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

METHODS
Database Generation
- Unsteady flow over a cylinder
- Simulations run in OpenFOAM®
- Post-processing:
  - Grid with two resolutions

General Equation for Non-Equilibrium
Reversible-Irreversible Coupling (GENERIC)\(^2,3\)
\[
\frac{dz}{dt} = L \frac{\partial E}{\partial z} + M \frac{\partial S}{\partial z}
\]
Symplectic manifold → Metrplectic manifold\(^4\)

Degeneracy conditions
Fulfills 1st and 2nd laws of Thermodynamics
\[
\begin{align*}
L \frac{\partial S}{\partial z} &= 0 \\
M \frac{\partial E}{\partial z} &= 0
\end{align*}
\]
\[
\Rightarrow \frac{dE}{dt} = 0, \quad \frac{dS}{dt} \geq 0
\]

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

REFERENCES

Inductive Biases
- Strong inductive bias
- No inductive bias

Deep Learning Framework
1. AAE - Adversarial Autoencoder
   - Learns a low dimensional manifold

2. SPNN - Structure Preserving Neural Network
   - Predicts the dynamical evolution of the system
   - Applies the metrplectic bias

3. SR - Superresolution Decoder
   - Enhances resolution from low dimensional manifold

\[\text{cbarbanjo@unizar.es}\]
\[@cbarbanjo\]
\[\text{github.com/cberbanjo}\]
\[\text{amb.unizar.es/people/carlos-bermejo-barbanjo}\]