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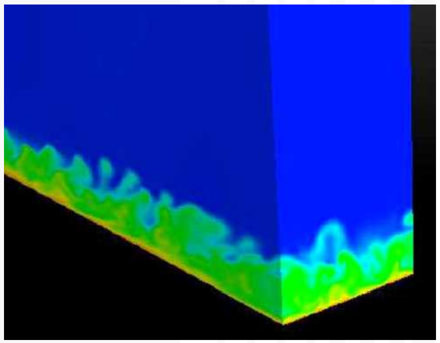

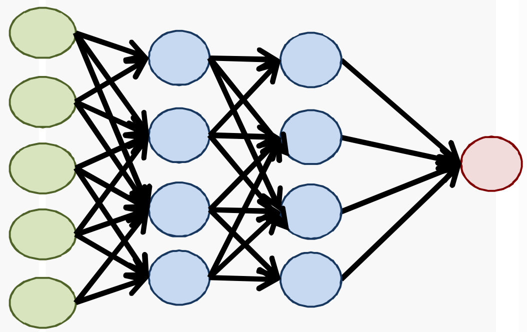

Sandia National Laboratories

Investigating Turbulent Wall Pressure Fluctuations using Machine Learning Techniques

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April 2017

U.S. DEPARTMENT OF ENERGY NNSA

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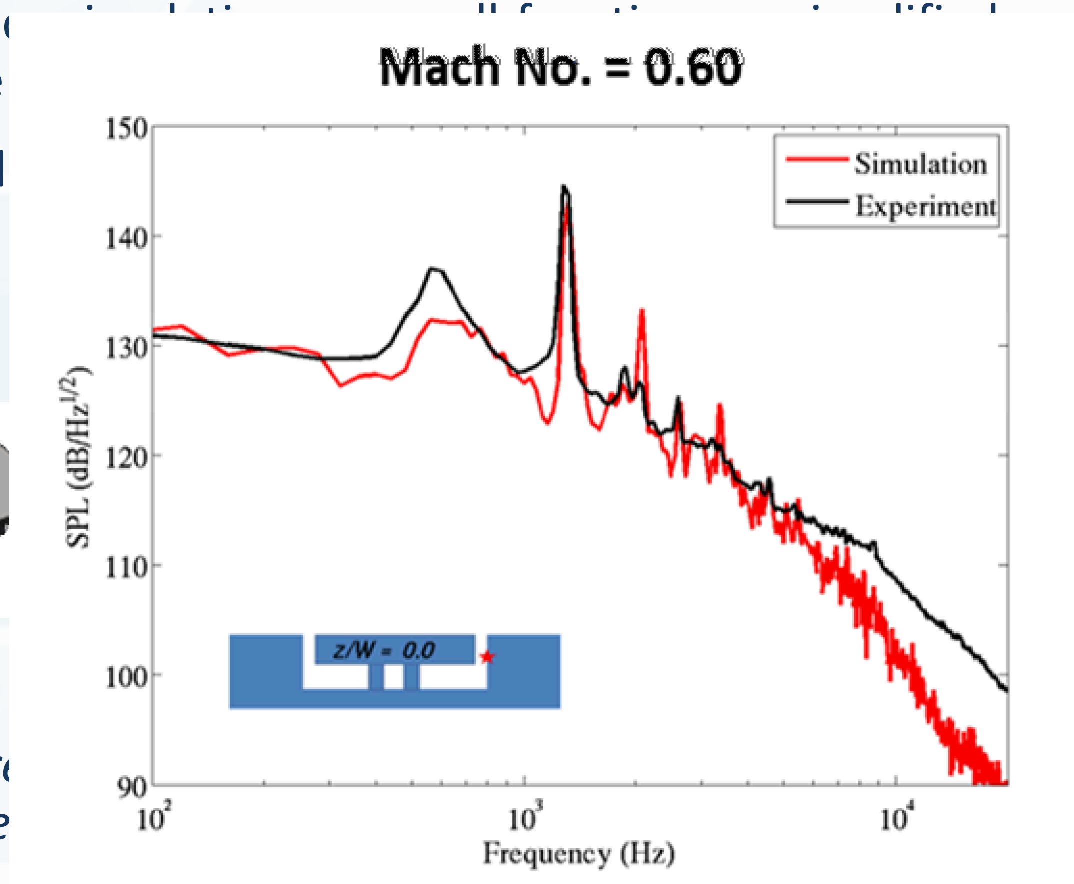
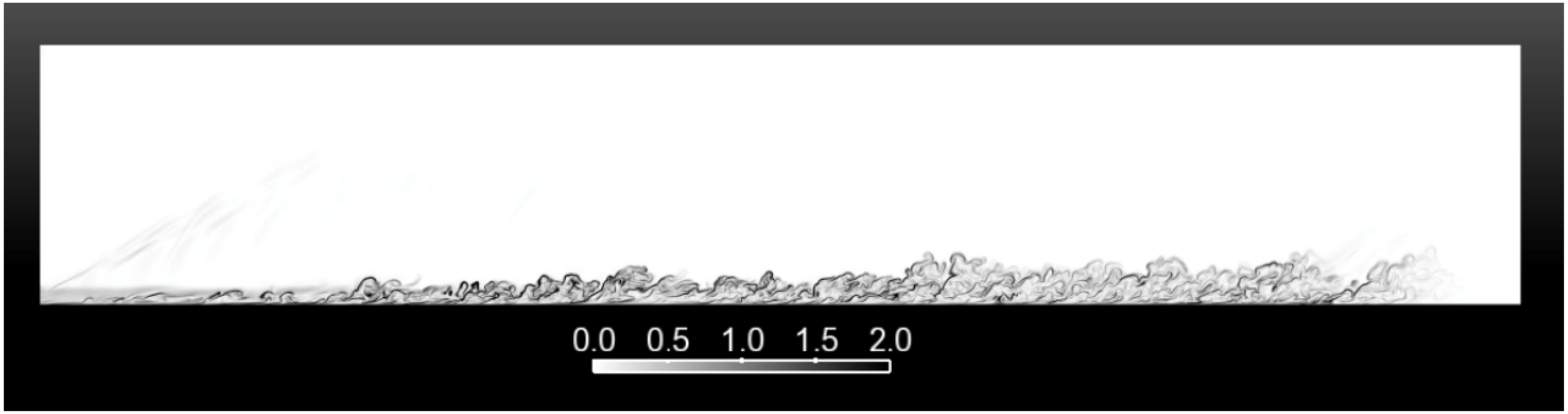
Motivation

