Evolutionary Stochastic Games

Concluding Remarks

Population Dynamics in Stochastic Games



Frank Thuijsman

joint work with J. Flesch, P. Uyttendaele, T. Parthasarathy

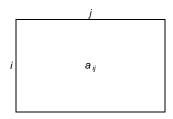
Frank Thuijsman, DKE, Maastricht University

Introduction	Stochastic Games	Evolutionary Games	Evolutionary Stochastic Games	Concluding Remarks
Outline				

- 1 Introduction
- 2 Stochastic Games
- **3** Evolutionary Games
- Evolutionary Stochastic Games
- **5** Concluding Remarks



2-Person Zerosum Games

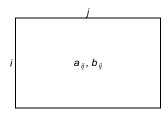


Existence of Value and Optimal Strategies

Frank Thuijsman, DKE, Maastricht University



n-Person Non-Zerosum Games

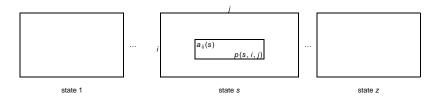


Existence of Equilibria

Frank Thuijsman, DKE, Maastricht University



2-Person Zerosum Stochastic Games

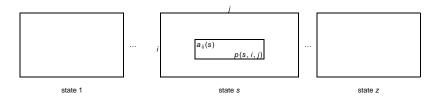


Existence of Value and Optimal Strategies

Frank Thuijsman, DKE, Maastricht University



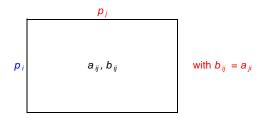
2-Person Zerosum Stochastic Games



Existence of Value and Optimal Strategies for Stopping Stochastic Games

Frank Thuijsman, DKE, Maastricht University





- Population consisting of Individuals of Different Types Playing against Itself
- Population Distribution $p = (p_1, p_2, \dots, p_n)$
- Individuals of Type k have Fitness $e_k A p^{\top}$ in Population p
- Concept of Evolutionarily Stable Strategies (ESS)

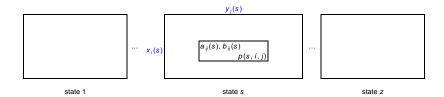
Frank Thuijsman, DKE, Maastricht University



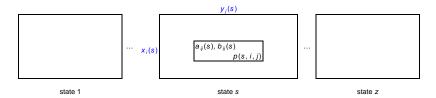
What if the Fitness of Population Members corresponds to Average Rewards in a Stochastic Game, rather than to Expected Payoffs in a One-Shot Game?

Frank Thuijsman, DKE, Maastricht University





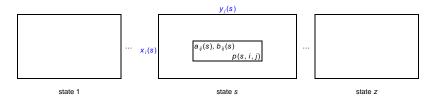




• Finitely Many States, Finitely Many Actions for each Player

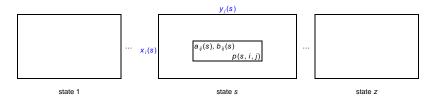
Frank Thuijsman, DKE, Maastricht University





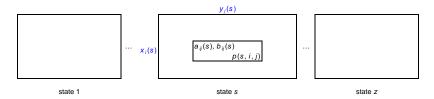
- Finitely Many States, Finitely Many Actions for each Player
- Payoffs and Transitions at each Stage 1, 2, 3, 4, ...





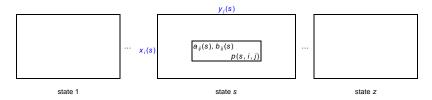
- Finitely Many States, Finitely Many Actions for each Player
- Payoffs and Transitions at each Stage 1, 2, 3, 4, ...
- Each State can serve as Initial State





- Finitely Many States, Finitely Many Actions for each Player
- Payoffs and Transitions at each Stage 1, 2, 3, 4, ...
- Each State can serve as Initial State
- Complete Information and Perfect Recall





