

## Game Theoretical Approaches to Modelling and Simulation

Michael H. F. Wilkinson

Institute for Mathematics and Computing Science University of Groningen The Netherlands

November 2004

Introduction to Computational Science



- Context
- A Classic: Hawks vs. Doves
- Pay-off matrices
- Nash-equilibria and Evolutionary Stable Strategies
- Pure vs. Mixed Strategies
- Population Games
- Replicator dynamics
- Asymmetric games: Bimatrix models
- Adaptive dynamics
- Evolution of cooperation





- Game theoretical models are commonly used in three contexts:
  - 1. Evolutionary theory
  - 2. Economics
  - 3. Sociology
- Less-known fields are e.g. in A.I. (deciding optimal strategies) and in computer games.
- The games involved are usually very simple: two players, only a few types of moves.



- The Hawks vs. Doves game tries to explain ritualized "fighting" behaviour in many animals.
- Many animal species rarely cause real damage during conflicts:
  - King-cobra males try to push each-other's heads to the ground rather than biting
  - Stags have roaring matches, walk parallel, and sometimes lock horns and push rather than trying to kill each-other
  - When cats fight they scream more than they actually fight
- The more dangerous the species, the more ritual the fight becomes.
- Naive reasoning using "survival of the fittest" suggest that killing rivals when an opportunity arises would be common





- Suppose two rivals of the same species meet at the location of some resource with value G.
- Suppose there are two "pure" strategies:
  - 1. Hawk: you always escalate the conflict until either the other withdraws, or you are badly hurt.
  - 2. Dove: you posture until the other withdraws, but you withdraw if the other escalates or seems too strong.
- If two hawks meet, one wins G but the other loses cost C, with G < C.
- If two doves meet, one withdraws and loses nothing, and the other wins G.
- $\blacksquare$  If a hawk meets a dove, the dove loses nothing and the hawk wins G.





We can formalize this in a payoff matrix:

	if it meets a hawk	if it meets a dove
a hawk receives	$\frac{G-C}{2}$	G
a dove receives	0	$\frac{G}{2}$

- In each cell the average payoff is listed for a given pair of strategies.
- We can now study the optimal behaviour, which depends on the population structure:
  - If doves dominate, it pays to be a hawk, because you almost always win G, vs.  $\frac{G}{2}$  for doves.
  - If hawks dominate, it pays to be a dove, because you almost always win  $0 > \frac{G-C}{2}$ .



Solution For a given population with fraction p of hawks and 1 - p of doves, the payoff for hawks  $P_h$  becomes:

$$P_{h} = \frac{G - C}{2}p + (1 - p)G$$
(1)

Under the same assumptions, the payoff for doves  $P_d$  is

$$P_d = (1-p)\frac{G}{2} \tag{2}$$

• The population reaches stability when  $P_h = P_d$  or

$$(1-p)\frac{G}{2} = \frac{G-C}{2}p + (1-p)G \quad \Rightarrow p = \frac{G}{C}$$
(3)

**9** So if the cost C is high (the animals are dangerous) hawks becomes rare.





- Let us introduce two new strategies:
  - 1. bullies: Simulate escalation but run away if the other fights back.
  - 2. retaliators: behaves like dove unless the other escalates, then it fights back.
- The payoff matrix becomes:

if it meets	a hawk	a dove	a bully	a retaliator
a hawk receives	$\frac{G-C}{2}$	G	G	$\frac{G-C}{2}$
a dove receives	0	$\frac{G}{2}$	0	$\frac{G}{2}$
a bully receives	0	G	$\frac{G}{2}$	0
a retaliator receives	$\frac{G-C}{2}$	$\frac{G}{2}$	G	$\frac{G}{2}$



- Let  $x_b$ ,  $x_d$ ,  $x_h$ ,  $x_r$ , denote the numbers of bullies, doves, hawks and retaliators, and  $P_b$ ,  $P_d$ ,  $P_h$ ,  $P_r$  their payoffs.
- The payoffs become:

$$P_h = (x_r + x_h)\frac{G - C}{2} + (x_b + x_d)G$$
(4)

$$P_d = (x_d + x_r) \frac{G}{2} \tag{5}$$

$$P_b = x_d G + x_b \frac{G}{2} \tag{6}$$

$$P_r = x_h \frac{G - C}{2} + (x_d + x_r) \frac{G}{2} + x_b G$$
(7)



Demanding that  $P_b = P_d$  at stability means that

$$x_r = x_b + x_d \tag{8}$$

If we insert this into (4) and (7), and then require that  $P_h = P_r$  we arrive at

$$x_r(G-C) = x_b G \tag{9}$$

- This can only be the case if the signs of  $x_r$  and  $x_b$  are different which is meaningless in this context.
- Therefore, no 4-strategy equilibrium exists in this case.





