

Section 01 : Mathematics of Dynamic Programming

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Outline

- ① Dynamic Programming
 - ① Sequence Problem to Functional Problem
- ② Policy Function
- ③ When does the (FE) problem have a solution?
 - Contraction Mapping Theorem
 - Blackwell's Sufficient Condition
- ④ How to Solve the Problem?
 - Guess and Verify Method
 - Functional Euler Equation
- ⑤ Optimal Stopping Problem

Optimal Growth Problem, Sequence Problem

- **Problem 1 (SP)**

$$\begin{aligned} \max_{\{c_t, k_{t+1}\}_{t=0}^{\infty}} \quad & \sum_{t=0}^{\infty} \beta^t U(c_t) \\ \text{s.t.} \quad & c_t + k_{t+1} \leq f(k_t), \quad c_t, k_{t+1} \geq 0, \quad \forall t \\ & \text{given } k_0 \end{aligned}$$

which is equivalent to

$$\begin{aligned} \max_{\{k_{t+1}\}_{t=0}^{\infty}} \quad & \sum_{t=0}^{\infty} \beta^t U(f(k_t) - k_{t+1}) \\ \text{s.t.} \quad & 0 \leq k_{t+1} \leq f(k_t) \quad \forall t \\ & \text{given } k_0 \end{aligned}$$

From the Sequence Problem to Functional Equation

① Sequence Problem (SP)

- The problem in the previous slide is referred to as the **sequence problem**.
- We would like to choose an infinite sequence $\{k_{t+1}\}_{t=0}^{\infty}$ from some space of infinite sequences, $\{\tilde{k}_{t+1}\}_{t=0}^{\infty}$

② Dynamic Programming: SP \rightarrow FE

- Here, we would like to transform a sequence problem to a functional equation.
- Instead of finding a sequence, we would like to find a function, as this often gives better insights, similar to the logic of comparing today and tomorrow.
- This formulation is sometimes easier to characterize analytically and numerically.

From the Sequence Problem to Functional Equation

$$V^*(k_0) = \max_{\{k_{t+1}\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t U(f(k_t) - k_{t+1}), \quad \text{s.t.} \quad k_{t+1} \in \Gamma(k_t) \quad \forall t$$

$$\begin{aligned} V^*(k_0) &= \max_{k_{t+1} \in \Gamma(k_t) \forall t} \sum_{t=0}^{\infty} \beta^t U(f(k_t) - k_{t+1}) \\ &= \max_{k_1 \in \Gamma(k_0)} \left[U(f(k_0) - k_1) + \max_{k_{t+1} \in \Gamma(k_t) \forall t} \sum_{t=1}^{\infty} \beta^t U(f(k_t) - k_{t+1}) \right] \\ &= \max_{k_1 \in \Gamma(k_0)} \left[U(f(k_0) - k_1) + \max_{k_{(t+1)+1} \in \Gamma(k_{t+1}) \forall t} \sum_{t=0}^{\infty} \beta^{t+1} U(f(k_{t+1}) - k_{(t+1)+1}) \right] \\ &= \max_{k_1 \in \Gamma(k_0)} \left[U(f(k_0) - k_1) + \beta \max_{k_{(t+1)+1} \in \Gamma(k_{t+1}) \forall t} \sum_{t=0}^{\infty} \beta^t U(f(k_{t+1}) - k_{(t+1)+1}) \right] \\ &= \max_{k_1 \in \Gamma(k_0)} [U(f(k_0) - k_1) + \beta V^*(k_1)] \end{aligned}$$

From the Sequence Problem to Functional Equation

- **Problem 2 (FE)**

$$\begin{aligned} V(k_0) &= \max_{k_1} \{U(f(k_0) - k_1) + \beta V(k_1)\} \\ \text{s.t. } k_1 &\in \underbrace{\Gamma(k_0)}_{=\text{Feasible Set}} = [0, f(k_0)], \text{ given } k_0 \end{aligned}$$

- We are now solving for a **function** V not a **sequence** $\{k_{t+1}\}_{t=0}^{\infty}$
- Here, instead of finding a sequence $\{k_{t+1}\}_{t=0}^{\infty}$, we would like to find a function $V(k)$, for all k , satisfying the Bellman equation defined as previous.
- Because the function V is defined **recursively**, this is often referred to as the **recursive formulation**.

