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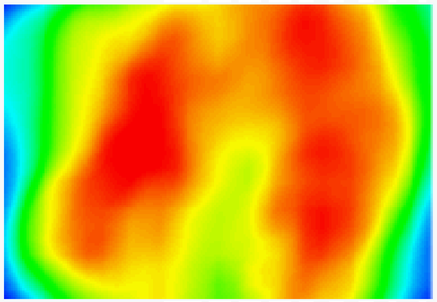

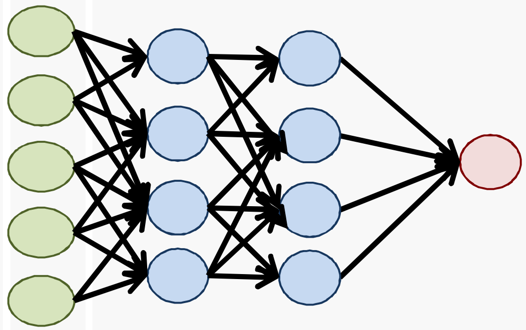

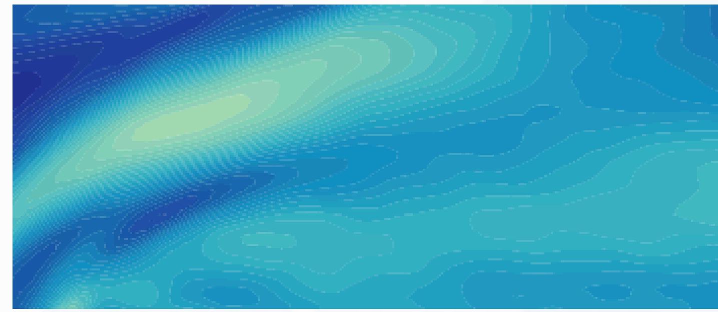

A COMPARATIVE STUDY OF CONTRASTING MACHINE LEARNING FRAMEWORKS APPLIED TO RANS MODELING OF JETS IN CROSSFLOW

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Motivation

For film cooling and many other applications, it is important that we be able to accurately simulate jets in crossflow

Current RANS models struggle with this flow

There have been many attempts to apply different RANS models to this flow, with varying degrees of success.

We seek **data-driven** non-linear eddy viscosity models to improve predictions in jets in crossflow

In this study, we compared two different machine learning approaches: Gene Expression Programming (GEP) and Deep Neural Networks (DNN)

