

# Lecture 7: Non-equilibrium Strategic Thinking

Till now: Game theoretic rationality with non-egoistic preferences

Now: models of boundedly rational behavior in games

Lecture 8: Learning models

This lecture: non-equilibrium behavior

models behavior in "new", unfamiliar strategic situations before players can learn from experience

# 1. Quantal Response (McKelvey and Palfrey 1995, Goeree, Holt, and Palfrey 2008)

Basic features

Player choose "noisy" best response

In equilibrium the likelihood of a strategy is increasing its expected payoff, taking the noisy strategies of the other players into account

$n$  player normal form game  $G$  (or normal form representation of an extensive form game)

$S_i$ : finite set of pure strategies of player  $i$ ,  $s_i \in S_i$

$S$ : set of pure strategy profiles,  $s \in S$

$s_{-i}$ : strategies of all players but  $i$

each player  $i$  endowed with payoff-function:

$$\pi_i : S \rightarrow \mathbb{R}$$

mixed strategy of player  $i$ ,  $\sigma_i$ : probability distribution over  $S_i$

$$\sigma_i \in \Sigma_i$$

$$\sigma = (\sigma_1, \sigma_2, \dots, \sigma_N), \sigma \in \Sigma = \prod_{i \in N} \Sigma_i$$

$i$ 's strategic behavior can be summarized by a function  $P_i: \mathbb{R}^{|S_i|} \rightarrow \Sigma_i$

$P_{ij}(u_i)$ : For a vector  $u = (u_{i1}, u_{i2}, \dots, u_{i|S_i|})$ ,  $P_{ij}(u_i)$  denotes the probability that player  $i$  chooses pure strategy  $j$ , if his payoff of choosing his strategy 1 is  $u_{i1}$ , of choosing his strategy 2 is  $u_{i2}$ , etc.

Definition:  $P_i$  is a quantal-response function, if the following conditions holds:

Continuity:  $P_{ij}(u_i)$  is continuously differentiable at all  $u_i$

Interiority:  $P_{ij}(u_i) > 0$  for all  $u_i$ .

Responsiveness:  $\frac{\partial P_{ij}(u_i)}{\partial u_{ij}} > 0$  for all  $j$  at all  $u_i$ .

Monotonicity:  $u_{ij} > u_{ik} \iff P_{ij}(u_i) > P_{ik}(u_i)$  for all  $j, k \in S_i$

All conditions exclude that  $P_i$  is equivalent to a best response correspondence, but conditions 3 and 4 keep the flavor of a best response  $\iff P_i$  models a smoothed, non-precise version of best response.

Definition: Take a normal form game  $G$  and let  $P = (P_1, P_2 \dots P_N)$  be a profile of quantal response functions. A mixed strategy profile  $\sigma^* \in \Sigma$  is a quantal response equilibrium (QRE) iff  $\sigma^* = P(\sigma^*)$ .

Theorem: For any game  $G$  and any profile of quantal response functions  $P$  there exists a QRE.

Theorem: Let  $P^n$  be a sequence of profiles of quantal response functions that converges to a profile equivalent to the best response correspondences. The resulting sequence of QREs converges to a Nash equilibrium.

QRE can explain many experimental results, but:

QRE depends on  $P$  which is of course not unique - too many degrees of freedom

## 2. Level-k-Models

### 2.1. Experimental evidence

Guessing game ("beauty contest") (Nagel 1995, Ho et al. 1998):

$n$  players choose simultaneously a number between  $\alpha$  and  $\beta$ ;  $\alpha \geq 0$ ,  $\beta > \alpha$

The person whose number is closest to  $x$  times the average number wins.  
Ties broken randomly

Unique Nash equilibrium:

$x < 1$ : all players choose  $\alpha$ .

$x > 1$ : all players choose  $\beta$ .

This equilibrium also results from iterated elimination of strictly dominated strategies

Experimental results in early rounds:

Most players choose numbers larger than zero

Spikes at  $\frac{\alpha+\beta}{2}x^k$ ,  $k = 1, 2$ , and  $3$ .

Inconsistent with quantal response

## 2.2. The model (Nagel 1995, Stahl and Wilson 1995)

$n$  player normal form game  $G$  (or normal form representation of an extensive form game)

$S_i$ : finite set of pure strategies of player  $i$ ,  $s_i \in S_i$

$S$ : set of pure strategy profiles,  $s \in S$

$s_{-i}$  strategies of all players but  $i$

each player  $i$  endowed with payoff-function:

$$\pi_i : S \rightarrow \mathbb{R}$$

Players are heterogenous and characterized by their sophistication level.

A  $L_0$  player  $i$  makes a random choice according to some probability distribution over  $S_i$  (for many applications equal distribution over feasible strategies assumed). Such  $L_0$  players do not actually exist, but they are needed to anchor the belief of all other players.

$L_1, L_2, L_3 \dots$  players play best response, but differ in terms of beliefs about what the other players do.

A  $L_1$  player  $i$  chooses a strategy  $s_i$  that maximizes his payoff under the believe that all other players are  $L_0$ .

A  $L_2$  player  $i$  chooses a strategy  $s_i$  that maximizes his payoff under the believe that all other players are  $L_1$ .

A  $L_3$  player  $i$  chooses a strategy  $s_i$  that maximizes his payoff under the believe that all other players are  $L_2$ .

etc.

Applied to the guessing game:

$L_0$ : random choice with equal distribution over numbers between  $\alpha$  and  $\beta$ .  
choice of strategy is random

$L_1$  players believe that other players are  $L_0 \Rightarrow$  average is  $\frac{\alpha+\beta}{2} \Rightarrow$  best response is  $\frac{\alpha+\beta}{2}x$

$L_2$  players believe that other players are  $L_1 \Rightarrow$  average is  $\frac{\alpha+\beta}{2}x \Rightarrow$  best response is  $\frac{\alpha+\beta}{2}x^2$

$L_3$  players believe that other players are  $L_2 \Rightarrow$  average is  $\frac{\alpha+\beta}{2}x^2 \Rightarrow$  best response is  $\frac{\alpha+\beta}{2}x^3$

Level-k models predict well actual behavior in many economically important experimental games, e.g. auctions

Variant of level-k model: Cognitive Hierarchy Model (Camerer et al 2004):

$L_k$  players do not play best response against belief that only  $L(k-1)$  players exist, but against a belief given by a distribution over all  $L(k-m)$  players with  $m = 1, 2, \dots, k$ .

Believed distribution of  $L(k-m)$  players is such that the relative frequency of all types are correct - A player does not realize that other players might be of the same or higher level than himself, but he correctly predicts the ratio between  $L(k-m)$  and  $L(k-n)$  players ( $m, n \in \{1, \dots, k\}$ )

Shortcomings of level-k models:

Cannot capture learning well - "short term" predictions

In many games, predictions depend on assumption about  $L(0)$ , and on size of  $L(1)$  players, etc.

Unclear, whether predictions are better than with QRE (Breitmoser 2012)