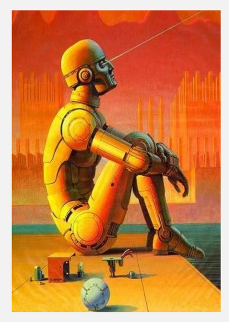
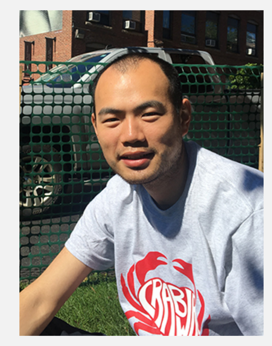
Data-Driven Cyberphysical Systems

Provably correct control in data rich/labels scarce scenarios.

Northeastern


Robust Systems Lab


Begüm Taşkazan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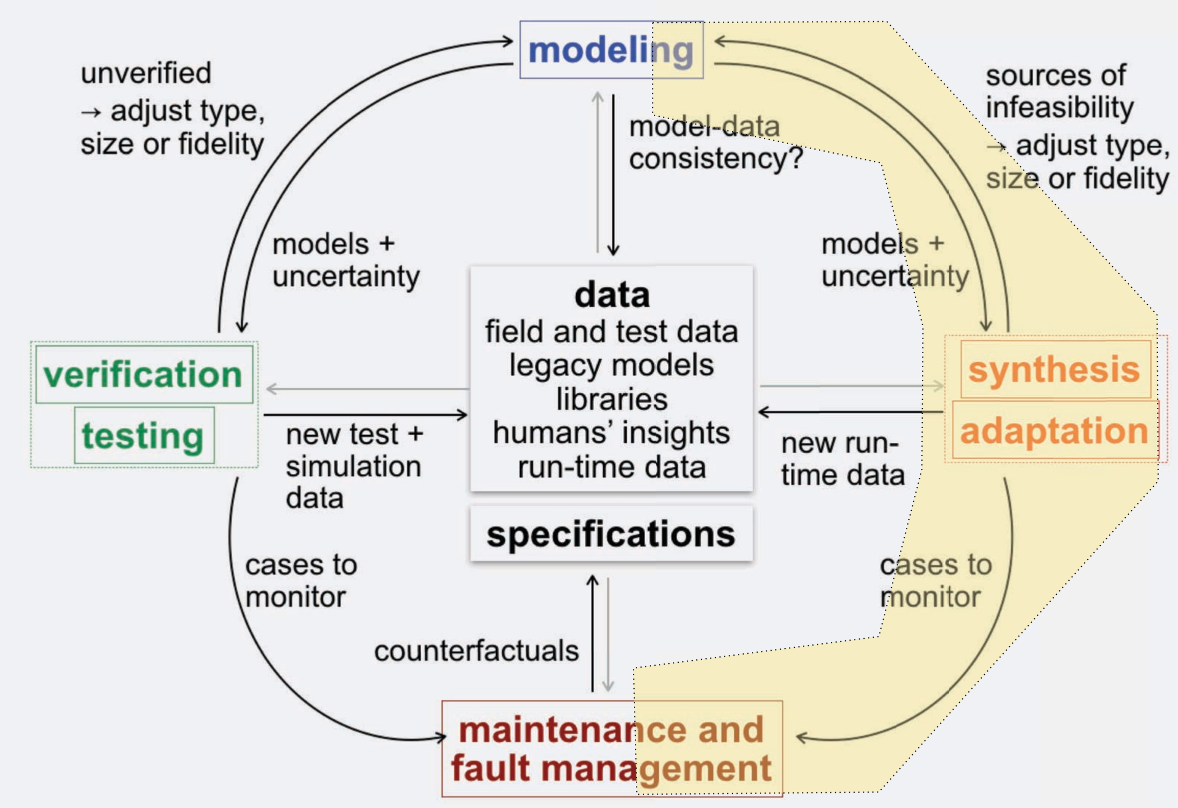
Motivation

How can we synthesize control strategies for CPS in scenarios with rich run-time data, but where labeling is expensive and off-line training may not capture rare but potentially catastrophic events?

