Data-Driven Cyberphysical Systems Provably correct control in data rich/labels scarce scenarios







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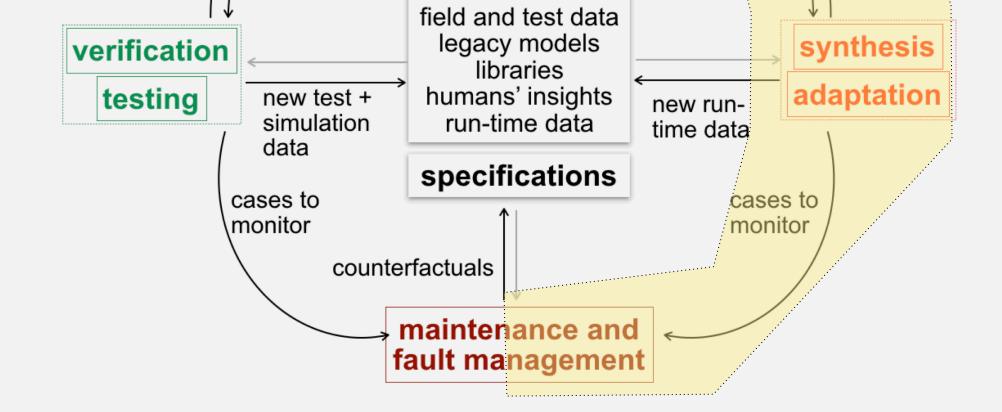
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nodelina unverified sources of Motivation infeasibility → adjust type model-data size or fidelity → adjust type consistency? How can we synthesize control strategies for CPS in scenarios with rich run-time data, but where size or fidelity models + labeling is expensive and off-line training may not capture rare but potentially catastrophic events? models uncertaint uncertain data

Challenges

- Obtaining space-spanning data, specially for situations involving unsafe operations
- Real-time labeling with certifiable performance, even for data previously unseen
- Synthesizing non-conservative, provably stabilizing control laws



Leveraging Simulations to Handle Scarce Labels

Goal: Leverage simulations to obtain spanning data

- Obtaining enough trajectory space spanning data for CPS can be costly or unfeasible
- Physics based simulators can generate data cheaply, but require costly tuning to match the actual CPS

Proposed approach: Domain adaptation

 Generate a large simulation dataset (source) and collect a smaller set of (labeled) real data (target)

Efficient Data Labeling

Goal: On the fly data labeling

- On the fly data labeling is challenging in the presence of rare events
- Traditional learning relying on large amounts of training data may not be feasible in some CPS applications

Proposed approach: SoS based classifiers

 Use empirical statistical information to build SoS polynomials that approximate the support of the data

Non-conservative Control Synthesis

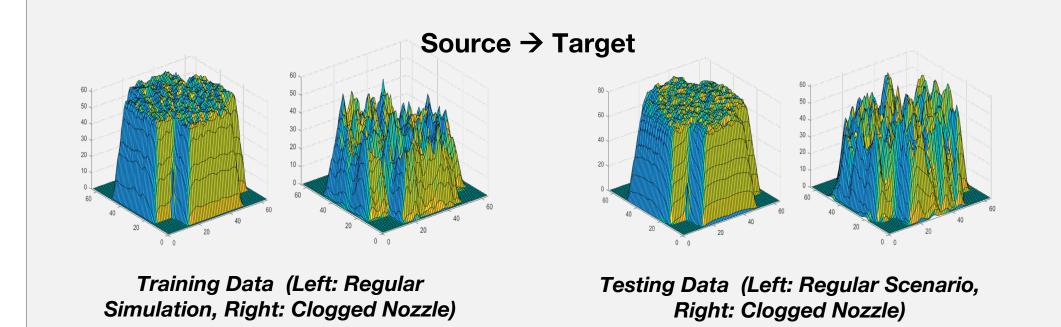
Goal: Synthesizing certified controllers

- Traditional approach based on SysId + Robust Control is computationally expensive and potentially conservative
- Existing model free data-driven approaches cannot certify stability or performance