Remarks on Bellman Equation

- **Bellman Equation**

$$V(k) = \max_{k'} \{U(f(k) - k') + \beta V(k)\}$$
$$\text{s.t. } k' \in \Gamma(k) = [0, f(k)]$$

- Note that $V(k)$ is a function. $V : K \rightarrow \mathbb{R}$.
- V does NOT depend on t . This implies that the above equation is **stationary**.
 - Note that finite-horizon problem is **non-stationary**, i.e. V depends on t , as it depends on the remaining time periods.
- How should we put $V(K)$ into the computer?

- **Bellman Equation**

$$V(k) = \max_{k'} \{U(f(k) - k') + \beta V(k)\}$$
$$\text{s.t. } k' \in \Gamma(k) = [0, f(k)]$$

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Policy Function

- This problem generates the solution, which is often called **policy function**, $G : K \rightarrow K$, determining the value of k' given k .

$$G(k) = \text{arg} \max_{k' \in \Gamma(k)} [U(f(k) - k') + \beta V(k')]$$

$$V(k) = U(f(k) - G(k)) + \beta V(G(k)), \quad \forall k \in K$$

Policy Function

Are the solutions of the two problems equivalent?

$$V^*(k_0) = \max_{\{0 \leq k_{t+1} \leq f(k_t)\}_{t=0}^{\infty}} \sum_{t=0}^{\infty} \beta^t \underbrace{F(k_t, k_{t+1})}_{=U(f(k_t)-k_{t+1})}, \quad \forall \quad t = 0, 1, \dots, \text{ given } k_0$$
$$V(k) = \max_{k' \in \Gamma(K)} \{F(k, k') + \beta V(k')\}$$

Want: Under what conditions, the two are equivalent?

Equivalence of Value Function and Policy Function

Want: Under what conditions, the two are equivalent?

To answer this, we'll need **some definitions**:

- A set of **feasible sequences** or plans with initial value of k_0 :

$$\Pi(k_0) = \{ \{k_{t+1}\}_{t=0}^{\infty} : k_{t+1} \in \Gamma(k_t), t = 0, 1, \dots, \}$$

- $\mathbf{k} = \{k_0, k_1, \dots\} \in \Pi(k_0)$.
- Let $V^*(k_0)$ be the maximum in Problem 1. (SP).
- Let $V(k_0)$ be the solution of the Problem 2. (FE).

Equivalence of Value Function and Policy Function

Equivalence Between Value Functions

- **(Assumption 1)**

- $\Gamma(k)$ is nonempty for all $k \in K$.
- For all $k_0 \in K$, and $\mathbf{k} \in \Pi(k_0)$, $\lim_{n \rightarrow \infty} \sum_{t=0}^n \beta^t F(k_t, k_{t+1})$ exists.

- Let K , Γ , F , and β satisfy (Assumption 1). Then

$$V^*(k_0) = \sup_{\mathbf{k} \in \Pi(k_0)} \sum_{t=1}^{\infty} \beta^t F(k_t, k_{t+1})$$

is the **unique** solution, to Problem 2 (SP), though there can be many \mathbf{k} that achieve this.

Equivalence of Value Function and Policy Function

Equivalence Between Value Functions

- Let K , Γ , F , and β satisfy (Assumption 1). If V (which is a solution of (FE)) satisfies

$$\lim_{n \rightarrow \infty} \beta^n V(k_n) = 0, \quad \text{for all } \{k_0, k_1, \dots\} \in \Pi(k_0), \quad \forall k_0 \in K,$$

then $V = V^*$.

