

# INFO-F-409

## Learning dynamics

Learning, evolutionary game theory and the evolution of co-operation



T. Lenaerts and A. Nowé  
MLG, Université Libre de Bruxelles and  
AI-lab, Vrije Universiteit Brussel



1

## Summary

- What? Why?
- Rational choice
- Strategic games
- Nash Equilibrium
- Best
- Dominance
- Mixed strategies
- Mixed-strategy Nash Equilibria
- Support finding
- Lemke-Howson algorithm
- Extensive-form games
- sub-game perfect equilibrium
- Simultaneous moves
- Chance moves
- Bayesian games
- Assignment I

2

## The formation of agents' beliefs

Now that we can determine the Nash and sub-game perfect equilibria ...

How can we reach them?

Which equilibrium preferred ?



3

## The formation of agents' beliefs

Can we expect that the equilibrium will be reached ?

Players could chose their action from an **introspective analysis of the game** : removing dominated strategies

**Learning** the beliefs about the other player in response of the information she receives :

1. Best response dynamics
2. Fictitious play
3. Stimulus-response or reinforcement learning
4. Evolutionary or cultural dynamics

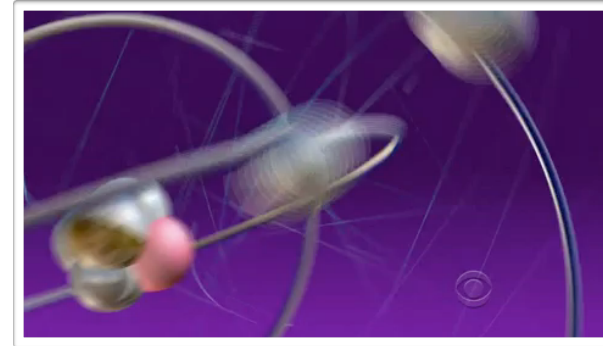
4

# Levels of learning



5

# Conditioning



Scene from the Big Bang Theory (S03E03, The Gothowitz Deviation)

6-1

# Conditioning



Scene from the Big Bang Theory (S03E03, The Gothowitz Deviation)

6-2

# Best-response dynamics



In the **first period**, choose a best response to an arbitrary deterministic belief about the other players' actions

In **every period after the first**, choose the best response to the other players' actions in the previous round

*An action profile that remains the same over time is a pure Nash equilibrium of the game*

7

# Best-response dynamics

	Bach	Strav.
Bach	1 2	0 0
Strav.	0 0	2 1

**Depending on the prior beliefs these dynamics may not converge**

Take for instance the Battle of the sexes, which has 3 equilibria  $((1,0),(1,0))$ ,  $((0,1),(0,1))$  and  $((2/3,1/3),(1/3,2/3))$

8-1

# Best-response dynamics

	Bach	Strav.
Bach	1 2	0 0
Strav.	0 0	2 1

**Depending on the prior beliefs these dynamics may not converge**

Take for instance the Battle of the sexes, which has 3 equilibria  $((1,0),(1,0))$ ,  $((0,1),(0,1))$  and  $((2/3,1/3),(1/3,2/3))$

BELIEF		
	A plays	B plays
prior	B	B
1	B	B
2	B	B
...	...	...

8-2

# Best-response dynamics

	Bach	Strav.
Bach	1 2	0 0
Strav.	0 0	2 1

**Depending on the prior beliefs these dynamics may not converge**

Take for instance the Battle of the sexes, which has 3 equilibria  $((1,0),(1,0))$ ,  $((0,1),(0,1))$  and  $((2/3,1/3),(1/3,2/3))$

BELIEF			BELIEF		
	A plays	B plays		A plays	B plays
prior	B	B	prior	S	S
1	B	B	1	S	S
2	B	B	2	S	S
...	...	...	...	...	...

8-3

# Best-response dynamics

	Bach	Strav.
Bach	1 2	0 0
Strav.	0 0	2 1

**Depending on the prior beliefs these dynamics may not converge**

Take for instance the Battle of the sexes, which has 3 equilibria  $((1,0),(1,0))$ ,  $((0,1),(0,1))$  and  $((2/3,1/3),(1/3,2/3))$

BELIEF			BELIEF			BELIEF		
	A plays	B plays		A plays	B plays		A plays	B plays
prior	B	B	prior	S	S	prior	S	B
1	B	B	1	S	S	1	B	S
2	B	B	2	S	S	2	S	B
...	...	...	...	...	...	...	...	...

