Discrete and Continuous Models in Population Dynamics

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The big question

Do we do the right thing?

If population dynamics is based on individuals, why do people use differential equations?

The big question

The question you never asked your professor...



Where do differential equations come from?

...and side effects



...and side effects

We will not answer the previous questions. \bigodot



But, we will analyze in detail a simple example.

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We establish the validity of the ODE model;

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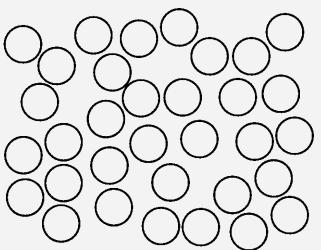


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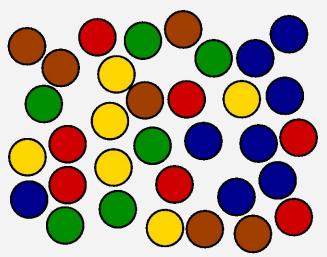
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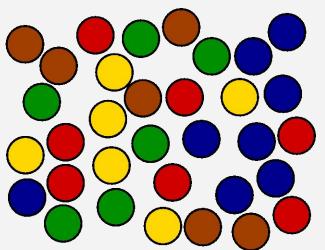
- We establish the validity of the ODE model;
- We find a better differential equation. This lead us naturally to singular partial differential equations.



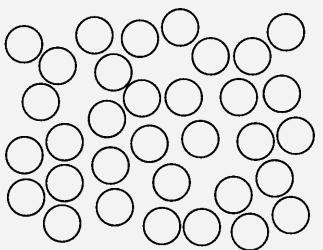
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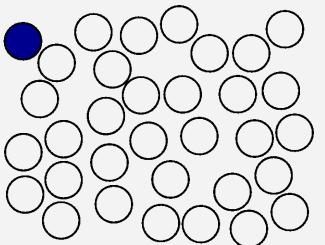
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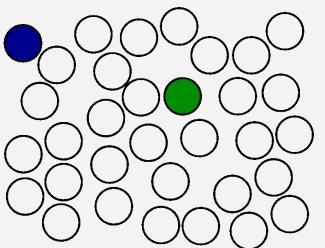


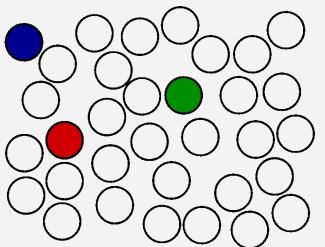
We consider a population of *N* individuals of *n* different types. We attribute to each type a number, called fitness.

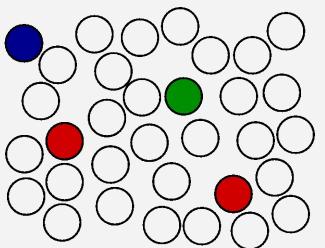


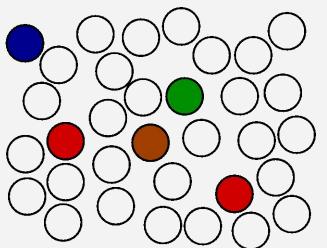
The next generation is obtained from the previous one:

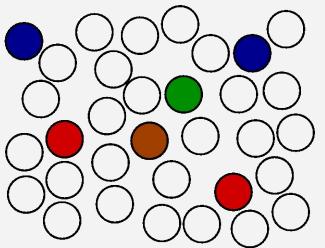


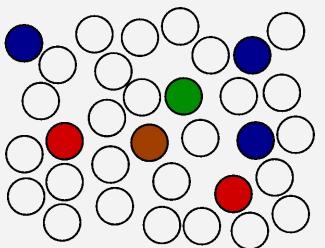


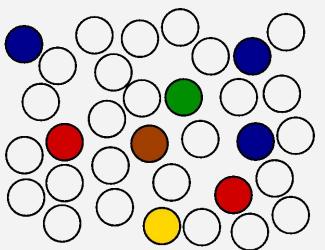


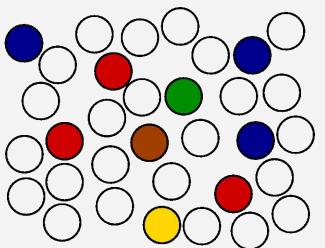


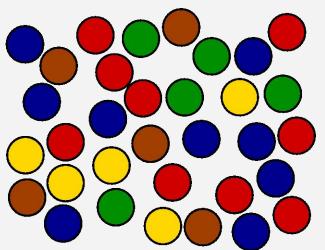












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The next generation is obtained from the previous one: each individual descend from one of the types, with probability proportional to the fitness. The transition probability from a state **y** to a new state **x** is given by

$$\Theta_{N}(\mathbf{y} \to \mathbf{x}) = \frac{N!}{(Nx_{1})!(Nx_{2})!\cdots(Nx_{n})!} \prod_{i=1}^{n} \left(\frac{y_{i}\Psi^{(i)}}{\bar{\Psi}}\right)^{Nx_{i}}.$$

A crash course on game theory

We consider two players, with two possible pure strategies, and associate a pay-off matrix:

$$\begin{array}{c|cccc} & I & II \\ \hline I & A & B \\ II & C & D \end{array}, \quad \text{with } A, B, C, D > 0.$$

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The Nash equilibrium is given by the strategy that is the best reply against itself: $p^* = \mathcal{R}(p^*)$.

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We say that E_p is an ESS if and only if:

$$\underbrace{\mathcal{W}(E_q, (1-\varepsilon)E_p + \varepsilon E_q)}_{\text{average invader's pay-off}} < \underbrace{\mathcal{W}(E_p, (1-\varepsilon)E_p + \varepsilon E_q)}_{\text{average resident's pay-off}}$$

for any strategy $E_q \neq E_p$ and ε small enough.