Equivalence of Value Function and Policy Function

Equivalence Between Policy Functions (Principle of Optimality)

- Let K , Γ , F , and β satisfy (Assumption 1). Let $\mathbf{k}^* \in \Pi(k_0)$ be a feasible plan that attains the maximum in Problem 1 (SP), starting with k_0 . Then

$$V^*(k_t^*) = F(k_t^*, k_{t+1}^*) + \beta V^*(k_{t+1}^*), \quad t = 0, 1, 2, \dots$$

Moreover, if any $\mathbf{k}^* \in \Pi(k_0)$ satisfies the above, then it attains the optimal value in

$$V(k^*) = F(k^*, k'^*) + \beta V(k'^*)$$

Equivalence of Value Function and Policy Function

Equivalence Between Policy Functions (Principle of Optimality)

$$\begin{aligned} V(k_0^*) &\geq F(k_0^*, k_1^*) + \beta V(k_1^*) \quad (\text{FE}) \\ &\geq \sum_{t=1}^T \beta^t F(k_t^*, k_{t+1}^*) + \beta^{T+1} V(k_{T+1}^*) \\ \lim_{T \rightarrow \infty} V(k_0^*) &\geq \lim_{T \rightarrow \infty} \sum_{t=0}^T \beta^t F(k_t^*, k_{t+1}^*) + \underbrace{\lim_{T \rightarrow \infty} \beta^{T+1} V(k_{T+1}^*)}_{=0 \text{ By Assumption}} \\ &= \sum_{t=0}^{\infty} \beta^t F(k_t^*, k_{t+1}^*) \\ &= V^*(k_0^*) \quad (\text{SP}) \end{aligned}$$

- Must be the same solution since $V^*(k_0^*)$ is unique

When Does a Solution Exist?

- To that end, let's formulate the Bellman Equation as a Mapping:

$$W(k) = T[V(k)]$$
$$T[V(k)] = \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\}$$

which maps function V to a new function W .

- Then, a **Fixed Point** of T , $T[V] = V$, will be a solution to this above problem.

When Does a Solution Exist?

- To see the existence of the solution, we need more assumption.
- **(Assumption 2)**
 - K is a compact subset of \mathbb{R}^K .
 - Γ is nonempty, compact-valued and continuous.
 - Moreover, let $A = \{(k, y) \in K \times K : y \in \Gamma(k)\}$ and $F : A \rightarrow \mathbb{R}$ be bounded and continuous.
- Remarks on Assumption 2
 - This assumption allows us to focus on the space of **bounded functions**, which implies that $V^*(K)$ is bounded as well.
 - Therefore, we can focus our attention on value functions in the space of $\mathbf{B}(K)$ of continuous bounded functions defined on K , with the natural norm on this space, the maximum norm (sup norm), $\|f\| = \max_{k \in K} |f(k)|$.

When Does a Solution Exist?

Let's look at the **Result** first:

- Let K , Γ , F , and β satisfy (Assumption 1) and (Assumption 2), and let $\mathbf{B}(X)$ be the space of bounded continuous functions $f : K \rightarrow \mathbb{R}$ with the sup (maximum) norm. Then the operator T maps $\mathbf{B}(K)$ into itself, *i.e.*

$$T : \mathbf{B}(X) \rightarrow \mathbf{B}(X),$$

and has a unique fixed point, $V \in \mathbf{B}(K)$, satisfying

$$\begin{aligned} V(k) &= \max_{k' \in \Gamma(k)} [F(k, k') + \beta V(k')] \\ T[V(k)] &= \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\} \end{aligned}$$

When Does a Solution Exist?

- To get to this **Result**, we need to know two (actually three) things:
 - ① Berge's Maximum Theorem
 - Is T well-defined?
 - *i.e.* Does the **maximization problem** of the RHS have a solution?
 - ② Contraction Mapping Theorem
 - Contraction Mapping
 - Blackwell's Sufficient Condition

Berge's Maximum Theorem

Let (X, d_X) , (Y, d_Y) be metric spaces. Consider the maximization problem:

$$\max_{y \in Y} f(x, y) \quad \text{s.t. } y \in \Gamma(x)$$

where $\Gamma : X \rightrightarrows Y$ and $f : X \times Y \rightarrow \mathbb{R}$. Suppose that f is continuous and Γ is compact-valued and continuous at x . Then

- ① $M(x) = \max_{y \in Y} \{f(x, y) : y \in \Gamma(x)\}$ exists and is continuous at x , and
- ② $G(x) = \arg \max_{y \in Y} \{f(x, y) : y \in \Gamma(x)\}$ is non-empty-valued, compact-valued, and upper hemicontinuous.
 - Note that upper-hemicontinuity is similar concept to examine continuity properties with *correspondence*.
 - Note that if $G(\cdot)$ is a function, then it is a continuous function since upper hemicontinuous functions are continuous.

