

Macroeconomics B Notes

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1 Dynamic Optimisation in Continuous Time

Continuous vs Discrete Time: in discrete time the intervals between periods are $\Delta > 0$ (e.g. the interval between t and $t + 1$ is 1), in continuous time the intervals between periods are $\Delta \rightarrow 0$

Continuous Variables Issue: while state variables are often naturally continuous, when using computational methods we can only evaluate the value function on a finite number of points

- Solution: we can address this problem via using (1) discretization of the state space, or, (2) polynomial approximation to the value function

Discretization Method: consider a problem with continuous state and control variables $\mathbf{x} \in \mathbb{R}$, discretization just replaces \mathbf{x} and \mathbf{u} by the finite grids $\hat{\mathbf{x}} = \{x^1, \dots, x^n\}$ and $\hat{\mathbf{u}} = \{u^1, \dots, u^n\}$

- Value Function Impact: now the value function becomes a finite list of numbers, $V = [V^1, \dots, V^n]^T$
- Advantage: the maximization step is much simpler than under the original bellman equation, which is a key advantage of discretization methods
- Disadvantage: there is a "curse of dimensionality" in multidimensional state spaces where we must decide whether to have N points for a one-dimensional state space vs N^k points for a k -dimensional state space
 - Grid Decision: requires some a-priori information about the state space, which is sometimes difficult to obtain (e.g. upper and lower bounds)
- Optimal Growth Illustration: suppose $V(k) = \max_{k'} \{\ln(Ak^\alpha - k') + \beta V(k')\}$ where in this case $\mathbf{x} = \mathbf{u}$

*Please see google notes

- Discretization: if we discretize \mathbf{x} then the Bellman equation becomes $V_i = \max_j \{ \ln(Ak_i^\alpha - k_j) + \beta V_j \}$ for all $i = 1, \dots, n$
- Value Function Iteration Solution: suppose we applied value function iteration and therefore iterate on the mapping $V_i^s = \max \{ \ln(Ak_i^\alpha - k_1) + \beta V_1^{s-1}, \dots, \ln(Ak_i^\alpha - k_n) + \beta V_n^{s-1} \}$ for all $i = 1, \dots, n$ where s indexes the iteration step

VF ITERATION

① Start w/ a guess:

$$V^0 = \begin{bmatrix} V_1^0 \\ V_2^0 \\ \vdots \\ V_n^0 \end{bmatrix}, \text{ where } V_i^0 \equiv V^0(k_i)$$

② Find V^1 by solving:

$$V_i^1 = \max_j \{ \ln(Ak_i^\alpha - k_j) + \beta V_j^0 \}$$

expanding

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$$V_i^1 = \max \begin{bmatrix} \ln(Ak_i^\alpha - k_1) + \beta V_1^0 \\ \ln(Ak_i^\alpha - k_2) + \beta V_2^0 \\ \vdots \\ \ln(Ak_i^\alpha - k_n) + \beta V_n^0 \end{bmatrix} \quad \text{for } i$$

so I end up with:

$$V^1 = \begin{bmatrix} V_1^1 \\ V_2^1 \\ \vdots \\ V_n^1 \end{bmatrix}$$

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③ Check for convergence :

$$\|V^1 - V^0\| \leq \epsilon \rightarrow \text{tolerance level}$$

$$\sqrt{\sum_{i=1}^n (V_i^1 - V_i^0)^2} \rightarrow \text{Euclidean Norm.}$$

④ Compute V^S by solving :

$$V_i^S = \max \{ \ln(Ah_i^\alpha - k_i) + \beta V_i^{S-1} \} \quad \forall i$$

⑤ Check convergence

$$\|V^S - V^{S-1}\| \leq \epsilon \quad \longrightarrow$$

* If $\|V^S - V^{S-1}\| \leq \epsilon$ holds \rightarrow STOP

* If $\|V^S - V^{S-1}\| > \epsilon$ does not hold
 \Rightarrow Go Back to step ④

Ordinary Differential Equations (ODEs): a "differential equation" is one where the unknown is a function (instead of a variable) and the equation includes one or more of the derivatives of the function, an "ordinary differential equation" equation is one for which the unknown is a function of only one variable (typically time)

- Partial ODEs: where the unknown is a function of more than one variable
- First-Order ODE Form: $\dot{x}(t) = F(t, x(t))$ where $\dot{x}(t) \equiv dx(t)/dt$ and $t \in [t_a, t_b]$
 - Unknown: here the unknown is a function $x(t)$ with $x : [t_a, t_b] \rightarrow \mathbb{R}$
 - Uniqueness: the solution is not unique with the form having infinitely many solutions indexed by an integrating constant C. However, generally the constant C can be uniquely determined by requiring the solution to pass through a given point on the tx -plane

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