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

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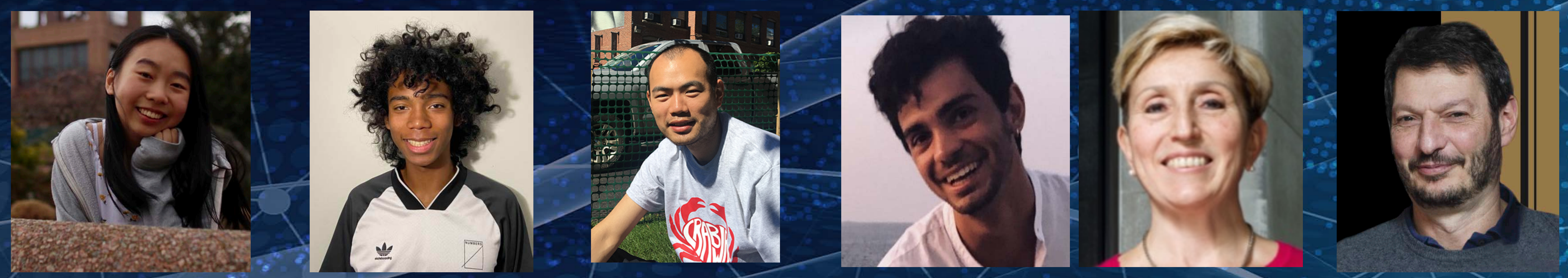

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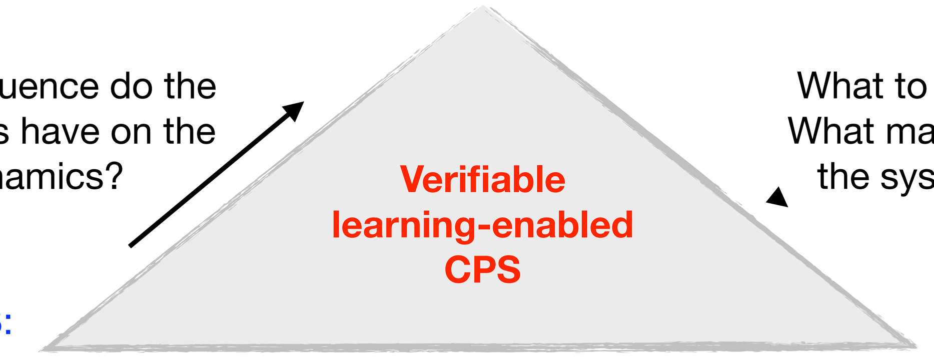
Motivation

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.

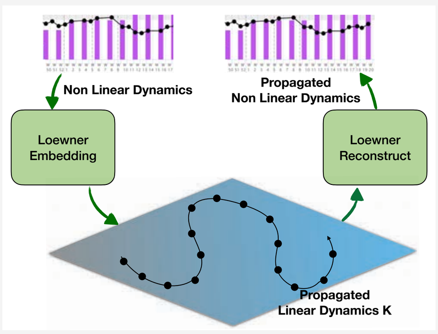


Joint learning of features and manifolds

- Goal: learn parsimonious dynamical representations.
- Main idea: search for manifold where the dynamics are linear (Koopman operators).
- Technical details:
  - Search for latent variables with low rank Gramian:

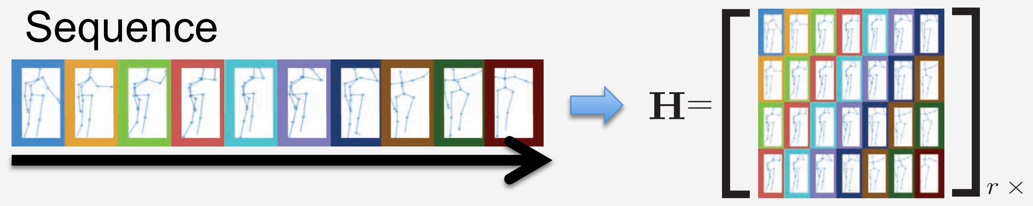
$$\mathbf{G} = \begin{bmatrix} \mathbf{y}_i^T\mathbf{y}_i & \mathbf{y}_i^T\mathbf{y}_{i+1} & \cdots & \mathbf{y}_i^T\mathbf{y}_{i+j} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{y}_{i+j}^T\mathbf{y}_i & \mathbf{y}_{i+J}^T\mathbf{y}_{i+1} & \cdots & \mathbf{y}_{i+j}^T\mathbf{y}_{i+j} \end{bmatrix}$$

