

Lecture Notes 8: Dynamic Optimization

Part 2: Optimal Control

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Statement of Basic Optimal Growth Problem

A **consumption path** \mathbf{C} is a mapping $[t_0, t_1] \ni t \mapsto C(t) \in \mathbb{R}_+$.

A **capital path** \mathbf{K} is a mapping $[t_0, t_1] \ni t \mapsto K(t) \in \mathbb{R}_+$.

Given $K(0)$ at time 0, the benevolent planner's **objective** is to choose the pair (\mathbf{C}, \mathbf{K}) in order to maximize

$$J(\mathbf{C}, \mathbf{K}) := \int_{t_0}^{t_1} e^{-rt} u(C(t)) dt$$

subject to the continuum of equality constraints

$$C(t) = f(K(t)) - \dot{K}(t)$$

Introduce the **Lagrange multiplier path** \mathbf{p} as a mapping $[t_0, t_1] \ni t \mapsto p(t) \in \mathbb{R}_+$.

Use it to define the **Lagrangian integral**

$$\mathcal{L}_{\mathbf{p}}(\mathbf{C}, \mathbf{K}) = \int_{t_0}^{t_1} e^{-rt} u(C(t)) dt - \int_{t_0}^{t_1} p(t) [C(t) - f(K(t)) + \dot{K}(t)] dt$$

Integrate by Parts

So we have the “Lagrangian”

$$\mathcal{L}_{\mathbf{p}}(\mathbf{C}, \mathbf{K}) = \int_{t_0}^{t_1} e^{-rt} u(C(t)) dt - \int_{t_0}^{t_1} p(t) [C(t) - f(K(t)) + \dot{K}(t)] dt$$

Integrating the last term by parts yields

$$- \int_{t_0}^{t_1} p(t) \dot{K}(t) dt = - \Big|_{t_0}^{t_1} p(t) K(t) + \int_{t_0}^{t_1} \dot{p}(t) K(t) dt$$

Hence

$$\mathcal{L}_{\mathbf{p}}(\mathbf{C}, \mathbf{K}) = \int_{t_0}^{t_1} [e^{-rt} u(C) + \dot{p} K - p C + p f(K)] dt - \Big|_{t_0}^{t_1} p(t) K(t)$$

For the moment we ignore the last “endpoint terms”,
and consider just the integral

$$\mathcal{I}_{\mathbf{p}}(\mathbf{C}, \mathbf{K}) := \int_{t_0}^{t_1} [e^{-rt} u(C) + \dot{p} K - p C + p f(K)] dt$$

Maximizing the Integrand

Evidently the two paths $t \mapsto C(t)$ and $t \mapsto K(t)$ jointly maximize the integral

$$\mathcal{I}_{\mathbf{p}}(\mathbf{C}, \mathbf{K}) = \int_{t_0}^{t_1} [e^{-rt} u(C) + \dot{p}K - pC + pf(K)] dt$$

with \mathbf{p} fixed, if and only if, for almost all $t \in (t_0, t_1)$, the pair $(C(t), K(t))$ jointly maximizes w.r.t. C and K the integrand

$$e^{-rt} u(C) + \dot{p}K - pC + pf(K)$$

The first-order conditions for maximizing this integrand, at any time $t \in (t_0, t_1)$, are found by differentiating partially:

1. w.r.t. $C(t)$ to obtain $e^{-rt} u'(C(t)) = p(t)$;
2. w.r.t. $K(t)$ to obtain $\dot{p}(t) = -p(t) f'(K(t))$;

There is also the equality constraint $\dot{K}(t) = f(K(t)) - C(t)$.

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Statement of Sufficient Conditions

Consider the static problem of maximizing the objective function $\mathbb{R}^n \supseteq D \ni \mathbf{x} \mapsto f(\mathbf{x}) \in \mathbb{R}$ subject to the vector constraint $\mathbf{g}(\mathbf{x}) \leq \mathbf{a} \in \mathbb{R}^m$ where $\mathbb{R}^n \supseteq D \ni \mathbf{x} \mapsto \mathbf{g}(\mathbf{x}) \in \mathbb{R}^m$.

Definition

The pair $(\mathbf{p}, \mathbf{x}^*) \in \mathbb{R}^m \times \mathbb{R}^n$

jointly satisfies **complementary slackness** just in case:

$$(i) \mathbf{p}^\top \geq 0; \quad (ii) \mathbf{g}(\mathbf{x}^*) \leq \mathbf{a}; \quad (iii) \mathbf{p}^\top [\mathbf{g}(\mathbf{x}^*) - \mathbf{a}] = 0$$

These are generally summarized as $\mathbf{p}^\top \geq 0$, $\mathbf{g}(\mathbf{x}^*) \leq \mathbf{a}$ (comp). \square

Theorem

Suppose that $\mathbf{x}^* \in \mathbb{R}^n$ is a global maximum over the domain D of the Lagrangian function $\mathcal{L}_{\mathbf{p}}(\mathbf{x}) = f(\mathbf{x}) - \mathbf{p}^\top [\mathbf{g}(\mathbf{x}) - \mathbf{a}]$

where $(\mathbf{p}, \mathbf{x}^*) \in \mathbb{R}^m \times \mathbb{R}^n$

jointly satisfy the complementary slackness conditions.

