CPS:Medium:Safe Learning-Enabled Cyberphysical Systems, CNS-2038493

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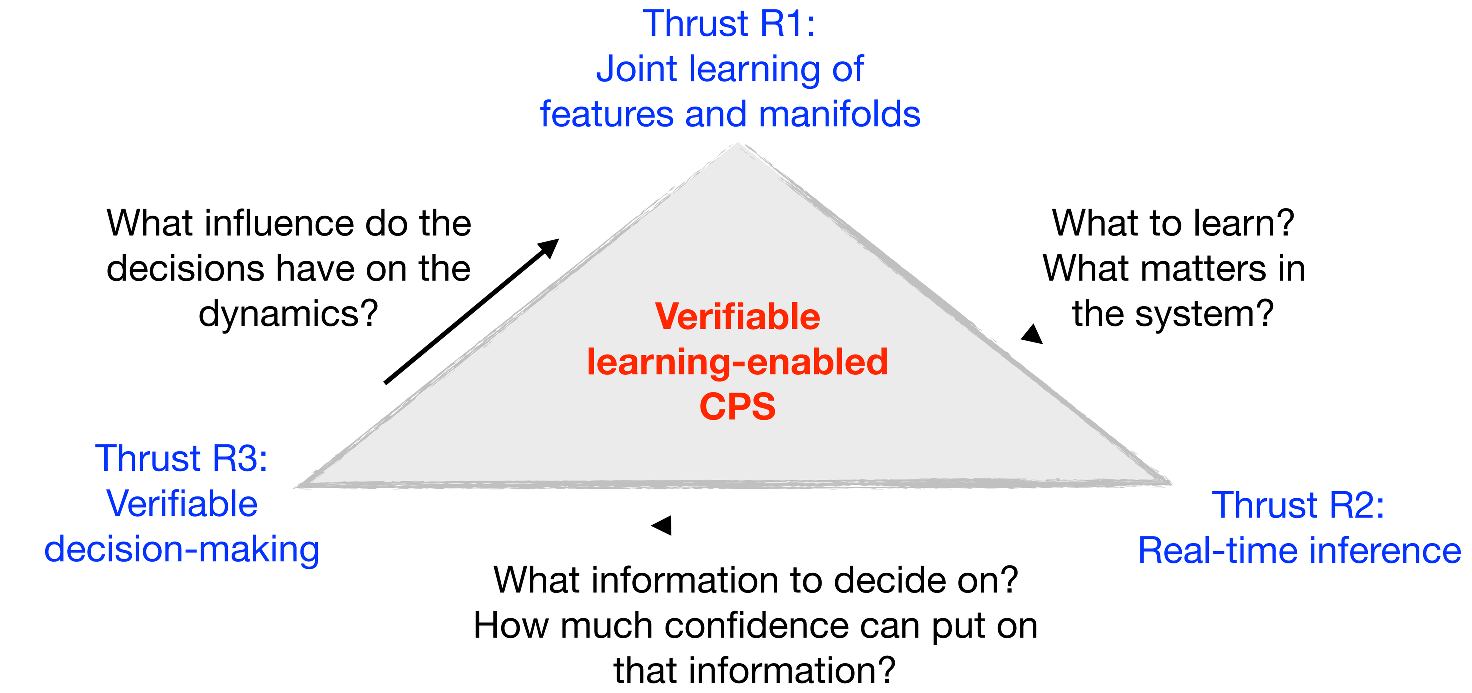
Motivation

Design autonomous CPS capable of safely operating in and adapting to previously unseen scenarios.
(Humans can do it!)

Challenges

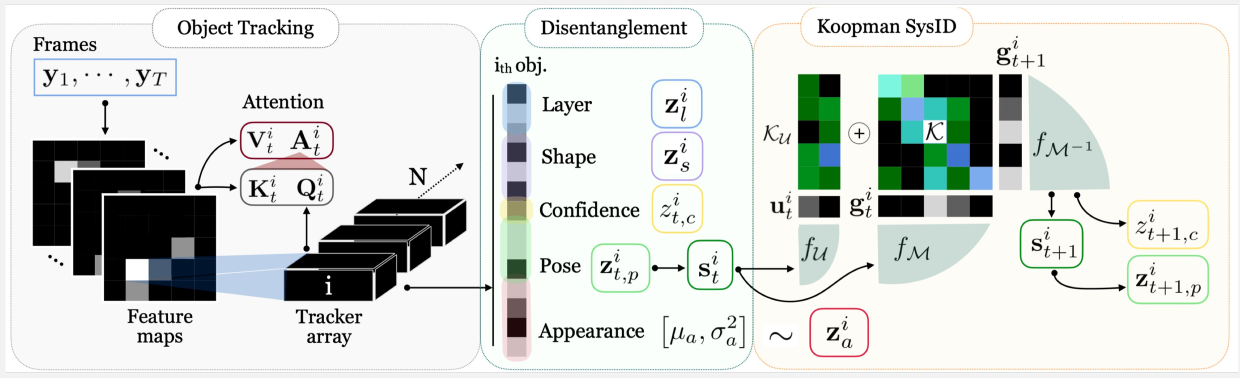
- Lack of training data (often single execution).
- Need to act while learning (no re-do!).
- Actionable information sparsely encoded in large data sets.