Non-Linear Eddy Viscosity Models

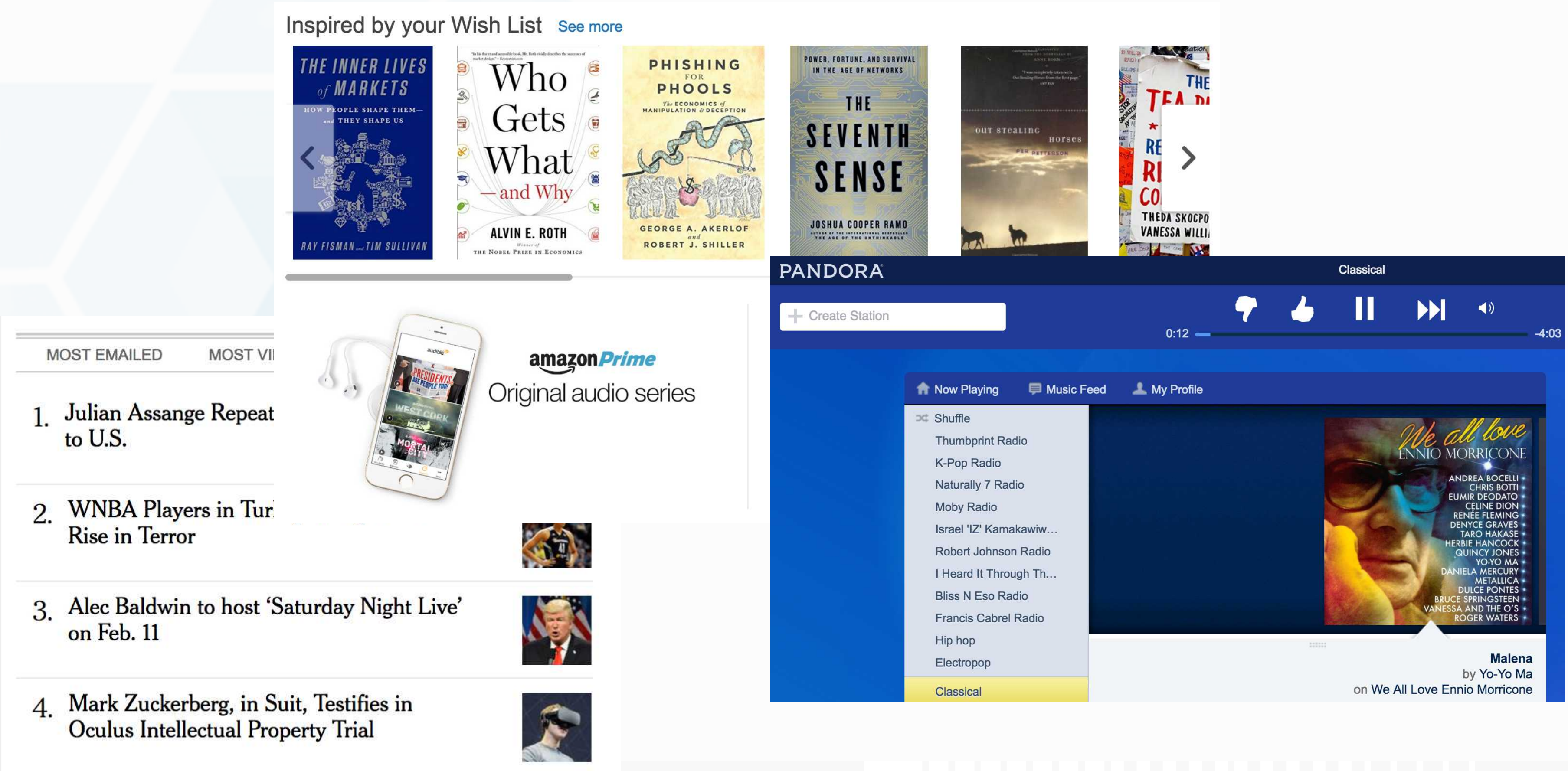
$$
\begin{aligned}
a_{ij} &\equiv \frac{\tau_{ij}}{2k} - \frac{1}{3}\delta_{ij} \\
&= -t_I S_{ij} && \text{(linear)} \\
&= a_{ij}(V_{ij}^1, V_{ij}^2, \ldots, I_1, I_2, \ldots) && \text{(EASM, GEP)} \\
&= a_{ij}(V_{ij}^{1*}, V_{ij}^{2*}, \ldots, I_1^*, I_2^*, \ldots), && \text{(EASM, DNN)}
\end{aligned}
$$

V: Galilean invariant tensor basis (polynomials in S and R)
I: Galilean invariant scalar basis (traces of polynomials in S and R)

The goal of the machine learning algorithms is to learn a mapping from V, I → a

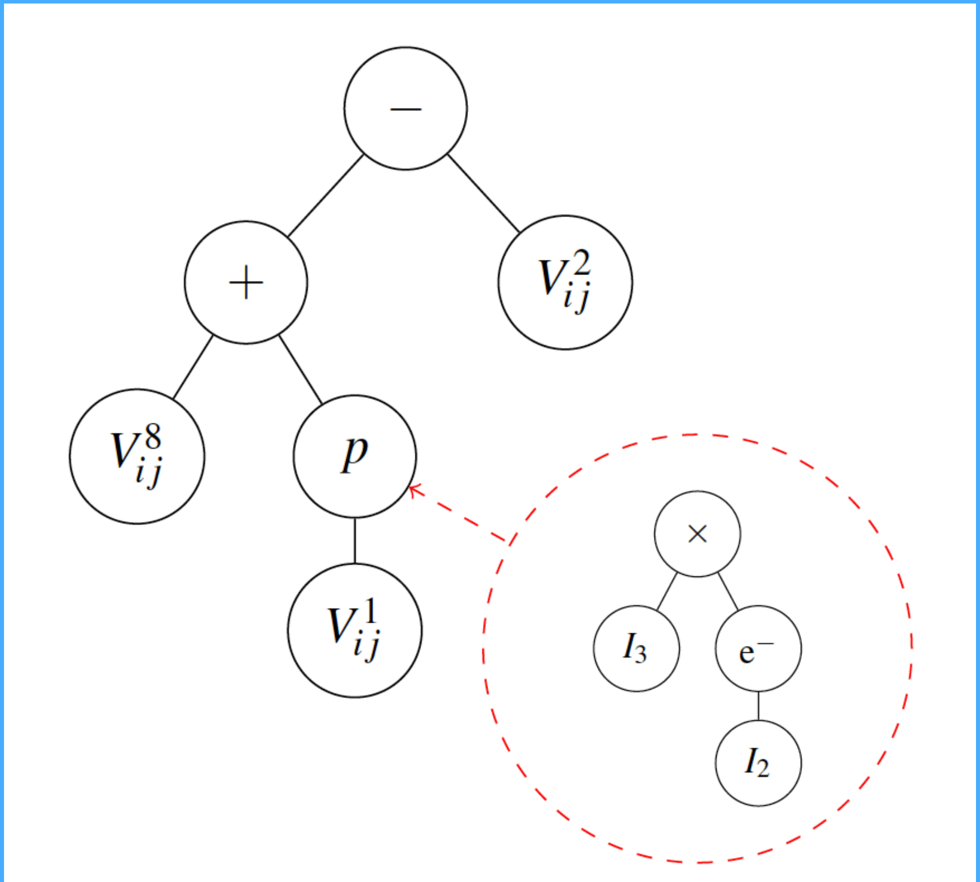
What is Machine Learning?

