

## Overview and Nonconvex Landscapes

- Policy optimization has achieved great empirical success in various applications.
- A strong theoretical foundation is lacking for continuous control tasks.
- LQR, LQG, H infinity control all have intriguing nonconvex landscapes.

LQG optimal control	H infinity robust control
$\min_u J_{\text{LQG}} := \lim_{T \rightarrow \infty} \mathbb{E} \left[ \frac{1}{T} \int_0^T (x^T Q x + u^T R u) dt \right]$	$\min_u J_{\infty} := \max_{\ d\  \leq 1} \int_0^{\infty} (x^T Q x + u^T R u) dt$
s. t. $\dot{x} = Ax + Bu + w$ $y = Cx + v$ $w, v$ white Gaussian noises	s. t. $\dot{x} = Ax + Bu + w, x(0) = 0$ $y = Cx + v$ $d = [w^T \ v^T]^T$

$$\min_{K \in \mathcal{K}} J(K)$$

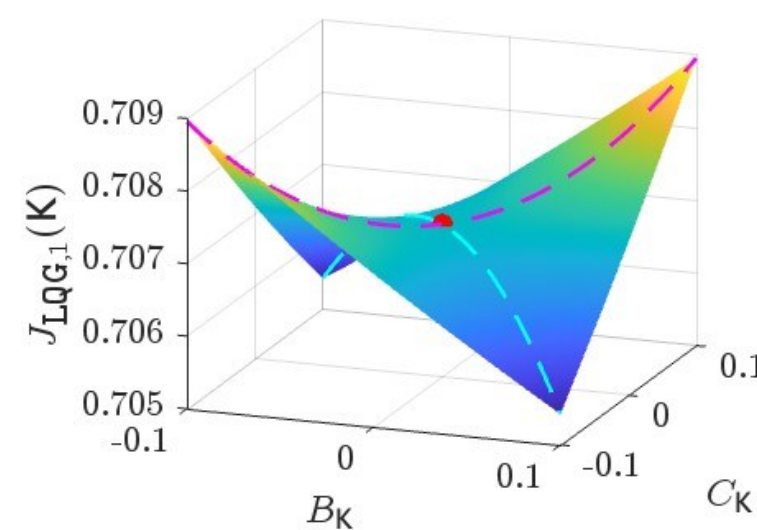
Dynamic policies

$$K = \begin{bmatrix} D_K & C_K \\ B_K & A_K \end{bmatrix}$$

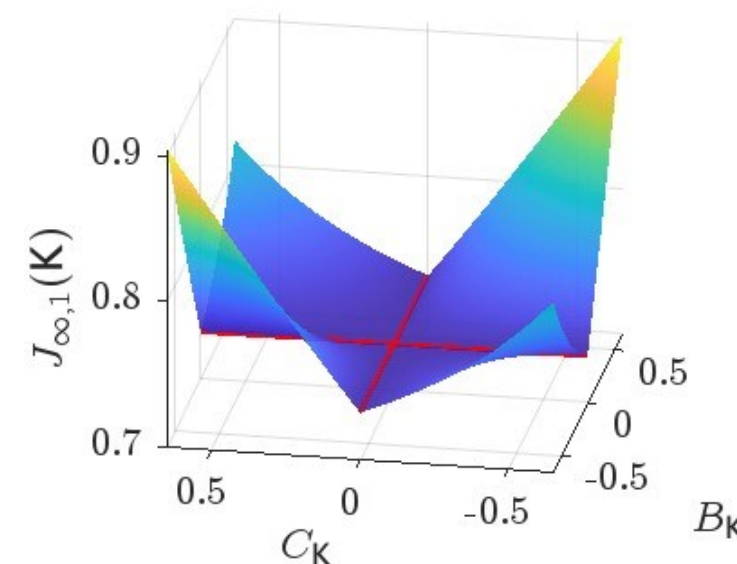
$$\dot{\hat{x}} = A_K \hat{x} + B_K y$$

$$u = C_K \hat{x} + D_K y$$

LQG: saddle point



H infinity: non-smooth



## Structure of Stationary Points

**Theorem 1** Any non-degenerate Clarke stationary point is globally optimal.

## Key Ideas

- Non-strict Linear Matrix Inequality (LMI)

