

# Numerical Optimal Control with DAEs

## Lecture 9: Indirect Optimal Control

Sébastien Gros

AWESCO PhD course

## Objectives of the Lecture

- Basics of the Pontryagin Maximum Principle (PMP)
- Numerical difficulties of PMP & how to tackle them
- Some properties of PMP
- Singular OCPs & their impact on Direct Optimal Control

# Outline

- 1 Introduction to the Pontryagin Maximum Principle (PMP)
- 2 Interpretation of  $H_u$
- 3 Input bounds in Indirect Optimal Control
- 4 Singular Optimal Control problems
- 5 General constraints in Indirect Optimal Control

# Pontryagin Maximum Principle

**Simple continuous problem:**

$$\min_{\mathbf{x}, \mathbf{u}} \phi(\mathbf{x}(t_f)) + \int_{t_0}^{t_f} L(\mathbf{x}(t), \mathbf{u}(t)) dt$$

$$\text{s.t. } \dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}),$$

$$\mathbf{x}(t_0) = \mathbf{x}_0$$

Define the Hamiltonian function

$$H(\mathbf{x}, \boldsymbol{\lambda}, \mathbf{u}) = L(\mathbf{x}, \mathbf{u}) + \boldsymbol{\lambda}^\top \mathbf{F}(\mathbf{x}, \mathbf{u})$$

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Get the optimal control solution from  $\mathbf{u} = \arg \min_{\mathbf{u}} H(\mathbf{x}, \boldsymbol{\lambda}, \mathbf{u})$

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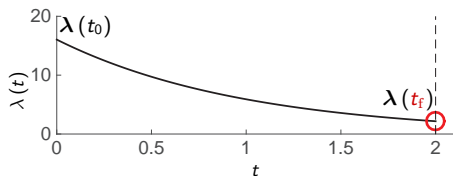
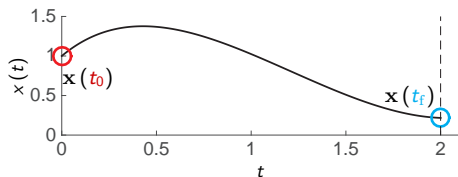
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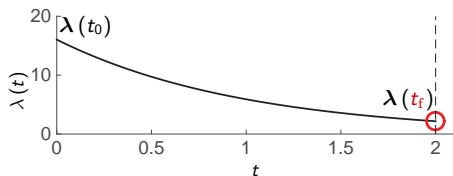
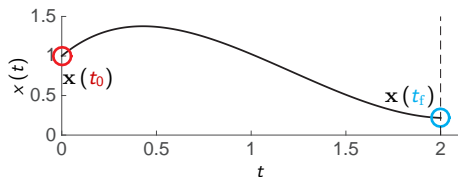
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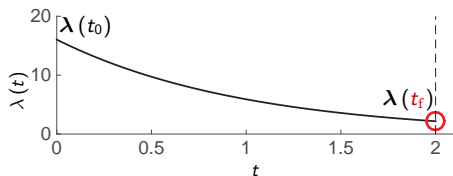
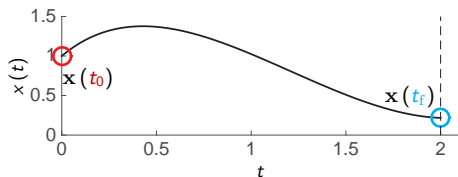
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Labelled a **Two Points Boundary Value Problem (TPBVP)**



## Overview

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Global	Hamilton-Jacobi-Bellman (HJB)	Dynamic Programming (DP)
Local	Pontryagin (PMP)	Direct Optimal Control (DOC)

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**PMP:** define the Hamiltonian function

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Use it in the state-costate integration:

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- PMP equations provide an "∞"-dimensional input profile  $\mathbf{u}(\cdot)$
- State constraints hard to handle

**PMP:** define the Hamiltonian function

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**D.O.C.** describes the solution as a finite set of variables  $\mathbf{w}$  transform the problem into a discrete one

Solve the resulting Nonlinear Program (NLP):

$$\min_{\mathbf{w}} \Phi(\mathbf{w})$$

$$\text{s.t. } \mathbf{g}(\mathbf{w}) = 0,$$

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- Input profile restricted to a finite-dimensional space (e.g. piecewise-constant)
- Easy to treat all types of constraints

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**"First optimise then discretize" (HJB & PMP)**

- First write the **continuous equations** describing the solution to the problem
- ... then **discretize the equations** & solve

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Note: the PMP "family" is referred to as *Indirect* optimal control here  
**vs.**

### "First discretize then optimise" (DP & DOC)

- **First discretize** the continuous OCP into a discrete one...
- ... then write the **discrete equations** describing the solution & solve



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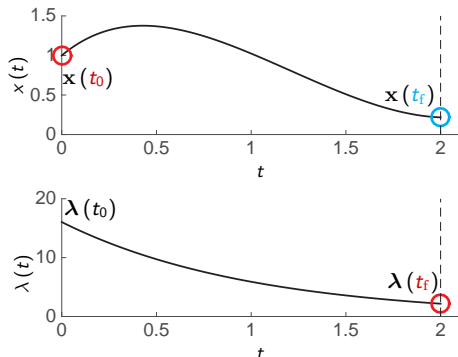
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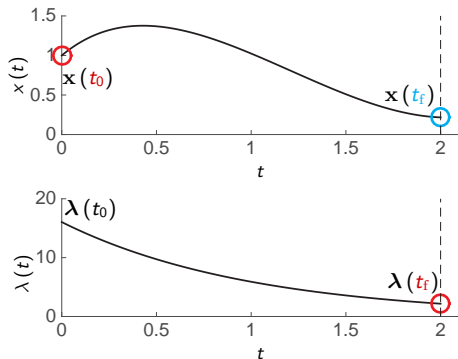
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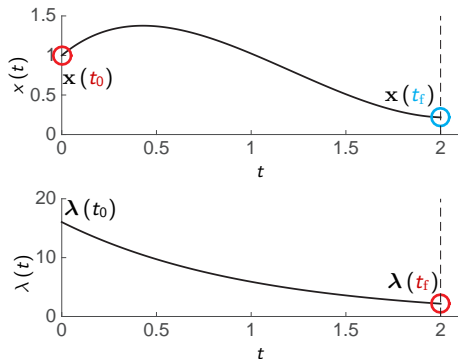
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## Two Points Boundary Value Problem

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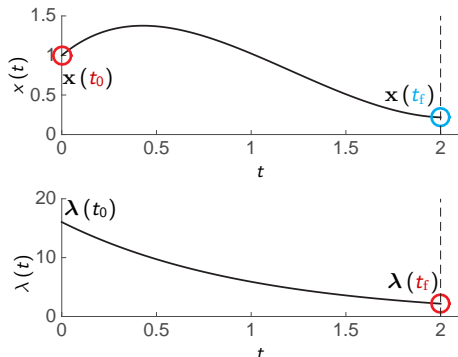
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- Integrate forward ? We have  $\mathbf{x}(t_0) = \mathbf{x}_0$ , but we don't have  $\boldsymbol{\lambda}(t_0)$ ...
- Integrate forward-backward ? Integrate state forward from  $\mathbf{x}(t_0) = \mathbf{x}_0$  then backward from  $\boldsymbol{\lambda}(t_f) = \nabla_{\mathbf{x}} \phi(\mathbf{x}(t_f))$ ... but we don't know  $\mathbf{u}$ ...

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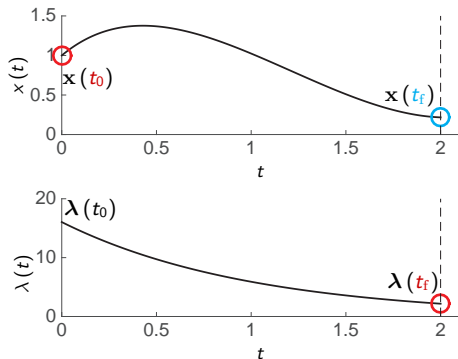
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## Two Points Boundary Value Problem

Note that the **entire** solution is "described by"  $\boldsymbol{\lambda}(t_0)$

## Solving the PMP equations / TPBVP

**Input:** Initial conditions  $\mathbf{x}_0$ , guess  $\lambda_0$

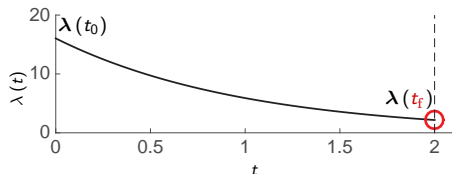
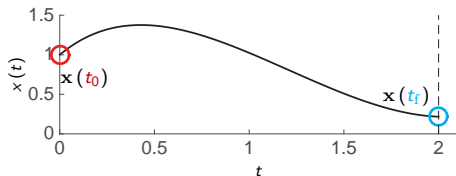
**while**  $\|\mathbf{r}\| > \text{tol}$  **do**

Integrate with  $\mathbf{u} = \arg \min_{\mathbf{u}} H(\mathbf{x}, \lambda, \mathbf{u})$ :

