

# Optimization in Continuous Time

Jesús Fernández-Villaverde

University of Pennsylvania

November 9, 2013

## Three Approaches

- We are interested in optimization in continuous time, both in deterministic and stochastic environments.
- Elegant and powerful math (differential equations, stochastic processes...).
- Three approaches:
  - ① Calculus of Variations.
  - ② Optimal Control.
  - ③ Dynamic Programming.
- We will focus on the last two:
  - ① Optimal control can do everything economists need from calculus of variations.
  - ② Dynamic programming is better for the stochastic case.

# Maximization Problem I

- Basic setup:

$$V(0, x(0)) = \max_{x(t), y(t)} \int_0^{\infty} f(t, x(t), y(t)) dt$$

$$\text{s.t. } \dot{x} = g(t, x(t), y(t))$$

$$x(0) = x_0, \quad \lim_{t \rightarrow \infty} b(t)x(t) \geq x_1$$

$$x(t) \in \mathcal{X}, y(t) \in \mathcal{Y}$$

- $x(t)$  is a state variable.
- $y(t)$  is a control variable.

## Maximization Problem II

- **Admissible pair:**  $(x(t), y(t))$  s.t. the previous conditions are satisfied.
- **Optimal pair:**  $(\hat{x}(t), \hat{y}(t))$  that reach  $V(0, x(0)) < \infty$ .  
Then:

$$V(0, x(0)) = \int_0^{\infty} f(t, \hat{x}(t), \hat{y}(t)) dt$$

- Two difficulties:
  - ① We need to find a whole function  $y(t)$  of optimal choices.
  - ② The constraint is in the form of a differential equation.

# Optimal Control

- Pontryagin and co-authors.

## Principle of Optimality

If  $(\hat{x}(t), \hat{y}(t))$  is an optimal pair, then:

$$V(t_0, x(t_0)) = \int_{t_0}^{t_1} f(t, \hat{x}(t), \hat{y}(t)) dt + V(t_1, \hat{x}(t_1))$$

for all  $t_1 \geq t_0$ .

- We will assume that there is an optimal path.
- Proving existence is, however, not a trivial task.

# Hamiltonian

- Define:

$$\mathcal{H}(t, x(t), y(t), \lambda(t)) = f(t, x(t), y(t)) + \lambda(t) g(t, x(t), y(t))$$

where  $\lambda(t)$  is the co-state multiplier.

- Necessary conditions:

$$\mathcal{H}_y(t, \hat{x}(t), \hat{y}(t), \lambda(t)) = 0$$

$$\dot{\lambda}(t) = -\mathcal{H}_x(t, \hat{x}(t), \hat{y}(t), \lambda(t))$$

$$\dot{x} = \mathcal{H}_\lambda(t, \hat{x}(t), \hat{y}(t), \lambda(t))$$

plus  $x(0) = x_0$  and  $\lim_{t \rightarrow \infty} b(t) x(t) \geq x_1$ .

# Exponential Discounting Case I

- More specific form:

$$\begin{aligned} V(x(0)) &= \max_{x(t), y(t)} \int_0^{\infty} e^{-\rho t} f(x(t), y(t)) dt \\ &\text{s.t. } \dot{x} = g(x(t), y(t)) \\ x(0) &= x_0, \quad \lim_{t \rightarrow \infty} b(t) x(t) \geq x_1 \\ x(t) &\in \text{Int}\mathcal{X}, y(t) \in \text{Int}\mathcal{Y} \end{aligned}$$

- $g(x(t), y(t))$  being autonomous is not needed but it helps to simplify notation.