- For fluid-structure interaction (FSI) applications, must be able to predict the pressure loading on a surface due to a turbulent flow
- Many turbulen ... dels near the wall due to the
- These near wal ... spectra distributions



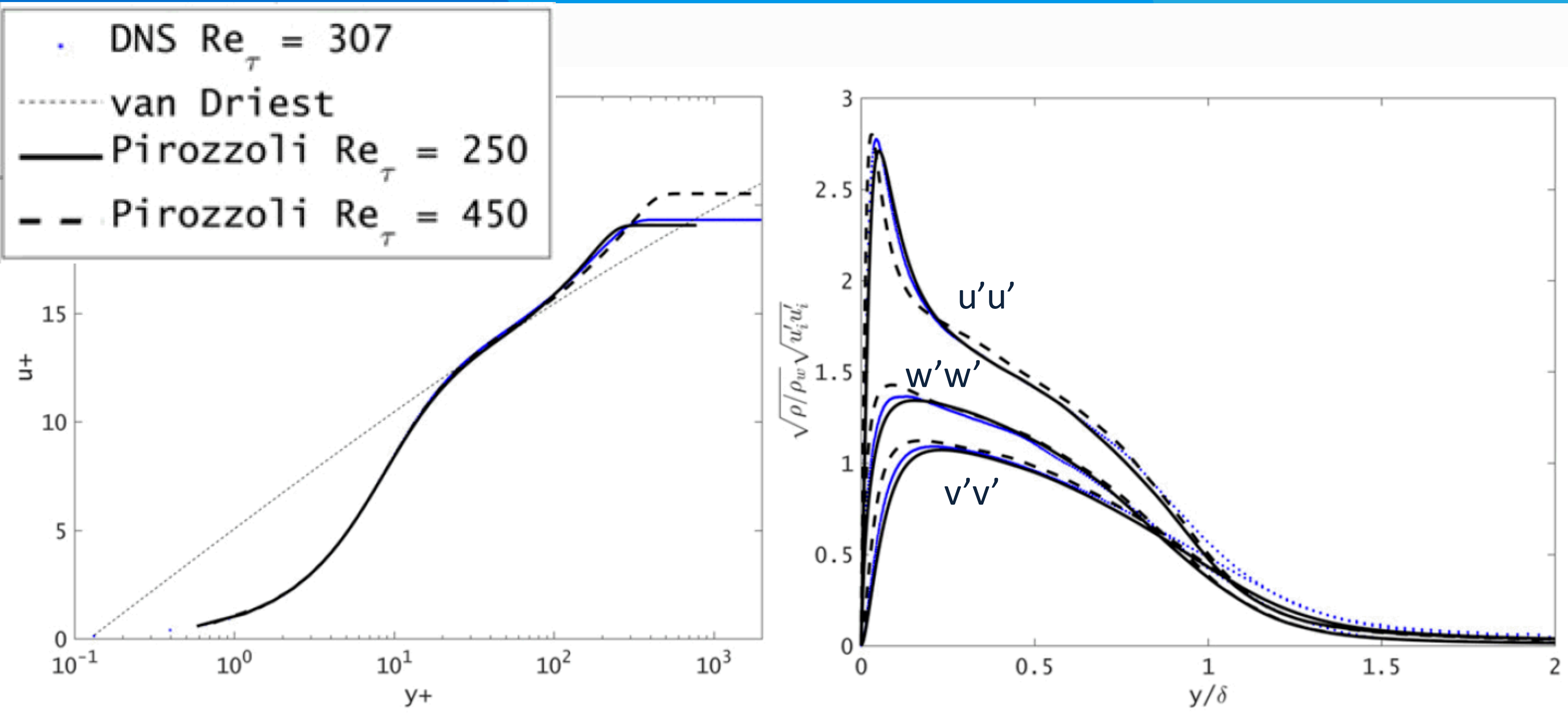
- Goal: *Use a Dir... w machine learning can be ... rface pressure fluctuations.*

DNS Data Set



- Mach 2.0 compressible flat plate turbulent boundary layer
- Low-dissipation 5th order upwind biased flux-reconstruction scheme
- Fourth order explicit Runge Kutta time integration
- 100.7 M mesh cells
  - Near wall resolution: $\Delta x^+ < 5$, $\Delta y^+ < 0.2$, $\Delta z^+ < 4$
- $1075 < Re_\Theta < 1310$
- Run for > 1200τ (where $\tau = \delta_0 / U_\infty$)

