

Computer simulations in Physics

Game models

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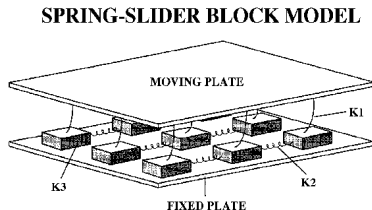
May 19, 2022

Self-Organized Criticality

- ▶ Critical state: inflection point in the critical isotherm
- ▶ Power law functions of correlation length, relaxation time
- ▶ Control parameter, generally temperature
- ▶ Critical point as an attractor?
- ▶ Why? Power law: We see many cases
 - ▶ $1/f$ noise (music, ocean, earthquakes, flames)
 - ▶ Lack of scales (market, earthquakes)
- ▶ Underlying mechanism?

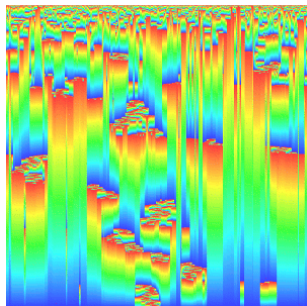
Bak-Tang-Wiesenfeld model

- ▶ Originally a sandpile model
- ▶ Better explained as a *Lazy Bureaucrat model*:
- ▶ Best application: Spring block model of earthquakes:
 - ▶ Masses sitting on a frictional plane in a grid are connected with springs to each other and to the top plate
 - ▶ Top plate moves slowly, increasing the stress on the top springs slowly and randomly
 - ▶ If force is large enough masses move which increases the stress on the neighboring masses



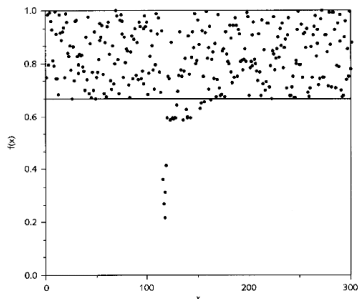
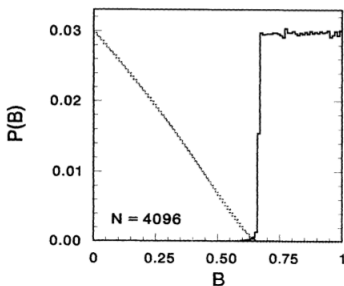
Bak-Sneppen model of evolution

- ▶ N species all depends on two other (ring geometry)
- ▶ Each species are characterized by a single *fitness*
- ▶ In each turn the species with the lowest fitness dies out and with it its two neighbors irrespective of their fitness
- ▶ These 3 species are replaced by new ones with random fitness
- ▶ Initial and update fitness is uniform between $[0, 1]$



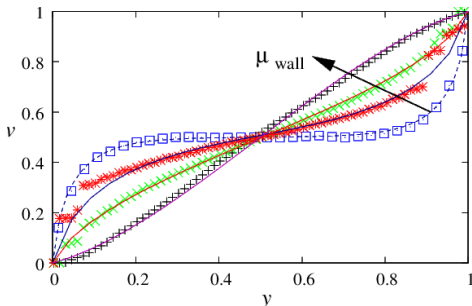
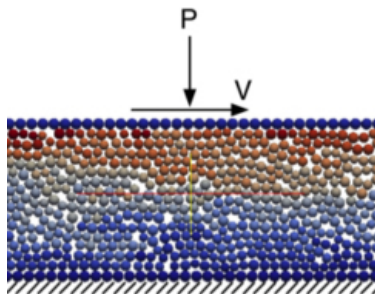
Bak-Sneppen model of evolution: Results

- ▶ Steady state with avalanches
- ▶ Avalanches start with a fitness $f > f_c \simeq 0.66$
- ▶ Avalanche size distribution power law
- ▶ Distance correlation power law



Bak-Sneppen model of evolution an application: Granular shear

- ▶ Fitness \rightarrow Effective friction coefficient
- ▶ Specimen with lowest fitness dies out \rightarrow block is sheared at weakest position (shear band)
- ▶ Neighbors, related species die out and replaced by new species \rightarrow structure gets random around the shear band.