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



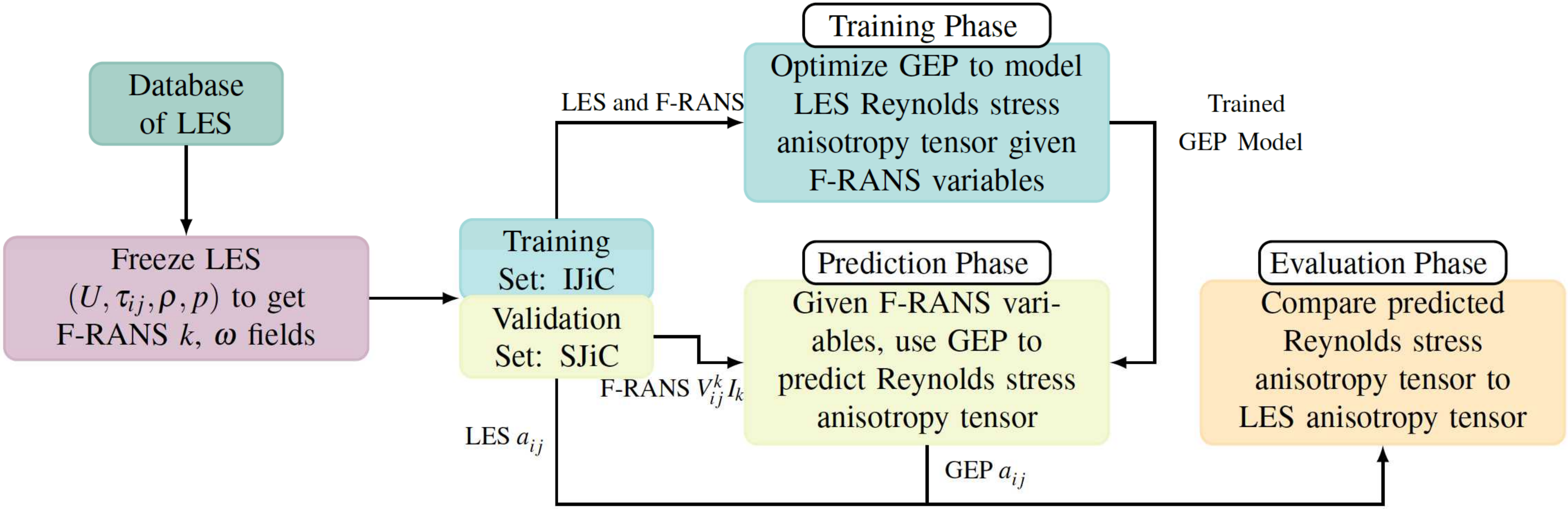
Gene Expression Programming

- Symbolic regression
- Each analytic expression is expressed as a chromosome
- Mutation, recombination, and survival of the fittest used to arrive at optimal expression