If  $x_b = 0$ , equating  $P_h$  and  $P_r$  yields

$$x_r = \frac{G}{C} x_d \tag{10}$$

- inserting this into (4) and (5) yields  $x_h = 0$
- If  $x_r = 0$ , equating  $P_b$  and  $P_d$  yields that  $x_b = -x_d$  which is again meaningless.
- The two-strategy options:
  - Doves and retaliators can live together in any ratio (why?)
  - Retaliators drive hawks to extinction (why?)
  - Retaliators drive bullies to extinction (why?)
  - Bullies drive doves into extinction
  - Bullies and hawks achieve the same equilibrium as hawks and doves.





- A strategy S is an Evolutionary Stable Strategy (ESS) if a pure population of S-strategists is stable against invasion by any other strategy.
- Let the fitness of an individual with strategy  $S_i$  is a population P be denoted  $F(S_i, P)$ .
- A population consisting of a mixture of individuals with N strategies P may be denoted as  $\sum_{j=1}^{N} p_j S_j$  with  $p_j$  the fraction of individuals with strategy  $S_j$ , and  $\sum_{j=1}^{N} p_j = 1$ .
- for a pure population of  $S_i$ -strategists we have  $P = S_i$ .
- $S_i$  is an ESS if

$$F(S_i, S_i) > F(S_j, S_i) \quad \forall j \neq i$$
(11)



- In the case above, neither hawks, doves, bullies nor retaliators are an ESS.
- ESSs are NOT unique: there are cases in which

$$F(S_1, S_1) > F(S_2, S_1)$$
 and  $F(S_2, S_2) > F(S_1, S_2)$  (12)

- An example is that of toxin producing bacteria and their susceptible counterparts
- The payoffs F(S, P) and F(T, P) of the susceptible strategy S and toxin producing strategy T in a population P = xS + (1 x)T are

$$F(S,P) = \mu - (1-x)\kappa \quad \text{and} \quad F(S,P) = \mu - \epsilon \tag{13}$$

with  $\mu$  the relative growth rate,  $\kappa$  the toxin kill rate and  $\epsilon$  the cost of toxin production.

• If 
$$\epsilon < \kappa$$
,  $F(S,S) = \mu > \mu - \epsilon = F(T,S)$  and  $F(T,T) = \mu - \epsilon > \mu - \kappa = F(S,T)$ .





- In general, if N pure strategies are available we can allow mixed strategies S by assigning each strategy  $S_i$  a given probability  $p_i$  to be used by an individual.
- each strategy is now a point in the simplex

$$R_N = \left\{ \mathbf{p} = (p_1, p_2, \dots, p_N), \sum_{i=1}^N p_i = 1 \right\}$$
(14)

- The corners of the simplex are given by the unit vectors along the coordinate axes: the pure strategies.
- The interior of the simplex consist of completely mixed strategies (all  $p_i > 0$ )
- On the boundary of the simplex are those strategies for which one or more  $p_i = 0$



- Each pure-strategy player using  $S_i$  extracts a payoff  $u_{ij}$  against a pure-strategy player using  $S_j$ .
- The  $N \times N$  matrix  $\mathbf{U} = (u_{ij})$  is the payoff matrix.
- An  $S_i$ -strategist extracts a payoff  $P_i$  against a p-strategist of

$$P_i = (\mathbf{U}\mathbf{p})_i = \sum_{j=1}^N u_{ij} p_j$$
(15)

For a mixed strategy q-player the payoff  $P_q$  against a p-strategist becomes

$$P_{\mathbf{q}} = \mathbf{q} \cdot \mathbf{U}\mathbf{p} = \sum_{j=1}^{N} \sum_{i=1}^{N} u_{ij} q_i p_j$$
(16)





- We denote the best replies to strategy  $\mathbf{p}$  as  $\beta(\mathbf{p})$
- This is the set of strategies q for which the map  $q \rightarrow q \cdot Up$  attains the maximum value.