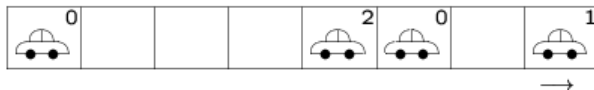


Traffic models



Nagel-Schreckenberg model

- ▶ Periodic 1d lattice (ring) Autobahn
- ▶ discretized in space and time
- ▶ Cars occupying a lattice moving with velocities $v = 0, 1, 2, 3, 4, 5$
- ▶ Remark, if max speed is 126 km/h, then lattice length is 7 m, a very good guess for a car in a traffic jam
- ▶ It uses parallel update: at each timestep all cars move v sites forward



Nagel-Schreckenberg model

► Algorithm:

1. **Acceleration:** All cars not at the maximum velocity increase their velocity by 1
2. **Slowing down:** Speed is reduced to distance ahead (1 sec rule)
3. **Randomization:** With probability p speed is reduced by 1
4. **Car motion:** Each car moves forward the number of cells equal to their velocity.

Configuration at time t :



a) Acceleration ($v_{max} = 2$):



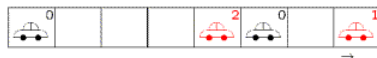
b) Braking:



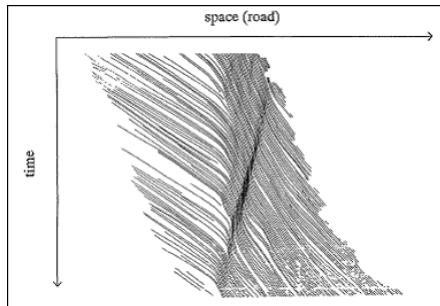
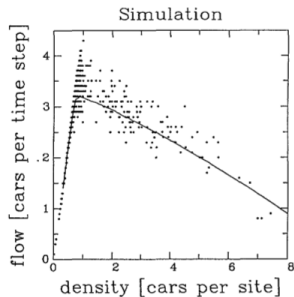
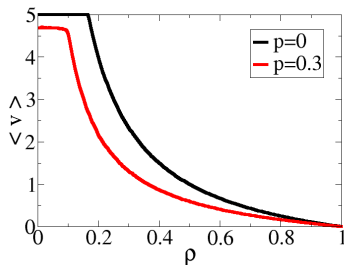
c) Randomization ($p = 1/3$):



d) Driving (= configuration at time $t + 1$):