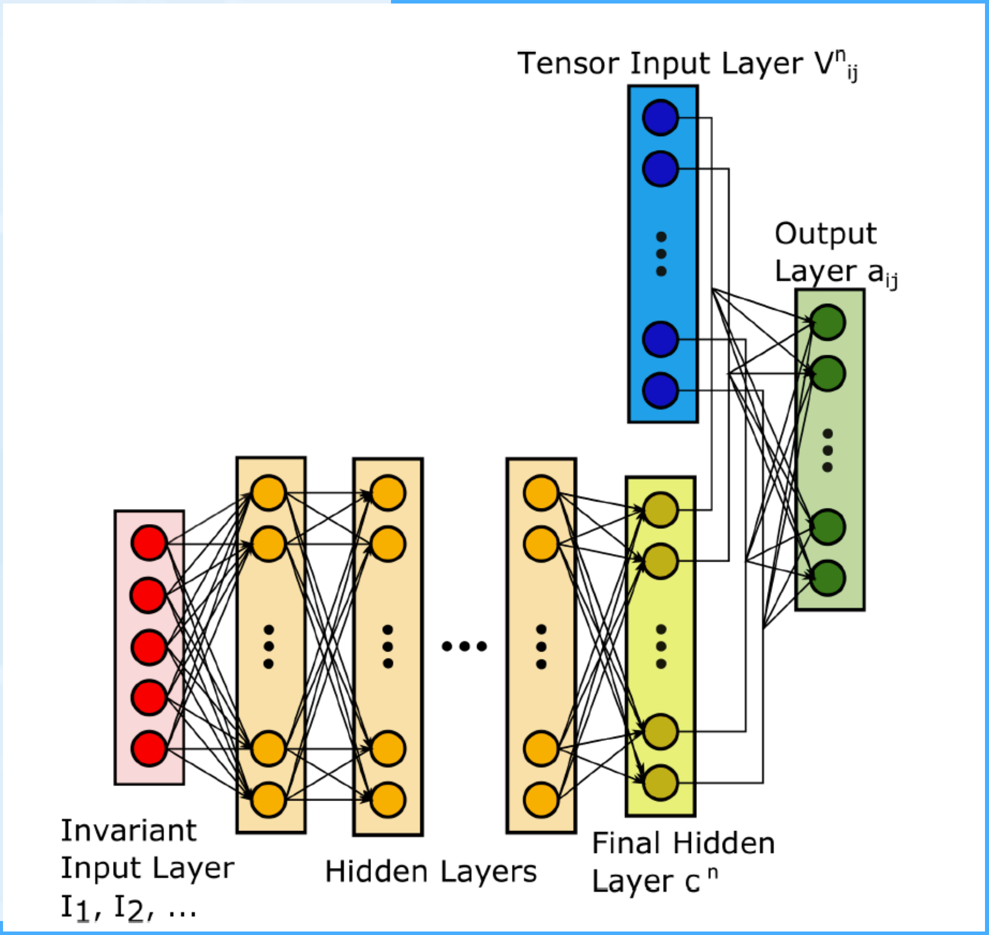
Weatheritt, Jack, and Richard Sandberg. "A novel evolutionary algorithm applied to algebraic modifications of the RANS stress–strain relationship." Journal of Computational Physics 325 (2016): 22-37.