Discrete and Continuous Models

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We call *n* the number of type I individuals. *Fitnesses* are identified with mean pay-off:

$$\Psi^{(I)}(n,N) = \frac{n-1}{N-1}A + \frac{N-n}{N-1}B,$$

$$\Psi^{(II)}(n,N) = \frac{n}{N-1}C + \frac{N-n-1}{N-1}D.$$

A crash course on game theory

For a continuous population the fraction $x = \frac{n}{N}$ of type I individuals is given by the replicator equation

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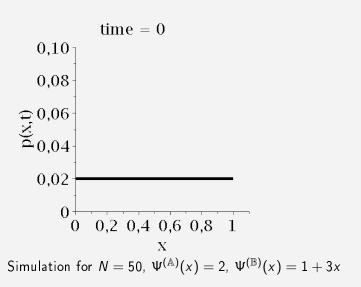
$$\dot{x} = x \left(\Psi^{(I)} - \bar{\Psi} \right) = x(1-x)\left(x\underbrace{(A-C)}_{\alpha} + (1-x)\underbrace{(B-D)}_{\beta}\right).$$

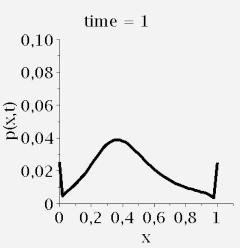
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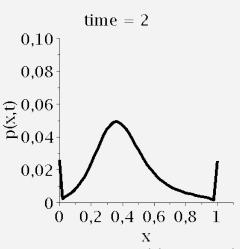
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When $\alpha<0$ and $\beta>0$ (the *Hawk-and-Dove* game) this equation has three equilibria: $x=0,\ x=1$ and $x=x^*=\frac{\beta}{\beta-\alpha}\in(0,1)$.

