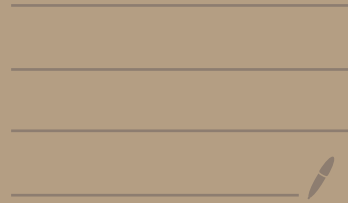


# Lecture 3

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## Bolza Problem

$$\inf_{\Theta \in L^\infty([t_0, t_1], \mathbb{R}^m)} J[\Theta] = \Phi(x(t_1)) + \int_{t_0}^{t_1} L(t, x(t), \Theta(t)) dt$$

$$\text{s.t. } \dot{x}(t) = f(t, x(t), \Theta(t)), \quad x(t_0) = x_0, \quad \Theta(t) \in \mathbb{R}^m \\ t \in [t_0, t_1]$$

Alternatively, this is constrained optimization problem

$$\inf_{\Theta, x} J[\Theta, x] = \dots \\ \text{subj to } \dot{x}(t) = f(t, x(t), \Theta(t))$$

- Lagrange multipliers.

$$\min_z \Phi(z) \text{ subj } g(z) = 0 \rightarrow \Phi(z) + \lambda g(z) = L(z, \lambda) \\ \partial_z L = 0, \quad \partial_\lambda L = 0.$$

- $\Phi \equiv 0$  (Lagrange problem)

$$\inf_{\theta, x} \int_{t_0}^{t_1} L(t, x(t), \theta(t)) dt \quad \text{subj to} \quad \dot{x}(t) - f(t, x(t), \theta(t)) = 0$$

$$\mathcal{L} = \int_{t_0}^{t_1} L(t, x(t), \theta(t)) dt + \int_{t_0}^{t_1} \lambda(t) [\dot{x}(t) - f(t, x(t), \theta(t))] dt$$

$$\nabla_{\lambda(t)} : \quad \dot{x} = f(t, x, \theta) \quad (\nabla_{\lambda} H)$$

$$\nabla_{x(t)} : \quad \nabla_x L(t, x(t), \theta(t)) - \dot{\lambda}(t) - \nabla_x f(t, x(t), \theta(t))^\top \lambda(t) = 0$$

$$\dot{\lambda}(t) = - \nabla_x \underbrace{(f(t, x(t), \theta(t))^\top \lambda(t) - L(t, x(t), \theta(t)))}_{H(t, x(t), \lambda(t), \theta(t))}$$

$$\nabla_{\theta(t)} : \quad \mathcal{L} = \int_{t_0}^{t_1} H(t, x(t), \lambda(t), \theta(t)) dt + \int_{t_0}^{t_1} \lambda(t) \dot{x}(t) dt$$

$$\nabla_{\theta} H(t, x(t), \lambda(t), \theta(t)) = 0$$

## Pontryagin's Maximum Principle

Define Hamiltonian  $H: [t_0, t_1] \times \mathbb{R}^d \times \mathbb{R}^d \times \mathbb{T} \rightarrow \mathbb{R}$ .

$$H(t, x, p, \theta) = p^\top f(t, x, \theta) - L(t, x, \theta)$$

### Theorem (PMP)

Let  $\underline{\theta}^*$  be an optimal control,  $\underline{x}^*$  be its controlled trajectory.  
Then, there exists  $p^*: [t_0, t_1] \rightarrow \mathbb{R}^d$  which is abs. cts. and

$$\begin{cases} \dot{x}^*(t) = f(t, x^*(t), \theta^*(t)) = \nabla_p H(t, x^*(t), p^*(t), \theta^*(t)), & x^*(0) = x_0 \\ \dot{p}^*(t) = -\nabla_x H(t, x^*(t), p^*(t), \theta^*(t)), & p^*(T) = -\nabla_x \Phi(x^*(T)) \\ H(t, x^*(t), p^*(t), \theta^*(t)) \geq H(t, x^*(t), p^*(t), \theta) \text{ for all } \theta \in \mathbb{T} \end{cases}$$

holds  $t$ -a.e.

$p^*$  is called the co-state / adjoint.

## Proof of the PMP

Step 1: Conversion to Mayer Problem ( $L \equiv 0$ )

Define  $\dot{x}^0(t) = L(t, x(t), \theta(t))$ ,  $x^0(0) = 0 \Rightarrow x^0(t) = \int_0^t L(\dots) dt$ .

