Non-convex Optimization for Linear Quadratic Gaussian (LQG) Control

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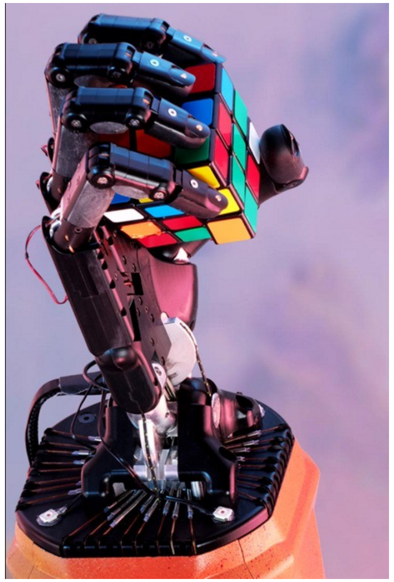
- Yang Zheng*, Yujie Tang*, and Na Li. "Analysis of the optimization landscape of linear quadratic gaussian (LQG) control." *arXiv preprint arXiv:2102.04393* (2021) *Equal contribution
- Yang Zheng*, Yue Sun*, Maryam Fazel, and Na Li. "Escaping High-order Saddles in Policy Optimization for Linear Quadratic Gaussian (LQG) Control." arXiv preprint arXiv:2204.00912 (2022). *Equal contribution

Motivation

❑ Model-free methods and data-driven control

- Use direct policy updates
- Become very popular in both academia and practice, from game playing, robotics, and drones, etc.

DeepMind



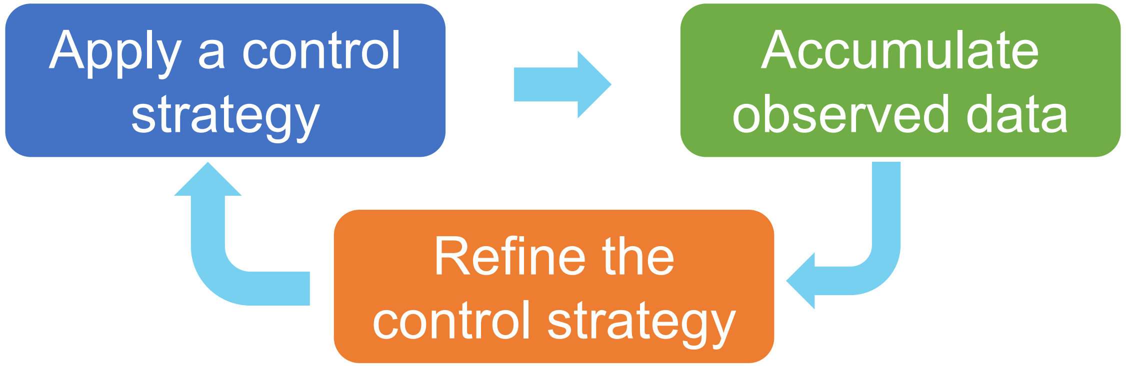
OpenAI

Applications

Duan et al. 2016; Silver et al., 2017; Dean et al., 2019; Tu and Recht, 2019;
Mania et al., 2019; Fazel et al., 2018; Recht, 2019;

Motivation

❑ Model-free methods and data-driven control



Opportunities

- Directly search over a given policy class
- Directly optimize performance on the true system, bypassing the model estimation (not on an approximated model)

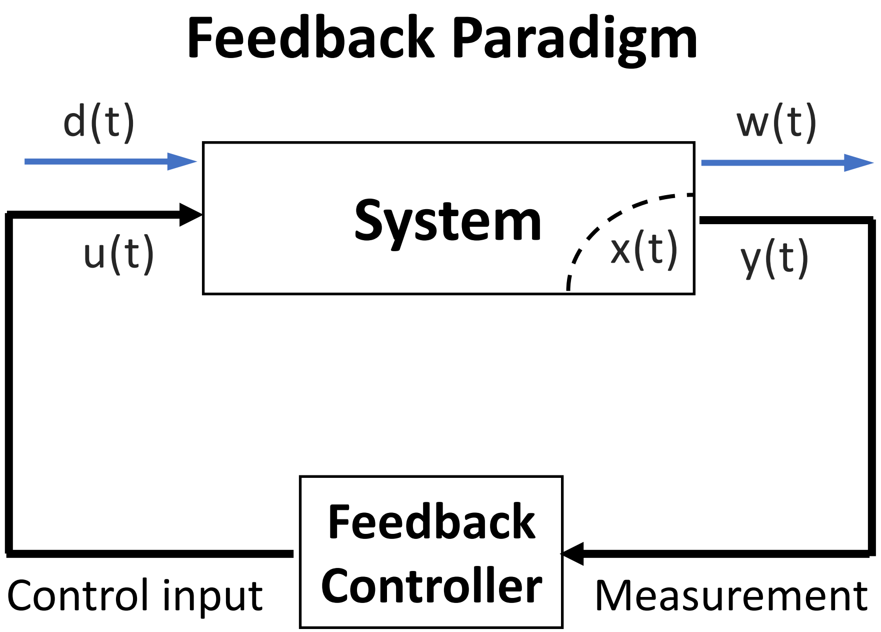
Challenges

- Lack of non-asymptotic performance guarantees
  - Convergence
  - Suboptimality
  - Sample complexity, etc.

❖ Highly nontrivial even for **linear dynamical systems**

Today's talk

❑ Optimal Control



Control theory: the principled use of feedback loops and algorithms to drive a dynamical system to its desired goal

Linear Quadratic Optimal control

$$\min_{u_1,u_2,\ldots,} \quad \lim_{T\to\infty} \mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T}\left(x_t^{\mathsf{T}} Q x_t + u_t^{\mathsf{T}} R u_t\right)\right]$$

$$\text{subject to} \quad x_{t+1} = Ax_t + Bu_t + w_t$$

$$y_t = Cx_t + v_t$$

- Many practical applications
- **Linear Quadratic Regulator (LQR)** when the state x_t is directly observable
- **Linear Quadratic Gaussian (LQG) control** when only partial output y_t is observed
- Extensive classical results (Dynamic programming, Separation principle, Riccati equations, etc.)

Major challenge: how to perform optimal control when the system is unknown?

Model-free: Direct policy iteration

❑ Controller parameterization

- Give a parameterization of control policies; say **neural networks?** ✖
- Control theory already tells us many structural properties
- **Linear feedback is sufficient for LQR** $u_t = K x_t$

$$\lim_{T \to \infty} \mathbb{E}\left[\frac{1}{T}\sum_{t=1}^{T}\left(x_t^{\mathsf{T}} Q x_t + u_t^{\mathsf{T}} R u_t\right)\right] := J(K)$$

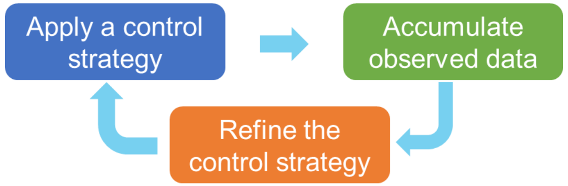
- Set of stabilizing controllers $K \in \mathcal{K}$

- A fast-growing list of references

LQR as an Optimization problem

$$\begin{aligned} \min_{K} \quad & J(K) \\ \text{s.t.} \quad & K \in \mathcal{K} \end{aligned}$$

Direct policy iteration



$$K_{i+1} = K_i - \alpha_i \nabla J(K_i)$$

✓ Good optimization landscape properties (Fazel et al., 2018)

- Connected feasible region
- Unique stationary point
- Gradient dominance

✓ Fast global convergence (linear)

➢ Fazel et al., ICML, 2018; Malik et al., 2019; Mohammadi et al., IEEE TAC, 2020; Li et al., 2019; K. Zhang, B. Hu, and T. Başar, 2021; Furieri et al., 2019; Feiran Zhao & Keyou You, 2021, and many others

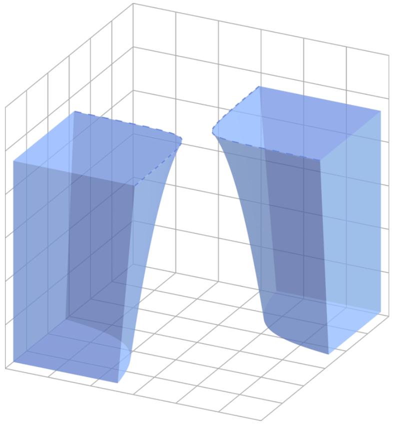
Challenges for partially observed LQG

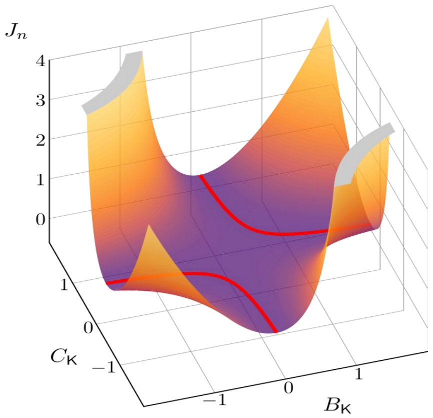
❑ Results on model-free LQG control are much fewer