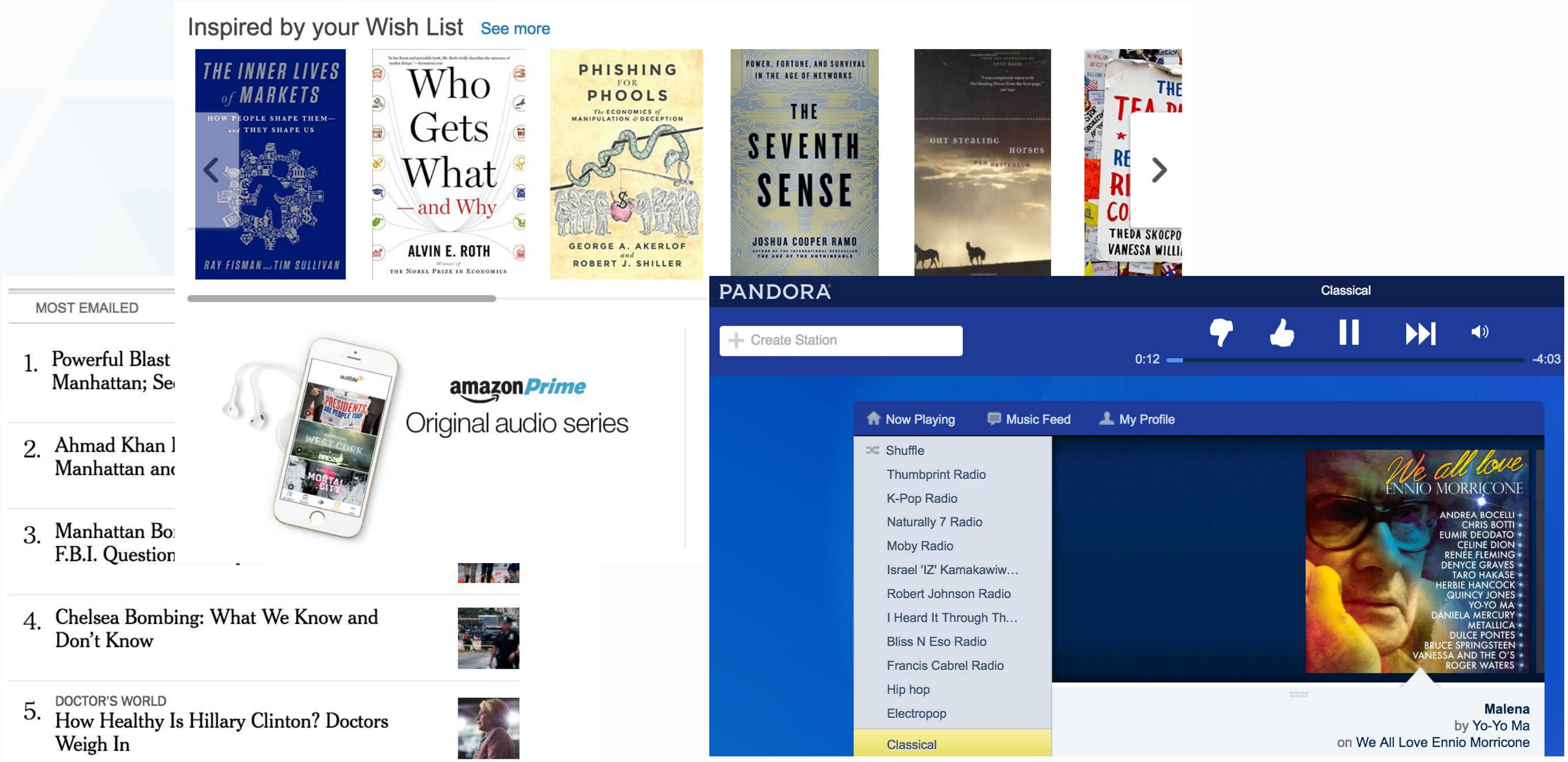
DNS “Verification”



- Our DNS: $Re_\tau = 302$
- Good agreement of mean velocity and Reynolds stress profiles with Pirozzoli et al. at $Re_\tau = 250, 450$

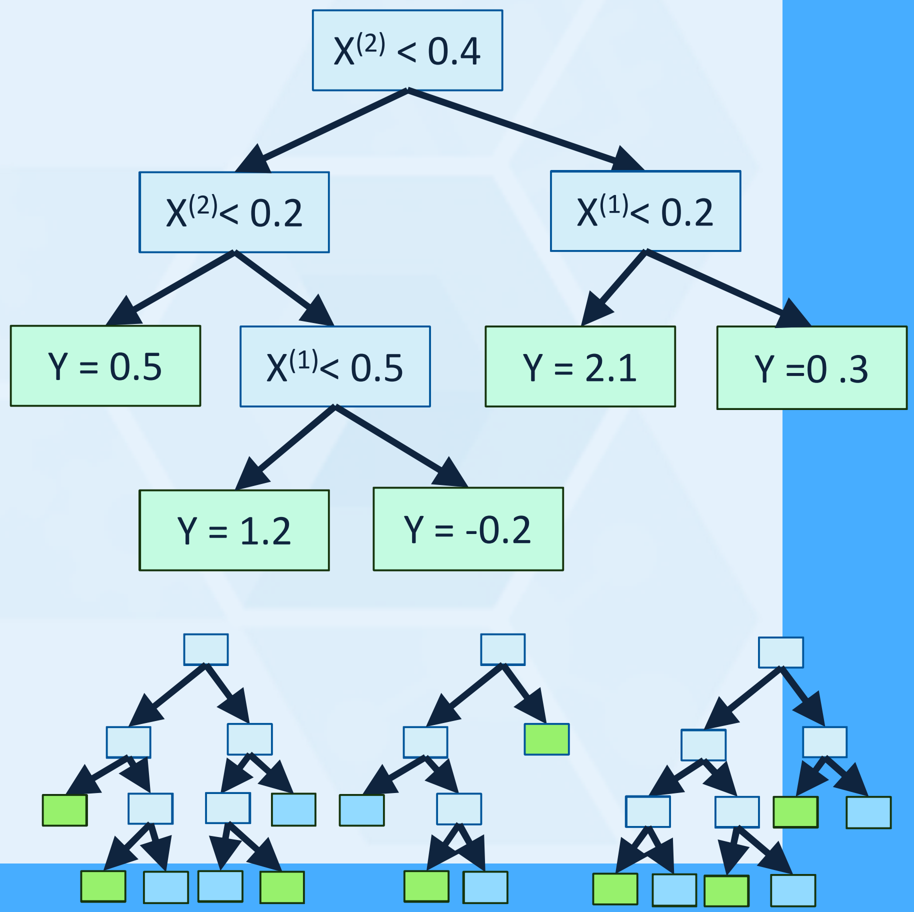
What is Machine Learning?

