Dynamic Optimization: Optimal Control

Introductory Mathematical Economics

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Current (Reward Function) Value Hamiltonian Periodic optimal solutions

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- s_t is a state variable at time t
- a_t is a control or (an) action variable at time t
- ► $U(s_t, a_t, t)$ is a single period reward or welfare function
- ► $s_{t+1} = g(s_t, a_t)$ or $s_{t+1} = s_t + f(s_t, a_t, t)$ is the transition equation for the state variable s_t
- ▶ t,T; $(T \leq \infty)$ is the time horizon which could be discrete or continuous

- s_0 is the initial state variable condition
- $s_T = k$ is a terminal condition when $T < \infty$
- $F(s_T)$ is the final period reward function

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A Dynamic Optimization Problem

$$\underset{(s_{t},a_{t}),0 \leq t \leq T}{\operatorname{argmax}} U(s_{0}, a_{0}, 0) + U(s_{1}, a_{1}, 1) + U(s_{2}, a_{2}, 2) + \dots + U(s_{T-1}, a_{T-1}, T-1) + F(s_{T})$$

s.t. $s_{1} = s_{0} + f(s_{0}, a_{0}, 0); \ s_{2} = s_{1} + f(s_{1}, a_{1}, 1) \ s_{3} = s_{2} + f(s_{2}, a_{2}, 2); \dots + s_{T} = s_{T-1} + f(s_{T-1}, a_{T-1}, T-1).$

Why don't we have a constraint for t = T?

$$\begin{split} \mathbf{L} &= [U(s_0, a_0, 0) + \lambda_1 (f(s_0, a_0, 0) + s_0 - s_1)] \\ &+ [U(s_1, a_1, 1) + \lambda_2 (f(s_1, a_1, 1) + s_1 - s_2)] \\ &+ [U(s_2, a_2, 2) + \lambda_3 (f(s_2, a_2, 2) + s_2 - s_3)] + \dots \\ &+ [U(s_{T-1}, a_{T-1}, T - 1) + \lambda_T (f(s_{T-1}, a_{T-1}, T - 1) + s_{T-1} - s_T)] \\ &+ F(s_T) \end{split}$$

$$FONCS(a_t, 0 \le t < T)$$
:

$$\begin{aligned} \frac{\delta \mathbf{L}}{\delta a_{0}} &= U_{2} + \lambda_{1} f_{2} = 0 \\ \frac{\delta \mathbf{L}}{\delta a_{1}} &= U_{2} + \lambda_{2} f_{2} = 0 \\ \frac{\delta \mathbf{L}}{\delta a_{2}} &= U_{2} + \lambda_{3} f_{2} = 0 \\ \vdots \\ \frac{\delta \mathbf{L}}{\delta a_{T-1}} &= U_{2} + \lambda_{T} f_{2} = 0 \end{aligned} \right\} \begin{cases} \frac{\delta \mathbf{L}}{\delta a_{t}} &= U_{2} + \lambda_{t+1} f_{2} = 0 \\ \frac{\delta \mathbf{L}}{\delta a_{T-1}} &= 0 \\ \frac{\delta \mathbf{L}}{\delta a_{T}} &= 0 \quad (why?) \end{aligned}$$

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$$\begin{split} & \text{FONCS}(s_t, \ 0 \leq t \leq T): \\ & \frac{\delta \mathbf{L}}{\delta s_0} = U_1 + \lambda_1 + \lambda_1 f_1 = 0 \\ & \frac{\delta \mathbf{L}}{\delta s_1} = U_1 + \lambda_2 + \lambda_2 f_1 - \lambda_1 = 0 \\ & \frac{\delta \mathbf{L}}{\delta s_2} = U_1 + \lambda_3 + \lambda_3 f_1 - \lambda_2 = 0 \\ & \vdots \\ & \frac{\delta \mathbf{L}}{\delta s_{T-1}} = U_1 + \lambda_T + \lambda_T f_1 - \lambda_{T-1} = 0 \end{split} \begin{cases} \frac{\delta \mathbf{L}}{\delta s_t} = U_1 + \lambda_{t+1} + \lambda_{t+1} f_1 - \lambda_t = 0 \\ & \vdots \\ & \frac{\delta \mathbf{L}}{\delta s_{T-1}} = U_1 + \lambda_T + \lambda_T f_1 - \lambda_{T-1} = 0 \end{cases} \end{split}$$