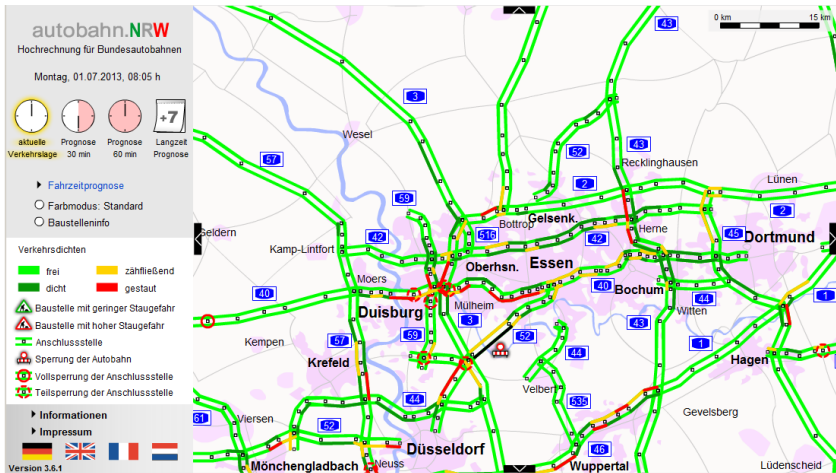


Emergence of traffic jams



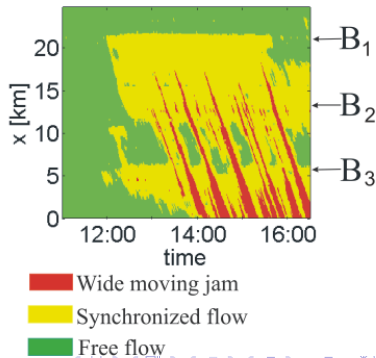
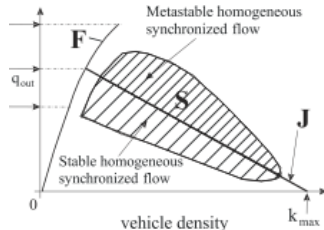
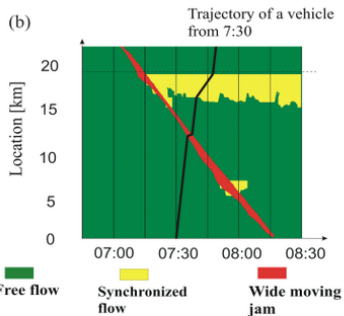
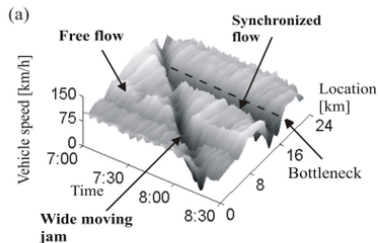
Nagel-Schreckenberg model

- ▶ Transition from free-flow to jammed state
- ▶ Jammed state is a phase-separated phase
- ▶ Without randomization a sharp transition
- ▶ Had been used in NRW to predict traffic jams



Three-phase traffic theory

Three traffic phases

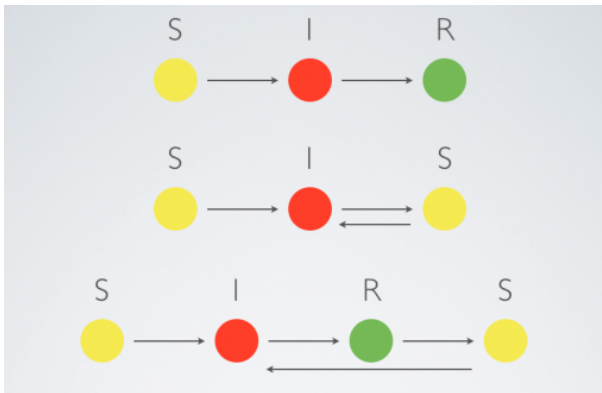


Disease spreading, SIR model

- ▶ S: susceptible (can be infected with prob. β if meets an infected)
- ▶ I: Infected (may infect susceptible, but may recover with prob. ν).
- ▶ R: Recovered (Immune to the disease)
- ▶ Other versions:
 - ▶ SI: agents do not recover (e.g. information spreading)
 - ▶ SIS: recovered people can get disease again
 - ▶ SIRS: recovered agents may become susceptible (e.g. influenza)

Disease spreading, SIR model

- ▶ S: susceptible
- ▶ I: Infected
- ▶ R: Recovered



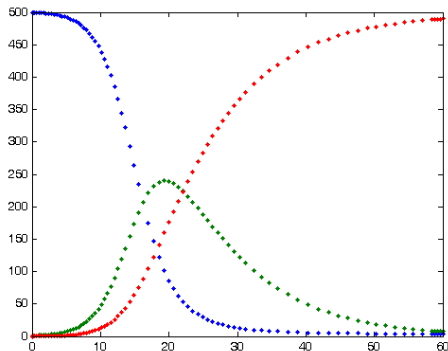
SIR model, connected graph

Governing equations:

$$\dot{S} = -\beta IS$$

$$\dot{I} = \beta IS - \nu I$$

$$\dot{R} = \nu I$$



SIR model, connected graph

Governing equations:

$$\dot{S} = -\beta IS$$

$$\dot{I} = \beta IS - \nu I$$

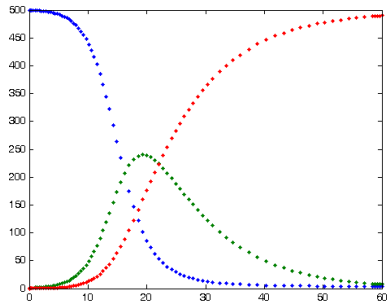
$$\dot{R} = \nu I$$

- ▶ Early stage $S \simeq 1$

$$I \simeq I_0 \exp[(\beta - \nu)t]$$

- ▶ $R = \beta/\nu$ epidemic threshold
 - ▶ $R > 1$ outbreak
 - ▶ $R < 1$ localized