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

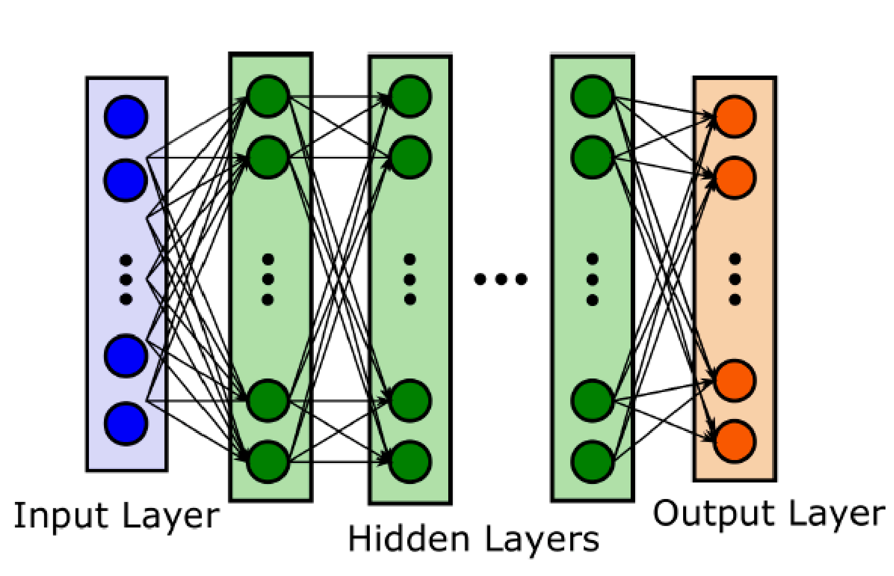


Machine Learning Algorithms

Random Forest

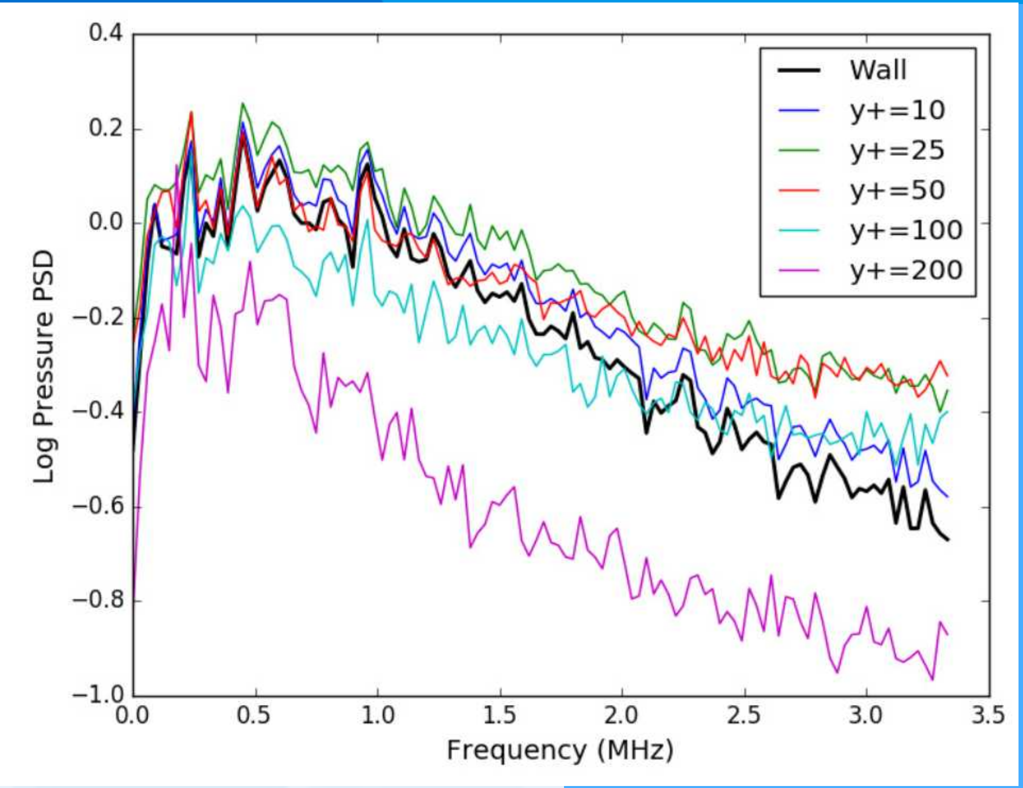


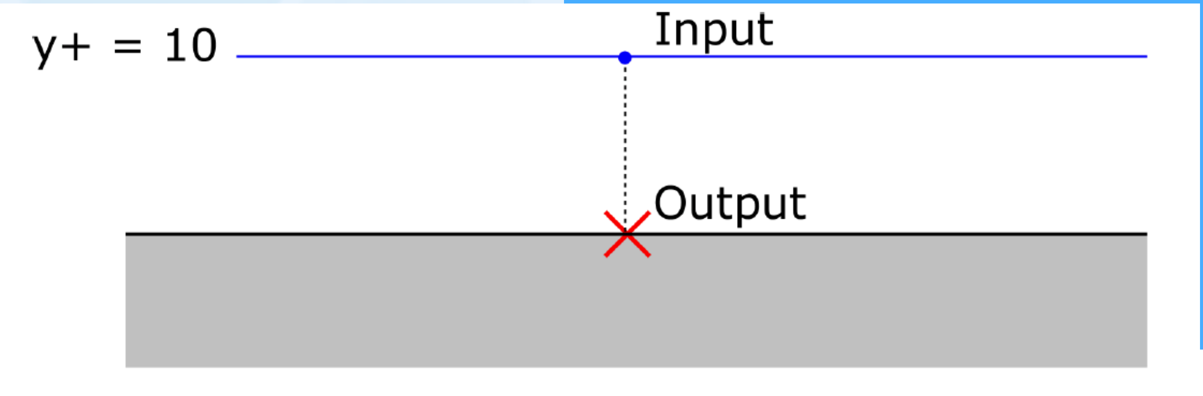
Neural Network



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

Machine Learning Framework



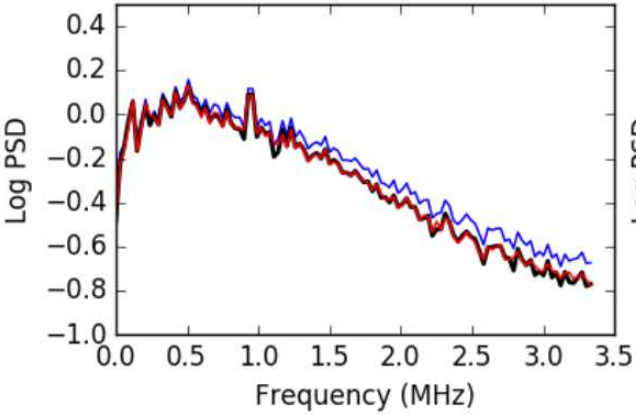


Given Pressure PSD at a point above the wall, can we predict the Wall Pressure PSD?