- LQG is more complicated than LQR
- Requires dynamical controllers
- Its non-convex landscape properties are much richer and more complicated than LQR

Our focus: non-convex optimization of LQG

- **Q1: Properties of the domain** (set of stabilizing controllers)
  - convexity, connectivity, open/closed?
- **Q2: Properties of the accumulated cost**
  - convexity, differentiability, coercivity?
  - set of stationary points/local minima/global minima?
- **Q3: Escape saddle points via Perturbed Gradient Descent (PGD)**

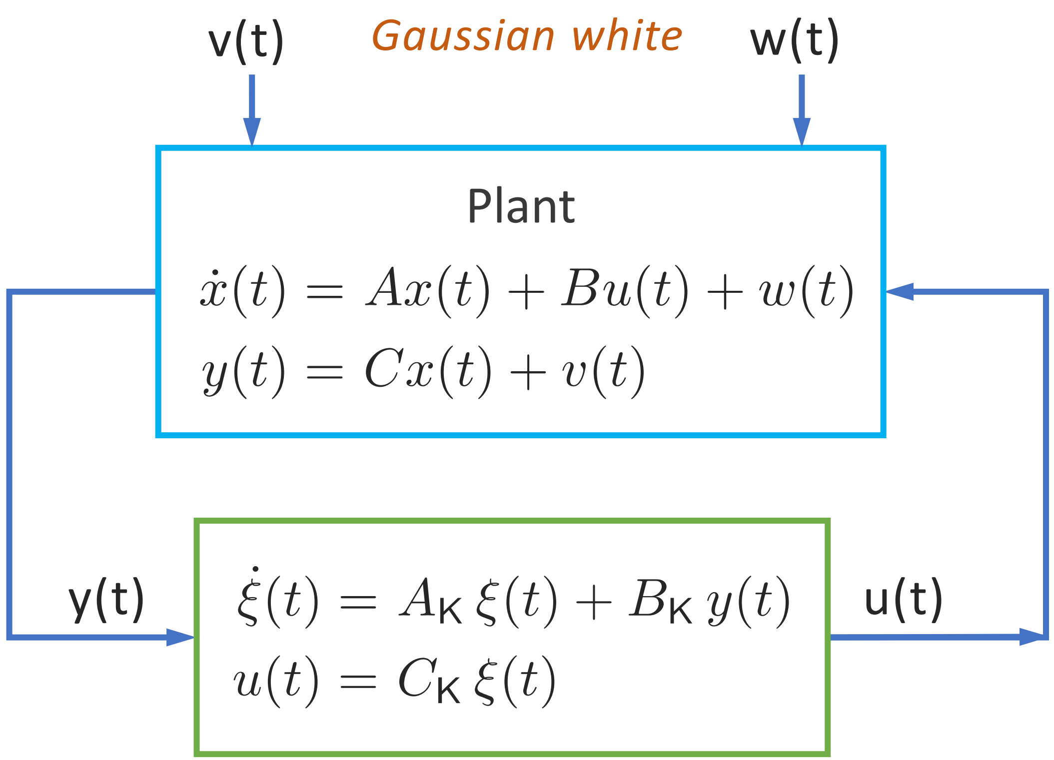




Outline

- ❑ **LQG problem Setup**
- ❑ Connectivity of the Set of Stabilizing Controllers
- ❑ Structure of Stationary Points of the LQG cost
- ❑ Escaping saddle points via PGD

LQG Problem Setup



dynamical controller

$\mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}})$

Standard Assumption	(A, B), $(A, W^{1/2})$	Controllable
	(C, A), $(Q^{1/2}, A)$	Observable

Objective: The LQG cost

$$\lim_{T\to+\infty} \frac{1}{T}\mathbb{E}\int_0^T (x^\top Qx + u^\top Ru)\,dt$$

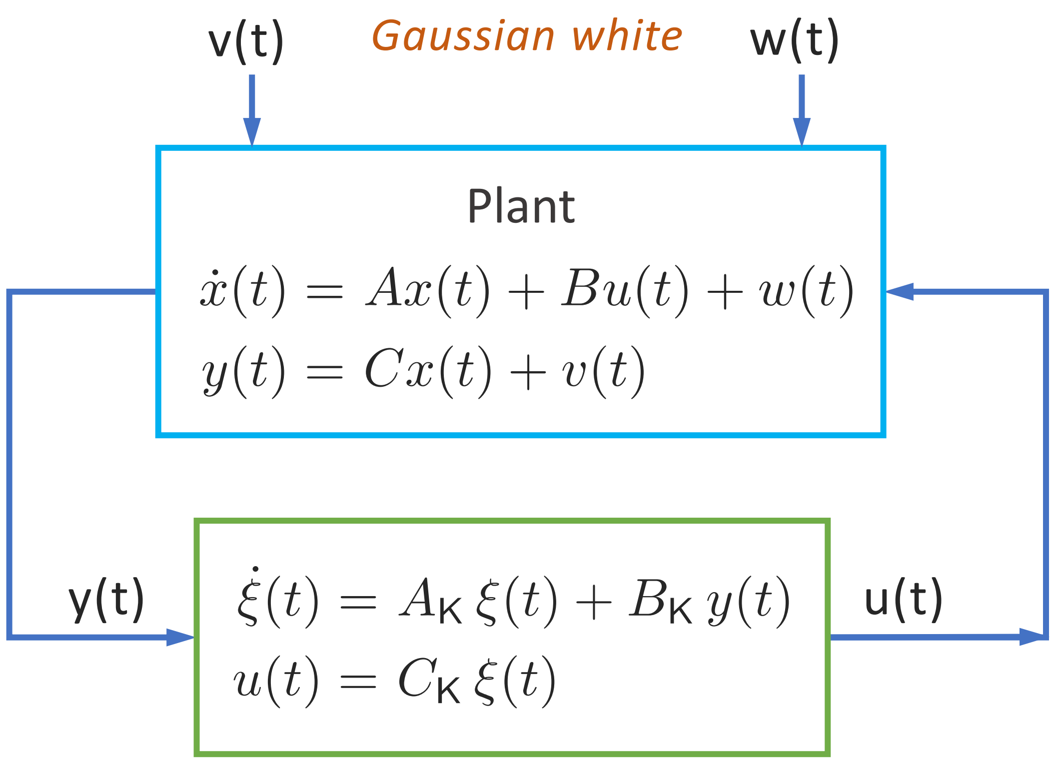
- $\xi(t)$ internal state of the controller
- $\dim \xi(t)$ order of the controller
- $\dim \xi(t) = \dim x(t)$ full-order
- $\dim \xi(t) < \dim x(t)$ reduced-order

Minimal controller

The input-output behavior cannot be replicated by a lower order controller.

* $(A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}})$ controllable and observable

Separation principle



dynamical controller

$$\mathsf{K} = (A_\mathsf{K}, B_\mathsf{K}, C_\mathsf{K})$$

Explicit dependence on the dynamics

Objective: The LQG cost

$$\lim_{T\to+\infty} \frac{1}{T}\mathbb{E}\int_0^T (x^\top Q x + u^\top R u)\, dt$$

Solution: Kalman filter for state estimation
+ LQR based on the estimated state

$$\dot{\xi} = (A - BK)\xi + L(y - C\xi),$$
$$u = -K\xi.$$

Two Riccati equations

- **Kalman gain** $L = PC^\mathsf{T} V^{-1}$

$$AP + PA^\mathsf{T} - PC^\mathsf{T} V^{-1} CP + W = 0,$$

- **Feedback gain** $K = R^{-1} B^\mathsf{T} S$

$$A^\mathsf{T} S + SA - SBR^{-1} B^\mathsf{T} S + Q = 0$$

Model-free Optimization formulation

❑ Closed-loop dynamics

$$\frac{d}{dt}\begin{bmatrix} x \\ \xi \end{bmatrix} = \begin{bmatrix} A & BC_{\mathsf{K}} \\ B_{\mathsf{K}}C & A_{\mathsf{K}} \end{bmatrix}\begin{bmatrix} x \\ \xi \end{bmatrix} + \begin{bmatrix} I & 0 \\ 0 & B_{\mathsf{K}} \end{bmatrix}\begin{bmatrix} w \\ v \end{bmatrix},$$

$$\begin{bmatrix} y \\ u \end{bmatrix} = \begin{bmatrix} C & 0 \\ 0 & C_{\mathsf{K}} \end{bmatrix}\begin{bmatrix} x \\ \xi \end{bmatrix} + \begin{bmatrix} v \\ 0 \end{bmatrix}.$$

❑ Feasible region of the controller parameters

$$\mathcal{C}_{\text{full}} = \left\{ \mathsf{K} \,\middle|\, \mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \text{ is full order } \begin{bmatrix} A & BC_{\mathsf{K}} \\ B_{\mathsf{K}}C & A_{\mathsf{K}} \end{bmatrix} \text{ is Hurwitz stable} \right\}$$

❑ Cost function

$$\lim_{T \to +\infty} \frac{1}{T}\mathbb{E}\int_0^T (x^\top Q x + u^\top R u)\, dt$$