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TPBVP





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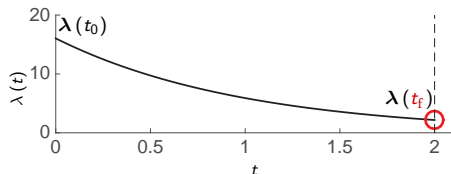
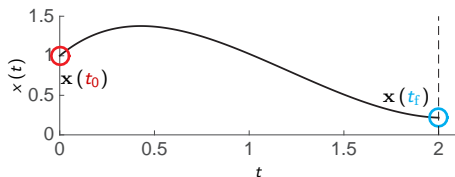
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Compute:

$$\mathbf{r} = \lambda(t_f) - \nabla_{\mathbf{x}} \phi(\mathbf{x}(t_f)) \quad \text{and} \quad \frac{\partial \mathbf{r}}{\partial \lambda_0}$$

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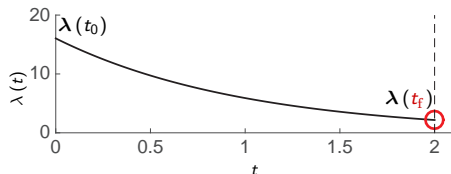
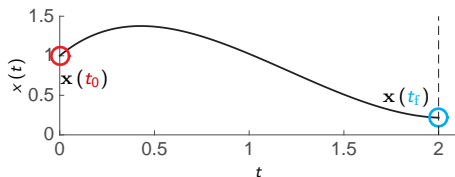
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Compute:

$$\mathbf{r} = \lambda(t_f) - \nabla_{\mathbf{x}} \phi(\mathbf{x}(t_f)) \quad \text{and} \quad \frac{\partial \mathbf{r}}{\partial \lambda_0}$$

$$\text{Newton step: } \lambda_0 \leftarrow \lambda_0 - \frac{\partial \mathbf{r}}{\partial \lambda_0}^{-1} \mathbf{r}$$

### TPBVP



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**while**  $\|\mathbf{r}\| > \text{tol}$  **do**

Integrate with  $\mathbf{u} = \arg \min_{\mathbf{u}} H(\mathbf{x}, \lambda, \mathbf{u})$ :

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Compute:

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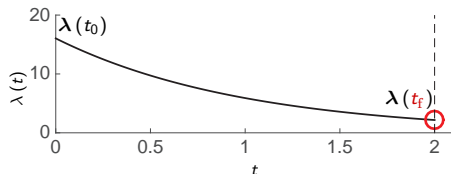
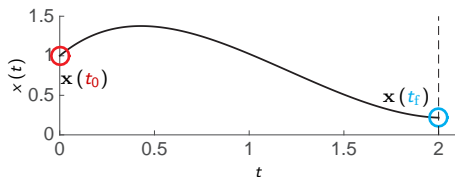
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**Example:**

$$\min_{\mathbf{x}, \mathbf{u}} \frac{1}{2} \int_0^4 (x^2 + u^2) dt$$

$$\dot{x} = u - \sin(x), \quad x(0) = 1$$

**TPBVP**



# Solving the PMP equations / TPBVP

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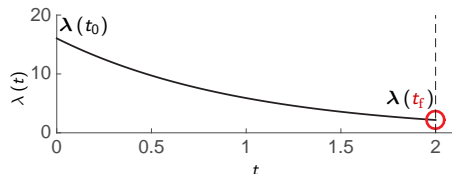
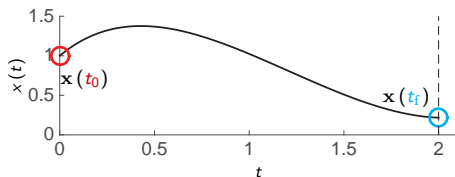
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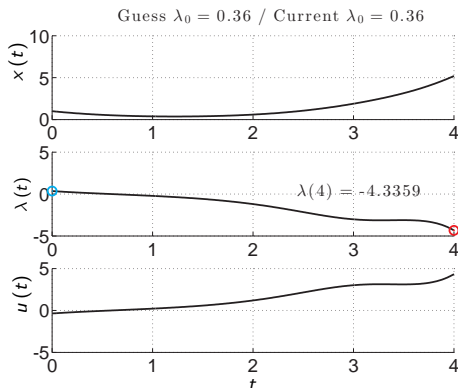
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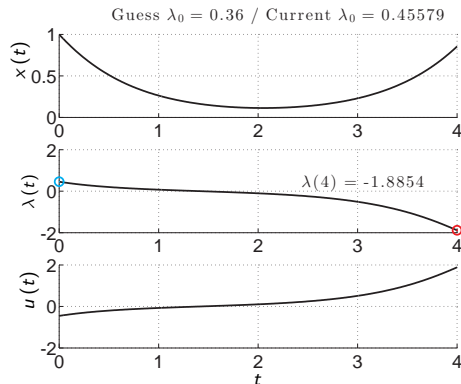
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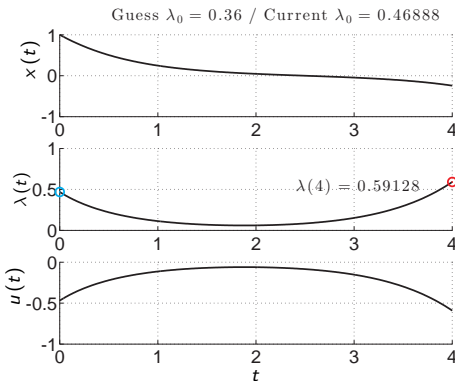
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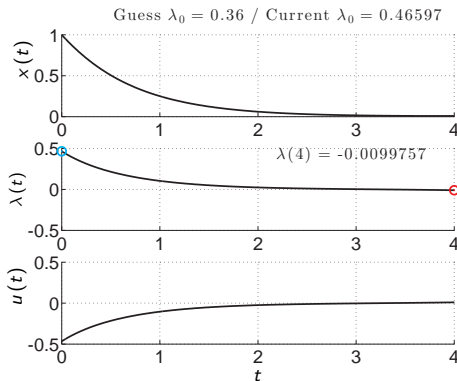
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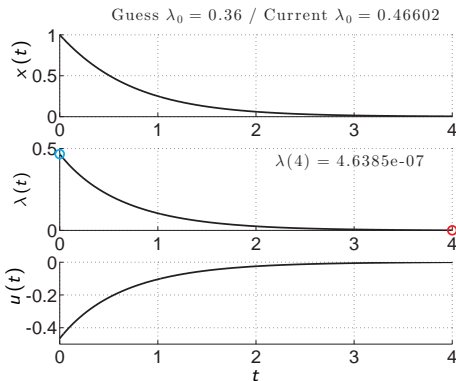
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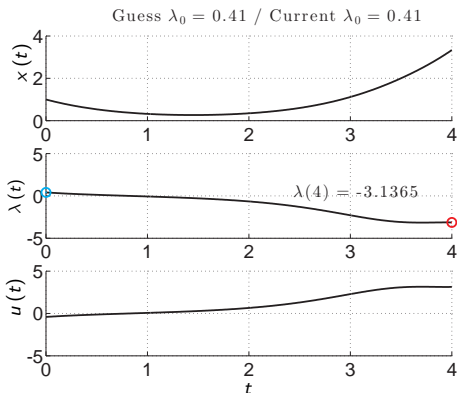
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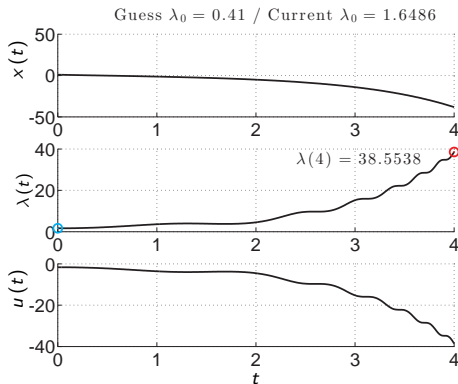
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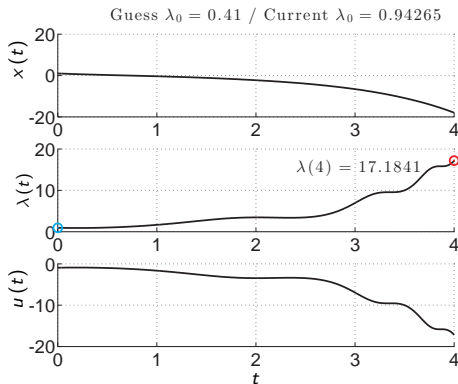
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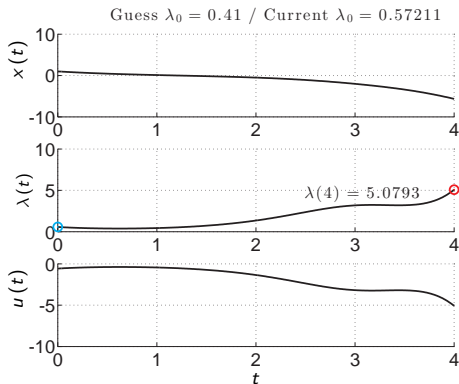
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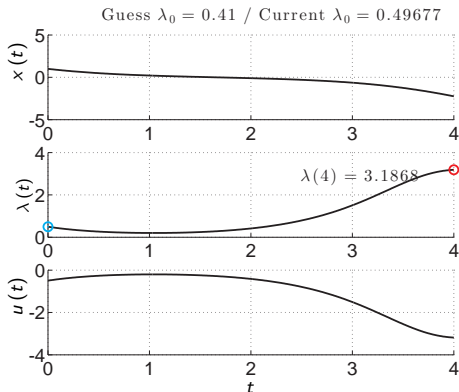
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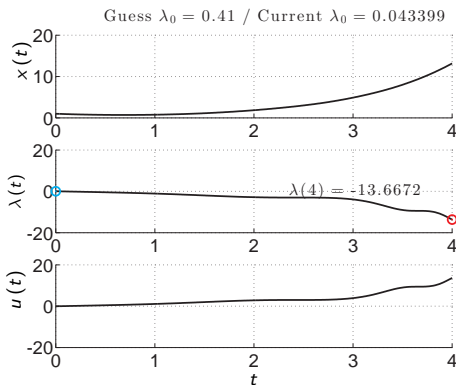
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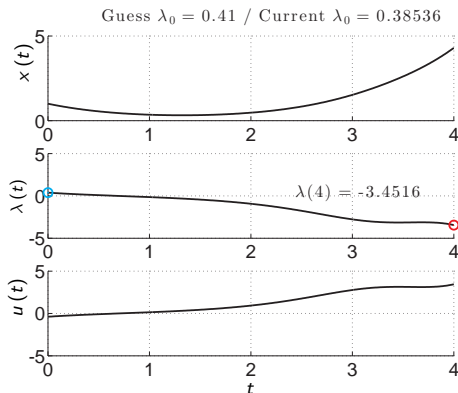
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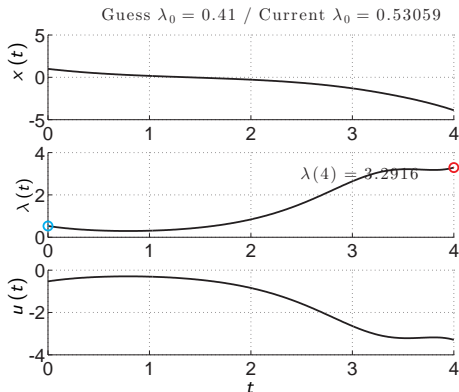
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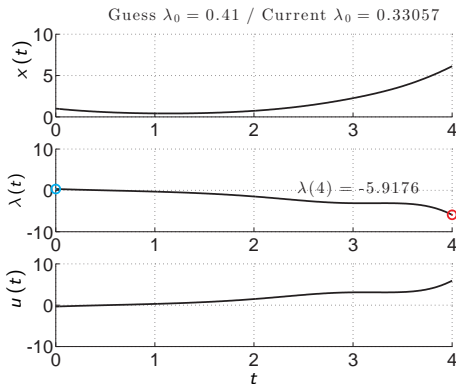
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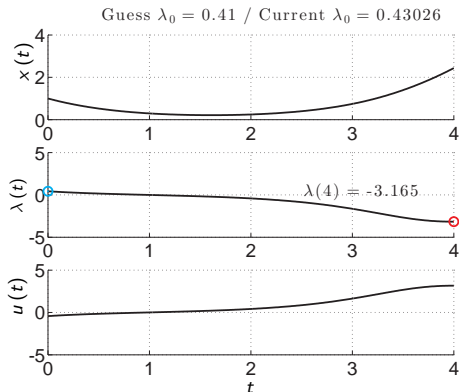
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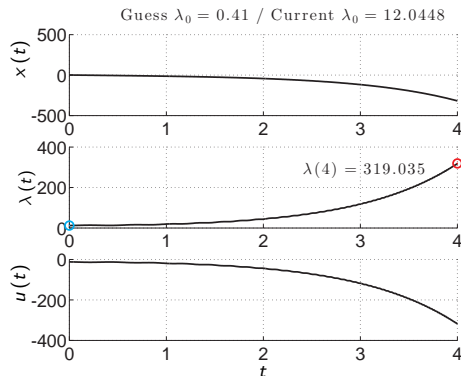
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What is going on !?!