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$$\begin{split} & \text{FONCS}(\lambda_{t}, \ 1 \leq t \leq T): \\ & \frac{\delta \mathbf{L}}{\delta \lambda_{1}} = s_{0} + f(.) - s_{1} = 0 \\ & \frac{\delta \mathbf{L}}{\delta \lambda_{2}} = s_{1} + f(.) - s_{2} = 0 \\ & \frac{\delta \mathbf{L}}{\delta \lambda_{3}} = s_{2} + f(.) - s_{3} = 0 \\ & \vdots \\ & \frac{\delta \mathbf{L}}{\delta \lambda_{T-1}} = s_{T-2} + f(.) - s_{T-1} = 0 \\ & \frac{\delta \mathbf{L}}{\delta \lambda_{T}} = s_{T-1} + f(.) - s_{T} = 0 \end{split}$$

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Definite Discrete Time Domain: Generalization

$$\begin{aligned} \operatorname*{argmax}_{s_t,a_t} \sum_{t=0}^{T-1} U(s_t, a_t, t), +F(s_T) \\ s.t. \ s_{t+1} &= g(s_t, a_t) \equiv s_{t+1} = s_t + f(s_t, a_t, t) \\ \mathrm{L} &= \sum_{t=0}^{T-1} [U(s_t, a_t, t) + \lambda_{t+1} (f(s_t, a_t, t) + s_t - s_{t+1})] + F(s_T) \\ FONCs: \ \frac{\delta \mathrm{L}}{\delta a_t} &= \frac{\delta U(.)}{\delta a_t} + \lambda_{t+1} \frac{\delta f(.)}{\delta a_t} = 0 \\ \frac{\delta \mathrm{L}}{\delta s_t} &= \frac{\delta U(.)}{\delta s_t} + \lambda_{t+1} + \lambda_{t+1} \frac{\delta f(.)}{\delta s_t} - \lambda_t = 0 \\ \frac{\delta \mathrm{L}}{\delta s_T} &= -\lambda_T + \frac{dF(.)}{ds_T} = 0 \ \& \ \frac{\delta \mathrm{L}}{\delta \lambda_{t+1}} = s_{t+1} = s_t + f(s_t, a_t, t) = 0 \end{aligned}$$

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Continuous Time Domain: Generalization

$$\begin{aligned} \operatorname*{argmax}_{s_{t},a_{t}} \int_{t=0}^{T-1} U(s(t),a(t),(t))dt + F(s(T)) \\ s.t. \ s'(t) &= f(s(t),a(t),(t)) \\ \mathrm{L} = \int_{t=0}^{T-1} [U(s(t),a(t),(t)) + \lambda(t)(f(s(t),a(t),t) - s'(t))]dt + F(s(T))) \\ FONCs: \ \frac{\delta \mathrm{L}}{\delta a(t)} &= \frac{\delta U(.)}{\delta a(t)} + \lambda(t)\frac{\delta f(.)}{\delta a(t)} = 0 \\ \frac{\delta \mathrm{L}}{\delta s(t)} &= \frac{\delta U(.)}{\delta s(t)} + \lambda(t)\frac{\delta f(.)}{\delta s(t)} - \lambda(t)\frac{\delta s'(t)}{\delta s(t)} = 0 \\ \frac{\delta \mathrm{L}}{\delta s(t)} &= \frac{dF(.)}{ds(T)} = 0 \\ \frac{\delta \mathrm{L}}{\delta \lambda(t)} &= f(s(t),a(t),(t)) - s'(t) = 0 \\ s'(t) &= S_{t+1} - S_{t} \end{aligned}$$

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The Hamiltonian

Axiom

Given that the constraint is transitory [has $s'(t) \equiv s_{t+1} - s_t$], we can remodel using the Hamiltonian (removing the transitory component) for easy calculations.