  - Find the mapping $\mathbf{x} \Longleftrightarrow \mathbf{y}$ using Loewner interpolation theory
  - Problem reduces to 2 convex SDPs



Real time inference

- Goal: compare and classify time series.
- Main idea: compare the underlying dynamics.
- Technical details:
  - Embed the data in the PSD manifold via Gram matrices

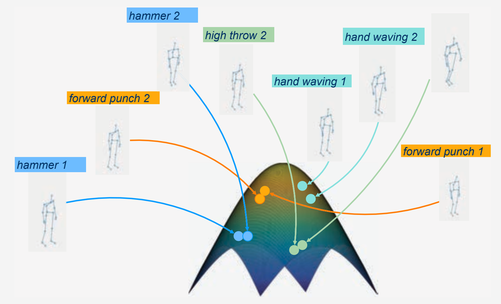


$$\hat{\mathbf{G}} = \frac{\mathbf{H}\mathbf{H}^\top}{\|\mathbf{H}\mathbf{H}^\top\|} + \sigma\mathbf{I}$$

  - Group data using Riemanian distance:

$$J_{ld}(\mathbf{G}_1, \mathbf{G}_2) \doteq \log\left|\frac{\mathbf{G}_1 + \mathbf{G}_2}{2}\right| - \frac{1}{2}\log|\mathbf{G}_1\mathbf{G}_2|$$

  - Complexity $\mathcal{O}(n^3)$
  - 100% accuracy on MHAD



Verifiable safe control

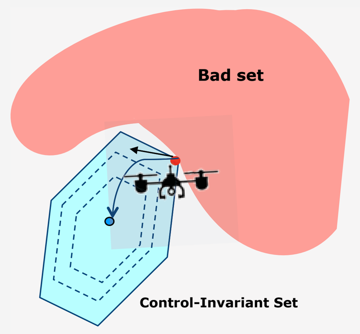
- Goal: data driven avoidance of an unsafe set.
- Main idea: enforce zero occupation measure.
- Technical details:
  - Prior: non linear dynamics of the form:

$$\dot{\mathbf{x}} = \mathbf{F}\phi(\mathbf{x}) + \mathbf{G}\gamma(\mathbf{x})\mathbf{u} + \eta \quad \mathbf{F}, \mathbf{G} \text{ unknown}$$

  - 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 $\rho(x), \psi(x)$

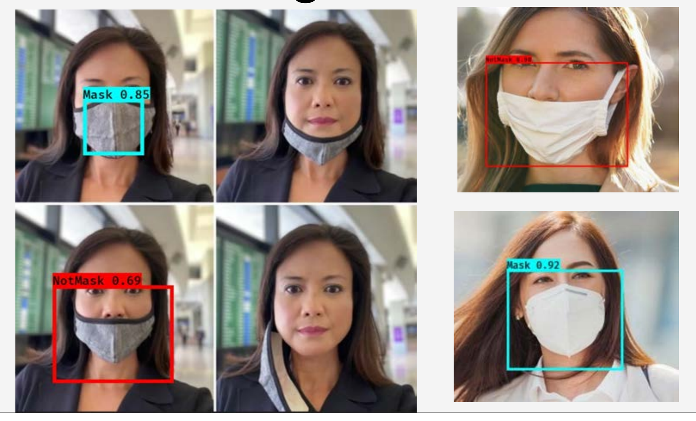
$$\begin{aligned} \nabla \cdot [\rho(x)\mathbf{f}(x) + \psi(x)\mathbf{g}(\mathbf{x})] &\geq 0 \\ \rho(x) \geq 0,\ x \in \mathcal{X}_o \text{ and } \rho(x) &< 0,\ x \in \mathcal{X}_u \end{aligned}$$

  for all plants that could have generated the data
  - Fact: reduces to a convex SDP via duality



Application

- Public space monitoring to detect unsafe situations.



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.

2021 NSF Cyber-Physical Systems Principal Investigators' Meeting

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Award CNS-2038493