Machine Learning-Based Reduced Order Modeling to Simulate the Hydrodynamics of Large Fish Schools

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Motivation

- Bio-robotic underwater drones can be developed that are fast, efficient, maneuverable, and stealthy; the next generation in underwater drones.
- A school of these devices can complete various distributed tasks such as surveillance/reconnaissance.
- Understanding the interaction forces and hydrodynamic benefits of schooling will aid in the design of *high-performance* bio-robotic schools.
- Learning about the energetics of fish schools can also provide insight into the fragility of fish populations to overfishing and climate change.

Background

- Computational methods are required to solve most non-idealized fluid mechanics models to find the velocity field and forces acting on submerged bodies.
- Traditional full order models (FOMs) scale poorly to large simulations.
- The small school simulation in Figure 2 took one day to complete
- These simulations need to be run thousands of times and include more swimmers in order to understand the parameter space.
- The question has been raised as to whether reduced order models (ROMs) can replicate and expedite their FOM counterparts.
- The Naval Research Lab (NRL) has developed a ROM conferring a 2000 times decrease in computational time with 0.1% error as compared to the FOM [1].

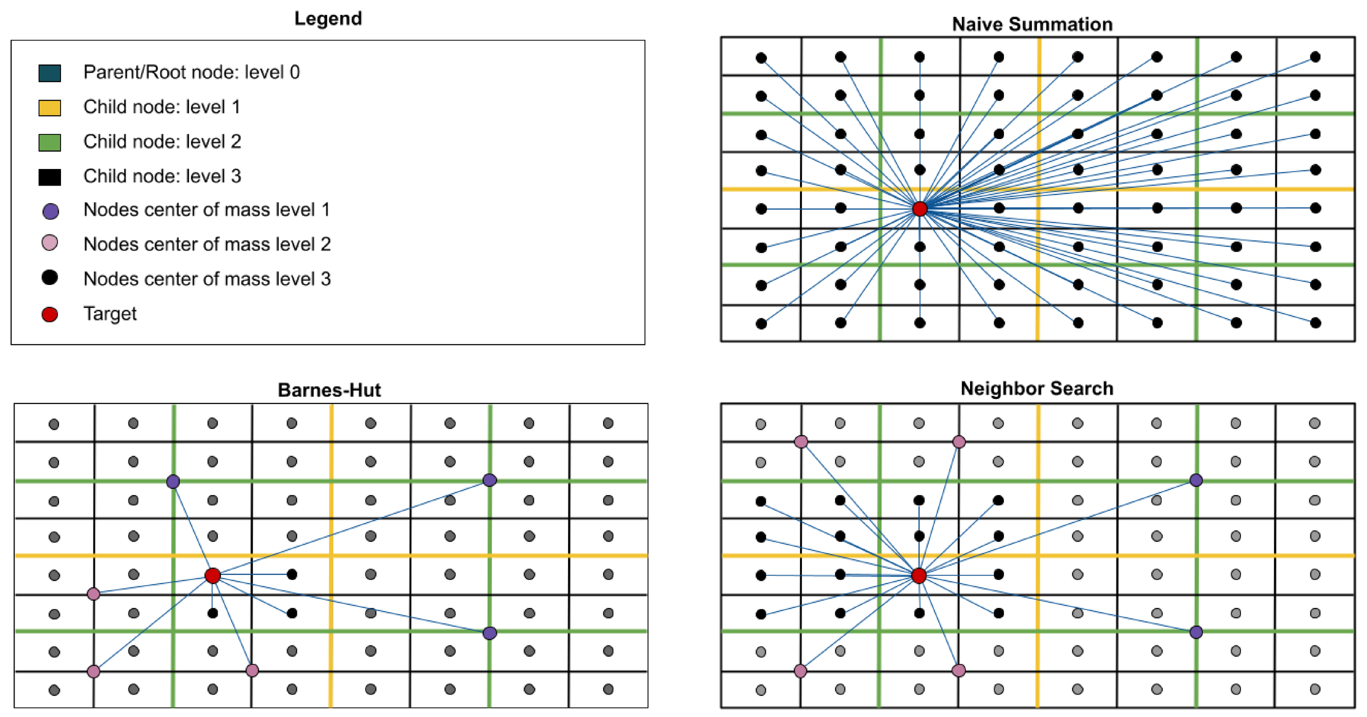

Figure 4. Resulting efficient neighbor search algorithms from the ROM as compared to the current (naïve summation) method of solutions [1].