- Finitely Many States, Finitely Many Actions for each Player
- Payoffs and Transitions at each Stage 1, 2, 3, 4, ...
- Each State can serve as Initial State
- Complete Information and Perfect Recall
- Discounting or Averaging the Stage Payoffs



a_{ii}(s), b_{ii}(s)

state s

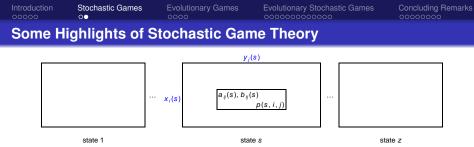
p(s, i, j)

state z

 $x_i(s)$

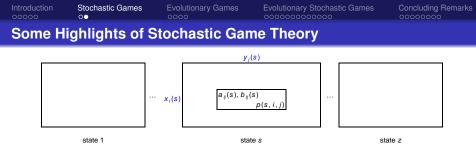
Frank Thuijsman, DKE, Maastricht University

state 1

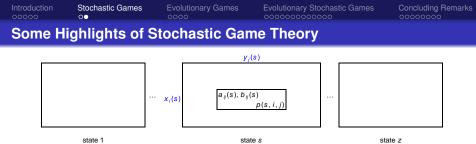


1953, L.S. Shapley:
 2-Person Zerosum Stopping Stochastic Games - Value

Frank Thuijsman, DKE, Maastricht University



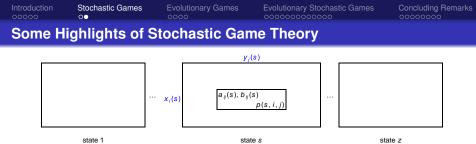
- 1953, L.S. Shapley:
 2-Person Zerosum Stopping Stochastic Games Value
- 1957, H. Everett / D. Gillette:
 2-Person Zerosum Undiscounted Stochastic Games



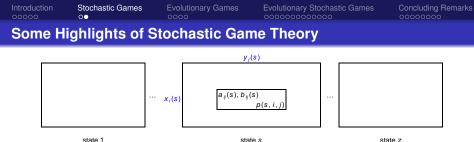
1953, L.S. Shapley:
 2-Person Zerosum Stopping Stochastic Games - Value

- 1957, H. Everett / D. Gillette:
 2-Person Zerosum Undiscounted Stochastic Games
- 1964, A.M. Fink / M. Takahashi: n-Person β-Discounted Stochastic Games - Equilibria

Frank Thuijsman, DKE, Maastricht University



- 1953, L.S. Shapley:
 2-Person Zerosum Stopping Stochastic Games Value
- 1957, H. Everett / D. Gillette:
 2-Person Zerosum Undiscounted Stochastic Games
- 1964, A.M. Fink / M. Takahashi: n-Person β-Discounted Stochastic Games - Equilibria
- 1981, J.-F. Mertens and A. Neyman:
 2-Person Zerosum Undiscounted Stochastic Games Value



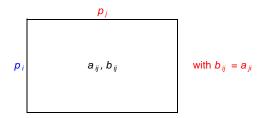
1953, L.S. Shapley:
 2-Person Zerosum Stopping Stochastic Games - Value

- 1957, H. Everett / D. Gillette:
 2-Person Zerosum Undiscounted Stochastic Games
- 1964, A.M. Fink / M. Takahashi: n-Person β-Discounted Stochastic Games - Equilibria
- 1981, J.-F. Mertens and A. Neyman:
 2-Person Zerosum Undiscounted Stochastic Games Value
- 2000, N. Vieille:

2-Person Undiscounted Stochastic Games - ε -Equilibria

Frank Thuijsman, DKE, Maastricht University

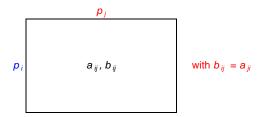




- Population consisting of Individuals of Different Types Playing against Itself
- Population Distribution $p = (p_1, p_2, \dots, p_n)$
- Individual of Type k has Fitness $e_k A p^{\top}$ in Population p
- Concept of Evolutionarily Stable Strategies (ESS)

Frank Thuijsman, DKE, Maastricht University

Introduction	Stochastic Games	Evolutionary Games	Evolutionary Stochastic Games	Concluding Remarks		
The ESS Concept						



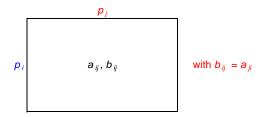
ESS: Population Distribution $p = (p_1, p_2, \dots, p_n)$ with

