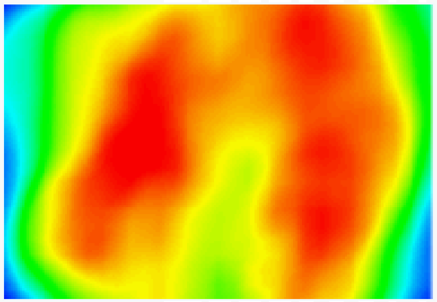
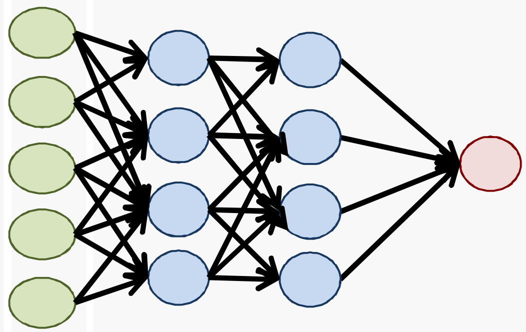
SAND2017-0870C





Sandia National Laboratories

Deep Learning for Turbulence Modeling

Julia Ling, Andrew Kurzawski, Jeremy Templeton

February 2017

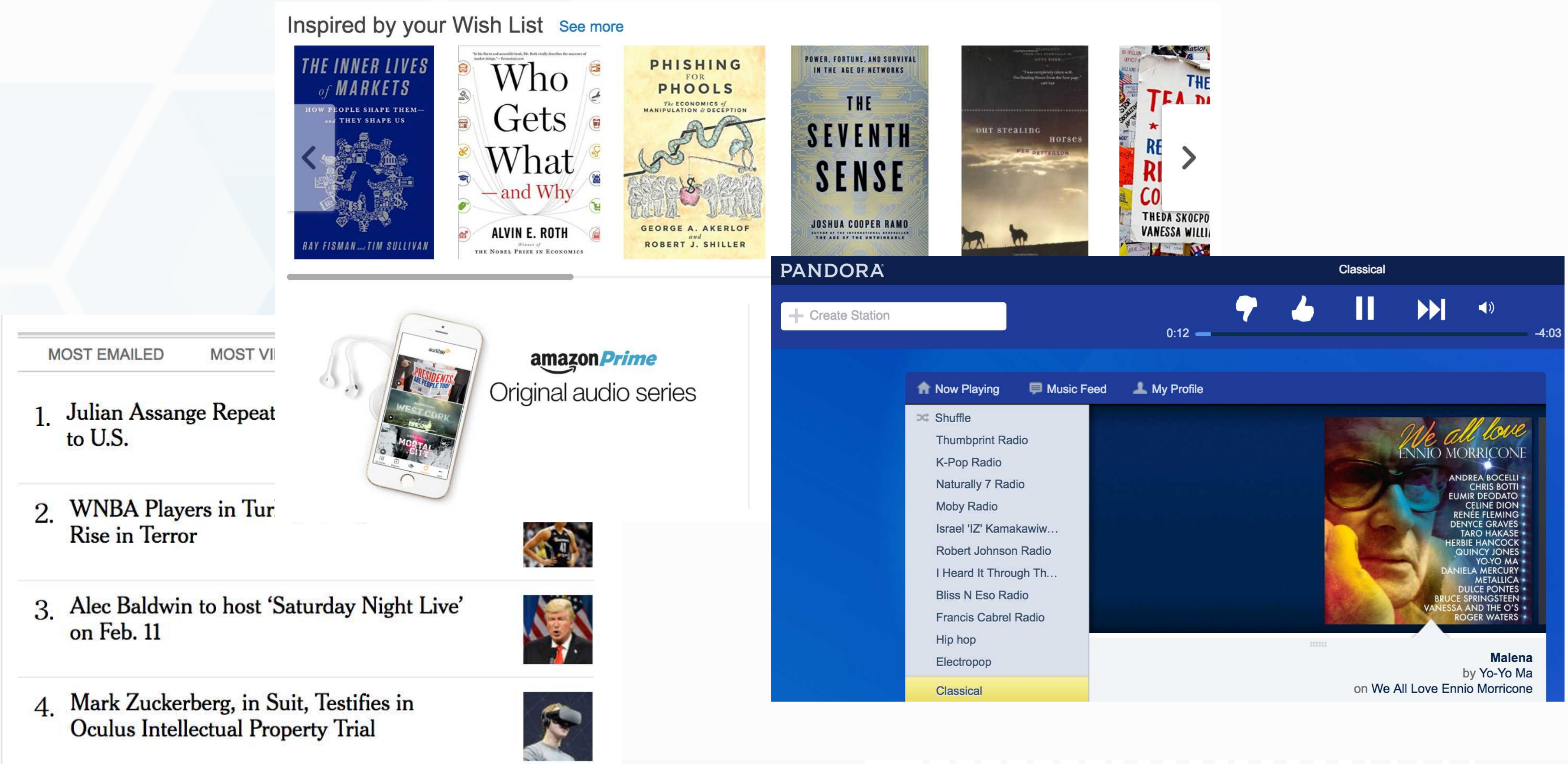
U.S. DEPARTMENT OF ENERGY