🍠 If

$$\mathbf{p} \in \beta(\mathbf{p}),\tag{1}$$

p is a Nash equilibrium.

Every normal form game has at least one Nash equilibrium.

🍠 If

$$\mathbf{q} \cdot \mathbf{U}\mathbf{p} < \mathbf{p} \cdot \mathbf{U}\mathbf{p}, \forall \mathbf{q} \neq \mathbf{p},$$
 (18)

 $\mathbf{p}$  is a *strict* Nash equilibrium.

All strict Nash equilibria are pure strategies



7)



- If a Nash equilibrium p is strict, any population consisting only of p-strategists cannot be invaded by other strategies.
- Such strict Nash equilibria are ESS!
- Non-strict Nash equilibria are not necessarily ESS.
- ESS requires TWO conditions:
  - 1. the equilibrium condition

$$\mathbf{q} \cdot \mathbf{U}\mathbf{p} \le \mathbf{p} \cdot \mathbf{U}\mathbf{p}, \quad \forall \mathbf{q} \in R_N$$
 (19)

2. the stability condition

 $\mathbf{q} \cdot \mathbf{U}\mathbf{q} < \mathbf{p} \cdot \mathbf{U}\mathbf{q}, \quad \text{if } \mathbf{q} \neq \mathbf{p}, \text{ and } \mathbf{q} \cdot \mathbf{U}\mathbf{p} = \mathbf{p} \cdot \mathbf{U}\mathbf{p}$  (20)





- Why do animals (including us) produce offspring of both sexes in equal numbers?
- Why is this a problem? Because populations with more females than males could reproduce faster (ask any farmer).
- However, if there are mostly females, then producing more males as offspring would be the better strategy:
  - some females might never find males
  - all males are likely to find females
- If males dominate producing females is better.
- Thus, the payoff of a strategy depends on the population, rather than on a single individual's strategy.
- This means, the Sex-Ratio Game is a Population Game.





- Consider the payoff in terms of the number of grandchildren
- Let p be the sex-ratio of a given individual, and m the average sex ratio in the population
- Let the number of children of the current population be N1, of which  $mN_1$  are males, and  $(1 m)N_1$  females.
- Let the number of grandchildren of the current generation be  $N_2$ .
- Each male child of the current generation produces an average of  $N_2/mN_1$  of these grandchildren
- Each female child  $N_2/(1-m)N_1$ .
- The number of grandchildren  $N_{2,p}$  of an individual with sex ratio p is

$$N_{2,p} = p \frac{N_2}{mN_1} + (1-p) \frac{N_2}{(1-m)N_1}$$
(21)





The fitness is proportional to

$$w(p,m) = \frac{p}{m} + \frac{1-p}{1-m}$$
 (22)

- If the population consists of a individuals with a sex ratio of q, is this evolutionary stable?
- Suppose a small fraction  $\epsilon$  of the population mutates into some other value p for the sex ratio. The population mean m is then

$$m = \epsilon p + (1 - \epsilon)q \tag{23}$$

- The q-strategy is only evolutionary stable if w(p,m) < w(q,m).
- If q = 0.5 it can easily be shown that this holds true for all  $p \neq q$ .





- This notion can be generalized by stating that the payoff  $P_i$  for a pure strategy player  $S_i$  depends on the probabilities of meeting a particular strategy in the population.
- More formally:  $P_i$  is a function of the frequencies  $m_j$  with which the pure strategies  $S_j$  are used in the population.
- Note that  $\mathbf{m} = (m_1, m_2, \dots, m_n)$  is just a point in the simplex  $R_N$ .
- The payoff  $P_{\mathbf{p}}$  for a  $\mathbf{p}$ -strategist is

$$P_{\mathbf{p}} = \sum_{i=1}^{N} p_i P_i(\mathbf{m}) = \mathbf{p} \cdot \mathbf{P}(\mathbf{m}).$$
 (24)