SIR model vs. reality



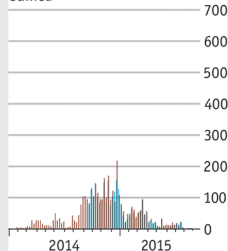
New cases* of Ebola infection per week

To August 23rd 2015

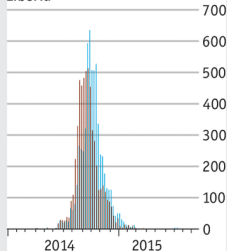
■ Patient database

■ WHO Situation Report

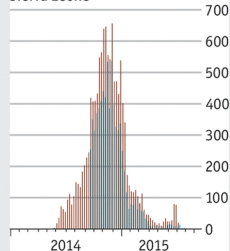
Guinea



Liberia



Sierra Leone†



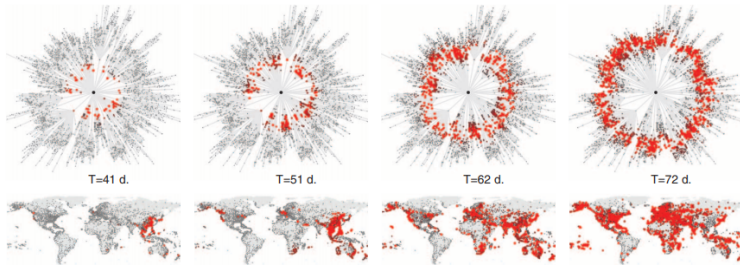
Source: WHO

*Confirmed and probable †Patient database not published from July 5th 2015

Algorithm for the SIR model

1. List of initially infected nodes is I
2. Get a random (infected) node u from the list I
3. For all neighbors w of u do 4.
4. If w is susceptible change it to infected with probability β , and enqueue it into list I
5. With probability ν change state of u to recovered otherwise put it back to I
6. If I is not empty go back to 2.

SIR on space and network



Predator prey model

- ▶ $N(t)$ number of predators
- ▶ $E(t)$ number of prey
- ▶ Model (Lotka 1925, Volterra 1926):

$$\begin{aligned}\dot{E}(t) &= \beta_E E(t) - [\mu_E N(t)] E(t) \\ \dot{N}(t) &= [\beta_N E(t)] N(t) - \mu_N N(t)\end{aligned}\tag{1}$$

- ▶ Solution $\dot{E} = \dot{N} = 0$:

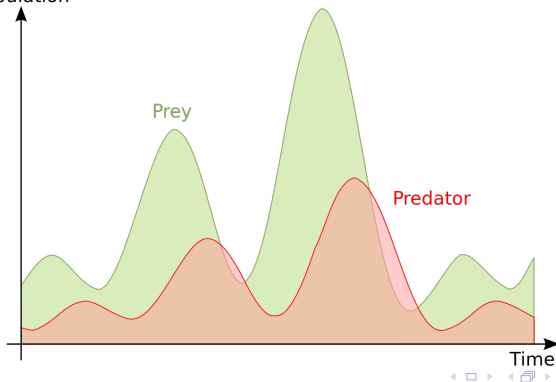
$$\begin{aligned}N &= E = 0 \\ N &= \beta_E / \mu_E, \quad E = \mu_N / \beta_N\end{aligned}\tag{2}$$

Predator prey model

- Solution $\dot{E} = \dot{N} = 0$:

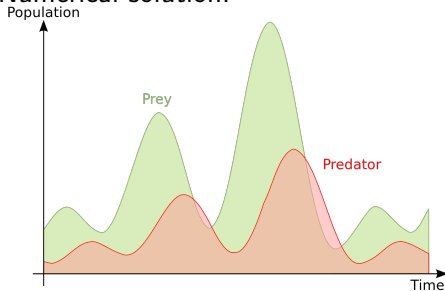
$$\begin{aligned} N &= E = 0 \\ N &= \beta_E / \mu_E, \quad E = \nu_N / \beta_N \end{aligned} \quad (3)$$

- Numerical solution:

