

# Advanced optimal control: from reusable rocket landing to efficient training of neural networks

IPSA course 2025

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Laboratoire des Signaux et Systèmes  
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# Course schedule

1. Optimal Control Problems (OCP): review of ordinary differential equations; existence of solutions to OCP.
2. Optimality Conditions for OCP: the Maximum Principle and structure of optimal controls; application to reusable rocket landing.
3. Python Session 1: real-world reusable rocket landing.
4. Python Session 2: training of neural networks through NeuralODE (this application might change depending on the course first outcomes).
5. Final presentation of the results.

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# Recap

Cost (functional)

$$\min_{u(\cdot) \in L^\infty} h(x(t_f)) + \int_0^{t_f} f^0(t, x(t), u(t)) dt$$

(Control) constraints

$$u(t) \in U \subseteq \mathbb{R}^m, \quad t \in [0, t_f]$$

Dynamics + initial/final conditions

$$\begin{cases} x(t) \in \mathbb{R}^n, & t \in [0, t_f], \\ \dot{x}(t) = f(t, x(t), u(t)), \\ x(0) = x_0, & g(x(t_f)) = 0 \end{cases}$$

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2. We studied conditions under which feasible OCP have at least one optimal solution  $u^*(\cdot) \in L^\infty([0, t_f], U)$ , with corresponding optimal trajectory  $x^* : [0, t_f] \rightarrow \mathbb{R}^n$ .

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3. Today's topic: characterize optimal solutions  $u^*(\cdot) \in L^\infty([0, t_f], U)$  to OCP via necessary conditions of optimality.



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Lecture 2 - Characterize the structure of solutions to OCP

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# Today's detailed schedule

1. Necessary conditions for optimality: the Pontryagin Maximum Principle (PMP).
2. Learn how to apply the PMP through simple optimal control problems.
3. Characterize optimal controls for the reusable rocket landing problem.

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Recall OCP:

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Key insight: OCP is a (infinite-dimensional) constrained optimization problem.

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Let us introduce such conditions for optimality for OCP, and characterize optimal controls!

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New variables: multipliers!

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- $\nabla_x H =$  gradient w.r.t.  $x$   
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- Backward linear ODE: unique solution exists

# The PMP - Theory

## 3. Theorem PMP (necessary conditions for optimality).

Let  $(u^*, x^*)$  be an optimal control-trajectory pair solution to OCP. There exists a pair  $(p^0, \mathbf{p}) \in \{-1, 0\} \times \mathbb{R}^\ell$  such that the following conditions hold true:

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Let  $p^* : [0, t_f] \rightarrow \mathbb{R}^n$  be the unique solution the the adjoint system:

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c. **Maximality condition:**  $u^*(t) \in \arg \max_{u \in U} H(t, x^*(t), u, p^*(t), p^0)$

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b. **Non-triviality:**  $(p^*(t), p^0) \neq 0$  for all  $t \in [0, t_f]$

c. **Maximality condition:**  $u^*(t) \in \arg \max_{u \in U} H(t, x^*(t), u, p^*(t), p^0)$

d. **Final condition (only if  $t_f$  is free!!!):**  $\max_{u \in U} H(t_f, x^*(t_f), u, p^*(t_f), p^0) = 0$

# The PMP - Theory

## 3. Theorem PMP (necessary conditions for optimality).

Let  $(u^*, x^*)$  be an optimal control-trajectory pair solution to OCP. There exists a pair  $(p^0, \mathbf{p}) \in \{-1, 0\} \times \mathbb{R}^\ell$  such that the following conditions hold true:

### a. Adjoint and adjoint system:

Let  $p^* : [0, t_f] \rightarrow \mathbb{R}^n$  be the unique solution the the adjoint system:

$$\begin{cases} \dot{p}^*(t) = -\nabla_x H(t, x^*(t), u^*(t), p^*(t), p^0), \\ p^*(t_f) = p^0 \nabla_x h(x^*(t_f)) + \mathbf{p}^\top J_x g(x^*(t_f)) \end{cases}$$

Used to find  
simpler forms  
of  $u^*(\cdot)$ .

b. Non-triviality:  $(p^*(t), p^0) \neq 0$  for all  $t \in [0, t_f]$

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# Today's detailed schedule

1. Necessary conditions for optimality: the Pontryagin Maximum Principle (PMP).
2. Learn how to apply the PMP through simple optimal control problems.
3. Characterize optimal controls for the reusable rocket landing problem.