Then \mathbf{x}^* is a global maximum of $f(\mathbf{x})$ subject to $\mathbf{g}(\mathbf{x}) \leq \mathbf{a}$.

Proof of Sufficient Conditions

Proof.

By definition of the Lagrangian $\mathcal{L}_{\mathbf{p}}(\mathbf{x}) = f(\mathbf{x}) - \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}) - \mathbf{a}]$, for every $\mathbf{x} \in D$ one has

$$f(\mathbf{x}) - f(\mathbf{x}^*) = \mathcal{L}_{\mathbf{p}}(\mathbf{x}) + \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}) - \mathbf{a}] - \mathcal{L}_{\mathbf{p}}(\mathbf{x}^*) - \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}^*) - \mathbf{a}]$$

By hypothesis one has $\mathcal{L}_{\mathbf{p}}(\mathbf{x}) \leq \mathcal{L}_{\mathbf{p}}(\mathbf{x}^*)$ for all $\mathbf{x} \in D$, so

$$f(\mathbf{x}) - f(\mathbf{x}^*) \leq \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}) - \mathbf{a}] - \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}^*) - \mathbf{a}] = \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}) - \mathbf{g}(\mathbf{x}^*)]$$

But the complementary slackness conditions

$$\mathbf{p}^{\top} \geq \mathbf{0}, \quad \mathbf{g}(\mathbf{x}^*) \leq \mathbf{a} \quad (\text{comp})$$

imply that for any $\mathbf{x} \in D$ satisfying the constraint $\mathbf{g}(\mathbf{x}) \leq \mathbf{a}$ one has $\mathbf{p}^{\top} \mathbf{g}(\mathbf{x}) \leq \mathbf{p}^{\top} \mathbf{a}$, whereas $\mathbf{p}^{\top} \mathbf{g}(\mathbf{x}^*) = \mathbf{p}^{\top} \mathbf{a}$.

Hence $f(\mathbf{x}) - f(\mathbf{x}^*) \leq \mathbf{p}^{\top}[\mathbf{g}(\mathbf{x}) - \mathbf{g}(\mathbf{x}^*)] \leq \mathbf{p}^{\top} \mathbf{a} - \mathbf{p}^{\top} \mathbf{a} = 0$. □

A Cheap Result on Necessary Conditions

Recall that we are considering the problem of choosing $\mathbf{x} \in D \subseteq \mathbb{R}^n$ in order to maximize $f(\mathbf{x})$ subject to $\mathbf{g}(\mathbf{x}) \leq \mathbf{a}$.

Suppose we know that any solution \mathbf{x}^* must be unique.

This will be the case, for example, if:

1. the common domain D of the functions $D \ni \mathbf{x} \mapsto f(\mathbf{x}) \in \mathbb{R}$ and $D \ni \mathbf{x} \mapsto \mathbf{g}(\mathbf{x}) \in \mathbb{R}^m$ is a convex subset of \mathbb{R}^n ;
2. the objective function $D \ni \mathbf{x} \mapsto f(\mathbf{x}) \in \mathbb{R}$ is strictly concave;
3. each component function $D \ni \mathbf{x} \mapsto g_j(\mathbf{x}) \in \mathbb{R}$ of the vector function $D \ni \mathbf{x} \mapsto \mathbf{g}(\mathbf{x}) \in \mathbb{R}^m$ is convex.

Suppose that the pair $(\mathbf{p}, \mathbf{x}^*) \in \mathbb{R}^m \times D$ jointly satisfy the sufficient conditions for maximizing the Lagrangian while also meeting the complementary slackness conditions.

Then it is **necessary** that the only possible maximum satisfy these sufficient conditions!

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Statement of General Problem

Given the time interval $[t_0, t_1] \subset \mathbb{R}$,
consider the general one-variable optimal control problem
of choosing paths:

1. $[t_0, t_1] \ni t \mapsto x(t) \in \mathbb{R}$ of **states**;
2. $[t_0, t_1] \ni t \mapsto u(t) \in \mathbb{R}$ of **controls**.

The **objective functional** is taken to be the integral

$$\int_{t_0}^{t_1} f(t, x(t), u(t)) dt$$

We fix the **initial state** $x(t_0) = x_0$, where x_0 is given.

We leave the **terminal state** $x(t_1)$ free.

Finally, we impose the **dynamic constraint** $\dot{x} = g(t, x, u)$
at every time $t \in [t_0, t_1]$.

The Lagrangian Integral

Consider the path $[t_0, t_1] \ni t \mapsto p(t) \in \mathbb{R}$
of a single **costate variable** or **shadow price** p .

Here $p(t)$ is the Lagrange multiplier
associated with the dynamic constraint at time t .

