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

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Overview

- Problem Summary
- Framework and Approach
- Data and Applications
- Results
- Conclusions

Problem

Problem Summary

- Scientific computation often involves running computationally intense simulation on HPC
- With the goal being the identification and detection of events of interest, the current strategies for detection are lacking due to the I/O overhead that prevents all data from being written out
- Given that the current HPC Simulation strategy for event and anomaly detection involves saving data at regular intervals, two primary problems surface as a result:
    1. Writing at infrequent intervals leads to missed events and/or loss of critical information
    2. When information is lost, it can only be regained by re-running the simulation and adjusting the save intervals

Framework and Approach

Signatures, Measures, Decisions

Framework – Signatures, Measures, Decisions

- **Project:** ASCR In-Situ Machine Learning for Intelligent Data Capture on Exascale Platforms (ISML)
- The *Signature-Measures-Decision* framework is a generalized way of performing unsupervised anomaly detection
- Data space is defined as the dimensional space that contains all points in the dataset
- Partitions are defined as sections (typically equal sized) of the data space that may or may not contain data points
- The goal of the approach is to detect events of interest—any local (within a partition) occurrences that differ significantly from the occurrences in other partitions or in the same partition at different time steps

Approach – Signatures, Measures, Decisions

Signatures are a compressed way of representing the data in a partition; the representation should contain the crucial aspects of the data such that spatial and/or temporal changes can be detected

Examples:

- Mean
- Min-max
- SVD[9]

Approach – Measures

Measures are functions applied to signatures to detect changes across space or time; spatial measures compare signatures of different partitions at one time and temporal measures compare signatures of a single partition over time

Examples:

- Maximum change (temporal)
- SVD_9 (temporal)
- Mean squared distance (spatial)
- Signature scaling (spatial)
- DBSCAN

Approach – Decisions

Decisions are functions that determine whether the measure should be flagged as anomalous

Examples:

- Threshold
- Compound threshold
- Memory
- Percentile

Data and Applications

Spatial and Temporal

Data: Spatial and Temporal Event/Activity Detection

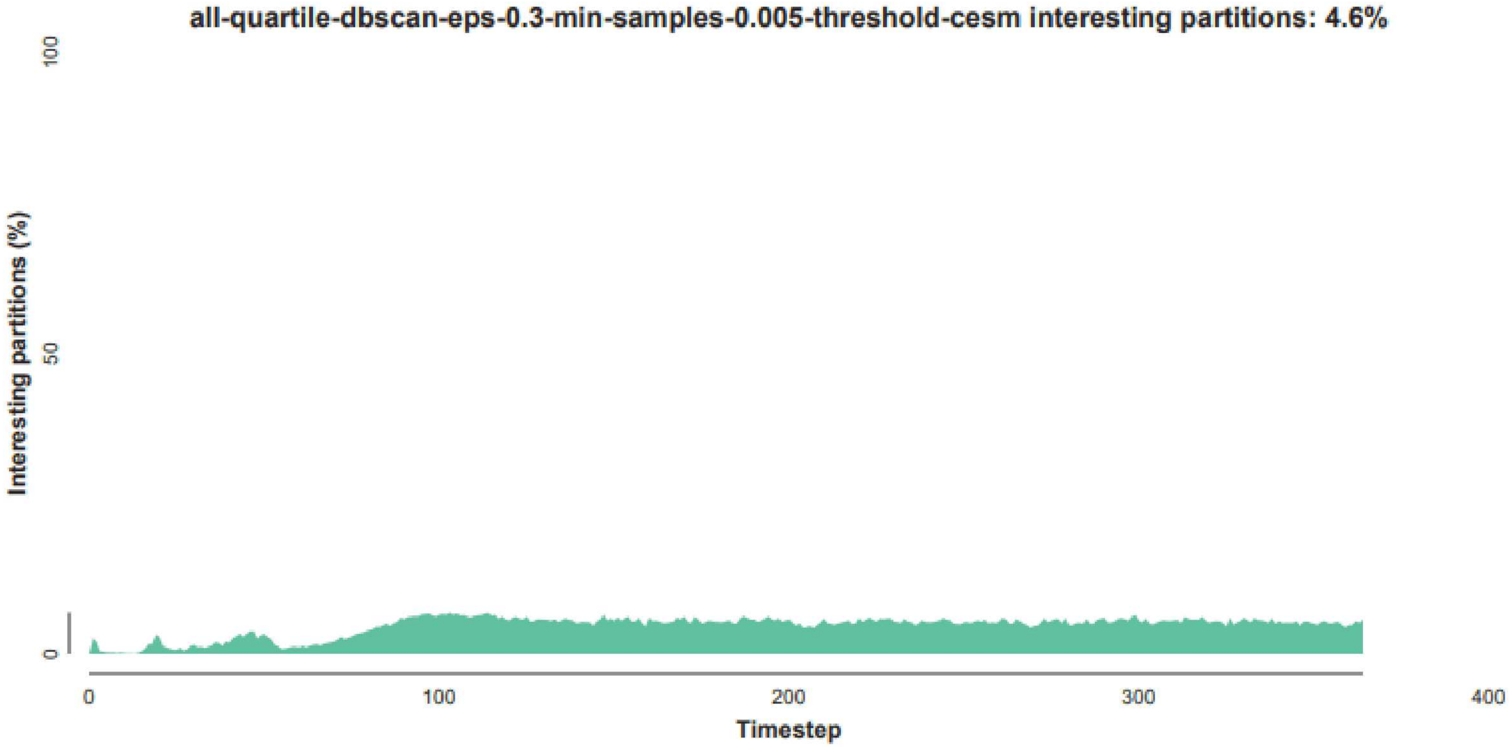
Simulation Case	Description	Features
Community Earth System Model (CESM)	Climate model simulation with events of interest being a set of cyclones throughout the simulation space	• Total Precipitation Rate • Surface Pressure • Lowest model level water vapor mixing ratio • Atmospheric air temperature • Lowest model level zonal wind • Lowest model level meridional wind • Atmospheric reference height
Mantaflow	Fluid model simulation with events of interest being the activity/changes throughout the simulation space	• Velocity X • Velocity Y • Density • Pressure

