

# Evolutionary Game Theory

+Learning: short-sighted agents that choose based on past experience.

+Evolution: strategies that are most successful grow faster.

Dynamic and Static concepts!

# Static: Evolutionary Stable Strategies

Idea: a strategy is ESS if it repels small invasions.

Example:

	C	D
C	1, 1	-1, 2
D	2, -1	0, 0

$D$  is ESS,  $C$  is not. Regardless of the proportions of  $C$  and  $D$ ,  $U(C) < U(D)$ . Therefore any small invasion of  $D$  would take over a population of all  $C$ . Any invasion of  $C$  would not take over a population of all  $D$ .

# Evolutionary Stable Strategies

Definition: A strategy  $\sigma$  is ESS if

$$U(\sigma, \varepsilon\sigma' + (1 - \varepsilon)\sigma) > U(\sigma', \varepsilon\sigma' + (1 - \varepsilon)\sigma) \text{ for all } \sigma', \text{ for all } \varepsilon > 0.$$

Proposition 1: A strategy  $\sigma$  is ESS if and only if

$$U(\sigma, \sigma) > U(\sigma', \sigma) \text{ or } U(\sigma, \sigma) = U(\sigma', \sigma) \text{ and } U(\sigma, \sigma') > U(\sigma', \sigma') \text{ for all } \sigma'.$$

Proof:

A strategy  $\sigma$  is ESS if

$$U(\sigma, \varepsilon\sigma' + (1 - \varepsilon)\sigma) > U(\sigma', \varepsilon\sigma' + (1 - \varepsilon)\sigma) \text{ for all } \sigma', \text{ for all } \varepsilon > 0.$$

Then,

$$\varepsilon U(\sigma, \sigma') + (1 - \varepsilon) U(\sigma, \sigma) > \varepsilon U(\sigma', \sigma') + (1 - \varepsilon) U(\sigma', \sigma) \text{ for all } \sigma', \text{ for all } \varepsilon > 0. \blacksquare$$

# Evolutionary Stable Strategies

Proposition 2: Every ESS is a NE.

Proof:

From proposition 1, if  $\sigma$  is ESS  $U(\sigma, \sigma) \geq U(\sigma', \sigma)$  ■

Proposition 3: Every strict NE is an ESS.

Proof:

If  $\sigma$  is SNE then  $U(\sigma, \sigma) > U(\sigma', \sigma)$  and  $\sigma$  is ESS by Proposition 1.

■

# Evolutionary Stable Strategies

Example 1 of NE that is not ESS:

	A	B
A	0, 0	0, 0
B	0, 0	1, 1

$A$  is a NE but is not ESS.

Example 2 of NE that is not ESS:

	A	B
A	2, 2	-100, 0
B	0, -100	1, 1

$\left(\frac{101}{103}A + \frac{2}{103}B, \frac{101}{103}A + \frac{2}{103}B\right)$  is NE but it is not ESS.

# Evolutionary Stable Strategies

Proposition 4: While mixed strategy equilibria can never be strict, it can however be ESS.

Proof by example:

	A	B
A	0, 0	1, 1
B	1, 1	0, 0

$(\frac{1}{2}A + \frac{1}{2}B, \frac{1}{2}A + \frac{1}{2}B)$  is mixed NE and ESS.

Invasion of  $\varepsilon$  of  $A$ , then:

$$U(\frac{1}{2}A + \frac{1}{2}B) = (1 - \varepsilon)\frac{1}{2} + \varepsilon\frac{1}{2}$$

$$U(A) = (1 - \varepsilon)\frac{1}{2} + \varepsilon 0$$

Then  $U(\frac{1}{2}A + \frac{1}{2}B) > U(A)$ .

Similarly for an invasion of B. ■

# Replicator Dynamics:

Explicit model of population dynamics.

Consider a single homogeneous population playing a symmetric game.

Continuous time.

$\phi_t(s)$  is the size of the population playing strategy  $s$  at time  $t$ .

Main Assumption:

$$\dot{\phi}_t(s) = \phi_t(s)u_t(s)$$

Net reproduction rate is proportional to payoff in stage game.

# Replicator Dynamics:

$\theta_t(s)$  is the proportion playing strategy  $s$  at time  $t$ .

$$\dot{\theta}_t(s) = \theta_t(s) (u_t(s) - \bar{u}_t)$$

Reason:

$$\theta_t(s) = \frac{\phi_t(s)}{\sum \phi_t(s)}$$

$$u_t(s) = \sum \theta_t(s') u(s, s')$$

$$\bar{u}_t = \sum \theta_t(s) u_t(s)$$

$$\dot{\theta}_t(s) = \frac{\dot{\phi}_t(s) \sum \phi_t(s') - \phi_t(s) \sum \dot{\phi}_t(s')}{(\sum \phi_t(s'))^2}$$

$$= \frac{\phi_t(s) u_t(s) \sum \phi_t(s') - \phi_t(s) \sum \phi_t(s') u_t(s')}{(\sum \phi_t(s'))^2}$$

$$= \frac{\phi_t(s) u_t(s) - \phi_t(s) \bar{u}_t}{\sum \phi_t(s')} = \theta_t(s) (u_t(s) - \bar{u}_t)$$

# Replicator Dynamics:

Proposition 1: Every NE is a steady state of the replicator dynamic.