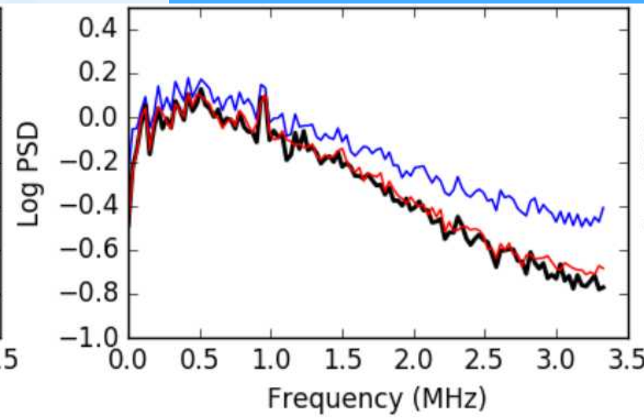
Split data sequentially into training and test set

Random Forest Predictions

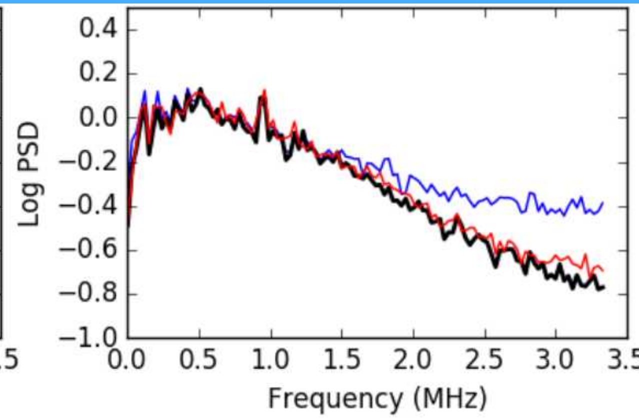
$y^+ = 10$



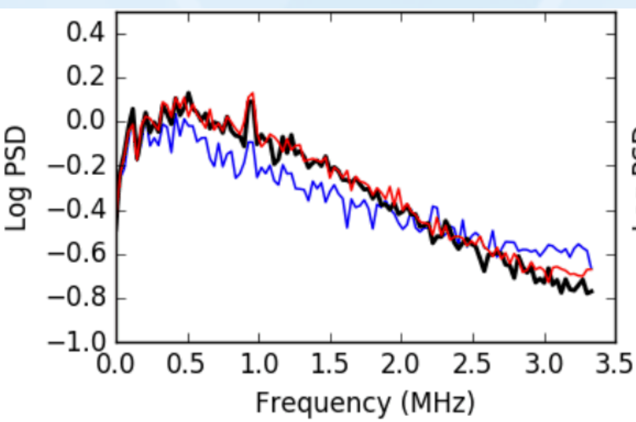
$y^+ = 25$



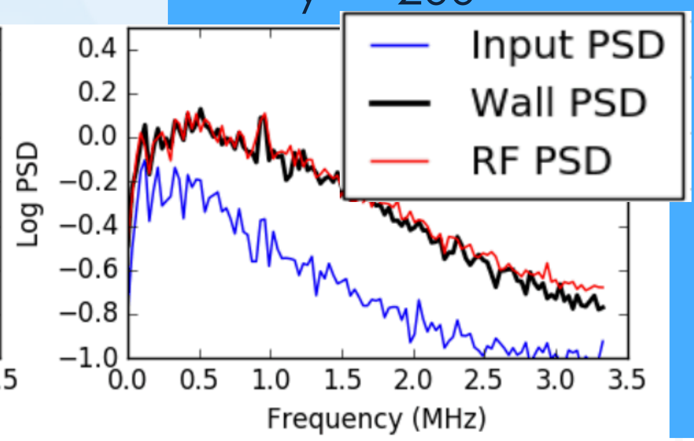