NNSA National Nuclear Security Administration

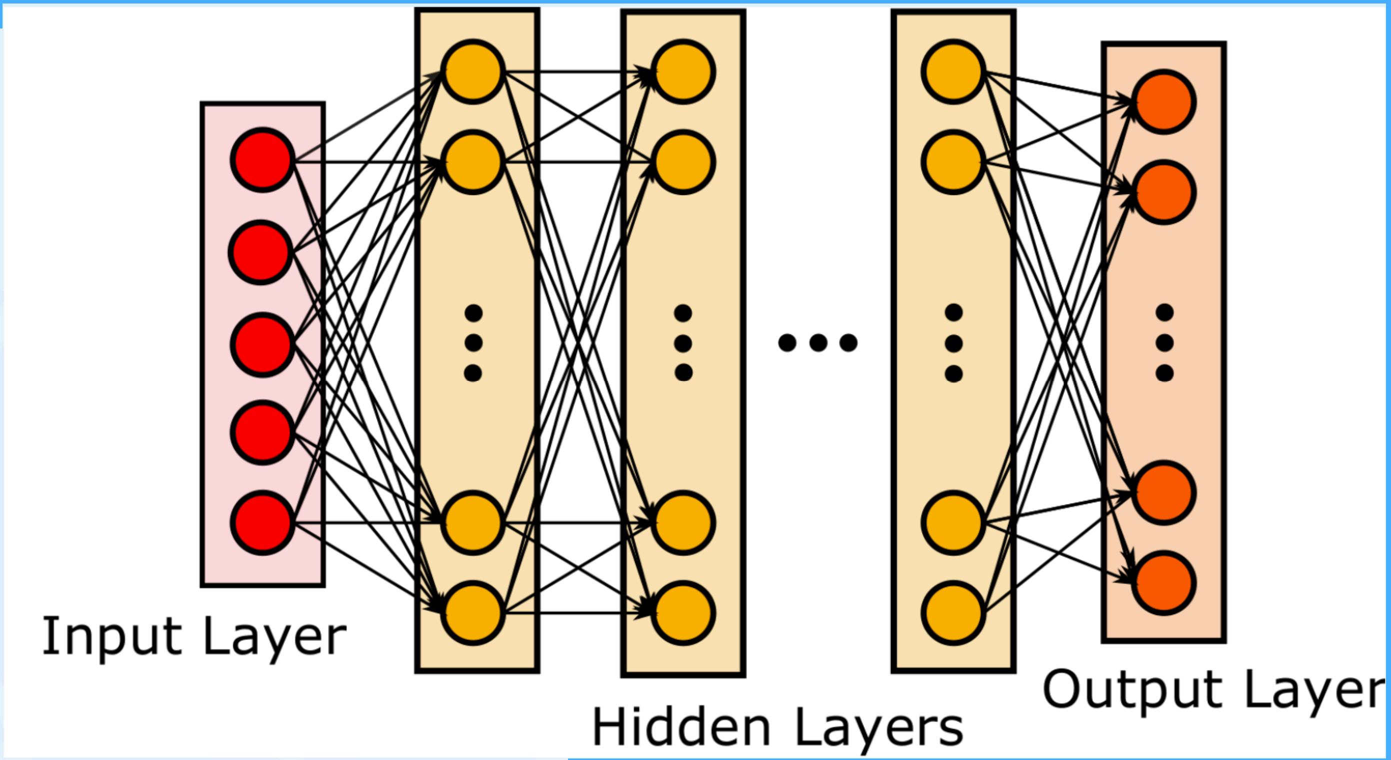
Sandia National Laboratories is a multi-program laboratory managed and operated by Sandia Corporation, a wholly owned subsidiary of Lockheed Martin Corporation, for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-AC04-94AL85000.