Let's try to understand the relationship  
 $\lambda_0 \rightarrow \lambda(t)$

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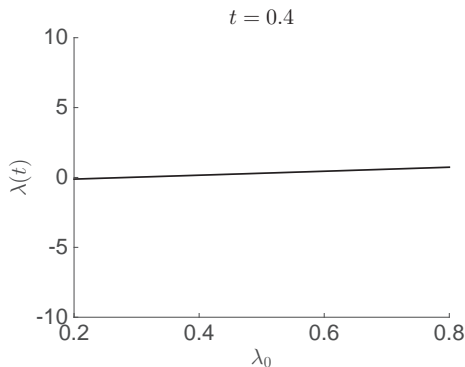
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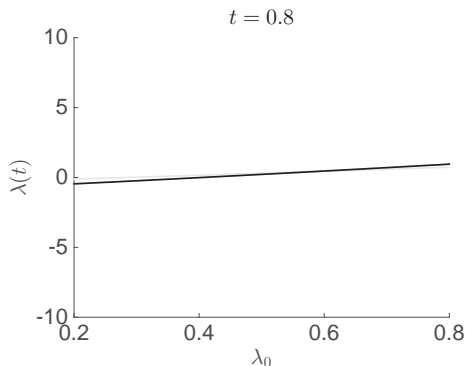
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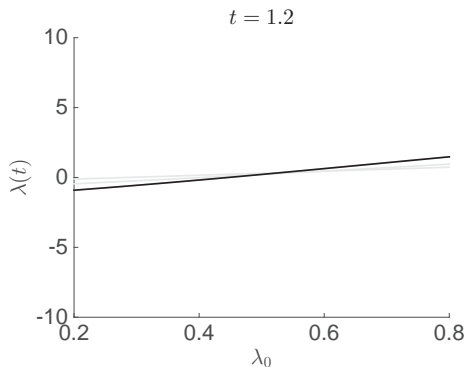
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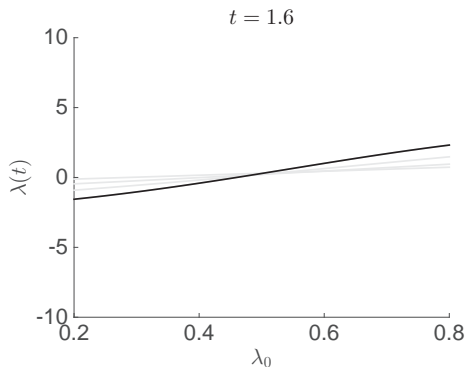
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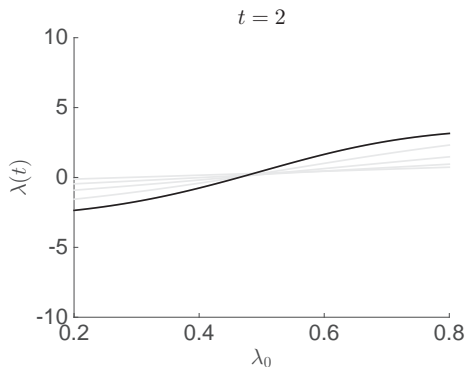
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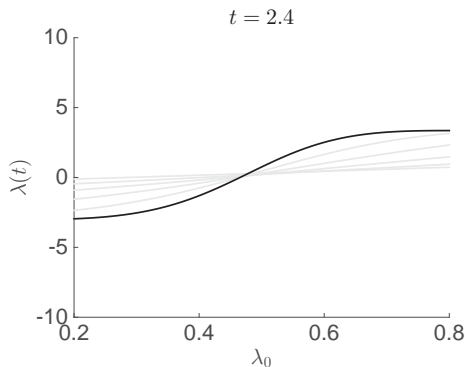
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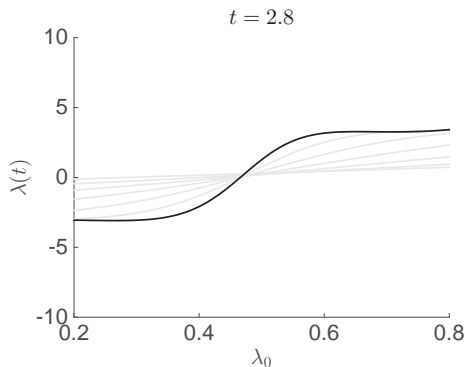
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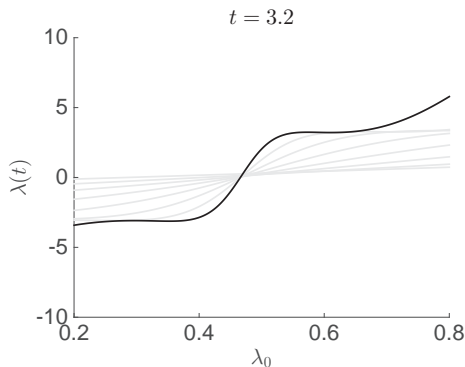
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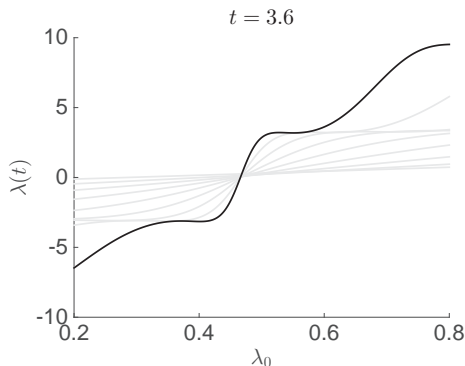
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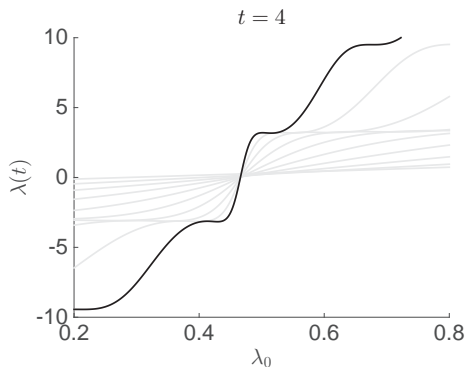
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## Conservation of volumes in the $\mathbf{x}, \boldsymbol{\lambda}$ space