Gene Expression Programming



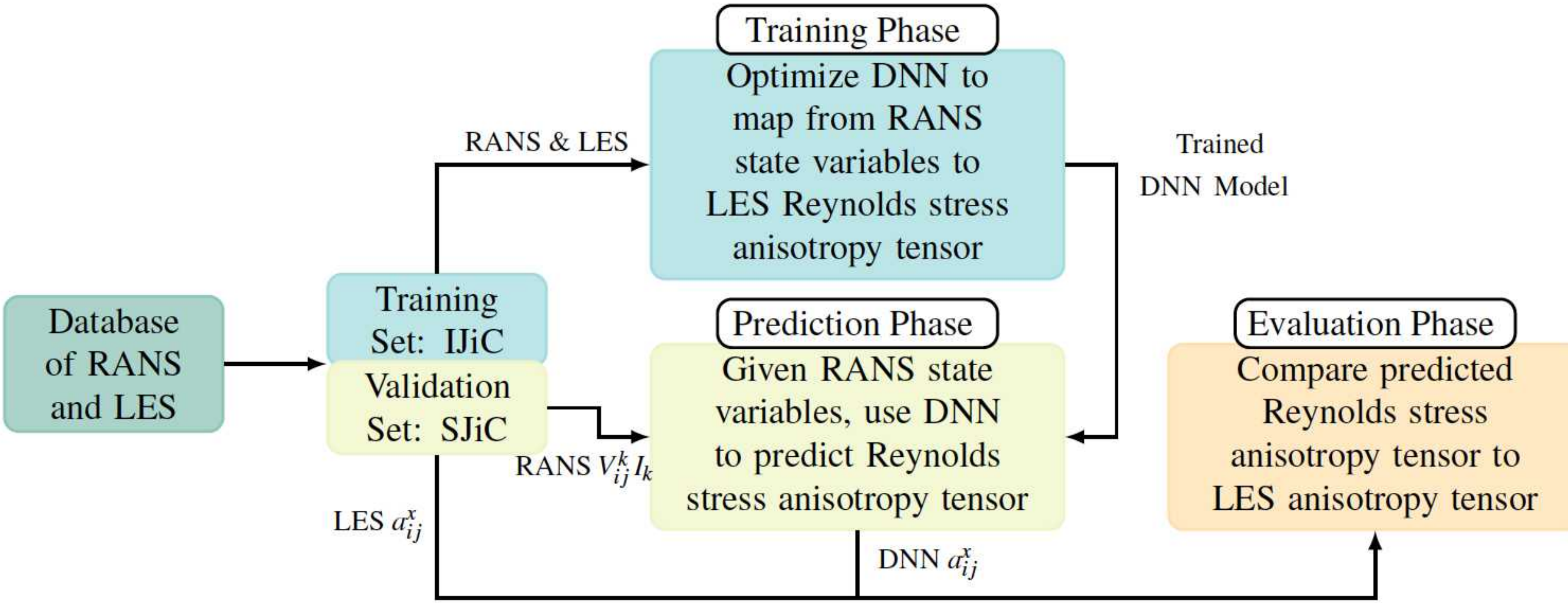
Deep Neural Networks

Tensor Basis Neural Network (TBNN)



Ling, Julia, Andrew Kurzawski, and Jeremy Templeton. "Reynolds averaged turbulence modelling using deep neural networks with embedded invariance." Journal of Fluid Mechanics 807 (2016): 155-166.

Deep Neural Network



Comparison of Methods

Data preparation:

- GEP approach uses frozen RANS
- DNN approach uses normal RANS

Algorithm:

- GEP approach uses symbolic regression
- DNN approach does not use any known functional form

Flow Configurations

Two jet in crossflow configurations:

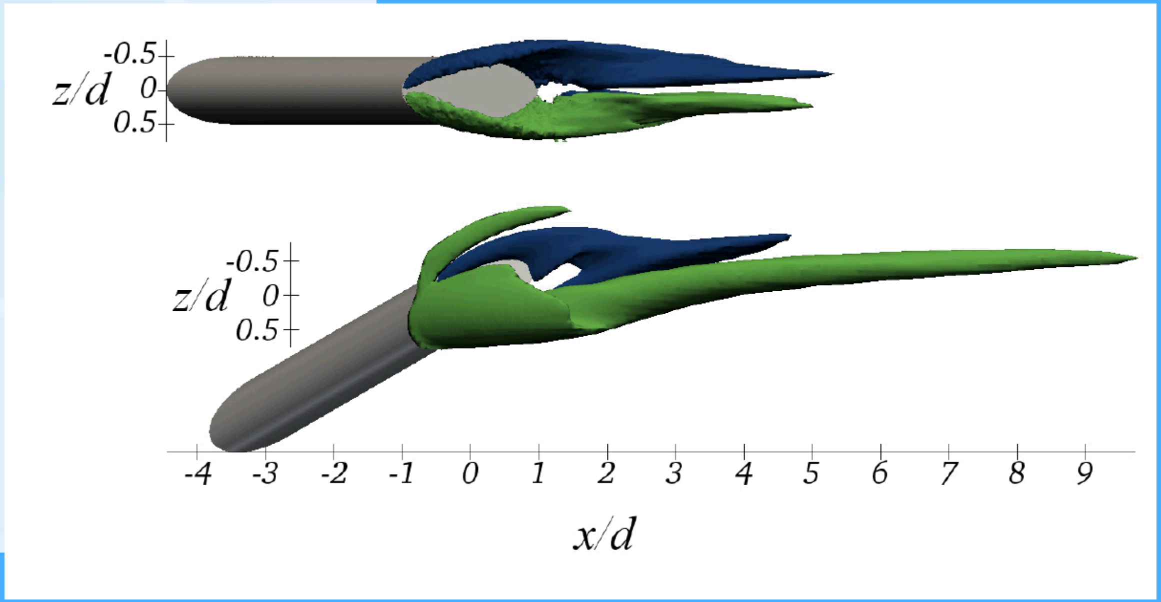
- Inclined Jet in Crossflow (IJiC): 52 M cell LES, used for training
- Skewed Jet in Crossflow (SJiC): 101 M cell LES, used for testing