What is Machine Learning?

- Data-driven algorithms to discern patterns and make predictions on big, high-dimensional data
- Linear regression, support vector machines, neural networks



Neural Networks and Deep Learning



$$y = f(w^T x)$$

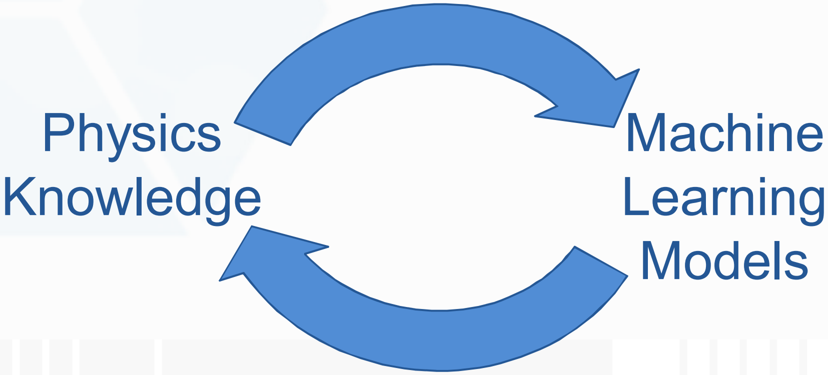
Turbulence Simulations

- Many physical processes are inherently multi-scale and require constitutive models
- Growing interest in applying machine learning to constitutive modeling
- Leverage the massive data sets from high fidelity simulations and high-res experiments
- We present a method for using deep neural networks to learn a turbulence model

Hokusai (c 1830)

http://www.windturbinesyndrome.com/2011/wind-turbine-turbulence-what-are-the-micro-climate-effects/

https://brilliant.org/wiki/rocket-physics/



Deep Learning for Turbulence Modeling

- In Reynolds Averaged Navier Stokes (RANS), use simplifying assumptions to get computational efficiency
  - Need model for unknown term: the Reynolds stress anisotropy tensor **A**
- Default model: Linear Eddy Viscosity Model
  - Based on theory + sparse experimental data
- Our approach: Deep neural network
- Inputs: Mean strain rate tensor **S**, mean rotation rate tensor **R**
- Outputs: Reynolds stress anisotropy **A**

W. P. JONES and B. E. LAUNDER

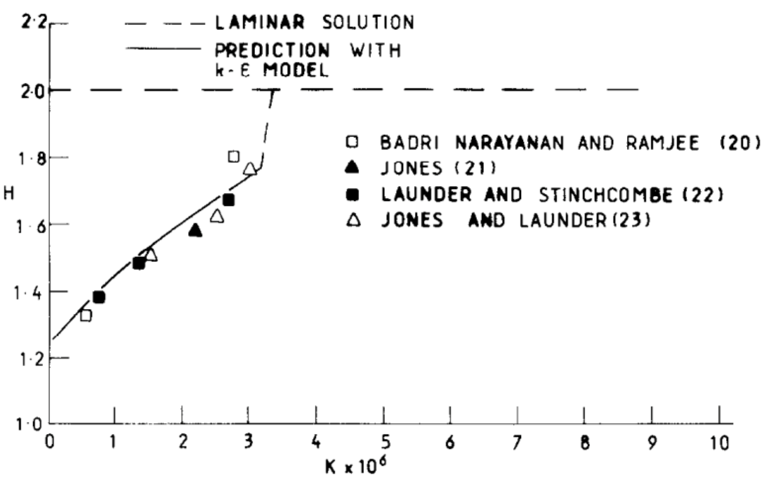


FIG. 2. Sink flow turbulent boundary layers.