Then, after dropping the time argument from p , x and u ,
the associated “Lagrangian integral” is

$$\mathcal{L} = \int_{t_0}^{t_1} f(t, x, u) dt - \int_{t_0}^{t_1} p[\dot{x} - g(t, x, u)] dt$$

Because $\frac{d}{dt} p x = \dot{p} x + p \dot{x}$, integrating by parts
gives $\int_{t_0}^{t_1} p \dot{x} dt = - \int_{t_0}^{t_1} \dot{p} x dt + \Big|_{t_0}^{t_1} p x$ and so

$$\mathcal{L} = \int_{t_0}^{t_1} [f(t, x, u) + \dot{p} x + p g(t, x, u)] dt - \Big|_{t_0}^{t_1} p x$$

The Hamiltonian

Definition

For the problem of maximizing $\int_{t_0}^{t_1} f(t, x, u) dt$
subject to $\dot{x} = g(t, x, u)$,
the **Hamiltonian function** is defined as

$$H(t, x, u, p) := f(t, x, u) + p g(t, x, u) \quad \square$$

With this definition, the integral part of the Lagrangian, which is

$$\int_{t_0}^{t_1} [f(t, x, u) + \dot{p} x + p g(t, x, u)] dt$$

can be written as $\int_{t_0}^{t_1} [H(t, x, u, p) + \dot{p} x] dt$.

The Maximum Principle

Recall the definition $H(t, x, u, p) := f(t, x, u) + p g(t, x, u)$.

Definition

According to the **maximum principle**, for a.e. $t \in [t_0, t_1]$, an **optimal control** should satisfy

$$u^*(t) \in \arg \max_u H(t, x, u, p) \text{ where } x = x(t) \text{ and } p = p(t)$$

Moreover the co-state variable $p(t)$ should evolve according to the vector differential equation

$$\dot{p} = -H'_x(t, x, u, p)$$

where $H'_x(t, x, u, p)$ denotes the partial derivative of the Hamiltonian H w.r.t. the state x .

An Extended Maximum Principle

Definition

Add an extra term $\dot{p}x$ to the Hamiltonian $H(t, x, u, p)$ in order to give the **extended Hamiltonian**

$$\tilde{H}(t, x, u, p) := H(t, x, u, p) + \dot{p}x = f(t, x, u) + pg(t, x, u) + \dot{p}x$$

According to the **extended maximum principle**, for a.e. (almost every) time $t \in [t_0, t_1]$, one should have

$$(u^*(t), x^*(t)) \in \arg \max_{(u, x)} \tilde{H}(t, x, u, p(t))$$

Remark

The first-order conditions for maximizing $\tilde{H}(t, x, u, p)$ include

$$\dot{p} = -f'_x(t, x, u) - pg'_x(t, x, u) = -H'_x(t, x, u, p)$$

as required by the maximum principle.

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A Macroeconomic Quadratic Control Problem: Statement

Let $c > 0$ denote an **adjustment cost parameter**.

Consider the problem of choosing the path $t \mapsto (u(t), x(t)) \in \mathbb{R}^2$ in order to **minimize** the quadratic integral $\int_0^T (x^2 + cu^2) dt$ subject to the dynamic constraint $\dot{x} = u$, as well as the initial condition $x(0) = x_0$ and the terminal condition allowing $x(T)$ to be chosen freely.

The associated Hamiltonian is

$$H = -x^2 - cu^2 + pu$$

with a minus sign to convert the minimization problem into a maximization problem.

The associated extended Hamiltonian, including the extra term $\dot{p}x$, is

$$\tilde{H} = -x^2 - cu^2 + pu + \dot{p}x$$

First-Order Conditions

Consider the problem of maximizing, at any time $t \in [0, T]$, either the Hamiltonian $H = -x^2 - cu^2 + pu$, or the extended Hamiltonian $\tilde{H} = -x^2 - cu^2 + pu + \dot{p}x$

The first-order conditions include $0 = H'_u = \tilde{H}'_u = -2cu + p$.

Either of these two equivalent conditions implies that $u^* = p/2c$.

A second first-order condition for maximizing w.r.t. x the extended Hamiltonian \tilde{H} is $\dot{p} = -H'_x = 2x$.

This coincides with the co-state differential equation.

Combining this with the dynamic constraint $\dot{x} = u$ leads to the following **coupled pair** of differential equations:

$$\dot{p} = -H'_x = 2x \quad \text{and} \quad \dot{x} = u^* = p/2c$$

Example: Solving the Coupled Pair

In order to solve the coupled pair

$$\dot{p} = 2x \quad \text{and} \quad \dot{x} = p/2c$$

- ▶ differentiate the first equation w.r.t. t to obtain $\ddot{p} = 2\dot{x}$;
- ▶ substitute in the second equation to obtain $\ddot{p} = 2\dot{x} = p/c$.

We need to consider the second-order differential equation

$$\ddot{p} = p/c$$

in p , whose associated characteristic equation is $\lambda^2 - 1/c = 0$.

