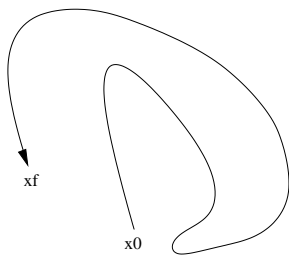


# Selected Topics in Numerical Linear Algebra and Control

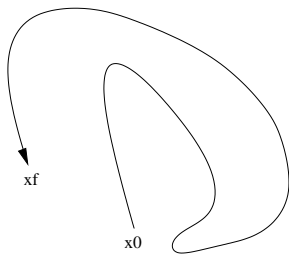
Optimal Control

Zlatko Drmač and Daniel Kressner  
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**Goal:** Find control  $u$  which drives  $x(0) = x_0$  to  $x(t_f) = x_f$ .

By  $x(t) \rightarrow x(t) - x_f$ , we can w.l.o.g. assume that  $x_f = 0$ . Thus, at least asymptotically, our goal can be reached by any stabilizing control.



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# Cart-pendulum example

$$\dot{x} = \begin{bmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ 0 & -19.6 & 0 & 0 \\ 0 & 29.4 & 0 & 0 \end{bmatrix} x + \begin{bmatrix} 0 \\ 0 \\ 1 \\ -1 \end{bmatrix} u, \quad x(0) = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}.$$

We want to bring cart and pendulum to rest at 0.

1. Moving poles to  $\{-1, -2, -3, -4\} \rightsquigarrow \|u\|_2 = 25$ .
2. Moving poles to  $\{-10, -20, -30, -40\} \rightsquigarrow \|u\|_2 = 587$ .
3. Lyapunov stabilization  $\rightsquigarrow \|u\|_2 = 58900$ .
4. **Optimal control**  $\rightsquigarrow \|u\|_2 = 3$  (corresponding closed loop poles:  $-5.4 \pm 0.0615j, -0.4129 \pm 0.4036j$ ).

# Linear optimal control problem

Minimize

$$\mathcal{J}(u) = \frac{1}{2} \left( x(t_f)^T M x(t_f) + \int_0^{t_f} [x(t)^T Q x(t) + u(t)^T R u(t)] dt \right)$$

under the dynamical constraint

$$\dot{x}(t) = Ax(t) + Bu(t), \quad x(0) = x_0.$$

Here,  $M, Q, R$  symmetric;  $u$  piecewise continuous.

1.  $x(t_f)^T M x(t_f)$  measures the distance of  $x(t_f)$  from 0;
2.  $\int x(t)^T Q x(t)$  measures the energy of the state trajectory;
3.  $\int u(t)^T R u(t)$  measures the energy of the input.

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# LQ optimal control and boundary value problem

Application of Pontryagin's maximum principle.

## Theorem

Let  $u_*$  be an optimal control with corresponding state trajectory  $x_*$ . Then there is a **co-state** (Lagrange multiplier)  $\mu(t) : [0, t_f] \rightarrow \mathbb{R}^n$  s.t.  $x_*(t), \mu(t), u_*(t)$  solve

$$\begin{bmatrix} A & 0 & B \\ Q & A^T & 0 \\ 0 & B^T & R \end{bmatrix} \begin{bmatrix} x(t) \\ \mu(t) \\ u(t) \end{bmatrix} = \begin{bmatrix} I & 0 & 0 \\ 0 & -I & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} \dot{x}(t) \\ \dot{\mu}(t) \\ \dot{u}(t) \end{bmatrix}$$

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This gives necessary conditions; to also obtain sufficient conditions we need more assumptions.

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If  $Q, R, M$  are **positive semidefinite**, then any solution  $x_*(t), \mu(t), u_*(t)$  of the BVP satisfies

$$\mathcal{J}(u) \geq \mathcal{J}(u_*)$$

for all piecewise continuous  $u$ .

Usually, one also assumes positive definiteness of  $R$  ("free" controls are often not meaningful). Then we can set  $u(t) = -R^{-1}B^T\mu(t)$  and the BVP becomes

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# Turning the BVP into an IVP

Using *ansatz*  $\mu(t) = X(t)x(t)$ , we have

$$\dot{\mu}(t) = \dot{X}(t)x(t) + X\dot{x}(t), \quad \mu(t_f) = X(t_f)x(t_f).$$

The latter can be satisfied by requiring  $X(t_f) = M$ . Moreover,

$$\dot{X}(t) = -(Q + A^T X(t) + X(t)A - X(t)BR^{-1}B^T X(t)). \quad (\text{DRE})$$

This is the matrix version of the **differential Riccati equation**. Since  $X^T(t)$  also solves (DRE), any solution must be symmetric.

## Theorem

*If  $M, Q \geq 0$  and  $R > 0$  then an optimal control  $u_*$  is given by*

$$u_*(t) = -R^{-1}B^T X_*(t)x_*(t),$$

*where  $X_*$  solves (DRE).*

$$\mathcal{J}(u_*) = \frac{1}{2}x_0^T X_*(0)x_0.$$

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$$t_f \rightarrow \infty$$

We set  $M = 0$  (closed loop system must be stable to attain goal).

