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# Machine Learning Models for Detection of Regions of High Model Form Uncertainty in RANS

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Sandia National Labs

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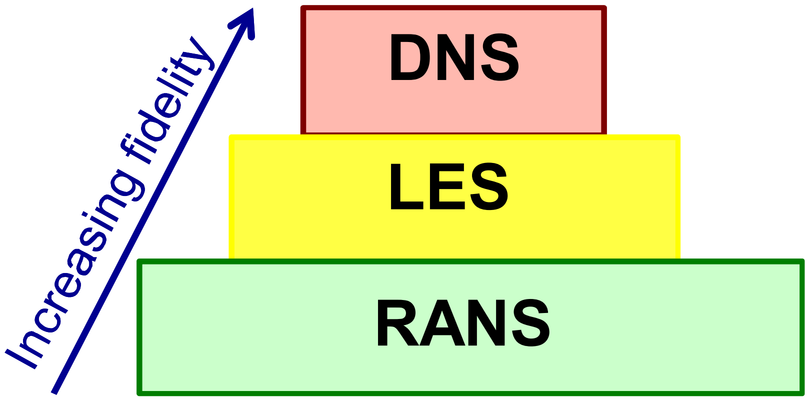
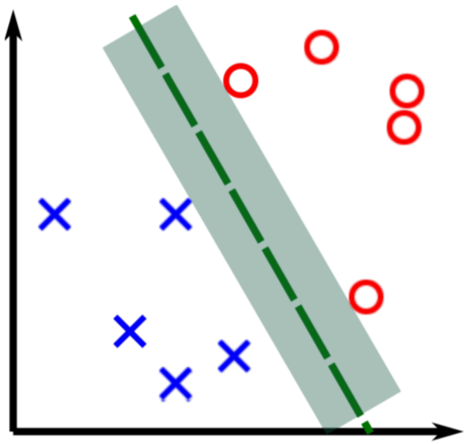
# Turbulence Simulations




- **RANS**:
  - Most widely used turbulence model
  - Relies on modeling assumptions→ Model form uncertainty
  - Very difficult to assess model form uncertainty
- **Idea**: Use machine learning to detect regions of high uncertainty based on when specific model assumptions are violated

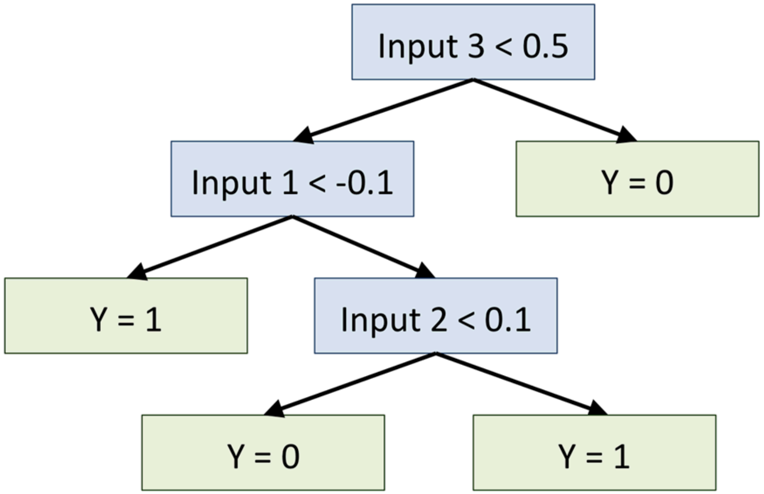
# Machine Learning

- Set of data-driven algorithms for regression, classification, clustering
- *E.g.*: linear regression, support vector machines, neural networks
- Have been broadly applied in finance, software engineering, retail
- Challenge: how to incorporate domain knowledge into machine learning algorithms
  - These techniques have a range of physics applications
- **For this application: use binary classifier to flag regions of high RANS uncertainty on a point-by-point basis**