8-4

# Fictitious play

Every agent starts with an arbitrary probabilistic belief about the other players actions.

In the first round she chooses a BR to this prior probabilistic belief and observes the other player's actions, say A.

she changes here belief so that A gets probability 1

In the second round, she produces a best response to this belief and observes the other player's action, say B

she changes here belief to one that assigns 1/2 to action A and 1/2 to action B

In the third round ...

9

# Fictitious play

Consider again the Battle of the sexes:

		BELIEF				
		A plays	B > A	B plays	A > B	
prior		(1,0)		(0,1)		
1	S	(1,1)	B	(1,1)	TOTAL = 2	
2	S	(1,2)	S	(1,2)	TOTAL = 3	
3	S	(1,3)	S	(1,3)	TOTAL = 4	
4	S	(2,3)	B	(1,4)	TOTAL = 5	
5	S	(2,4)	S	(1,5)	TOTAL = 6	
6	S	(2,5)	S	(1,6)	TOTAL = 7	
7	...	...	...	...		

		Bach	Strav.
Bach		1	0
Strav.		0	2

10

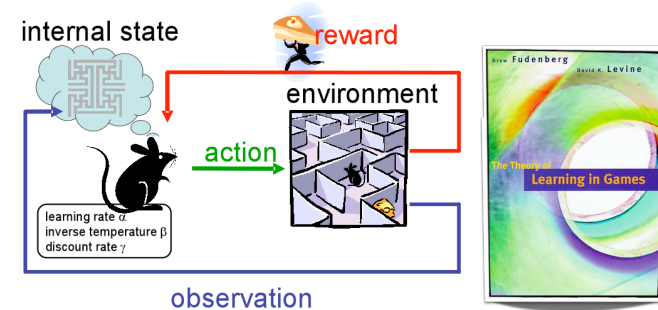
# Fictitious play

So in any period, the agent adopts the belief that her opponent is using a mixed strategy in which the probability of each action is proportional to the frequency with which her opponent has chosen that action in the previous rounds

The process converges to a mixed strategy Nash equilibrium from initial beliefs

11

# Stimulus-response learning



12

# Stimulus-response learning

Stochastic dynamic models of individual behavior ...

Bush, R. R., & Mosteller, F. (1951). **A mathematical model for simple learning.** Psychological review, 58(5), 313–323.

Roth, A. E., & Erev, I. (1995). **Learning in extensive-form games: Experimental data and simple dynamic models in the intermediate term.** Games and Economic Behavior, 8(1), 164–212.

Erev, I., & Roth, A. E. (1998). **Predicting how people play games: reinforcement learning in experimental games with unique, mixed strategy equilibria.** The American Economic Review, 88(4), 848–881.

13

# Stimulus-response learning

Take for instance the model proposed by Roth and Erev (1995)

A player is defined by:

A **propensity score**  $q_{Ak}(t)$ , which expresses the propensity of player  $A$  to play action  $k$  at time  $t$

A **probability function**  $p_{Ak}(t) = q_{Ak}(t) / \sum_j q_{Aj}(t)$ , which expresses the probability of  $A$  to play action  $k$  at time  $t$

An **update function**  $q_{Ak}(t+1) = q_{Ak}(t) + x$ , where  $x$  is the payoff from the interaction. The other actions  $q_{Aj}(t)$  remain the same.

Hence actions with a higher probability are more likely to be played (**Law of effect**)

Aim was to design a model that fits psychological literature

14

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2
	0	1

player 1	$q_{1k}(t)$	$p_{1k}(t)$
Bach	1	1/2
Stravinsky	1	1/2

player 2	$q_{2k}(t)$	$p_{2k}(t)$
Bach	1	1/2
Stravinsky	1	1/2

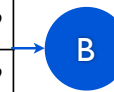
15-1

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2
	0	1

player 1	$q_{1k}(t)$	$p_{1k}(t)$
Bach	1	1/2
Stravinsky	1	1/2



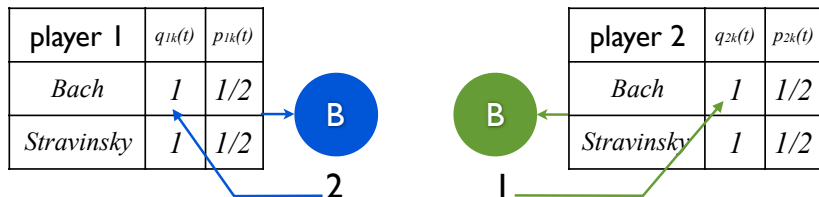
player 2	$q_{2k}(t)$	$p_{2k}(t)$
Bach	1	1/2
Stravinsky	1	1/2