The two roots are $\lambda_{1,2} = \pm c^{-1/2} = \pm r$ where $r := c^{-1/2}$.

The general solution of this homogeneous equation is $p = Ae^{rt} + Be^{-rt}$ for arbitrary constants A and B .

Explicit Solution

In addition to $p = Ae^{rt} + Be^{-rt}$ with $r := c^{-1/2}$ and $\dot{p} = 2x$, we also have $\dot{x} = p/2c$, along with the initial condition $x(0) = x_0$ and the terminal condition $p(T) = 0$.

This terminal condition implies $Ae^{rT} + Be^{-rT} = 0$, from which one obtains $B = -Ae^{2rT}$.

Also differentiating $p = Ae^{rt} + Be^{-rt}$ w.r.t. t implies $\dot{p} = r(Ae^{rt} - Be^{-rt})$.

At time $t = 0$ one has $\dot{p}(0) = 2x_0$ and so $r(A - B) = 2x_0$.

Substituting $B = -Ae^{2rT}$ gives $r(A + Ae^{2rT}) = 2x_0$, so $A = 2x_0/r(1 + e^{2rT}) = 2x_0e^{-rT}/r(e^{-rT} + e^{rT})$ implying that $B = -2x_0e^{rT}/r(e^{-rT} + e^{rT})$.

So $p = Ae^{rt} + Be^{-rt} = 2x_0(e^{-r(T-t)} - e^{r(T-t)})/r(e^{-rT} + e^{rT})$

and $x = \dot{p}/2 = x_0(e^{-r(T-t)} + e^{r(T-t)})/(e^{-rT} + e^{rT})$.

Also $u = \dot{x} = rx_0(e^{-r(T-t)} - e^{r(T-t)})/(e^{-rT} + e^{rT})$.

The Case of an Infinite Horizon

Multiply both numerator and denominator of the right-hand side of each equation by e^{-rT} , leading to the explicit solution:

$$\begin{aligned}p(t) &= \frac{2x_0 [e^{-r(T-t)} - e^{r(T-t)}]}{r [e^{-rT} + e^{rT}]} = \frac{2x_0 [e^{-r(2T-t)} - e^{-rt}]}{r(e^{-2rT} + 1)} \\x(t) &= \frac{x_0 [e^{-r(T-t)} + e^{r(T-t)}]}{r(e^{-rT} + e^{rT})} = \frac{x_0 [e^{-r(2T-t)} + e^{-rt}]}{r(e^{-2rT} + 1)} \\u(t) &= \frac{x_0 [e^{-r(T-t)} - e^{r(T-t)}]}{e^{-rT} + e^{rT}} = \frac{x_0 [e^{-r(2T-t)} - e^{-rt}]}{e^{-2rT} + 1}\end{aligned}$$

Taking the limit as $T \rightarrow \infty$, one has $p(t) \rightarrow -2x_0 e^{-rt}/r$.

Similarly $x(t) = \frac{1}{2}\dot{p} \rightarrow x_0 e^{-rt}$, and $u(t) = \dot{x}(t) \rightarrow -x_0 e^{-rt}$.

Finally, $(p(t), x(t), u(t)) \rightarrow (0, 0, 0)$ as $t \rightarrow \infty$.

See page 311 of FMEA.

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Mangasarian and Arrow's Sufficient Conditions

At any fixed time t , let $(\mathbf{x}^*(t), \mathbf{u}^*(t))$ be a stationary point w.r.t. (\mathbf{x}, \mathbf{u}) of the extended Hamiltonian

$$\tilde{H}(t, \mathbf{x}, \mathbf{u}, \mathbf{p}(t)) := H(t, \mathbf{x}, \mathbf{u}, \mathbf{p}(t)) + \dot{\mathbf{p}}^\top(t) \mathbf{x}$$

That is, suppose that the respective partial gradients satisfy

$$H'_{\mathbf{u}}(t, \mathbf{x}^*(t), \mathbf{u}^*(t), \mathbf{p}(t)) = 0 \quad \text{and} \quad \dot{\mathbf{p}}(t) = -H'_x(t, \mathbf{x}^*(t), \mathbf{u}^*(t), \mathbf{p}(t))$$

Here are two alternative sufficient conditions for $(\mathbf{x}^*(t), \mathbf{u}^*(t))$ to maximize the extended Hamiltonian.

1. See FMEA Theorem 9.7.1, due to Mangasarian.

Suppose that $(\mathbf{x}, \mathbf{u}) \mapsto H(t, \mathbf{x}, \mathbf{u}, \mathbf{p}(t))$ is concave, which implies that $(\mathbf{x}, \mathbf{u}) \mapsto \tilde{H}(t, \mathbf{x}, \mathbf{u}, \mathbf{p}(t))$ is also concave.

2. See FMEA Theorem 9.7.2, due to Arrow.

Define $\hat{H}(t, \mathbf{x}, \mathbf{p}(t)) := \max_{\mathbf{u}} H(t, \mathbf{x}, \mathbf{u}, \mathbf{p}(t))$, and suppose that $\mathbf{x} \mapsto \hat{H}(t, \mathbf{x}, \mathbf{p}(t))$ is concave.