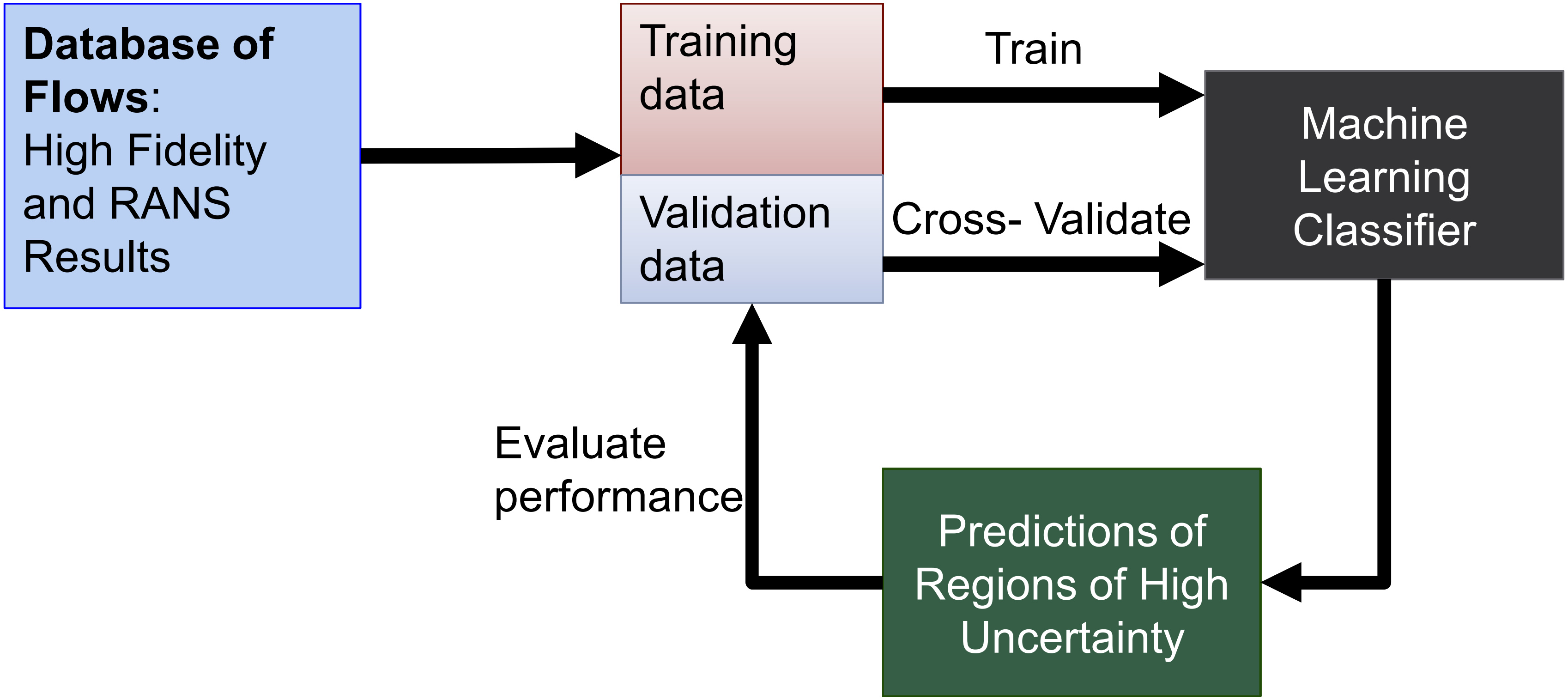
# Random Forests

- Binary Decision Trees:
  - “If-then” logic

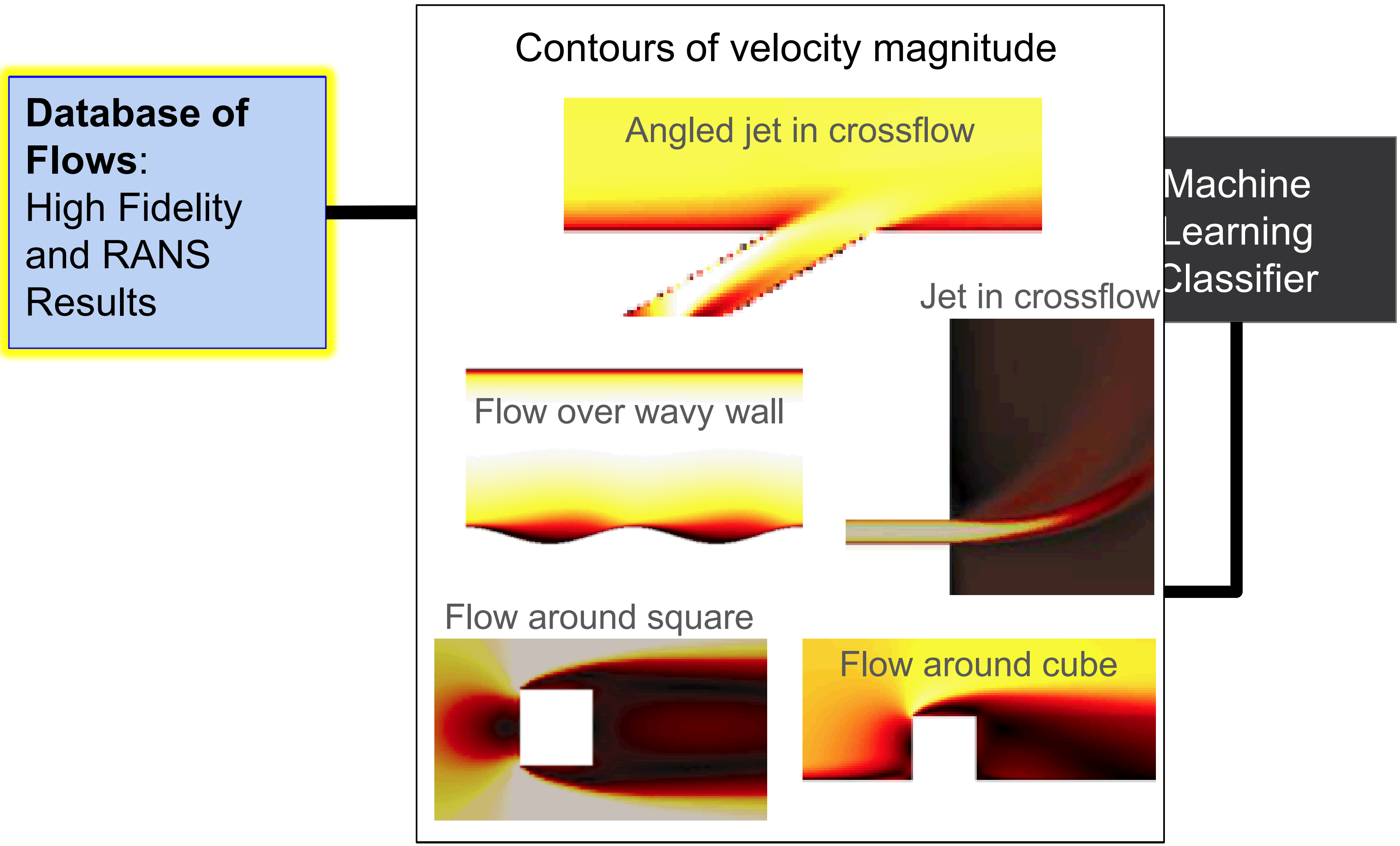



- Ensembles of Decision Trees:
  - Random sampling with replacement to create subsets of training data