Results

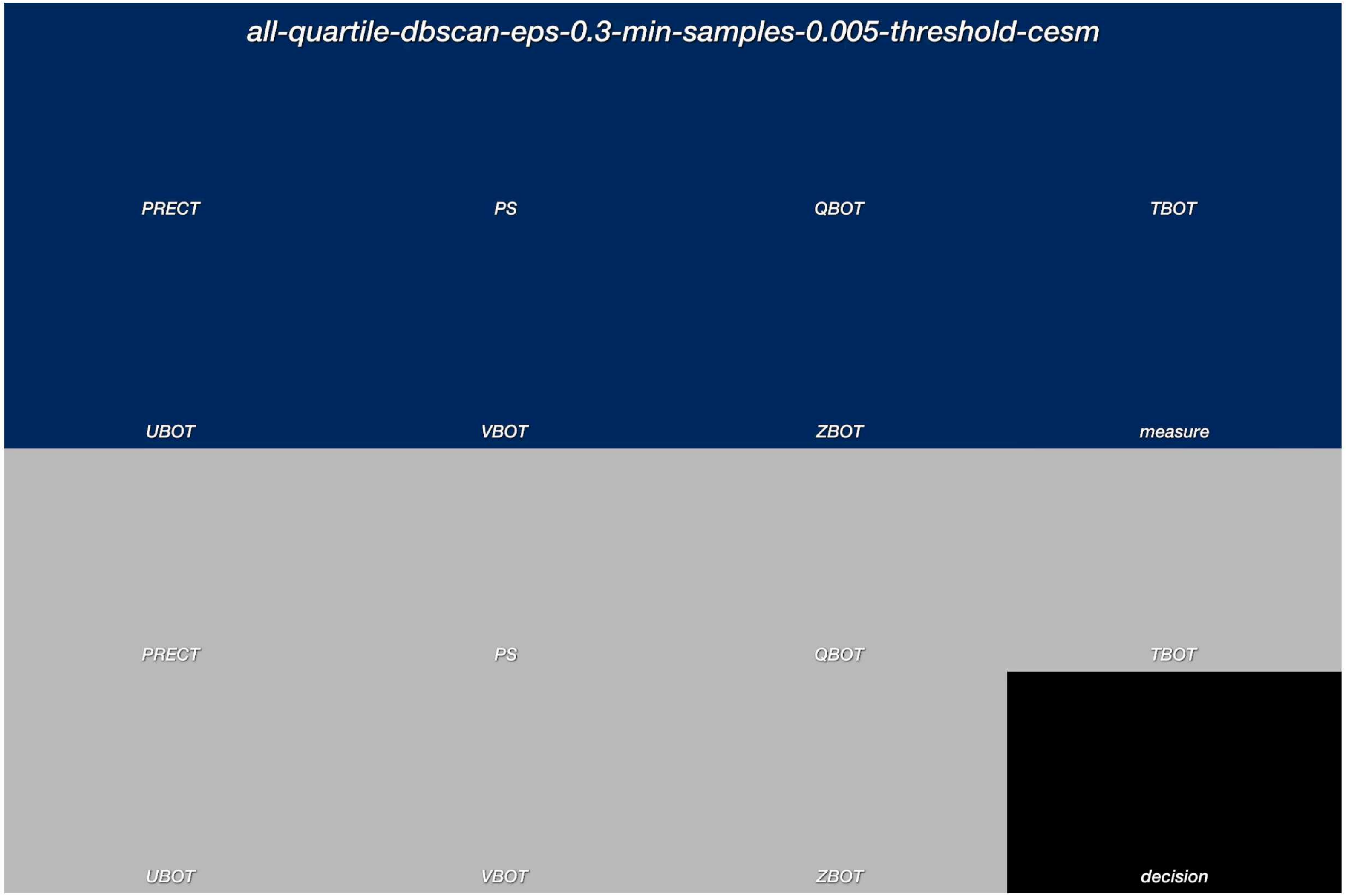
Spatial and Temporal

Results

Percentage of Data Saved Over Time

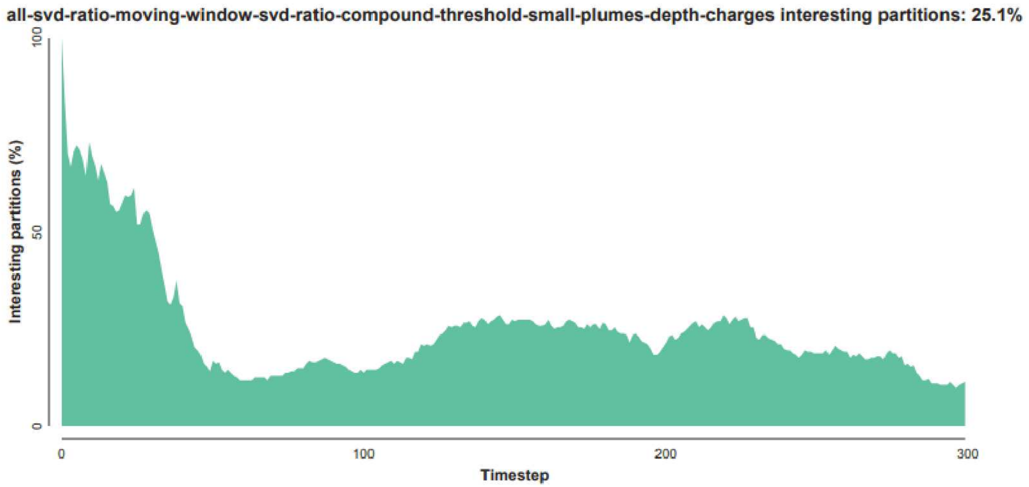


Results: Spatial Event/Activity Detection – Cyclones (CESM)