$(x^0, x) \rightarrow \tilde{x}$ ,  $(L, f) \rightarrow \tilde{f}$ ,  $\tilde{\Phi}(\tilde{x}) = \Phi(x) + x^0$ .

$\Rightarrow \inf_{\theta} \tilde{\Phi}(x(t, \cdot))$  subj  $\dot{\tilde{x}} = \tilde{f}(t, x, \theta)$ .  $x(0) = x_0$ .

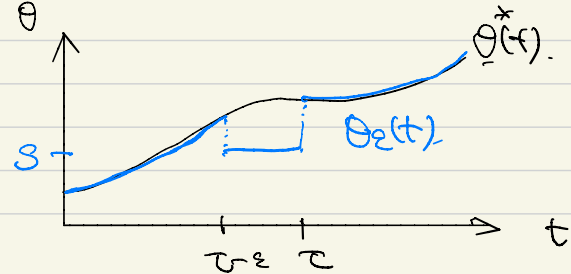
Step 2: Needle perturbation.

Let  $\underline{\theta}^*$  be an optimal control.

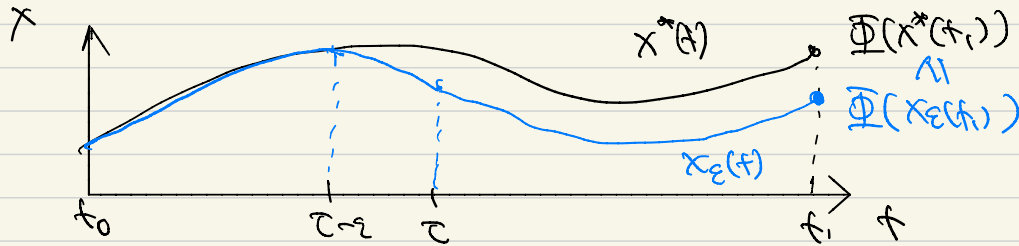
Fix  $\tau \in (t_0, t_1)$ ,  $s \in \mathbb{R}$ ,  $\varepsilon > 0$ .

Define  $\underline{\theta}_\varepsilon$  with

$$\theta_\varepsilon(t) = \begin{cases} s & t \in [\tau - \varepsilon, \tau] \\ \theta^*(t) & \text{otherwise} \end{cases}$$



Define  $\dot{x}_\varepsilon(t) = f(t, x_\varepsilon(t), \theta(t))$   $x_\varepsilon(0) = x_0$



Step 3: Variational Equation

Define  $v(t) = \lim_{\varepsilon \rightarrow 0^+} \frac{x_\varepsilon(t) - x^*(t)}{\varepsilon}$   $t \in [\tau, t_1]$

ON  $t \in [\tau, t_1]$ ,  $x^*$ ,  $x_\varepsilon$  satisfies the same equation  
 $\dot{x} = f(t, x, \theta^*)$

$\Rightarrow \dot{v}(t) = \nabla_x f(t, x^*(t), \theta^*(t)) v(t)$ ,  $v(\tau) = v_0$ .

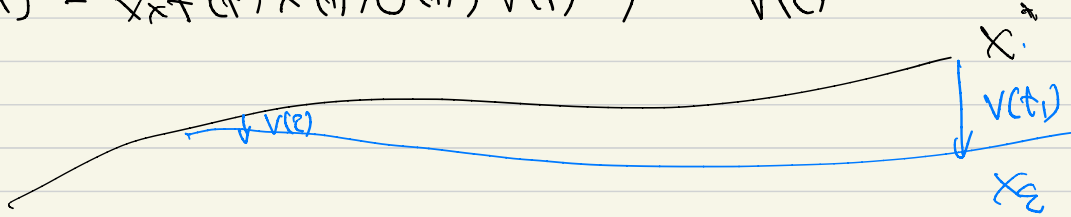
$$v(\tau) = v_0 = \lim_{\varepsilon \rightarrow 0^+} \left\{ \frac{1}{\varepsilon} \left( \underbrace{x_0 + \int_0^\tau f(t, x_\varepsilon(t), \theta_\varepsilon(t)) dt}_{x_\varepsilon(\tau)} - \underbrace{x_0 - \int_0^\tau f(t, x^*(t), \theta^*(t)) dt}_{x^*(\tau)} \right) \right\}$$

