XII Jornada de Jóvenes Investigadores/as del I3A

Super-resolution by thermodynamics-informed neural networks for fluid-dynamics problems

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INTRODUCTION

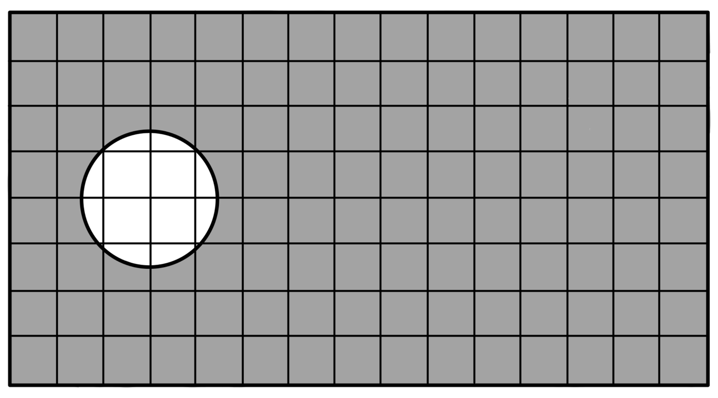
- **Complex dynamic** systems → High **computational cost**
- **Digital twins**: need for **real-time** preditions
- Data coming from **sensors**: **SPARSE**
    - Space
    - Time
- Deep learning + **guidance**: **Physics**

METHODS

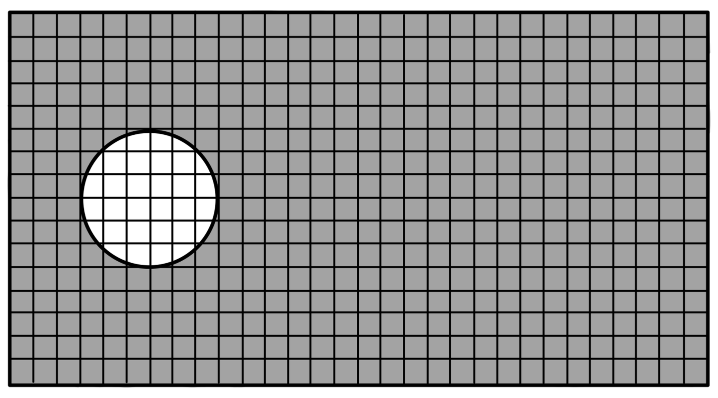
Database Generation

- **Unsteady** flow over a **cylinder**
- Simulations run in **OpenFOAM**[1]
- **Post-processing**:
    - **Grid** with two **resolutions**

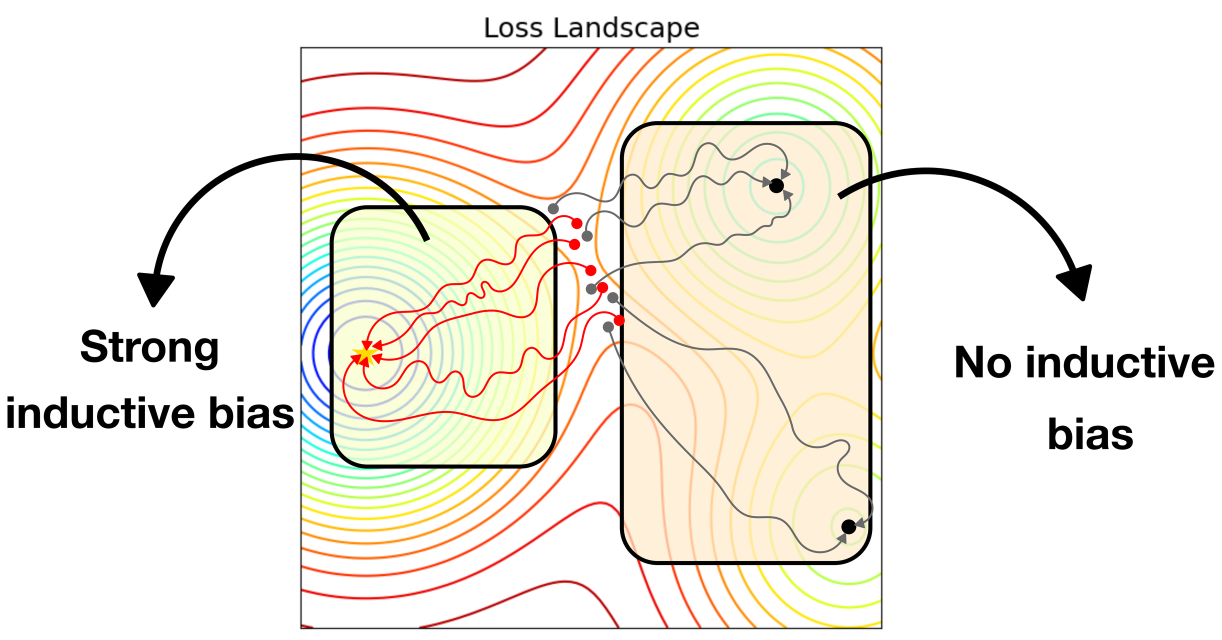
Low resolution: 16 x 48 px



High resolution: 64 x 192 px



Inductive Biases



General Equation for Non-Equilibrium Reversible-Irreversible Coupling (GENERIC)[2,3]