$y^+ = 50$



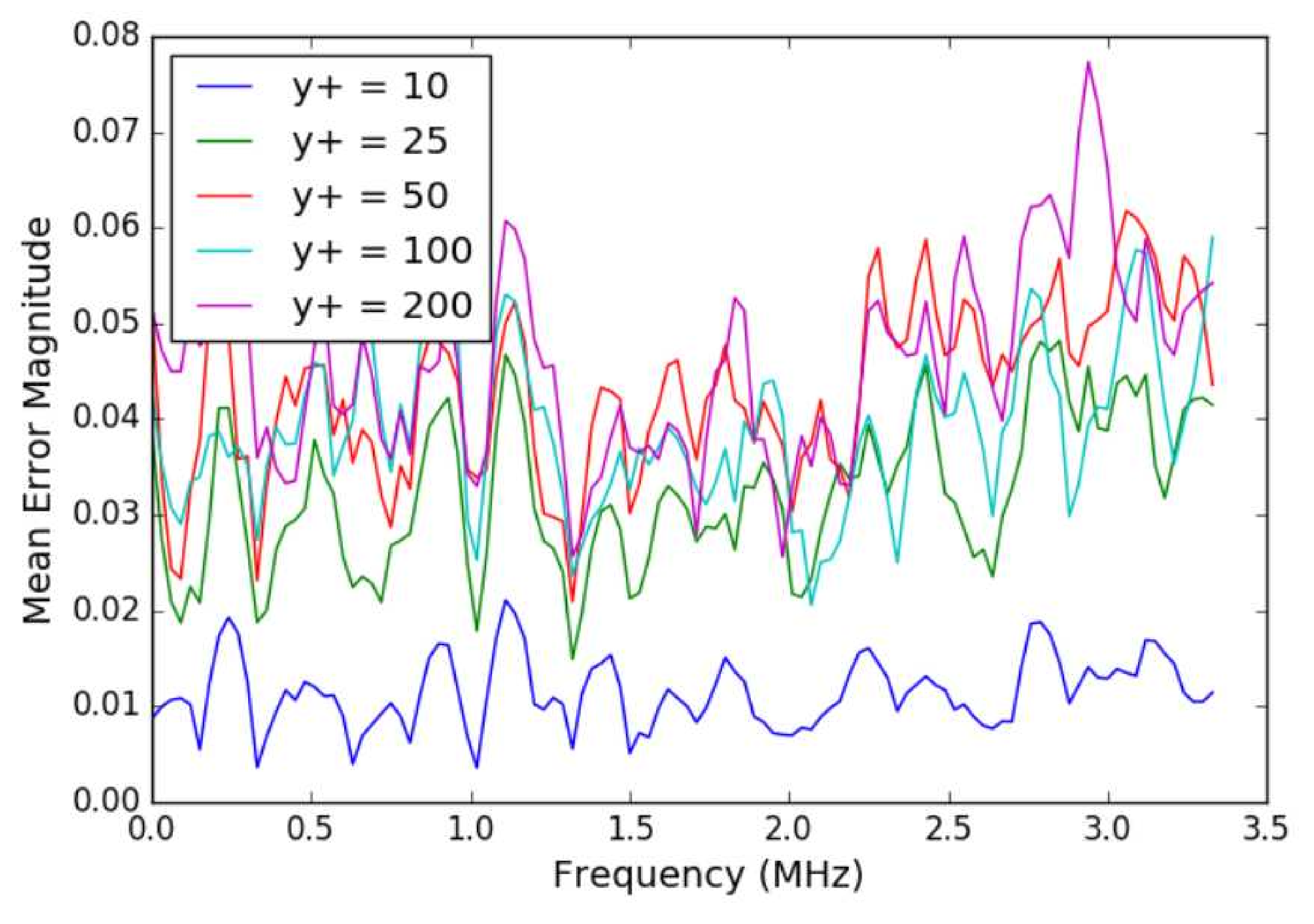
$y^+ = 100$



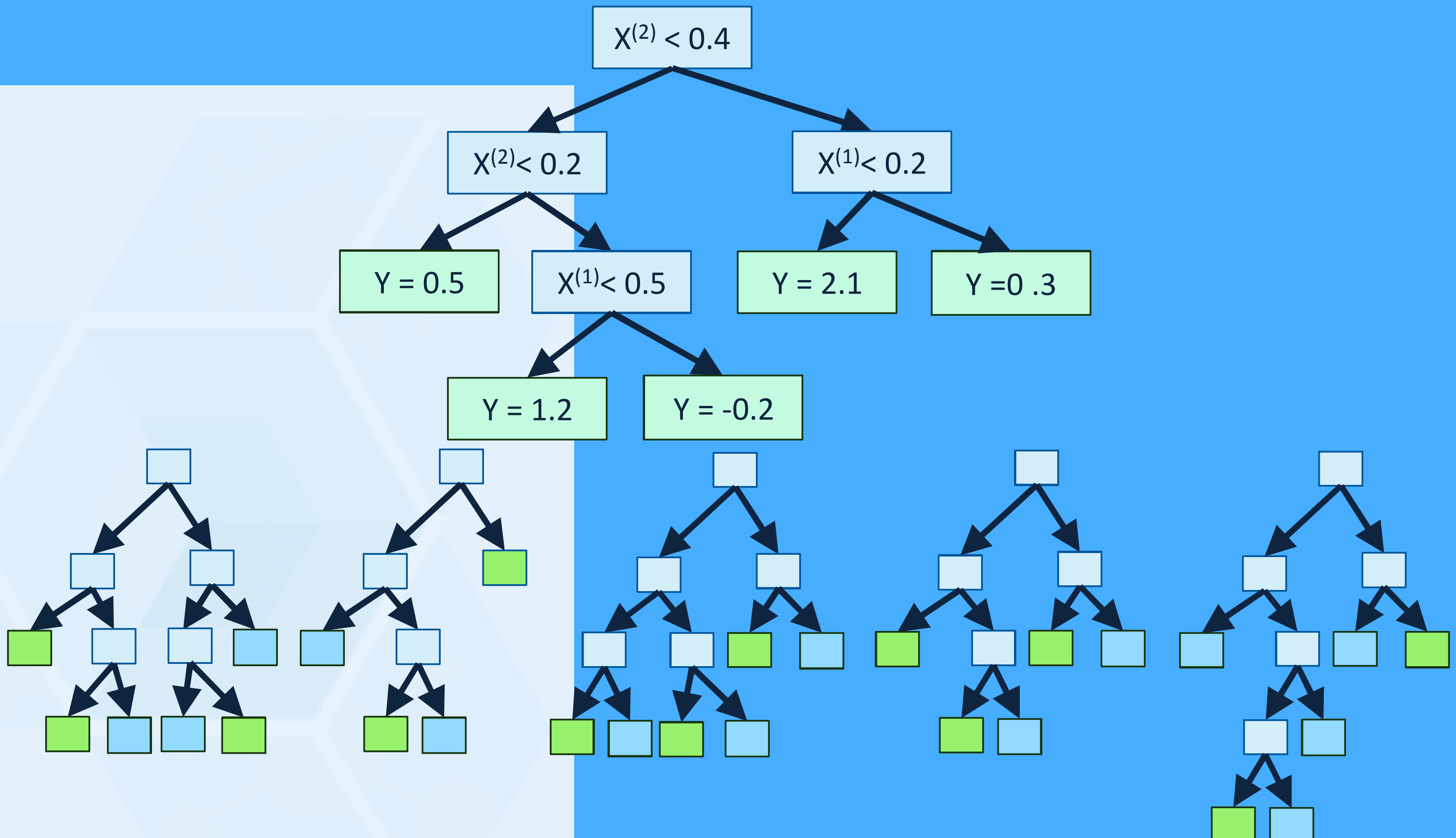
$y^+ = 200$



Frequency-Dependence of Random Forest Accuracy

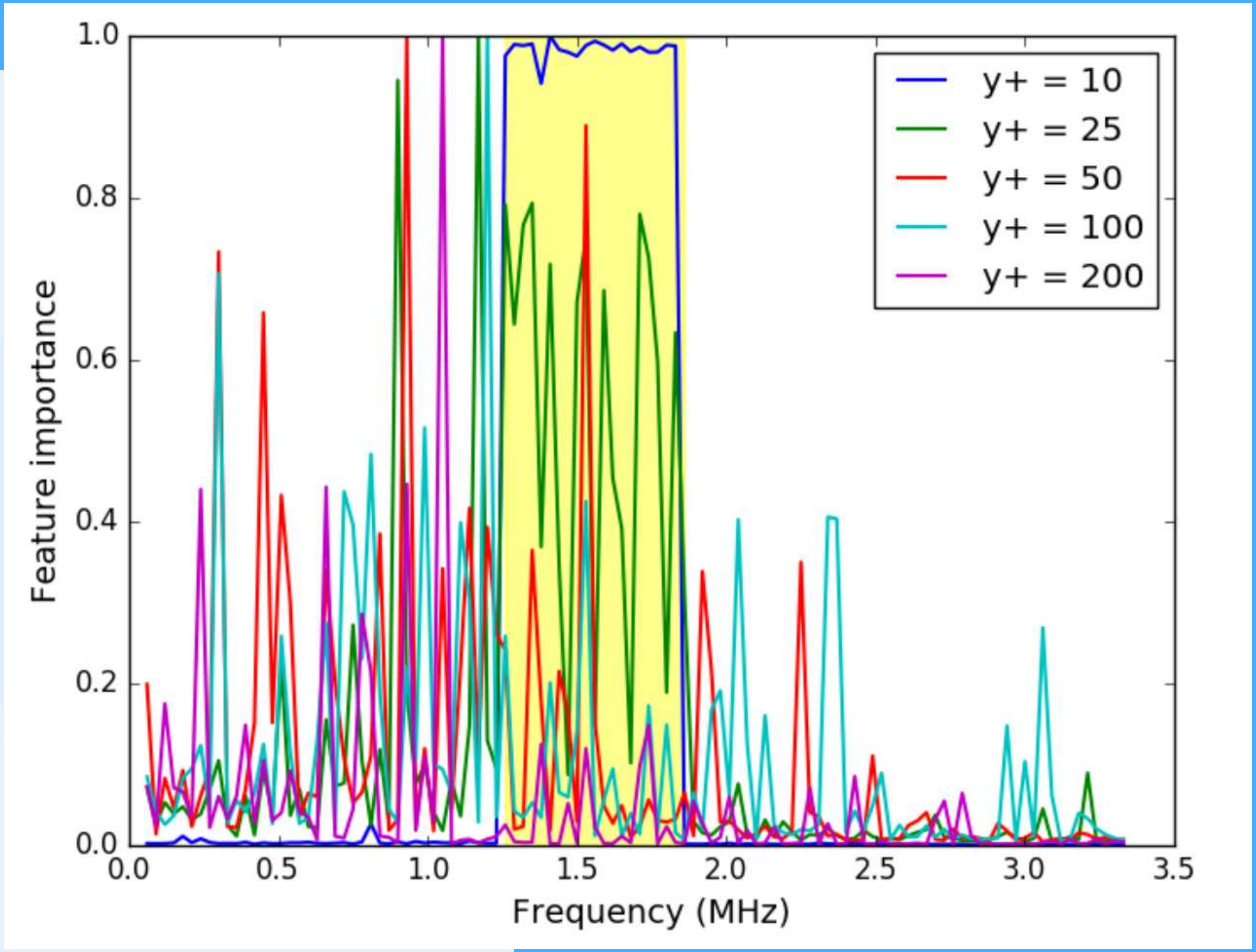


Random Forest Feature Importance