# Classifier Development

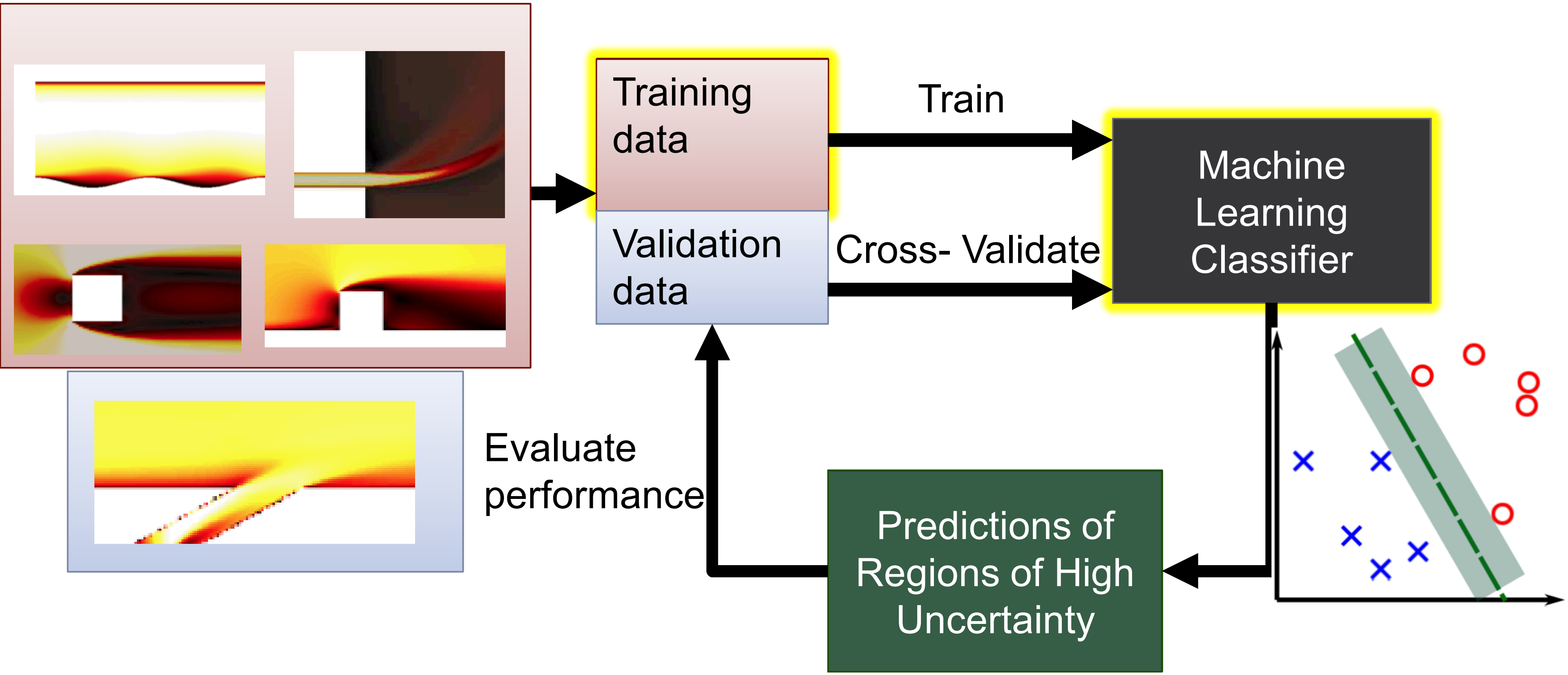


# Classifier Development



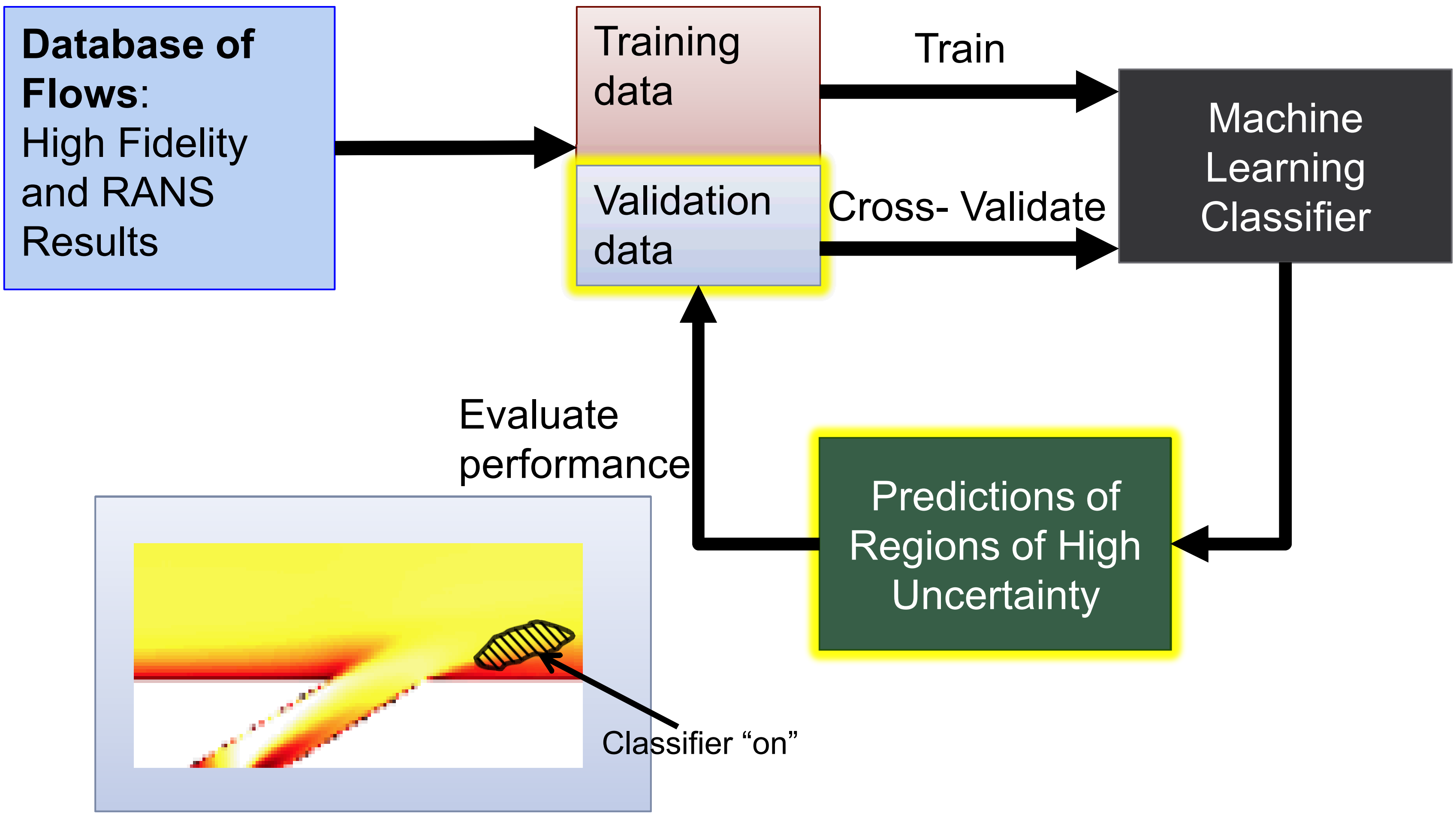

- Have database of canonical “building block” flows

# Classifier Development



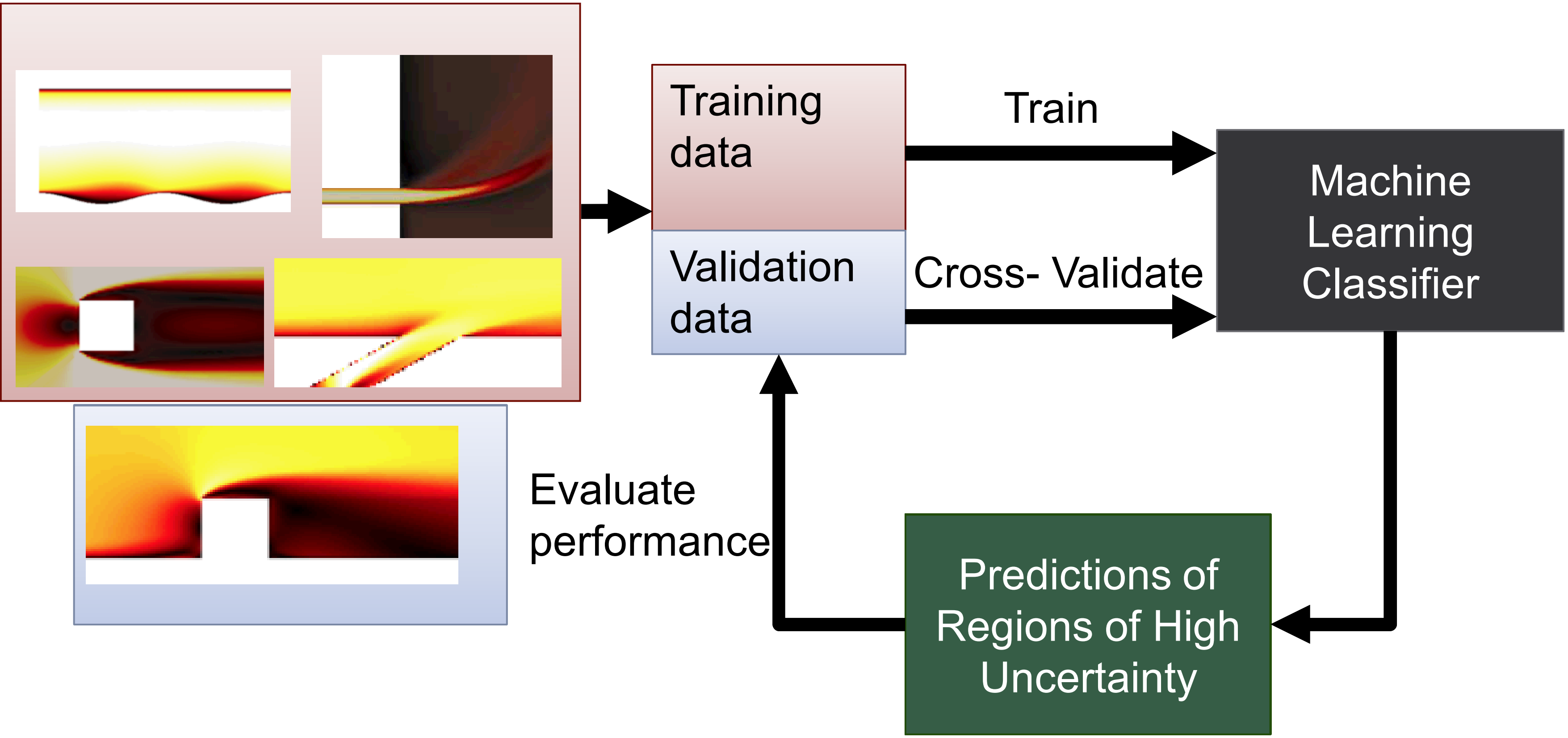

- Split data base into training and validation sets
- Train classifier
  - Input: Local flow variables from RANS