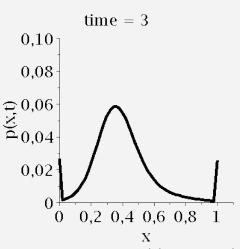




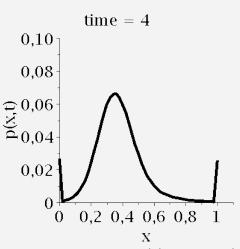
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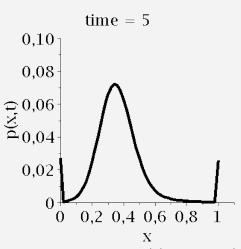
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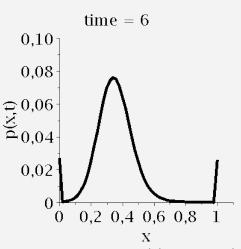
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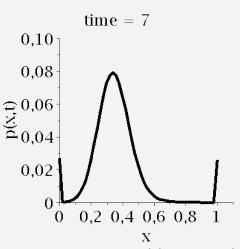
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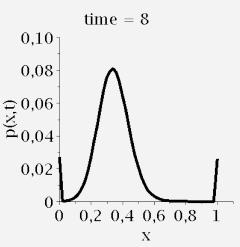
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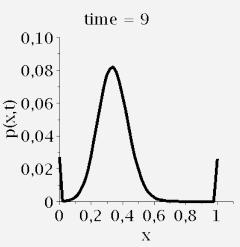
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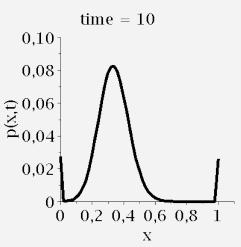
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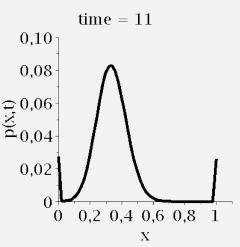
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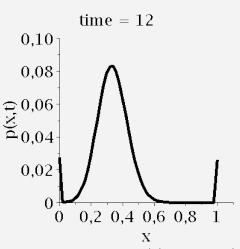
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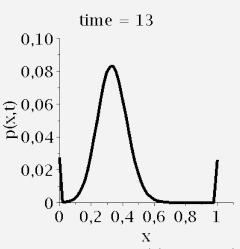
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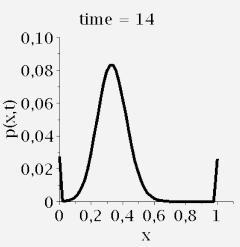
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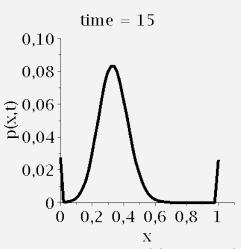
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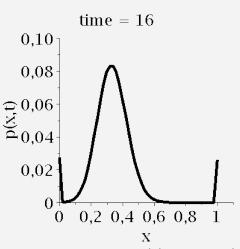
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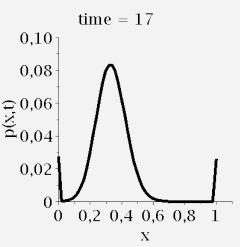
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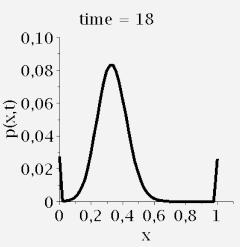
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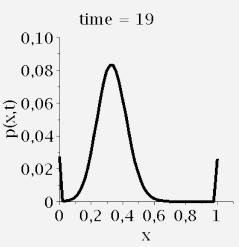
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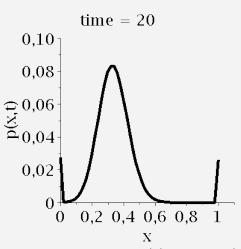
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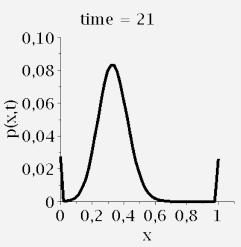
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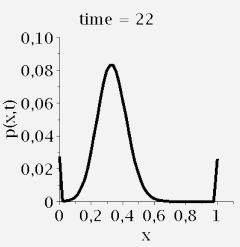
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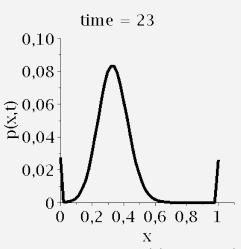
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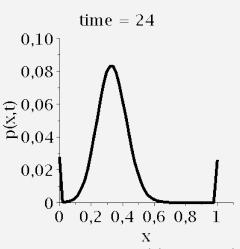
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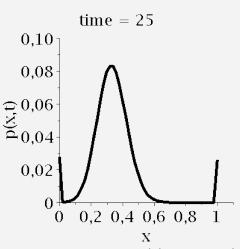
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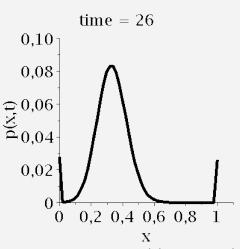
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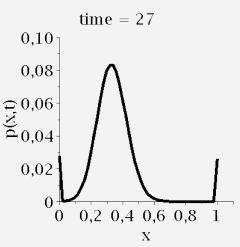
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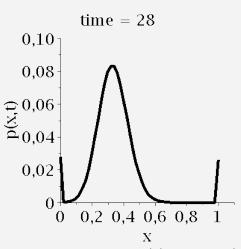
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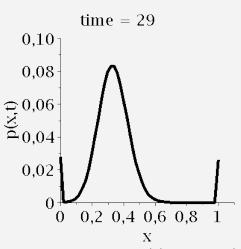
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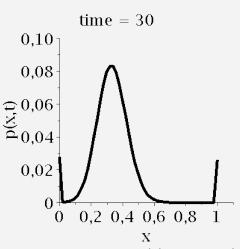
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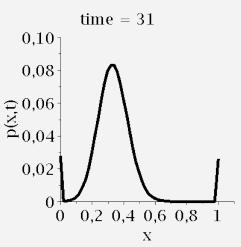
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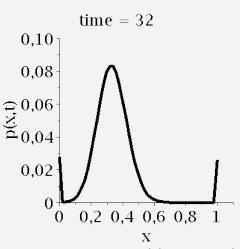
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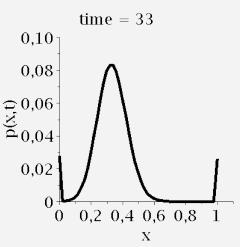
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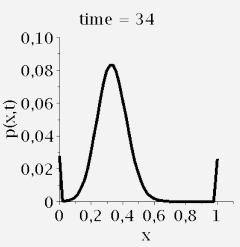
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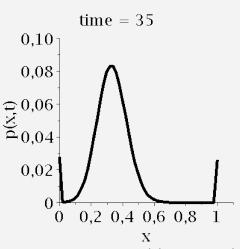
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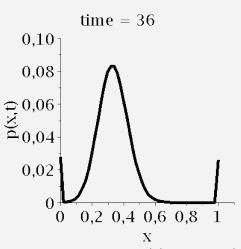
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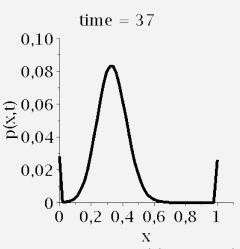
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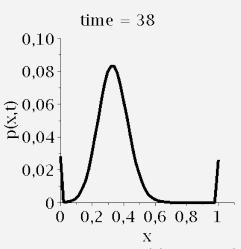
