Clustering Reduced Order Models for Computational Fluid Dynamics

Gabriele Boncoraglio and Forest James Charles Fraser
{gbonco, forestf}@stanford.edu

Overview

Improving the design of aircrafts requires solving PDE-constrained optimization problems such as maximizing the lift/drag with respect to some parameters, $\mu$. To find the optimal $\mu$, we must update it iteratively, running an expensive computational fluid dynamics (CFD) simulation at each optimization step.

Objective: Accelerate the optimization process by using clustering/classification techniques to generate and use multiple reduced order models (ROMs) for less expensive, yet still accurate simulations.

Background

Running a CFD simulation involves solving for the state of the fluid, $w$. To speed up CFD simulations ROMs are used to approximate the results of a full simulation. The ROM approximates the fluid state as: $w \approx V_{gl}(\mu)w_f$ where the reduced order basis (ROB), $V_{gl}$ is built using precomputed solution $\{w_1, w_2, \ldots, w_k\}$ computed at $\{\mu_1, \mu_2, \ldots, \mu_k\}$.

Usually one global ROM is constructed, however we propose building multiple, smaller, more localized ROMs, since they may have fewer unknowns, hence simulations are faster and may more accurately approximate the full simulation within a sub-region of the design space, $D$.

Key Issues

Our proposed methodology solves a PDE-constrained optimization problem in two phases, an offline phase and an online phase.

Offline Phase

In the offline phase, we cluster precomputed training solutions, from which we build our ROMs that are used in the online phase.

Online Phase

In the online phase, we query multiple $\mu_i$ during the optimization process. For each queried $\mu_i$, we need select which ROM ($V_i$) to use. Then we run the simulation to compute $w_i(\mu_i)$ and $\text{lift/drag}(\mu_i)$.

Methodology

Our proposed methodology solves a PDE-constrained optimization problem in two phases, an offline phase and an online phase.

Experiments & Results

Using our validation set we tested which clustering and classification algorithms performed best using 4 clusters, $\{\mu_{\text{lift/drag}}\}$ as clustering features and $\mu$ as the classification feature.

Finally we tested the performance of the clustered ROMs on the test set using the optimal parameters found from validation.

Conclusions and Future Work

- Using our methodology allows us to either accelerate the optimization process or achieve a higher simulation accuracy when compared with a global ROM.
- In the future, we would like develop an accurate predictor for determining the optimal parameters for clustering/classification.

Sampling

- We sample a set of $\{\mu_1, \mu_2, \ldots, \mu_n\}$ for which we calculate the states $\{w_1, w_2, \ldots, w_n\}$ using full simulations.
- From our set of $\mu$ and $w$ we randomly split our data into training/validation/test sets of size 50, 30 and 10 respectively.