  - Output: Binary flag– “on” if RANS assumption violated, “off” otherwise

# Classifier Development




- Use classifier to make predictions on validation set
- Evaluate classifier by comparing to high fidelity results

# Classifier Development




- Cross-validate to ensure generalization

# Assumptions Tested

$$\overline{u_i'u_j'} = \frac{2}{3}k\delta_{ij} - 2\nu_t S_{ij}$$

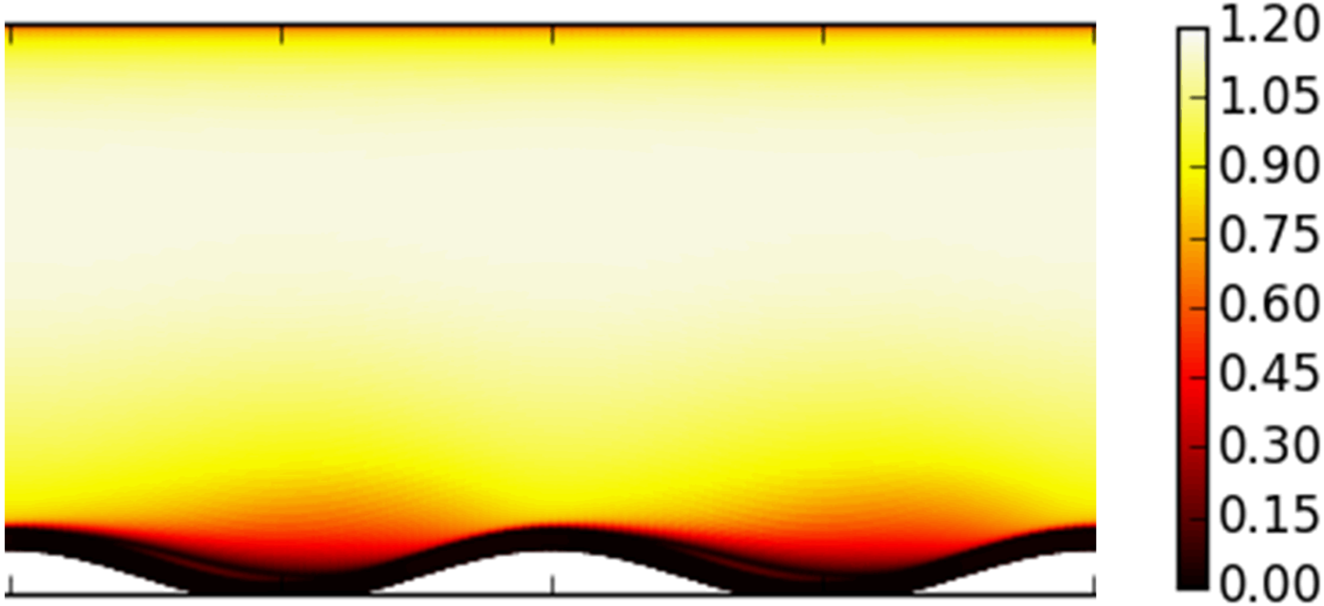
1. Non-negativity of eddy viscosity
   - Classifier should be “on” when LES/DNS eddy viscosity goes negative
2. Isotropy of Reynolds stresses
   - Classifier should be “on” when anisotropy is high
3. Linearity of Boussinesq hypothesis
   - Classifier should be “on” when cubic eddy viscosity very different from linear eddy viscosity