(1973)

Deep Learning for Turbulence Modeling

- Inputs: Tensors **S**, **R**
- Output: Tensor **A**

- Would like to enforce Galilean invariance
  - Invariance to inertial coordinate frame transformations

$$\mathbf{A}(\mathbf{Q}\mathbf{S}\mathbf{Q}^T, \mathbf{Q}\mathbf{R}\mathbf{Q}^T) = \mathbf{Q}\mathbf{A}(\mathbf{S}, \mathbf{R})\mathbf{Q}^T$$

  - Borrow some ideas from group theory, representation theory
  - All Galilean invariant tensors that are a function of **S** and **R** lie on a tensor basis: the *integrity basis* of **S** and **R** for the orthogonal group

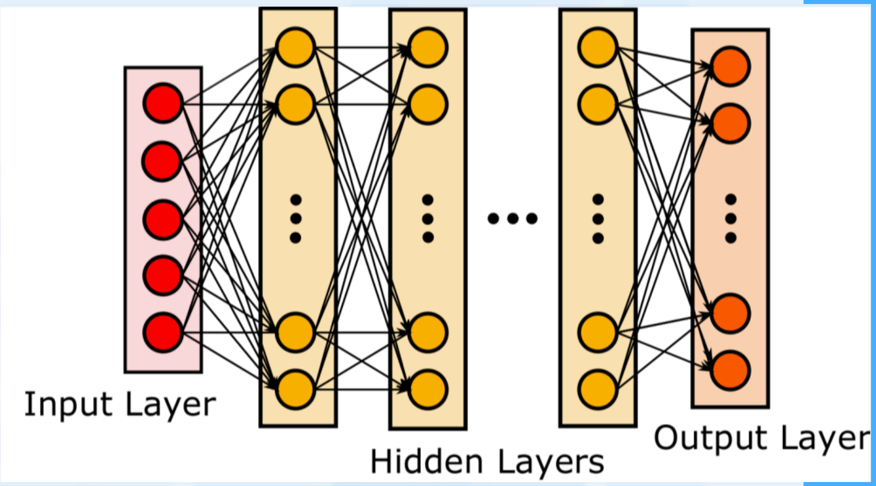
$$\mathbf{A} = \sum_{n=1}^{10} f^{(n)} \mathbf{B}^{(n)}$$