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

Symplectic manifold → Metriplectic manifold[4]

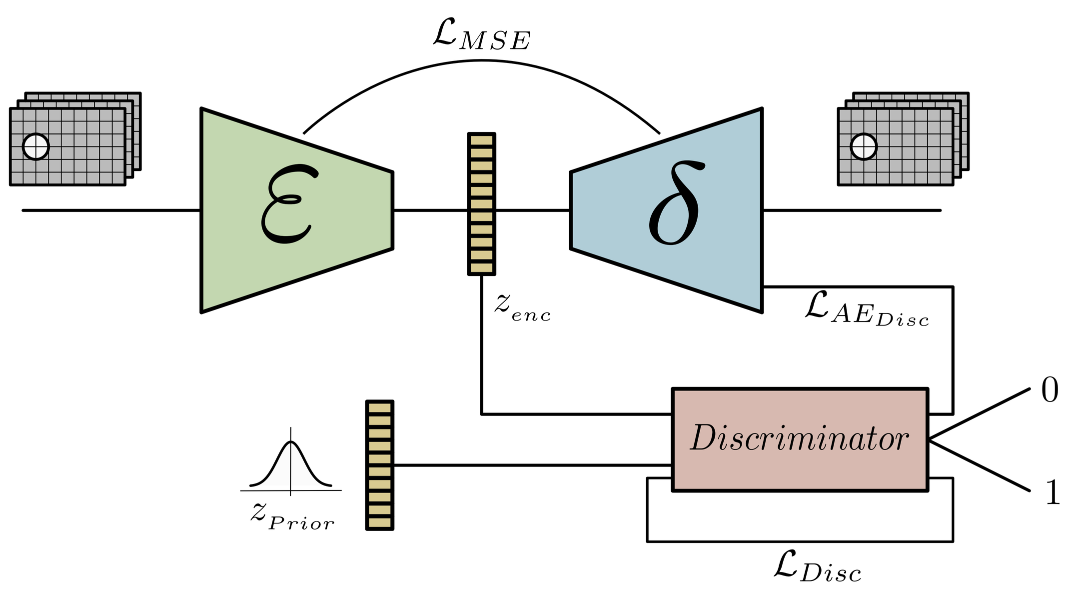
Degeneracy conditions / **Fulfills 1st and 2nd laws of Thermodynamics**

