GCM

Student Project Proposal

Latent Space Physical Simulation

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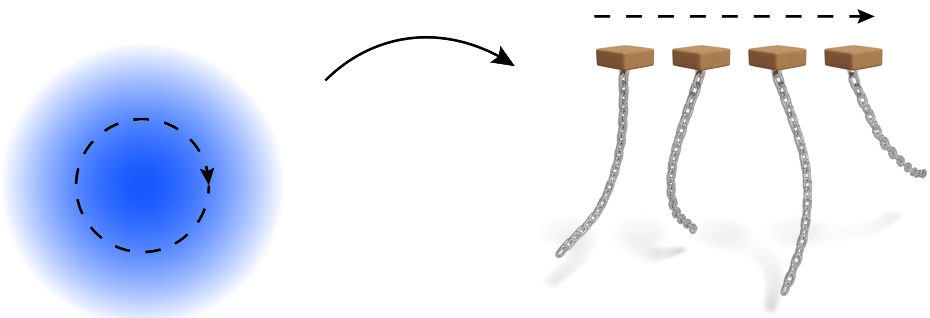

Figure 1: Each point in the latent space (left) corresponds to a state in the configuration space (right). By navigating in a learned latent space along chosen paths (here circles), one could simulate the temporal evolution of a physical system. In addition to speeding up simulation, the latent space could be structured in such a way that smaller circles around the origin have lesser total energy *i.e.*, the latent space is made interpretable. The chain system under gravity illustration is taken from Sharp and colleagues [4].

Description

When subject to external forces, physical systems describe trajectories in their configuration space that are governed by laws of physics. For instance, in case of conservative forces only (and time-invariant potential), these paths are isolines of the total energy of the system. Computing such paths can be done by integrating the Hamiltonian equations, for which the Hamiltonian can be learned [5], or by equivalently integrating equations of motion (Newton's second law).

To cut computation costs while preserving predictive accuracy, many works focus on building lower dimensional simulation spaces that capture most of the system's behavior [1]. In such setups, the integration happens directly in the subspace, see Brandt and coworkers [3] for instance. Following that idea, Sharp and colleagues [4] recently proposed a data-free method to learn such simulation subspaces. While appealing at first glance for reduced simulation, their method is meant to find low **potential energy** configurations of the system. High potential energy configuration are discarded, and potential energy varies little on the subspace. This prohibits exchanges between kinetic and potential energy, and leads to loss in the total energy of the system during simulation.

We are interested in adapting their framework so that traveling along certain chosen paths (e.g., straight lines, circles) in the learned subspace amounts to integrating NSL in the full configuration space. The training algorithm has to change. For instance, it could evaluate how likely it is for two states to be separated by a time increment h using the proximal operator defined in Bouaziz and colleagues [2], Equation (4).

Milestones

The goals of the project may be summarized as

- Reproduce results from Sharp and colleagues [4], and evaluate conservation of energy using their latent space simulation method;
- Implement a simple yet illustrative differentiable physical simulation to compare the baseline method and the developed one;
- Learn a latent space for which simple paths map to physically plausible trajectories in the configuration space;
- Organize the latent space so that navigating is human interpretable e.g., one latent direction orthogonal to the latent paths could correspond to changing the total energy of the system.

Prerequisites

Good knowledge of Python is required, along with experience with one auto-differentiation framework (preferrably JAX). Experience with physical simulation will be helpful.

Remarks

The project is intended for Master students in the context of a 8 or 12 credits semester project.

References

[1] Peter Benner, Serkan Gugercin, and Karen Willcox. A survey of projection-based model reduction methods for parametric dynamical systems. *SIAM review*, 57(4):483–531, 2015.

[2] Sofien Bouaziz, Sebastian Martin, Tiantian Liu, Ladislav Kavan, and Mark Pauly. Projective dynamics: Fusing constraint projections for fast simulation. In *Seminal Graphics Papers: Pushing the Boundaries, Volume 2*, pages 787–797. 2023.

[3] Christopher Brandt, Elmar Eisemann, and Klaus Hildebrandt. Hyper-reduced projective dynamics. *ACM Transactions on Graphics (TOG)*, 37(4):1–13, 2018.

[4] Nicholas Sharp, Cristian Romero, Alec Jacobson, Etienne Vouga, Paul Kry, David IW Levin, and Justin Solomon. Data-free learning of reduced-order kinematics. In *ACM SIGGRAPH 2023 Conference Proceedings*, pages 1–9, 2023.

[5] Peter Toth, Danilo J. Rezende, Andrew Jaegle, Sébastien Racanière, Aleksandar Botev, and Irina Higgins. Hamiltonian generative networks. In *International Conference on Learning Representations*, 2020.