Unknown coefficients

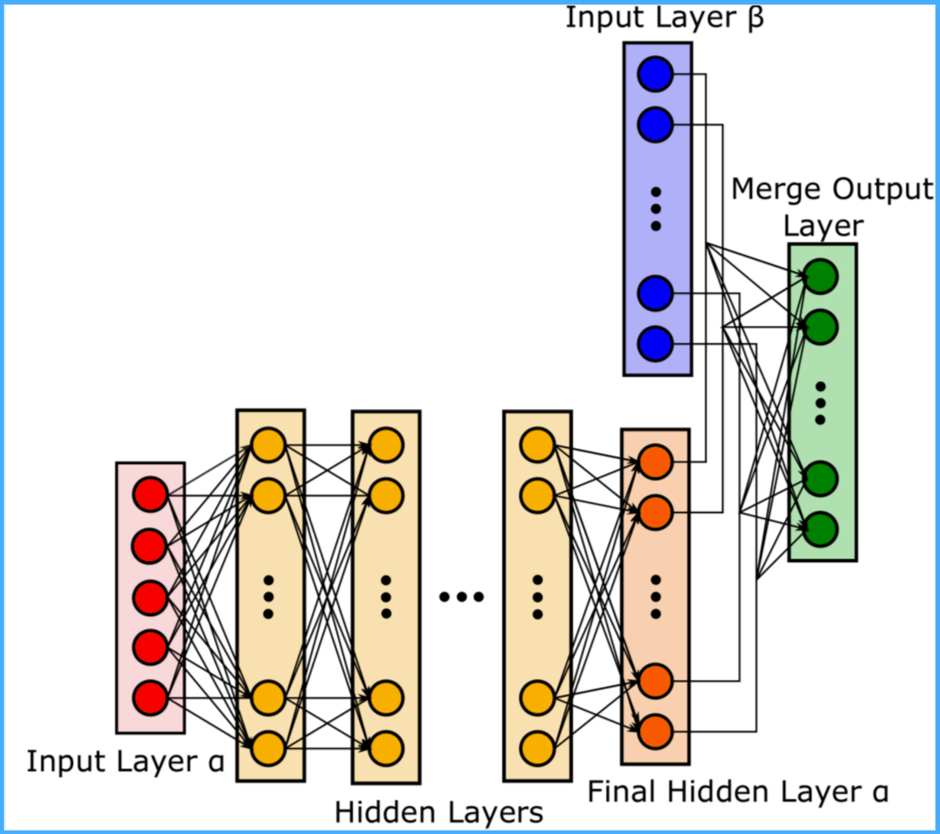
Known Tensor Basis

Embedding Galilean Invariance

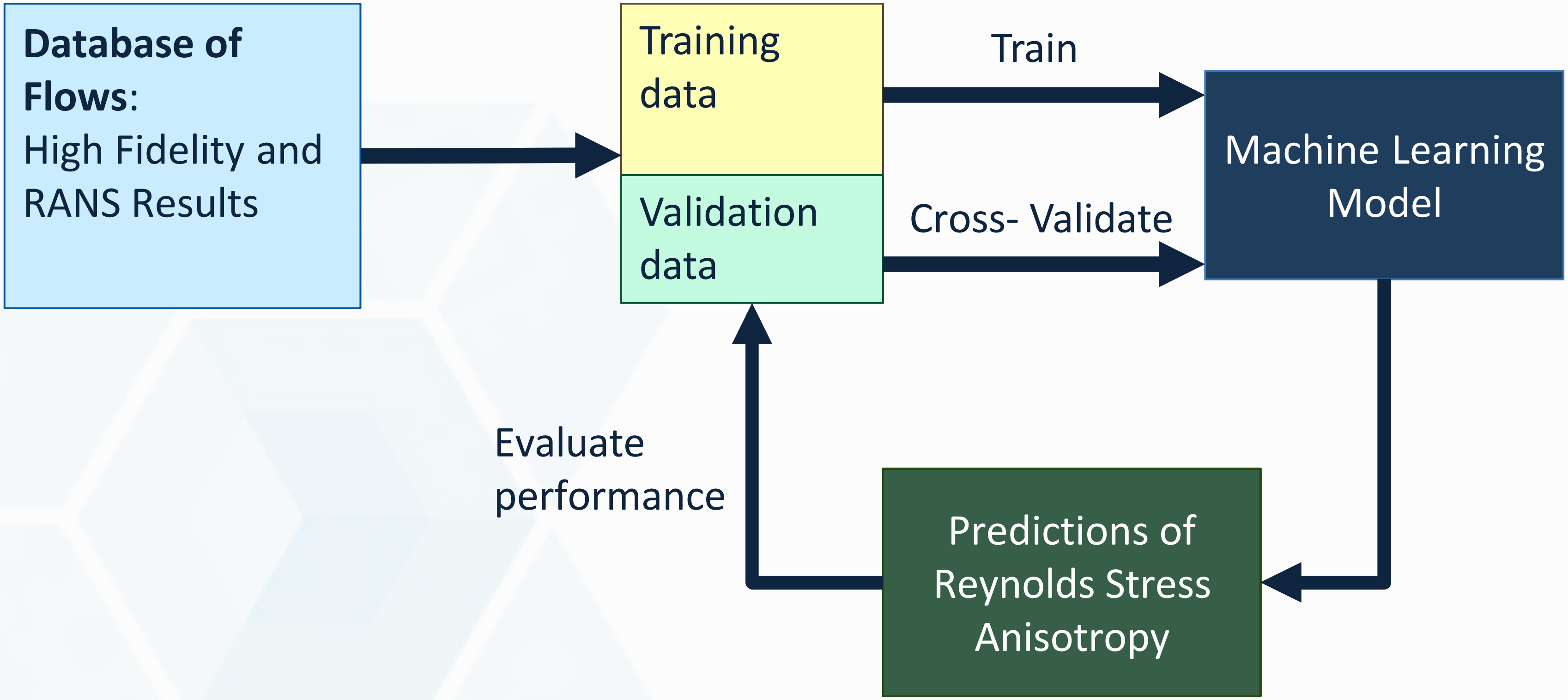
Multi-Layer Perceptron (MLP)



