

Implicit predictors in regularized data-driven predictive control (DPC)

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Motivation

- Instead of a model, DPC uses collected **trajectory data** directly for predictions
- DPC predictions need **regularization** in presence of **noise** or **nonlinearities**
- **Choice** and **tuning** of regularization drastically impact DPC performance

Contributions

- We introduce **implicit predictors**, which characterize the **predictive behavior** that DPC implicitly attributes to the system
- Their **structure** mainly depends on regularization and (output) constraints
- Choice and tuning of regularization is comparable to **traditional model selection**

Implicit predictors for DPC with 2-norm regularization

Implicit predictors: $\hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f)$

$$\min_{\mathbf{u}_f, \mathbf{y}_f, \mathbf{a}} \|\mathbf{y}_f\|_Q^2 + \|\mathbf{u}_f\|_R^2 + h(\mathbf{a}) \text{ s.t.}$$

$$\begin{pmatrix} \boldsymbol{\xi} \\ \mathbf{u}_f \\ \mathbf{y}_f \end{pmatrix} = \mathcal{D}\mathbf{a} = \begin{pmatrix} \mathbf{W}_p \\ \mathbf{U}_f \\ \mathbf{Y}_f \end{pmatrix} \mathbf{a}, \quad (\mathbf{u}_f, \mathbf{y}_f) \in \mathcal{U} \times \mathcal{Y}$$

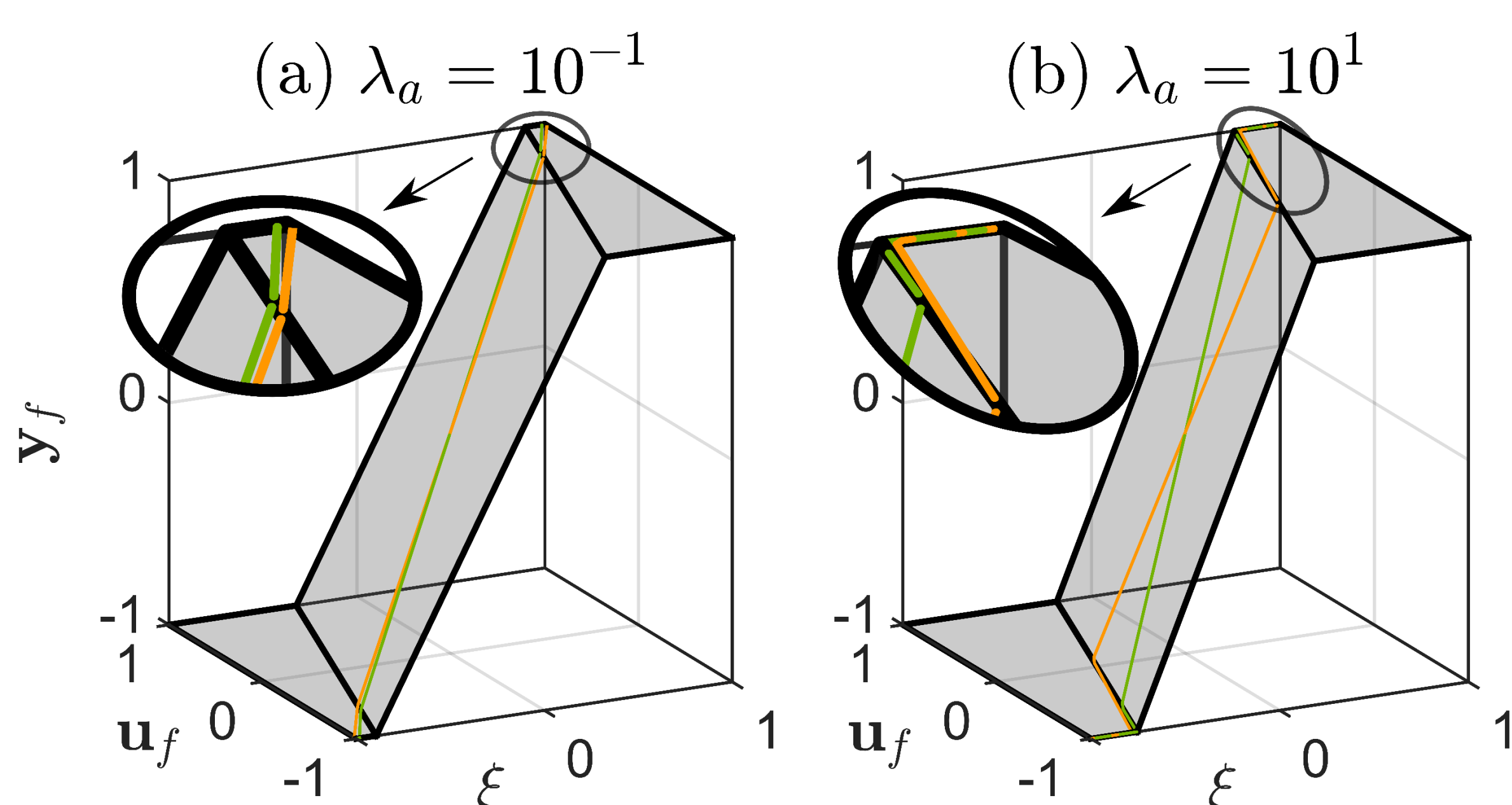
- Deterministic and LTI: **Rank deficiency** of \mathcal{D} implies predictor (choose $h(\mathbf{a}) = 0$)
- **Noise**: \mathcal{D} (likely) has full row rank but $h(\mathbf{a})$ implies predictor **via optimality**
- Parametrically solve for predictor via $\hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f) = \arg \min_{\mathbf{y}_f} \min_{\mathbf{a}} \dots \text{ s.t. } \dots$
- Adding constraint $\mathbf{y}_f = \hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f)$ **would not change solutions**

Unconstrained with 2-norm

- Popular choice: $h(\mathbf{a}) = \lambda_a \|\mathbf{a}\|_2^2$
- $\hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f)$ is linear and “tilts” between...
 - linear least squares fit $\hat{\mathbf{y}}_{\text{SPC}}(\boldsymbol{\xi}, \mathbf{u}_f)$
 - unregularized solution $\arg \min_{\mathbf{y}_f} \|\mathbf{y}_f\|_Q^2 = \mathbf{0}$ depending on λ_a

Adding constraints

- Affected by $\mathbf{y}_f \in \mathcal{Y}$ but not $\mathbf{u}_f \in \mathcal{U}$
- Intuition: **Changing predictor** such that $\hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f) \in \mathcal{Y}$ holds is always more optimal than **infeasibility**



Grey: $\hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f)$, Orange/Green: parametric DPC solutions
“Plateaus” forming due to $\hat{\mathbf{y}}_{\text{DPC}}(\boldsymbol{\xi}, \mathbf{u}_f) \in \mathcal{Y}$

Outlook

- Analyze **other regularizations**, e.g., $\|\mathbf{a}\|_p$
- Add common DPC **modifications**
- Explain **popular experiments** from new viewpoint of implicit predictors
- Give practical choice/tuning **guidelines**