Consider a compact domain  $D(t)$  in the  $\mathbf{x}(t), \boldsymbol{\lambda}(t)$  space, with boundary  $\partial D(t)$ . The volume of  $D(t)$  say  $\rho(D(t)) \in \mathbb{R}$  is given by:

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The volume of  $D(t)$  is constant throughout the integration of  $\mathbf{x}, \boldsymbol{\lambda}$  !!

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\* See Liouville's Theorem on phase-space distribution functions in [Hamiltonian mechanics](#)

## Conservation of volumes in the $x, \lambda$ space (cont')

Problem:

$$\min_{x, u} \frac{1}{2} \int_0^{t_f} (x^2 + u^2) dt$$
$$\dot{x} = u - \sin(x), \quad x(0) = 1$$

Yields

$$H(x, u, \lambda) = \frac{1}{2} (x^2 + u^2) + \lambda (u - \sin(x))$$

Hamiltonian is minimised by  $u = -\lambda$ .

The dynamics become

$$\dot{x} = -\lambda - \sin(x)$$

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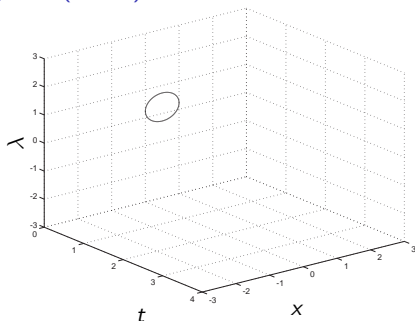
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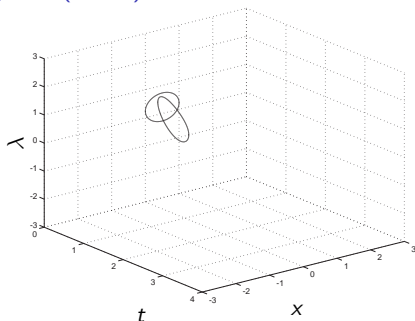
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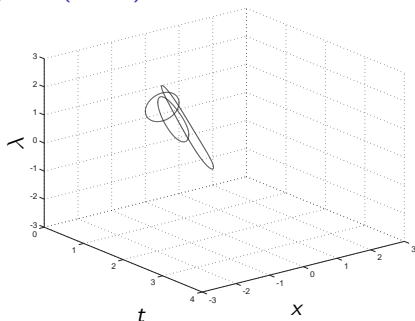
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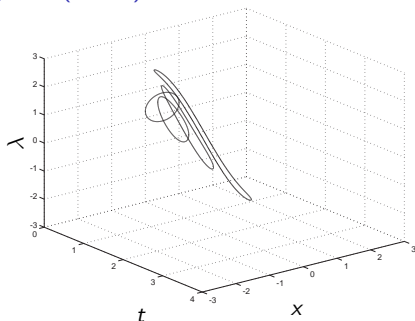
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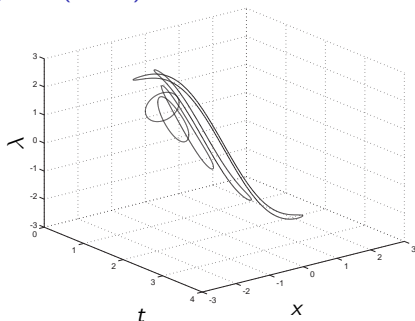
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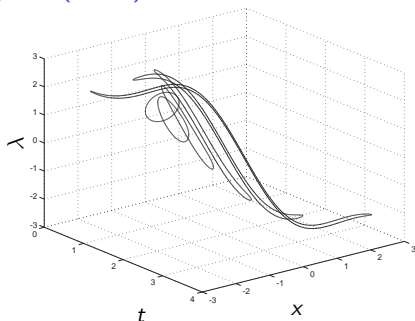
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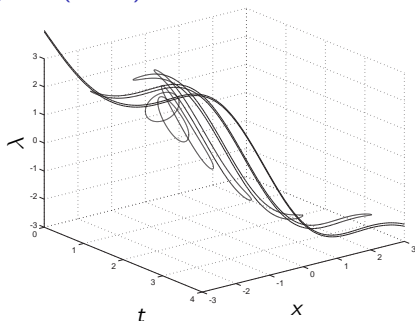
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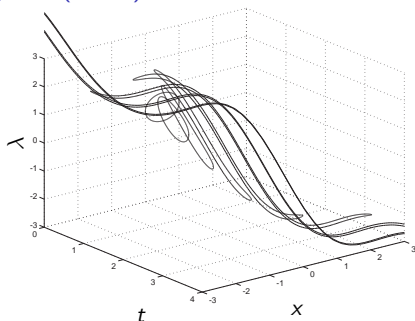
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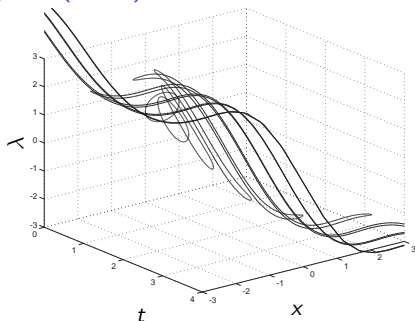
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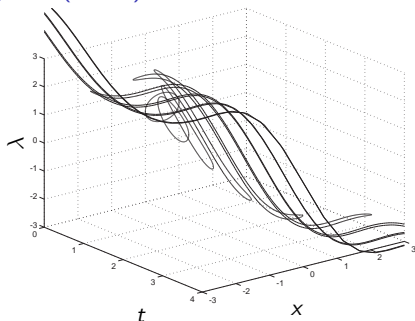
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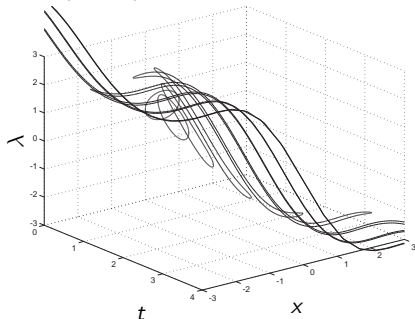
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the states  $x$  and costates  $\lambda$  cannot be both stable, as it would imply  $\rho(D(t)) \rightarrow 0$  !!

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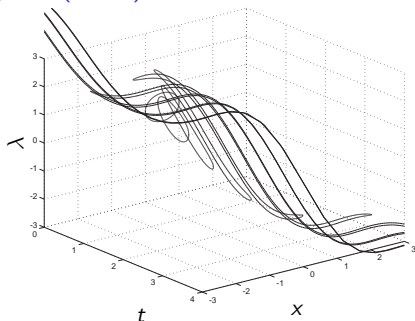
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Important consequence: the condition

$$\lambda(t_f) = \frac{\partial \phi}{\partial \mathbf{x}}(\mathbf{x}(t_f))$$

is often very sensitive to  $\lambda_0$  !!