Using discrete time domain

$$\mathbf{L} = \sum_{t=0}^{T-1} [U(s_t, a_t, t) + \lambda_{t+1}(f(s_t, a_t, t) + s_t - s_{t+1})] + F(s_T)$$

$$\mathbf{L} = \sum_{t=0}^{T-1} [U(s_t, a_t, t) + \lambda_{t+1} f(s_t, a_t, t) + \lambda_{t+1} [s_t - s_{t+1}]] + F(s_T)$$

$$Let \ H(a_t, s_t, t) = U(s_t, a_t, t) + \lambda_{t+1} f(s_t, a_t, t)$$

Therefore,

$$\mathbf{L} = \sum_{t=0}^{T-1} [H(s_t, a_t, t) + \lambda_{t+1}[s_t - s_{t+1}]] + F(s_T)$$

$$FONCs: \quad \frac{\delta \mathbf{E}}{\delta a_t} = \frac{\delta H(.)}{\delta a_t} = 0$$

$$\frac{\delta \mathbf{L}}{\delta s_t} = \frac{\delta H(.)}{\delta s_t} + \lambda_{t+1} - \lambda_t = 0 \equiv -\frac{\delta H(.)}{\delta s_t} = \lambda_{t+1} - \lambda_t$$

$$\frac{\delta \mathbf{L}}{\delta s_T} = -\lambda_T + \frac{dF(.)}{ds_T} = 0$$

$$\frac{\delta \mathbf{L}}{\delta \lambda_{t+1}} = \frac{\delta H(.)}{\delta \lambda_{t+1}} + s_t - s_{t+1} = 0$$

In conclusion,

$$\frac{\delta H(.)}{\delta a_t} = 0 \rightarrow \frac{\delta U(.)}{\delta a_t} + \lambda_{t+1} \frac{\delta f(.)}{\delta a_t}$$
$$-\frac{\delta H(.)}{\delta s_t} = \lambda_{t+1} - \lambda_t \rightarrow -\frac{\delta U(.)}{\delta s_t} - \lambda_{t+1} \frac{\delta f(.)}{\delta s_t} = \lambda_{t+1} - \lambda_t$$
$$\frac{dF(.)}{ds_T} = \lambda_T \rightarrow \frac{dF(.)}{ds_T} = \lambda_T$$
$$\frac{\delta H(.)}{\delta \lambda_{t+1}} = s_{t+1} - s_t \rightarrow f(s_t, a_t, t) = s_{t+1} - s_t$$

Similar, applying the Hamiltonian approach to continuous time:

Continuous time domain Hamiltonian

Recall
$$\underset{s_{t},a_{t}}{\operatorname{argmax}} \int_{t=0}^{T-1} U(s(t), a(t), (t)) + F(s(T))$$
$$s.t. \ s'(t) = f(s(t), a(t), (t))$$

We therefore define the Hamiltonian:

$$H(a(t), s(t), t) = U(s(t), a(t), t) + \lambda(t)f(s(t), a(t), t)$$
$$FONCs : \frac{\delta H(.)}{\delta a(t)} = 0 \rightarrow \frac{\delta U(.)}{\delta a(t)} + \lambda(t)\frac{\delta f(.)}{\delta a(t)} = 0$$
$$-\frac{\delta H(.)}{\delta s(t)} = \lambda'(t) \rightarrow -\frac{\delta U(.)}{\delta s(t)} - \lambda(t)\frac{\delta f(.)}{\delta s(t)} = \lambda'(t)$$
$$-\lambda_T + \frac{dF(.)}{ds(T)} = 0 \rightarrow \frac{dF(.)}{ds(T)} = \lambda(T)$$
$$\frac{\delta H(.)}{\delta \lambda(t)} = s'(t) \rightarrow f(s(t), a(t), t) = s'(t)$$

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The Idea

Discount rates (δ) and Discount factors $(1 + \delta)^{-t}$ for discrete time & $e^{-\delta t}$ for continuous time, where $t \leq T$, are used to discount the Hamiltonian to a present value Hamiltonian such that the Hamiltonian doesn't depend **explicitly** but **implicitly** on time (t) through the discount factor.

