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DEEP LEARNING OF DYNAMICAL SYSTEMS WITH GEOMETRY AND THERMODYNAMICS

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Deep learning-based artificial intelligence success in computer science has encouraged many authors to transfer this new technology to the physical simulation field. The challenging task of those research lines is to adapt state-of-the-art deep learning tools into physics and engineering, two disciplines with centuries of experimental and theoretical background. In our work, we develop a deep learning framework to predict the evolution of complex physical systems using that knowledge in a form of several inductive biases, which guide the learning algorithm to find the physically consistent target function.

The first inductive bias enforces the metriplectic structure of dissipative dynamics via the GENERIC formalism [1]. This formulation imposes the physical consistency by using thermodynamics, being able to model both conservative and dissipative dynamics. In order to learn this structure, we develop a graph-based architecture to take advantage of the mesh geometric information and make computations over the topology of the domain, also called as geometric deep learning [2]. Furthermore, several symmetries can be imposed to the problem, such as permutation or translational invariance, which decrease the data consumption of the method. The combined use of the metriplectic and geometric bias is tested with several nonlinear examples of solid and fluid mechanics.

REFERENCES

[1] Q. Hernández, A. Badías, D. González, F. Chinesta and E. Cueto. Structure-preserving neural networks, *Journal of Computational Physics* (2021) **426**: 109950.

[2] M. M. Bronstein, J. Bruna, Y. LeCun, A. Szlam and P. Vandergheynst. Geometric deep learning: going beyond euclidean data, *IEEE Signal Processing Magazine* (2017) **34(4)**: 18-42.