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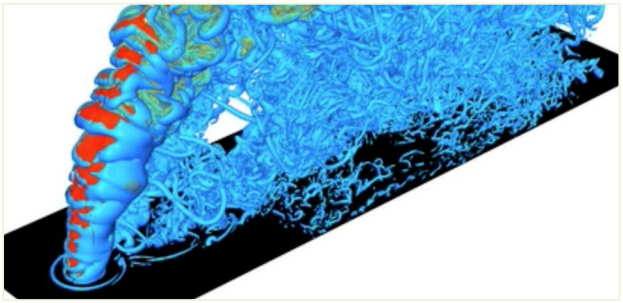

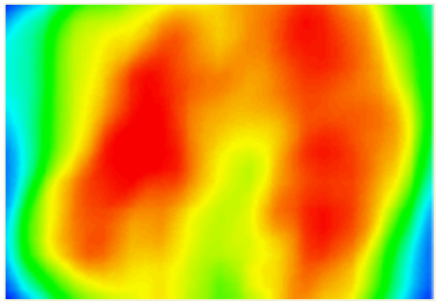

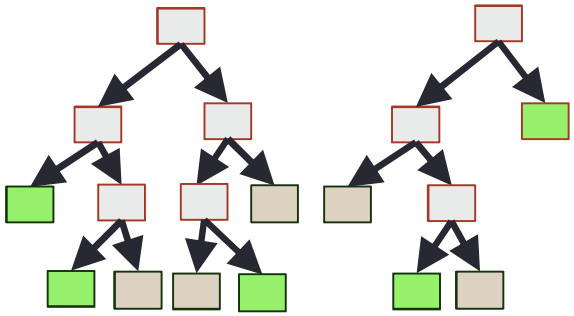

MACHINE LEARNING FOR TURBULENCE MODELING

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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.

About Me

- B.A. in Physics from Princeton
- M.S., Ph.D. in Mechanical Engineering from Stanford
  - Doctoral research focused on optimizing a heat transfer model for gas turbine film cooling applications
- Currently a Truman Fellow at Sandia National Labs in Livermore, CA
- Interested in machine learning on scientific/engineering applications
- Other interests: Tennis, scuba, surfing

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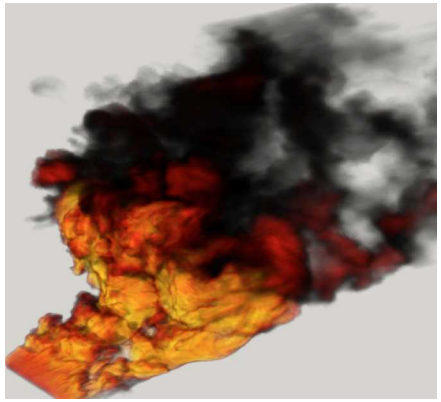
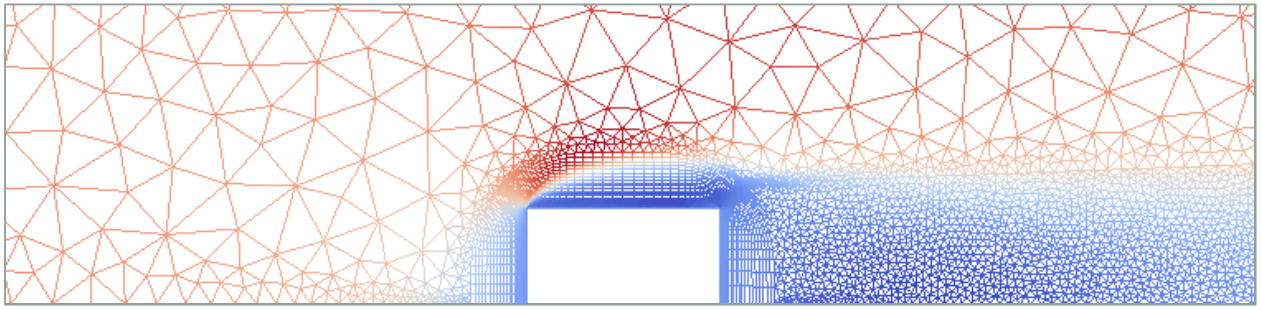
Turbulence Simulations





