Timothy M. Shead, Konduri Aditya, Hemanth Kolla, Daniel M. Dunlavy, W. Philip Kegelmeyer, Warren L. Davis IV. "Embedding Python for In-Situ Analysis." *SAND2018-9009*. August 2018.
- Davis IV, Warren Leon; Shead, Timothy M.; Kolla, Hemanth; Popoola, Gabriel; Kegelmeyer, Philip; Konduri, Aditya. "The Potential of Integrated Machine Learning Algorithms for Tropical Cyclone Detection in Advanced Climate Modeling." *American Geophysical Union Fall Meeting*, December 2019.

- For more information, contact: Warren L. Davis IV (wldavis@sandia.gov)

Backup



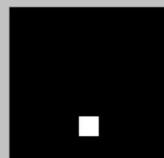
Fluid Flow (Snapshots)



- *density*
- *density (masked)*



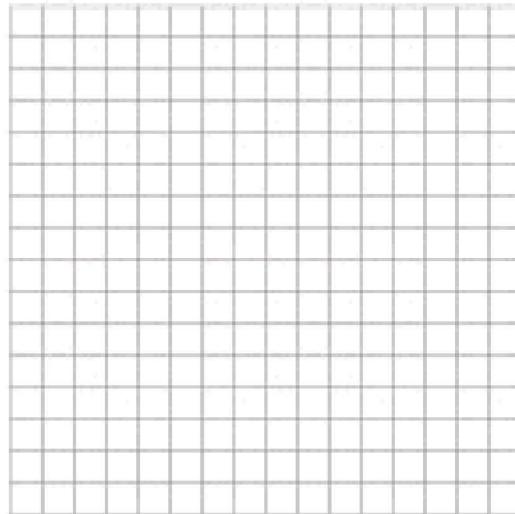
- *density*



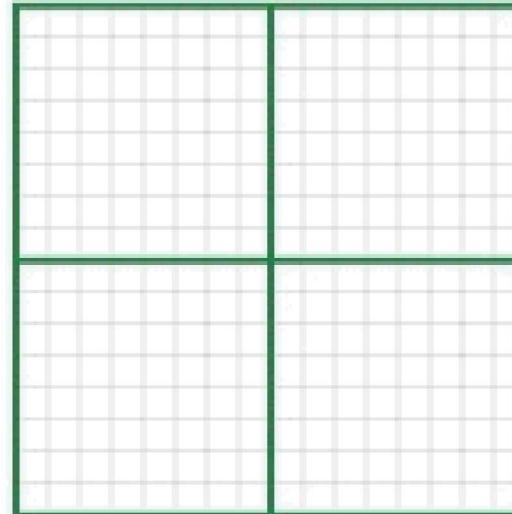
- *density (masked)*



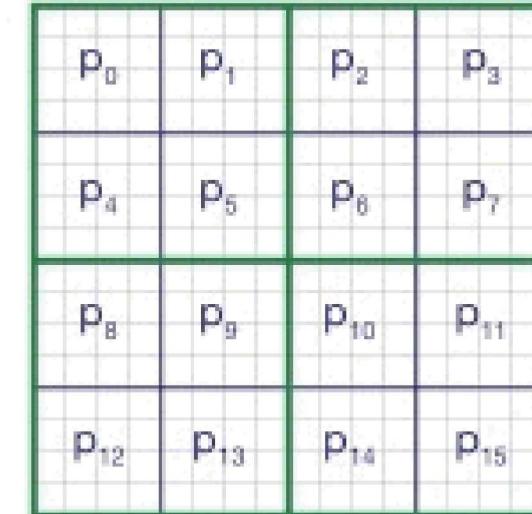
Communication is a constraint for In-Situ HPC Anomaly Detection



Simulation Domain



Processors



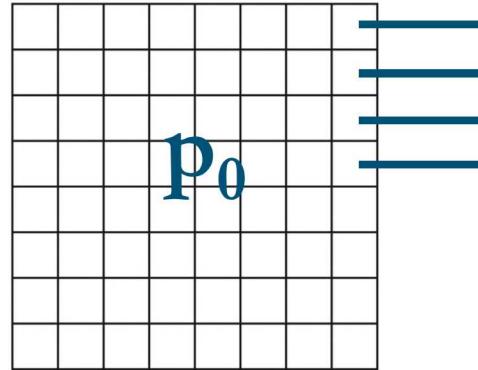
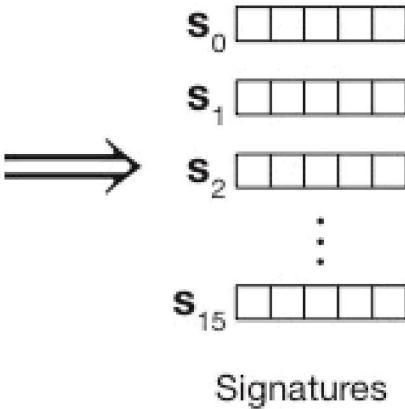
Analysis Partitions

