Decision Superiority AI

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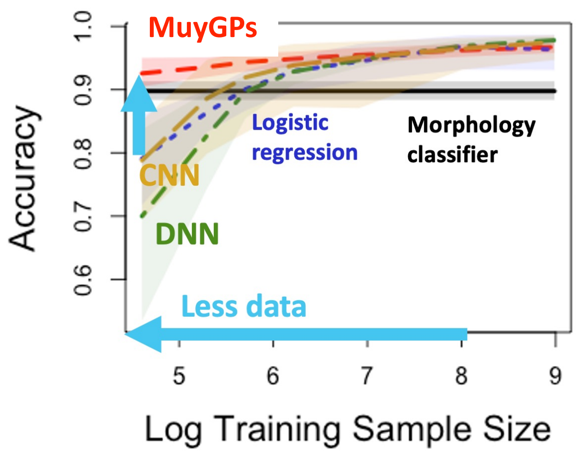
So what? Who cares?

- **Space:** CBP processing of massive data with AI
- **Problem:** Can't get enough data and time to market is too long
- **Solution:** Novel computing and algorithm approaches short-circuit neural network requirements for big data and expensive training
- **Results:** Tools applied to numerous problems and are applicable to CBP
- **TRL:** 5

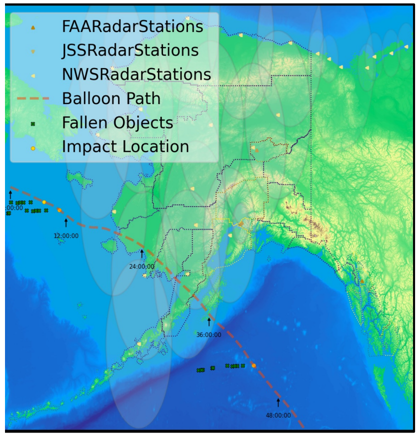
Given limited training data, LLNL's MuyGPs code performs much better than conventional deep learning for an image classification task.



https://github.com/LLNL/MuyGPyS

LLNL's data-driven environment generator shortens time to market for scenario analysis and decision support; easily configurable for CBP problems

Alaska air defense scenario against foreign balloon overflight



Built in 4 months

< 5 min to reconfigure

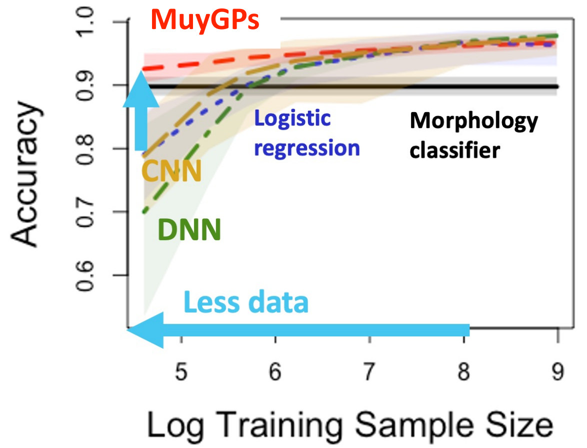
Data Types
US Topographic
US Bathymetric
Global Bathymetric
3D Building Information
US Census Bureau
Weather

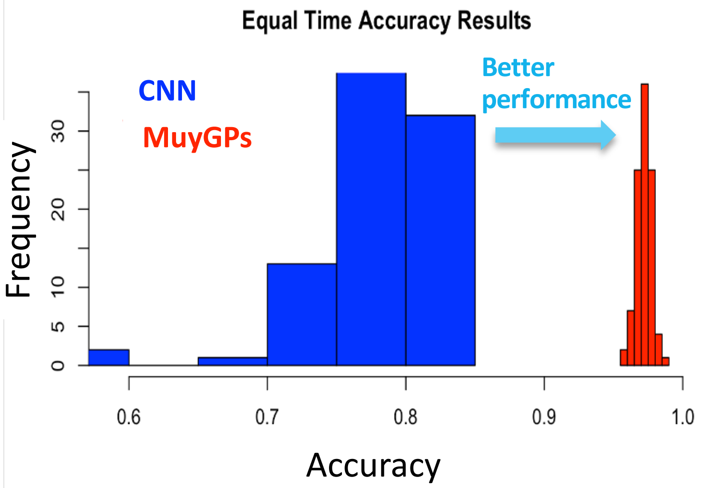
GLOBAL SECURITY

DECISION SUPERIORITY LABORATORY

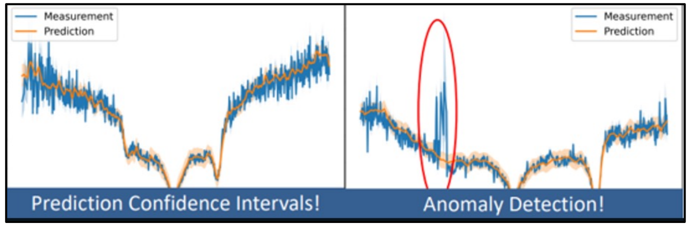
Real-time technical assessments enabled by a new LLNL-developed machine learning code that leads several benchmarks

Given limited training data (left) or a fixed amount of time to re-train (right),LLNL's `MuyGPyS` code performs much better than conventional deep learning for an image classification task.