## How to actually use PMP then ?

**PMP equations:**  $\mathbf{u}^* = \arg \min_{\mathbf{u}} H(\mathbf{x}, \boldsymbol{\lambda}, \mathbf{u})$  with:

$$\text{States : } \dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}), \quad \mathbf{x}(t_0) = \bar{\mathbf{x}}_0$$

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**Key idea:** apply the multiple-shooting principle to the PMP equations

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State-costate

$$\mathbf{s} = \begin{bmatrix} \mathbf{x} \\ \boldsymbol{\lambda} \end{bmatrix}$$

Optimal control

$$\mathbf{u}(\mathbf{s}) = \arg \min_{\mathbf{u}} H(\mathbf{u}, \mathbf{s})$$

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**Root-finding** problem over the variables  $\mathbf{s}_0, \dots, \mathbf{s}_N$ :

$$\mathbf{r}(\mathbf{s}) = \begin{bmatrix} \mathbf{x}_0 - \bar{\mathbf{x}}_0 \\ \xi(\mathbf{s}_0) - \mathbf{s}_1 \\ \vdots \\ \xi(\mathbf{s}_{N-1}) - \mathbf{s}_N \\ \boldsymbol{\lambda}_N - \nabla_{\mathbf{x}} \phi(\mathbf{x}_N) \end{bmatrix} = 0$$

## Indirect multiple-shooting

**Problem:**

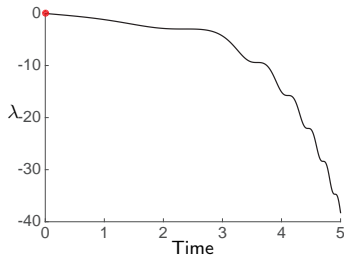
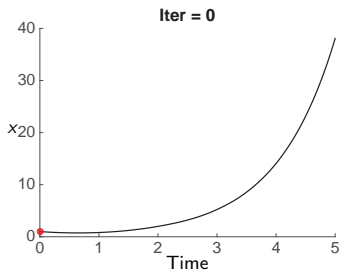
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# of shooting interval = 1 (single shooting)





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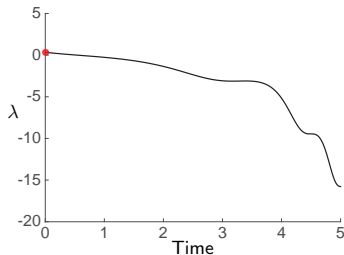
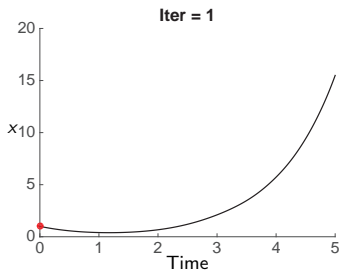
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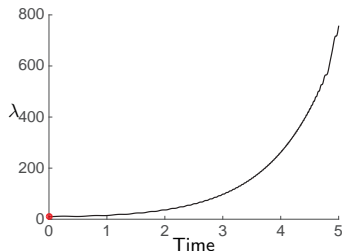
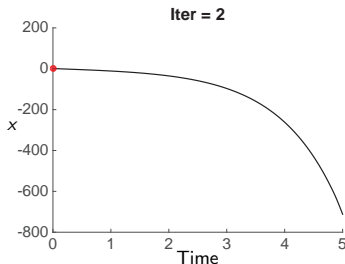
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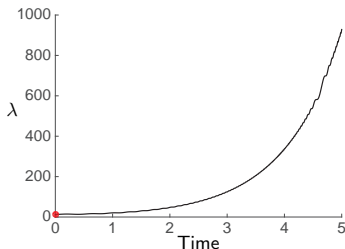
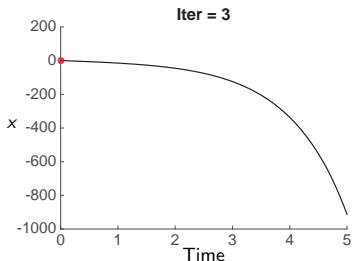
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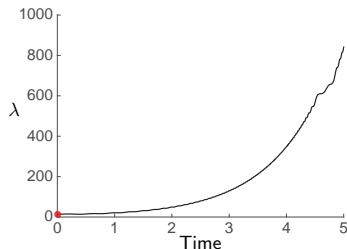
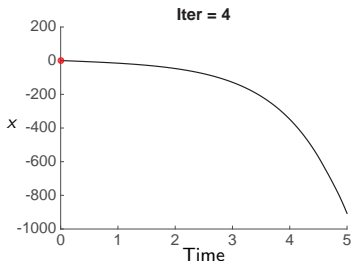
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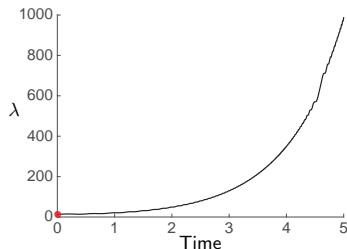
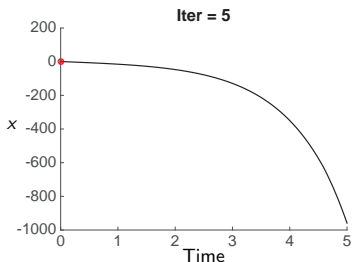
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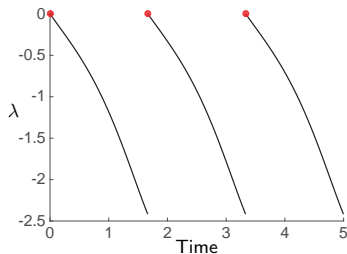
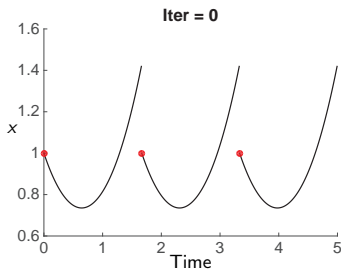
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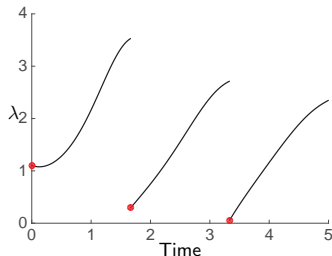
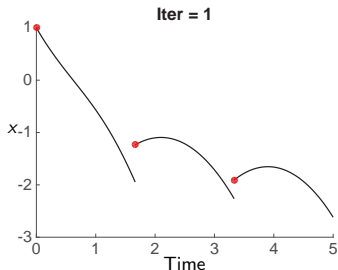
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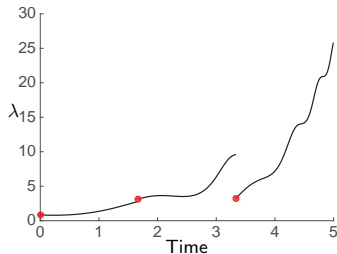
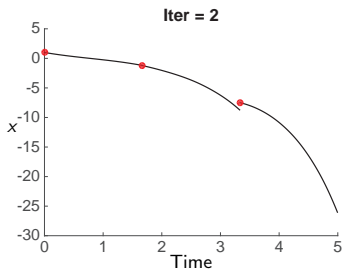
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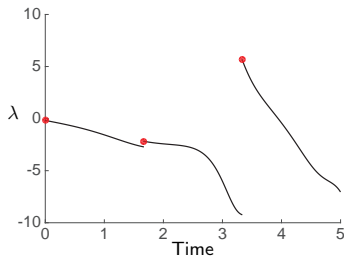
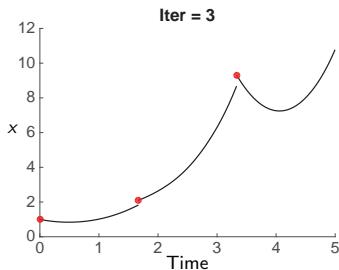
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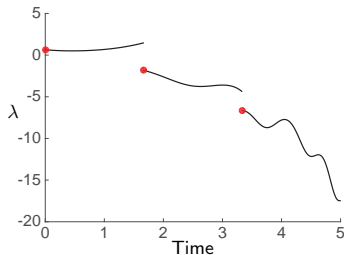
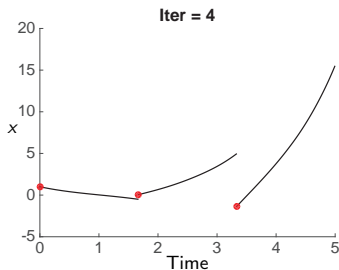
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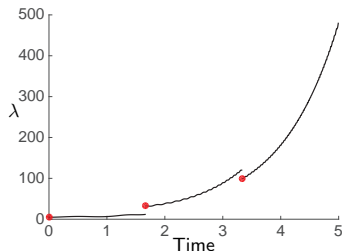
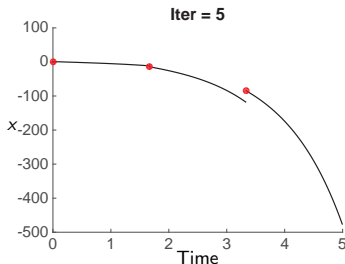
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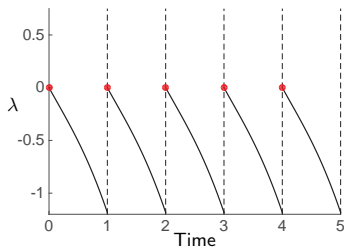
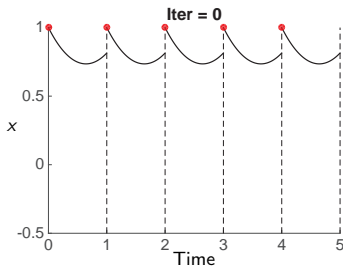
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# of shooting interval = 5