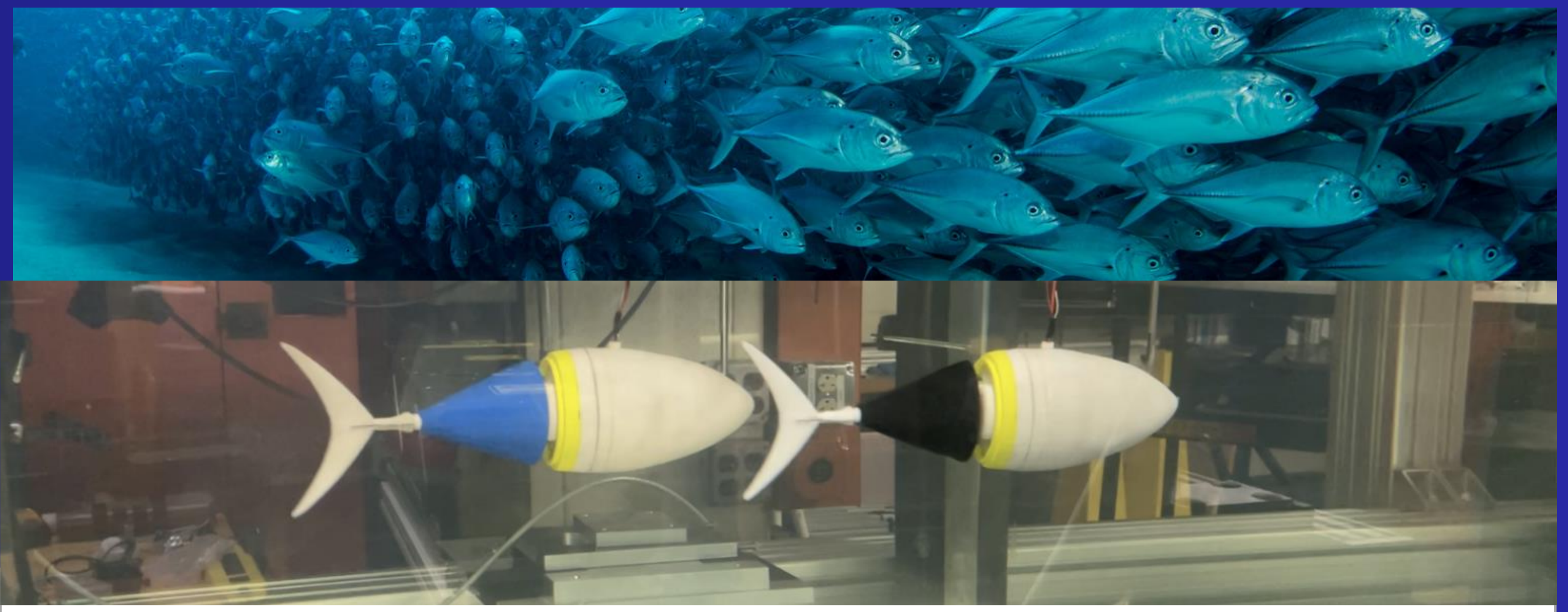

Figure 1.Tuna schooling in the ocean (top), and Tunabots constructed to measure hydrodynamic forces acting on a leader and a follower (bottom).