# The PMP - Examples

Minimal energy double integrator - Used in electronic circuit eco-phasing

$$\min_{u(\cdot) \in L^\infty([0, t_f], [-1, 1])} \int_0^{t_f} u(t)^2 dt, \quad t_f > 0 \text{ fixed}$$
$$\begin{cases} \dot{y}(t) = z(t) \\ \dot{z}(t) = u(t) \end{cases} \quad \text{with} \quad \begin{cases} y(0) = 1, \quad z(0) = 0 \\ y(t_f) = z(t_f) = 0 \end{cases}$$

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1. Write the **Hamiltonian**:

$$x \triangleq (y, z) \in \mathbb{R}^2, \quad u \in \mathbb{R}, \quad p \triangleq (p_y, p_z) \in \mathbb{R}^2, \quad p^0 \in \{0, -1\}$$

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$$H(t, x, u, p, p^0) = p^\top f(t, x, u) + p^0 f^0(t, x, u) = p_y z + p_z u + p^0 u^2$$

# The PMP - Examples

2. Given the Hamiltonian  $H(t, x, u, p, p^0) = p_y z + p_z u + p^0 u^2$ , there exist a vector  $\mathbf{p} \in \mathbb{R}^2$  and an adjoint  $p^* : [0, t_f] \rightarrow \mathbb{R}^2$  satisfying the adjoint system:

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In particular, we compute

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$$\begin{pmatrix} \dot{p}_y^*(t) \\ \dot{p}_z^*(t) \end{pmatrix} = \begin{pmatrix} -\frac{\partial H}{\partial y}(t, x^*(t), u^*(t), p^*(t), p^0) \\ -\frac{\partial H}{\partial z}(t, x^*(t), u^*(t), p^*(t), p^0) \end{pmatrix} = \begin{pmatrix} 0 \\ -p_y^*(t) \end{pmatrix}$$

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$$p^*(t_f) = p^0 \nabla_x h(x^*(t_f)) + \mathbf{p}^\top J_x g(x^*(t_f)) = (\mathbf{p}_y, \mathbf{p}_z) \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = (\mathbf{p}_y, \mathbf{p}_z)$$

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Thus: 
$$p_y^*(t) = \mathbf{p}_y, \quad p_z^*(t) = \mathbf{p}_z + \mathbf{p}_y(t_f - t), \quad t \in [0, t_f]$$

# The PMP - Examples

3. Given the Hamiltonian  $H(t, x, u, p, p^0) = p_y z + p_z u + p^0 u^2$  and the adjoint  $p_y^*(t) = p_y$ ,  $p_z^*(t) = p_z + p_y(t_f - t)$ , solve the **maximality condition**

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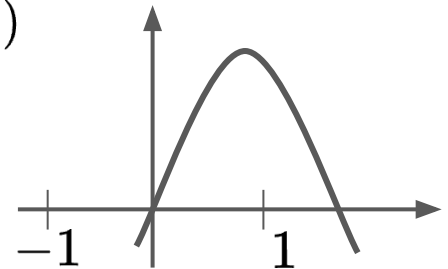
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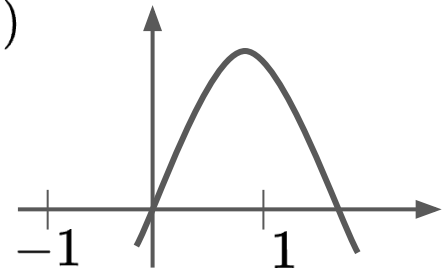
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Solutions depend on the value of  $p^0$ !