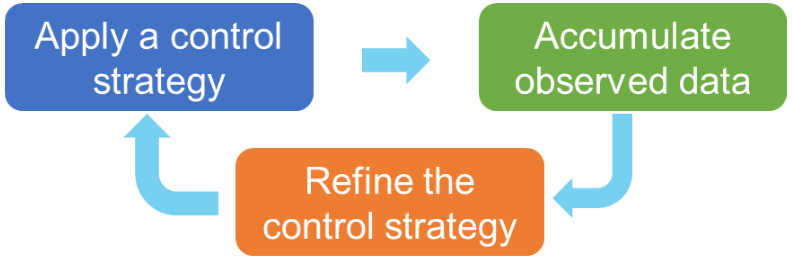
$$J(\mathsf{K}) = \operatorname{tr}\left(\begin{bmatrix} Q & 0 \\ 0 & C_{\mathsf{K}}^{\mathsf{T}} R C_{\mathsf{K}} \end{bmatrix} X_{\mathsf{K}}\right) = \operatorname{tr}\left(\begin{bmatrix} W & 0 \\ 0 & B_{\mathsf{K}} V B_{\mathsf{K}}^{\mathsf{T}} \end{bmatrix} Y_{\mathsf{K}}\right)$$

$X_{\mathsf{K}}, Y_{\mathsf{K}}$ Solution to Lyapunov equations

LQG as a non-convex optimization problem

$$\min_{\mathsf{K}} \quad J(\mathsf{K})$$
$$\text{s.t.} \quad \mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$$

Direct policy iteration $\mathsf{K}_{i+1} = \mathsf{K}_i - \alpha_i \nabla J(\mathsf{K}_i)$

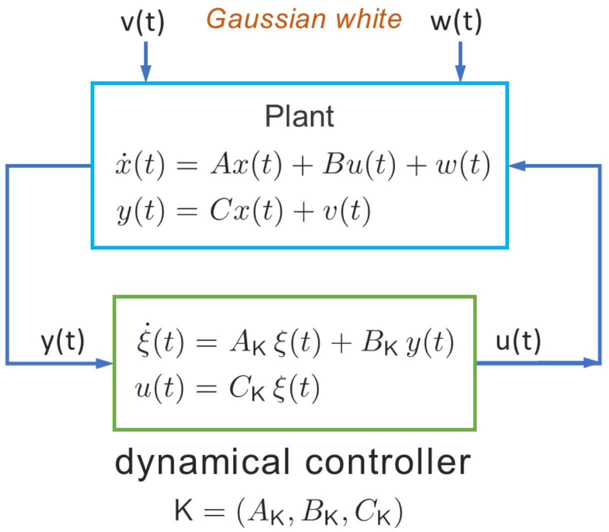


- ✓ **Does it converge at all?**
- ✓ **Converge to which point?**
- ✓ **Convergence speed?**

Optimization Landscape Analysis

Hyland, David, and Dennis Bernstein. "The optimal projection equations for fixed-order dynamic compensation." *IEEE Transactions on Automatic Control* 29.11 (1984): 1034-1037.

Model-free Optimization formulation



LQG as a Non-convex Optimization Problem

$$\min_{K} \quad J(K)$$
$$\text{s.t.} \quad K = (A_K, B_K, C_K) \in \mathcal{C}_{\text{full}}$$

Non-convex Landscape Analysis

- **Q1: Connectivity of the feasible region $\mathcal{C}_{\text{full}}$**
  - Is it connected?
  - If not, how many connected components can it have?
- **Q2: Structure of stationary points of $J(K)$**
  - Are there spurious (strictly suboptimal, saddle) stationary points?
  - How to check if a stationary point is globally optimal?
- **Q3: How to escape high-order saddle points via PGD?**

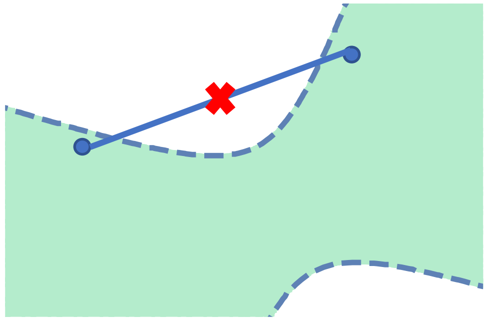
Outline

- LQG problem Setup
- **Connectivity of the Set of Stabilizing Controllers**
- Structure of Stationary Points of the LQG cost
- Escaping saddle points via PGD

Connectivity of the feasible region

❑ Simple observation: non-convex and unbounded

Lemma 1: the set $\mathcal{C}_{\text{full}}$ is non-empty, unbounded, and can be non-convex.



Example

$$\dot{x}(t) = x(t) + u(t) + w(t)$$
$$y(t) = x(t) + v(t)$$

$$\mathcal{C}_{\text{full}} = \left\{ \mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathbb{R}^{2\times 2} \,\middle|\, \begin{bmatrix} 1 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \text{ is stable} \right\}.$$

$$\mathsf{K}^{(1)} = \begin{bmatrix} 0 & 2 \\ -2 & -2 \end{bmatrix}, \qquad \mathsf{K}^{(2)} = \begin{bmatrix} 0 & -2 \\ 2 & -2 \end{bmatrix}$$

Stabilize the plant, and thus belong to $\mathcal{C}_{\text{full}}$

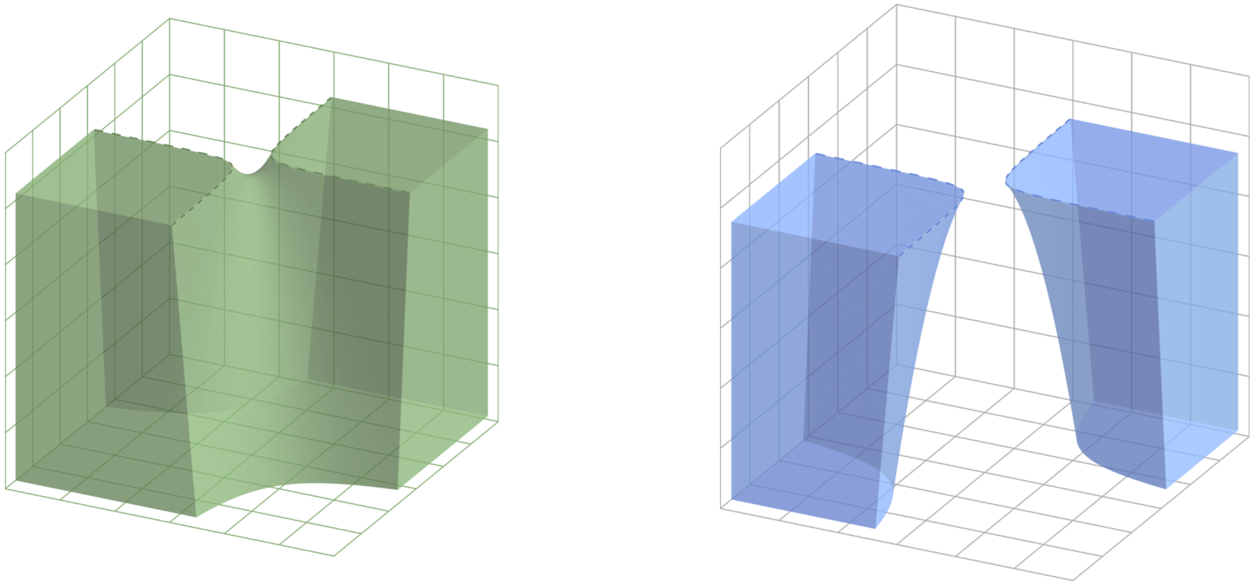
$$\hat{\mathsf{K}} = \frac{1}{2}\left(\mathsf{K}^{(1)} + \mathsf{K}^{(2)}\right) = \begin{bmatrix} 0 & 0 \\ 0 & -2 \end{bmatrix}$$

Fails to stabilize the plant, and thus outside $\mathcal{C}_{\text{full}}$

Connectivity of the feasible region

❑ Main Result 1: dis-connectivity

Theorem 1: The set $\mathcal{C}_{\text{full}}$ can be disconnected but has at most 2 connected components.

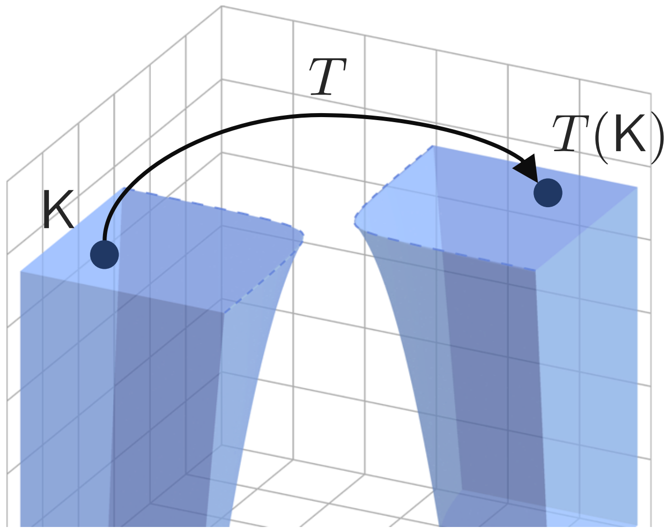


- ✓ Different from the connectivity of static stabilizing state-feedback controllers, which is always connected!
- ✓ **Is this a negative result for gradient-based algorithms?** → **No**

Connectivity of the feasible region

❑ Main Result 2: dis-connectivity

Theorem 2: If $\mathcal{C}_{\text{full}}$ has 2 connected components, then there is a smooth bijection T between the 2 connected components that has the same cost function value.



$$J(\mathsf{K}) = J(T(\mathsf{K}))$$

✓ In fact, the bijection T is defined by a similarity transformation (change of controller state coordinates)

$$\mathscr{T}_T(\mathsf{K}) := \begin{bmatrix} D_{\mathsf{K}} & C_{\mathsf{K}}T^{-1} \\ TB_{\mathsf{K}} & TA_{\mathsf{K}}T^{-1} \end{bmatrix}.$$

Positive news: For gradient-based local search methods, it makes no difference to search over either connected component.