# Inputs:

- Non-dimensional, rotationally invariant local flow variables from RANS

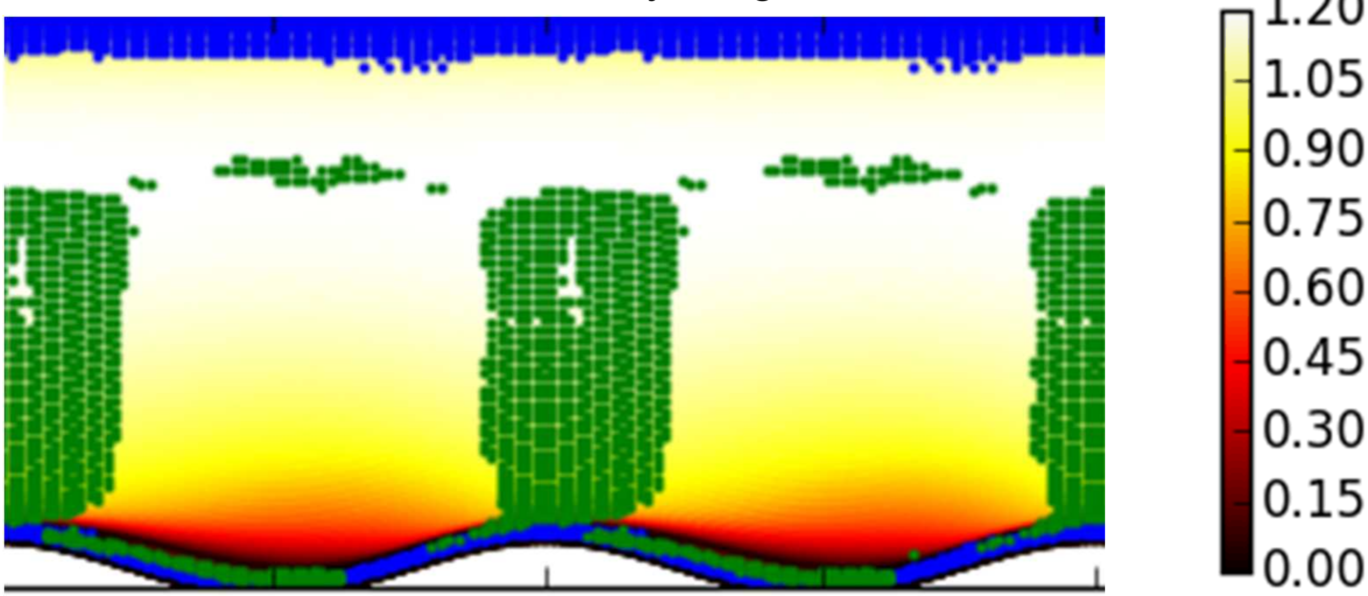
# The Status Quo

Contours of velocity magnitude



# A Better Option

Contours of velocity magnitude




Blue: Regions where classifier predicts isotropy assumption violated

Green: Regions where classifier predicts linearity assumption violated

- 3 X more accurate than current state of the art physics-driven classifier of Gorle et al.
  - Gorle et al.'s classifier is used as an input to the ML classifier

# Impacts

- Classifiers for RANS model uncertainty can transform the way RANS results are post-processed and understood
  - Clarify when RANS simulations are predictive
  - Machine learning methods can significantly reduce classifier error rate

- Develop techniques for using machine learning algorithms on physical systems
  - Leverage domain knowledge and physical constraints to develop algorithms
  - Use data-driven algorithms to learn about the physical system

# Acknowledgments

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# References

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," ICMLA, (2015) *accepted.*

C. Gorle, J. Larsson, M. Emory, G. Iaccarino, "The deviation from parallel shear flow as an indicator of linear eddy viscosity model inaccuracy," Physics of Fluids, (2014).