Berge's Maximum Theorem

What does this mean?

- When solving a constrained optimization problem, if
 - The objective function is continuous, and
 - The correspondence defining the constraint set is continuous, compact, and non-empty,

then,

- The problem has a solution.
- The optimized function is continuous.
- The function defining the optimal choice set is continuous.

⇒ So, the RHS of the (FE) is well-defined.

Contraction Mapping

We say that (S, d) is a metric space if S is a space and d is a metric defined over this space with the usual properties (loosely corresponding to “distance” between elements of S).

- **A Contraction Mapping:** Let (S, d) be a metric space and $T : S \rightarrow S$ be an operator mapping S into itself. If for some $\beta \in (0, 1)$,

$$d(Tv_1, Tv_2) \leq \beta d(v_1, v_2) \quad \forall \quad v_1, v_2 \in S,$$

then T is a contraction mapping (with modulus β).

Contraction Mapping Theorem

Recall that a metric space (S, d) is complete if every Cauchy sequence in S converges to an element in S , and a Cauchy sequence, $\{k_i\}$ is the one that satisfies for any $\epsilon > 0$, there exists a number M such that

$$\forall n, l \geq M, \quad d(k_n, k_l) < \epsilon,$$

- **(Contraction Mapping Theorem)** Let (S, d) be a complete metric space and suppose that $T : S \rightarrow S$ is a contraction. Then T has a unique fixed point, \hat{v} ; that is there exists a unique $\hat{v} \in S$ such that

$$T\hat{v} = \hat{v}.$$

Blackwell's Sufficient Conditions for a Contraction

- **(Blackwell's Sufficient Conditions for a Contraction)** Let $X \subseteq \mathbb{R}^K$, and $\mathbf{B}(X)$ be the space of bounded functions $f : X \rightarrow \mathbb{R}$ defined on X equipped with the max norm $\|\cdot\|$. Suppose that $T : \mathbf{B}(X) \rightarrow \mathbf{B}(X)$ be an operator satisfying the following two conditions:
 - ① Monotonicity: For any $f, g \in \mathbf{B}(X)$, $f(x) \leq g(x)$ for all $x \in X$ implies $(Tf)(x) \leq (Tg)(x)$ for all $x \in X$; and
 - ② Discounting: There exists $\beta \in (0, 1)$ such that

$$[T(f + c)](x) \leq (Tf)(x) + \beta c(x)$$

for all $f \in \mathbf{B}(X)$, $c(x) = c \geq 0$, and $x \in X$.

Then T is a contraction mapping with modulus β on $\mathbf{B}(X)$.

Remarks on Blackwell's Sufficient Conditions

- **Berge's Maximum Theorem** (Birges) tells us that the RHS maximization problem has a solution, T is defined
- **Blackwell's Sufficient Conditions** (Blackwells) tells us that, as long as $T : \mathbf{B}(X) \rightarrow \mathbf{B}(X)$ satisfies the two conditions (actually three conditions), then T is a contraction mapping.
- Then, from the **Contraction Mapping Theorem** (CMT), this T has a *unique fixed point*, which is a solution of the Bellman equation.

Application - **Step1:** Berge's Maximum Theorem

$$V(k) = \max_{k' \in \Gamma(k)} [F(k, k') + \beta V(k')]$$
$$T[V(k)] = \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\}$$

- Note that $k \in \Gamma(k) = [0, f(k)]$ is a compact set and continuous at k , and $F(k, k') = U(f(k) - k')$ is a bounded, continuous function, with regular utility functions and production functions.
 - What utility function $U()$ or production function $f()$ could violate this condition?
- Therefore, the (RHS) has a solution, and continuous at k . So the above mapping, T is well-defined.