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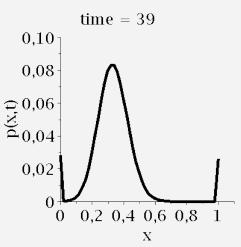
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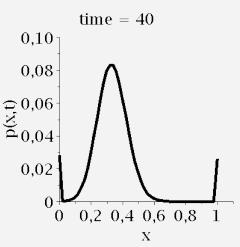
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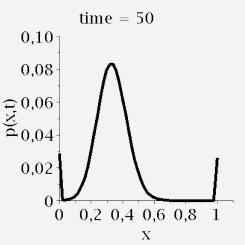
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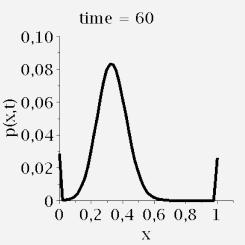
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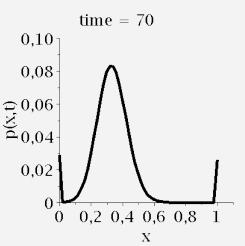
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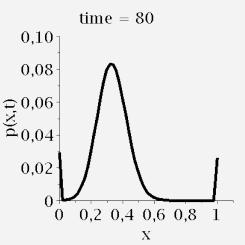
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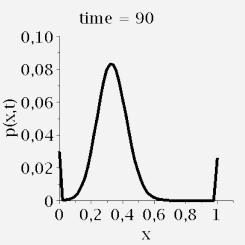
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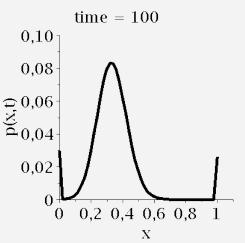
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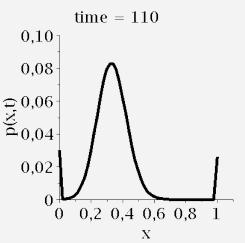
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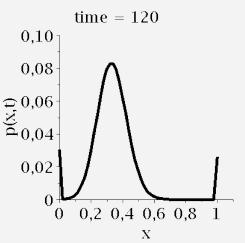
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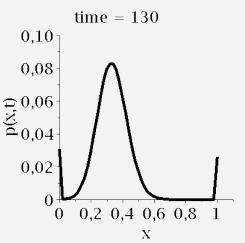
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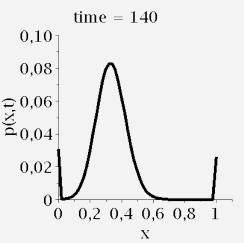
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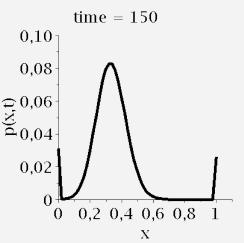
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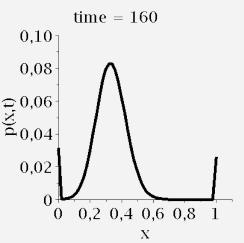
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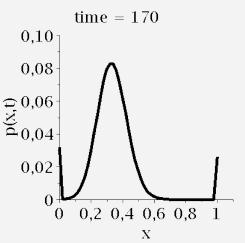
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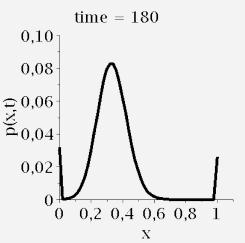
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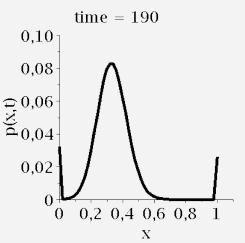
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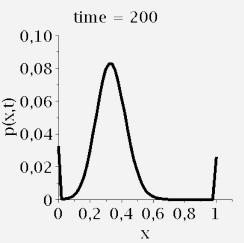
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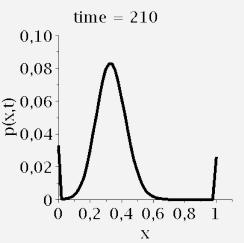
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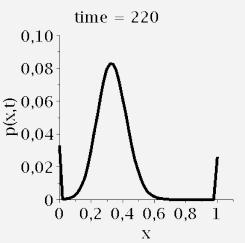
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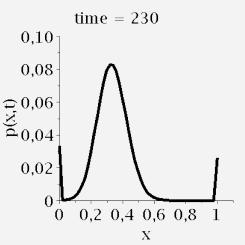
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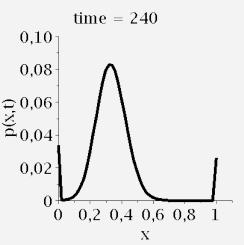
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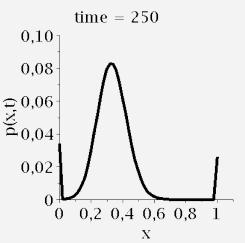
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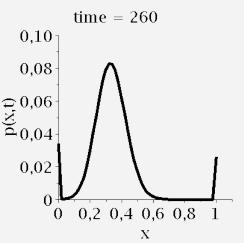
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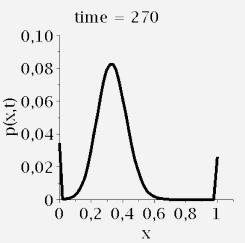
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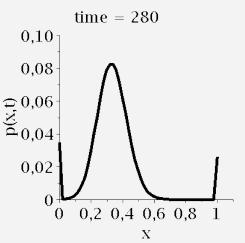
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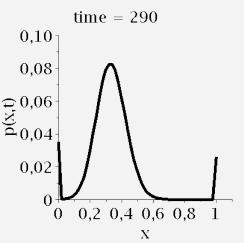
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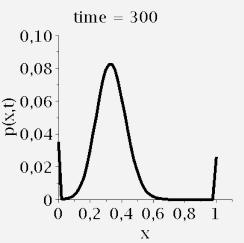
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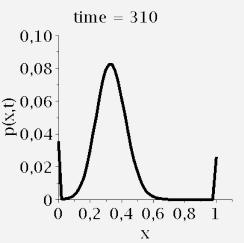
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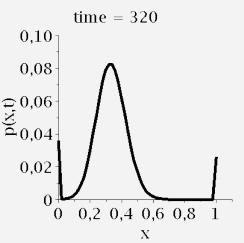
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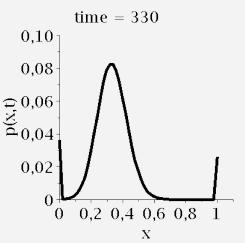
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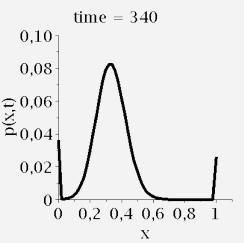
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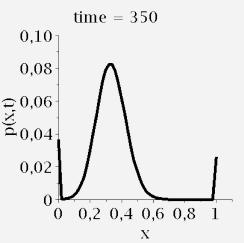
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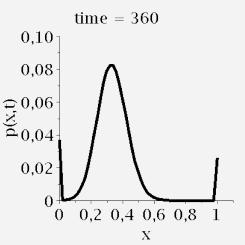
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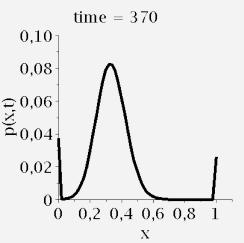
