Recognizing physical systems by machine learning

- **Goal**: To develop a machine-learning methodology for recognizing physical systems based on snapshots of their evolution (for instance Figure 1).

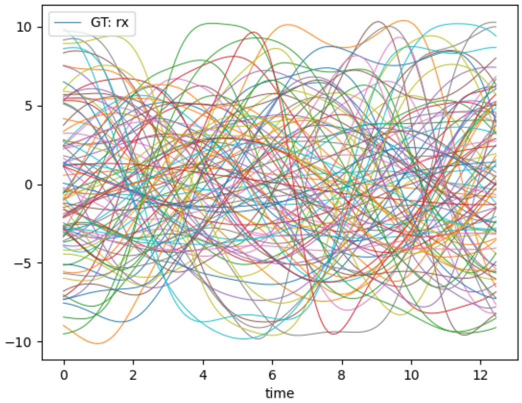

Figure 1: For instance, our Direct Poisson Neural networks identify what Hamiltonian system has generated these trajectories[2].

- **Methodology**: Figure 2 shows the main tool to learn the underlying physics – neural networks.

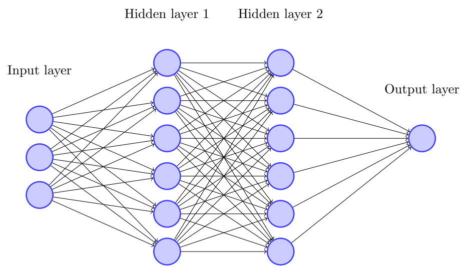

Figure 2: A neural networks approximates a multi-dimensional mapping. The approximation is a composition of mappings starting at the leftmost (input) layer and giving the rightmost (output) values.

  The networks encode the underlying Poisson bracket and energy that describe the motion of a Hamiltonian system. For dissipative systems, we shall use the framework of General Equation for Non-Equilibrium Reversible-Irreversible Coupling (GENERIC) [1].

- **Specific tasks**:
  1. Cleaning our numerical code.
  2. Extending the code to learn also dissipative systems.

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References

[1] M. Pavelka, V. Klika, and M. Grmela. *Multiscale Thermo-Dynamics*. de Gruyter, Berlin, 2018.

[2] M. Šípka, M. Pavelka, O. Esen, and M. Grmela. Direct Poisson neural networks: learning non-symplectic mechanical systems. *Journal of Physics A: Mathematical and Theoretical*, 56(49), 2023. `https://github.com/enaipi/direct-Poisson-neural-networks`.