- These describe the evolution of the frequencies with which different strategies occur in the population
- Assume we have n types in the population with frequencies  $x_1$  to  $x_n$ .
- As above, the fitness  $f_i$  will be a function of the state  $\mathbf{x} = (x_1, x_2, \dots, x_n)$ .
- We assume that the population is large enough to model the rate of change of x as a function of time by differential equations.
- We assume the change in frequency is linked to its fitness compared to the average population fitness

$$\frac{1}{x_i}\frac{dx_i}{dt} = f_i(\mathbf{x}) - \bar{f}(\mathbf{x}) \quad \text{or} \quad \frac{dx_i}{dt} = (f_i(\mathbf{x}) - \bar{f}(\mathbf{x}))x_i$$
(25)



- Assume that the replicator dynamics derive from a normal form game with N pure strategies  $S_1, S_2, \ldots, S_N$  (note  $N \neq n$ ), and payoff matrix U.
- The *n* types in the population correspond to (possibly mixed) strategies  $\mathbf{p}^1, \mathbf{p}^2, \dots, \mathbf{p}^n$ .
- The state of the system is given by  $\mathbf{x} = (x_1, x_2, \ldots, x_n)$ , which is a point in simplex  $R_n$  (not  $R_N$ ).
- Let matrix  $\mathbf{A} = (a_{ij}) = (\mathbf{p}^i \cdot \mathbf{U}\mathbf{p}^j).$
- The fitness  $f_i$  now becomes

$$f_i(\mathbf{x}) = \sum_{j=1}^n a_{ij} x_j = (\mathbf{A}\mathbf{x})_i$$
(26)





The replicator equation (25) becomes

$$\frac{dx_i}{dt} = (((Ax)_i - \mathbf{x} \cdot \mathbf{A}\mathbf{x})x_i$$
(27)

We now say that a point  $y \in R_n$  is a Nash equilibrium if

$$\mathbf{x} \cdot \mathbf{A}\mathbf{y} \le \mathbf{y} \cdot \mathbf{A}\mathbf{y} \quad \forall \mathbf{x} \in R_n$$
 (28)

It is an evolutionary stable state (not strategy!) if

$$\mathbf{x} \cdot \mathbf{A}\mathbf{x} < \mathbf{y} \cdot \mathbf{A}\mathbf{x} \quad \forall \mathbf{x} \neq \mathbf{y}$$
 (29)

in a neighbourhood of  $\mathbf{y}$ .

Introduction to Computational Science





- A simple example of replicator dynamics is in the Hawk-Dove game
- For two strategies we can simplify the replicator equation by replacing  $x_1$  by x and  $x_2$  by 1 x. We obtain

$$\frac{dx}{dt} = x(1-x)((\mathbf{A}\mathbf{x})_1 - (\mathbf{A}\mathbf{x})_2)$$
(30)

In the Hawk-Dove case we obtain

$$\frac{dx}{dt} = x(1-x)(G-Cx) \tag{31}$$

• This has a point attractor G/C for the domain ]0,1[.





- More complex dynamics are obtained with the so called Rock-Scissors-Paper game.
- We now have a zero sum payoff matrix

$$\mathbf{A} = \begin{pmatrix} 0 & 1 & -1 \\ -1 & 0 & 1 \\ 1 & -1 & 0 \end{pmatrix}$$
(32)

This yields replicator equations

$$\frac{dx_1}{dt} = x_1(x_2 - x_3)$$
(33)  

$$\frac{dx_2}{dt} = x_2(x_3 - x_1)$$
(34)  

$$\frac{dx_3}{dt} = x_3(x_1 - x_2)$$
(35)



## This yields equilibria at

 $\mathbf{x} = (1/3, 1/3, 1/3) \tag{36}$ 

$$\mathbf{x} = (1, 0, 0)$$
 (37)

$$\mathbf{x} = (0, 1, 0)$$
 (38)

$$\mathbf{x} = (0, 0, 1)$$
 (39)

(how do we find these?)

• The system will typically oscillate in orbits in which  $x_1x_2x_3 = c$ , centred on (1/3, 1/3, 1/3).





- In the previous cases we have looked at symmetric games:
  - If moves are interchanged from player to player, so are the payoffs
  - Modelling is done using a single payoff matrix
- In practice, games between players may be asymmetric
- The goals may be different to players
- The values of resources may be different to different players: why is a hare faster than a fox? A hare runs for his life, a fox for his meal!
- The roles may be different (e.g. parent child)
- To model such games we use two payoff matrices, or a bimatrix.