New *ansatz*:  $\mu(t) = Xx(t)$  with constant matrix  $X$ . Then (DRE) reduces to **algebraic Riccati equation**

$$Q + A^T X + XA - XBR^{-1}B^T X = 0. \quad (ARE)$$

In contrast to (DRE), (ARE) has infinitely many solutions for  $n > 1$ .

However, together with the stabilization property

$$\Lambda(A - BR^{-1}B^T X) \subseteq \mathbb{C}^-,$$

(ARE) is uniquely solvable under fairly mild conditions.

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# ARE and Hamiltonian matrices

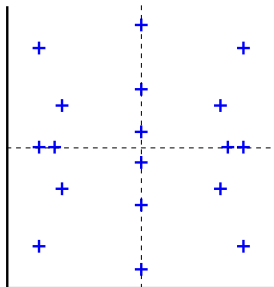
Let

$$H = \begin{bmatrix} A & -BR^{-1}B^T \\ -Q & -A^T \end{bmatrix}, \quad T = \begin{bmatrix} I & 0 \\ X & I \end{bmatrix},$$

where  $X$  solves (ARE). Then

$$T^{-1}HT = \begin{bmatrix} A - BR^{-1}B^T X & -BR^{-1}B^T \\ 0 & -(A - BR^{-1}B^T X)^T \end{bmatrix}.$$

Remember that eigenvalues of  $H$  come in pairs  $(\lambda, -\lambda)$ .



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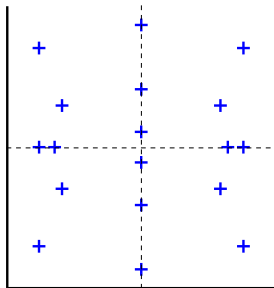
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We want  $A - BR^{-1}B^T X$  to contain only stable eigenvalues. This is possible iff  $H$  has no eigenvalues on the imaginary axis.

## Theorem

*If  $(A, B)$  is stabilizable and  $(A, Q)$  is detectable with  $Q \geq 0$ . Then the corresponding Hamiltonian matrix  $H$  has no eigenvalues on the imaginary axis.*

Compute block Schur decomposition of  $H$  such that

$$\begin{bmatrix} U_{11} & U_{12} \\ U_{21} & U_{22} \end{bmatrix}^T H \begin{bmatrix} U_{11} & U_{12} \\ U_{21} & U_{22} \end{bmatrix} = \begin{bmatrix} H_{11} & H_{12} \\ 0 & H_{22} \end{bmatrix}$$

such that  $\Lambda(H_{11}) \subset \mathbb{C}^-$ . Then  $X_* = U_{21} U_{11}^{-1}$  is a stabilizing solution of (ARE).

One can show that solution is unique and s.p.sd.

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## Theorem

Let  $Q \geq 0$  and  $R > 0$ ,  $(A, B)$  stabilizable,  $(A, Q)$  detectable. Then an optimal, stabilizing control  $u_*$  for  $t_f = \infty$  is given by

$$u_*(t) = -R^{-1}B^T X_* x_*(t),$$

where  $X_*$  is the stabilizing solution of (ARE).

$$\mathcal{J}(u_*) = \frac{1}{2} x_0^T X_* x_0.$$

# Newton for ARE

A different approach for solving (ARE) is obtained by applying Newton to

$$\mathcal{R}(X) = Q + A^T X + XA - XBR^{-1}B^T X = 0$$

The Fréchet derivative of  $\mathcal{R}$  in a direction  $Z$  can be computed as

$$\begin{aligned}\mathcal{R}'_X(Z) &= \lim_{t \rightarrow 0} \frac{1}{t} (\mathcal{R}(X + tZ) - \mathcal{R}(X)) \\ &= (A - BR^{-1}B^T X)^T Z + Z(A - BR^{-1}B^T X).\end{aligned}$$

Newton step given by  $X_{k+1} = X_k + N_k = X_k - \mathcal{R}'_{X_k}(Z)^{-1} \mathcal{R}(X_k)$ , i.e.,

$$(A - BR^{-1}B^T X_k)^T N_k + N_k(A - BR^{-1}B^T X_k) = -\mathcal{R}(X_k).$$

Let  $X_0$  be symmetric s.t.  $\Lambda(A - BR^{-1}B^T X_0) \subset \mathbb{C}^-$ .

for  $k = 0, 1, 2 \dots$

1. Solve Lyapunov eq.

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2. Set  $X_{k+1} = X_k + N_k$ .

Then it can be shown (assuming  $(A, Q)$  detectable).

- ▶  $\Lambda(A - BR^{-1}B^T X_k) \subset \mathbb{C}^-$  for all  $k$ ;
- ▶  $X_\star \leq \dots \leq X_3 \leq X_2 \leq X_1$ .
- ▶  $X_k \rightarrow X_\star$  as  $k \rightarrow \infty$

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