•
$$pAp^{\top} \ge qAp^{\top} \ \forall q$$

• If $q \ne p$ and $qAp^{\top} = pAp^{\top}$, then $pAq^{\top} > qAq^{\top}$

Frank Thuijsman, DKE, Maastricht University





Population Development by the Replicator Equation:

•
$$\dot{p}_k = p_k \left(e_k A p^\top - p A p^\top \right)$$

Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Concluding Remarks on ESS and Asymptotic Stability

Frank Thuijsman, DKE, Maastricht University



• A Static Concept and a Dynamic Process

Frank Thuijsman, DKE, Maastricht University



- A Static Concept and a Dynamic Process
- ESS Not Always Exists



- A Static Concept and a Dynamic Process
- ESS Not Always Exists
- Replicator Dynamic Not Always Converges



- A Static Concept and a Dynamic Process
- ESS Not Always Exists
- Replicator Dynamic Not Always Converges
- Any ESS is Asymptotically Stable

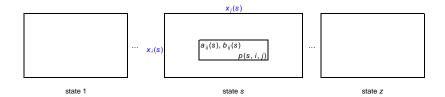


- A Static Concept and a Dynamic Process
- ESS Not Always Exists
- Replicator Dynamic Not Always Converges
- Any ESS is Asymptotically Stable
- Limit Points of Dynamic Not Always ESS



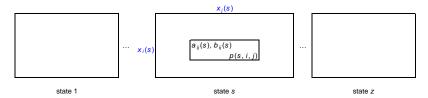
- A Static Concept and a Dynamic Process
- ESS Not Always Exists
- Replicator Dynamic Not Always Converges
- Any ESS is Asymptotically Stable
- Limit Points of Dynamic Not Always ESS

$$\begin{pmatrix} 0 & 6 & -4 \\ -3 & 0 & 5 \\ -1 & 3 & 0 \end{pmatrix}$$
 (Hofbauer and Sigmund, 1998)



Frank Thuijsman, DKE, Maastricht University

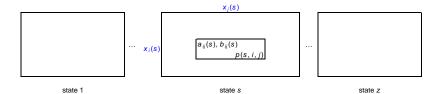
Introduction Stochastic Games Evolutionary Games Stochastic Games Concluding Remark



Population playing against Itself

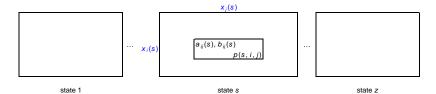
Frank Thuijsman, DKE, Maastricht University





- Population playing against Itself
- Symmetric Payoffs: $b_{ij} = a_{ji}$





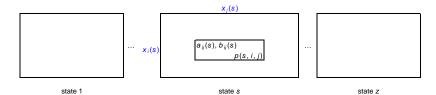
- Population playing against Itself
- Symmetric Payoffs: $b_{ij} = a_{ji}$
- Symmetric Transitions: p(s, i, j) = p(s, j, i)





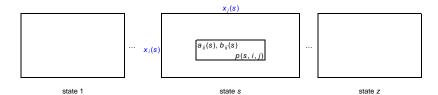
- Population playing against Itself
- Symmetric Payoffs: $b_{ij} = a_{ji}$
- Symmetric Transitions: p(s, i, j) = p(s, j, i)
- Irreducible Stochastic Game





- Population playing against Itself
- Symmetric Payoffs: $b_{ij} = a_{ji}$
- Symmetric Transitions: p(s, i, j) = p(s, j, i)
- Irreducible Stochastic Game All States communicate for all Stationary Strategies



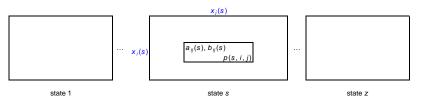


- Population playing against Itself
- Symmetric Payoffs: $b_{ij} = a_{ji}$
- Symmetric Transitions: p(s, i, j) = p(s, j, i)
- Irreducible Stochastic Game All States communicate for all Stationary Strategies
- Types correspond to Pure Stationary Strategies

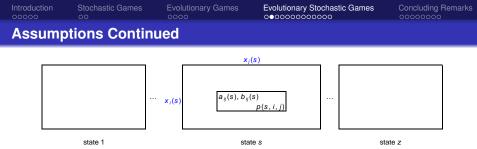
Frank Thuijsman, DKE, Maastricht University