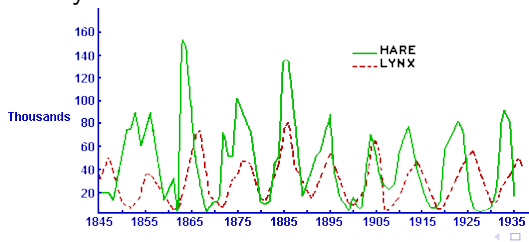


Predator prey model

► Numerical solution:



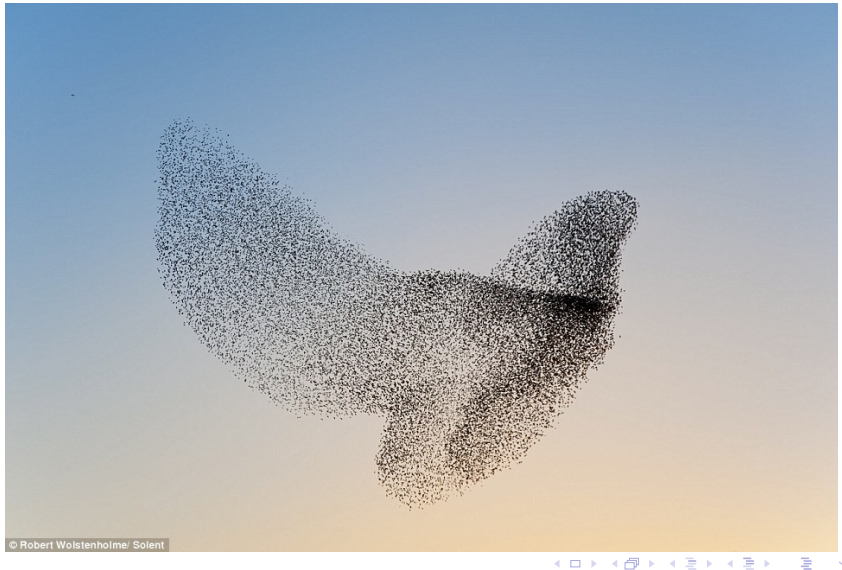
► Reality:



Other agent based models

- ▶ Agents are nodes
- ▶ Interactions through links
- ▶ Any network:
 - ▶ Lattices
 - ▶ Random networks
 - ▶ Scale-free
 - ▶ Fully connected graphs
- ▶ Examples:
 - ▶ Opinion models (not this time)
 - ▶ Minority models
 - ▶ Game models

Flocking Model



Flocking model

- ▶ Birds move with constant velocity (v_0)
- ▶ Align themselves to neighbors
- ▶ Some noise due to inaccurate averaging
- ▶ Differential equation

$$\theta_i(t + \Delta t) = \langle \theta(t) \rangle_{|r_i - r_j| < R} + \xi$$

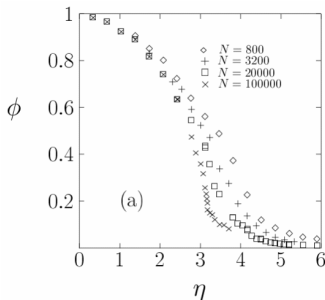
- ▶ Upgrade position:

$$r_i(t + \Delta t) = r_i(t) + v_0 e(\theta_i(t)) \Delta t$$

where $e(\theta)$ is a unit vector in the direction of θ .

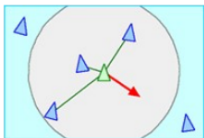
Flocking model

- ▶ Birds move with constant velocity (v_0)
- ▶ Align themselves to neighbors
- ▶ Some noise due to inaccurate averaging
- ▶ Phase diagram 1d:

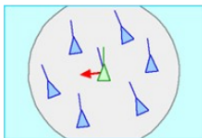


Flocking model

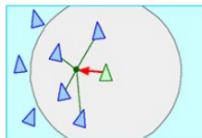
- ▶ Birds move with constant velocity (v_0)
- ▶ Align themselves to neighbors
- ▶ Some noise due to inaccurate averaging
- ▶ Non-physicist model:



Separation: steer to avoid crowding local flockmates



Alignment: steer towards the average heading of local flockmates



Cohesion: steer to move toward the average position of local flockmates

<http://www.red3d.com/cwr/boids/>

Minority models

"It is not worth an intelligent man's time to be in the majority. By definition, there are already enough people to do that."