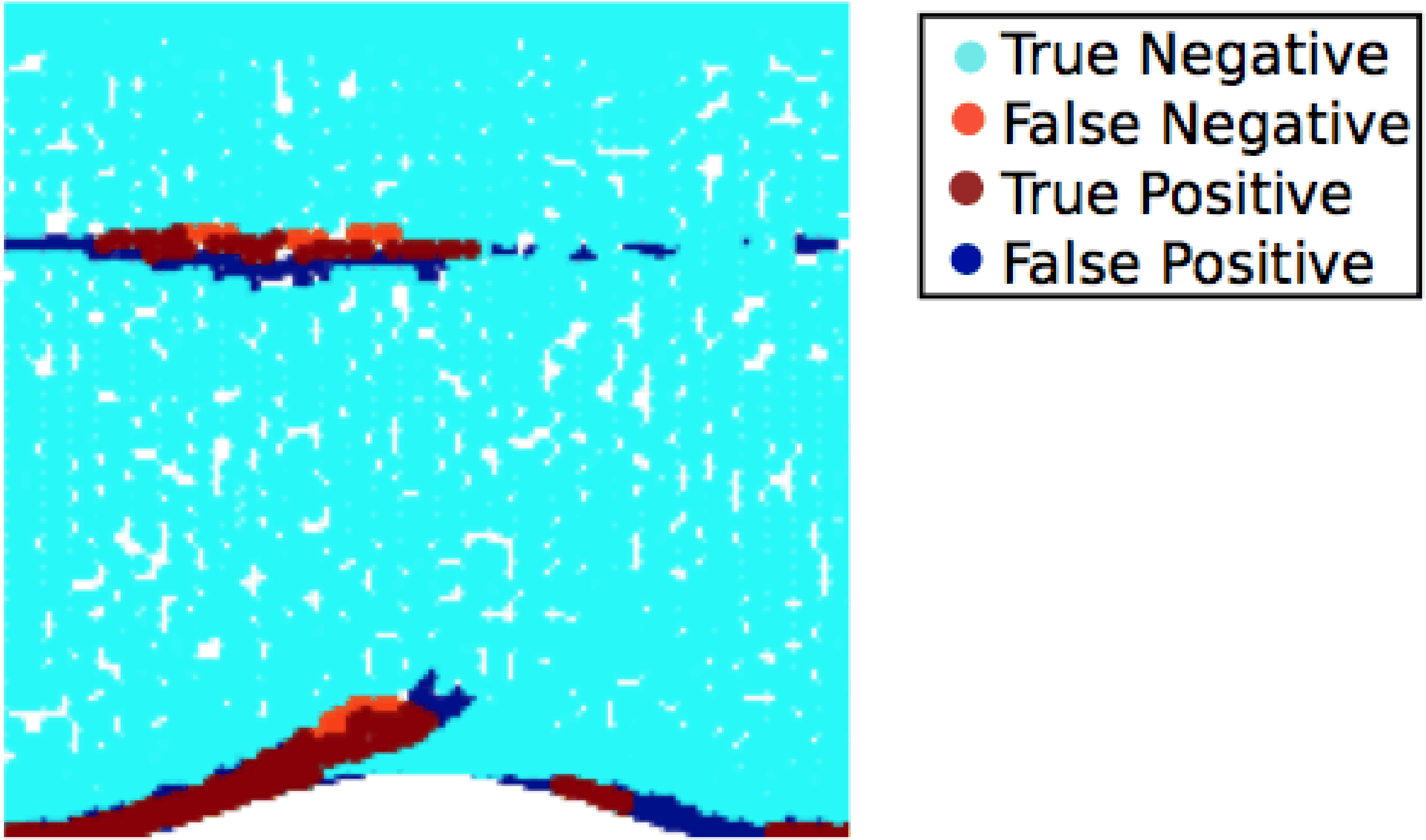
# Opportunities

Postdocs and internships available—come talk to me!

# Applications of Classifiers

- Can quickly post-process RANS simulation to determine whether it's reliable in region of interest
  - Don't have to wait around for validation data set
  - Can determine what corrections to implement
- Can enable adaptive corrections during run time
- Experimental design
  - Design experiments to provide the strongest validation
- LES-RANS hybrids
  - Use classifiers to inform switching function