Connectivity of the feasible region

❑ Main Result 3: conditions for connectivity

Theorem 3: 1) $\mathcal{C}_{\text{full}}$ is connected if there exists a reduced-order stabilizing controller.

2) The sufficient condition above becomes necessary if the plant is single-input or single-output.

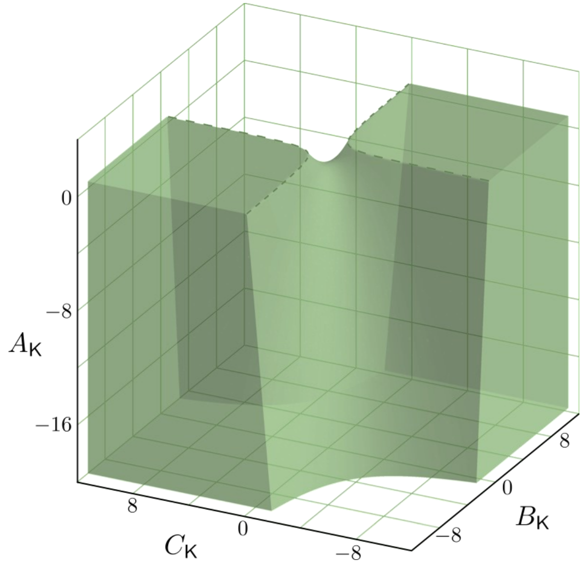
Corollary 1: Given any open-loop stable plant, the set of stabilizing controllers $\mathcal{C}_{\text{full}}$ is connected.

Example: Open-loop stable system

$$\dot{x}(t) = -x(t) + u(t) + w(t)$$
$$y(t) = x(t) + v(t)$$

Routh--Hurwitz stability criterion

$$\mathcal{C}_{\text{full}} = \left\{ \mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathbb{R}^{2\times 2} \middle| A_{\mathsf{K}} < 1, B_{\mathsf{K}} C_{\mathsf{K}} < -A_{\mathsf{K}} \right\}.$$



Connectivity of the feasible region

❑ Main Result 3: conditions for connectivity

Example: Open-loop unstable system (SISO)

$$\dot{x}(t) = x(t) + u(t) + w(t)$$
$$y(t) = x(t) + v(t)$$

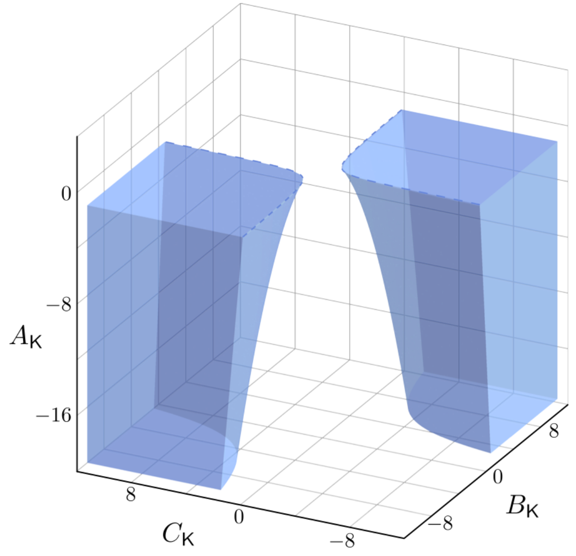
- **Routh--Hurwitz stability criterion**

$$\mathcal{C}_{\text{full}} = \left\{ \mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathbb{R}^{2\times 2} \,\middle|\, \begin{bmatrix} A & BC_{\mathsf{K}} \\ B_{\mathsf{K}}C & A_{\mathsf{K}} \end{bmatrix} \text{ is stable} \right\}$$
$$= \left\{ \mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathbb{R}^{2\times 2} \,\middle|\, A_{\mathsf{K}} < -1,\ B_{\mathsf{K}}C_{\mathsf{K}} < A_{\mathsf{K}} \right\}.$$

- **Two path-connected components**

$$\mathcal{C}_1^+ := \left\{ \mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathbb{R}^{2\times 2} \,\middle|\, A_{\mathsf{K}} < -1,\, B_{\mathsf{K}}C_{\mathsf{K}} < A_{\mathsf{K}},\, B_{\mathsf{K}} > 0 \right\},$$
$$\mathcal{C}_1^- := \left\{ \mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathbb{R}^{2\times 2} \,\middle|\, A_{\mathsf{K}} < -1,\, B_{\mathsf{K}}C_{\mathsf{K}} < A_{\mathsf{K}},\, B_{\mathsf{K}} < 0 \right\}.$$

Disconnected feasible region



Proof idea: Lifting via Change of Variables

❑ Change of variables in state-space domain: Lyapunov theory

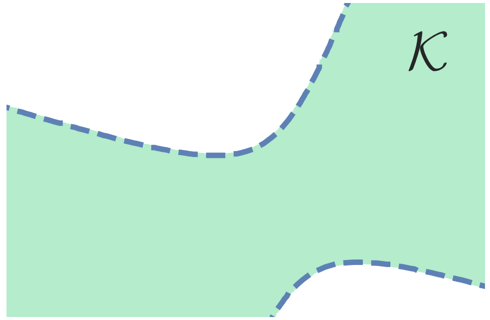
- Connectivity of the static stabilizing state feedback gains

$$\{K \in \mathbb{R}^{m\times n} \mid A - BK \text{ is stable}\}$$

$$\iff \{K \in \mathbb{R}^{m\times n} \mid \exists P \succ 0, P(A-BK)^{\mathsf{T}} + (A-BK)P \prec 0\}$$

$$\iff \{K \in \mathbb{R}^{m\times n} \mid \exists P \succ 0, PA^{\mathsf{T}} - L^{\mathsf{T}}B^{\mathsf{T}} + AP - BL \prec 0, L = KP\}$$

$$\iff \{K = LP^{-1} \in \mathbb{R}^{m\times n} \mid \exists P \succ 0, PA^{\mathsf{T}} - L^{\mathsf{T}}B^{\mathsf{T}} + AP - BL \prec 0\}.$$



Open, connected, possibly nonconvex

- How about the set of stabilizing dynamical controllers

$$\begin{bmatrix} A & BC_{\mathsf{K}} \\ B_{\mathsf{K}}C & A_{\mathsf{K}} \end{bmatrix} \text{ is stable}$$

$$\iff \quad \exists P \succ 0,\ P\begin{bmatrix} A & BC_{\mathsf{K}} \\ B_{\mathsf{K}}C & A_{\mathsf{K}} \end{bmatrix}^{\mathsf{T}} + \begin{bmatrix} A & BC_{\mathsf{K}} \\ B_{\mathsf{K}}C & A_{\mathsf{K}} \end{bmatrix} P \prec 0,$$

Change of variables for output feedback control is highly non-trivial

[Gahinet and Apkarian, 1994]
[Scherer et al., IEEE TAC 1997]

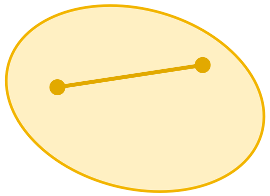
Proof idea: Lifting via Change of Variables

❑ Change of variables in state-space domain: Lyapunov theory

$$\Phi(\mathsf{Z}) = \begin{bmatrix}\Phi_D(\mathsf{Z}) & \Phi_C(\mathsf{Z}) \\ \Phi_B(\mathsf{Z}) & \Phi_A(\mathsf{Z})\end{bmatrix} := \begin{bmatrix} I & 0 \\ YB & \Xi \end{bmatrix}^{-1} \begin{bmatrix} G & H \\ F & M - YAX \end{bmatrix} \begin{bmatrix} I & CX \\ 0 & \Pi \end{bmatrix}^{-1}.$$

[Scherer et al., IEEE TAC 1997]
[Gahinet and Apkarian, 1994]

$$\mathcal{F} \times \mathrm{GL} \xrightarrow[\text{surjective}]{\Phi} \mathcal{C}_{\text{full}}$$