Sufficient Conditions

Consider the single variable problem
of choosing the paths $t \mapsto (x(t), u(t)) \in \mathbb{R}^2$
in order to maximize $\int_0^T f(t, x, u) dt$
subject to $\dot{x} \leq g(t, x, u)$ (all $t \in [0, T]$)
as well as $x(0) \leq x_0$, $x(T) \geq x_T$.

Including the extra term $\dot{p}x$, the extended Hamiltonian is

$$\tilde{H}(t, x, u, p) = f(t, x, u) + p g(t, x, u) + \dot{p}x$$

Suppose that for all $t \in [0, T]$ the path $t \mapsto (x^*(t), u^*(t)) \in \mathbb{R}^2$
satisfies the **extended maximization condition**

$$(x^*(t), u^*(t)) \in \arg \max_{x, u} \tilde{H}(t, x, u, p(t))$$

as well as the three complementary slackness conditions:

1. $p(t) \geq 0$, $\dot{x}^*(t) \leq g(t, x^*(t), u^*(t))$ (comp) (all $t \in [0, T]$);
2. $p(0) \geq 0$, $x^*(0) \leq x_0$ (comp);
3. $p(T) \geq 0$, $x^*(T) \geq x_T$ (comp).

Proof of Sufficiency, I

Consider any alternative feasible path $t \mapsto (x(t), u(t))$ satisfying all the constraints.

Define $D(\mathbf{x}, \mathbf{u}) := \int_0^T [f(t, x(t), u(t)) - f(t, x^*(t), u^*(t))] dt$.

After dropping the time arguments from $x(t), u(t), x^*(t), u^*(t)$, the definition $\tilde{H} = f + pg + p\dot{x}$ implies that

$$D(\mathbf{x}, \mathbf{u}) = \int_0^T \left\{ \left[\tilde{H}(t, x, u, p) - pg(t, x, u) - \dot{p}x \right] - \left[\tilde{H}(t, x^*, u^*, p) - pg(t, x^*, u^*) - \dot{p}x^* \right] \right\} dt$$

The maximization hypothesis implies that, for all $t \in (0, T)$, one has $\tilde{H}(t, x(t), u(t), p(t)) \leq \tilde{H}(t, x^*(t), u^*(t), p(t))$.

From this it follows that

$$D(\mathbf{x}, \mathbf{u}) \leq \int_0^T \{ [-pg(t, x, u) - \dot{p}x] - [-pg(t, x^*, u^*) - \dot{p}x^*] \} dt$$

Proof of Sufficiency, II

We have shown that

$$D(\mathbf{x}, \mathbf{u}) \leq \int_0^T \{[-p g(t, x, u) - \dot{p} x] - [-p g(t, x^*, u^*) - \dot{p} x^*]\} dt$$

But feasibility implies that $\dot{x}(t) \leq g(t, x, u)$

and prices satisfy $p(t) \geq 0$, so $p(t) \dot{x}(t) \leq p(t) g(t, x, u)$.

Furthermore, the complementary slackness conditions for optimality imply that $p(t) g(t, x^*(t), u^*(t)) = p(t) \dot{x}^*(t)$.

It follows that

$$\begin{aligned} D(\mathbf{x}, \mathbf{u}) &\leq \int_0^T [-p \dot{x} - \dot{p} x + p \dot{x}^* + \dot{p} x^*] dt \\ &= \int_0^T \frac{d}{dt} [-p(t) x(t) + p(t) x^*(t)] dt \\ &= -p(T) [x(T) - x^*(T)] + p(0) [x(0) - x^*(0)] \end{aligned}$$

Proof of Sufficiency, III

So far, we have shown that

$$D(\mathbf{x}, \mathbf{u}) \leq -\rho(T) [x(T) - x^*(T)] + \rho(0) [x(0) - x^*(0)]$$

But, together with feasibility and non-negativity of prices, the second and third complementary slackness conditions regarding the endpoints at times $t = 0$ and $t = T$ imply that

$$\begin{aligned} \rho(T) x(T) &\geq \rho(T) x_T & ; & & \rho(T) x^*(T) &= \rho(T) x_T & ; \\ \rho(0) x(0) &\leq \rho(0) x_0 & ; & & \rho(0) x^*(0) &= \rho(0) x_0 . \end{aligned}$$

It follows that

$$\rho(T) x(T) \geq \rho(T) x^*(T) \quad \text{and} \quad \rho(0) x(0) \leq \rho(0) x^*(0)$$

which together imply that $D(\mathbf{x}, \mathbf{u}) \leq 0$.