Godfrey Harold Hardy

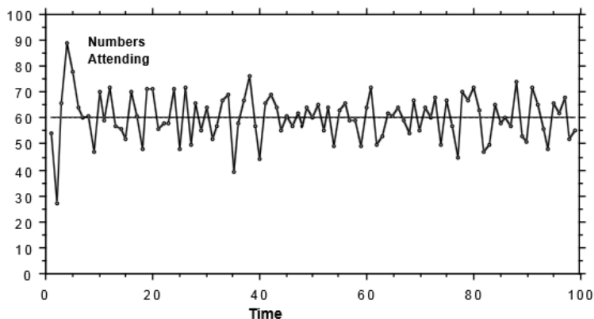
"Csak a döglött hal úszik az árral" - "Only dead fish swim with the tide"

- ▶ El Farol Bar problem
- ▶ Irish Music Thursdays
- ▶ Music is unenjoyable if more than 60 people go



Minority models

- ▶ El Farol Bar problem
- ▶ Irish Music Thursdays
- ▶ Music is unenjoyable if more than 60 people go
- ▶ After a transient attendance fluctuates around 60%
- ▶ In late stages regularities (cycles) are *arbitraged* away



Memory

- ▶ Intentionalism: I know that he know that I know what he ...
- ▶ Intelligent animals: 2 levels
- ▶ Children: 2 levels
- ▶ Strong autists: 1 level
- ▶ Humans 5-7 levels



El Farol problem, strategy

- ▶ Attendance was: 44 78 56 15 23 67 84 34 45 76
- ▶ Should I stay or should I go now?
- ▶ N agents with strategies
- ▶ Agents change their strategy with respect to performance
- ▶ Similar problems:
 - ▶ Traffic decisions
 - ▶ Animals food/water
 - ▶ Shopping times

Minority model

- ▶ N players (odd for simplicity)
- ▶ Action of player i at time t is $a_i(t) = \{+1, -1\}$
- ▶ Total action: $A(t) = \sum_i a_i(t)$
- ▶ Payoff: $p_i(t) = -a_i(t)g[A(t)]$, $g(a)$ is an odd function, e.g. $\text{sign}(x)$
- ▶ Information: $W(t+1) = g[A(t)] = \text{sign}[A(t)]$
- ▶ Memory: limited to the last m values of W
- ▶ Strategy: A table from the 2^m possible inputs to the corresponding output

Minority model: strategy

- ▶ Memory: limited to the last m values of W
- ▶ Strategy: A table from the 2^m possible inputs to the corresponding output

input			output
-1	-1	-1	-1
-1	-1	+1	+1
-1	+1	-1	+1
-1	+1	+1	-1
+1	-1	-1	+1
+1	-1	+1	-1
+1	+1	-1	+1
+1	+1	+1	-1

Random strategy

- ▶ Having N agents, the probability of having $n + 1$ follows a binomial distribution

$$P(n) = \binom{N}{n} p^n (1 - p)^{N-n}$$

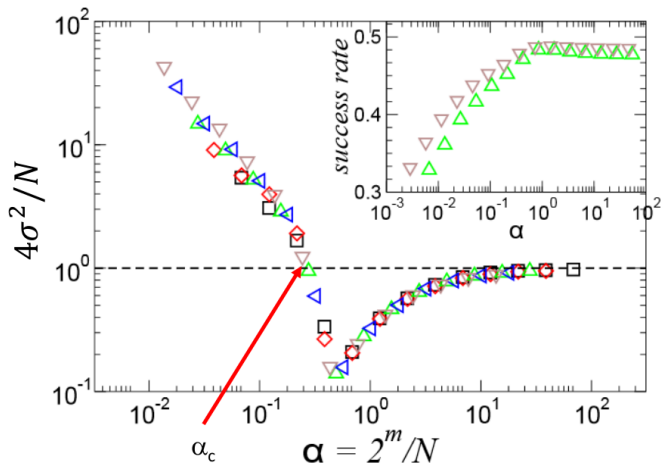
- ▶ Average: $\langle n \rangle = pN$, $\langle n \rangle (p = 1/2) = N/2$
- ▶ Variance: $\sigma^2 = Np(1 - p)$, $\sigma^2 (p = 1/2) = N/4$
- ▶ Minority game:
- ▶ Average: $\langle A(t) \rangle = 0$
- ▶ Variance: σ^2/N is function of $\alpha = 2^m/N$ with

$$\lim_{\alpha \rightarrow \infty} \sigma^2/N = 1/4$$

So the strategy with infinite memory becomes random

- ▶ At low values of α the variance increases as a power law
 $\sigma^2/N \sim \alpha^{-1}$