## Indirect multiple-shooting

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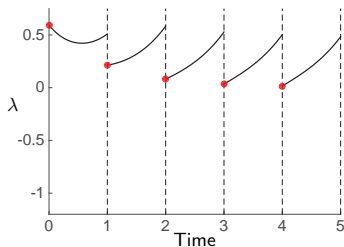
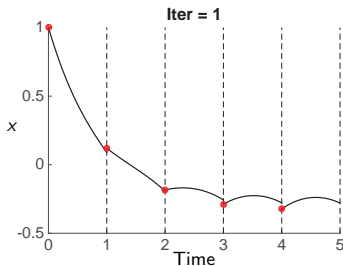
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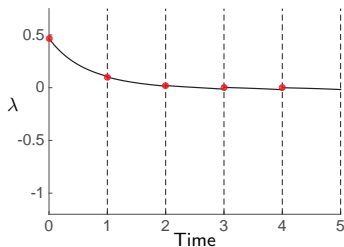
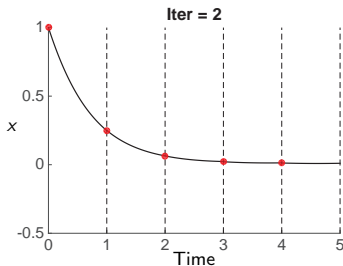
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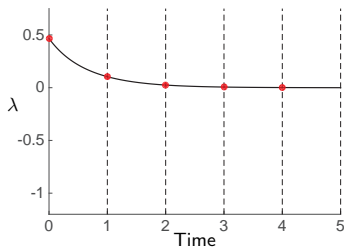
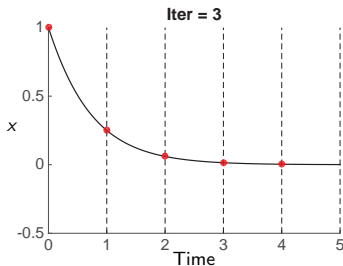
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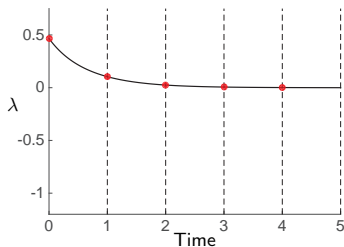
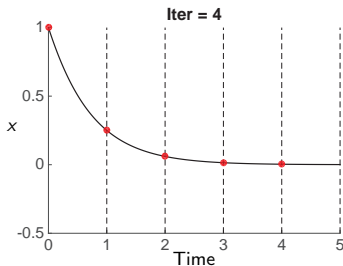
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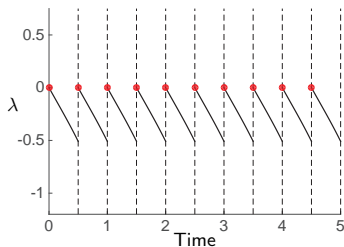
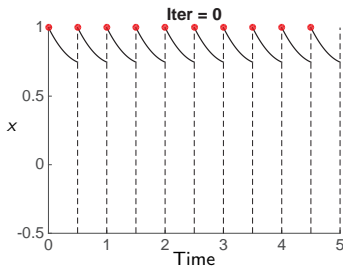
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# of shooting interval = 10



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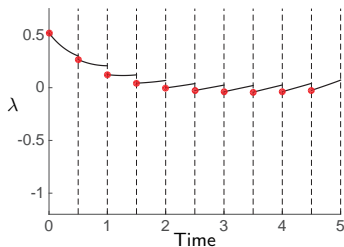
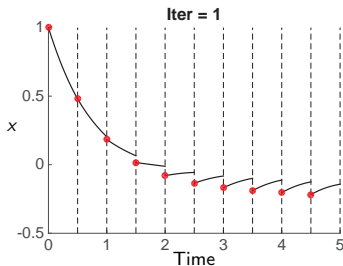
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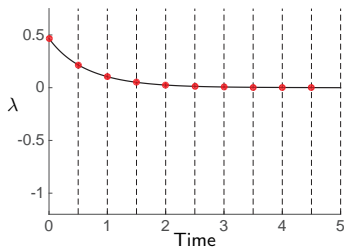
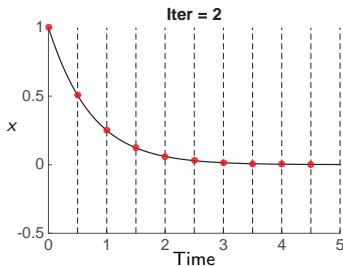
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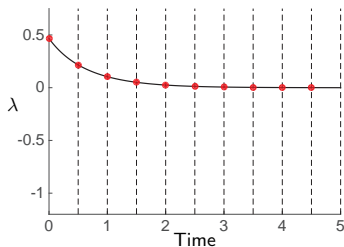
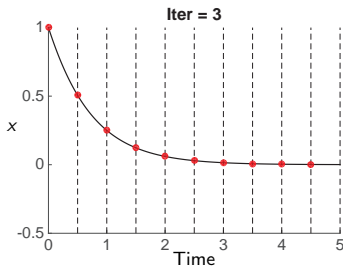
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# Outline

- 1 Introduction to the Pontryagin Maximum Principle (PMR)
- 2 Interpretation of  $H_u$
- 3 Input bounds in Indirect Optimal Control
- 4 Singular Optimal Control problems
- 5 General constraints in Indirect Optimal Control

## Interpretation of $H_{\mathbf{u}}$

Consider the **functional**:

$$J[\mathbf{u}(\cdot)] = \phi(\mathbf{x}(t_f)) + \int_{t_0}^{t_f} L(\mathbf{x}, \mathbf{u}) dt$$

s.t.  $\dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}), \quad \mathbf{x}(t_0) = \mathbf{x}_0$

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**Gâteaux derivative** (see Calculus of Variations)

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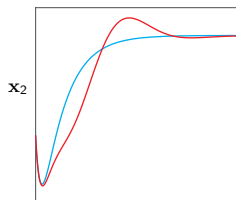
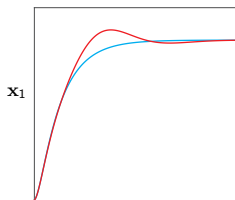
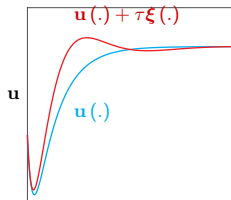
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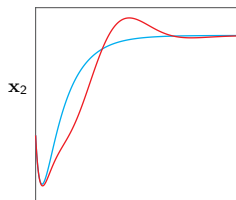
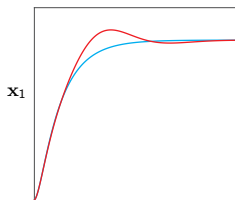
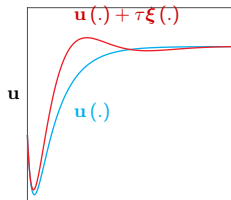
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**What if  $\mathbf{u}(\cdot)$  is restricted to some (Banach) space ?** E.g. piecewise-constant...

**... then  $\xi(\cdot)$  is restricted to the same space !**

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## Interpretation of $H_{\mathbf{u}}$ (cont')

Consider a piecewise-constant parametrization of  $\mathbf{u}(\cdot)$ ...

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Piecewise-constant parametrization

$$\mathbf{u}(t) = \mathbf{u}_k \quad \forall t \in [t_k, t_{k+1}]$$

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When solving an OCP using Direct Optimal Control, one can see the NLP solver as trying to get  $\int_{t_k}^{t_{k+1}} H_u(\mathbf{x}(t), \boldsymbol{\lambda}(t), \mathbf{u}_k) dt = 0$  !!

# Outline

- 1 Introduction to the Pontryagin Maximum Principle (PMR)
- 2 Interpretation of  $H_u$
- 3 Input bounds in Indirect Optimal Control**
- 4 Singular Optimal Control problems
- 5 General constraints in Indirect Optimal Control

## Input bounds in indirect optimal control

**OCP with input bounds:**

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When  $\mathbf{u}$  hits the bounds,  $\boldsymbol{\mu}$  "creates a gradient" in  $H$  to enforce feasibility

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Note: optimality reads as...

$$\int_0^{t_f} \mathcal{L}_{\mathbf{u}}(\mathbf{x}(t), \boldsymbol{\lambda}(t), \mathbf{u}(t)) \cdot \boldsymbol{\xi}(t) dt \geq 0 \quad \text{for any feasible direction } \boldsymbol{\xi}(\cdot)$$

## Input bounds in indirect optimal control

OCP with input bounds:

$$\min_{\mathbf{x}, \mathbf{u}} \quad \phi(\mathbf{x}(t_f)) + \int_{t_0}^{t_f} L(\mathbf{x}(t), \mathbf{u}(t)) dt$$

$$\text{s.t.} \quad \dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}), \quad \mathbf{x}(t_0) = \mathbf{x}_0$$

$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

Note:  $\mathbf{u}^*$  is now a **non-smooth** function of  $\mathbf{x}$ ,  $\boldsymbol{\lambda}$ . Must be handled carefully when solving TPBVP via Newton !!