Proposed approach: Lyapunov based DD control

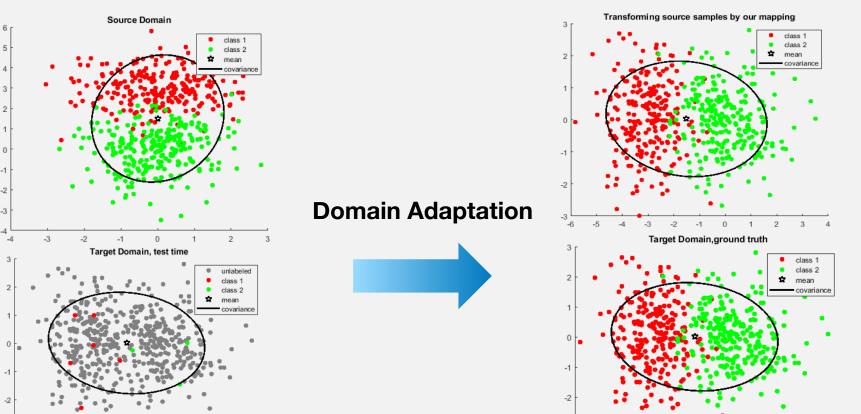
Define the consistency set S as the set of all plants compatible with existing priors and experimental data
(non-conservatively) parameterize the set of all controllers the can stabilize S in terms of a polyhedral Lyapunov function V

- Find a transformation from source to target that optimizes classification accuracy
- Use simulator adapted data for classification and controller design

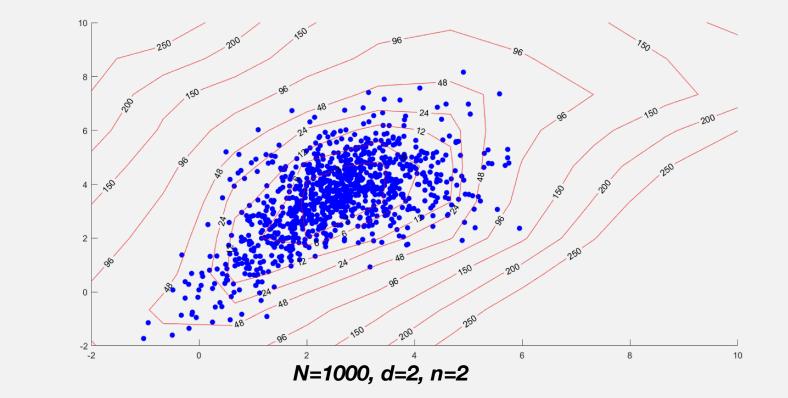


Technical details:

- Align covariances and use the extra degrees of freedom to optimize classification accuracy
- Optimization problem solvable via Sum of Squares



 Given an unknown sample, assign it to the most likely distribution or label it as "unseen before" (with certified probability of miss-classification)



Technical details:

Lift the data:

$$\mathbf{x} \doteq \begin{bmatrix} x_1 \dots x_d \end{bmatrix} \rightarrow \mathbf{v}_n(\mathbf{x}) \doteq \begin{bmatrix} 1 & x_1 & x_2 & \dots & (x_1^{\alpha_1} x_2^{\alpha_2} \cdots x_d^{\alpha_d}) \dots & x_d^n \end{bmatrix}^T$$

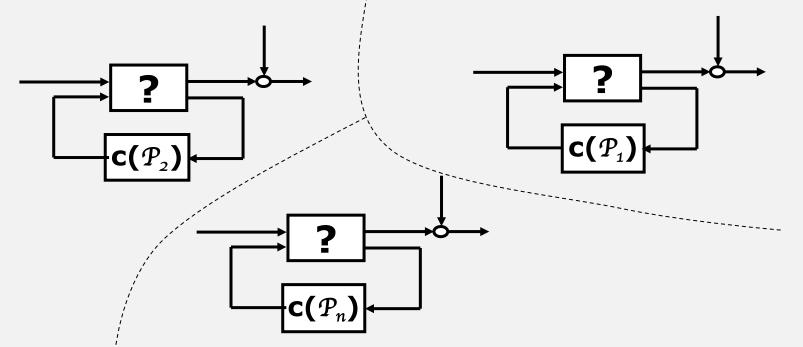
Create the moment matrix:
 M = 1/N \$\sum_{i=1}^{N} \mathbf{v}_n(\mathbf{x}_i) \mathbf{v}_n^T(\mathbf{x}_i)\$
 Classify unknown samples y according to:

 $Q(\mathbf{y}) \doteq \mathbf{v}_n^T(\mathbf{y}) \mathbf{M}^{-1} \mathbf{v}_n(\mathbf{y})$

Certificate:

$$\operatorname{prob} \{Q(\mathbf{v}) > t\} < \frac{t}{-} \operatorname{where} s = \begin{pmatrix} d+n \end{pmatrix}$$