Evolutionary Stochastic Games 000000000000

Assumptions Continued



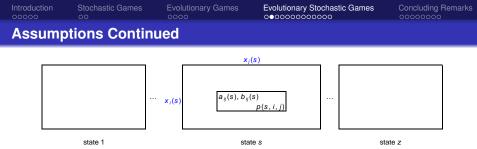
Frank Thuijsman, DKE, Maastricht University



$$\bar{x} = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n)$$

is Average Reward $\gamma(e_k, x)$
where *x* Stationary Strategy determined by \bar{x}

Frank Thuijsman, DKE, Maastricht University

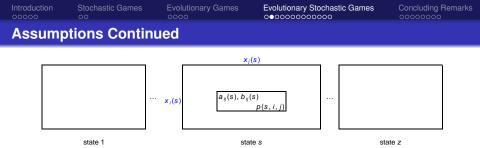


$$\bar{x} = (\bar{x}_1, \bar{x}_2, \ldots, \bar{x}_n)$$

is Average Reward $\gamma(e_k, x)$

where x Stationary Strategy determined by \bar{x}

Different Populations can give Same Stationary Strategy



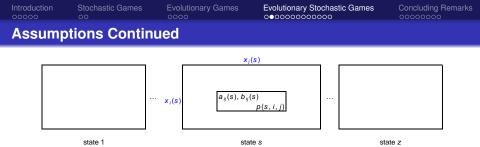
$$\bar{x} = (\bar{x}_1, \bar{x}_2, \dots, \bar{x}_n)$$

is Average Reward $\gamma(e_k, x)$
where *x* Stationary Strategy determined by \bar{x}

- Different Populations can give Same Stationary Strategy
- Stationary Strategy x is ESS if
 - $\gamma(x, x) \ge \gamma(y, x) \forall$ Stationary Strategies y

• If
$$y \neq x$$
 and $\gamma(y, x) = \gamma(x, x)$, then $\gamma(x, y) > \gamma(y, y)$

Frank Thuijsman, DKE, Maastricht University



$$\bar{\mathbf{x}} = (\bar{\mathbf{x}}_1, \bar{\mathbf{x}}_2, \dots, \bar{\mathbf{x}}_n)$$

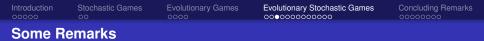
is Average Reward $\gamma(e_k, x)$

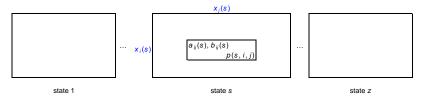
where x Stationary Strategy determined by \bar{x}

- Different Populations can give Same Stationary Strategy
- Stationary Strategy x is ESS if
 - $\gamma(x, x) \ge \gamma(y, x) \forall$ Stationary Strategies y
 - If $y \neq x$ and $\gamma(y, x) = \gamma(x, x)$, then $\gamma(x, y) > \gamma(y, y)$
- Population Development by Replicator Dynamic

•
$$\dot{\bar{x}}_k = \bar{x}_k \left(\gamma(e_k, x) - \gamma(x, x) \right)$$

Frank Thuijsman, DKE, Maastricht University



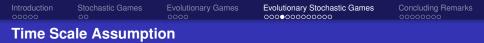


- ESS Not Always Exists
- Replicator Dynamic Not Always Converges
- Limit Points of Dynamic Not Always give ESS

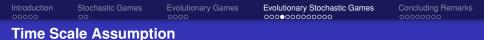
Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Evolutionary Stochastic Games Concluding Rem

Frank Thuijsman, DKE, Maastricht University



 We assume that the Stochastic Game Horizon corresponds to Individual Life Time, which is Negligibly Small compared to the Time Scale of the Evolutionary Population Dynamics



- We assume that the Stochastic Game Horizon corresponds to Individual Life Time, which is Negligibly Small compared to the Time Scale of the Evolutionary Population Dynamics
- The Infinite Horizon Average Reward approximates the Finite Horizon Average Reward



Example

In a Game with 2 States and 2 Actions, *T* and *B*, in each State:

$$\frac{1}{2} \cdot (T,T) + \frac{1}{2} \cdot (B,B) = ((\frac{1}{2},\frac{1}{2}),(\frac{1}{2},\frac{1}{2})) = \frac{1}{2} \cdot (T,B) + \frac{1}{2} \cdot (B,T)$$