## Exponential Discounting Case II

- Hamiltonian:

$$\begin{aligned}\mathcal{H}(t, x(t), y(t), \lambda(t)) &= e^{-\rho t} f(x(t), y(t)) + \lambda(t) g(x(t), y(t)) \\ &= e^{-\rho t} [f(x(t), y(t)) + \mu(t) g(x(t), y(t))]\end{aligned}$$

where

$$\mu(t) = e^{\rho t} \lambda(t)$$

- Current-Value Hamiltonian:

$$\hat{\mathcal{H}}(x(t), y(t), \mu(t)) = f(x(t), y(t)) + \mu(t) g(x(t), y(t))$$



# Maximum Principle for Discounted Infinite-Horizon Problems

## Theorem

*Under some technical conditions, the optimal pair  $(\hat{x}(t), \hat{y}(t))$  satisfies the necessary conditions:*

- ①  $\hat{\mathcal{H}}_y(x(t), y(t), \mu(t)) = 0$  for  $\forall t \in \mathbb{R}_+$ .
- ②  $\hat{\mathcal{H}}_x(x(t), y(t), \mu(t)) = \rho\mu(t) - \dot{\mu}(t)$  for  $\forall t \in \mathbb{R}_+$ .
- ③  $\hat{\mathcal{H}}_\mu(x(t), y(t), \mu(t)) = \dot{x}(t)$  for  $\forall t \in \mathbb{R}_+$ ,  $x(0) = x_0$  and  $\lim_{t \rightarrow \infty} x(t) \geq x_1$ .
- ④  $\lim_{t \rightarrow \infty} e^{-\rho t} \hat{\mathcal{H}}(x(t), y(t), \mu(t)) = \lim_{t \rightarrow \infty} e^{-\rho t} \mu(t) \hat{x}(t) = 0$ .

## Sufficiency Conditions

- Previous theorem only delivers necessary conditions.
- However, we also need sufficient conditions.

### Theorem

*Mangasarian Sufficient Conditions for Discounted Infinite-Horizon Problems. The necessary conditions will be sufficient if  $f$  and  $g$  are continuously differentiable and weakly monotone and  $\mathcal{H}(t, x(t), y(t), \lambda(t))$  is jointly concave in  $x(t)$  and  $y(t)$  for  $\forall t \in \mathbb{R}_+$ .*

- We will skip sufficiency arguments. They will be relevant later in models of endogenous growth.

## Example I

- Consumption-savings problem:

$$V(a) = \max_{a,c} \int_0^{\infty} e^{-\rho t} u(c) dt$$

$$\dot{a} = ra + w - c$$

- Hamiltonian:

$$\hat{\mathcal{H}}(a, c, \mu) = u(c) + \mu(ra + w - c)$$

- Necessary conditions:

$$\hat{\mathcal{H}}_c(a, c, \mu) = 0 \Rightarrow u'(c) - \mu = 0 \Rightarrow u'(c) = \mu$$

$$\hat{\mathcal{H}}_a(a, c, \mu) = \rho\mu - \dot{\mu} \Rightarrow r\mu = \rho\mu - \dot{\mu} \Rightarrow \frac{\dot{\mu}}{\mu} = -(r - \rho)$$

## Example II

- Then:

$$u''(c) \dot{c} = \dot{\mu} \Rightarrow$$

$$\frac{u''(c)}{u'(c)} \dot{c} = \frac{\dot{\mu}}{\mu} = -(r - \rho)$$

- Assume, for instance:

$$u(c) = \log c$$

and we get:

$$\frac{\dot{c}}{c} = r - \rho$$

- Comparison with bang-bang solutions (linear returns and bounded controls).

# Dynamic Programming

- Dynamic programming is a more flexible approach (for example, later, to introduce uncertainty).
- Instead of searching for an optimal path, we will search for decision rules.
- Cost: we will need to solve for PDEs instead of ODEs.
- But at the end, we will get the same solution.

## Hamilton-Jacobi-Bellman (HJB) Equation

- When  $V(t, x(t))$  is differentiable,  $(\hat{x}(t), \hat{y}(t))$  satisfies:

$$f(t, \hat{x}(t), \hat{y}(t)) + \dot{V}(t, \hat{x}(t)) + V_x(t, \hat{x}(t)) g(t, \hat{x}(t), \hat{y}(t)) = 0$$

- Similar the Euler equation from a value function in discrete time.
- Other way to write the formula, closer to the Bellman equation:

$$-\dot{V}(t, \hat{x}(t)) = \max_{x(t), y(t)} f(t, x(t), y(t)) + g(t, x(t), y(t)) V_x(t, x(t))$$

- Tight connection between  $V_x(t, x(t))$  and  $\mu(t)$ .