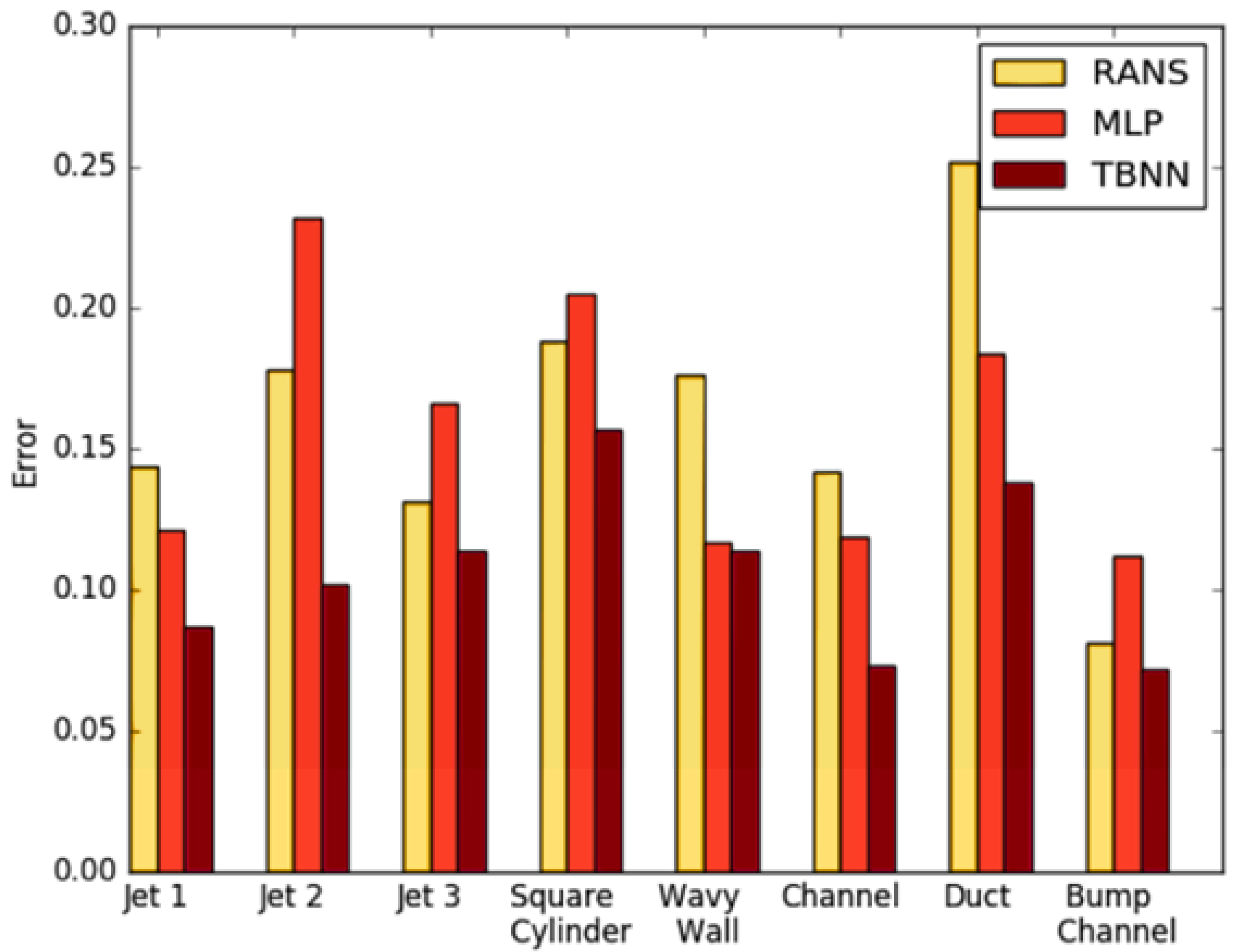
Tensor Basis Neural Network (TBNN)