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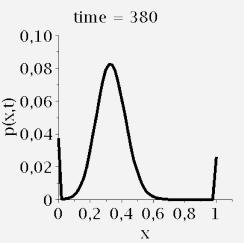
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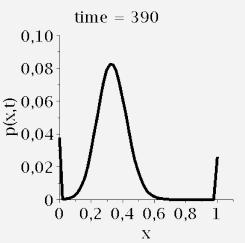
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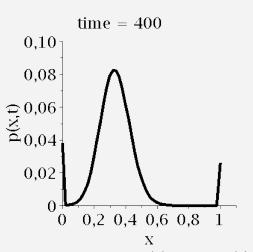
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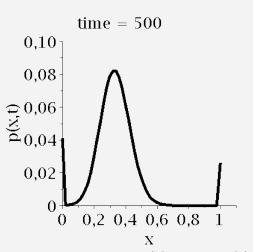
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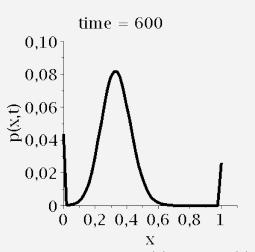
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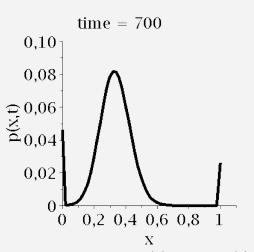
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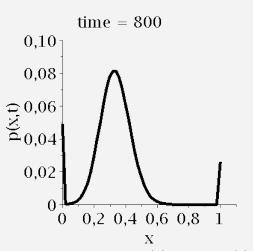
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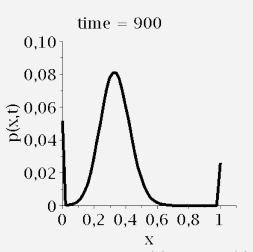
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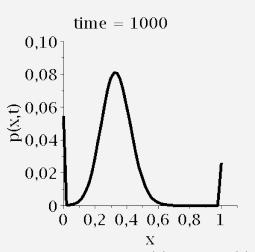
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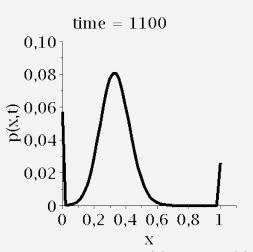
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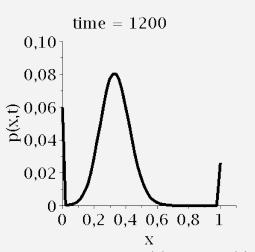
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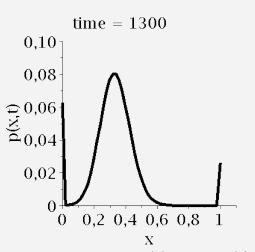
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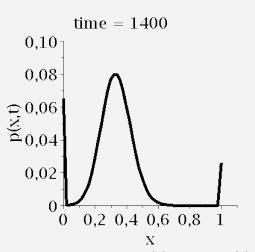
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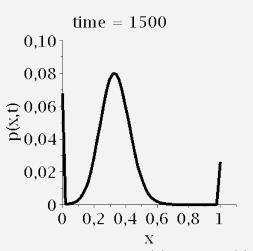
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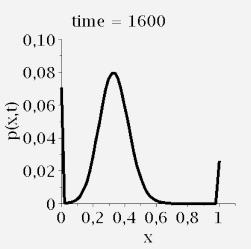
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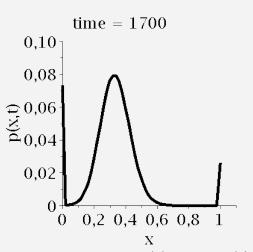
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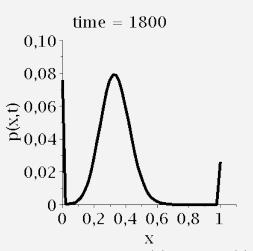
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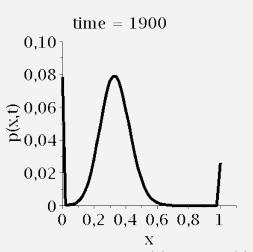
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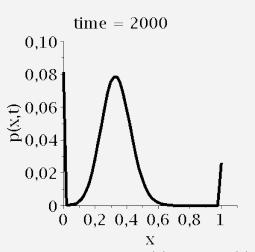
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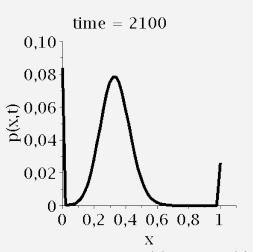
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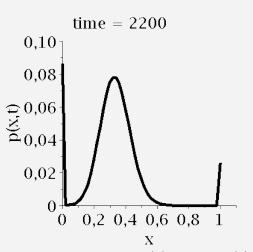
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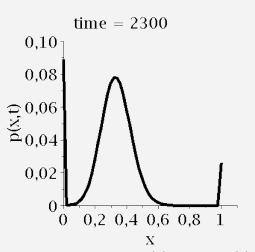
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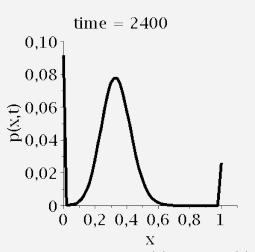
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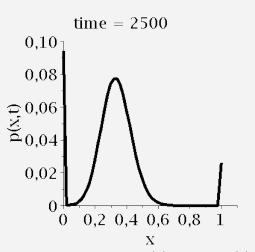
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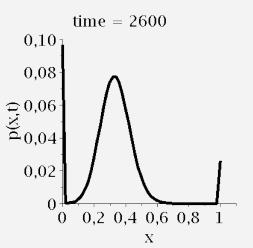
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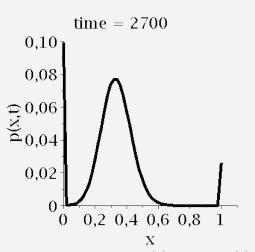
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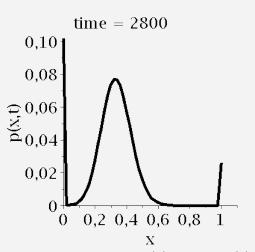
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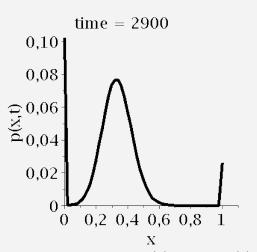
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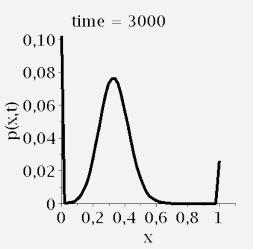
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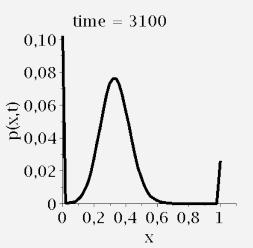
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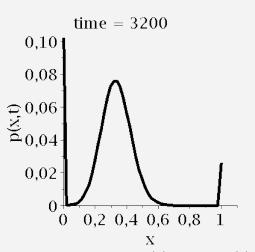
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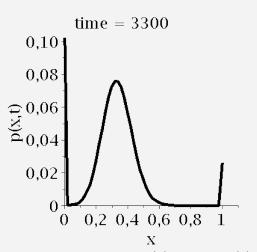
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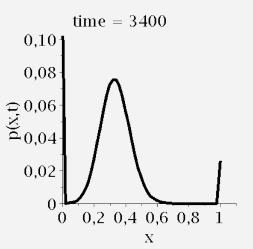
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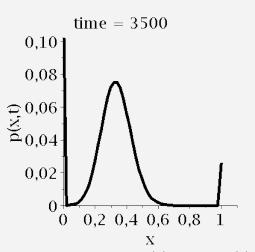