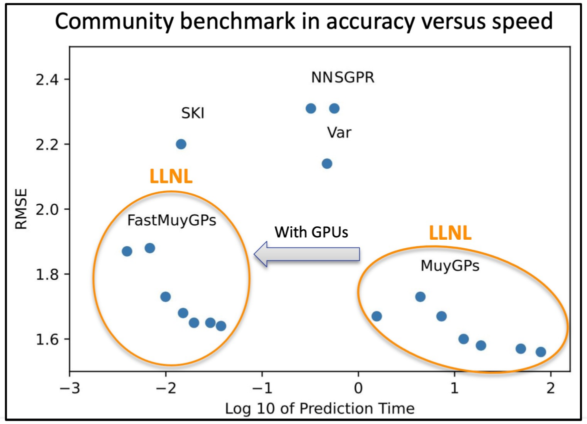




Distribution-based uncertainty quantification enables anomaly identification against historical patterns of life



Best ML paper at 2022 AMOS tech conference



- Faster to train and more accurate than neural networks for noisy, sparse, or incomplete data
- Native and meaningful uncertainty quantification to aid interpretability
- More robust to neural network adversarial attacks
- Based on linear algebra operations that are already tuned for conventional HPC
- Traditional HPC parallelism enabled using bespoke LLNL codes
- Open-source code, https://github.com/LLNL/MuyGPyS

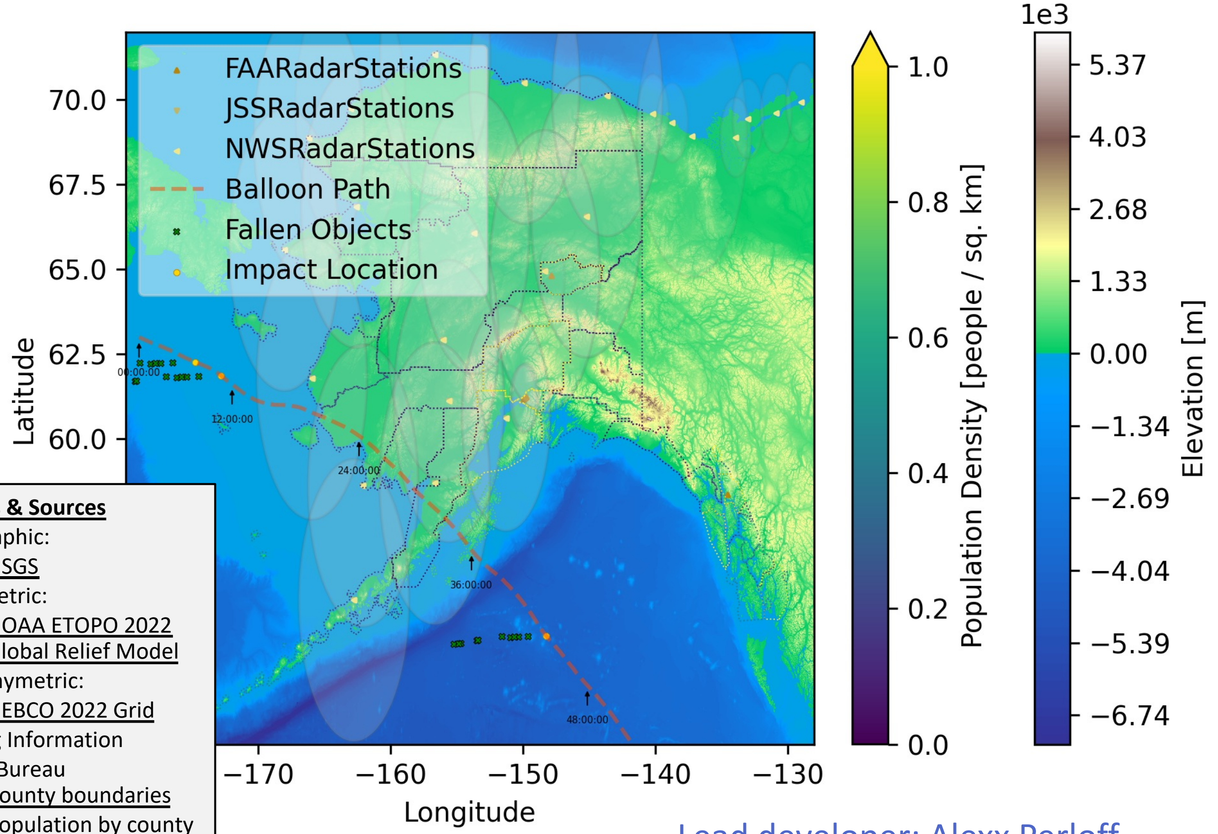
Project led by Amanda Muyskens, Ben Priest