Application - **Step2**: T is a Contraction Mapping

$$T[V(k)] = \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\}$$

- i. Bounded $T : \mathbf{B}(K) \rightarrow \mathbf{B}(K)$:
As long as $F(k, k')$ bounded, V bounded, giving TV being bounded.
- ii. Monotonicity: Consider $V, W \in \mathbf{B}(K)$, with $W(k) \leq V(k)$ for all $k \in K$, and let $G_w(k)$ be the optimal policy corresponding to W for all $k \in K$. Then

$$\begin{aligned} T[W(k)] &= F(k, G_w(k)) + \beta W(G_w(k)) \\ &\leq F(k, G_w(k)) + \beta V(G_w(k)) \\ &\leq \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\} = T[V(k)]. \end{aligned}$$

Application - **Step2**: T is a Contraction Mapping

$$T[V(k)] = \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\}$$

iii. Discounting: For $c(x) = c \geq 0$, and $k \in K$,

$$\begin{aligned} [T(V + c)](k) &= \max_{k' \in \Gamma(k)} \{F(k, k') + \beta(V(k') + c)\} \\ &= \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\} + \beta c \\ &= [TV](k) + \beta c. \end{aligned}$$

\Rightarrow So T satisfies Blackwell's sufficient conditions, meaning that T is a contraction mapping. Therefore, a contraction mapping theorem says that a unique $V \in \mathbf{B}(K)$ satisfying the problem exists.

Other Useful Theorems

- **(Assumption 3)** For each k' , $F(\cdot, k')$ is strictly increasing in each of its first K arguments, and Γ is monotone in a sense that $k_1 \leq k_2$ implies $\Gamma(k_1) \subseteq \Gamma(k_2)$.
- **(Properties of V)** Let K , Γ , F , and β satisfy (Assumption 2) and (Assumption 3), and let V be the unique solution to the above mapping. Then V is strictly increasing.
- **(Assumption 4)** F is strictly concave, and Γ is convex.
- **(Properties of V and k)** Let K , Γ , F , and β satisfy (Assumption 2), (Assumption 3), and (Assumption 4), and let V be the unique solution to the above mapping. Then V is strictly concave and G is continuous, single-valued function.

- So far, we have examined properties of the Bellman Equations in a non-stochastic setting.
- The problems we see in the papers, however, are usually *stochastic*.
- Luckily, with a slight modification of all the assumptions here, most of the results still hold in a *stochastic* setting as well.
 - ⇒ Please see the Chapter 16 of Acemoglu (2005) for the assumptions and theorems in a stochastic setting.

How to Solve the Bellman Equation?

Now that we know the solution exists, let's solve the problem.

- ① Guess and Verify \Rightarrow Today
- ② Numerical Solution \Rightarrow (Section 2 and 3)
 - Value Function Iteration
 - Policy Function Iteration
 - Howard Policy Improvement

Let's Take A Breather

7-10 Minute break to ask questions or just relax

Topics we've discussed so far:

- Sequential Problem vs. Functional Equation
- Value Function vs. Policy Function
- Berge's Maximum Theorem
- Contraction Mapping Theorem
- Blackwell's Sufficient Conditions

Food for Thought: Why are we using these techniques rather than the tools from growth (Hamiltonian, etc.)?

Guess and Verify

$$V(k) = \max_{k' \in \Gamma(k)} \{ \log(k^\alpha - k') + \beta V(k') \}$$

Guess that $V(k) = A + B \log k$.

$$V(k) = \max_{k' \in \Gamma(k)} \{ \log(k^\alpha - k') + \beta (A + B \log k') \}$$

Then the first order condition is

$$0 = -\frac{1}{k^\alpha - k'} + \beta \frac{B}{k'} \quad \Rightarrow \quad k' = \frac{\beta B}{1 + \beta B} k^\alpha.$$

Guess and Verify

$$V(k) = \log(k^\alpha - \frac{\beta B}{1 + \beta B} k^\alpha) + \beta A + \beta B \log\left(\frac{\beta B}{1 + \beta B} k^\alpha\right)$$

$$= \log \frac{1}{1 + \beta B} k^\alpha + \beta A + \beta B \log\left(\frac{\beta B}{1 + \beta B} k^\alpha\right)$$

$$A + B \log k = \log \frac{1}{1 + \beta B} k^\alpha + \beta A + \beta B \log\left(\frac{\beta B}{1 + \beta B} k^\alpha\right)$$

$$(1 - \beta)A + B \log k = \log \frac{(\beta B)^{(\beta B)}}{(1 + \beta B)^{(1 + \beta B)}} + \alpha(1 + \beta B) \log k$$