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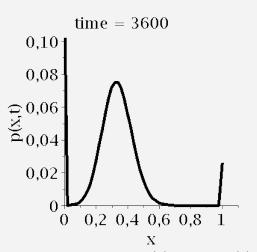
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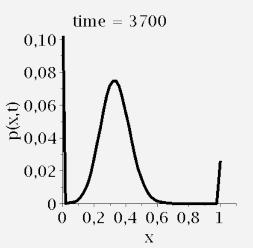
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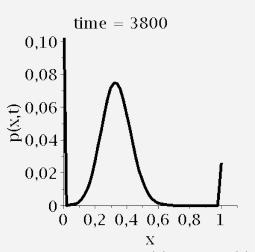
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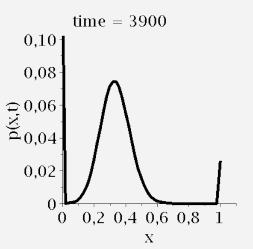
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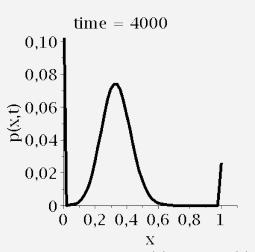
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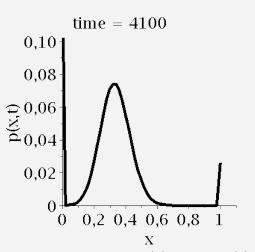
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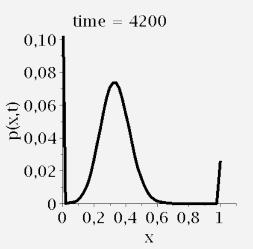
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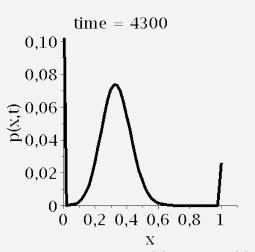
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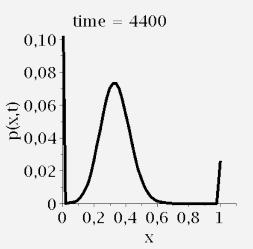
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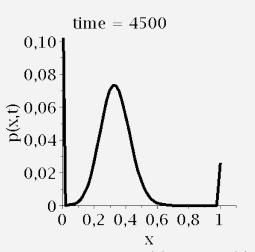
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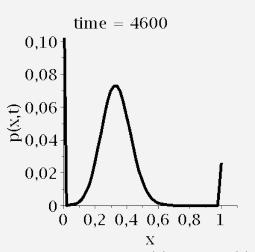
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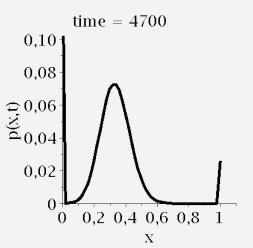
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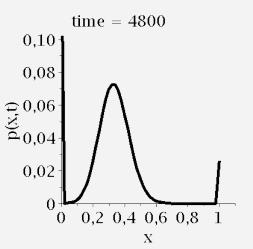
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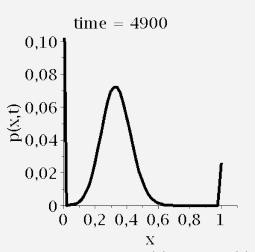
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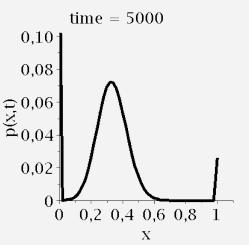
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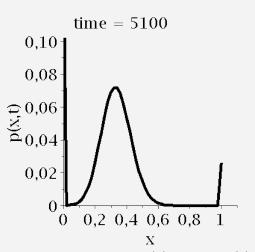
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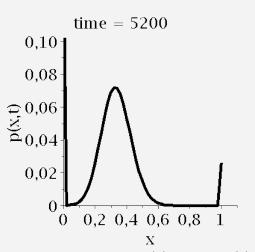
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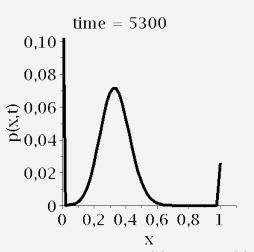
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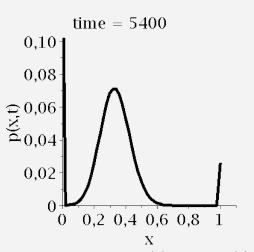
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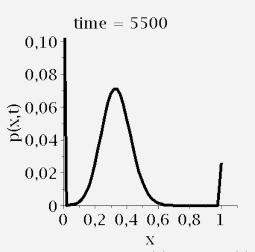
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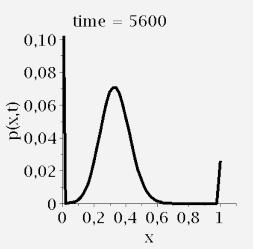
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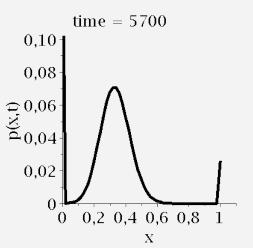
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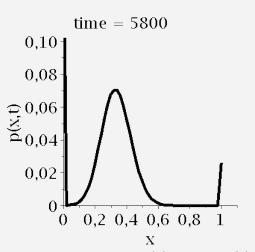
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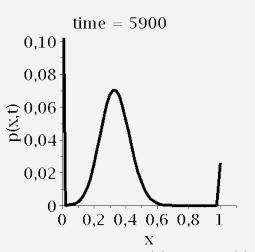
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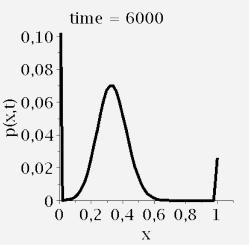
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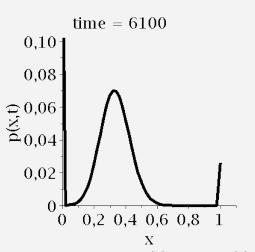
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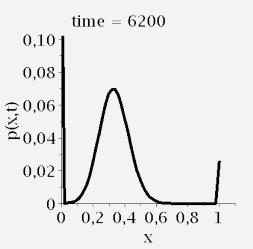
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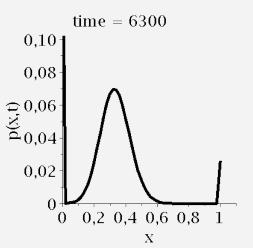
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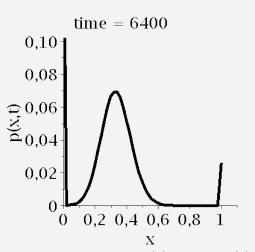
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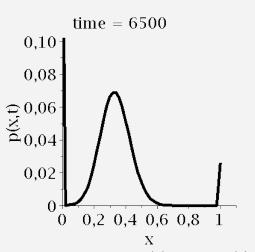
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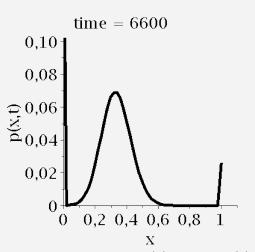
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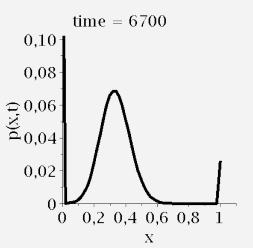
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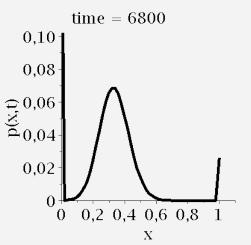
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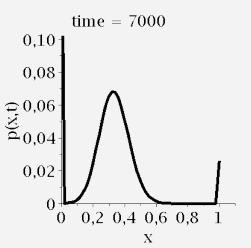
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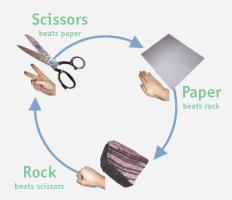


