XIII JORNADAS DE JÓVENES INVESTIGADORES/AS DEL I3A

Flow estimation around arbitrary geometries by thermodynamics-informed neural networks

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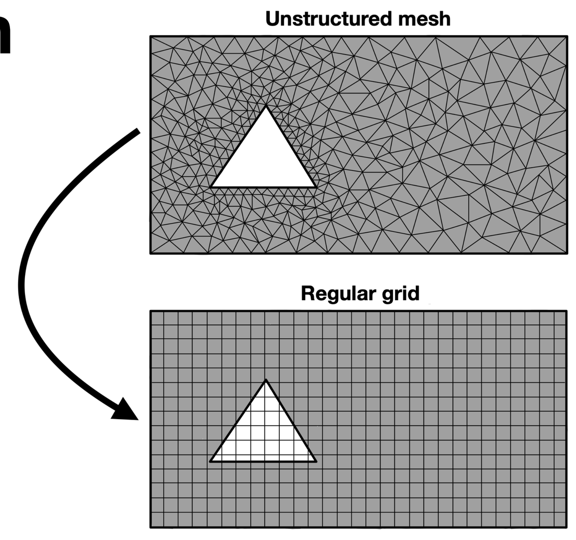
INTRODUCTION

- **Complex dynamic** systems → High **computational cost**
- **Digital twins, AR, VR**: need for **real-time** predictions
- Machine learning approaches
  + Very **fast predictions**
  - **Lack of physics**
- Solution: deep learning **+ physics guidance**

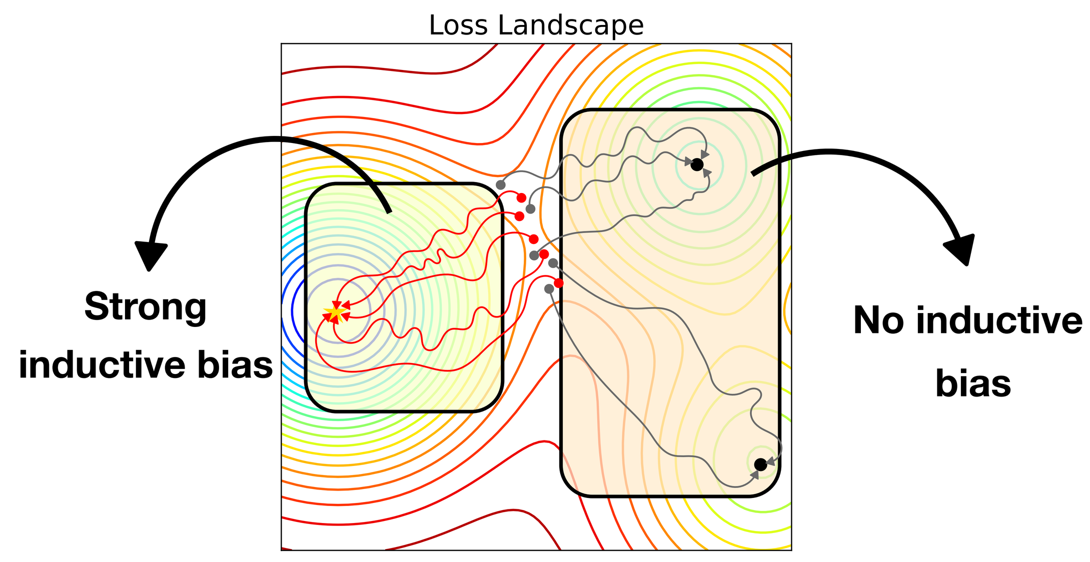
METHODS

Database Generation

- **Unsteady** flow over a **2D primitive geometries**
- Simulations run in **OpenFOAM**[1]
- **Post-processing**:
  - **Unstructured mesh** to **grid**



Inductive Biases



Deep Learning Framework

1. **AAE - Adversarial Autoencoder**[2]
   - **Learns** a **low dimensional manifold**
2. **SPNN - Structure Preserving Neural Network**[3]
   - Predicts the **dynamical evolution** of the system
   - Applies the **metriplectic bias - GENERIC Formalism**

General Equation for Non-Equilibrium Reversible-Irreversible Coupling (GENERIC)[4,5]