Finally, after recalling the definition

$$D(\mathbf{x}, \mathbf{u}) := \int_0^T [f(t, x(t), u(t)) - f(t, x^*(t), u^*(t))] dt$$

one concludes that the path $t \mapsto (x^*(t), u^*(t))$ is optimal. □

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The Infinite Horizon Problem

We consider the problem of choosing $[0, \infty) \ni t \mapsto (x(t), u(t))$ to maximize the **infinite horizon** objective functional

$$\int_0^{\infty} f(t, x(t), u(t)) dt$$

subject to $\dot{x} = g(t, x, u)$ at every time $t \in [0, \infty)$, as well as $x(0) = x_0$, where x_0 is given.

As before, the extended maximum principle suggests looking for a path $[0, \infty) \ni t \mapsto p(t)$ of co-state variables, as well as a path $[0, \infty) \ni t \mapsto (x^*(t), u^*(t))$ of the state and control variables which maximizes the extended Hamiltonian

$$\tilde{H}(t, x, u, p) := f(t, x, u) + p(t)g(t, x, u) + \dot{p}(t)x$$

— i.e., for (almost) all $t \in [0, \infty)$ one has

$$(x^*(t), u^*(t)) \in \arg \max_{(u, x)} \tilde{H}(t, x, u, p)$$

Implications of the Extended Maximum Principle, I

Consider any alternative feasible path $t \mapsto (x(t), u(t))$ satisfying all the constraints.

We start by repeating our earlier argument for a finite horizon.

Define $D^T(\mathbf{x}, \mathbf{u}) := \int_0^T [f(t, x(t), u(t)) - f(t, x^*(t), u^*(t))] dt$.

After dropping the time arguments from $x(t), u(t), x^*(t), u^*(t)$, this difference $D^T(\mathbf{x}, \mathbf{u})$ equals

$$\int_0^T \left\{ \left[\tilde{H}(t, x, u, p) - p g(t, x, u) - \dot{p} x \right] - \left[\tilde{H}(t, x^*, u^*, p) - p g(t, x^*, u^*) - \dot{p} x^* \right] \right\} dt$$

The extended maximum principle implies that for all $t \in [0, T]$ one has

$$\tilde{H}(t, x(t), u(t), p(t)) \leq \tilde{H}(t, x^*(t), u^*(t), p(t))$$

Implications of the Extended Maximum Principle, II

Arguing as before, from $(x^*(t), u^*(t)) \in \arg \max_{(u,x)} \tilde{H}(t, x, u, p)$ where $\tilde{H}(t, x, u, p) := f(t, x, u) + p(t)g(t, x, u) + \dot{p}(t)x$, it follows that for all finite T the difference $D^T(\mathbf{x}, \mathbf{u})$ satisfies

$$\begin{aligned} D^T(\mathbf{x}, \mathbf{u}) &:= \int_0^T [f(t, x(t), u(t)) - f(t, x^*(t), u^*(t))] dt \\ &= \int_0^T \left\{ \left[\tilde{H}(t, x, u, p) - p g(t, x, u) - \dot{p} x \right] \right. \\ &\quad \left. - \left[\tilde{H}(t, x^*, u^*, p) - p g(t, x^*, u^*) - \dot{p} x^* \right] \right\} dt \\ &= \int_0^T \left[\tilde{H}(t, x, u, p) - \tilde{H}(t, x^*, u^*, p) \right] dt \\ &\quad - \int_0^T [p g(t, x, u) + \dot{p} x - p g(t, x^*, u^*) - \dot{p} x^*] dt \\ &\leq - \int_0^T [p \dot{x} + \dot{p} x - p \dot{x}^* - \dot{p} x^*] dt \\ &= - \int_0^T \frac{d}{dt} [p x - p x^*] dt \\ &= -p(T) [x(T) - x^*(T)] + p(0) [x(0) - x^*(0)] \\ &= p(T) [x^*(T) - x(T)] \text{ given that } x(0) = x^*(0) = x_0 \end{aligned}$$

A Transversality Condition

Consider the **transversality** condition

$$\limsup_{T \rightarrow \infty} \rho(T) [x^*(T) - x(T)] = 0$$

If this were satisfied, it would imply that

$$\begin{aligned} 0 &\geq \limsup_{T \rightarrow \infty} D^T(\mathbf{x}, \mathbf{u}) \\ &= \limsup_{T \rightarrow \infty} \int_0^T [f(t, x(t), u(t)) - f(t, x^*(t), u^*(t))] dt \end{aligned}$$

In the case when

$$\int_0^T f(t, x^*(t), u^*(t)) dt \rightarrow \int_0^\infty f(t, x^*(t), u^*(t)) dt$$

as $T \rightarrow \infty$, it would imply that

$$\limsup_{T \rightarrow \infty} \int_0^T f(t, x(t), u(t)) dt \leq \int_0^\infty f(t, x^*(t), u^*(t)) dt$$

Malinvaud's Transversality Condition

Edmond Malinvaud (1953) "Capital Accumulation and Efficient Allocation of Resources" *Econometrica* 21: 233–268.

In many economic contexts, feasibility requires that, for all t , one has both $x(t) \geq 0$ and $\dot{x}(t) \leq g(t, x(t), u(t))$.