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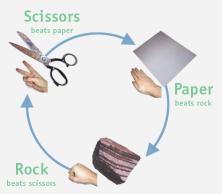


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Now, we consider n = 3 types and define the Rock-Scissor-Paper game:



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Fitnesses are calculated from the matrix:

	Rock	Scissor	Paper
Rock	30	81	29
Scissor	6	30	104
Paper	106	4	30

$$\Psi^{(\mathbb{A})}(x) = 30x + 81y + 29z ,$$

$$\Psi^{(\mathbb{B})}(x) = 6x + 30y + 104z ,$$

$$\Psi^{(\mathbb{C})}(x) = 106x + 4y + 30z .$$

The replicator dynamics is given by:

$$\dot{x} = x(-74x + 4y - 1 + 75x^2 + 96xy + 48y^2) ,$$

$$\dot{y} = y(-173x - 122y + 74 + 75x^2 + 96xy + 48y^2) ,$$

where $x \ge 0$ is the frequency of type 1, $y \ge 0$ of type 2 and $z = 1 - x - y \ge 0$ (i.e., $x + y \le 1$) of type 3.

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1
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, everybody is of type 3;

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The only stationary solutions are:

- (x,y) = (0,0), everybody is of type 3;
- (x,y) = (0,1), everybody is of type 2;

The replicator dynamics is given by:

$$\begin{split} \dot{x} &= x \big(-74x + 4y - 1 + 75x^2 + 96xy + 48y^2 \big) \;, \\ \dot{y} &= y \big(-173x - 122y + 74 + 75x^2 + 96xy + 48y^2 \big) \;, \end{split}$$

where $x \ge 0$ is the frequency of type 1, $y \ge 0$ of type 2 and $z = 1 - x - y \ge 0$ (i.e., $x + y \le 1$) of type 3.

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 - (x,y) = (0,1), everybody is of type 2;
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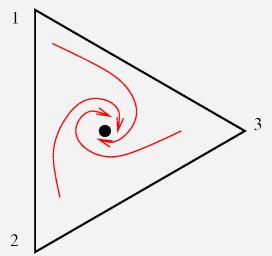
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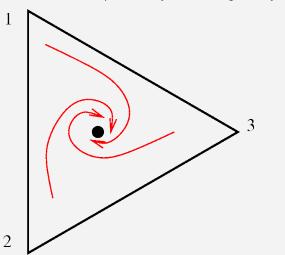
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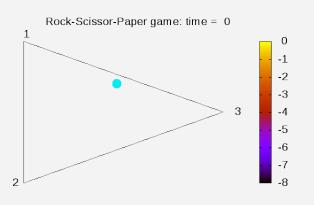
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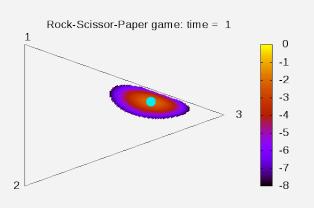
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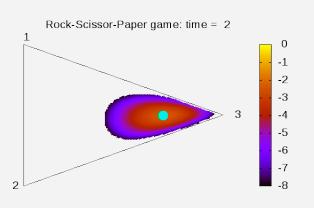
The vertexes of the simplex are unstable stationary points, while the center of the simplex is the only stable stationary point of the replicator dynamics.