Direct Numerical Simulation (DNS)

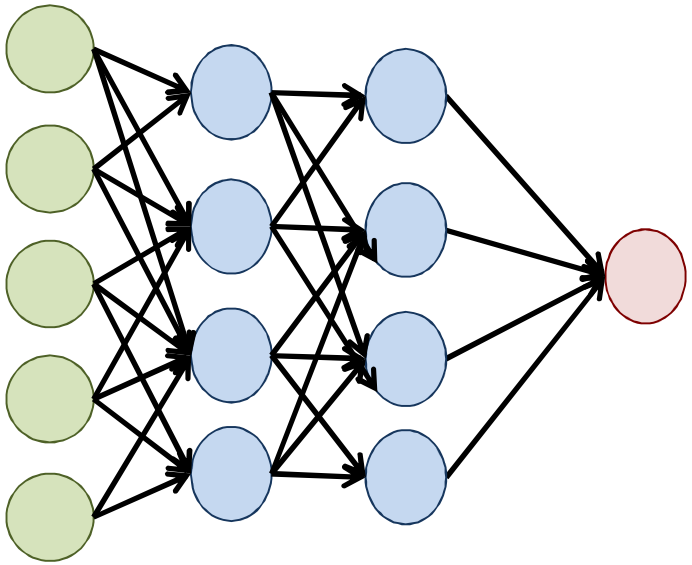
- Hundreds of millions of core hours for even simple flows
- Exact

Reynolds Averaged Navier Stokes (RANS)

- Orders of magnitude less computationally expensive
- Approximate

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 **b**
- Default model: Linear Eddy Viscosity Model (LEVM)
- Our approach: Deep neural network
- Inputs: mean strain rate tensor **S**, mean rotation rate tensor **R**
- Outputs: Reynolds stress anisotropy **b**



Galilean Invariance

Not your typical machine learning problem: tensor inputs and outputs

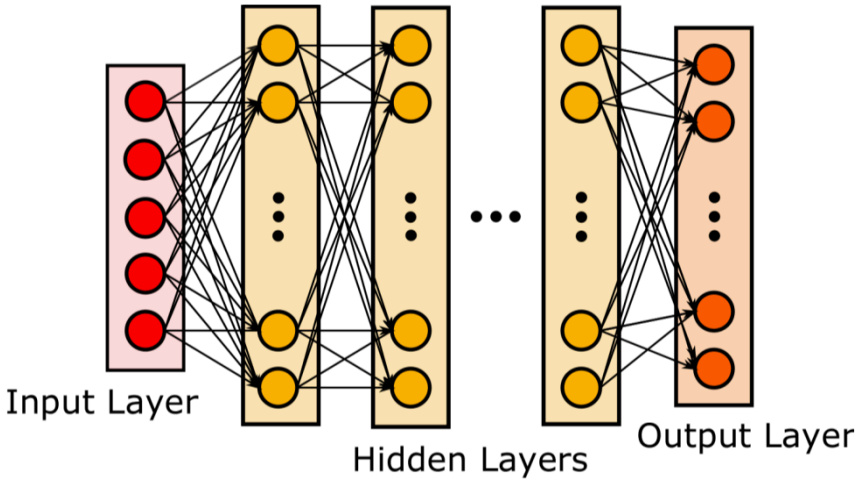
Would like to enforce Galilean invariance

- Invariance to inertial coordinate frame transformations
- 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