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 to train supervised fault detection algorithms.

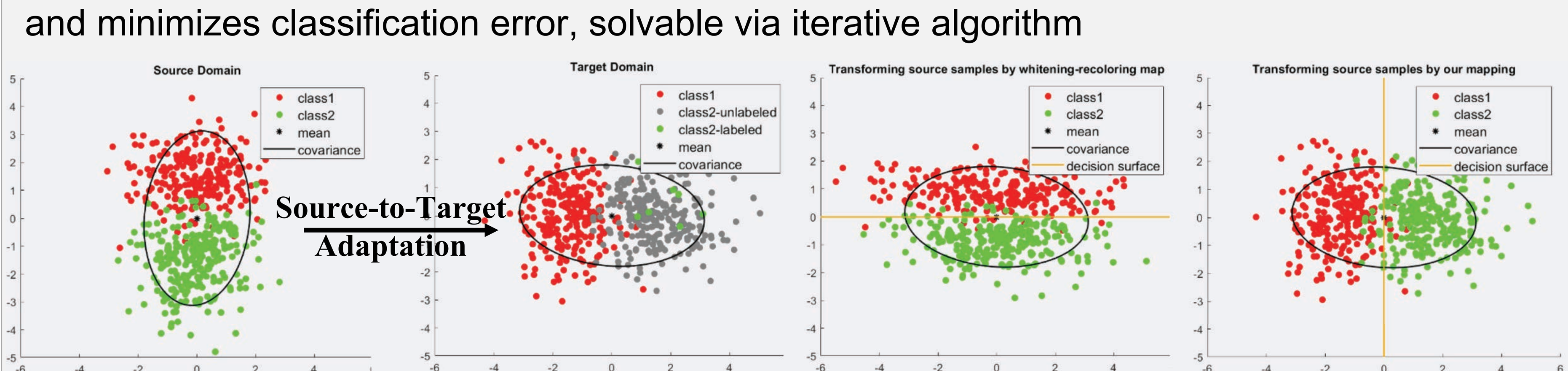
- Obtaining enough trajectory space spanning data for CPS can be costly or unfeasible especially when the data is required to be obtained under abnormal conditions
- Physics based simulators can generate data cheaply, but require costly tuning

Proposed Approach: Domain adaptation.

- Generate a large simulation dataset (source) and collect a smaller set of (labeled) real data (target) which has limited number of faulty data points (label imbalance)
- Find a transformation between domains that optimizes classification accuracy
- Use simulator adapted data for classification and controller design

Technical Details:

a. SVM Based Fault Detector: Joint training that aligns covariances via linear transformation and minimizes classification error, solvable via iterative algorithm



(a) Source domain ground truth (b) Target domain (only a few labels from the second class are known) (c) Classifier obtained by conventional covariance alignment (unsupervised) (d) Classifier obtained using the proposed method (semi-supervised)

b. SoS Based Fault Detector

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

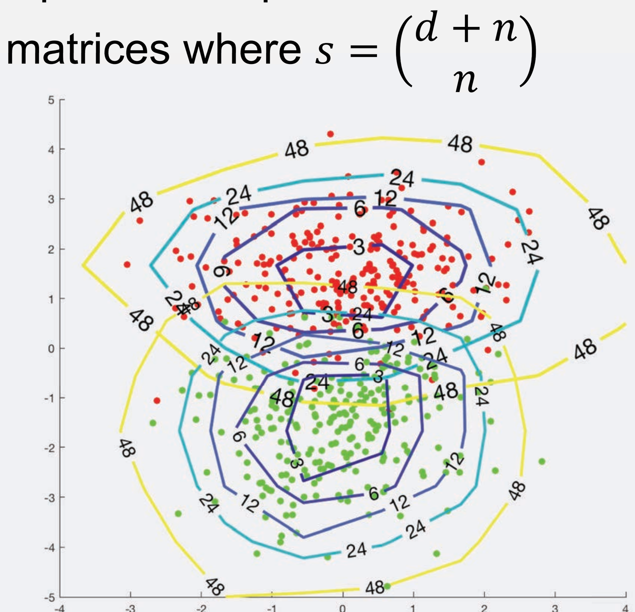
$$\mathbf{x} \doteq [x_1 \dots x_d] \rightarrow \mathbf{v}_n(\mathbf{x}) \doteq [1 \quad x_1 \quad x_2 \quad \dots (x_1^{\alpha_1} x_2^{\alpha_2} \cdots x_d^{\alpha_d}) \dots x_d^n]^T \qquad \mathbf{M} \doteq \frac{1}{N}\sum_{i=1}^{N} \mathbf{v}_n(\mathbf{x}_i)\mathbf{v}_n^T(\mathbf{x}_i)$$