Signatures Represent the Data on a Partition

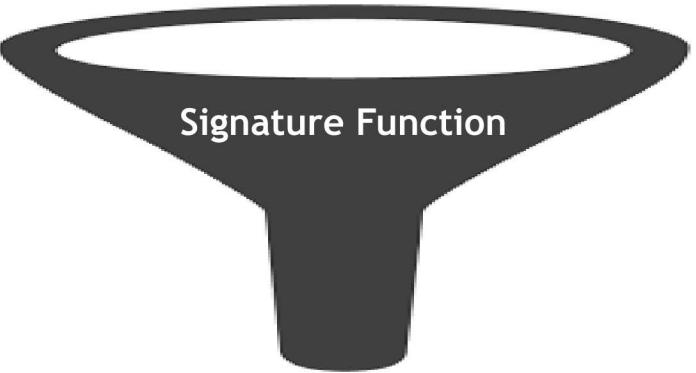


P_0	P_1	P_2	P_3
P_4	P_5	P_6	P_7
P_8	P_9	P_{10}	P_{11}
P_{12}	P_{13}	P_{14}	P_{15}

Analysis Partitions

Individual mesh attributes for P_0

Density	Pressure	Vx	Vy
10	4	2	4
20	10	8	8
30	8	8	12
40	6	2	16
.	.	.	.
40	6	2	16



- m Number of mesh points
- a Attributes per mesh point
- t m^*a , the total number of values on a partition

Signatures can be shorter or longer than a , as long as they are shorter than t



Signatures Can Take Many Forms

Examples

- Mean
 - Individual attribute mean values over the mesh points on a partition
- FIEDA Feature Importance Metric (FIM) scores *
 - First, kernel-density estimation to produce a probability distribution over the state variables
 - Next, random forests to predict the pdf given the state variables
 - Lastly, extract feature importance values from the random forest and use as a signature

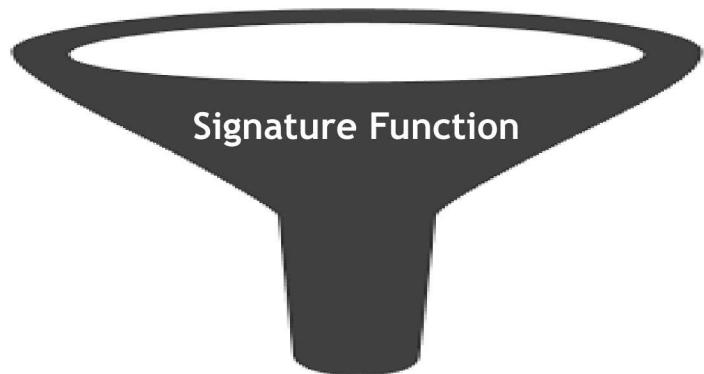
*Ling et al. “Using feature importance metrics to detect events of interest in scientific computing applications.” *2017 IEEE 7th Symposium on Large Data Analysis and Visualization (LDAV)* (2017): 55-63.

Signatures are significantly smaller than all the data on a partition, and can be communicated with little cost, comparatively.

Individual mesh attributes for P_0

Density	Pressure	Vx	Vy
10	4	2	4
20	10	8	8
30	8	8	12
40	6	2	16
		.	
		.	
		.	

40 6 2 16



25 7 5 10

Measures Indicate the Distance of a Signature From Neighbors

Measures take as input a list of $T P \times S$ matrices where T is the number of elapsed timesteps and each $P \times S$ matrix contains the signatures for the partitions at a given timestep.

Measures can be specific to a type of signature, or general measures, including typical anomaly detection algorithms

Examples

- Mean-Squared Distance
- DBSCAN
- FIEDA M1*

*Ling et al. “Using feature importance metrics to detect events of interest in scientific computing applications.” *2017 IEEE 7th Symposium on Large Data Analysis and Visualization (LDAV)* (2017): 55-63.

Decisions Allow for Customization



Measures are scalar values that do not, by themselves, answer whether something is anomalous.

Different applications can decide an appropriate anomalousness point

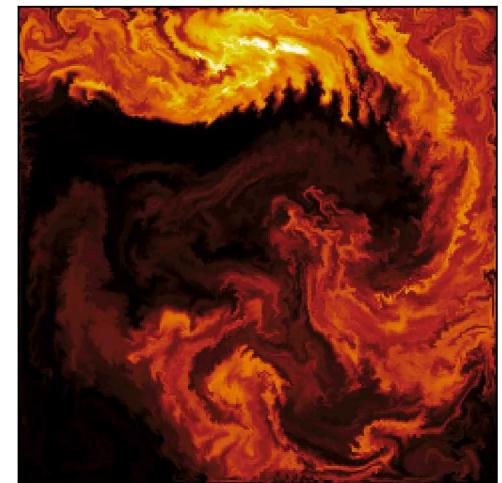
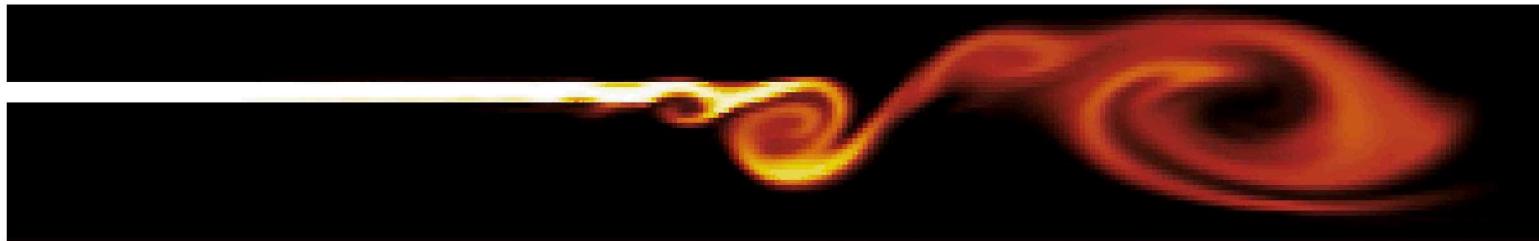
Examples