High fidelity LES available for both flows

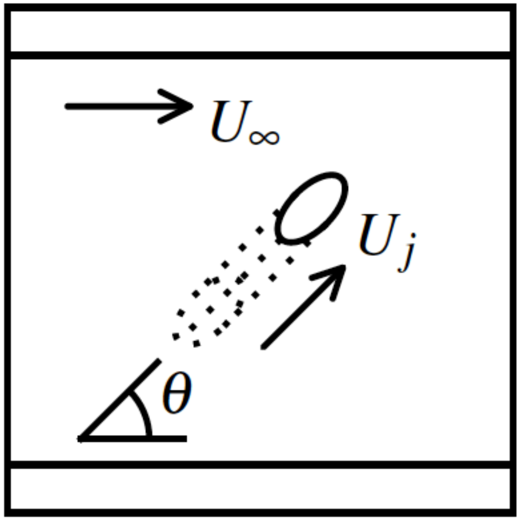
- Thoroughly validated against experimental results

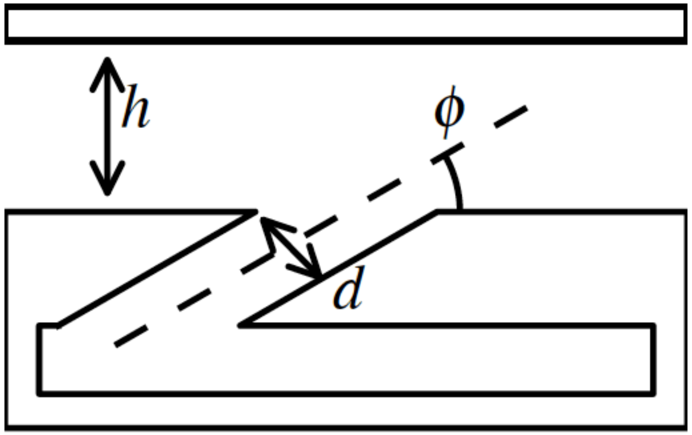
IJiC

SJiC



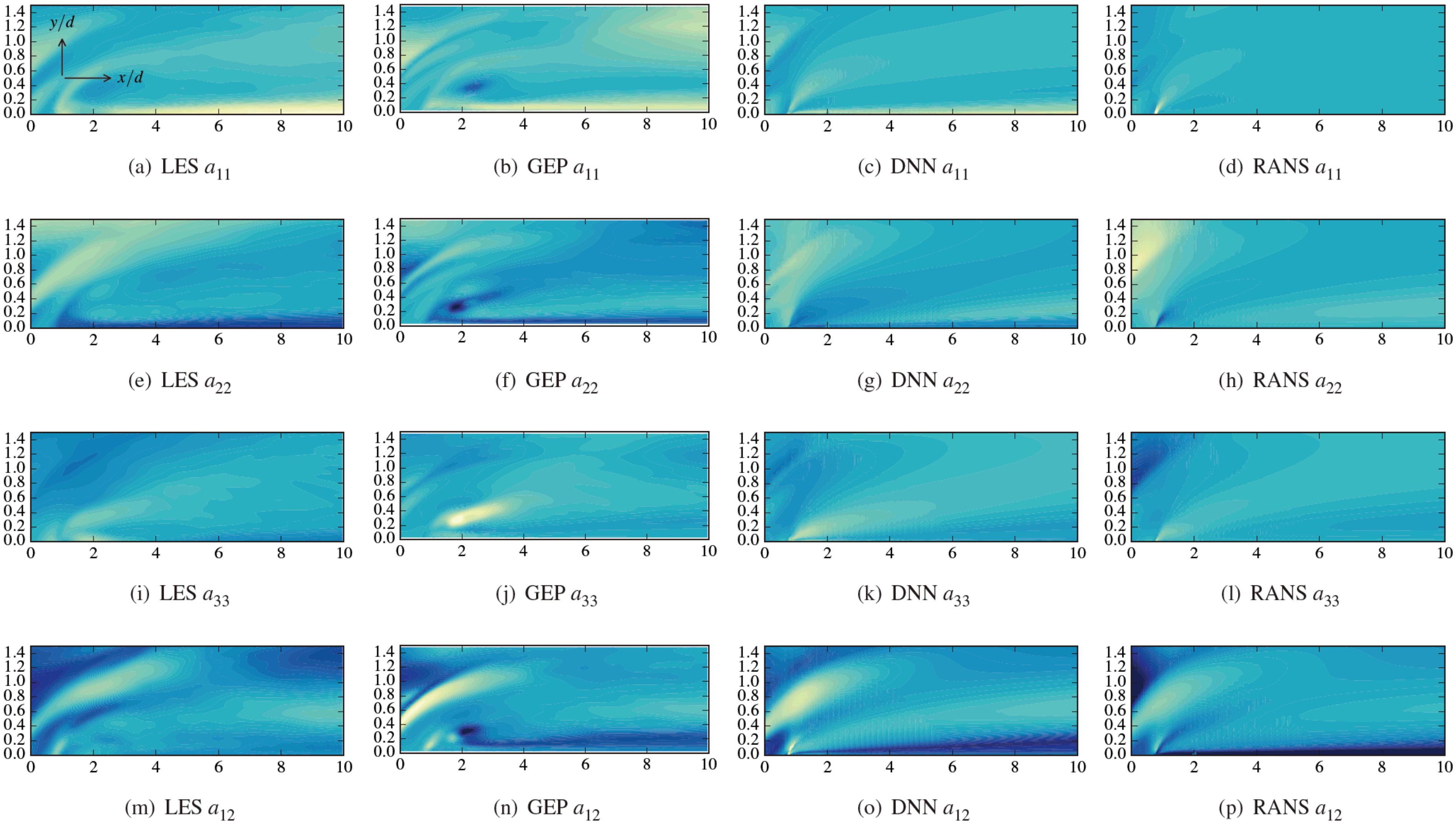
Flow Configuration





	ϕ	θ	r	J	Re_j	δ/d	Re_h