# Classifier Performance



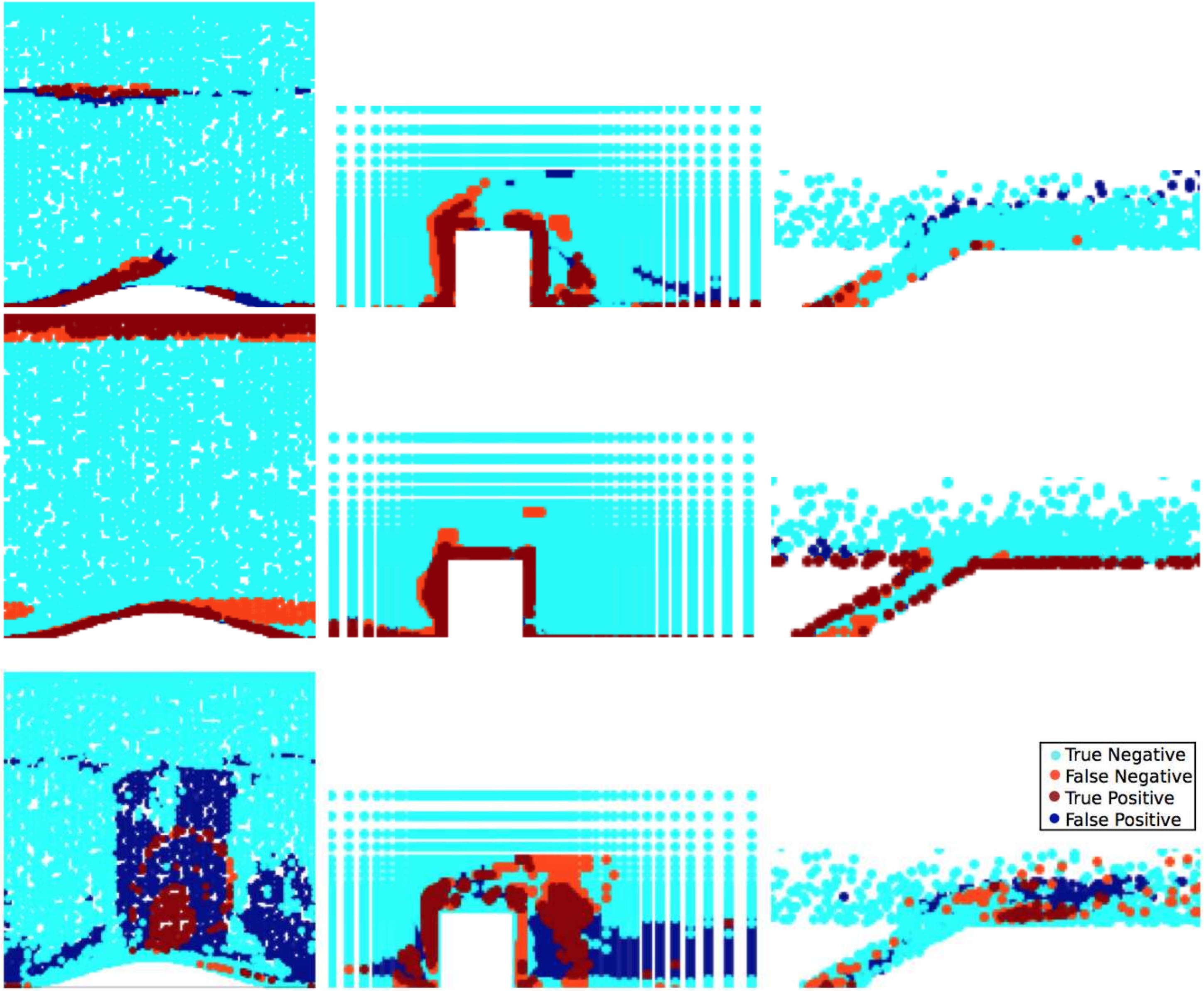

(a)Case 1, Marker 1:
Negative $\nu_t$

# Classifier Performance

Non-negativity assumption

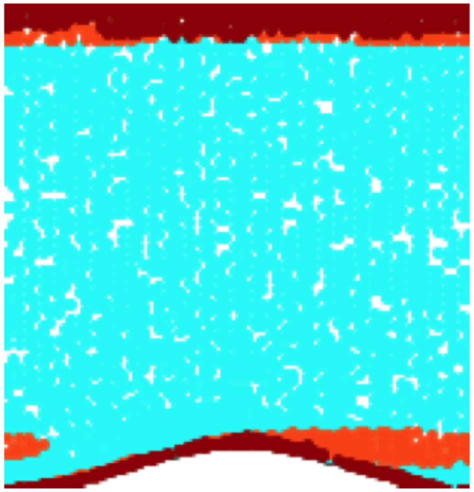
Isotropy assumption

Linearity assumption



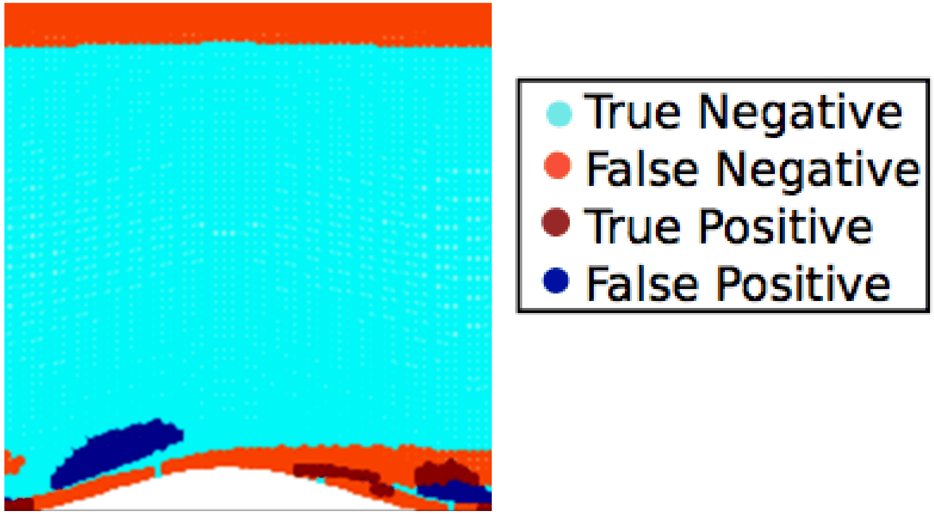
# Comparison against State of the Art

Machine Learned Classifier



Cross-validation
Error rate: 11%

Physics-based Classifier of Gorle et al.




Cross-validation
Error rate: 33%

- 3 X more accurate than current state of the art physics-driven classifier of Gorle et al.
    - Gorle et al.'s classifier is used as an input to the ML classifier