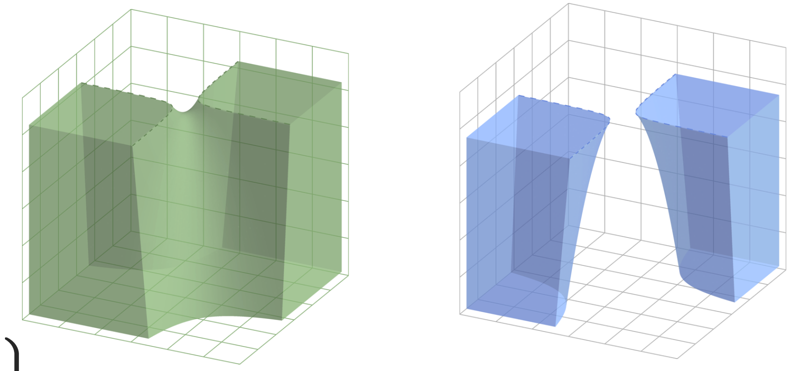
Convex thus connected

General linear group: the set of invertible matrices (similarity transformation)

at most 2 connected components

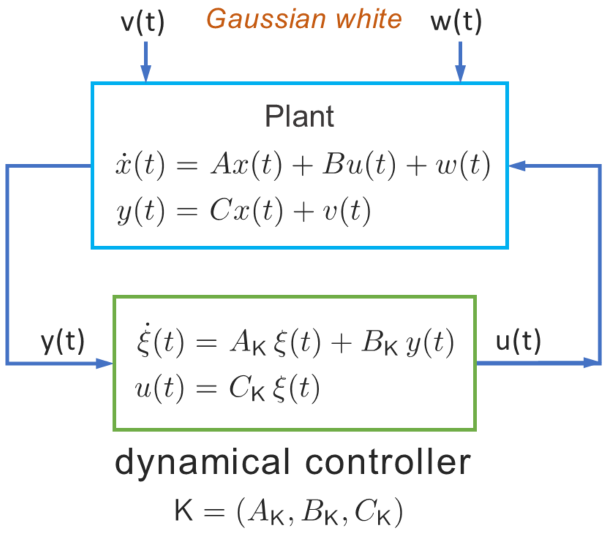
Two connected components

$$\mathrm{GL}_n^+ = \{\Pi \in \mathbb{R}^{n\times n} \mid \det \Pi > 0\},$$
$$\mathrm{GL}_n^- = \{\Pi \in \mathbb{R}^{n\times n} \mid \det \Pi < 0\}.$$



$$\mathcal{F} = \left\{ (X, Y, M, H, F) | X, Y \in \mathbb{S}^n, M \in \mathbb{R}^{n\times n}, H \in \mathbb{R}^{n\times p}, F \in \mathbb{R}^{m\times n}, \begin{bmatrix} X & I \\ I & Y \end{bmatrix} \succ 0, \begin{bmatrix} AX+BF & A \\ M & YA+HC \end{bmatrix} + \begin{bmatrix} AX+BF & A \\ M & YA+HC \end{bmatrix}^{\top} \prec 0 \right\}$$

Model-free Optimization formulation



Non-convex Landscape Analysis

LQG as a Non-convex Optimization Problem

$$\min_{\mathsf{K}} \quad J(\mathsf{K})$$
$$\text{s.t.} \quad \mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$$

- **Q1: Connectivity of the feasible region $\mathcal{C}_{\text{full}}$**
  - Is it connected? **No**
  - If not, how many connected components can it have? **Two**
- **Q2: Structure of stationary points of $J(\mathsf{K})$**
  - Are there spurious (strictly suboptimal, saddle) stationary points?
  - How to check if a stationary point is globally optimal?
- **Q3: How to escape high-order saddle points via PGD?**

Outline

- ❑ LQG problem Setup
- ❑ Connectivity of the Set of Stabilizing Controllers
- ❑ **Structure of Stationary Points of the LQG cost**
- ❑ Escaping saddle points via PGD

Structure of Stationary Points

Simple observations

1) $J(\mathsf{K})$ is a real analytic function over its domain (smooth, infinitely differentiable)

2) $J(\mathsf{K})$ has **non-unique** and **non-isolated** global optima

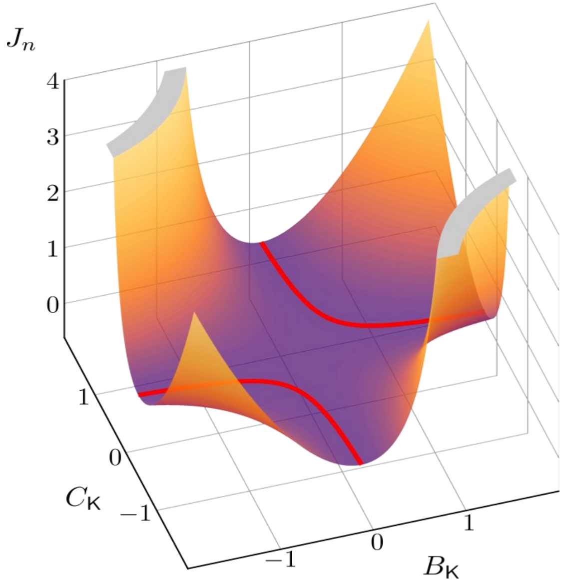
LQG as an Optimization problem

$$\min_{\mathsf{K}} \quad J(\mathsf{K})$$
$$\text{s.t.} \quad \mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$$

$$\dot{\xi}(t) = A_{\mathsf{K}}\,\xi(t) + B_{\mathsf{K}}\,y(t)$$
$$u(t) = C_{\mathsf{K}}\,\xi(t)$$

Similarity transformation

$$(A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \mapsto (TA_{\mathsf{K}}T^{-1}, TB_{\mathsf{K}}, C_{\mathsf{K}}T^{-1})$$



- $J(\mathsf{K})$ is invariant under similarity transformations.
- It has many stationary points, unlike the LQR with a unique stationary point

Structure of Stationary Points

❑ Gradient computation

Lemma 1: For every $\mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$, we have

$$\frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} = 2\left(Y_{12}^{\mathsf{T}} X_{12} + Y_{22} X_{22}\right),$$
$$\frac{\partial J(\mathsf{K})}{\partial B_{\mathsf{K}}} = 2\left(Y_{22} B_{\mathsf{K}} V + Y_{22} X_{12}^{\mathsf{T}} C^{\mathsf{T}} + Y_{12}^{\mathsf{T}} X_{11} C^{\mathsf{T}}\right),$$
$$\frac{\partial J(\mathsf{K})}{\partial C_{\mathsf{K}}} = 2\left(R C_{\mathsf{K}} X_{22} + B^{\mathsf{T}} Y_{11} X_{12} + B^{\mathsf{T}} Y_{12} X_{22}\right),$$

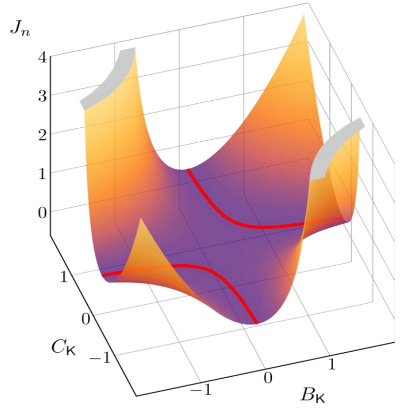
where $X_{\mathsf{K}} = \begin{bmatrix} X_{11} & X_{12} \\ X_{12}^{\mathsf{T}} & X_{22} \end{bmatrix}, \qquad Y_{\mathsf{K}} = \begin{bmatrix} Y_{11} & Y_{12} \\ Y_{12}^{\mathsf{T}} & Y_{22} \end{bmatrix}$

are the unique positive semidefinite solutions to two Lyapunov equations.

How does the set of Stationary Points look like?

$$\left\{ \mathsf{K} \in \mathcal{C}_{\text{full}} \;\middle|\; \frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} = 0, \; \frac{\partial J(\mathsf{K})}{\partial B_{\mathsf{K}}} = 0, \; \frac{\partial J(\mathsf{K})}{\partial C_{\mathsf{K}}} = 0, \right\}$$

- ❑ Non-unique, non-isolated
- ❑ Local minimum, local maximum, saddle points, or globally minimum?



Structure of Stationary Points

❑ Main Result: existences of strict saddle points

Theorem 4: Consider any open-loop stable plant. The zero controller with any stable A_{K}

$$\mathsf{K} = (A_{\mathsf{K}}, 0, 0) \in \mathcal{C}_{\text{full}}$$

is a stationary point. Furthermore, the corresponding hessian is either indefinite (**strict saddle point**) or equal to zero (**high-order saddle or else**).