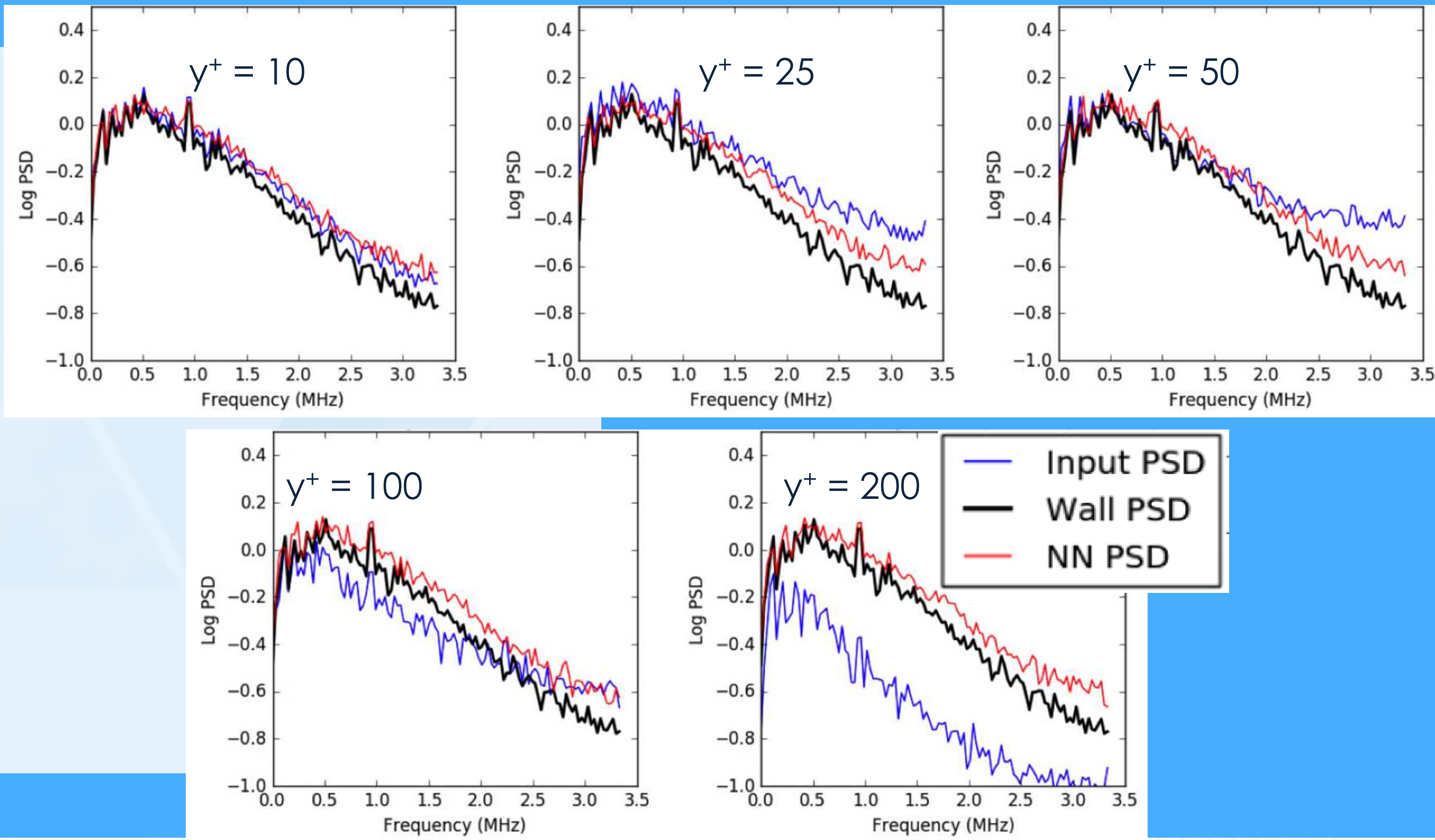


- Each split in decision tree is based on greedily maximizing the reduction in variance
- Feature importance is based on how often each feature is used in a split and the aggregated reduction in variance over those splits