IJiC	30°	0°	1	1	5,400	1	45,800
SJiC	30°	30°	1	1	5,800	1.9	50,000

Results



(a) LES a_{11} (b) GEP a_{11} (c) DNN a_{11} (d) RANS a_{11}

(e) LES a_{22} (f) GEP a_{22} (g) DNN a_{22} (h) RANS a_{22}

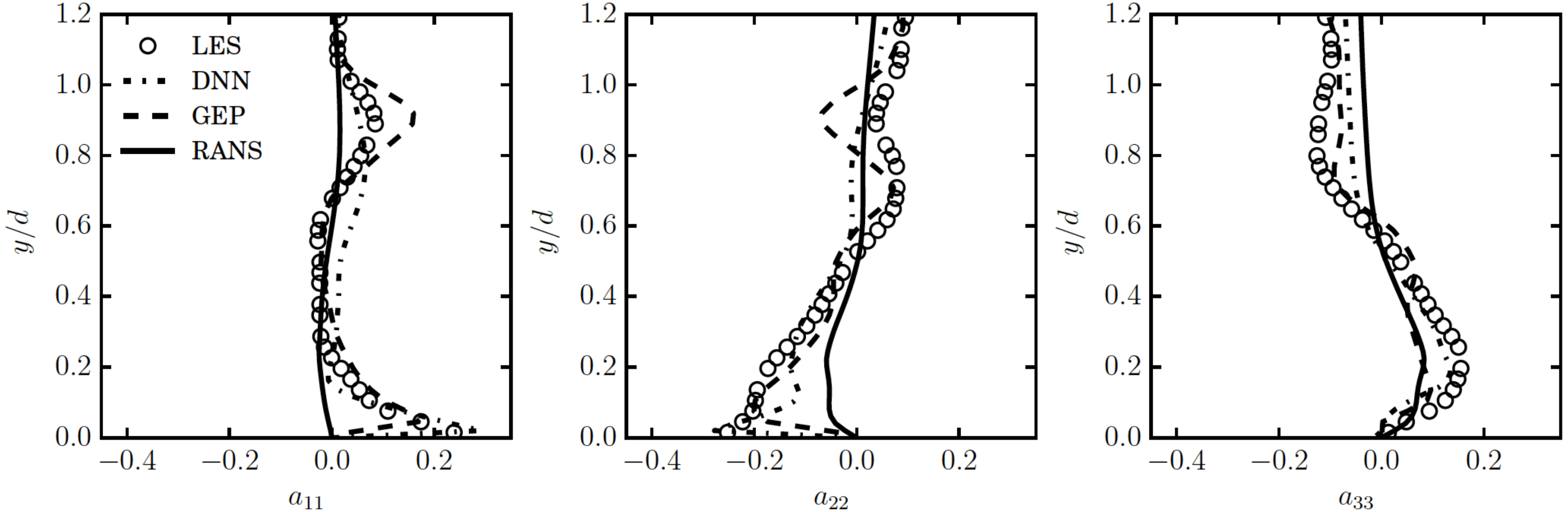
(i) LES a_{33} (j) GEP a_{33} (k) DNN a_{33} (l) RANS a_{33}