Example:

$$\dot{x}(t) = -x(t) + u(t) + w(t)$$
$$y(t) = x(t) + v(t)$$

$$Q = 1, R = 1, V = 1, W = 1$$

Stationary point: $\mathsf{K}^\star = \begin{bmatrix} 0 & 0 \\ 0 & a \end{bmatrix} \in \mathbb{R}^{2\times 2}, \qquad \text{with } a < 0$

- **Cost function:** $J\left(\begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix}\right) = \dfrac{A_{\mathsf{K}}^2 - A_{\mathsf{K}}(1 + B_{\mathsf{K}}^2 C_{\mathsf{K}}^2) - B_{\mathsf{K}} C_{\mathsf{K}}(1 - 3B_{\mathsf{K}} C_{\mathsf{K}} + B_{\mathsf{K}}^2 C_{\mathsf{K}}^2)}{2(-1 + A_{\mathsf{K}})(A_{\mathsf{K}} + B_{\mathsf{K}} C_{\mathsf{K}})}.$

- **Hessian:** $\begin{bmatrix} \frac{\partial J^2(\mathsf{K})}{\partial A_{\mathsf{K}}^2} & \frac{\partial J^2(\mathsf{K})}{\partial A_{\mathsf{K}} \partial B_{\mathsf{K}}} & \frac{\partial J^2(\mathsf{K})}{\partial A_{\mathsf{K}} \partial C_{\mathsf{K}}} \\ \frac{\partial J^2(\mathsf{K})}{\partial B_{\mathsf{K}} A_{\mathsf{K}}} & \frac{\partial J^2(\mathsf{K})}{\partial B_{\mathsf{K}}^2} & \frac{\partial J^2(\mathsf{K})}{\partial B_{\mathsf{K}} \partial C_{\mathsf{K}}} \\ \frac{\partial J^2(\mathsf{K})}{\partial C_{\mathsf{K}} A_{\mathsf{K}}} & \frac{\partial J^2(\mathsf{K})}{\partial C_{\mathsf{K}} B_{\mathsf{K}}} & \frac{\partial J^2(\mathsf{K})}{\partial \partial C_{\mathsf{K}}^2} \end{bmatrix}\Bigg|_{\mathsf{K}^\star = \begin{bmatrix} 0 & 0 \\ 0 & a \end{bmatrix}} = \dfrac{1}{2(1-a)} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix},$

Indefinite with eigenvalues:

$0 \text{ and } \pm\frac{1}{2(1-a)}$

Structure of Stationary Points

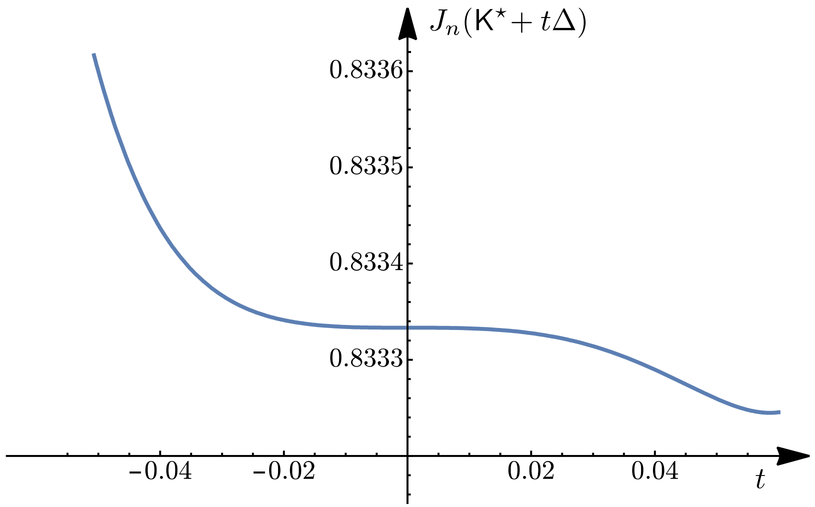
❑ Main Result: existences of strict saddle points

Theorem 4: Consider any open-loop stable plant. The zero controller with any stable A_{K}

$$\mathsf{K} = (A_{\mathsf{K}}, 0, 0) \in \mathcal{C}_{\text{full}}$$

is a stationary point. Furthermore, the corresponding hessian is either indefinite (**strict saddle point**) or equal to zero (**high-order saddle or else**).

Another example with zero Hessian



How does the set of Stationary Points look like?

$$\left\{ \mathsf{K} \in \mathcal{C}_{\text{full}} \;\middle|\; \begin{aligned} \frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} &= 0, \\ \frac{\partial J(\mathsf{K})}{\partial B_{\mathsf{K}}} &= 0, \\ \frac{\partial J(\mathsf{K})}{\partial C_{\mathsf{K}}} &= 0, \end{aligned} \right\}$$

- ❑ Non-unique, non-isolated
- ❑ Strictly suboptimal points; Strict saddle points
- ❑ All bad stationary points correspond to non-minimal controllers

Structure of Stationary Points

❑ Main Result

Theorem 5: All stationary points corresponding to controllable and observable controllers are globally optimum.

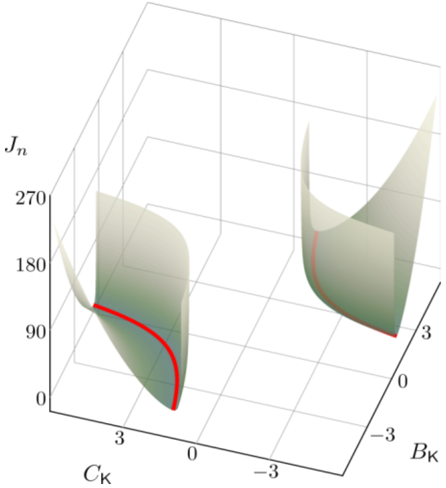
$$\left\{ \mathsf{K} \in \mathcal{C}_{\text{full}} \;\middle|\; \frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} = 0, \; \frac{\partial J(\mathsf{K})}{\partial B_{\mathsf{K}}} = 0, \; \frac{\partial J(\mathsf{K})}{\partial C_{\mathsf{K}}} = 0, \right\}$$

Particularly, given a stationary point that is a **minimal** controller

1) This stationary point is a global optimum of $J(\mathsf{K})$
2) The set of all global optima forms a manifold with 2 connected components. They are connected by a similarity transformation.

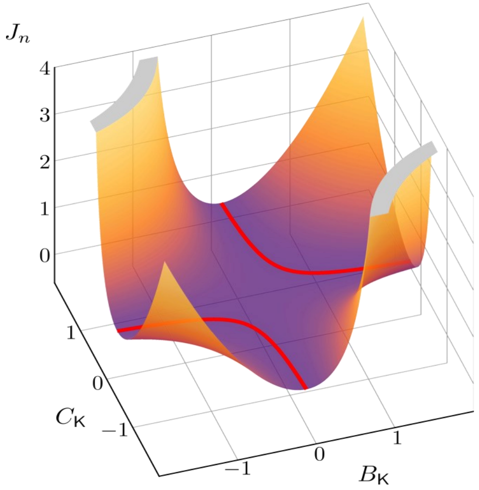
Example: open-loop unstable system

$$\dot{x}(t) = x(t) + u(t) + w(t)$$
$$y(t) = x(t) + v(t)$$



Example: open-loop stable system

$$\dot{x}(t) = -x(t) + u(t) + w(t)$$
$$y(t) = x(t) + v(t)$$



Proof idea

❑ Proof: all minimal stationary points are unique up to a similarity transformation

All minimal stationary points $\mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$ to the LQG problem are in the form of

$$A_{\mathsf{K}} = T(A - BK - LC)T^{-1}, \qquad B_{\mathsf{K}} = -TL, \qquad C_{\mathsf{K}} = KT^{-1},$$

$$K = R^{-1}B^{\mathsf{T}}S,\ L = PC^{\mathsf{T}}V^{-1},$$

T is an invertible matrix and P, S are the unique positive definite solutions to the Riccati equations

$$\left\{ \mathsf{K} \in \mathcal{C}_{\text{full}} \;\middle|\; \frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} = 0,\ \frac{\partial J(\mathsf{K})}{\partial B_{\mathsf{K}}} = 0,\ \frac{\partial J(\mathsf{K})}{\partial C_{\mathsf{K}}} = 0, \right\}$$

Minimal controller

$$\frac{\partial J_n(\mathsf{K})}{\partial B_{\mathsf{K}}} = 0 \quad \Longrightarrow \quad B_{\mathsf{K}} = -TPC^{\mathsf{T}}V^{-1}$$

$$\frac{\partial J_n(\mathsf{K})}{\partial C_{\mathsf{K}}} = 0 \quad \Longrightarrow \quad C_{\mathsf{K}} = R^{-1}B^{\mathsf{T}}ST^{-1}$$

$$\frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} = 0 \quad \Longrightarrow \quad A_{\mathsf{K}} = T(A - PC^{\mathsf{T}}V^{-1}C - BR^{-1}B^{\mathsf{T}}S)T^{-1}$$

$$\frac{\partial J(\mathsf{K})}{\partial A_{\mathsf{K}}} = 2\left(Y_{12}^{\mathsf{T}}X_{12} + Y_{22}X_{22}\right),$$

$$\frac{\partial J(\mathsf{K})}{\partial B_{\mathsf{K}}} = 2\left(Y_{22}B_{\mathsf{K}}V + Y_{22}X_{12}^{\mathsf{T}}C^{\mathsf{T}} + Y_{12}^{\mathsf{T}}X_{11}C^{\mathsf{T}}\right),$$

$$\frac{\partial J(\mathsf{K})}{\partial C_{\mathsf{K}}} = 2\left(RC_{\mathsf{K}}X_{22} + B^{\mathsf{T}}Y_{11}X_{12} + B^{\mathsf{T}}Y_{12}X_{22}\right),$$