The Transformation

$$\begin{array}{l} H(a_t, s_t, t) = U(s_t, a_t, t) + \lambda_{t+1} f(s_t, a_t, t) \\ H(a, s) = U(s, a) (1 + \delta)^{-t} + \lambda f(s, a) \end{array} \right\} Discrete \ Time \ Horizon$$

$$\begin{array}{c} H(a(t),s(t),t) = U(s(t),a(t),t) + \lambda(t)f(s(t),a(t),t) \\ H(a,s) = U(s,a)e^{-\delta t} + \lambda f(s,a) \end{array} \right\} Continuous$$

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These are the Hamiltonian for discrete and continuous horizon and their present value Hamiltonian . Note: F(s(T)) becomes $F(s(T))e^{-\delta T}$. Applying the Hamiltonian Approach:

$$H(a,s) = U(s,a)e^{-\delta t} + \lambda f(s,a)$$

FONCs of PVH

$$FONC(a): \quad U_a(s,a)e^{-\delta t} + \lambda f_a(s,a) = 0$$

$$FONC(s): \quad -U_s(s,a)e^{-\delta t} - \lambda f_s(s,a) = \lambda'$$

$$FONC(\lambda): \quad f(s,a) = s'$$

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Periodic optimal solutions

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The idea here is to explicitly make the Hamiltonian independent of time (t). However, the current reward function value of hamiltonian is still **implicitly** dependent on time(t). The later will be clear soon, while getting the FONCs of a current value hamiltonian.

The Transformation

$$H(a,s) = U(s,a)e^{-\delta t} + \lambda f(s,a) \dots PVH$$
$$\hat{H}(s,a) = H(a,s) \times e^{\delta t} = U(s,a) + \lambda e^{\delta t} f(s,a)$$
$$Let \quad \mu = \lambda e^{\delta t}$$
$$\hat{H}(s,a) = U(s,a) + \mu f(s,a) \dots CVH$$

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$$FONC(\mu): f(s,a) = s'$$

$$FONC(a): U_a(s,a) + \mu f_a(s,a) = 0$$

$$FONC(s): -U_s(s,a) - \mu f_s(s,a) = \lambda' e^{\delta t}$$

Note: The FONCs of CVH = $e^{\delta t} PVH$. However, we do not have λ in CVH, so what is $\lambda' e^{\delta t}$?

λ'			

$$\mu = \lambda e^{\delta t}$$

Recall, λ **implicitly** depends on time, so $\lambda' = \frac{d\lambda}{dt}$ exits. Clearly, we can write

$$\mu' = \lambda \delta e^{\delta t} + \lambda' e^{\delta t}$$
$$\lambda' e^{\delta t} = \mu' - \delta \lambda e^{\delta t}$$
$$\lambda' e^{\delta t} = \mu' - \delta \mu$$

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Clearly, we can rewrite the FONCs of a CVH as

$$\frac{\delta \hat{H}}{\delta \mu} = s'$$
$$\frac{\delta \hat{H}}{\delta a} = 0$$
$$-\frac{\delta \hat{H}}{\delta s} = \mu' - \delta \mu$$

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Examples

The Fishery Problem

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Fishery Problem

- $\blacktriangleright \ U(s(t),a(t).t) = \ln(a(t))$
- $\blacktriangleright \ s'(t) = f(s(t), a(t))$
- ► $f(s(t), a(t)) = s(t)[1 \frac{s(t)}{s(0)}] a(t)$
- $\delta = 0.2$
- ► s(0) = 100
- ▶ a(t) is fish harvest at time (t); s(t) is the stock of fish at time (t); & U(s(t),a(t)) is the reward function at time (t)