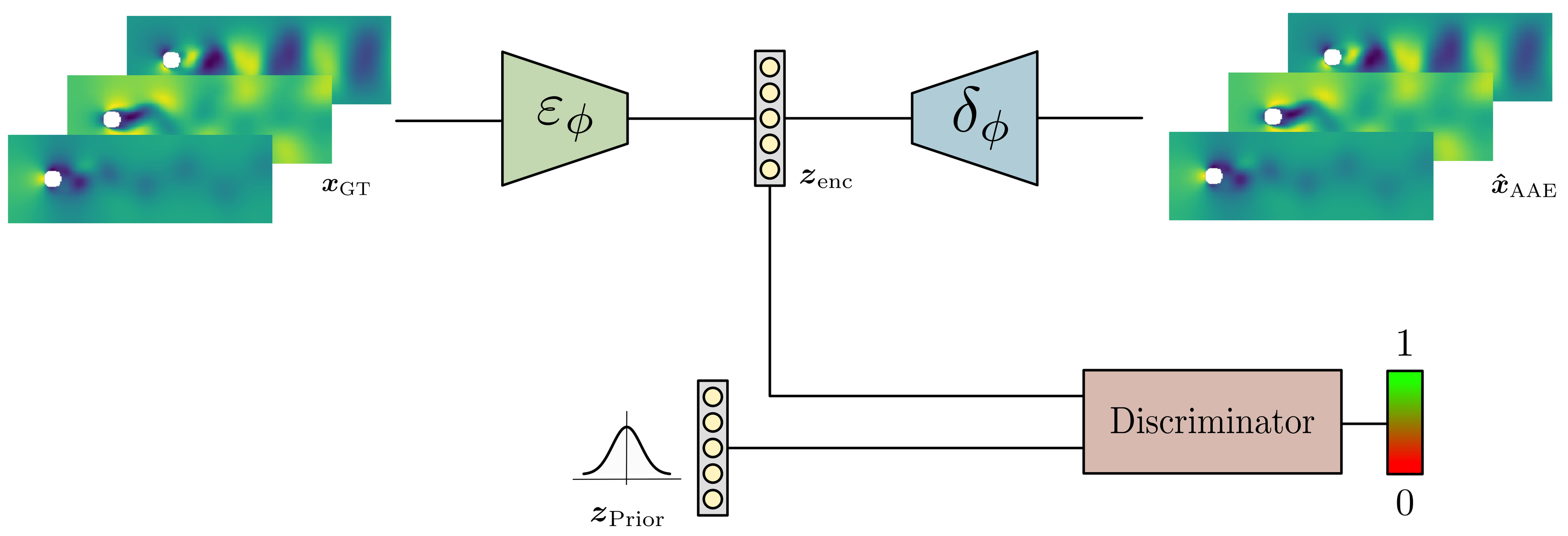
$$\frac{d\mathbf{z}}{dt} = \mathbf{L}\frac{\partial E}{\partial \mathbf{z}} + \mathbf{M}\frac{\partial S}{\partial \mathbf{z}}$$

Symplectic manifold → Metriplectic manifold[6]

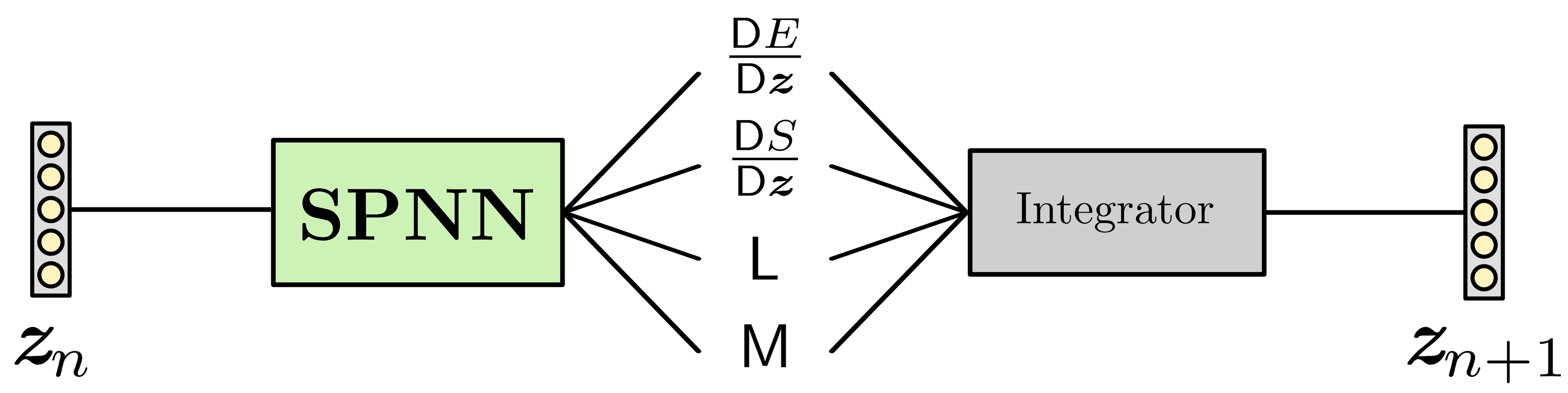
Degeneracy conditions — **Fullfills 1st and 2nd laws of Thermodynamics**