- Find one-to-one mappings between classes of source and target domains that guarantee overall moment alignment between source and target

$$\mathbf{A}_j^* = \underset{\mathbf{A}_j}{\operatorname{argmin}} \left(C \sum_{i \in class_j} (\mathbf{A}_j v(x_i^t))^T \mathbf{M}_j^{-1} \mathbf{A}_j v(x_i^t) - \sum_{i \notin class_j} (\mathbf{A}_j v(x_i^t))^T \mathbf{M}_j^{-1} \mathbf{A}_j v(x_i^t) \right)$$

$$\text{where } \mathbf{A}_j = \mathbf{M}_S^{1/2} \mathbf{U}_j \mathbf{M}_T^{-1/2} \text{ and } \mathbf{U}_j \mathbf{U}_j^T = \mathbf{I}$$

- Optimization problem has a closed form solution which only requires SVD of two $s \times s$ matrices where $s = \binom{d+n}{n}$



$d = 2,\ n = 2,\ N_1 = 248,\ N_2 = 252$

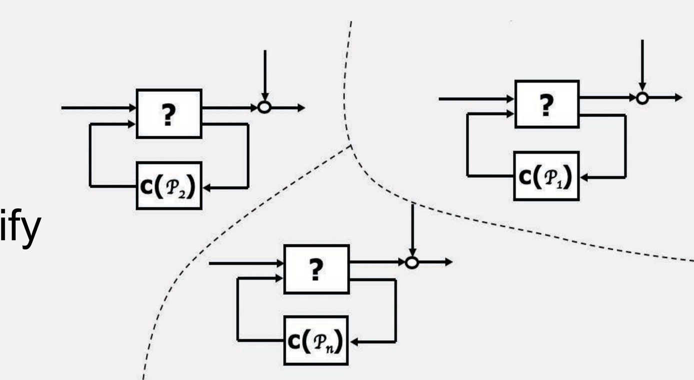
Results:

	Trained with...	SVM	SoS
F1 Score	Src Tested on Src	0.9086	0.9634
	Src Tested on Tgt	0.8736	0.8505
	Tgt Tested on Tgt	0.6671	0.6022
	Adaptation (ours)	0.9524	0.9385
Precision	Src Tested on Src	0.8883	0.9293
	Src Tested on Tgt	0.8884	0.7399
	Tgt Tested on Tgt	0.9919	0.9953
	Adaptation (ours)	0.9391	0.8940
Recall	Src Tested on Src	0.9298	1
	Src Tested on Tgt	0.8592	1
	Tgt Tested on Tgt	0.5026	0.4317
	Adaptation (ours)	0.9661	0.9877

Data-Driven Control & Estimation

Goal: Design directly from data.

- Model-based method is computationally expensive and potentially conservative
- Existing model free data-driven approaches cannot certify stability or performance



Proposed Approach:

a. Lyapunov Based DD Control

- Define the consistency set S as the set of all plants compatible with existing priors and experimental data
- Parametrize the set of all controllers the can stabilize S in terms of a polyhedral Lyapunov function $\mathcal{V}(\mathbf{x}) = ||\mathbf{V}\mathbf{x}||_\infty$
- Find V by solving a polynomial optimization

b. Hankel Based DD Estimation

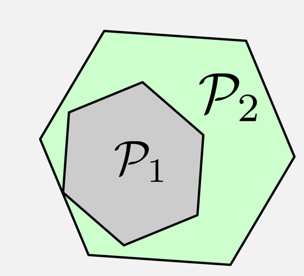
- Build Hankel matrix with experimental data
- Minimize the rank of Hankel matrix to find the set of the noise that could explain the data
- Worst-case optimal estimator is the Chebyshev center $\hat{y}_k = \tilde{y}_k + \frac{1}{2}(\eta_{max} + \eta_{min})$