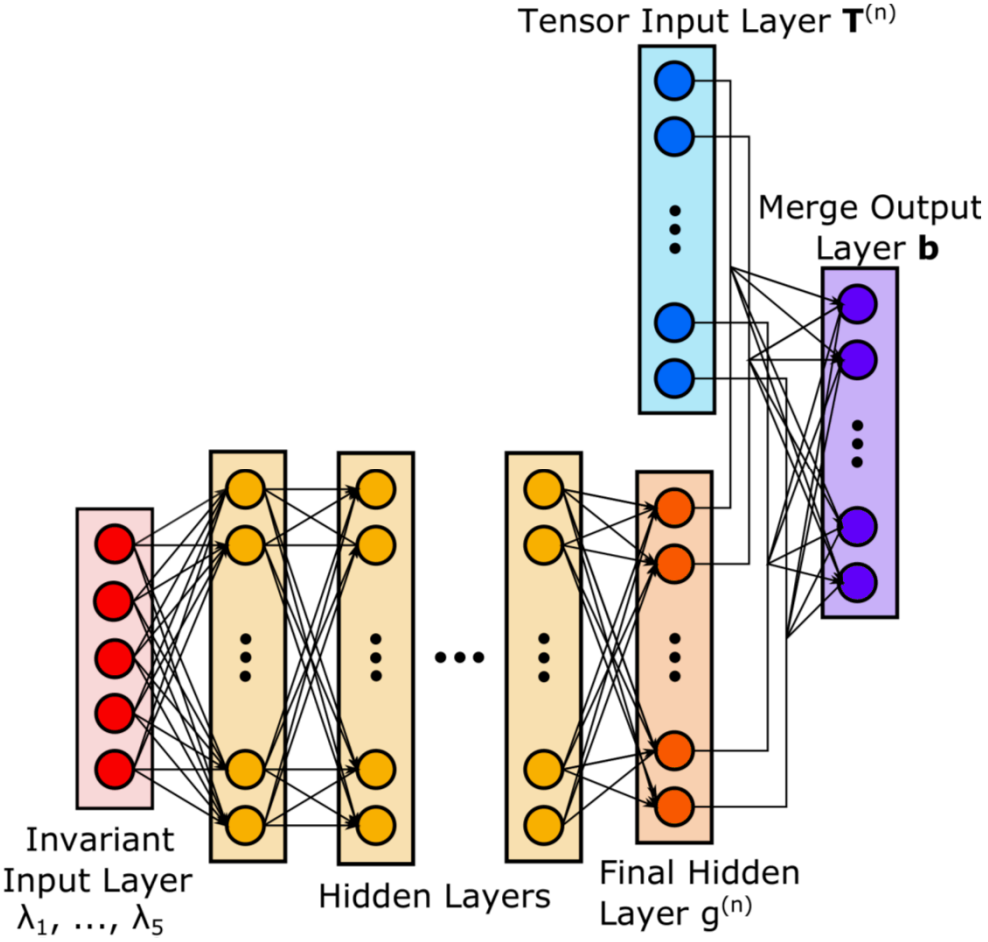
$$\boldsymbol{b} = \sum_{n=1}^{10} g^{(n)}(\lambda_1, ..., \lambda_5)\boldsymbol{T}^{(n)}$$