ArXiv papers: 2104.14581, 2105.01106, 2107.09246, 2205.10879, 2208.14592, 2209.11280

GISKARD: A data-driven dynamic environment generator supports real-time algorithmic planning

- Real-time environment built & updated by multiple open-source data feeds
- Pull in and process information relevant to the problem:
  - Location
  - Scale/fidelity
  - Time
- Use best, most relevant information available
- Low time to completion

Alaska air defense scenario against foreign balloon overflight



Data Types & Sources
US Topographic:
USGS
US Bathymetric:
NOAA ETOPO 2022
Global Relief Model
Global Bathymetric:
GEBCO 2022 Grid
3D Building Information
US Census Bureau
County boundaries
Population by county
Weather

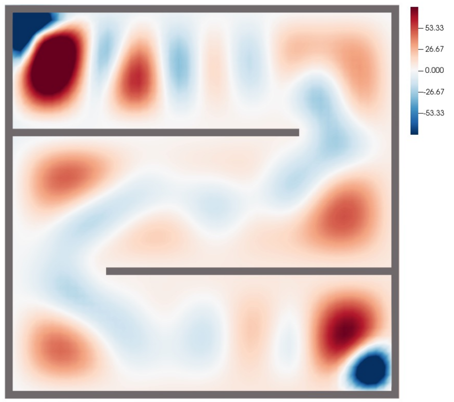
Lead developer: Alexx Perloff

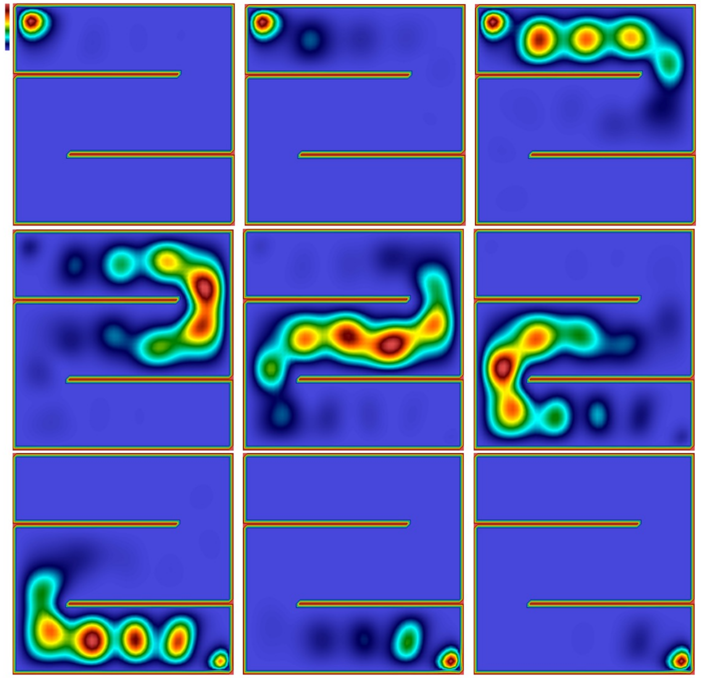
Enables flexible threat and response assessments with real-time data

LLNL's Parallel Agent Dynamical Learning (PADL) code applies novel algorithms to scalable real-time training of AI agents

- Use the digital environment and add a <u>learned component</u> for an AI agent to <u>optimally achieve a specified objective</u> (*i.e.*, engagement windows, paths, operational initiatives, etc.)
- Expensive offline training simulations in conventional RL are traded for <u>real-time adaptation</u> to dynamic environments
- Parallelizable computation allows for large scale (physical space, time, complexity) solutions
- The environment and the learned insights overlays can be exported to other platforms for visualization and interpretation

Bellman optimization (which is the foundation of both optimal control and reinforcement learning) is solved via a recently discovered equivalent dynamical system representation, which requires only well-established parallel numerical methods.





The probability density of an optimally controlled agent navigating a simple maze can be predicted by solving a completely integrable system.

Source: https://arxiv.org/abs/2212.00249

Lead developer: Jane Pratt

Decision superiority is enabled by optimizing threat response dynamics to achieve operational objectives

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Collaborations welcome on data feeds, environment models, and AI/ML applications.

Lawrence Livermore National Laboratory

LLNL is developing custom tools to address capability gaps in real-time decision support applications

Interpretable AI at the edge, with (re-)training in near-real-time

MACHINE LEARNING (MUYGPS)

Real-time global data integration

GEOSPATIAL INFORMATION SYSTEM FOR KNOWLEDGE AND RAPID DECISIONS (GISKARD)

Scalable online planning

PARALLEL AGENT DYNAMICAL LEARNING (PADL)