Special case in Theorem 20.6 of Zhou et al., 1996 and Section II of Hyland, 1984

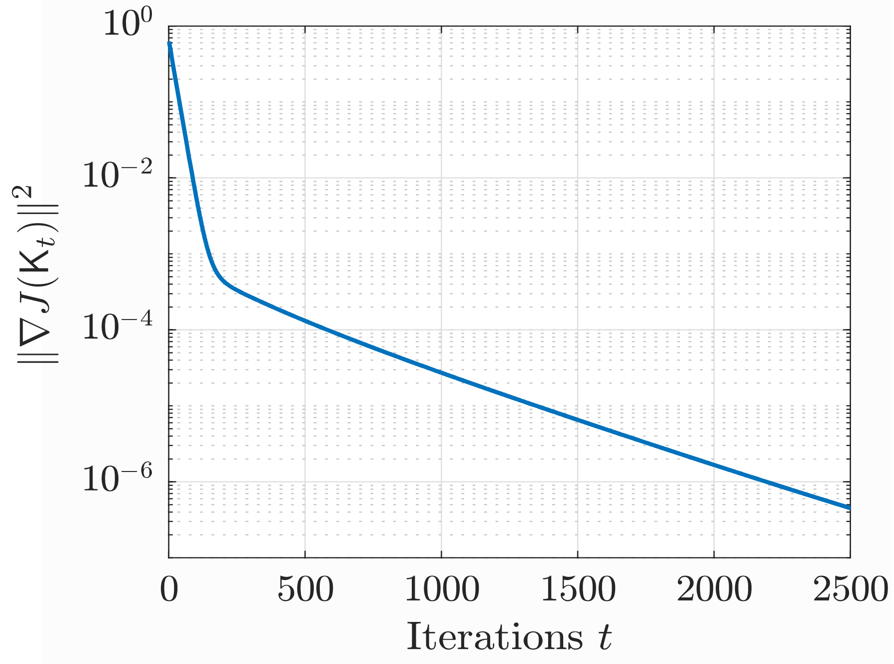
Structure of Stationary Points

❑ Implication

Corollary: Consider gradient descent iterations

$$\mathsf{K}_{t+1} = \mathsf{K}_t - \alpha \nabla J(\mathsf{K}_t)$$

If the iterates converge to a minimal controller, then this minimal controller is a global optima.



More questions:

- ✓ Escaping saddle points?
- ✓ Convergence conditions?
- ✓ Convergence speed?
- ✓ Alternative model-free parameterization?

Comparison with LQR

	LQR as an Optimization problem	LQG as an Optimization problem
	$\min_{K} \; J(K)$ s.t. $\; K \in \mathcal{K}$	$\min_{\mathsf{K}} \; J(\mathsf{K})$ s.t. $\; \mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$
Connectivity of feasible region	❖ Always connected	❖ Disconnected, but at most 2 connected comp. ❖ They are almost identical to each other
Stationary points	❖ Unique	❖ Non-unique, non-isolated stationary points ❖ Spurious stationary points (strict saddle, nonminimal controller) ❖ **All mini. stationary points are globally optimal**
Gradient Descent	❖ Gradient dominance ❖ Global fast convergence (like strictly convex)	❖ No gradient dominance ❖ Local convergence/speed (**unknown**) ❖ **Many open questions**
References	Fazel et al., ICML, 2018; Malik et al., 2019; Mohammadi et al., IEEE TAC, 2020; Li et al., 2019; K. Zhang, B. Hu, and T. Başar, 2021; Furieri et al., 2019; Feiran Zhao & Keyou You, 2021, and many others	Zheng*, Tang*, Li. 2021, link (* equal contribution)

Outline

- ❑ LQG problem Setup
- ❑ Connectivity of the Set of Stabilizing Controllers
- ❑ Structure of Stationary Points of the LQG cost
- ❑ **Escaping saddle points via PGD**

Perturbed Gradient Descent

❑ Local geometry

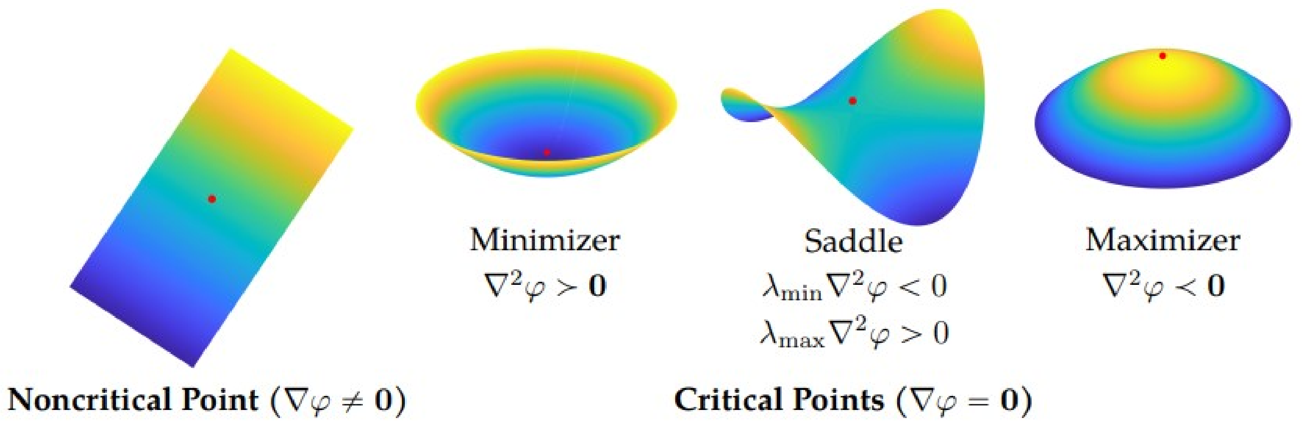
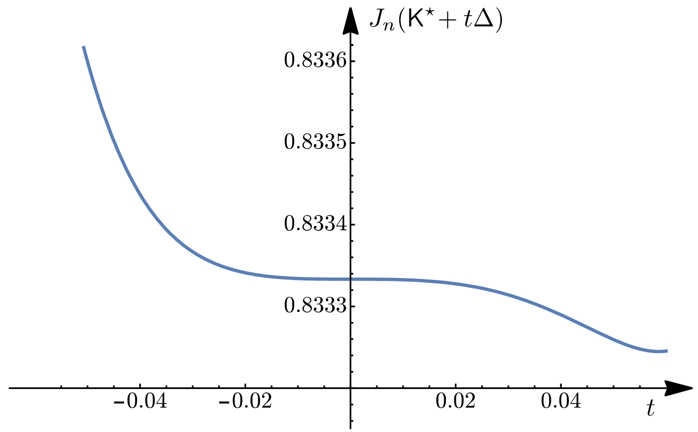


Figure taken from Zhang et al., 2020

LQG as a non-convex optimization problem

$$\min_{\mathsf{K}} \quad J(\mathsf{K})$$
$$\text{s.t.} \quad \mathsf{K} = (A_{\mathsf{K}}, B_{\mathsf{K}}, C_{\mathsf{K}}) \in \mathcal{C}_{\text{full}}$$



High-order saddle point
with zero hessian

- ❑ **Strict saddle points**: the hessian has a strict negative eigenvalue (i.e., escaping direction)
- ❑ **Non-strict (high-order) saddle points**: no such escaping direction, i.e., minimum eigenvalue is zero.
- ❑ **Simple perturbed gradient descent (PGD)** methods can escape strict saddle points efficiently (e.g., Jin et al., 2017)

✓ Zhang, Yuqian, Qing Qu, and John Wright. "From symmetry to geometry: Tractable nonconvex problems." *arXiv preprint arXiv:2007.06753* (2020).
✓ Jin, C., Ge, R., Netrapalli, P., Kakade, S. M., & Jordan, M. I. (2017, July). How to escape saddle points efficiently. In *International Conference on Machine Learning* (pp. 1724-1732). PMLR.