- A classic example for a bimatrix game is the battle of the sexes, which concerns parental investment in the offspring
- For males who abandon the females after mating can go on to mate with other females.
- Females could prevent this by being "coy", demanding an investment E from the male before mating, during a so-called "engagement" period.
- After such an investment, it would pay more for a male to help raise his young (because he is now relatively sure they are his), rather than find another mate (by which time the mating season may be over).
- However, once all males have been selected for faithfulness, a "fast" female, who will mate without engagement cost will gain
- This in turn leads to the appearance of "philandering" males, who will mate and desert the females to mate with another



- We can formalize this:
  - If a coy female mates with a faithful male, they both win gain G and share the cost of upbringing C, and both pay E, so each wins G C/2 E.
  - If a fast female mates with a faithful male, they both win gain G and share the cost of upbringing C, without the cost E, so each wins G C/2.
  - If a fast female meets a philandering male, she gets G C, whereas he gets G.
  - If a coy female encounters a philandering male, she refuses to mate, so both receive 0
- In terms of payoff matrices we have

$$\mathbf{A} = \begin{bmatrix} 0 & G \\ G - \frac{C}{2} - E & G - \frac{C}{2} \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} 0 & G - \frac{C}{2} - E \\ G - C & G - \frac{C}{2} \end{bmatrix}$$
(40)

with  $\mathbf{A}$  the matrix for males and  $\mathbf{B}$  the matrix for females

It turns out there is no stable equilibrium for this case.





- In the previous models we only look at single encounters
- Strategies change in a population through competition or copying
- Each strategy consists of a fixed set of probabilities for each move
- Unless mutations are allowed, no new strategies are developed
- In reality, players may change their strategy, depending on previous experience.
- Adaptive strategies are formulated differently;
  - The set of probabilities for moves is a function of the state of the player
  - The state of a player depends on previous games, either of the player himself, or those of others.
- The resulting adaptive dynamics can be highly complex





- One field in which adaptive dynamics are important is that of the emergence of cooperation
- This emergence might concerns the evolution of cooperative behaviour in animals (not just the lack of aggression as in the Hawk-Dove game)
- It might also be the cooperation in economics and sociology: formation of coalitions, companies, etc.
- The core question is always: Why, when faced with an easy quick win at the expense of another, do many people or animals take a lower profit which does not harm the other.
- Another way of looking at the problem might be: why do we have such a strong feeling of fairness? Why do we get angry seeing someone cheat another when he should have shared?
- It turns out that single encounter games cannot solve this problem





- Iterated prisoner's dilemma is the classic example for adaptive strategies and the evolution of cooperation
- Prisoner's dilemma is a simple two player game in which there are two possible moves: cooperate (C) or defect (D)
- If both players cooperate, they receive a reward R
- $\checkmark$  If both players defect, they receive a punishment P
- $\checkmark$  If a player defects, but the other cooperates, he receives a temptation T
- $\checkmark$  If a player cooperates and the opponent defects, he receives the sucker's reward S
- In all cases we assume

$$T > R > P > S$$
 and  $2R > T + S$  (41)



## The payoff matrix is

	C	D
C	R	S
D	T	P

- If the game is played once: the best strategy is always defect (AIID):
  - If the other cooperates, cooperating gets you R.
  - If the other cooperates, defecting gets you T > R.
  - If the other defects, cooperating gets you S.
  - If the other defects, defecting yourself gets you P > S.

Therefore, you are always better off defecting

This basically formalizes the selfishness problem





- Now consider the case when you will encounter the same player again, with a probability w.
- Let  $A_n$  denote the payoff in the *n*-th round, the total expected payoff is given by

$$A = \sum_{n=0}^{\infty} A_n w^n \tag{42}$$

In the limiting case of w = 1, this diverges, so instead we take the limit of the mean

$$A = \lim_{n \leftarrow \infty} \frac{\sum_{n=0}^{N} A_n w^n}{N+1}$$
(43)

Obviously, if w is very small, each player should still just defect, since the possibilities for revenge are small.