$$\begin{cases} \mathbf{L}\frac{\partial S}{\partial \mathbf{z}} = 0 \\ \mathbf{M}\frac{\partial E}{\partial \mathbf{z}} = 0 \end{cases} \Rightarrow \quad \frac{dE}{dt} = 0, \quad \frac{dS}{dt} \geq 0$$

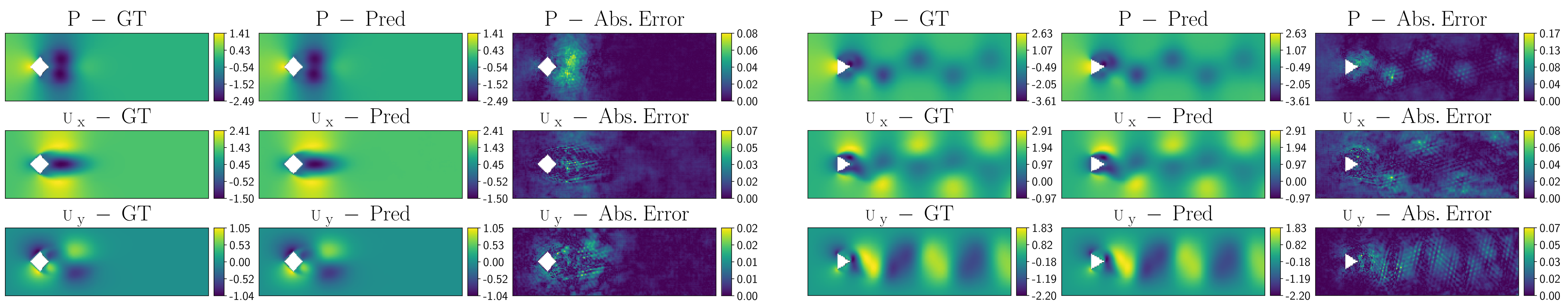
1. **Adversarial Autoencoder**



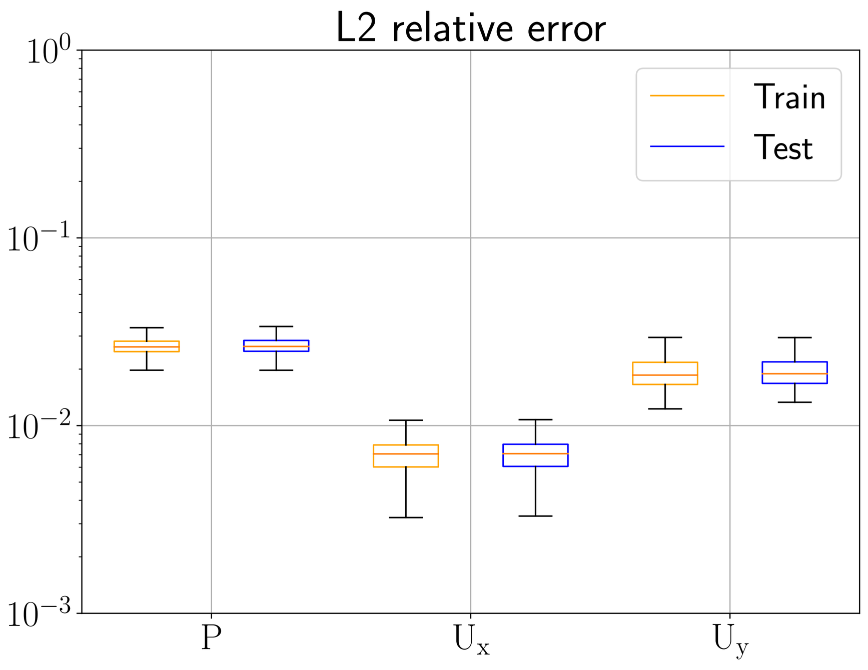
2. **Structure Preserving Neural Network**