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Let us solve:  $\arg \max_{u \in U} H(t, x^*(t), u, p^*(t), p^0) = \arg \max_{u \in [-1, 1]} (p_z^*(t)u + p^0 u^2)$

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a. Case  $p^0 = -1$

Maximizing a parabola:

$$u^*(t) = \arg \max_{u \in [-1,1]} (p_z^*(t)u - u^2)$$

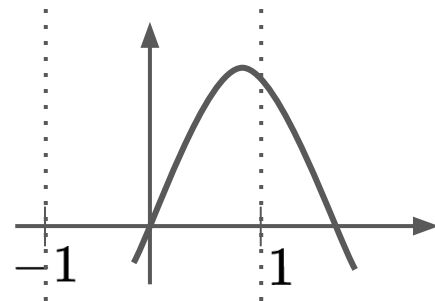
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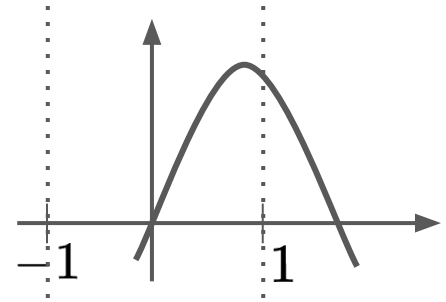
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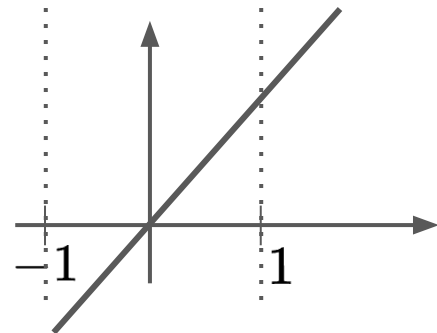
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Maximizing a straight line in  $[-1,1]$

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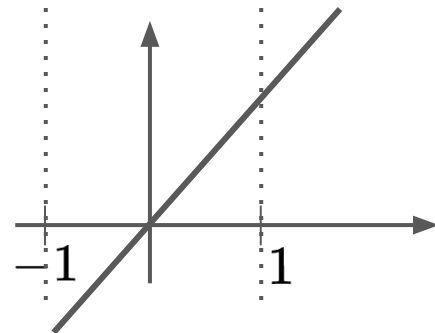
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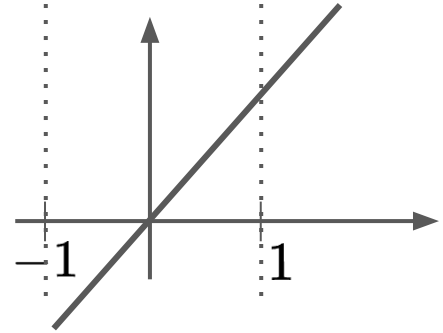
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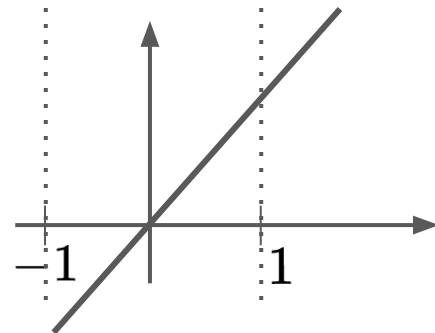
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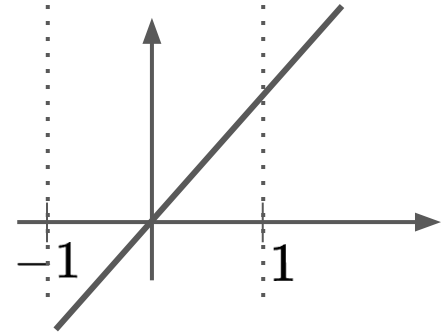
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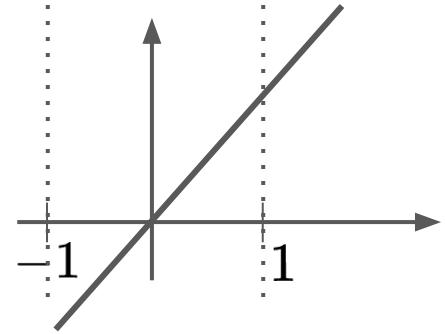
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# The PMP - Examples