- Strategies in IPD are programs which tell you which move to make in each round.
- Strategies are sometimes classified as:

Nice: Does not defect first
Retaliatory: Punishes defection
Forgiving: Returns to cooperation following cooperation of opponent
Suspicious: Does not cooperate until the other cooperates
Generous: Does not always retaliate at a first defection

No best strategy exist, it all depends on the opponent



If the opponent is an AIIC player, AIID is best, because its payoff will be

$$A = \sum_{n=0}^{\infty} Tw^n = \frac{T}{1-w}$$
(44)

However, if the opponent is Grim, who is nice, retaliatory and totally unforgiving, the payoff after your first defection will be

$$A = \sum_{n=0}^{\infty} Pw^n = \frac{P}{1-w}$$
(45)

at best!

• This means AllC would perform better (A = R/(1 - w)), provided

$$w > \frac{T-R}{T-P} \tag{46}$$





- A simple strategy which does very well in round-robin tournaments (each player competes in turn with each other player) is *Tit-For-Tat* (TFT).
- Curiously, TFT never gets more points per game than its opponent.
- **It starts of with** C, so it is nice
- It then copies the opponents last move
- This behaviour makes it retaliatory, because a defection will be repayed by a defection
- It is also forgiving, because it will return to playing C if the opponent returns to C
- It can outcompete a population of AIID and gain dominance if

$$w \ge \max\left(\frac{T-R}{T-P}, \frac{T-R}{R-S}\right)$$
(47)





- TFT has two weaknesses:
  - 1. It is sensitive to noise: if there is a small probability of a message (C or D) being misinterpreted, two TFT players enter into a round of mutual retaliations
  - 2. It is sensitive to invasion by other strategies such as *Pavlov*, or any nice strategy.
- Pavlov takes both his own and the opponents last move into account to compute the next
- This can be formalized as a function of the last reward
  - $\checkmark$  If the last reward is R, play C
  - **9** If the last reward is P, play C
  - If the last reward is S, play D
  - **I** If the last reward is T, play D
- In effect, *Pavlov* retains his strategy after high payoff (T or R) and changes strategy after low payoff (S or P).
- It can correct for occasional mistakes
- Strict cooperators cannot invade





- The success of TFT resulted in the development of some variants
- *Tit-For-Two-Tats* (TF2T), which retaliates only after two *Ds*.
  - More generous
  - More tolerant for errors
  - Co-exists with TFT
- Suspicious-Tit-For-Tat (STFT) which starts with D instead of C, so it is not nice (gets on with TFT like a house on fire).
- Observer Tit-For-Tat Uses observations of potential opponents in other games to decide whether to start with D or C.
  - Requires the possibility of observations
  - Suppresses "Roving" strategies (AIID strategies which try to reduce w by selecting new opponents)





- Rather than using strict strategies, we can define probabilities with which strategies are used.
- This models:
  - Noise in the communications process
  - Faulty memory
- It also has the advantage that the importance of the initial move is lost after a sufficient number of moves.
- One way to define stochastic strategies is by defining 2-tuples (p,q) which denote the probabilities of a C after an opponent's C or D (respectively).
- Nowak and Sigmund (1992) found that generous TFT with p = 1 and

$$q = \min\left(1 - \frac{T - R}{R - S}, \frac{R - P}{T - P}\right)$$
(48)

was the optimum in the case of w = 1.





- Note that Grim cannot be modelled using the 2-tuple approach
- The above stochastic model can be extend to include more strategies.
- By setting the probability of cooperation after receiving a reward R, S, T, orP we can devise a large space of possible strategies, *including* 
  - **• TFT**: (1, 0, 1, 0)
  - **Pavlov:** (1,0,0,1)
  - *Grim*: (1,0,0,0)
  - AIID: (0,0,0,0)
  - AllC: (1,1,1,1)
- Strictly speaking, we should also add a fifth probability, i.e. the probability for C on the first move.





- Using 100 random starting points in the 2-tuples-models, and a genetic algorithm using payoff as fitness function was implemented.
- Initially AIID-like strategies increased rapidly and AIIC-like "suckers" were removed.
- Then, if sufficient TFT-like strategies were in the initial population, they eradicated the AIID-like strategies
- After this GTFT appeared and started to dominate.
- Similar results were obtained using the 4-tuple approach, but here Pavlov could appear, and did so (it was discovered this way).