$$\downarrow$$

$$= \lim_{\varepsilon \rightarrow 0^+} \left\{ \frac{1}{\varepsilon} \int_{\tau-\varepsilon}^{\tau} f(t, x_2(t), \delta) dt - \frac{1}{\varepsilon} \int_{\tau-\varepsilon}^{\tau} f(t, x^*(t), \theta^*(t)) dt \right\}$$

$$\stackrel{\tau\text{-a.e.}}{=} f(t, x^*(\tau), \delta) - f(t, x^*(\tau), \theta^*(\tau)) \quad \left[ \text{Lebesgue diff theorem} \right]$$

$$\dot{V}(t) = \nabla_x f(t, x^*(t), \theta^*(t)) V(t), \quad V(\tau)$$



Step 4: Optimality Condition.

$$\underbrace{V(t)}_{\text{depends on } \tau, \delta} \nabla \Phi(x^*(t, \cdot)) \geq 0$$

$\Rightarrow$  Go to adjoint equation.

$$\Gamma \quad \dot{v}(t) = A(t)v(t) \quad \text{adjoint: } \dot{p}(t) = -A(t)^\top p(t).$$

$$\frac{d}{dt}(v^\top p)(t) = v^\top \dot{p} + p^\top \dot{v}$$

$$= v^\top (-A^\top) p + p^\top A v = 0.$$

$$(v^\top p)(t) \approx \text{constant in } t$$

Define co-state, or adjoint.

$$\begin{cases} p^*(t_1) = -\nabla \Phi(x^*(t_1)) \\ \dot{p}^*(t) = -\nabla_x f(t, x^*(t), \theta^*(t))^\top p^*(t) \end{cases}$$

$$p^*(t_1)^\top v(t_1) = p^*(t_1)^\top v(t_1) \leq 0.$$

$$\Rightarrow \underbrace{p^*(\tau)^\top f(\tau, x^*(\tau), s)}_H \leq \underbrace{p^*(\tau)^\top f(\tau, x^*(\tau), \theta^*(\tau))}_{H(\tau, x^*(\tau), p^*(\tau), \theta^*(\tau))}$$



Step 5: convert back to Bolza problem

$$\begin{aligned} \dot{p}^{*0}(t) &= 0, & (p^*)^0(t_1) &= -\nabla_{x^0} \tilde{\Phi} \\ & & &= -\nabla_{x^0} (\Phi(x) + x^0) \\ & & &= -1. \end{aligned}$$

$$\Rightarrow p^{*0}(t) = -1 \quad \forall t.$$

$$\underbrace{p^*(c)^T f(\tau, x^*(\tau), s) - L(\tau, x^*(\tau), s)}_H \leq \leftarrow$$

$$\int L(t, x, \dot{x}) dt$$

$\swarrow v$   
 $\underline{\underline{\dot{x} = \theta = v}}$

$\dot{x} = v$   
 $x = f(t, x, \theta)$

$$\rightarrow H(t, x, p) = \sup_v (p^T v - L(t, x, v))$$

$$\rightarrow H(t, x, p, v) = \sup_v p^T v - L(t, x, v)$$

$$\underline{H(t, x, p^*, v^*)}$$

Bolza Problem with fixed end point, variable time.

$$\inf_{\theta} J[\theta] = \int_{t_0}^{t_1} L(t, x(t), \theta(t)) dt + \cancel{\Phi(x(t_1))}$$

$$\text{Subj to } \dot{x} = f(t, x, \theta), \quad t \in [t_0, t_1], \quad x(t_0) = x_0$$

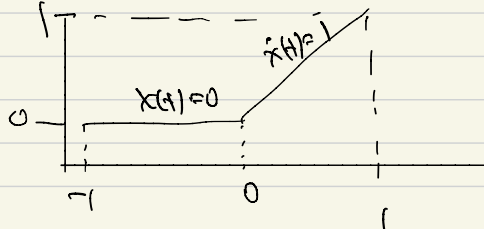
$$x(t_1) = x_1$$

PMP.