**An equivalent but simpler approach:** define the **Lagrange** function

$$\mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \mathbf{u}) = L(\mathbf{x}, \mathbf{u}) + \boldsymbol{\lambda}^\top \mathbf{F}(\mathbf{x}, \mathbf{u})$$

Get the input from:  $\mathbf{u} = \underset{\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}}{\operatorname{argmin}} \mathcal{L}(\mathbf{x}, \boldsymbol{\lambda}, \mathbf{u})$ , with:

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# Outline

- 1 Introduction to the Pontryagin Maximum Principle (PMR)
- 2 Interpretation of  $H_u$
- 3 Input bounds in Indirect Optimal Control
- 4 Singular Optimal Control problems**
- 5 General constraints in Indirect Optimal Control

# Singular Optimal Control problems

Consider

$$\min_{\mathbf{u}, \mathbf{x}} \phi(\mathbf{x}(t_f))$$

$$\text{s.t. } \dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}), \quad \mathbf{x}(0) = \bar{\mathbf{x}}_0$$

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**PMP** equations with  $\mathcal{L}(\mathbf{x}, \mathbf{u}, \boldsymbol{\lambda}) = \boldsymbol{\lambda}^\top \mathbf{F}$

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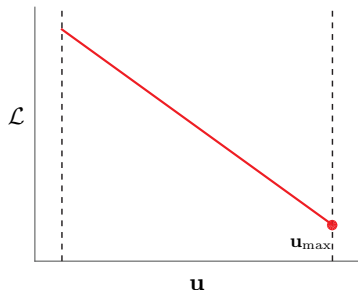
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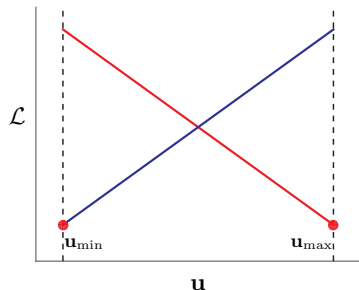
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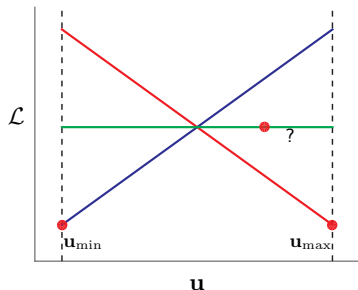
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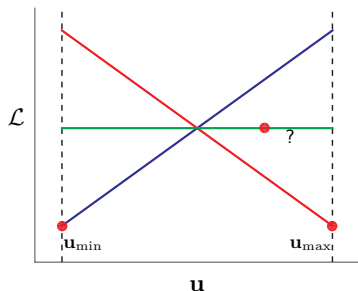
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Find  $\mathbf{u}$  when  $\boldsymbol{\lambda}^\top \mathbf{g}(\mathbf{x}) = 0$  ?

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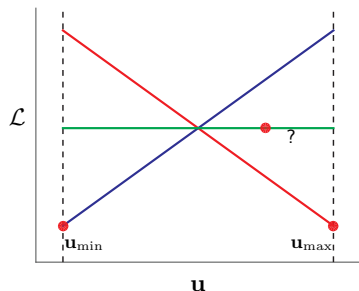
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Find  $\mathbf{u}$  when  $\boldsymbol{\lambda}^\top \mathbf{g}(\mathbf{x}) = 0$ ?

$$\text{Use } \frac{d^i}{dt^i} \mathcal{L}_{\mathbf{u}} = 0, \quad i > 0$$

for some  $i$ , the input  $\mathbf{u}$  appears in  $\frac{d^i}{dt^i} \mathcal{L}_{\mathbf{u}}$ . Then solve  $\frac{d^i}{dt^i} \mathcal{L}_{\mathbf{u}} = 0$  for  $\mathbf{u}$  !!

## Singular Optimal Control - Example

$$\min_{\mathbf{x}(\cdot), \mathbf{u}(\cdot)} \frac{1}{2} \int_0^1 \mathbf{x}_1^2 dt$$

$$\text{s.t. } \dot{\mathbf{x}} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \mathbf{x} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mathbf{u}, \quad \mathbf{x}(0) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$-5 \leq \mathbf{u} \leq 5$$

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- Bang-bang input until  $\mathbf{x}$ ,  $\lambda = 0$  (4 conditions)
- $\mathcal{L}_{\mathbf{u}}$  is "controlled" via its 4<sup>th</sup>-order derivative
- Problem has a *degree of singularity* of  $\frac{4}{2} = 2$  (# of derivatives to get  $\mathbf{u}$  is always even)

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$$\mathcal{L}_{\mathbf{u}} = \lambda_2 \quad \frac{d}{dt} \mathcal{L}_{\mathbf{u}} = -\lambda_1 \quad \frac{d^2}{dt^2} \mathcal{L}_{\mathbf{u}} = \mathbf{x}_1 \quad \frac{d^3}{dt^3} \mathcal{L}_{\mathbf{u}} = \mathbf{x}_2 \quad \frac{d^4}{dt^4} \mathcal{L}_{\mathbf{u}} = \mathbf{u}$$

**Optimal input:**

$$\mathbf{u}^* = \begin{cases} \mathbf{u}_{\min} & \text{if } \lambda_2 > 0 \\ \mathbf{u}_{\max} & \text{if } \lambda_2 < 0 \\ 0 & \text{if } \frac{d^i}{dt^i} \mathcal{L}_{\mathbf{u}} = 0 \end{cases}$$

- Input is either in the bounds or zero !!
- Bang-bang input until  $\mathbf{x}$ ,  $\lambda = 0$  (4 conditions)
- $\mathcal{L}_{\mathbf{u}}$  is "controlled" via its 4<sup>th</sup>-order derivative
- Problem has a *degree of singularity* of  $\frac{4}{2} = 2$  (# of derivatives to get  $\mathbf{u}$  is always even)
- Degrees of freedom:  $\lambda(0) \in \mathbb{R}^2$  and switching times in the bang-bang...

## Singular Optimal Control - Example

$$\min_{\mathbf{x}(\cdot), \mathbf{u}(\cdot)} \frac{1}{2} \int_0^1 \mathbf{x}_1^2 dt$$

$$\text{s.t. } \dot{\mathbf{x}} = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \mathbf{x} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} \mathbf{u}, \quad \mathbf{x}(0) = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

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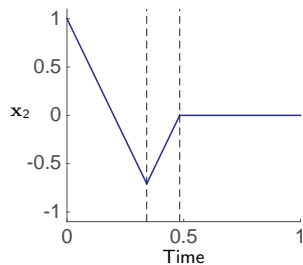
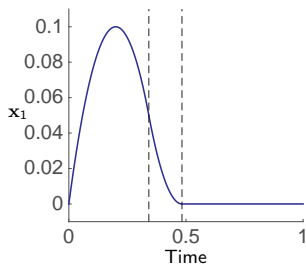
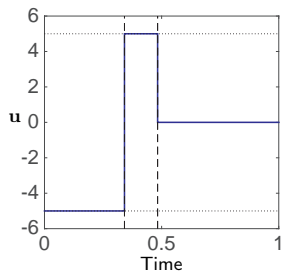
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- Degrees of freedom:  $\lambda(0) \in \mathbb{R}^2$  and switching times in the bang-bang...
- We will have 2 switching times, to have  $2 + 2 = 4$

## Singular Optimal Control - Example

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### Optimal solution

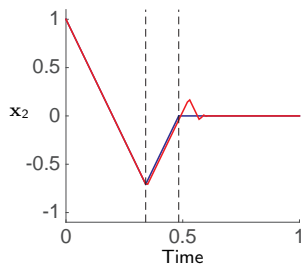
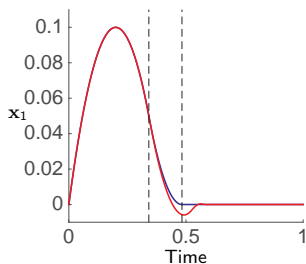
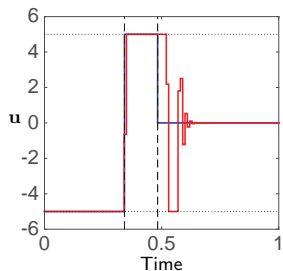


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**Optimal solution** vs. solution from **multiple-shooting** ( $t_{k+1} - t_k = 0.01$ )

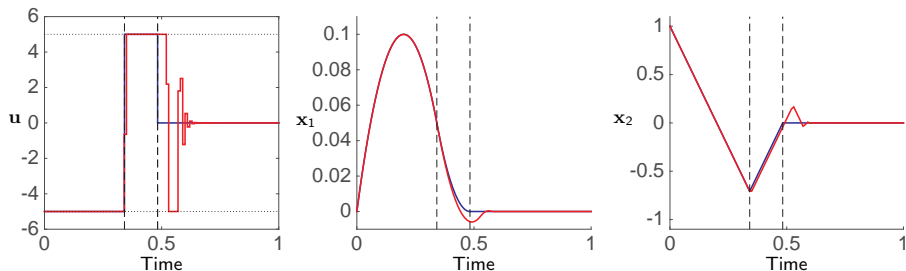


## Singular Optimal Control - Example

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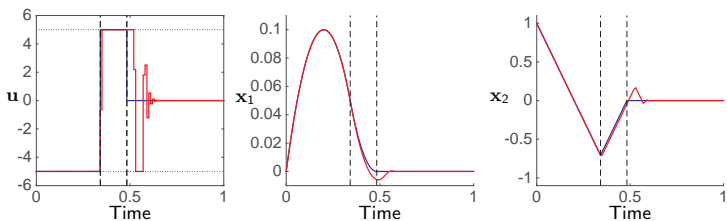
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**Optimal solution** vs. solution from **multiple-shooting** ( $t_{k+1} - t_k = 0.01$ )



Very common behavior of direct optimal control for singular problems.  
What is going on ???

