

DATA-DRIVEN MODEL-BASED APPROACHES FOR EFFICIENT FLOW CONTROL

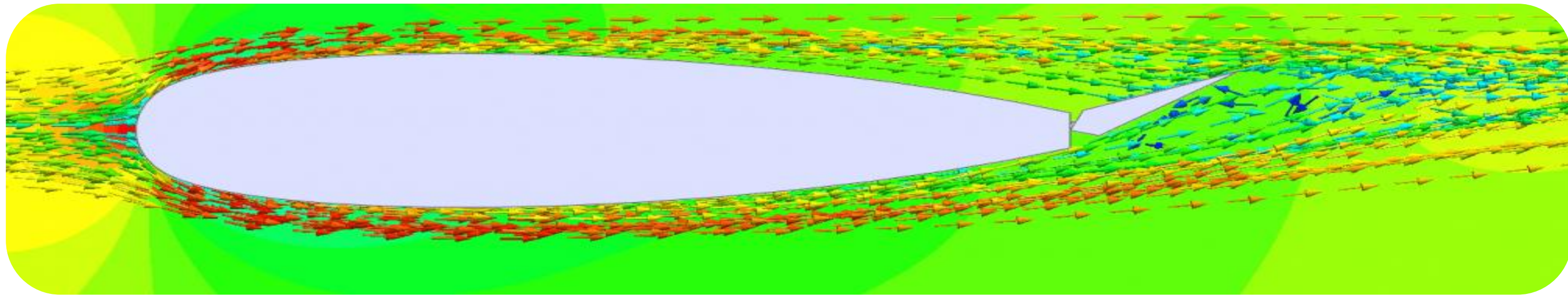
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Motivation

Modern aerospace systems require **efficient** and **robust** flow control strategies but:

- Fluid flows are highly **non-linear** and **high-dimensional**.



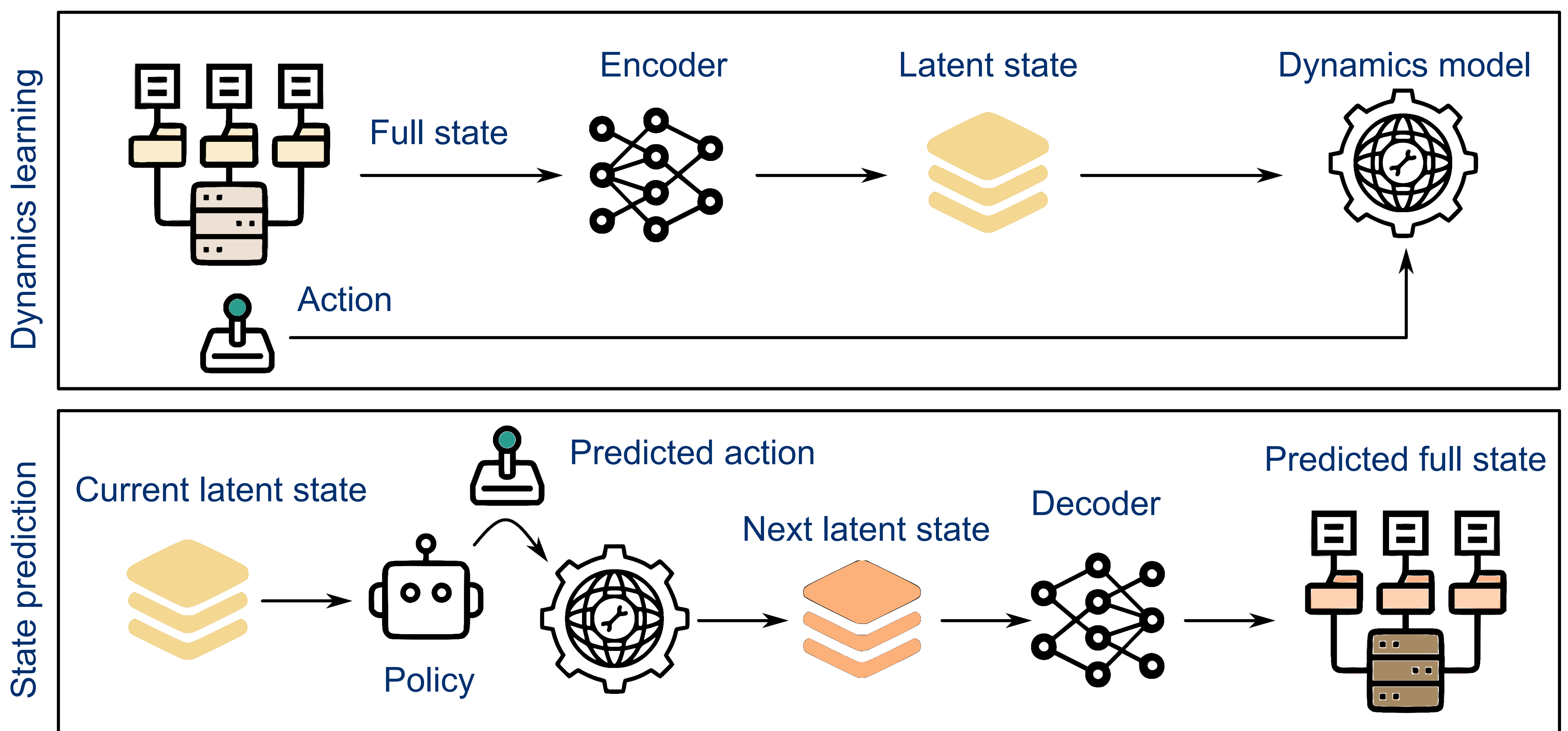
- Classical** controllers struggle in transient/chaotic regimes.
- High-fidelity simulations are **computationally expensive**.