Minority model: variance



$N = 101,$
 $201, 301,$
 $501, 701$
 $(\square, \blacklozenge, \triangle,$
 $\triangleright, \nabla)$

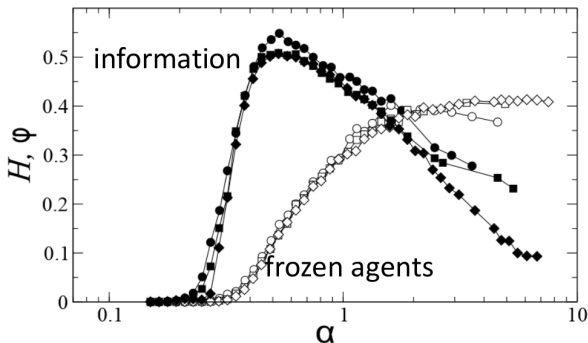
Minority model: order parameter

- ▶ Can we predict the sign of $A(t)$?
 - ▶ $\alpha < \alpha_c$: No, we have not enough information, agents are random
 - ▶ $\alpha > \alpha_c$: Yes, strong dependence, in market this can be exploited (arbitrage)
- ▶ Order parameter: information

$$H = \frac{1}{2^m} \sum_{\nu} \langle W(t+1) | W(t) = \nu \rangle$$

Minority model: variance

- ▶ Can we predict the sign of $A(t)$?
 - ▶ $\alpha < \alpha_c$: No, we have not enough information, agents are random
 - ▶ $\alpha > \alpha_c$: Yes, strong dependence, in market this can be exploited (arbitrage)

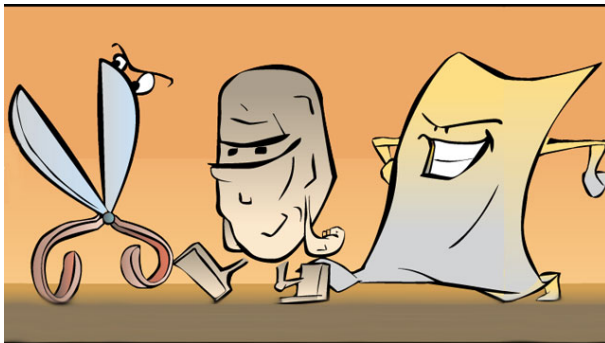


Game models:

- ▶ Rock-paper-scissors
- ▶ Prisoner's dilemma
- ▶ Chicken, hawk-dove game

Rock-paper-scissors

- ▶ No winning strategy on (truly) random opponent
- ▶ E.g bacterian and antibiotics in mice
- ▶ Grass-rabbit-fox
- ▶ Popular in games



Prisoner's Dilemma

- ▶ Two people playing the game
- ▶ Two options: Cooperate, Defect
- ▶ Cooperate: Confess the crime
- ▶ Defect: deny the crime
- ▶ Result: years in prison

	Cooperate	Defect
Cooperate	-1, -1	-3, 0
Defect	0, -3	-2, -2

Prisoner's Dilemma

- ▶ Payoff matrix
- ▶ Reward for actions based on other player's actions

	Cooperate	Defect
Cooperate	2, 2	0, 3
Defect	3, 0	1, 1

	Cooperate	Defect
Cooperate	1, 1	0, 2
Defect	0, 2	0, 0

Prisoner's Dilemma

- ▶ Each player with a preferred strategy that collectively results in an inferior outcome
- ▶ Dominating strategy regardless of the opponent's action
- ▶ Nash equilibrium, from which no individual player benefits from deviating