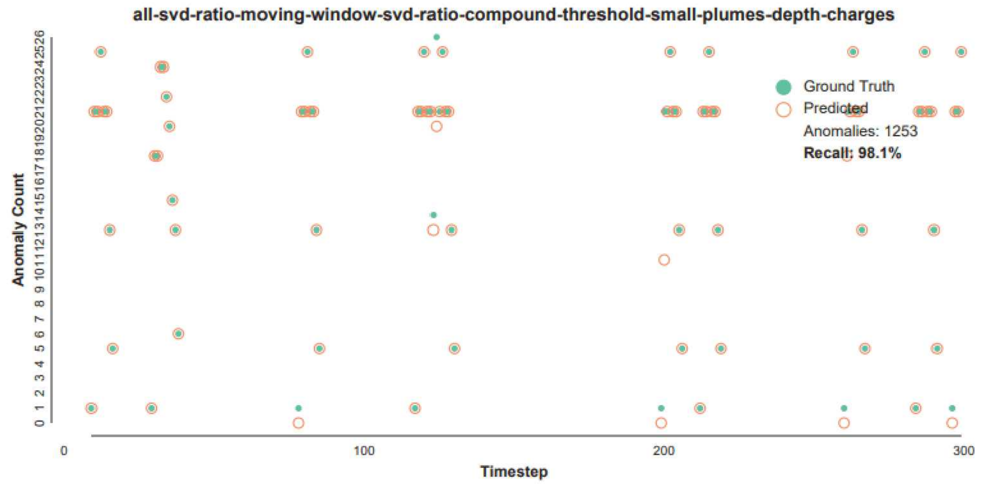


Results

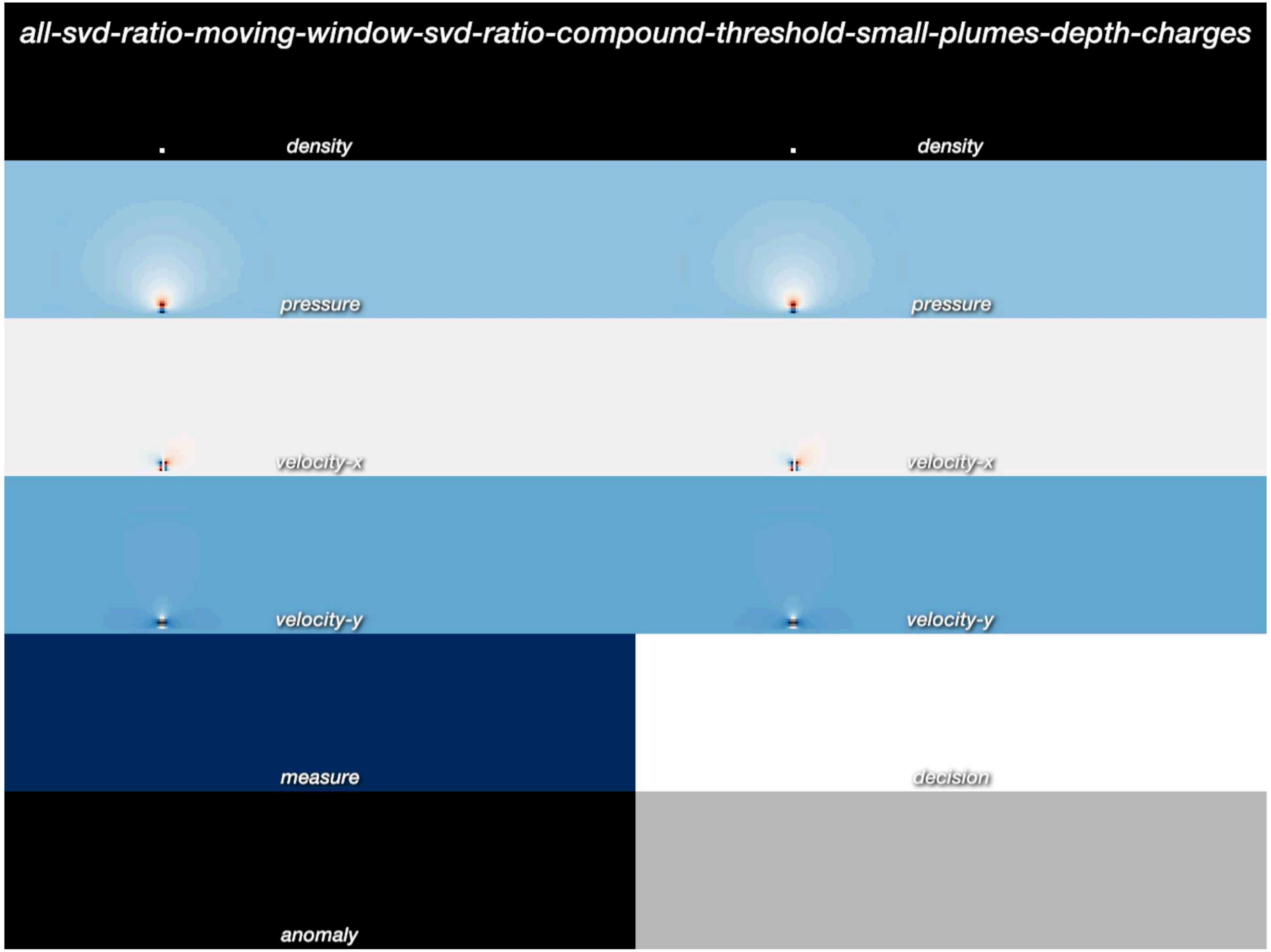
Percentage of Data Saved Over Time



Recall



Results: Temporal Event/Activity Detection – Smoke Plumes



Conclusion

- The framework is capable of detecting events of interest with high and similar accuracy, whether detecting events spatially or temporally
- Though the experiments have been run on simulation data so far, the approach can generalized to other fields and application domains (cyber security, satellite image analysis)
- A major key in applying the framework to other areas is the ability to extract quantifiable features from the data
- The in-situ detection is efficient and accurate

Questions?

Relevant Literature

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