Model Development



Deep Learning for Turbulence Modeling

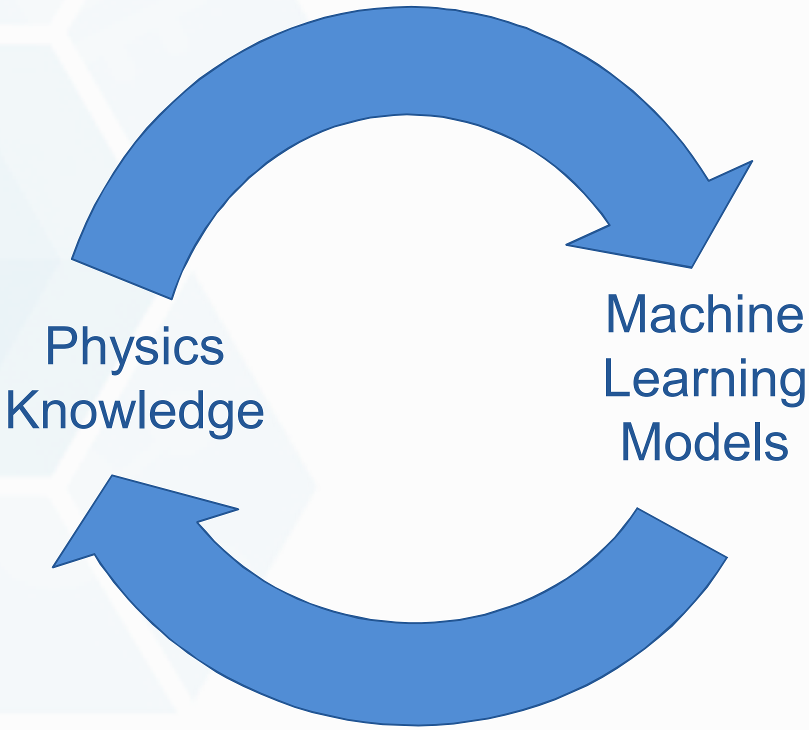


Conclusions

- Developed network architecture to embed known tensor invariance property
- Demonstrated significant improvement over conventional eddy viscosity models, at orders of magnitude lower computational cost than DNS
- First application of deep learning to RANS turbulence modeling

Machine Learning on Physics Systems

Directly embedding scientific domain knowledge into machine learning models can give improved performance, especially in data-limited scenarios



References

- J. Ling, A. Kurzawski, and J. Templeton, “Reynolds Averaged Turbulence Modeling using Deep Neural Networks with Embedded Invariance,” Journal of Fluid Mechanics, (2016).
- J. Ling and J. Templeton, “Evaluation of machine learning algorithms for prediction of regions of high Reynolds averaged Navier Stokes uncertainty,” Physics of Fluids, (2015).
- J. Ling, A. Ruiz, G. Lacaze, and J. Oefelein, “Uncertainty analysis and data-driven model advances for a Jet-in-Crossflow,” Journal of Turbomachinery, (2016).
- J. Ling, R. Jones, and J. Templeton, “Machine Learning Strategies for Systems with Invariance Properties,” J. Comp. Phys., (2016).

Questions?