

Machine Learning and Turbulent Flows: Learning from Turbulence Simulation Data Sets

Sandia National Laboratories

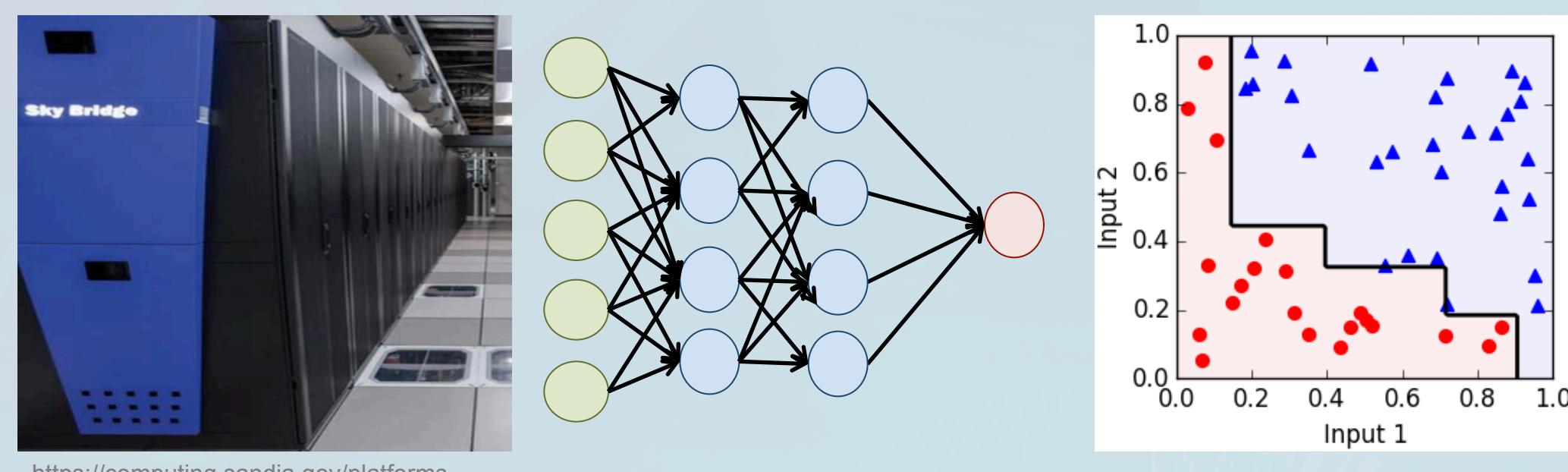
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Problem

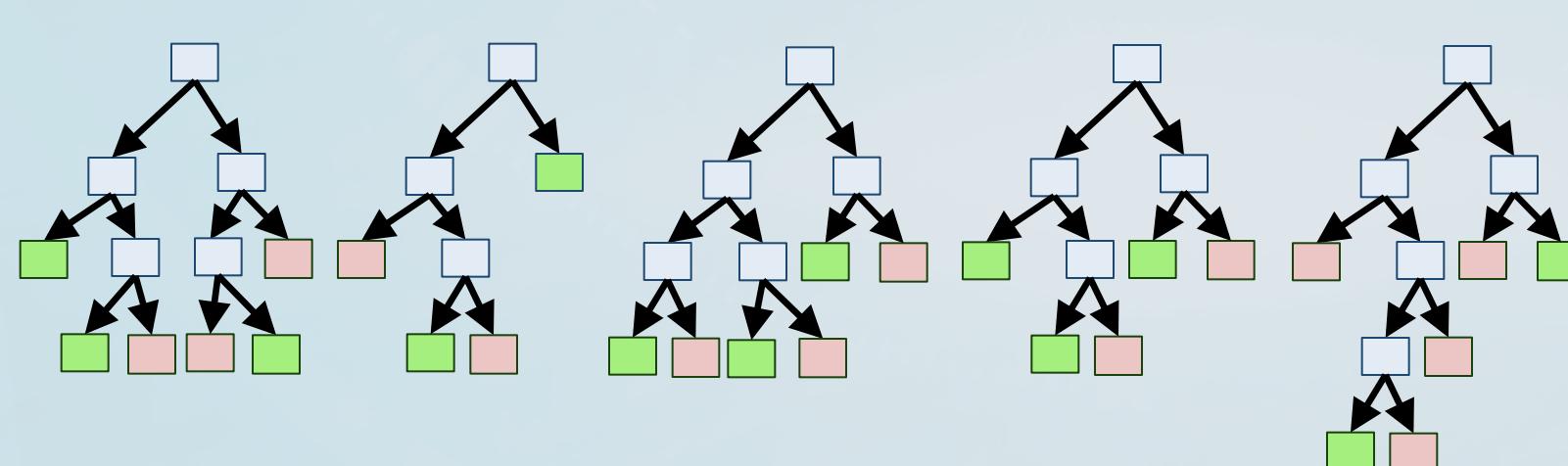


- Turbulent flows occur in many applications of interest at Sandia
- High fidelity Direct Numerical Simulations (DNS) are computationally expensive—not feasible for many flows
- Reynolds Averaged Navier Stokes (RANS) turbulence models are used to simulate these flows in a computationally tractable way
 - These models suffer from high model form uncertainty in many engineering-relevant flows
- Key Sandia applications in energy, safety, and security require accurate turbulence models with quantified uncertainty