Then, since $p(t) \geq 0$,

for any alternative feasible path $x(t)$ and any terminal time T , one has $p(T) [x^*(T) - x(T)] \leq p(T) x^*(T)$.

Definition

The **Malinvaud transversality condition**

is that $p(T) x^*(T) \rightarrow 0$ as $T \rightarrow \infty$.

When this Malinvaud transversality condition is satisfied, evidently

$$\limsup_{T \rightarrow \infty} p(T) [x^*(T) - x(T)] \leq \limsup_{T \rightarrow \infty} p(T) x^*(T) = 0$$

Hence, the general transversality condition is also satisfied.

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A Problem with Exponential Discounting

Consider the general problem of choosing paths:

1. $[t_0, t_1] \ni t \mapsto x(t) \in \mathbb{R}$ of **states**;
2. $[t_0, t_1] \ni t \mapsto u(t) \in \mathbb{R}$ of **controls**.

The **objective functional** is taken to be the integral

$$\int_{t_0}^{t_1} e^{-rt} f(x(t), u(t)) dt$$

where: (i) f is independent of t ;

(ii) there is a constant discount rate r

and associated exponential discount factor e^{-rt} .

Assume too that the dynamic constraint is $\dot{x} = g(x, u)$,
at every time $t \in [t_0, t_1]$, where g is independent of t .

Fix the **initial state** $x(t_0) = x_0$, where x_0 is given.

But leave the **terminal state** $x(t_1)$ free.

Present versus Current Value Hamiltonian

Up to now, we have considered the **present value Hamiltonian**

$$H(t, x, u, p) := e^{-rt} f(x, u) + p g(x, u)$$

We remove the discount factor e^{-rt}
by defining the **current value Hamiltonian**

$$H^C(x, u, q) := f(x, u) + q g(x, u)$$

with the **current value co-state variable** $q := e^{rt} p$.

These definitions imply that

$$H(t, x, u, p) = e^{-rt} [f(x, u) + e^{rt} p g(x, u)] = e^{-rt} H^C(x, u, q)$$

where $q = e^{rt} p$, so $\dot{q} = r e^{rt} p + e^{rt} \dot{p} = r q + e^{rt} \dot{p}$.

Present and Current Value Maximum Principles

The (present value) maximum principle states that for (almost) all $t \in [0, \infty)$ one has

$$u^*(t) \in \arg \max_u H(t, x, u, p) \quad \text{and} \quad \dot{p} = -H'_x(t, x, u, p)$$

By definition, one has $H(t, x, u, p) = e^{-rt} H^C(x, u, q)$ where $q = e^{rt} p$.

Because e^{-rt} is independent of u , it follows that $u^*(t) \in \arg \max_u H^C(x, u, q)$.

Also $\dot{q} - rq = e^{rt} \dot{p} = -e^{rt} H'_x(t, x, u, p) = -H^{C'}_x(x, u, q)$.

We have derived the **current value** maximum principle states that for (almost) all $t \in [0, \infty)$ one has

$$u^*(t) \in \arg \max_u H^C(x, u, q) \quad \text{and} \quad \dot{q} - rq = -H^{C'}_x(x, u, q)$$

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Statement of the Problem

The problem will be to choose:

1. a consumption stream $\mathbb{R}_+ \ni t \mapsto C(t) \in \mathbb{R}_{++}$;
2. a stream $\mathbb{R}_+ \ni t \mapsto K(t) \in \mathbb{R}_{++}$ of capital stocks.

At any time t , given capital K , output will be $Y = aK - bK^2$, where $a, b \in \mathbb{R}$ are positive parameters, with $a > r > 0$.

Output is divided between consumption C and investment \dot{K} , so $\dot{K} = Y - C$; there is no depreciation.

The planner's objective is to maximize the utility integral $\int_0^\infty e^{-rt} u(C(t)) dt$.

We assume that the utility function $\mathbb{R}_{++} \ni C \mapsto u(C)$ takes the isoelastic form with $u'(C) = C^{-\epsilon}$.

The constant elasticity parameter $\epsilon > 0$ is a constant degree of relative fluctuation aversion.

The Current Value Maximum Principle

The optimal growth problem is to maximize $\int_0^\infty e^{-rt} u(C(t)) dt$ subject to $\dot{K} = aK - bK^2 - C$ where $u'(C) = C^{-\epsilon}$.

With λ as the co-state variable, the current value Hamiltonian is

$$H^C(K, C) := u(C) + \lambda(aK - bK^2 - C)$$

The first-order condition for maximizing $(K, C) \mapsto H^C(K, C)$ w.r.t. C is $u'(C) = \lambda$, which implies $C^{-\epsilon} = \lambda$ and so $C = \lambda^{-1/\epsilon}$.

Because $C \mapsto u(C)$ is strictly concave, this is the unique maximum.