	Cooperate	Defect
Cooperate	2, 2	0, 3
Defect	3, 0	1, 1

	Cooperate	Defect
Cooperate	1, 1	0, 2
Defect	0, 2	0, 0

Prisoner's Dilemma

- ▶ One game \rightarrow defect
- ▶ Fixed number of games \rightarrow defect

Chicken game, Hawk-Dove game

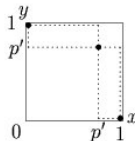
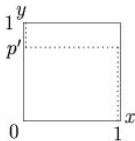
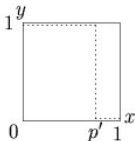


Chicken game, Hawk-Dove game

- ▶ No preferred strategy
- ▶ The best strategy is to anti-coordinate with your opponent

	Cooperate	Defect
Cooperate	0, 0	-1, 2
Defect	2, -1	-5, -5

- ▶ Example: Cold war
- ▶ Solution: anti-correlated pure strategy
- ▶ Probabilistic, or mixed strategy (play Hawk with p')



Chicken game, Hawk-Dove game difference to Prisoner's dilemma

	Cooperate	Defect
Cooperate	Reward	S, T
Defect	T, S	Punish

	Hawk-Dove			Prisoner's dilemma	
	C	D		C	D
C	2, 2	1, 3	C	2, 2	0, 3
D	3, 1	0, 0	D	3, 0	1, 1

- ▶ Prisoner's dilemma:
 $\text{Temptation}(T) > \text{Reward}(R) > \text{Punish}(P) > \text{Sucker}(S)$
- ▶ Chicken game:
 $\text{Temptation}(T) > \text{Reward}(R) > \text{Sucker}(S) > \text{Punish}(P)$

Stag game

Prisoner's dilemma

	C	D
C	2, 2	0, 3
D	3, 0	1, 1

Hawk-Dove

	C	D
C	2, 2	1, 3
D	3, 1	0, 0

Stag game

	C	D
C	3, 3	0, 2
D	2, 0	1, 1

- ▶ Prisoner's dilemma:
Temptation(T) > Reward(R) > Punish(P) > Sucker(S)
- ▶ Chicken game:
Temptation(T) > Reward(R) > Sucker(S) > Punish(P)
- ▶ Stag game:
Reward(R) > Temptation(T) > Punish(P) > Sucker(S)

Prisoner's dilemma: multiple agents

- ▶ Against all others
- ▶ Against itself
- ▶ Against a fully random agent
- ▶ Number of agents: 14, 62

Prisoner's dilemma: multiple agents: Strategies

- ▶ Strategies for repeated games in Axelrod's tournament (1980):
- ▶ ALLD: choosing D always (unconditional defector, the bad guy, ...)
- ▶ ALLC: choosing C always („the good guy” or sucker)
- ▶ Random: chooses D or C with probabilities q or $(1-q)$
- ▶ TFT (Tit-for tat): chooses C first, then she repeats/reciprocates the previous strategy of the co-player
- ▶ Generous TFT: TFT, but chooses C (instead of D) with a probability q
- ▶ WSLS (win-stay-lose-shift): first C or D, then she changes it if her payoff is smaller than an aspiration level ($U_x < a$)
- ▶ Stochastic reactive strategies: Chooses C or D with probabilities dependent on the previous decision of the co-player
- ▶ Stochastic reactive strategies with longer memory: Etc.
- ▶ Go-by-Majority cooperates on the first round, then takes majority strategy.

Multiple agents: Winning strategy

- ▶ The winner is: Tit-for-tat!
- ▶ Human law
- ▶ Note that Common good was not included
- ▶ Why not “always defect”(AD), which is the Nash equilibrium of the
- ▶ Prisoners' dilemma for any finite number of plays?
- ▶ Nash equilibrium means that AS is the best strategy against AD
- ▶ AS is not dominant strategy
- ▶ It is not the best strategy for all strategies

Multiple agents: Best strategy

- ▶ Large pool of players (movie):
- ▶ It can be shown that for a repeated PD game there is no best strategy for all possible strategies
- ▶ But for a good strategy it has to be
 - ▶ Nice (do not defect first)
 - ▶ Punish others for being nasty
 - ▶ Forgive fast
 - ▶ Be efficient against yourself