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

Deep Learning Framework

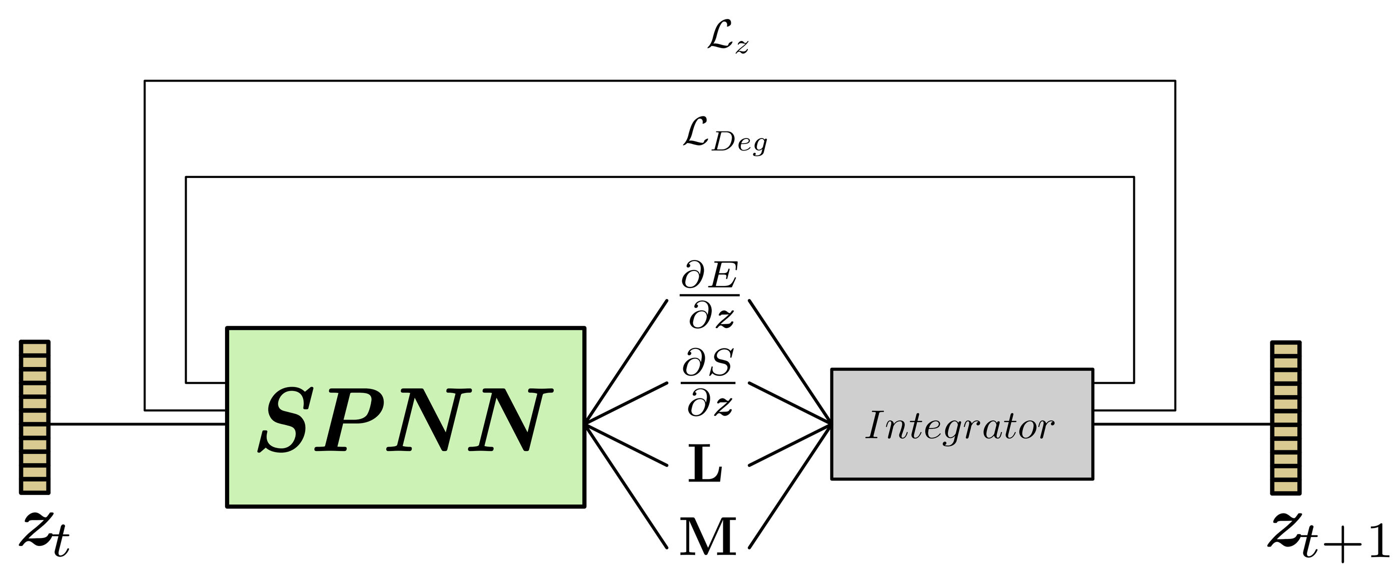
1 **AAE - Adversarial Autoencoder[5]**

- **Learns** a **low dimensional manifold**



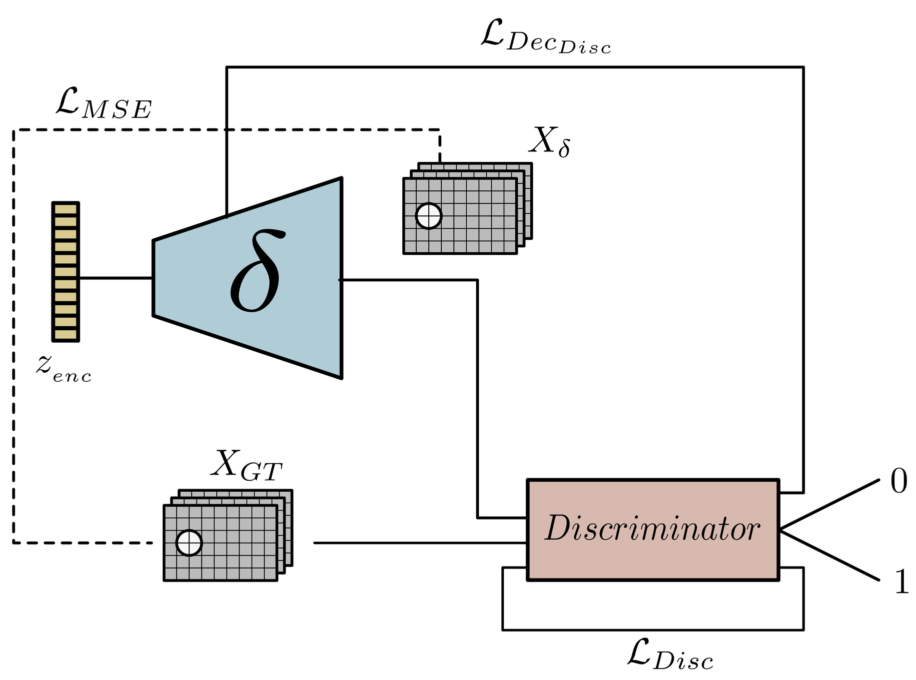
2 **SPNN - Structure Preserving Neural Network[6]**

- Predicts the **dynamical evolution** of the system
- Applies the **metriplectic bias**