Approach



- Computational Fluid Dynamics (CFD) simulations are being run on bigger and bigger machines, and are generating more and more data
- What we need is a way to learn from all this data
- Machine learning is a set of data-driven algorithms for regression, classification, clustering
 - Scalable to high-dimensional, big data
- Use machine learning methods to flag regions of high uncertainty in empirical RANS simulations
 - Random Forests are a supervised classification algorithm based on an ensemble of decision trees



- We use Random Forest classifiers trained on a database of flows for which both high fidelity (DNS) as well as RANS results are available
- Scientific domain knowledge and machine learning should work synergistically

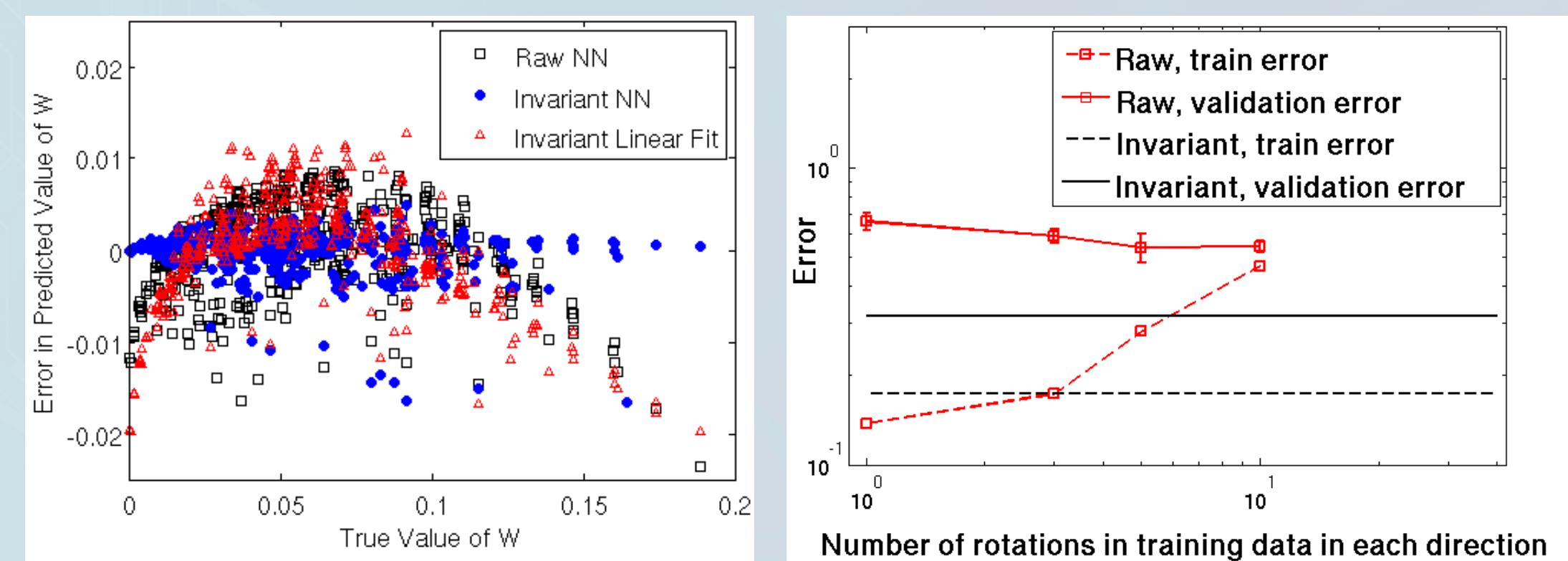
References

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Results

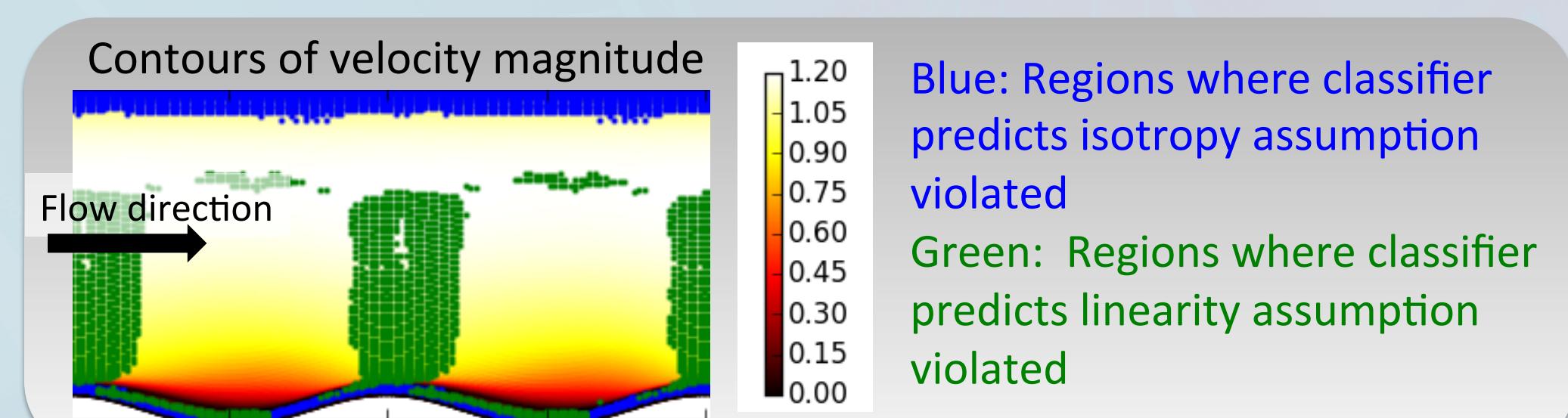
Embed Physical Symmetries

- Many physical systems have known invariance properties
- Applied concepts from group theory and representation theory to create a basis of invariant inputs for the machine learning models