Reason: All strategies in a NE have the same payoff.

Proposition 2: Any pure action is a steady state.

Then, we need to look at stability.

# Review of Dynamical Systems:

Basic definitions:

State:  $\theta_t(s) \in (0, 1)$ ,  $s \in S$ .

State vector:  $\theta_t$

Law of Motion:  $\dot{\theta}_t = f(\theta_t)$

Flow:  $F_t(\theta_0)$ .

Definition 1:  $\hat{\theta}$  is a steady state if  $F_t(\hat{\theta}) = \hat{\theta}$ , for all  $t$ .

Definition 2: A steady state  $\hat{\theta}$  is stable if for all neighborhood  $U$  of  $\hat{\theta}$ , there exists a neighborhood  $U_1$  of  $\hat{\theta}$  such that if  $\theta_0 \in U_1$ ,  $F_t(\theta_0) \in U$  for all  $t$ .

Definition 3: A steady state  $\hat{\theta}$  is asymptotically stable if it is stable and in addition if  $\theta_0 \in U_1$ , then  $\lim_{t \rightarrow \infty} F_t(\theta_0) = \hat{\theta}$ .

Definition 4: A basin of attraction of a steady state  $\hat{\theta}$  is the set of points  $\theta_0$  such that  $\lim_{t \rightarrow \infty} F_t(\theta_0) = \hat{\theta}$ .

# Replicator Dynamics:

Proposition 1: A stable steady state of the Replicator Dynamics is a Nash equilibrium of the stage game.

Proof: Assume not. Then, there exists  $s$  in the support of  $\hat{\theta}$  and  $s' \in S$  such that  $U(s', \hat{\theta}) > U(s, \hat{\theta})$ . By continuity of payoffs, for all  $\theta'$  close to  $\hat{\theta}$  we have that  $U(s', \theta') > U(s, \theta')$ . But then  $\theta_t(s) \rightarrow 0$ . ■

The converse is not necessarily true.

Example

	A	B
A	0, 0	0, 0
B	0, 0	1, 1

Proposition 2: An asymptotically stable steady state of the Replicator Dynamics is a trembling-hand-perfect and isolated Nash equilibrium of the stage game.

# Replicator Dynamics and ESS:

Proposition 3: Every ESS is an asymptotically stable SS of the Replicator Dynamics.

Reason: If  $s$  is ESS,  $U(s, \varepsilon s' + (1 - \varepsilon)s) > U(s', \varepsilon s' + (1 - \varepsilon)s)$  and  $s$  will grow faster.

# Long Run Stability:

Kandori, M., Mailath, G. and Rob, R. (1993). "Learning, Mutation and Long Run Equilibria in Games," *Econometrica*, 61.

Study dynamics with persistent randomness.

Consider:

2x2 coordination game with  $A$  risk dominant.

$N$  players.

Best response dynamic:

state  $\theta$  is the number of  $A$ s.

$N$  large enough so that exists  $N^*$  such that  $\alpha^* N \leq N^* \leq \frac{1}{2}N$ .

$$\theta_{t+1} = \begin{cases} N & \text{if } \theta_t \geq N^* \\ 0 & \text{otherwise} \end{cases}$$

Two stable and ESS steady states:

$\theta = N$  and  $\theta = 0$ .

# Long Run Stability:

Adding persistent mutations will help us eliminate one of the steady states!

At each point in time each player can mutate with probability  $\varepsilon$ .

What matters is in which basin of attraction the system is in.

$$q_{AB} = P(\theta_{t+1} \in D_A / \theta_t \in D_B)$$

Markov process, then find stationary distribution:

$$\begin{bmatrix} \varphi_A \\ \varphi_B \end{bmatrix} = \begin{bmatrix} 1 - q_{BA} & q_{AB} \\ q_{BA} & 1 - q_{AB} \end{bmatrix} \begin{bmatrix} \varphi_A \\ \varphi_B \end{bmatrix}$$

$$\frac{\varphi_A}{\varphi_B} = \frac{q_{AB}}{q_{BA}}$$

# Long Run Stability:

For BR dynamic with mutations  $\varepsilon$ :

$$\frac{\varphi_A^\varepsilon}{\varphi_B^\varepsilon} = \frac{q_{AB}^\varepsilon}{q_{BA}^\varepsilon} = \frac{\binom{N}{N^*} \varepsilon^{N^*} (1-\varepsilon)^{N-N^*}}{\binom{N}{N^*} \varepsilon^{N-N^*} (1-\varepsilon)^{N^*}}$$

$$\frac{\varphi_A^\varepsilon}{\varphi_B^\varepsilon} = \frac{(1-\varepsilon)^{N-2N^*}}{\varepsilon^{N-2N^*}}$$

Since  $2N^* \leq N$ :  $\lim_{\varepsilon \rightarrow 0} \frac{\varphi_B^\varepsilon}{\varphi_A^\varepsilon} = 0$

Risk dominant survives in the long run.

# Long Run Stability:

Step 1: Specify a state space  $\theta$ .

Step 2: Specify an "intentional" dynamic: replicator, best response, Darwinian that may have many steady states.

Step 3: Introduce noise that makes the system ergodic (unique  $\varphi^\varepsilon$ ).

Step 4: Find  $\lim_{\varepsilon \rightarrow 0} \varphi^\varepsilon = \varphi^*$  (long run stable equilibrium).