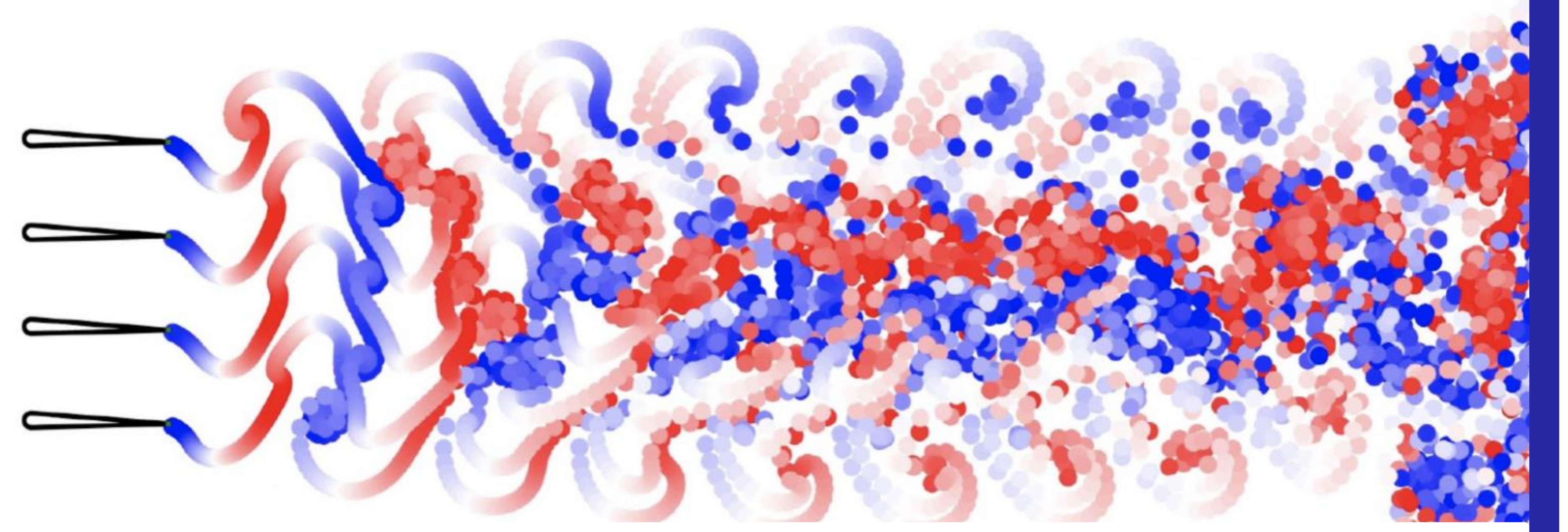

Figure 2. Simulation of four swimmers interacting and shedding wake elements in the clockwise (blue) and counterclockwise (red) sense.

Reduced Order Model Overview

- Run training simulations for the full time of the FOM for a down-sampled parametric space.
- Choose the parameters on which to train (design-of-experiment).
- Perform dimensional reduction (SVD or Autoencoders).
- Introduce low dimensional variables into model reduction framework to speed up the simulation.

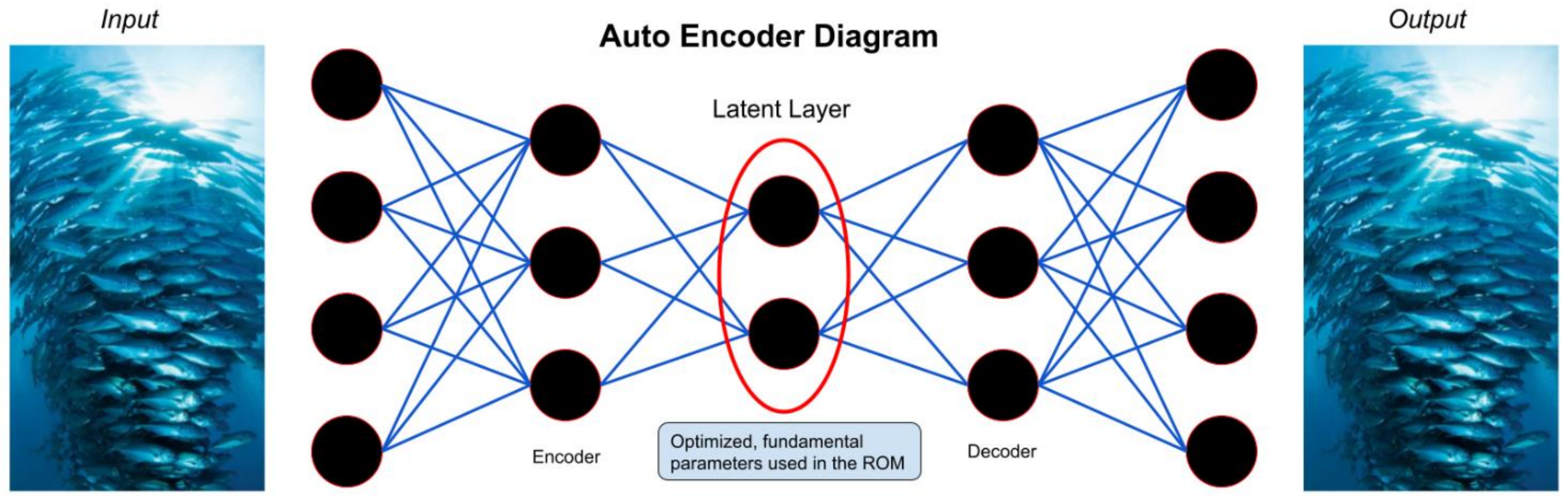

Figure 3. Diagram of an autoencoder for dimensional compression to obtain the most fundamental basis of the simulation.

Implementation & Next Steps

- Use the FOM to train the ROM.
- Implement the ROM to simulate large numbers of swimmers previously unobtainable with the FOM.
- Gather quantities of interest using the ROM for post processing.

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[1] Rodriguez, S. N., et al. "Projection-tree reduced order modeling for fast N-body computations." *arXiv preprint arXiv:2103.01983* (2021).

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