15-2

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2



15-3

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2



16

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2



17-1

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2

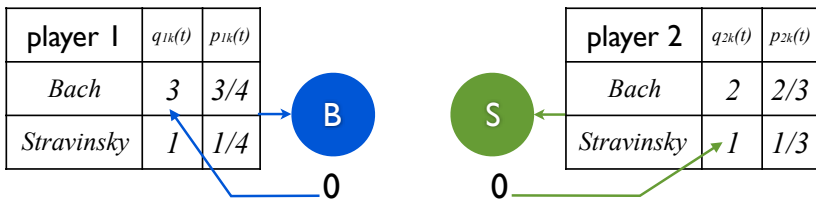


17-2

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2
	0	1

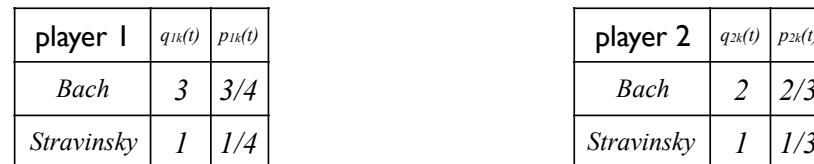


17-3

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2
	0	1

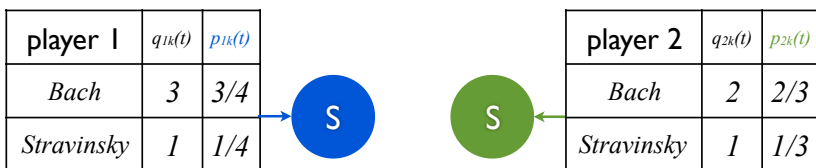


18

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2
	0	1

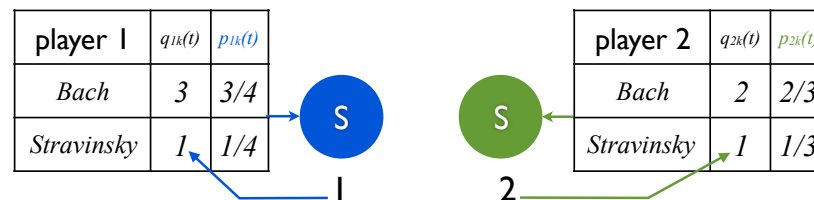


19-1

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2
	0	1



19-2

# Stimulus-response learning

Consider again the Battle of the sexes:

	Bach	Strav.
Bach	1	0
Strav.	0	2

player 1	$q_{1k}(t)$	$p_{1k}(t)$
Bach	3	3/5
Stravinsky	2	2/5

player 2	$q_{2k}(t)$	$p_{2k}(t)$
Bach	2	2/5
Stravinsky	3	3/5

Continue until convergence

20

# Stimulus-response learning

Three extensions were introduced into this model:

A **cutoff parameter**  $\mu$  which ensure that  $q_{Ak}(t)$  and  $p_{Ak}(t)$  can become zero in finite time : when  $p_{Ak}(t) \leq \mu, q_{Ak}(t) = p_{Ak}(t) = 0$

An **error/exploration parameter**  $\epsilon$  which prevents a probability  $p_{Ak}(t)$  can become zero if it is close to a successful strategy:  $q_{Ak}(t+1) = q_{Ak}(t) + (1-\epsilon)x$  for the successful strategy and  $q_{Aj}(t+1) = q_{Aj}(t) + \epsilon x$  for the adjacent strategies

An **forgetting parameter**  $\phi$  which gradually reduces the importance of each propensity  $q_{Ak}(t)$  over time by multiplying each propensity by  $(1-\phi)$ .

**More details on reinforcement learning by Prof. Nowé**

21