Data-Driven Stabilization Using Prior Knowledge on Stabilizability and Controllability

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  - Bypassing system identification (De Persis and Tesi, 2020)*.

*C. De Persis, P. Tesi, "Formulas for data-driven control: Stabilization, optimality, and robustness," *IEEE Transactions on Automatic Control*, vol. 65, no. 3, pp. 909–924, 2020.

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* H. J. van Waarde, J. Eising, H. L. Trentelman, M. K. Camlibel, "Data informativity: A new perspective on data-driven analysis and control," *IEEE Transactions on Automatic Control*, vol. 65, no. 11, pp. 4753–4768, 2020.

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  - Known bounds on the system parameters (Berberich et al., 2020)*.

* J. Berberich, C. W. Scherer, F. Allgöwer, "Combining prior knowledge and data for robust controller design," *IEEE Transactions on Automatic Control*, vol. 68, no. 8, pp. 4618–4633, 2022.

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*H. Huang, M. K. Camlibel, R. Carloni, H. J. van Waarde, "Data-driven stabilization of polynomial systems using density functions," *arXiv preprint*, 2025.

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- Prior knowledge in system identification:
  - Stability (van Gestel et al., 2002, Lacy & Bernstein, 2003)
  - Eigenvalue constraints (Miller & De Callafon, 2013)
  - Positivity (De Santis & Farina, 2002)
  - Passivity (Goethals et al., 2003, Shali & van Waarde, 2024)

Problem Formulation

Consider the true system

$$x(t+1) = A_{\text{true}}x(t) + B_{\text{true}}u(t), \qquad (\star)$$

where $x(t) \in \mathbb{R}^n$ and $u(t) \in \mathbb{R}^m$.

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- We have access to input-state data of the form

$$\mathcal{D} := \left(\begin{bmatrix} u(0) & u(1) & \cdots & u(T-1) \end{bmatrix}, \begin{bmatrix} x(0) & x(1) & \cdots & x(T) \end{bmatrix}\right).$$

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- We denote the data matrices

$$X_- := \begin{bmatrix} x(0) & x(1) & \cdots & x(T-1)\end{bmatrix}, \quad U_- := \begin{bmatrix} u(0) & u(1) & \cdots & u(T-1)\end{bmatrix},$$
$$X_+ := \begin{bmatrix} x(1) & x(2) & \cdots & x(T)\end{bmatrix}.$$

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We say $\mathcal{D}$ is informative for stabilization if there exists a $K \in \mathbb{R}^{m \times n}$ such that $A + BK$ is Schur for all $(A, B) \in \Sigma_{\mathcal{D}}$.

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Proposition (van Waarde et al., 2020)

The data $\mathcal{D}$ is informative for stabilization if and only if there exists $\Theta \in \mathbb{R}^{T \times n}$ such that

$$X_- \Theta = \Theta^\top X_-^\top \quad \text{and} \quad \begin{bmatrix} X_- \Theta & X_+ \Theta \\ \Theta^\top X_+^\top & X_- \Theta \end{bmatrix} > 0. \qquad (\star)$$

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Moreover, $K = U_- \Theta (X_- \Theta)^{-1}$ is such that $A + BK$ is Schur for all $(A, B) \in \Sigma_{\mathcal{D}}$.

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- We focus on two types of prior knowledge $\Sigma_{\text{pk}} = \Sigma_{\text{cont}}$ and $\Sigma_{\text{pk}} = \Sigma_{\text{stab}}$.

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Problem Statement

Find necessary and sufficient conditions under which $\mathcal{D}$ is

(i) Σ_{cont}–informative for stabilization;

(ii) Σ_{stab}–informative for stabilization.

Controllability as Prior Knowledge

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Moreover, if K is such that $A + BK$ is Schur for all $(A, B) \in \Sigma_{\mathcal{D}} \cap \Sigma_{\text{cont}}$, then $A + BK$ is Schur for all $(A, B) \in \Sigma_{\mathcal{D}}$.

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▷ Prior knowledge on controllability is not helpful!

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Theorem (Full-rank state data)

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- If $(A_{\text{true}}, B_{\text{true}})$ is not controllable, and $x(0) = 0$, then

$$\operatorname{rank} X_- \neq n,$$

no matter what the input signal is.