(m) LES a_{12} (n) GEP a_{12} (o) DNN a_{12} (p) RANS a_{12}

Results

Anisotropy along vertical profile at x/d = 4, z/d = -0.5

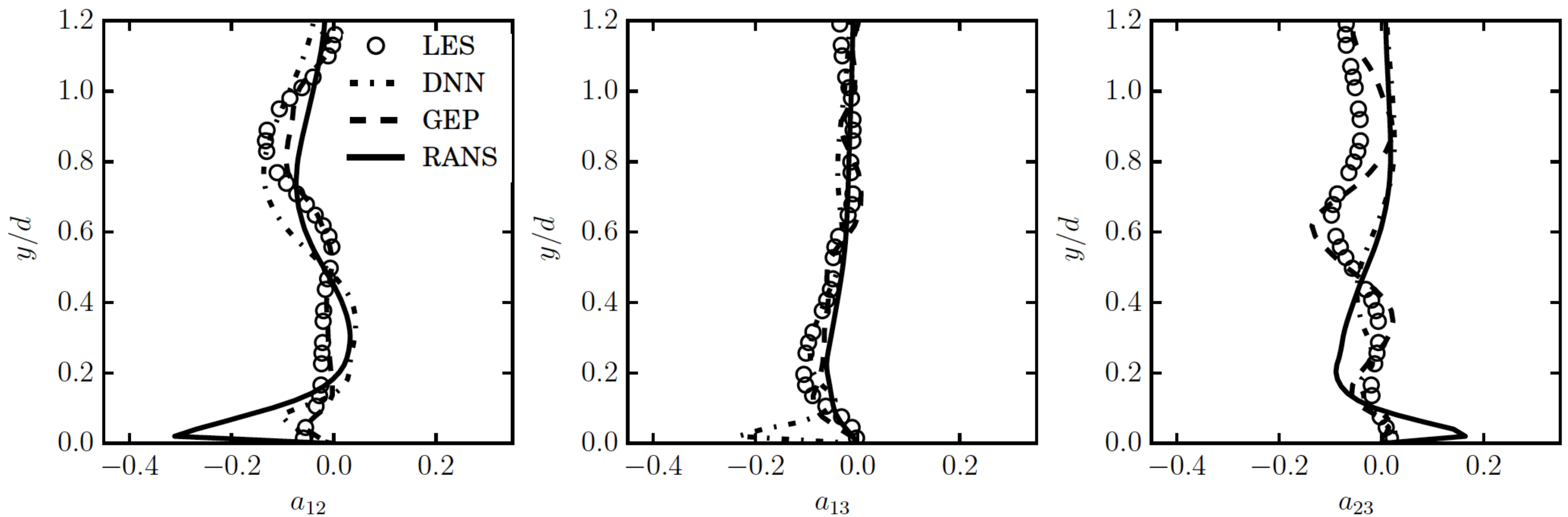
a_{11} a_{22} a_{33}



Results

Anisotropy along vertical profile at x/d = 4, z/d = -0.5

a_{12} a_{13} a_{23}



Results

$$\mathrm{RMSE}(a_{ij}^{\mathrm{mod}}) = \sqrt{\frac{1}{6N}\sum_{\alpha=1}^{N}\sum_{i=1}^{3}\sum_{j=1}^{i}(a_{ij} - a_{ij}^{\mathrm{mod}})^2}$$

GEP	F-RANS	DNN	RANS
0.078	0.141	0.093	0.152

GEP reduces RMSE by 45% compared to F-RANS
DNN reduces RMSE by 39% compared to RANS

Conclusions

Two different machine learning methodologies applied to JiC flow configurations

After being trained on just one JiC data set, both methods were able to provide significantly improved anisotropy predictions on a second (more complex) JiC data set

Take aways:

- Side by side comparisons of data driven approaches are critical for moving this field forward
- These methods have the potential to fundamentally change how we simulate flows and how we leverage data

Next steps:

- Try mixing and matching data prep and algorithmic approaches
- Train and validate on many more flows
- Forward propagation to mean flow field

References

- Ling, Julia, Andrew Kurzawski, and Jeremy Templeton. "Reynolds averaged turbulence modelling using deep neural networks with embedded invariance." Journal of Fluid Mechanics 807 (2016): 155-166.
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Questions?