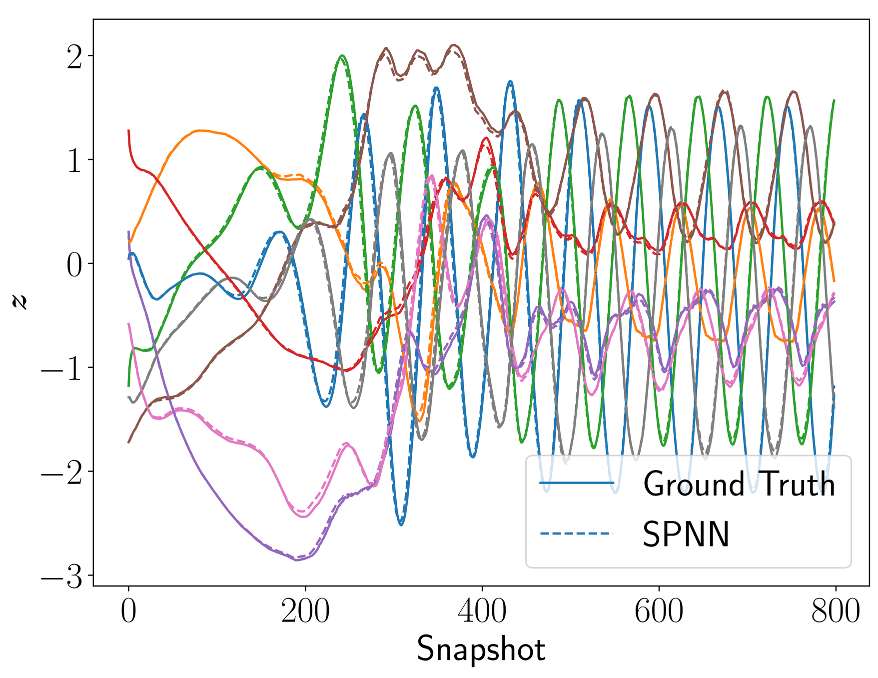


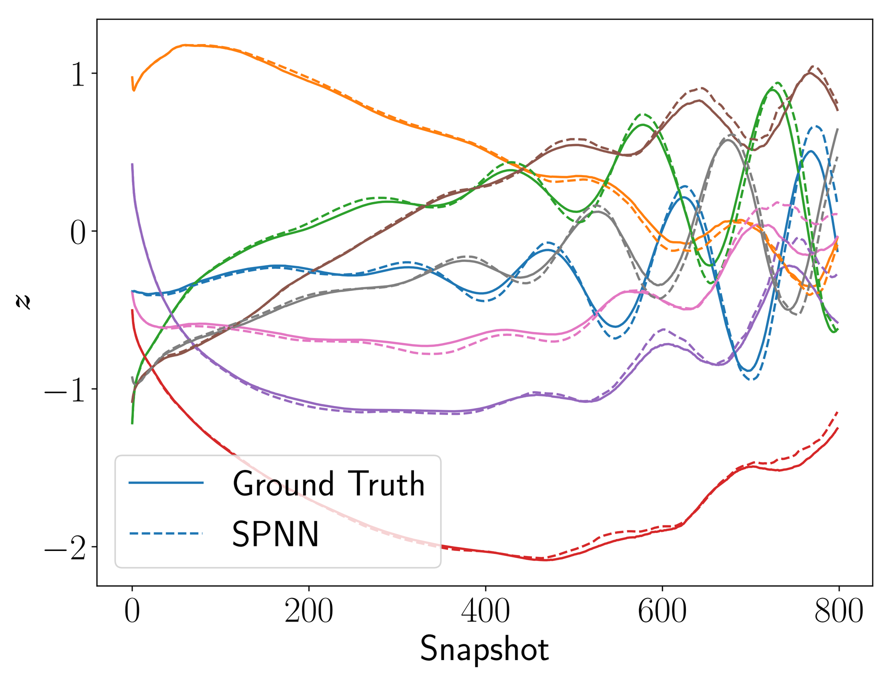
RESULTS



VIDEOS HERE!







CONCLUSIONS

-**Successful** codification of the flow achieved by the **AAE**

- **Thermodynamics-based biases** help to improve **robustness** and **generalization**

FUTURE WORK

- Apply **metriplectic** and **geometric** biases together - **GNN**

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References

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