• Find V by solving a polynomial optimization

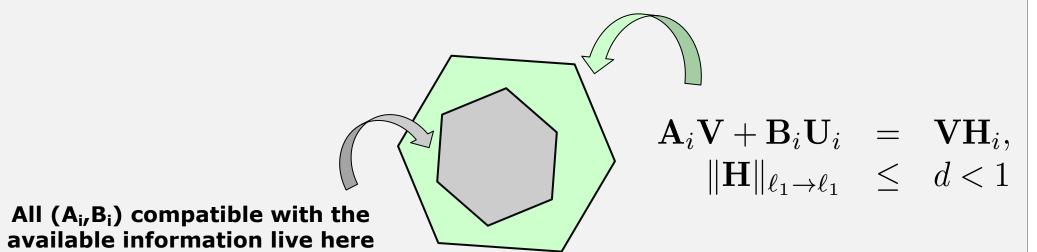


Technical details:

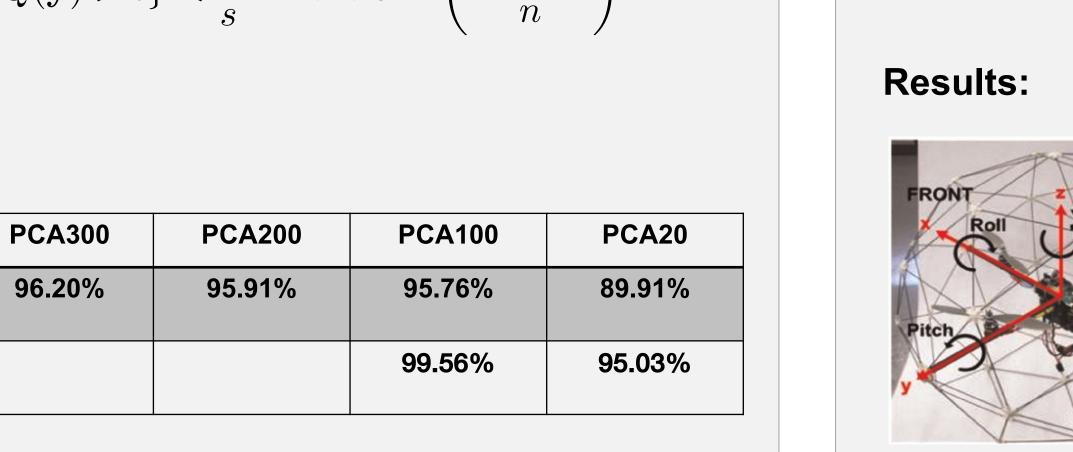
- The set of all (LTI) plants in S is a polytope P
- Use the fact that U_i stabilizes (A_i, B_i) iff there exist V, H_i

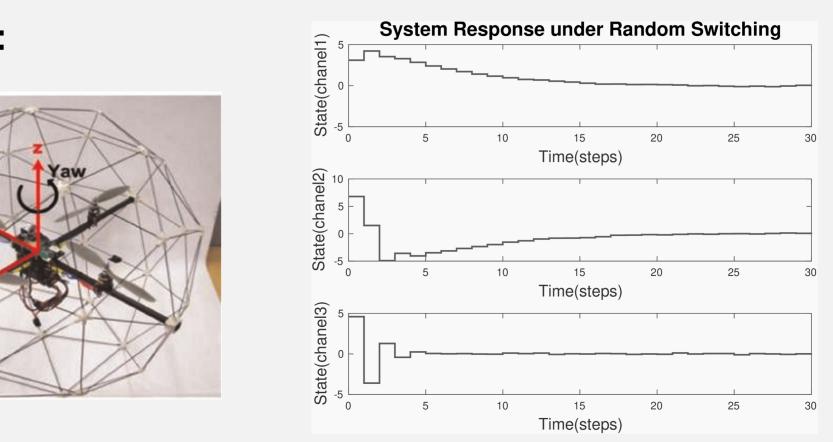
 $\begin{aligned} \mathbf{A}_i \mathbf{V} + \mathbf{B}_i \mathbf{U}_i &= \mathbf{V} \mathbf{H}_i, \\ \|\mathbf{H}\|_{\ell_1 \to \ell_1} &\leq d < 1 \end{aligned}$

• Use Farkas Lemma to impose stability of P



Training Input (Top: Source, Bottom: Target)		Training Output /Testing (Top: Transformed Source, Bottom: Ground Truth Target)				
esults:	Results:					
	PCA300	PCA200	PCA100	PCA20		
Accuracy on	85.91%	86.45%	86%	81.67%	Accuracy (SVM)	
Target after adaptation	(†11.26%)	(↑12.94%)	(↑11%)	(↑2.64%)	Accuracy (SoS)	





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