Minimal energy double integrator - Used in electronic circuit eco-phasing

$$\min_{u(\cdot) \in L^\infty([0, t_f], [-1, 1])} \int_0^{t_f} u(t)^2 dt, \quad t_f > 0 \text{ fixed}$$
$$\begin{cases} \dot{y}(t) = z(t) \\ \dot{z}(t) = u(t) \end{cases} \quad \text{with} \quad \begin{cases} y(0) = 1, \quad z(0) = 0 \\ y(t_f) = z(t_f) = 0 \end{cases}$$

We have finally showed that optimal controls for this OCP can only take two forms:

# The PMP - Examples

Minimal energy double integrator - Used in electronic circuit eco-phasing

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$$\begin{cases} \dot{y}(t) = z(t) \\ \dot{z}(t) = u(t) \end{cases} \quad \text{with} \quad \begin{cases} y(0) = 1, \quad z(0) = 0 \\ y(t_f) = z(t_f) = 0 \end{cases}$$

We have finally showed that optimal controls for this OCP can only take two forms:

By denoting  $a \triangleq t_f - \frac{2 - p_z}{p_y}$ ,  $b \triangleq t_f + \frac{2 + p_z}{p_y}$ , and  $c \triangleq t_f + \frac{p_z}{p_y}$ , we have

# The PMP - Examples

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Just find  $0 \leq a < b \leq t_f$  OR  $0 \leq c \leq t_f$   
numerically!!!

# Existence of solutions to OCP - Examples

Minimal energy reusable rocket landing

$$\min_{u \in L^\infty([0, t_f], U)} \int_0^{t_f} \|u(t)\|^2 dt, \quad t_f > 0 \text{ fixed}$$

$$U \triangleq \{u \in \mathbb{R}^3 : \|u\| \leq u_{\max}\} \subseteq \mathbb{R}^3 \quad \frac{d}{dt} \begin{pmatrix} r \\ v \end{pmatrix} (t) = \begin{pmatrix} v(t) \\ \frac{T_{\max} u(t)}{\bar{m}} - g_r \end{pmatrix} \quad \begin{cases} (r, v)(0) = (r_0, v_0) \\ (r, v)(t_f) = (0, 0) \end{cases}$$

It's your turn: By assuming that this OCP has at least one optimal control-trajectory pair  $(u^*, x^*)$ , **apply the PMP and show  $u^*(\cdot)$  is of the form** (20/30 minutes):

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Solution: See the blackboard.



# Today's detailed schedule

1. Necessary conditions for optimality: the Pontryagin Maximum Principle (PMP).
2. Learn how to apply the PMP through simple optimal control problems.
3. Characterize optimal controls for the reusable rocket landing problem.

# Characterize optimal controls for rocket landing

Minimal fuel consumption reusable rocket landing (with fixed or free final time)

$$\begin{aligned} \min_u \quad & -m(t_f) \\ 0 < u_{\min} \leq \|u(t)\| \leq u_{\max} \quad & \frac{d}{dt} \begin{pmatrix} r \\ v \\ m \end{pmatrix} (t) = \begin{pmatrix} v \\ \frac{T_{\max} u}{m} - g_r \\ -q \|u\| \end{pmatrix} (t) \quad (r, v, m)(0) = (r_0, v_0, m_0), \\ & (r, v)(t_f) = (0, 0) \end{aligned}$$

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1-2. For the Hamiltonian and the adjoint system we have (see the blackboard):

$$x \triangleq (r, v, m) \in \mathbb{R}^7, \quad u \in \mathbb{R}^3, \quad p \triangleq (p_r, p_v, p_m) \in \mathbb{R}^7, \quad p^0 \in \{0, -1\}$$

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$$\Psi(t) \triangleq \frac{\|p_v^*(t)\|}{m(t)} - p_m^*(t) q$$

What if  $\Psi(t) = 0$  ???