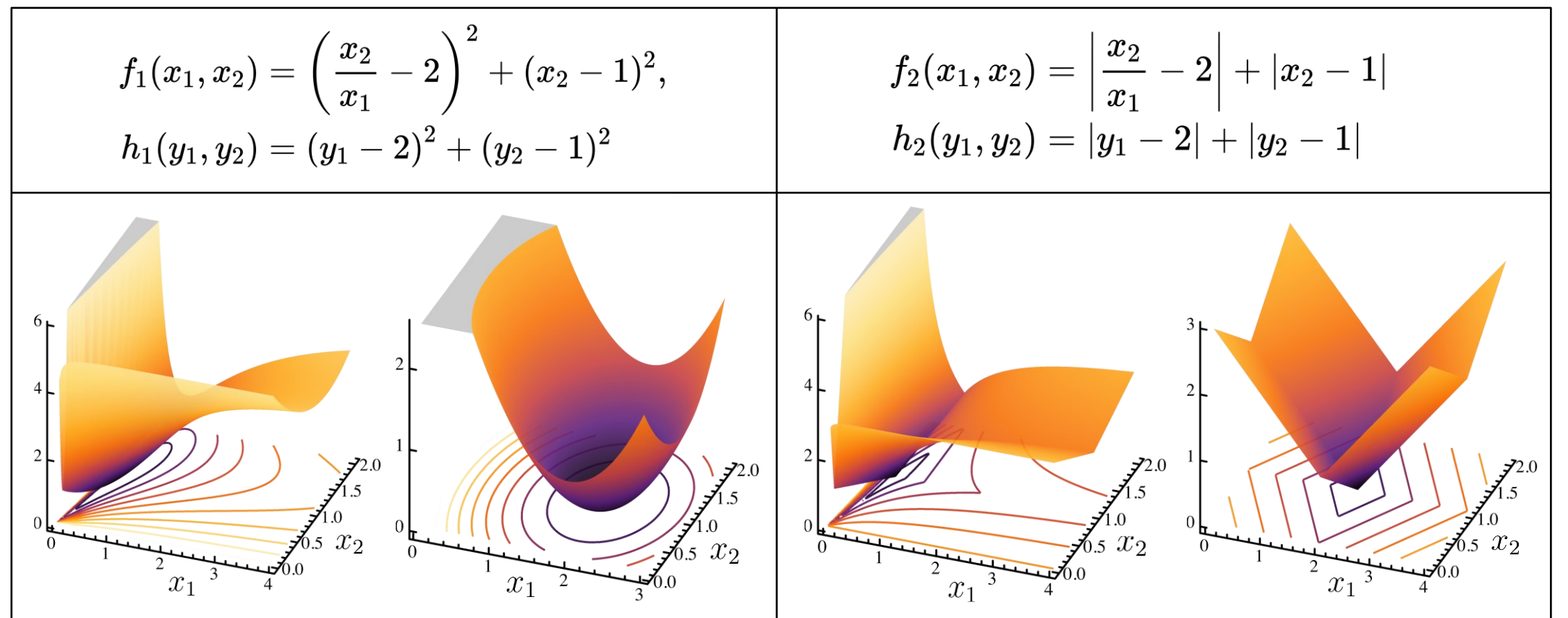
$$J_{\text{LQG},n}(K) \leq \gamma \text{ if } \exists P, \Gamma \text{ s.t. } \begin{bmatrix} A_{\text{cl}}(K)^T P + P A_{\text{cl}}(K) & P B_{\text{cl}}(K) \\ B_{\text{cl}}(K)^T P & -\gamma I \end{bmatrix} \preceq 0, \\ \begin{bmatrix} P & C_{\text{cl}}(K)^T \\ C_{\text{cl}}(K) & \Gamma \end{bmatrix} \succeq 0, P \succ 0, \text{trace}(\Gamma) \leq \gamma.$$