Frank Thuijsman, DKE, Maastricht University



Example

In a Game with 2 States and 2 Actions, T and B, in each State:

$$\frac{1}{2} \cdot (T,T) + \frac{1}{2} \cdot (B,B) = ((\frac{1}{2},\frac{1}{2}),(\frac{1}{2},\frac{1}{2})) = \frac{1}{2} \cdot (T,B) + \frac{1}{2} \cdot (B,T)$$

Question

Suppose $((\frac{1}{2}, \frac{1}{2}), (\frac{1}{2}, \frac{1}{2}))$ is an ESS, does it imply $\gamma(T, T) = \gamma(B, B) = \gamma(T, B) = \gamma(B, T)$?

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

Irreducible Markov Decision Problems

Theorem

If x^* is a Stationary Optimal Strategy in an Irreducible MDP and x is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is Optimal as well.

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

Irreducible Markov Decision Problems

Theorem

If x^* is a Stationary Optimal Strategy in an Irreducible MDP and x is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is Optimal as well.

Here Irreducibility is Essential!

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

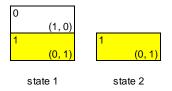
Irreducible Markov Decision Problems

Theorem

If x^* is a Stationary Optimal Strategy in an Irreducible MDP and x is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is Optimal as well.

Here Irreducibility is Essential!

Example



Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Concluding Remain Concluding Remain

Theorem

If x^* is a Stationary Optimal Strategy in an Irreducible MDP and x is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is Optimal as well.

Proof follows by showing that:

Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Evolutionary Stochastic Games Concluding Remarks

Irreducible Markov Decision Problems

Theorem

If x^* is a Stationary Optimal Strategy in an Irreducible MDP and x is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is Optimal as well.

Proof follows by showing that: For a Stationary Strategy in an Irreducible MDP the Average Reward is a Convex Combination of the Averages for the Pure Stationary Strategies in its Carrier

Frank Thuijsman, DKE, Maastricht University

Corollary

If x^* is an ESS in an Evolutionary Stochastic Game and $x \neq x^*$ is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is no ESS.

Frank Thuijsman, DKE, Maastricht University

Corollary

If x^* is an ESS in an Evolutionary Stochastic Game and $x \neq x^*$ is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is no ESS.

Proof:

Frank Thuijsman, DKE, Maastricht University

Corollary

If x^* is an ESS in an Evolutionary Stochastic Game and $x \neq x^*$ is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is no ESS.

Proof:

```
If x^* ESS and C(x_s) \subset C(x_s^*) \ \forall s,
```

Frank Thuijsman, DKE, Maastricht University

Corollary

If x^* is an ESS in an Evolutionary Stochastic Game and $x \neq x^*$ is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is no ESS.

Proof:

If x^* ESS and $C(x_s) \subset C(x_s^*) \forall s$, then $\gamma(x, x^*) = \gamma(x^*, x^*)$ by previous Theorem,

Frank Thuijsman, DKE, Maastricht University

Corollary

If x^* is an ESS in an Evolutionary Stochastic Game and $x \neq x^*$ is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is no ESS.

Proof:

If x^* ESS and $C(x_s) \subset C(x_s^*) \forall s$, then $\gamma(x, x^*) = \gamma(x^*, x^*)$ by previous Theorem, then $\gamma(x^*, x) > \gamma(x, x)$ by 2nd ESS Condition,

Frank Thuijsman, DKE, Maastricht University

Corollary

If x^* is an ESS in an Evolutionary Stochastic Game and $x \neq x^*$ is a Stationary Strategy with $C(x_s) \subset C(x_s^*)$ for each s, then x is no ESS.

Proof:

If $x^* \text{ ESS and } C(x_s) \subset C(x_s^*) \forall s$, then $\gamma(x, x^*) = \gamma(x^*, x^*)$ by previous Theorem, then $\gamma(x^*, x) > \gamma(x, x)$ by 2nd ESS Condition, which implies x is no ESS. \Box

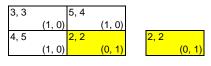
Frank Thuijsman, DKE, Maastricht University

Example



Frank Thuijsman, DKE, Maastricht University

Example



state 1

state 2

No Symmetric Equilibrium in Stationary Strategies

Frank Thuijsman, DKE, Maastricht University

Introduction	Stochastic Games	Evolutionary Games	Evolutionary Stochastic Games	Concluding Remarks

Theorem

For every Symmetric Irreducible Stochastic Game there exists a Symmetric Stationary Equilibrium.