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Theorem (Rank–deficient state data)

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(a) $\operatorname{im} X_+ \subseteq \operatorname{im} X_-$,

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- Let $\hat{X}_+ \in \mathbb{R}^{r \times n}$ be defined as $\hat{X}_+ := \begin{bmatrix} I_r & 0 \end{bmatrix} SX_+$.

Stabilizability as Prior Knowledge

Proposition (Data-driven feedback design with rank–deficient state data)

Suppose that $(A_{\text{true}}, B_{\text{true}}) \in \Sigma_{\text{stab}}$, $\mathcal{D}$ is Σ_{stab}–informative for stabilization, and $\operatorname{rank} X_- < n$. Then, the following statements hold:

(a) There exists $\Theta \in \mathbb{R}^{T \times r}$ such that the following LMI is feasible:

$$\hat{X}_-\Theta = \Theta^\top \hat{X}_-^\top \quad \text{and} \quad \begin{bmatrix} \hat{X}_-\Theta & \hat{X}_+\Theta \\ \Theta^\top \hat{X}_+^\top & \hat{X}_-\Theta \end{bmatrix} > 0. \qquad (\star)$$

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(b) Suppose that Θ satisfies LMI ($\star$). Let $K = \begin{bmatrix} K_1 & K_2 \end{bmatrix} S$, where $K_1 = U_-\Theta(\hat{X}_-\Theta)^{-1}$ and $K_2 \in \mathbb{R}^{m\times(n-r)}$ is arbitrary. Then, $A + BK$ is Schur for all $(A, B) \in \Sigma_{\mathcal{D}} \cap \Sigma_{\text{stab}}$.

Example

Consider the following system:

$$A_{\text{true}} = \begin{bmatrix} 0.9429 & 0.0473 & 0.0012 \\ 0.0473 & 0.9524 & 0.0476 \\ 0 & 0 & 0.9512 \end{bmatrix},$$

$$B_{\text{true}} = \begin{bmatrix} 0.0024 \\ 0.0976 \\ 0 \end{bmatrix}.$$

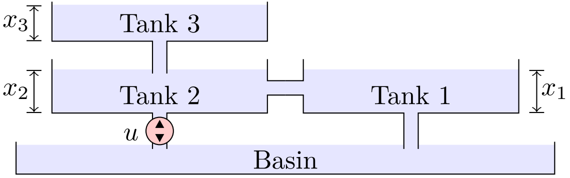

Figure: Three-tank system.

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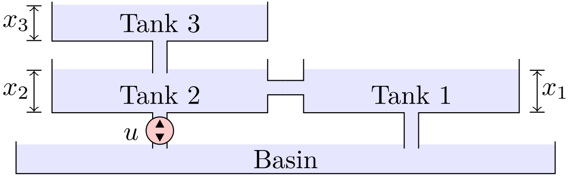
- Monte Carlo simulations with 1000 scenarios;



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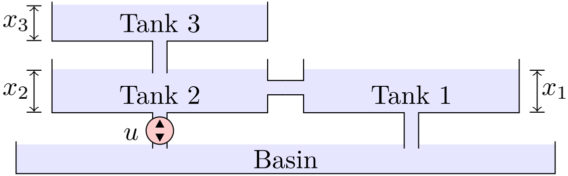

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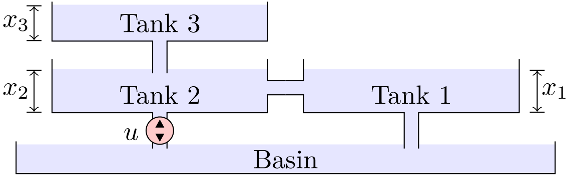

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- We use the first T samples for each round of analysis; $T = 3, 4, 5, 10, 100$.

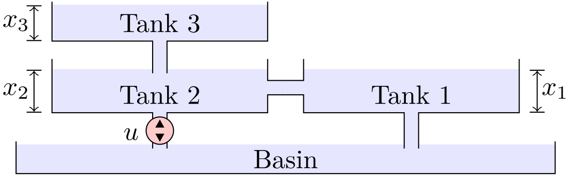

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Table: Informativity of randomly generated data.

T	Informative for system identification	Σ_{pk}–informative for stabilization	
		$\Sigma_{\text{pk}} = \mathcal{M}$	$\Sigma_{\text{pk}} = \Sigma_{\text{stab}}$
3	0%	8.1%	42%
4	62.4%	63.2%	99.4%
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- Future work:
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  - Extensions to input-output data and the noisy setting.