Guess and Verify

Equation Coefficients generates

$$\begin{aligned} B &= \alpha(1 + \beta B) \\ \Rightarrow B &= \frac{\alpha}{1 - \alpha\beta}. \\ A(1 - \beta) &= \log \frac{(\beta B)^{(\beta B)}}{(1 + \beta B)^{(1 + \beta B)}} \\ \Rightarrow A &= \frac{\log(1 - \alpha\beta)}{1 - \beta} + \frac{\alpha\beta \log(\alpha\beta)}{(1 - \beta)(1 - \alpha\beta)}. \end{aligned}$$

Policy Function

$$\begin{aligned} k' &= \frac{\beta B}{1 + \beta B} k^\alpha \\ \Rightarrow k' &= \alpha\beta k^\alpha \end{aligned}$$

The Functional Euler Equation

$$V(k) = \max_{k' \in \Gamma(k)} \{F(k, k') + \beta V(k')\}$$

$$V(k) = F(k, G(k)) + \beta V(G(k)), \quad k' = G(k).$$

Note that from the FOC of the first equation, we have

$$0 = F_2(k, k') + \beta V'(k').$$

This implies that with $k' = G(k)$,

$$0 = F_2(k, G(k)) + \beta V'(G(k)).$$

Here, the problem is that $V'(\cdot)$ is NOT known.

The Functional Euler Equation

$$V'(k) = F_1(k, G(k)) + \underbrace{G'(k) (F_2(k, G(k)) + \beta V'(G(k)))}_{=0}$$

This is an application of the EVT (Envelop Theorem).

$$V'(k) = F_1(k, G(k)) \Rightarrow V'(k') = F_1(k', G(k')) = F_1(G(k), G(G(k))).$$

$$F_2(k, k') + \beta F_1(k', k'') = 0, \quad \forall k.$$

With $F(k, k') = U(f(k) - k') = \log(k^\alpha - k')$, we have

$$\frac{1}{k^\alpha - G(k)} = \alpha \beta G(k)^{\alpha-1} \frac{1}{G(k)^\alpha - G(G(k))}.$$

The Functional Euler Equation

Now guess that $G(k) = \sigma k^\alpha$, we have

$$\frac{1}{(1 - \sigma)k^\alpha} = \frac{\alpha\beta(\sigma k^\alpha)^{\alpha-1}}{(\sigma k^\alpha)^\alpha - \sigma(\sigma k^\alpha)^\alpha}$$

generating that

$$\sigma = \alpha\beta,$$

which is the same as previous.

Flexibility of the DP: Optimal Stopping Problem

- Consider a simpler version of the Eat-the-Pie Problem in Pset 2.
- Assume that $R = 1$, and that the pie must be eaten in one period. This is an example of **optimal stopping problem** as in problem 3 of the Pset 2. The common element in all these problems is the timing of a single event: when to eat the pie, or when to take a job.
- Assume also that there is a taste shock, ϵ , which affects the satisfaction of eating the pie. So the utility over consumption is now given by

$$\epsilon U(C).$$

- Assume also that this taste shock takes on only two values $\epsilon \in \{\epsilon_h, \epsilon_l\}$, and follows a first-order Markov process, with $\pi_{ij} = \text{Prob}(\epsilon' = \epsilon_j | \epsilon = \epsilon_i)$.
- Assume also that now the pie depreciates at rate $\rho < 1$.

Flexibility of the DP: Optimal Stopping Problem

Let $V^E(A, \epsilon)$ and $V^N(A, \epsilon)$ be the value of eating the size A pie now (E) and waiting (N), respectively, given the current taste shock, $\epsilon \in \{\epsilon_h, \epsilon_l\}$. Then,

$$V^E(A, \epsilon) = \epsilon U(A)$$

$$V^N(A, \epsilon) = \beta \mathbb{E}_{\epsilon' | \epsilon} V(\rho A, \epsilon'),$$

$$V(A, \epsilon) = \max \{V^E(A, \epsilon), V^N(A, \epsilon)\}.$$