The co-state variable evolves according to the equation

$$\dot{\lambda} - r\lambda = -H_K^C(K, C) = -\lambda(a - 2bK)$$

Finally, therefore, we have the coupled differential equations

$$\dot{K} = aK - bK^2 - \lambda^{-1/\epsilon} \quad \text{and} \quad \dot{\lambda} = \lambda(r - a + 2bK)$$

Steady State of Coupled Differential Equations

The coupled differential equations

$$\dot{K} = aK - bK^2 - \lambda^{-1/\epsilon} \quad \text{and} \quad \dot{\lambda} = \lambda(r - a + 2bK)$$

have a steady state at any point satisfying $\dot{K} = 0$ and $\dot{\lambda} = 0$.

There is a unique steady state at the point $(K, \lambda) = (K^*, \lambda^*)$ with $K^* = (r - a)/2b$ and $\lambda^* = [K^*(a - bK^*)]^{-\epsilon}$.

Phase Diagram Analysis of Coupled Differential Equations

We have the coupled differential equations

$$\dot{K} = aK - bK^2 - \lambda^{-1/\epsilon} \quad \text{and} \quad \dot{\lambda} = \lambda(r - a + 2bK)$$

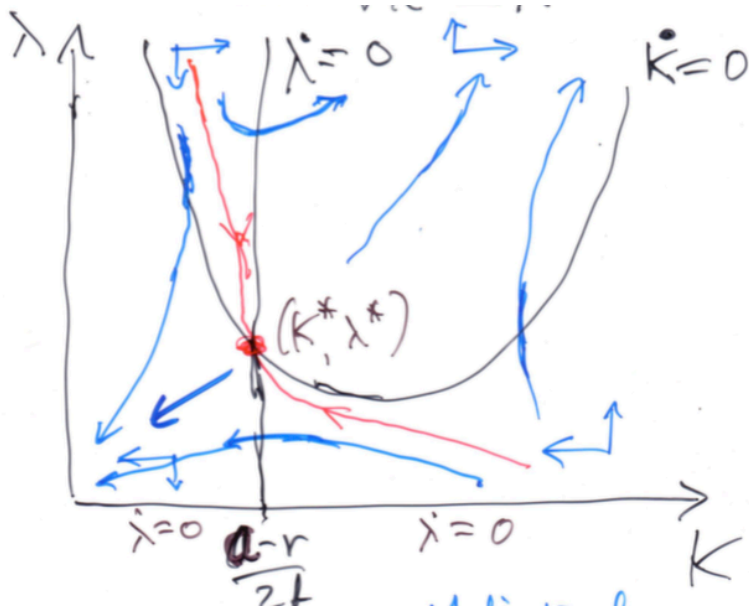
with a unique steady state at

$$K^* = (a - r)/2b, \quad \lambda^* = [K^*(a - bK^*)]^{-\epsilon}$$

The phase diagram on the next slide shows:

1. the two “isoclines” where $\dot{K} = 0$ and $\dot{\lambda} = 0$ respectively;
2. the intersection of these two isoclines at the unique stationary point (K^*, λ^*) ;
3. the division of the plane of (K, λ) values into four different “phases” according as $\dot{K} \gtrless 0$ and $\dot{\lambda} \gtrless 0$, marked by blue arrows pointing in the relevant direction;
4. six possible different solutions of the coupled equations, which are marked by blue curves.

Phase Diagram



Suboptimal Solutions to the Differential Equations

Paths of pairs (K, λ) where λ starts out too low,
and so $C = \lambda^{-1/\epsilon}$ starts out too high:

1. pass below and to the left of the steady state (K^*, λ^*) ;
2. eventually reach the phase where $\dot{K} < 0$ and $\dot{\lambda} < 0$;
3. in that profligate phase, where $K(t)$ reaches 0 in finite time,
after which there is no output
and so $C = K = 0$ for ever thereafter.

Such paths could be optimal for a suitable finite horizon,
but with an infinite horizon, they end in disaster.

Paths of pairs (K, λ) where λ starts out too high,
and so $C = \lambda^{-1/\epsilon}$ starts out too low:

1. pass above and to the right of the steady state (K^*, λ^*) ;
2. eventually reach the phase where $\dot{K} > 0$ and $\dot{\lambda} > 0$;
3. in that phase of wasteful over-accumulation
one has $K(t) \rightarrow \infty$ yet $C(t) \rightarrow 0$ as $t \rightarrow \infty$.

Optimal Solutions to the Differential Equations

The red curve in the phase diagram shows the unique solution curve that passes through the steady state (K^*, λ^*) .

Along this solution curve where $(K, \lambda) \rightarrow (K^*, \lambda^*)$ as $t \rightarrow \infty$ lies the happy medium between:

1. profligacy, where $K(t)$ reaches 0 in finite time;
2. wasteful over-accumulation, where $K(t) \rightarrow \infty$ yet $C(t) \rightarrow 0$ as $t \rightarrow \infty$.

Furthermore, the present discounted value $e^{-rt} \lambda(t) K(t)$ of the capital stock converges to zero.

So the Malinvaud transversality condition is satisfied.

This completes the proof that the path whose graph is the red curve solves the infinite-horizon optimal growth problem.