Joint learning of features and manifolds

- Goal: learn parsimonious dynamical representations.
- Main idea: search for manifold where the dynamics are linear (Koopman operators).
- Technical details:
  - Use delayed coordinates and attention based tracking
  - Enforce linear manifold dynamic
  - Interpretable, manipulable representations

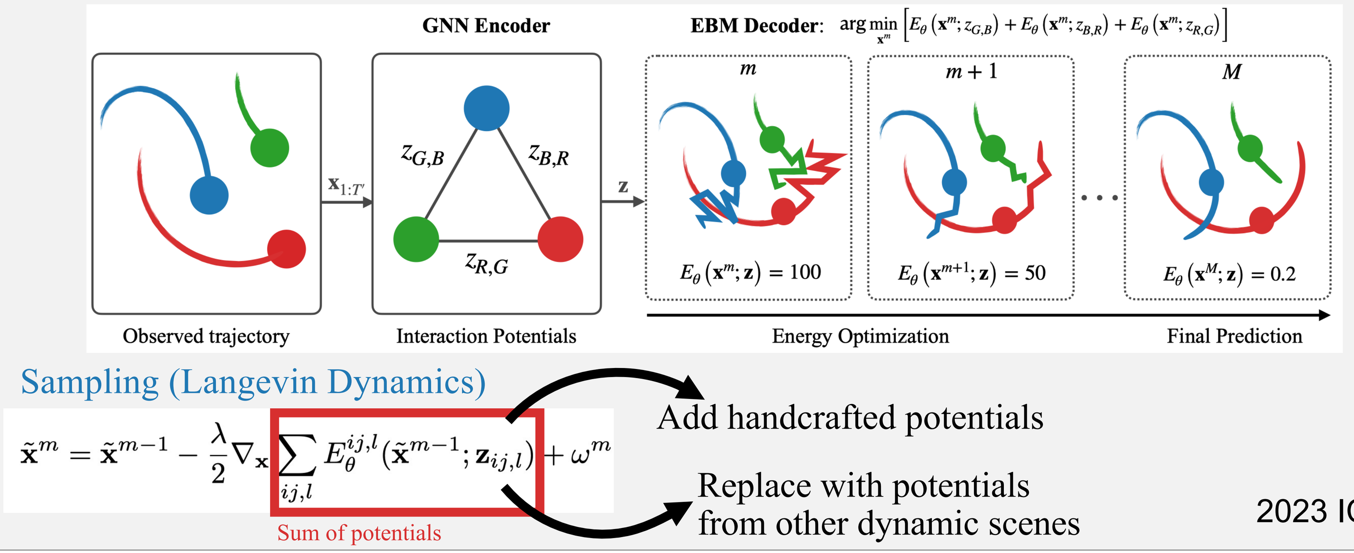
OKID: Object-centric Koopman-based Interpretable Decomposition



2023 L4DC

Learning dynamic interactions

- Goal: explain complex dynamics of interacting agents.
- Main idea: model interactions with a fully-connected graph and Energy-based Models (EBM).
- Technical details:
  - Trajectories are encoded as sets of potentials conditioning EBMs
  - At inference time, trajectories are predicted by satisfying these potentials



2023 ICML (Oral)

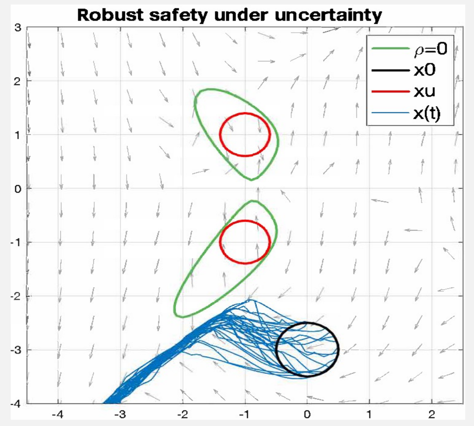
Verifiable safe data driven control

- Goal: data driven avoidance of an unsafe set.
- Main idea: enforce robust Nagumo-invariance .
- Technical details:
  - Prior: non linear dynamics of the form:
    $\dot{\mathbf{x}} = \mathbf{F}\phi(\mathbf{x}) + \mathbf{G}\gamma(\mathbf{x})\mathbf{u} + \eta \quad \mathbf{F}, \mathbf{G}$ unknown
  - Initial condition set: $\mathcal{X}_o$, bad set: $\mathcal{X}_u \doteq \{\mathbf{x} : h(\mathbf{x}) \geq 0\}$
  - Experimental data: $(\mathbf{u}(t_k), \mathbf{x}(t_k), \dot{\mathbf{x}}(t_k)),\ 0 \leq t_k \leq T$
  - Fact: bad set is avoided if there exist $\rho(x), \psi(x)$
    $\rho(\mathbf{x}) \geq 0,\ \forall \mathbf{x} \in \mathcal{X}_0,\ \rho(\mathbf{x}) < 0, \forall \mathbf{x} \in \mathcal{X}_u$ and

$$\nabla \cdot \left[\rho(\mathbf{x})\Big(\sum_i \alpha_i \mathbf{f}_i(\mathbf{x}(t)) + \mathbf{w}\Big) + \psi(\mathbf{x}) \sum_j \beta_j \mathbf{g}_j(\mathbf{x})\right] - \rho(\mathbf{x})h(\mathbf{x}) > 0$$

for all plants that could have generated the data

  - Fact: reduces to a convex SDP via duality
  - Fact: only imposes $d\rho/dt < 0$ when $\rho = 0$



2023 IEEE LCSS

Application

- Public space monitoring to mitigate unsafe situations.


Monitoring social distancing

Active shooter scenario (joint with M. Siami)

Scientific Impact

- Rapprochement of Systems Theory, ML, Viability.
- Efficient extraction of actionable information from large data sets.
- Frugal, explainable architectures for dynamics oriented learning.

Broader Impact and Outreach

- Certified safe learning enabled systems that can operate in close proximity to humans.
- Applications: health care, infrastructure monitoring, public space monitoring.
- Outreach through Northeastern's UPLIFT program.
- Internships at Adobe, Mathworks, Google.

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Award CNS-2038493