$$\begin{cases} \dot{x}^* = \nabla_p H(t, x^*, p^*, \theta^*) & x^*(t_0) = x_0 \quad x^*(t_1) = x_1 \\ \dot{p}^* = -\nabla_x H(t, x^*, p^*, \theta^*) & \cancel{p^*(t_1) = -\nabla \Phi(x^*(t_1))} \\ H(t, x^*(t), p^*(t), \theta^*(t)) \geq H(t, x^*(t), p^*(t), \theta) \quad \forall \theta \in \Theta \end{cases}$$

# Example

$$\min_x \int_{-1}^1 x(t)^2 (\theta(t) - 1)^2 dt$$



$$\dot{x}(t) = \theta(t)$$

$$x(-1) = 0, \quad x(1) = 1$$

$$\theta^*(t) = \begin{cases} 0 & -1 \leq t \leq 0 \\ t & 0 < t \leq 1 \end{cases}$$

$\underline{x}^*$  is global minimizer.

$$L(t, x, \theta) = x^2 (\theta - 1)^2$$

$$H(t, x, p, \theta) = p\theta - x^2 (\theta - 1)^2$$

PMP:  $\dot{x}^*(t) = \theta^*(t) \quad x^*(-1) = 0, \quad x^*(1) = 1$

$$\dot{p}^*(t) = 2x^*(t)(1 - \theta^*(t))^2$$

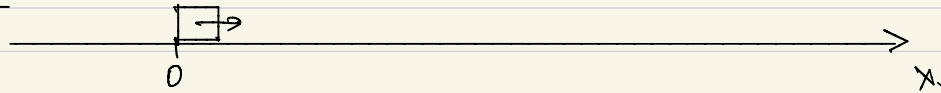
$$\theta^*(t) \in \underset{\theta}{\operatorname{argmax}} \left\{ p^*(t)\theta - [x^*(t)]^2(1 - \theta^2) \right\}$$

$$\theta^*(t) = \begin{cases} 0 & -1 \leq t \leq 0 \\ 1 & 0 < t \leq 1 \end{cases}$$

$$p^*(t) = 0 \quad \forall t$$

Example

$x(t)$  position of car at time  $t$ .



$$\ddot{x}(t) = \theta(t)$$

$$\theta(t) \in [-1, 1]$$

$$\inf_{\theta} J[\theta] = -x(T) + \int_0^T \frac{1}{2} \max(0, \theta(t))^2 dt$$

$\xrightarrow{\text{blue arrow}} \underline{\underline{\max(0, \theta(t))}}$

$$\begin{aligned} \dot{x} &= v \\ \dot{v} &= \theta \end{aligned}$$

$$x(0) = 0$$

$$v(0) = 0$$

$$\theta(t) \in \textcircled{[-1, 1]} = [-1, 1]$$

Solution using PMP.

$$H(t, x, v, p_x, p_v, \theta) = \begin{pmatrix} p_x \\ p_v \end{pmatrix}^T \begin{pmatrix} v \\ \theta \end{pmatrix} - \frac{1}{2} \max(0, \theta)^2$$

$$= p_x v + p_v \theta - \underline{\underline{\frac{1}{2} \max(0, \theta)^2}}$$

# PMP Equations

$$\begin{cases} \dot{x}^* = v^* \\ \dot{v}^* = \theta^* \\ \dot{p}_x^* = 0 \\ \dot{p}_v^* = -p_x^* \end{cases} \quad \begin{cases} x^*(0) = 0 \\ v^*(0) = 0 \\ p_x^*(T) = 1 \\ p_v^*(T) = 0 \end{cases}$$

$$\Rightarrow p_x^*(t) = 1 \quad \forall t \Rightarrow p_v^*(t) = T - t$$

$$H(t, x^*(t), v^*(t), p_x^*(t), p_v^*(t), \theta) = v^*(t) + \theta(T-t) - \frac{1}{2} \max(0, \theta)^2$$

$$\theta^*(t) = \operatorname{argmax}_{\theta \in [-1, 1]} H$$

$$= \min(T-t, 1)$$