- Demonstrated 100 X reduction in training time versus brute force approach that did not embed symmetry
- Applied to cases in turbulence modeling and crystal elasticity



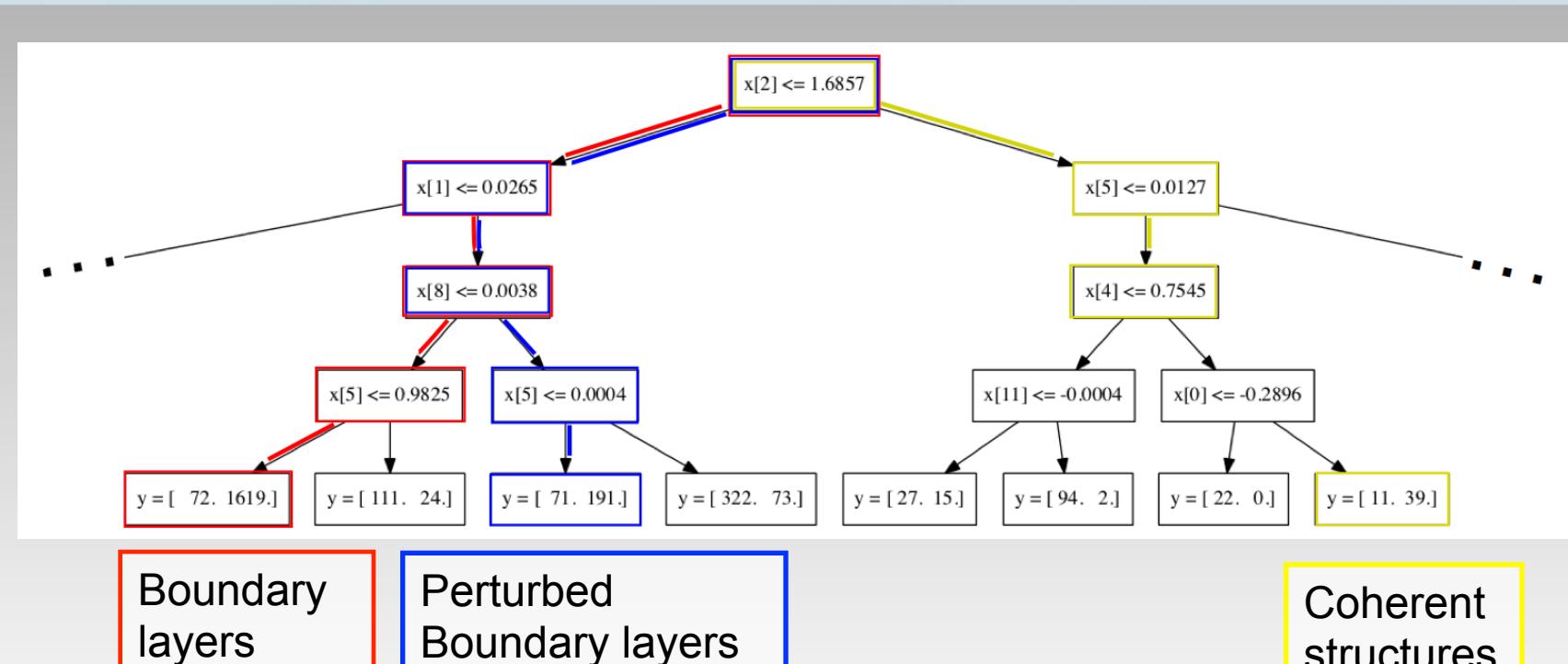
Flag Regions of High RANS Uncertainty

- Developed machine learning classifiers to flag regions where turbulence model assumptions are violated
 - Inputs are local RANS flow variables
- Achieved 3 X more accurate error detection than previous state-of-the-art



Rule Extraction for Physical Intuition

- Machine learning models are often treated as "black boxes"
- Used rule extraction to regain physical intuition for improved turbulence models from these complex data-driven models



Significance

- Machine learning enables the assessment of model form uncertainty in turbulence models used for mission applications
- Rule extraction provides physical intuition for the development of new turbulence models with improved accuracy
- Future work will develop data-driven model closures to achieve predictive accuracy in turbulence simulations on Sandia applications