# Solution of the HJB Equation I

- The HJB equation allows for easy derivations.
- For exponential discount problems:

$$V(t, \hat{x}(t)) = \int_t^{\infty} e^{-\rho s} f(\hat{x}(s), \hat{y}(s)) ds$$

- Note that:

$$V(t, \hat{x}(t)) = e^{-\rho t} \int_t^{\infty} e^{-\rho(s-t)} f(\hat{x}(s), \hat{y}(s)) ds$$

and the integral on the right hand side does not depend on  $t$ .

## Solution of the HJB Equation II

- Then:

$$\begin{aligned}
 \dot{V}(t, \hat{x}(t)) &= -\rho e^{-\rho t} \int_t^{\infty} e^{-\rho(s-t)} f(\hat{x}(s), \hat{y}(s)) ds \\
 &= -\rho \int_t^{\infty} e^{-\rho s} f(\hat{x}(s), \hat{y}(s)) ds \\
 &= -\rho V(t, \hat{x}(t))
 \end{aligned}$$

- Simplifying notation:

$$\rho V(x) = \max_{x,y} f(x, y) + g(x, y) V'(x)$$



## Solution of the HJB Equation III

- Characterized by a necessary condition:

$$f_y(x, y) + g_y(x, y) V'(x) = 0$$

and an envelope condition:

$$(\rho - g_x(x, y)) V'(x) - f_x(x, y) = g(x, y) V''(x)$$

- Then:

$$V'(x) = -\frac{f_y(x, y)}{g_y(x, y)} = h(x, y)$$

and

$$V''(x) = h_x(x, y) + h_y(x, y) \frac{dy}{dx}$$

## Solution of the HJB Equation IV

- We can plug these two equations in the envelope condition, to get:

$$\begin{aligned} & (\rho - g_x(x, y)) h(x, y) - f_x(x, y) \\ = & \left( h_x(x, y) + h_y(x, y) \frac{dy}{dx} \right) g(x, y) \end{aligned}$$

an ODE on  $\frac{dy}{dx}$ .

- Analytical solutions?
- Standard numerical solution methods.

## Solution of the HJB Equation V

- With our previous example:

$$\rho V(a) = \max_{a,c} u(c) + (ra + w - c) V'(a)$$

- Then:

$$h(a, c) = u'(c)$$

and:

$$-(r - \rho) u'(c) = u''(c) \frac{dc}{da} \dot{a} = u''(c) \dot{c}$$

- Therefore, as before:

$$\frac{u''(c)}{u'(c)} \dot{c} = -(r - \rho)$$

## Comparison with Discrete Time

- HJB versus Bellman equation:

$$\rho V(a) = \max_{a,c} u(c) + (ra + w - c) V'(a)$$

$$V(a) = \max_{a,c} u(c) + \beta V((1+r)a + w - c)$$

- Optimality conditions:

$$\frac{u''(c)}{u'(c)} \dot{c} = -(r - \rho)$$

$$\frac{u'(c')}{u'(c)} = \beta(1+r)$$

# Stochastic Case

- We move now into the stochastic case.
- Handling it with calculus of variations or optimal control is hard.
- At the same time, there are many problems in macro with uncertainty which are easy to formulate in continuous time.

# Stochastic Problem

- Consider the problem:

$$V(x(0)) = \max_{x(t), y(t)} \mathbb{E} \int_0^{\infty} e^{-\rho t} f(x(t), y(t)) dt$$

$$\text{s.t. } dx(t) = g(x(t), y(t)) dt + \sigma(x(t)) dW(t)$$

give some initial conditions.

- The evolution of the state is a controlled diffusion.
- If  $f$  is continuous and bounded, the integral is well defined.