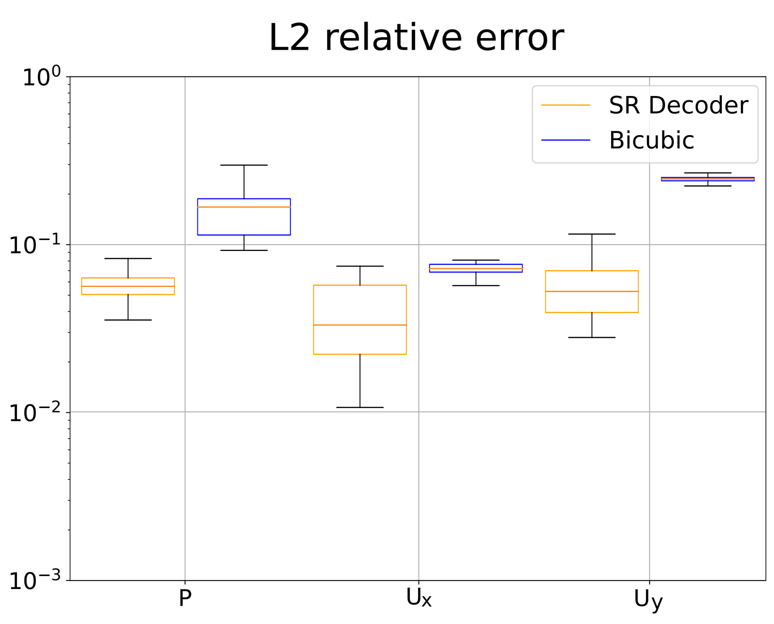
3 **SR - Superresolution Decoder**

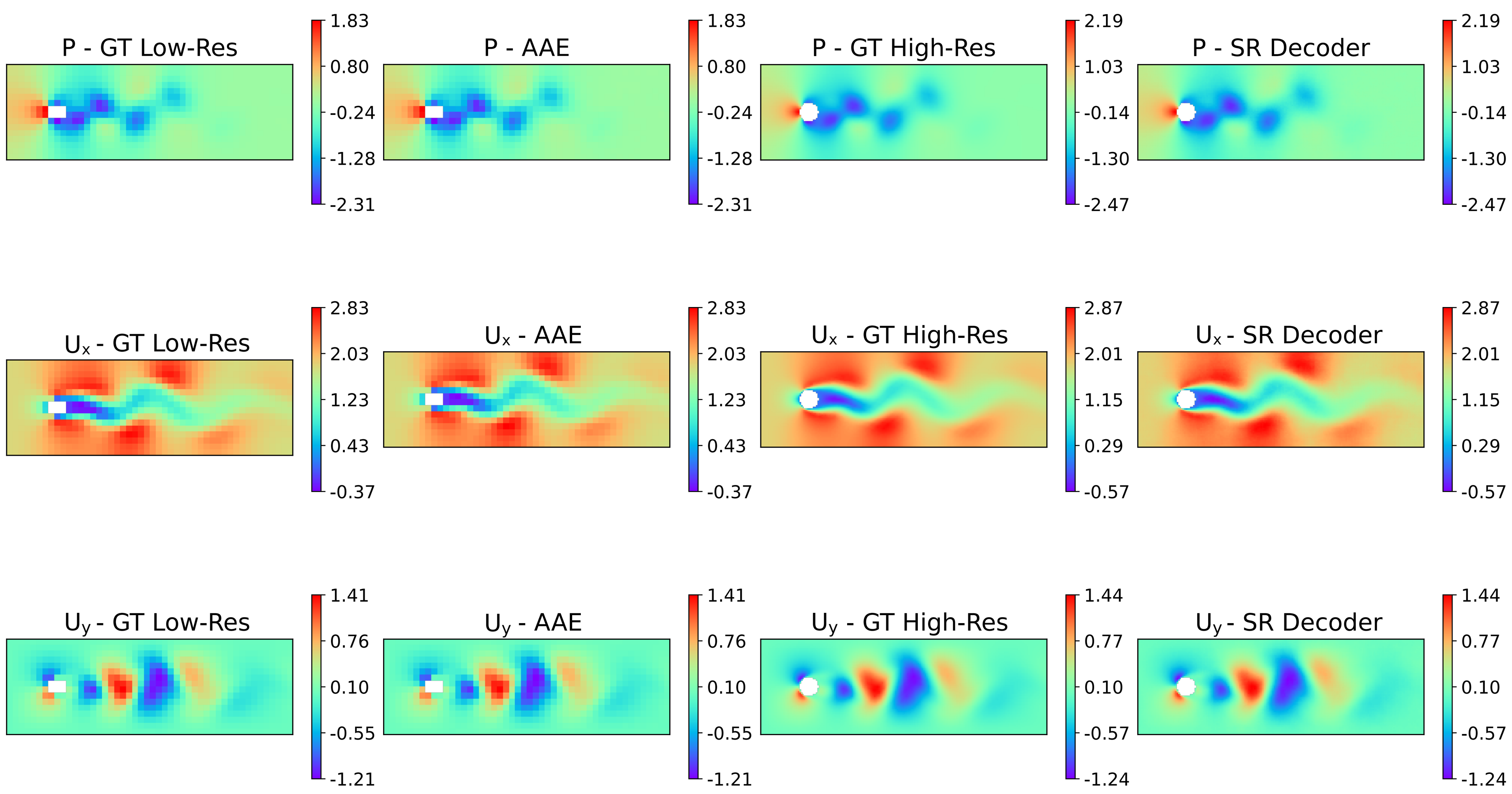
- **Enhances resolution** from low dimensional manifold.



RESULTS

- **AAE** Reconstruction **error** between **1 - 2%**
- **SR Decoder** reconstruction **error < 7%**
- **SR Decoder outperforms** results achieved by **bicubic interpolation** methods while being **faster**





CONCLUSIONS

- **Successful** codification of the flow achieved by the **AAE**
- **Thermodynamics-based biases** help to improve **robustness** and **generalization**
- Successful **enhancement** of the spatial **resolution**

FUTURE WORK

- Apply the method to **different** flows
- Introduce **physics biases** in the **Superresolution** decoder

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References

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[2] GRMELA, M. and ÖTTINGER, H.C. (1997). Dynamics and thermodynamics of complex fluids. I. Development of a general formalism. Physical Review E 56. 56(6), p.6620.

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[4] MORRISON, P.J. (1986). A paradigm for joined Hamiltonian and dissipative Systems. Physica D: Nonlinear Phenomena. 18(1-3), 410 - 419.

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