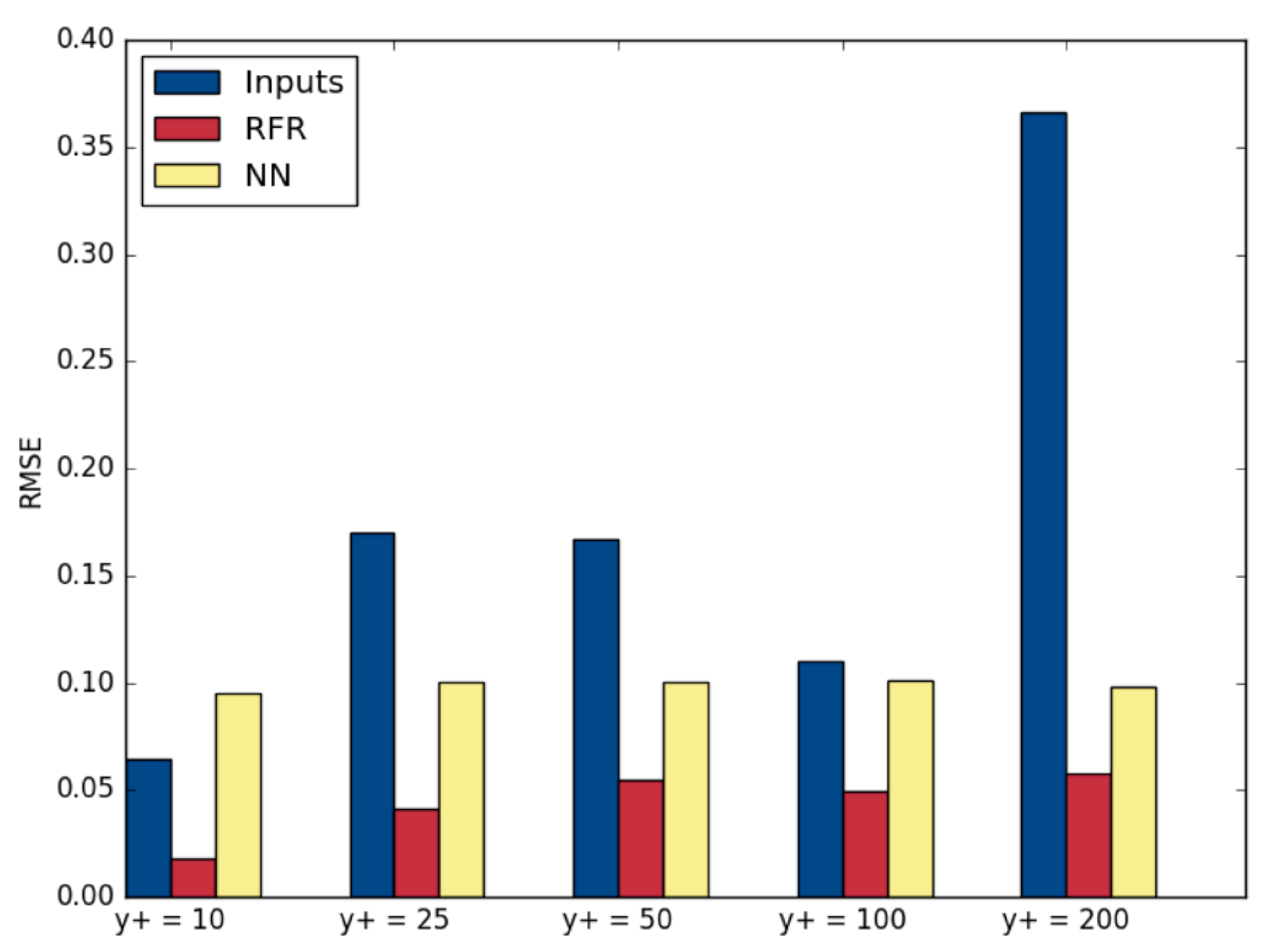
Random Forest Feature Importance



Neural Network Predictions



Machine Learning Performance

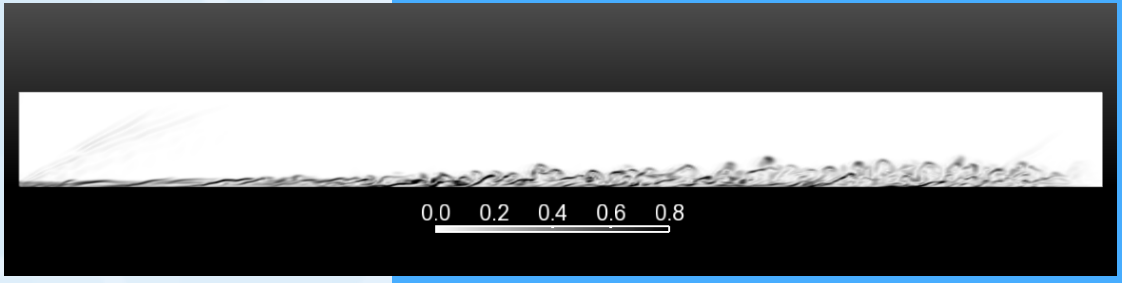


Conclusions

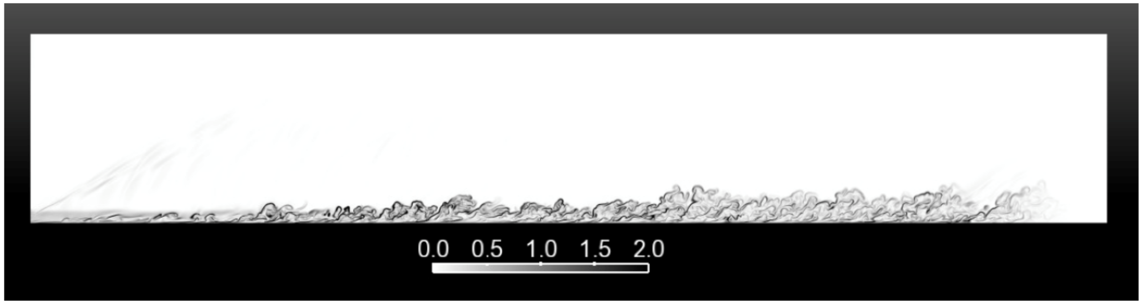
- Performed and validated a DNS of a compressible flat plate boundary layer
- Developed machine learning framework to predict wall pressure PSD given pressure PSD (or other inputs) above the wall
- Evaluated two different ML algorithms
  - Random Forest provided better performance than simple multi-layer perceptron neural network
- Evaluated machine learning performance using input data at different wall distances
  - Data out to $y^+ = 100$ allows accurate reconstruction of wall pressure PSD
  - Higher frequencies are harder to predict using information farther from the wall
  - These results suggest that it should be possible to create a data-driven wall model for the pressure PSD

Next Steps

- Train and validate across wider range of Mach numbers, different flow configurations
- Given WMLES data, try to predict DNS wall pressure PSD
- Evaluate more complex neural network architectures to see if improved neural network performance is achieved



WMLES



DNS

Questions?