Technical Details:

a. Farkas Lemma + Moments

$$\mathcal{P}_1 \doteq \{\mathbf{A}_i, \mathbf{B}_i : ||\mathbf{x}_{k+1}^i - \mathbf{A}_i \mathbf{x}_k^i - \mathbf{B}_i \mathbf{u}_k^i||_\infty \leq \epsilon \text{ for all k, i}\}$$

$$\mathcal{P}_2 \doteq \{\mathbf{A}_i, \mathbf{B}_i : \mathbf{V}(\mathbf{A}_i + \mathbf{B}_i \mathbf{F}_i) = \mathbf{H}_i \mathbf{V}, ||\mathbf{H}_i||_\infty \leq d < 1 \text{ for all k, i}\}$$



b. Line Search + HDC + Moments

$$\mathbf{H} = \begin{bmatrix} \tilde{y}_1 + \eta_1 & \dots & \tilde{y}_{1+n_a} + \eta_{1+n_a} & u_1 & \dots & u_{n_b} \\ \tilde{y}_2 + \eta_2 & \dots & \tilde{y}_{2+n_a} + \eta_{2+n_a} & u_2 & \dots & u_{1+n_b} \\ \vdots & & \vdots & \vdots & & \vdots \\ \tilde{y}_{k-n_a} + \eta_{k-n_a} & \dots & \tilde{y}_k + \eta_k & u_{k-n_b} & \dots & u_{k-1} \end{bmatrix}$$

$$\eta_{max} = argmax\ \eta_k \quad \text{and } \eta_{min} = argmin\ \eta_k$$
$$\text{subject to} \quad \text{rank}(\mathbf{H}) \leq R \text{ and } \|\boldsymbol{\eta}\|_\infty \leq \epsilon$$

Hybrid Decoupling Constraints

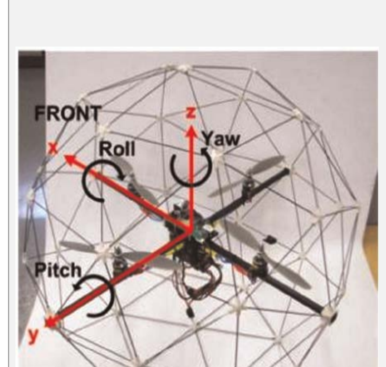
$$\prod_{\gamma=1}^{s} \mathbf{d}_k^T \mathbf{c}_\gamma = 0 \quad \Longrightarrow \quad \boldsymbol{v}_s^T(\mathbf{d}_k)\hat{\mathbf{c}}_\gamma = 0$$

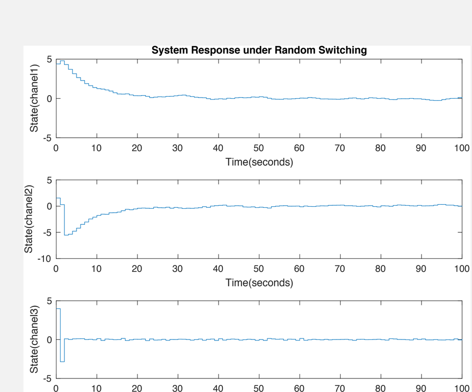
Veronese Map

$$\boldsymbol{v}_s(\mathbf{d}_k)^T = [y_k^2, -y_k y_{k-1}, -y_k u_{k-1}, y_{k-1}^2, u_{k-1}^2, y_{k-1} u_{k-1}]$$

Results:

$$\begin{bmatrix} \dot{X} \\ \ddot{X} \\ \dot{v} \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & \frac{4K sin(\theta)}{M} \\ 0 & 0 & -\omega \end{bmatrix} \begin{bmatrix} X \\ \dot{X} \\ v \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ \omega \end{bmatrix} u_Z$$





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