## Value Function and a Bellman-Type Property

- Given a small interval of time  $\Delta t$ , we get:

$$V(x(0)) \approx \max_{x,y} f(x(0), y(0)) \Delta t + \frac{1}{1 + \rho \Delta t} \mathbb{E}[V(x(0 + \Delta t))]$$

- Multiply by  $(1 + \rho \Delta t)$  and subtract  $V(x(0))$ :

$$\rho V(x(0)) \Delta t \approx \max_{x,y} f(x(0), y(0)) \Delta t (1 + \rho \Delta t) + \mathbb{E}[\Delta V]$$

- Divide by  $\Delta t$

$$\rho V(x(0)) \approx \max_{x,y} f(x(0), y(0)) (1 + \rho \Delta t) + \frac{1}{\Delta t} \mathbb{E}[\Delta V]$$

- Letting  $\Delta t \rightarrow 0$  and taking the limit:

$$\rho V(x(0)) = \max_{x,y} f(x(0), y(0)) + \frac{1}{dt} \mathbb{E}[dV]$$

# Hamilton-Jacobi-Bellman (HJB) Equation I

- Given a small interval of time  $\Delta t$ , we get:

$$\rho V(x) = \max_{x,y} f(x,y) + \frac{1}{dt} \mathbb{E}[dV]$$

- Applying previous results:

$$\frac{1}{dt} \mathbb{E}[dV] = \left[ gV' + \frac{1}{2} \sigma^2 V'' \right]$$

we have

$$\rho V(x) = \max_{x,y} f(x,y) + g(x,y) V'(x) + \frac{1}{2} \sigma^2(x) V''(x) \quad \forall x$$

- Important observation: thanks to Itô's lemma, the HJB is not stochastic.



## Hamilton-Jacobi-Bellman (HJB) Equation II

- Comparison with deterministic case:

$$\rho V(x) = \max_{x,y} f(x,y) + g(x,y) V'(x)$$

$$\rho V(x) = \max_{x,y} f(x,y) + g(x,y) V'(x) + \frac{1}{2} \sigma^2(x) V''(x)$$

Extra term  $\frac{1}{2} \sigma^2(x) V''(x)$  corrects for curvature.

- Concentrated HJB:

$$\rho V(x) = f(x, y(x)) + g(x, y(x)) V'(x) + \frac{1}{2} \sigma^2(x) V''(x)$$

is the Feynman–Kac formula that links parabolic partial differential equations (PDEs) and stochastic processes.

# Hamilton-Jacobi-Bellman (HJB) Equation III

- Characterized by a necessary condition:

$$f_y(x, y) + g_y(x, y) V'(x) = 0$$

and an envelope condition:

$$(\rho - g_x(x, y)) V'(x) - f_x(x, y) = \\ g(x, y) V''(x) + \frac{1}{2} \sigma^2(x) V'''(x) + \sigma(x) \sigma'(x) V''(x)$$

- Solutions:
  - Theoretical: classical, viscosity, backward SDE, martingale duality.
  - Numerical.

# Real Business Cycle I

- Standard business cycle framework without labor choice:

$$\begin{aligned} \max_{\{c(t), k(t)\}_{t=0}^{\infty}} \quad & \mathbb{E}_0 \int_0^{\infty} e^{-\rho t} u(c(t)) dt \\ \text{s.t.} \quad & \dot{k} = e^z k^\alpha - \delta k - c \\ & dz = -\lambda z dt + \sigma z dW \end{aligned}$$

- HJB:

$$\begin{aligned} \rho V(k, z) = \\ u(c) + (e^z k^\alpha - \delta k - c) V_1(k, z) - \lambda z V_2(k, z) + \frac{1}{2} (\sigma z)^2 V_{22}(k, z) \end{aligned}$$

## Real Business Cycle II

- Necessary condition

$$u'(c(t)) - V_1(k, z) = 0$$

and envelope condition:

$$\begin{aligned} & (\rho - (\alpha e^z k^{\alpha-1} - \delta)) V_1(k, z) \\ = & (e^z k^\alpha - \delta k - c) V_{11}(k, z) - \lambda z V_{21}(k, z) \\ & + \frac{1}{2} (\sigma z)^2 V_{221}(k, z) + \sigma^2 z V_{22}(k, z) \end{aligned}$$