## Singular optimal control with direct methods



Consider the problem:

$$J(\mathbf{u}) = \phi(\mathbf{x}(\cdot), \mathbf{u}(\cdot))$$

$$\text{s.t. } \dot{\mathbf{x}}(t) = \mathbf{F}(\mathbf{x}(t), \mathbf{u}(t))$$

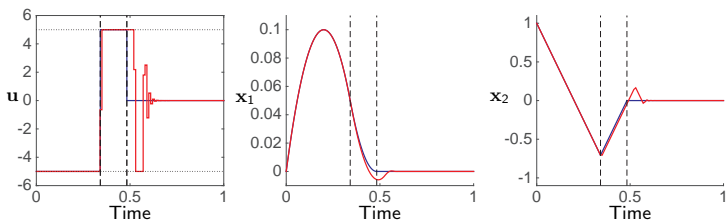
$$\mathbf{x}(t_0) = \mathbf{x}_0$$

$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

with  $\mathbf{u}(t) = \mathbf{u}_k$  for  $t \in [t_k, t_{k+1}]$ .



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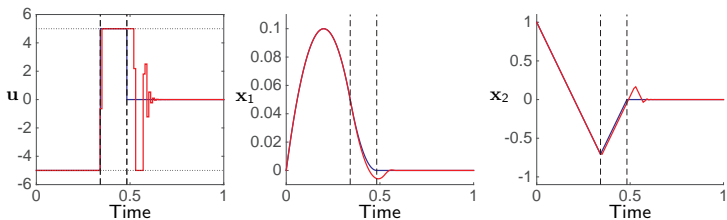
$$\mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max}$$

with  $\mathbf{u}(t) = \mathbf{u}_k$  for  $t \in [t_k, t_{k+1}]$ . Then

$$\frac{\partial J}{\partial \mathbf{u}_k} = \int_{t_k}^{t_{k+1}} \mathcal{L}_{\mathbf{u}}(\mathbf{x}(t), \boldsymbol{\lambda}(t), \mathbf{u}_k) dt$$

is zero when  $\mathbf{u}_k$  is off the bounds.

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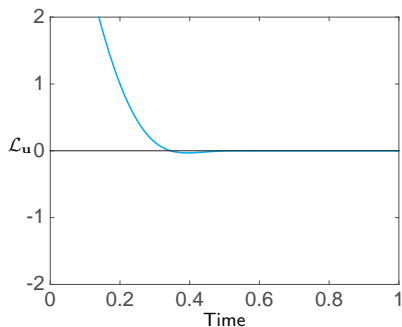
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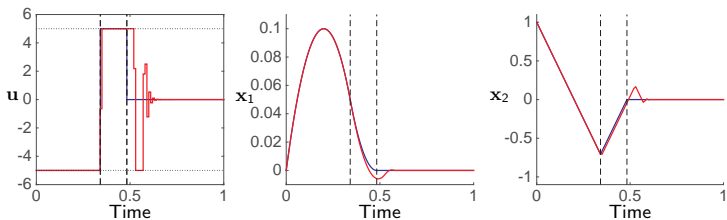
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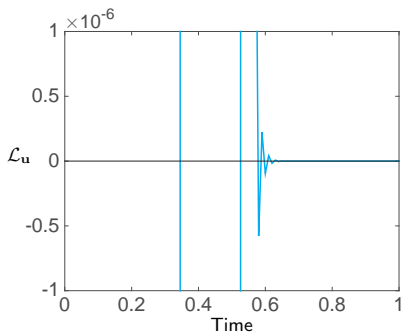
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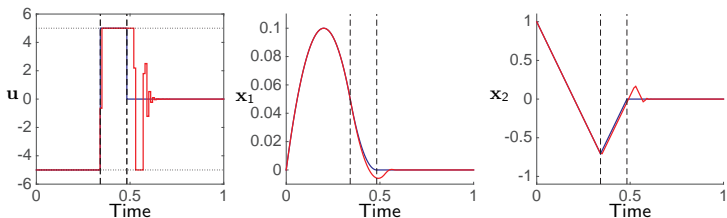
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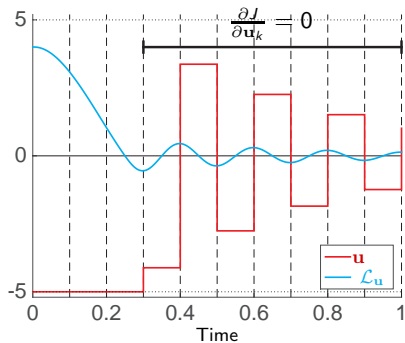
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# Outline

- 1 Introduction to the Pontryagin Maximum Principle (PMR)
- 2 Interpretation of  $H_u$
- 3 Input bounds in Indirect Optimal Control
- 4 Singular Optimal Control problems
- 5 General constraints in Indirect Optimal Control**

## State constraints in indirect optimal control

**OCP with state (mixed) constraints:**

$$\begin{aligned} \min_{\mathbf{x}, \mathbf{u}} \quad & \phi(\mathbf{x}(t_f)) + \int_{t_0}^{t_f} L(\mathbf{x}(t), \mathbf{u}(t)) dt \\ \text{s.t.} \quad & \dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}), \quad \mathbf{x}(t_0) = \mathbf{x}_0 \\ & \mathbf{h}(\mathbf{x}, \mathbf{u}) \leq 0 \end{aligned}$$

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Define the Hamiltonian function

$$H(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \mathbf{u}) = L(\mathbf{x}, \mathbf{u}) + \boldsymbol{\lambda}^\top \mathbf{F}(\mathbf{x}, \mathbf{u}) + \boldsymbol{\mu}^\top \mathbf{h}(\mathbf{x}, \mathbf{u})$$

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Get the optimal control solution from:  $\mathbf{u}^* = \underset{\mathbf{u}}{\operatorname{argmin}} H(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \mathbf{u})$ , with:



## State constraints in indirect optimal control

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$$\text{Costates : } \dot{\boldsymbol{\lambda}} = -\nabla_{\mathbf{x}} H, \quad \boldsymbol{\lambda}(t_f) = \nabla_{\mathbf{x}} \phi(\mathbf{x}(t_f))$$

## State constraints in indirect optimal control

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## State constraints in indirect optimal control

OCP with state (mixed) constraints:

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The PMP equations can be hard to solve in general. No good PMP-based general-purpose solver available.

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Tentative solutions based on IP method

$$\text{Stationarity : } H_{\mathbf{u}}(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \mathbf{u}) = 0$$

$$\text{States : } \dot{\mathbf{x}} = \mathbf{F}(\mathbf{x}, \mathbf{u}), \quad \mathbf{x}(t_0) = \mathbf{x}_0$$

$$\text{Costates : } \dot{\boldsymbol{\lambda}} = -\nabla_{\mathbf{x}} H(\mathbf{x}, \boldsymbol{\lambda}, \boldsymbol{\mu}, \mathbf{u}), \quad \boldsymbol{\lambda}(t_f) = \nabla_{\mathbf{x}} \phi(\mathbf{x}(t_f))$$

$$\text{Feasibility : } \mathbf{h}(\mathbf{x}, \mathbf{u}) \leq 0, \quad \boldsymbol{\mu} \geq 0$$

$$\text{Complementary slack. : } \boldsymbol{\mu}^{\top} \mathbf{h}(\mathbf{x}, \mathbf{u}) = \tau$$

- Handle dynamics + constraints  $H_{\mathbf{u}} = 0$  and  $\boldsymbol{\mu}^{\top} \mathbf{h} = \tau$  as a DAE (c.f. next week)
- Handle  $\mathbf{h}(\mathbf{x}, \mathbf{u}) \leq 0$  and  $\boldsymbol{\mu} \geq 0$  via step length (c.f. IP lecture)
- Also done using Primal IP approach (move  $\mathbf{h}$  in the cost using log barrier)