- Threshold
- Percentile-Change
- Memory / Feathering

Decision functions are meant to be adjustable to fit application needs and are the final arbiter of what is “interesting” in a simulation.

Rapid Development and Testing

- S3D is useful but too unwieldy for rapid experimentation
- Mantaflow (ETH Zurich, Technical University of Munich)
 - Mini-app that can be run on the desktop
 - Modified to simulate HPC environment (partitioning, inter-partition communication model)

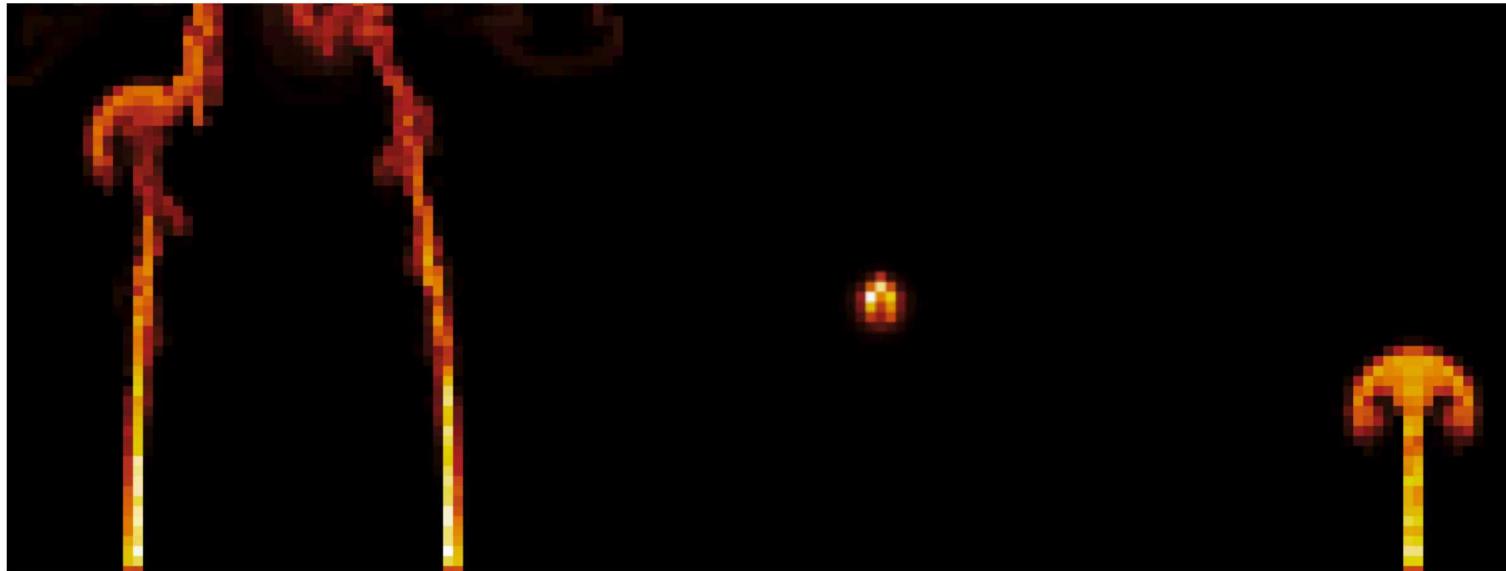


Approximately 30 new viable algorithms, some of which perform better than our previous published algorithms

Experiments and the Complexity of Measuring Performance



- Buoyant fluid injections simulated in Mantaflow
- Various algorithms capture different aspects of the simulation
 - Hard to get a crisp definition of accuracy vs. data efficiency
 - We devised a way of adding anomalies independent of the flow simulation
 - Modifications to mesh attributes that wouldn't be congruent with the simulation
 - Determining *recall* in relation to data export is now possible



We can measure the accuracy of our methods along with the data savings and compare to “snapshotting” and other approaches.

Summary

- Conventional approaches to anomaly detection in HPC simulations is insufficient, and this problem will grow
- Experiments have shown that in-situ anomaly detection is possible, both implementation-wise and algorithmically
- In-situ detection is more accurate and efficient
- Developed new algorithms and a framework for rapid development and testing