Frank Thuijsman, DKE, Maastricht University

Introduction	Stochastic Games	Evolutionary Games	Evolutionary Stochastic Games	Concluding Remarks

Theorem

For every Symmetric Irreducible Stochastic Game there exists a Symmetric Stationary Equilibrium.

For Discounted as well as for Undiscounted (Average) Rewards

Frank Thuijsman, DKE, Maastricht University

Introducti	on Stochastic Games	Evolutionary Games	Evolutionary Stochastic Games	Concluding Remarks

Theorem

For every Symmetric Irreducible Stochastic Game there exists a Symmetric Stationary Equilibrium.

For Discounted as well as for Undiscounted (Average) Rewards

Proof follows by:

- a Fixed Point Argument for the Discounted Best Reply Map
- taking the Limit of Discounted Fixed Points for the Undiscounted Case

Frank Thuijsman, DKE, Maastricht University

ction Stochas

chastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 2 State Example with Replicator Dynamics

1, 1		4, 3	
	(0, 1)		(.5, .5)
3, 4		2, 2	
	(.5, .5)		(0, 1)

state	1
-------	---

3, 3		5, 4	
	(1, 0)		(.5, .5)
4, 5		2, 2	
	(.5, .5)		(1, 0)

state 2

Frank Thuijsman, DKE, Maastricht University

tion Stochastic

hastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 2 State Example with Replicator Dynamics

1, 1		4, 3	
	(0, 1)		(.5, .5)
3, 4		2, 2	
	(.5, .5)		(0, 1)

3, 3		5, 4	
	(1, 0)		(.5, .5)
4, 5		2, 2	
	(.5, .5)		(1, 0)

state 1

state 2

(Trajectory)

Frank Thuijsman, DKE, Maastricht University

uction Stocha

chastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 2 State Example with Replicator Dynamics

1, 1		4, 3	
	(0, 1)		(.5, .5)
3, 4		2, 2	
	(.5, .5)		(0, 1)

state	1
-------	---

3, 3		5, 4	
	(1, 0)		(.5, .5)
4, 5		2, 2	
	(.5, .5)		(1, 0)

state 2

Frank Thuijsman, DKE, Maastricht University

tion Stochastic

hastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 2 State Example with Replicator Dynamics

1, 1		4, 3	
	(0, 1)		(.5, .5)
3, 4		2, 2	
	(.5, .5)		(0, 1)

3, 3		5, 4	
	(1, 0)		(.5, .5)
4, 5		2, 2	
	(.5, .5)		(1, 0)

state 1

state 2

(Trajectory)

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 3 State Example with Replicator Dynamics

1, 1	4, 3
(.5, 0, .5)	(.5, .5, 0)
3, 4	2, 2
(.5, .5, 0)	(0, .5, .5)

3, 3	5, 4
(1, 0, 0)	(.5, 0, .5)
4, 5	2, 2
(.5, 0, .5)	(0, 0, 1)

4, 4	6, 7
(0, 1, 0)	(0, .5, .5)
7, 6	5, 5
(0, .5, .5)	(1, 0, 0)

state 1

state 2

state 3

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 3 State Example with Replicator Dynamics

1, 1	4, 3
(.5, 0, .5)	(.5, .5, 0)
3, 4	2, 2
(.5, .5, 0)	(0, .5, .5)

3, 3	5, 4
(1, 0, 0)	(.5, 0, .5)
4, 5	2, 2
(.5, 0, .5)	(0, 0, 1)

4, 4	6, 7
(0, 1, 0)	(0, .5, .5)
7, 6	5, 5
(0, .5, .5)	(1, 0, 0)

state 1

state 2

state 3

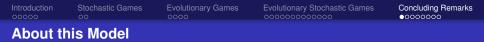
(Trajectory)