Embedding Galilean Invariance

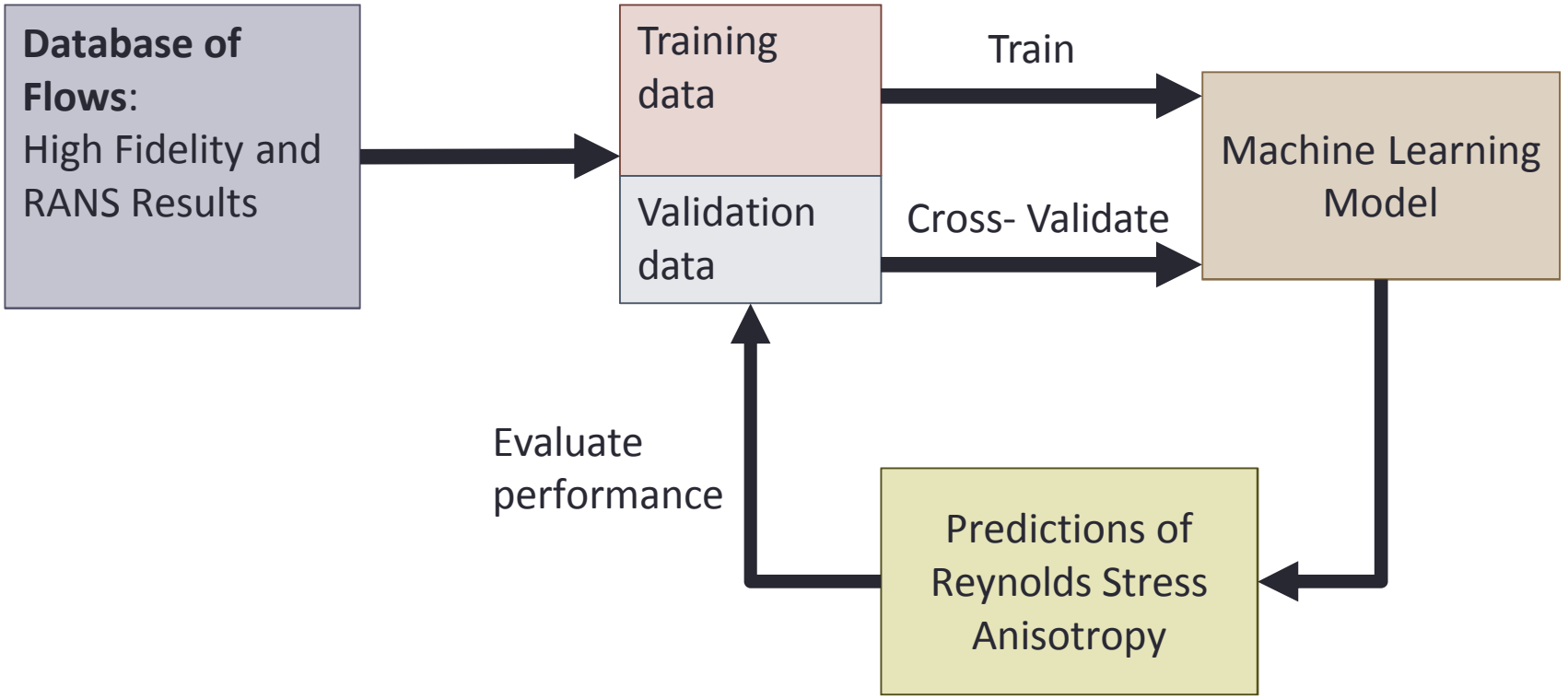
Generic MLP



Tensor Basis Neural Network

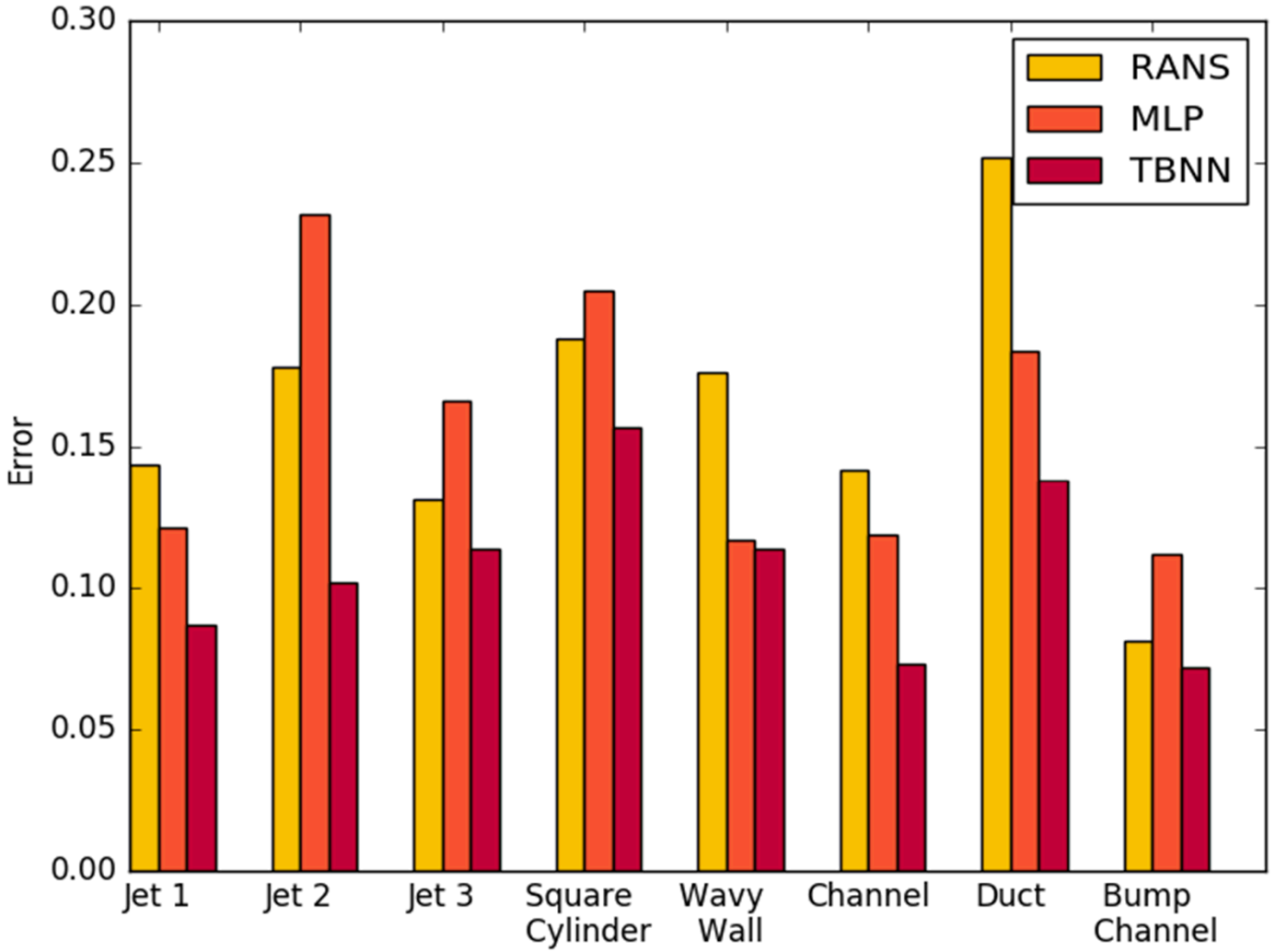


Model Development



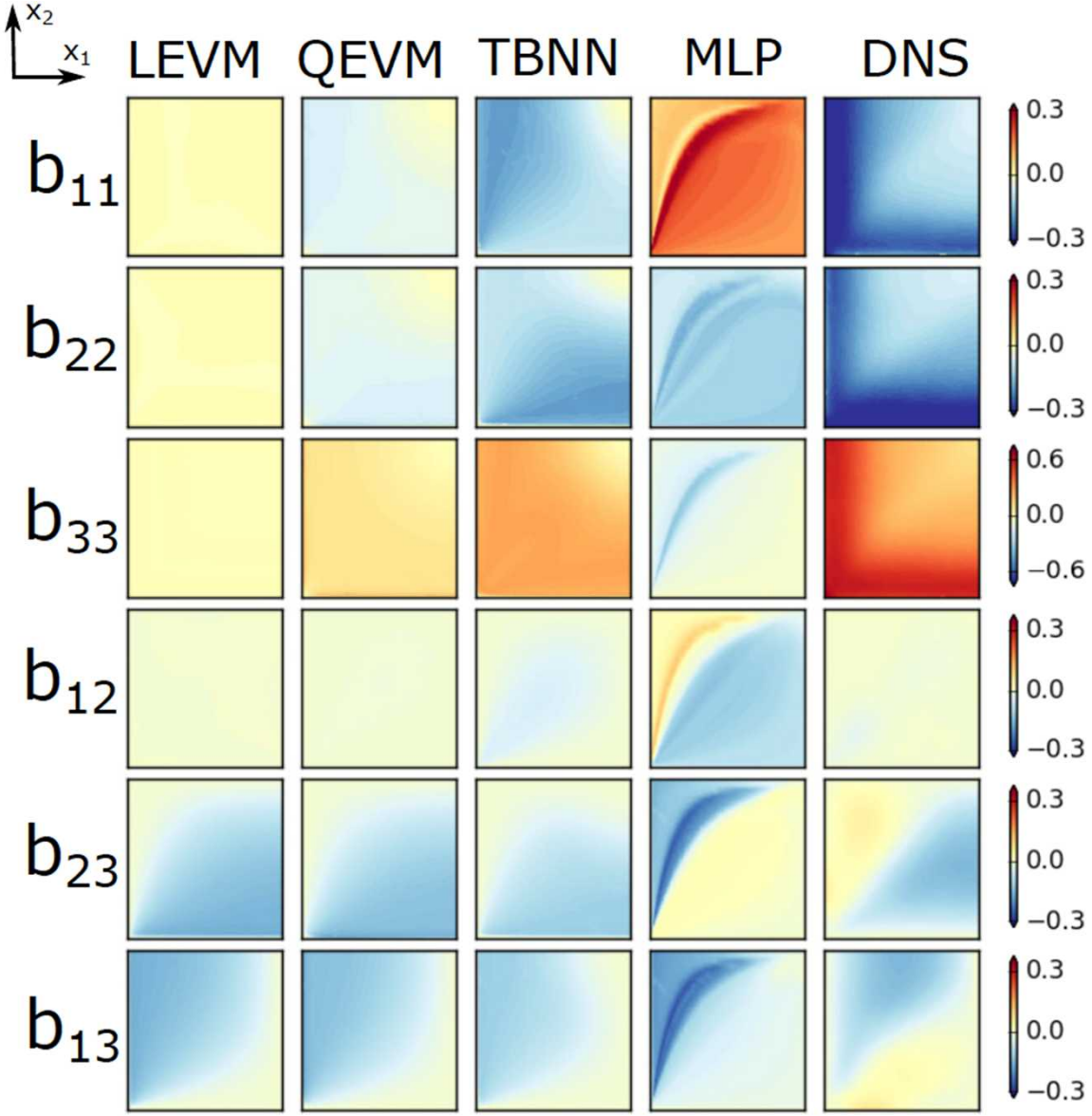
- Deep neural networks implemented using the Lasagne library: built on Theano
- Bayesian optimization used to tune the network hyper-parameters
- Trained an ensemble of networks to provide regularization

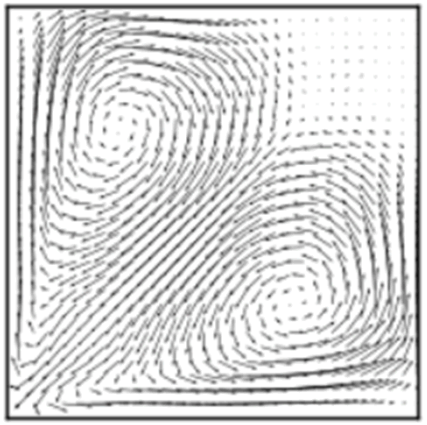
Deep Learning for Turbulence Modeling



- TBNN provided consistently lower root mean squared error
  - On average, 31% lower error than default LEVM

Deep Learning for Turbulence Modeling





- TBNN gave significantly improved predictions: 44% lower error than default LEVM model on this test case
- Forward propagated these predictions to the velocity field—was able to predict corner vortices

Conclusions

- Developed network architecture to embed known invariance property
- Applied this neural network to turbulence modeling
- Demonstrated significant improvement over conventional eddy viscosity models
- First application of deep learning to turbulence modeling

- Next steps:
  - Train and validate across wider range of flows
  - Integrate into modeling suite

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**, "Using Machine Learning to Understand and Mitigate Model Form Uncertainty in Turbulence Models," IEEE ICMLA, (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).
- **J. Ling**, F. Coletti, S. Yapa, J. Eaton, "Experimentally informed optimization of turbulent diffusivity for a discrete hole film cooling geometry," International Journal of Heat and Fluid Flow, (2013).

Questions

Questions

- Have you looked at applications outside of fluid mechanics?
- If you don't embed the invariance properties, can't the neural network *learn* the invariance given enough data?
- Besides neural networks, what other machine learning algorithms have you tried?
- What do these neural networks mean? How can we interpret their results?