Perturbed Gradient Descent

Our idea: a structural perturbation

A high-order saddle → A strict saddle point with the same LQG cost

- **Theorem 1 (informal): all bad stationary points are in the same form**

If $\mathsf{K} = \begin{bmatrix} 0 & C_{\mathsf{K}} \\ B_{\mathsf{K}} & A_{\mathsf{K}} \end{bmatrix} \in \mathcal{C}_n$ is a stationary point but not minimal, then $\tilde{\mathsf{K}} = \left[\begin{array}{c:cc} 0 & \hat{C}_{\mathsf{K}} & 0 \\ \hdashline \hat{B}_{\mathsf{K}} & \hat{A}_{\mathsf{K}} & 0 \\ 0 & 0 & \Lambda \end{array}\right] \in \mathcal{C}_n$ is also a stationary point with the same LQG cost, where $\hat{\mathsf{K}} = \begin{bmatrix} 0 & \hat{C}_{\mathsf{K}} \\ \hat{B}_{\mathsf{K}} & \hat{A}_{\mathsf{K}} \end{bmatrix} \in \mathcal{C}_q$ is a minimal realization

- **Theorem 2 (informal): Choosing the diagonal stable block Λ randomly leads to a strict saddle point with probability almost 1**

See details in our paper:

✓ Yang Zheng*, Yue Sun*, Maryam Fazel, and Na Li. "Escaping High-order Saddles in Policy Optimization for Linear Quadratic Gaussian (LQG) Control." arXiv preprint arXiv:2204.00912 (2022). *Equal contribution

Perturbed Gradient Descent

Our idea: a structural perturbation

A high-order saddle → A strict saddle point with the same LQG cost

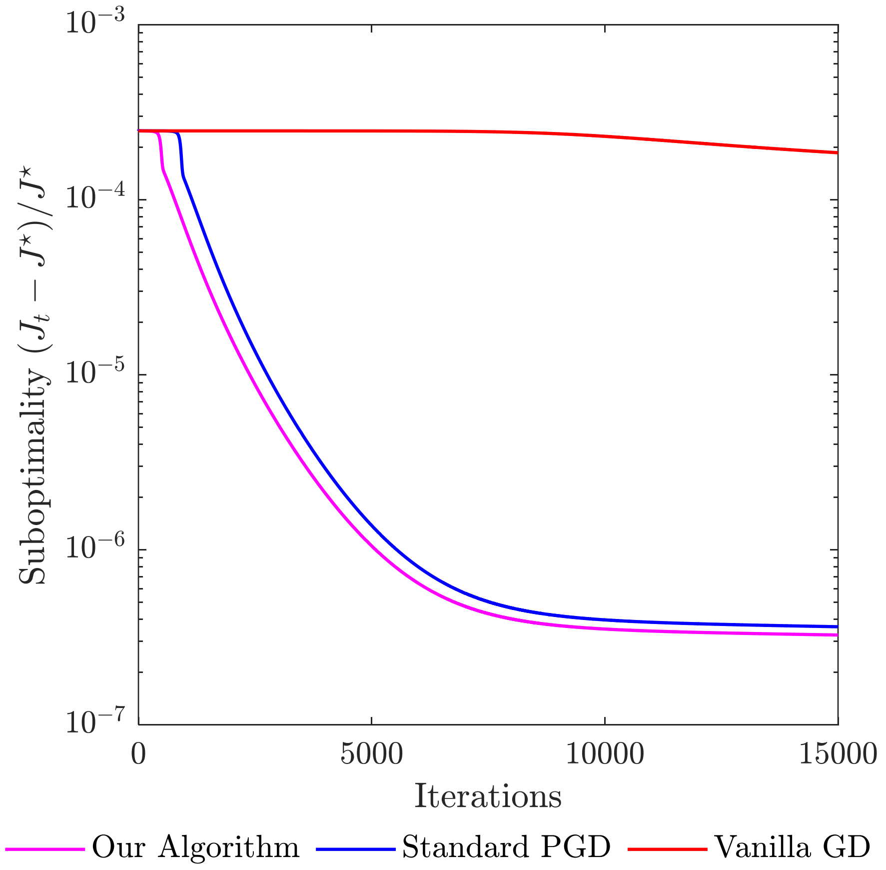
LQG example

$$A = \begin{bmatrix} -0.5 & 0 \\ 0.5 & -1 \end{bmatrix}, \; B = \begin{bmatrix} -1 \\ 1 \end{bmatrix}, \; C = \begin{bmatrix} -\frac{1}{6} & \frac{11}{12} \end{bmatrix},$$

$$W = Q = I_2, V = R = 1.$$

Close to be a high-order saddle with zero hessian

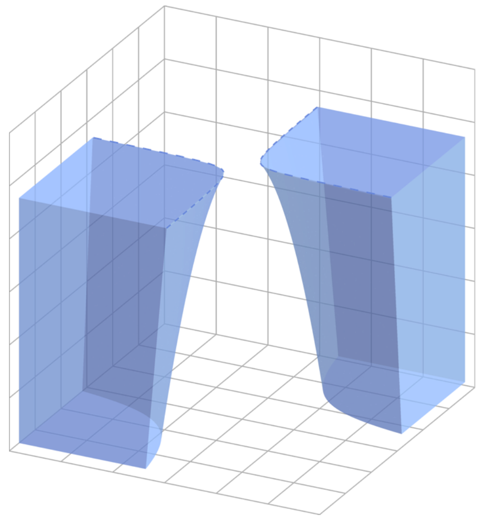
$$A_{\mathsf{K},0} = -0.5 I_2, \; B_{\mathsf{K},0} = \begin{bmatrix} 0 \\ 0.01 \end{bmatrix}, \; C_{\mathsf{K},0} = [0, -0.01]$$

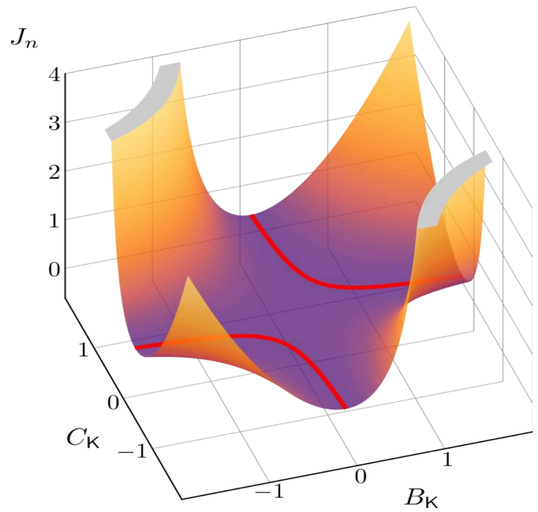


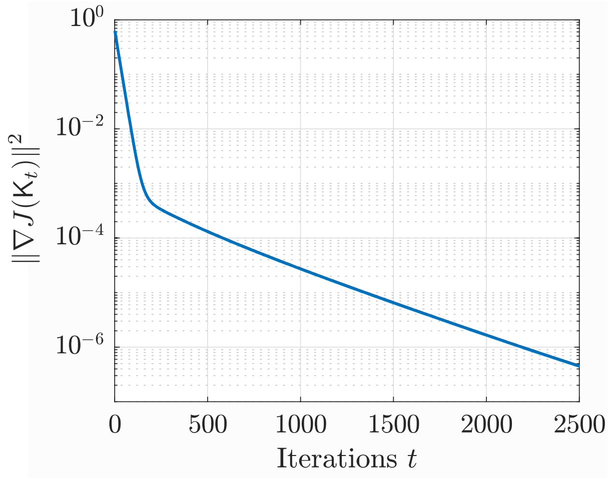
Conclusions

Non-convex optimization for LQG control

- Much richer and more complicated than LQR
- Disconnected, but at most 2 connected components
- Non-unique, non-isolated stationary points, strict saddle points
- Minimal stationary points are globally optimal
- A new perturbed gradient descent algorithm







Ongoing and Future work

- How to certify the optimality of a non-minimal stationary point
- Convergence proof of perturbed policy gradient (PGD)
- More quantitative analysis of PGD algorithms for LQG
- Alternative model-free parametrization of dynamical controllers
  - ✓ Better optimization landscape structures, smaller dimension

Non-convex Optimization for Linear Quadratic Gaussian (LQG) Control

Thank you for your attention!

Q & A

More details. Check out our papers:
https://arxiv.org/abs/2102.04393;
https://arxiv.org/abs/2204.00912

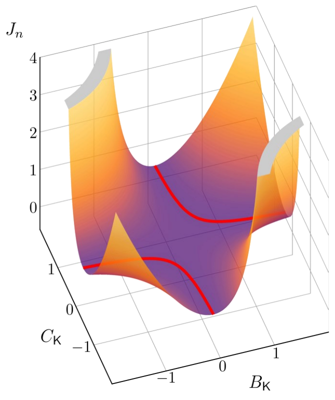
SOC lab at UC San Diego

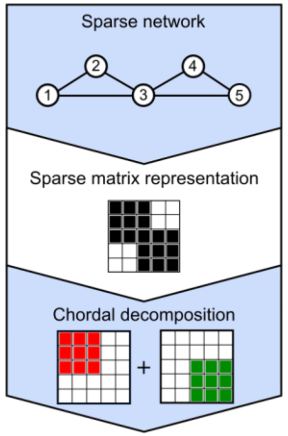
Data-driven and learning-based control

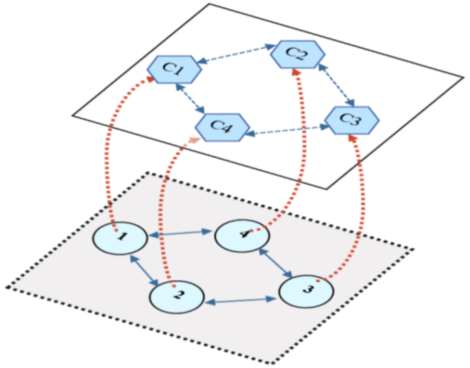
Sparse conic optimization

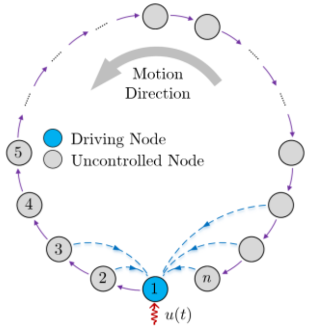
Scalable distributed control

Connected and autonomous vehicles (CAVs)









Check out our webpage: https://zhengy09.github.io/soclab.html