- Convex Reformulation with change of variables

$$\text{when } \gamma = J_{\text{LQG},n}(K) \text{ and } P_{12} \succ 0, \text{ where } P = \begin{bmatrix} P_{11} & P_{12} \\ P_{12}^T & P_{22} \end{bmatrix}$$



## Unified Framework: Extended Convex Lifting (ECL)



The tuple  $(\mathcal{L}_{\text{lift}}, \mathcal{F}_{\text{cvx}}, \mathcal{G}_{\text{aux}}, \Phi)$  is an ECL of  $f$  if

- 1)  $\mathcal{L}_{\text{lift}} \subseteq \mathbb{R}^d \times \mathbb{R} \times \mathbb{R}^{d_{\xi}}$  is a lifted set with an extra variable  $\xi \in \mathbb{R}^{d_{\xi}}$ , such that the canonical projection of  $\mathcal{L}_{\text{lift}}$  onto the first  $d+1$  coordinates, given by  $\pi_{x,\gamma}(\mathcal{L}_{\text{lift}}) = \{(x, \gamma) : \exists \xi \in \mathbb{R}^{d_{\xi}} \text{ s.t. } (x, \gamma, \xi) \in \mathcal{L}_{\text{lift}}\}$ , satisfies

$$\text{epi}_{>}(f) \subseteq \pi_{x,\gamma}(\mathcal{L}_{\text{lift}}) \subseteq \text{cl epi}_{\geq}(f). \quad (6a)$$

- 2)  $\mathcal{F}_{\text{cvx}} \subseteq \mathbb{R} \times \mathbb{R}^{d_1}$  is a convex set,  $\mathcal{G}_{\text{aux}} \subseteq \mathbb{R}^{d_2}$  is an auxiliary set, and  $\Phi$  is a  $C^2$ -diffeomorphism from  $\mathcal{L}_{\text{lift}}$  to  $\mathcal{F}_{\text{cvx}} \times \mathcal{G}_{\text{aux}}$ .
- 3) For any  $(x, \gamma, \xi) \in \mathcal{L}_{\text{lift}}$ , we have

$$\Phi(x, \gamma, \xi) = (\gamma, \zeta_1, \zeta_2) \quad \text{and} \quad (\gamma, \zeta_1) \in \mathcal{F}_{\text{cvx}} \quad (6b)$$

for some  $\zeta_1 \in \mathbb{R}^{d_1}$  and  $\zeta_2 \in \mathcal{G}_{\text{aux}}$  (i.e., the map  $\Phi$  directly outputs  $\gamma$  in the first component).

**Non-degenerate points**  $x \in \mathcal{D}_{\text{nd}} : (x, f(x)) \in \pi_{x,\gamma}(\mathcal{L}_{\text{lift}})$

**Theorem 2** Convex reformulation  $\inf_{x \in \mathcal{D}} f(x) = \inf_{(\gamma, \zeta_1) \in \mathcal{F}_{\text{cvx}}} \gamma.$

**Theorem 3**  $x^* \in \mathcal{D}_{\text{nd}}$  and  $0 \in \partial f(x^*) \Rightarrow f(x^*) = \inf_{x \in \mathcal{D}} f(x)$

**No spurious stationary points**

## References & Acknowledgement

- Yang Zheng, Chih-fan Pai, and Yujie Tang. "Benign Nonconvex Landscapes in Optimal and Robust Control, Part I: Global Optimality." *arXiv:2312.15332*, 2023.
- Zheng, Yang, Chih-Fan Pai, and Yujie Tang. "Benign Nonconvex Landscapes in Optimal and Robust Control, Part II: Extended Convex Lifting." *arXiv:2406.04001* (2024).
- Zheng and Pai are supported by NSF ECCS-2154650, CMMI-2320697, and CAREER 2340713.