Frank Thuijsman, DKE, Maastricht University

Introduction	Stochastic Games	Evolutionary Games	Evolutionary Stochastic Games	Concluding Remarks
About th	nis Model			

Further Research:

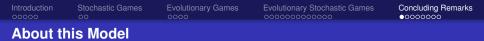
Frank Thuijsman, DKE, Maastricht University



Further Research:

• Finding Real Life Applications that Fit

Frank Thuijsman, DKE, Maastricht University



Further Research:

- Finding Real Life Applications that Fit
- Exploring the Relation between Replicator Dynamic and Fictitious Play for Symmetric Stochastic Games

Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Stochastic Games Concluding Remarks

The Fictitious Play Process:

Playing Best Replies against Observed Action Frequencies

Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Evolutionary Stochastic Games Concluding Remarks

The Fictitious Play Process:

Playing Best Replies against Observed Action Frequencies

• For Matrix Games FP leads to Optimal Strategies

Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Evolutionary Stochastic Games Concluding Remarks

The Fictitious Play Process:

Playing Best Replies against Observed Action Frequencies

- For Matrix Games FP leads to Optimal Strategies
- No FP Convergence for Bimatrix Games (Shapley, 1964)

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 2 State Example with Fictitious Play

1, 1		4, 3	
	(0, 1)		(.5, .5)
3, 4		2, 2	
	(.5, .5)		(0, 1)

	(1, 0)		(.5, .5)
4, 5		2, 2	
	(.5, .5)		(1, 0)

3, 3

state 1

state 2

5, 4

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 2 State Example with Fictitious Play

1, 1		4, 3	
	(0, 1)		(.5, .5)
3, 4		2, 2	
	(.5, .5)		(0, 1)

3, 3		5, 4	
	(1, 0)		(.5, .5)
4, 5		2, 2	
	(.5, .5)		(1, 0)

state 1

state 2

(Trajectory)

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 3 State Example with Fictitious Play

1, 1 (.5, 0, .5)	4, 3
(.5, 0, .5)	(.5, .5, 0)
3, 4	2, 2
(.5, .5, 0)	(0, .5, .5)

3, 3	5, 4
(1, 0, 0)	(.5, 0, .5)
4, 5	2, 2
(.5, 0, .5)	(0, 0, 1)

4, 4	6, 7
(0, 1, 0)	(0, .5, .5)
7, 6	5, 5
(0, .5, .5)	(1, 0, 0)

state 1

state 2

state 3

Frank Thuijsman, DKE, Maastricht University

Stochastic Games

Evolutionary Games

Evolutionary Stochastic Games

Concluding Remarks

A 3 State Example with Fictitious Play

1, 1 (.5, 0, .5)	4, 3
(.5, 0, .5)	(.5, .5, 0)
3, 4	2, 2
(.5, .5, 0)	(0, .5, .5)

3, 3	5, 4
(1, 0, 0)	(.5, 0, .5)
4, 5	2, 2
(.5, 0, .5)	(0, 0, 1)

4, 4	6, 7
(0, 1, 0)	(0, .5, .5)
7, 6	5, 5
(0, .5, .5)	(1, 0, 0)

state 1

state 2

state 3

(Trajectory)

Frank Thuijsman, DKE, Maastricht University

Introduction Stochastic Games Evolutionary Games Evolutionary Stochastic Games Concluding Remarks

Frank Thuijsman, DKE, Maastricht University



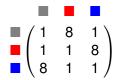
Examining the effects of periodic fitness in replicator dynamics

(Trajectory)

Frank Thuijsman, DKE, Maastricht University



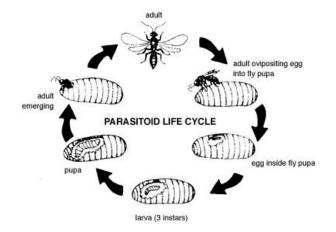
Examining the dynamics of local interactions Dynamic Stability: Predator-Prey Behaviour



Frank Thuijsman, DKE, Maastricht University



Studying sex choice ovipositioning behavior of parasitoid wasps



Frank Thuijsman, DKE, Maastricht University



Thank you for your attention! Any comment is welcome!

Paper and presentation will soon be available at www.personeel.unimaas.nl/F-Thuijsman

Frank Thuijsman, DKE, Maastricht University