State of the Art

- Classical flow control is hindered by **non-linearity** and is **expensive** for large discretizations [1, 2].
- Deep Reinforcement Learning (DRL) has been applied to fluid mechanics as it is adaptive and non-linear, though it can be **sample-inefficient** and **unstable** [3, 4].
- Recent model-based RL approaches leverage learned surrogate dynamics to accelerate control learning, yet robust **latent state** representations for complex flow regimes remain an open challenge.

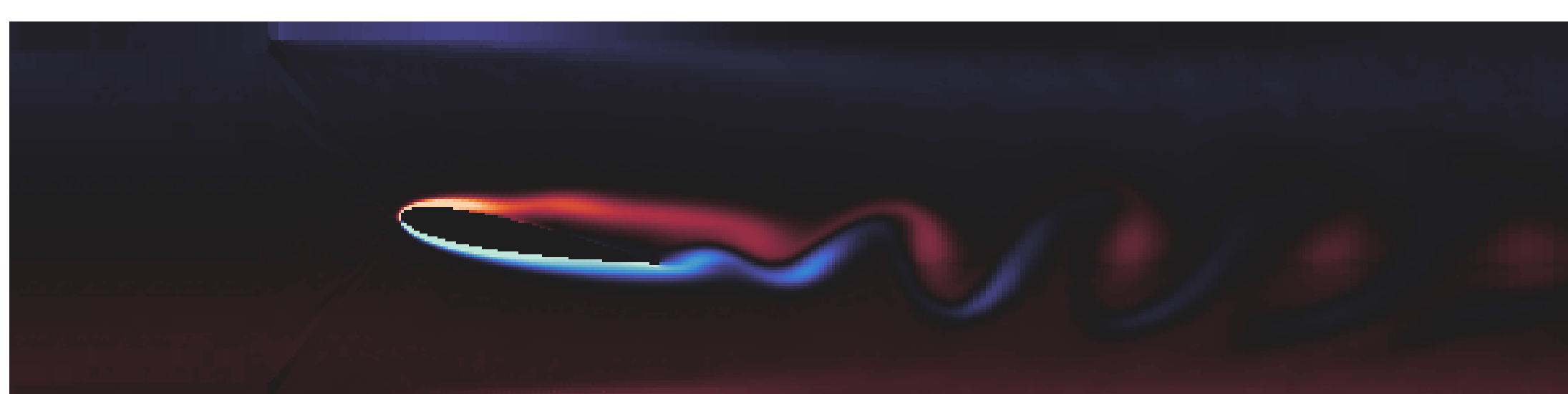
Methodology

Develop a **model-based** reinforcement learning framework using **latent flow representations** for efficient control, improving **data efficiency**, exploiting **learned physics**, and making CFD-based control **tractable**.



Preliminary Research

- Application of *offline* DRL methods to fluid dynamic data.
- Model-based frameworks based on low-dimensional projections.



References

- [1] Peitz *et al.*, arXiv:1510.05819
- [2] Ravindran, j.cma.2006.11.026
- [3] Buşoniu *et al.*, j.arcontrol.2018.09.005
- [4] Moslem *et al.*, j.oceaneng.2025.120989