Tasks:

- 1. Solve for the steady state values μ^{\star} , a^{\star} , and s^{\star}
- 2. Conduct a stability analysis
- 3. What type of local or global steady state exists in this problem

Solving for the steady state values

$$H = \ln(a(t))e^{-0.2t} + \lambda[s(t)(1 - \frac{s(t)}{100}) - a(t)]$$
$$\hat{H} = \ln(a) + \mu[s(1 - \frac{s}{100}) - a]$$

are the PVH and CVH respectively.

FONCs of CVH

$$\frac{1}{a} - \mu = 0 \quad eqn(1)$$
$$-\mu(1 - \frac{s}{50}) = \mu' - 0.2\mu \quad eqn(2)$$
$$s[1 - \frac{s}{100}] - a = s' \quad eqn(3)$$

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From eqn.(2)

$$s = 40 + 50 \frac{\mu'}{\mu} \to s^* = 40 |\mu' = 0$$

From eqn.(3)

$$a^{\star} = s^{\star} [1 - \frac{s^{\star}}{100}] | s' = 0 \to a^{\star} = 24$$

From eqn.(1)

$$\mu^{\star} = \frac{1}{a^{\star}} \to \frac{1}{24}$$

Therefore,

$$s^{\star} = 40, \quad a^{\star} = 24 \quad \mu^{\star} = \frac{1}{24}$$

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Conducting a stability analysis

Recall our system of equations:

$$\frac{1}{a} - \mu = 0 \quad eqn(1)$$
$$-\mu(1 - \frac{s}{50}) = \mu' - 0.2\mu \quad eqn(2)$$
$$s(t)[1 - \frac{s}{100}] - a = s' \quad eqn(3)$$

We need a DTE system of equations for the action and state variables.

Combine (1) and (2)

$$-a^{-1}[1 - s50^{-1}] = -a^{-2}a' - 0.2a^{-1}$$
$$a' = [0.8 - \frac{s}{50}]a$$
$$s' = s[1 - \frac{s}{100}] - a \quad eqn(3)$$

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From $s' = s[1 - \frac{s}{100}] - a$ we set s' = 0 and plot $a = s[1 - \frac{s}{100}]$ using the fact that a is concave in s (concave parabola i.e. negative quadratic coefficient).Consider what happens to s' when a increases and decreases. 1.) From s' = 0 upwards, a increases $\rightarrow s'$ decreases from $s' = s[1 - \frac{s}{100}] - a$ 2.)From s' = 0 downwards, adecreases and s' increases.

Figure 1: s' Isocline

From $a' = [0.8 - \frac{s}{50}]a$ we set a' = 0 and plot s = 40. Consider what happens to a' when s increases and decreases. 1.)From a' = 0 rightward, s increases and a' decreases 2.)From a' = 0 leftward, s decreases

and a' increases



Figure 2: a' Isocline

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Combining the Isoclines



Figure 3: Phase Diagram

Type of Stability

Recall

$$a' = [0.8 - \frac{s}{50}]a \rightarrow G(s, a)$$
$$s' = s[1 - \frac{s}{100}] - a \quad \rightarrow F(s, a)$$

$$s^{\star} = 40, \quad a^{\star} = 24$$

To calculate the stability form, we need to examine the eigenvalues using the Jacobian matrix.

$$J = \begin{bmatrix} F_s(s,a) & F_a(s,a) \\ G_s(s,a) & G_a(s,a) \end{bmatrix} | s^*, a^* = \begin{bmatrix} 0.2 & -1 \\ -0.48 & 0 \end{bmatrix}$$
$$\begin{bmatrix} 0.2 - \lambda & -1 \\ -0.48 & -\lambda \end{bmatrix} \rightarrow \lambda = 0.8 \quad or \quad -0.6$$

Therefore, we have a local saddle point (since the eigenvalues are positive and negative).