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4. Luckily, it can never happen  $\Psi(t) = \frac{\|p_v^*(t)\|}{m(t)} - p_m^*(t)q = 0$  . Otherwise:

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In turn, we have

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a. Indeed, the adjoint system yields

$$\begin{cases} \dot{p}_v^*(t) = -p_r^*(t) \\ p_v^*(t_f) = \mathfrak{p}_v \end{cases} \quad \curvearrowright \quad \frac{d}{dt} \left( -p_r^*(t) \cdot p_v^*(t) \right) = \|p_r^*(t)\|^2 \geq 0$$

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c. In addition, the adjoint system yields

$$\begin{cases} \dot{p}_m^*(t) = \frac{p_v^*(t) \cdot u^*(t)}{m(t)^2} \\ p_m^*(t_f) = -p^0 \end{cases} \quad \curvearrowright \quad p_m^*(0) \leq 1 - \int_0^{t_f} \frac{\alpha(t) \|p_v^*(t)\|}{m(t)^2} dt$$

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$$\begin{cases} \dot{p}_v^*(t) = -p_r^*(t) \\ p_v^*(t_f) = p_v \end{cases} \quad \longrightarrow \quad \frac{d}{dt} \left( -p_r^*(t) \cdot p_v^*(t) \right) = \|p_r^*(t)\|^2 \geq 0$$

In particular, the function  $t \in [0, t_f] \mapsto -p_r^*(t) \cdot p_v^*(t)$  is non-decreasing.

b. From  $\dot{\Psi}(t) = -\frac{p_r^*(t) \cdot p_v^*(t)}{m(t) \|p_v^*(t)\|}$ , it follows that  $\dot{\Psi}(t)$  is either always non-negative or it changes sign at maximum once (from - to +).

c. In addition, the adjoint system yields  $\text{Recall } u^*(t) = \alpha(t) \frac{p_v^*(t)}{\|p_v^*(t)\|}, \alpha(t) \in [u_{\min}, u_{\max}]$

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e. We conclude:

$$u^*(t) = \begin{cases} u_{\min}, & \Psi(t) < 0 \\ u_{\max}, & \Psi(t) > 0 \end{cases} \quad \rightarrow \quad u^*(t) = \begin{cases} u_{\max} \frac{w_1 + w_2 t}{\|w_1 + w_2 t\|}, & t \in [0, t_1] \\ u_{\min} \frac{w_1 + w_2 t}{\|w_1 + w_2 t\|}, & t \in (t_1, t_2], \\ u_{\max} \frac{w_1 + w_2 t}{\|w_1 + w_2 t\|}, & t \in (t_2, t_f] \end{cases} \quad \begin{matrix} 0 \leq t_1 \leq t_2 \leq t_f \\ w_1, w_2 \in \mathbb{R}^3 \end{matrix}$$

# Characterize optimal controls for rocket landing

Minimal fuel consumption reusable rocket landing (with fixed or free final time)

$$\begin{aligned} \min_u \quad & -m(t_f) \\ 0 < u_{\min} \leq \|u(t)\| \leq u_{\max} \quad & \frac{d}{dt} \begin{pmatrix} r \\ v \\ m \end{pmatrix} (t) = \begin{pmatrix} v \\ \frac{u}{m} - g_r \\ -q\|u\| \end{pmatrix} (t) \quad \begin{aligned} (r, v, m)(0) &= (r_0, v_0, m_0), \\ (r, v)(t_f) &= (0, 0) \end{aligned} \end{aligned}$$

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We have reduced the problem to a finite-dimensional optimization problem: just find  $0 \leq t_1 \leq t_2 \leq t_f$  and  $w_1, w_2 \in \mathbb{R}^3$  numerically!!!

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Next lecture!

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Bring your  
laptops with  
Conda installed!!!

# End of lecture 2

Questions?

Otherwise, see you in two weeks!