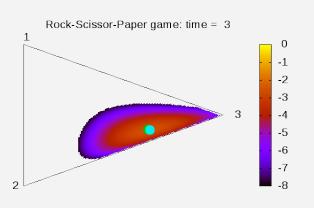
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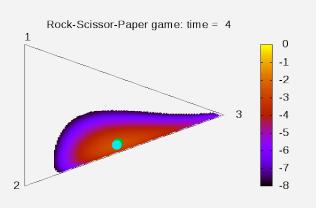
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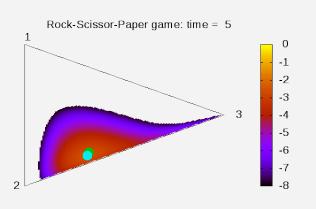
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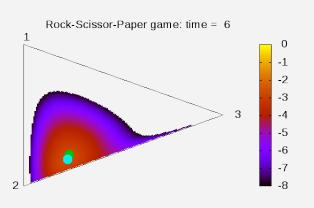
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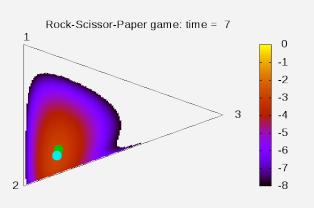
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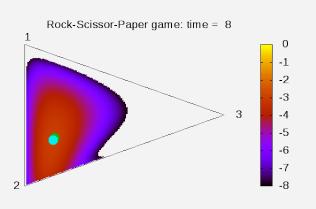
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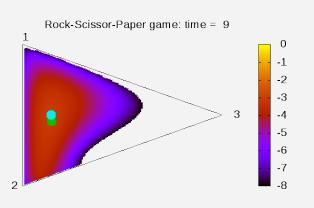
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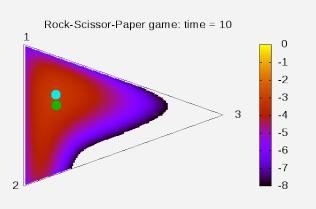
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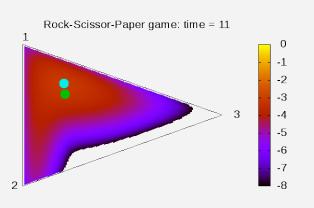
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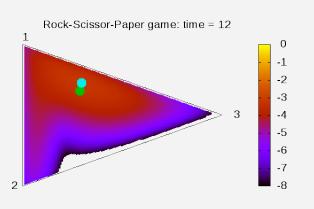
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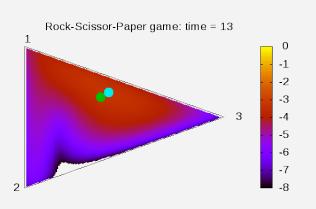
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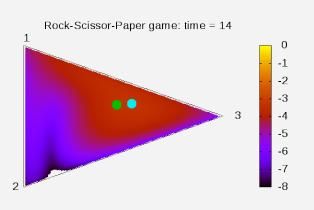
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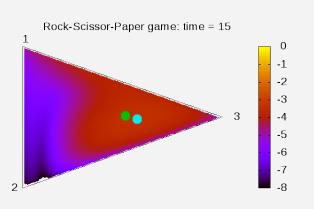
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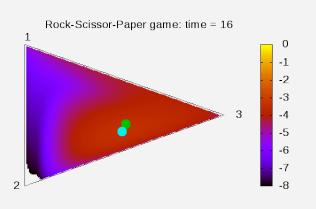
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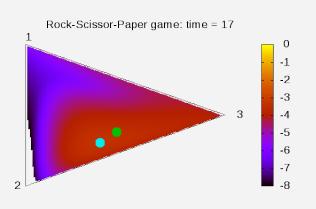
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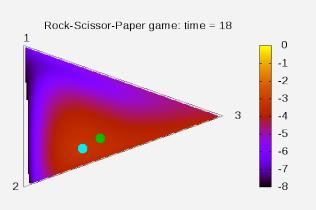
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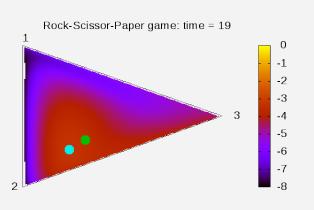
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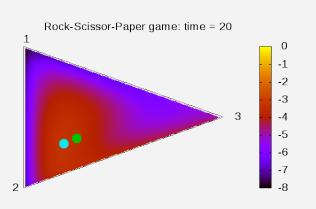
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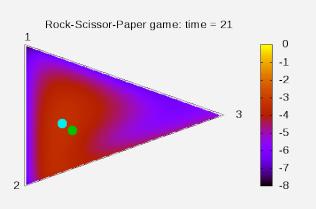
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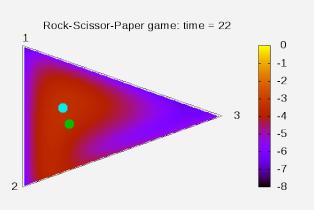
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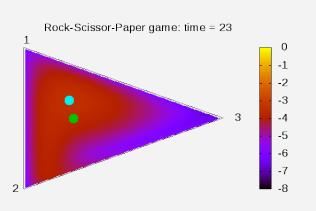
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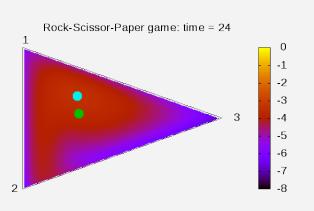
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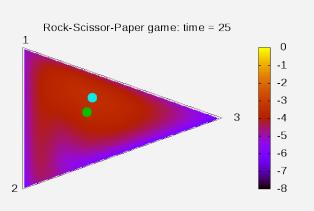
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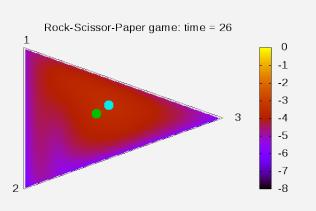
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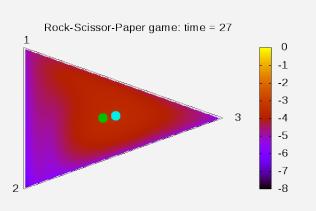
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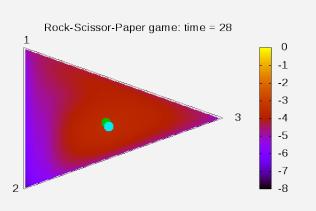
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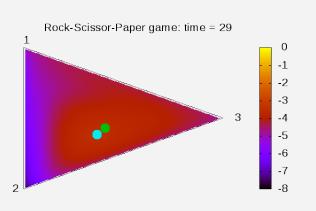
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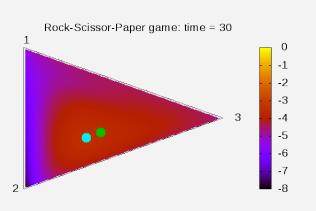
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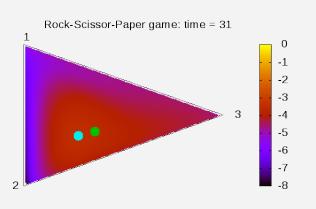
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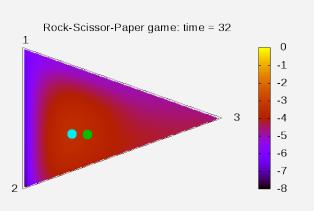
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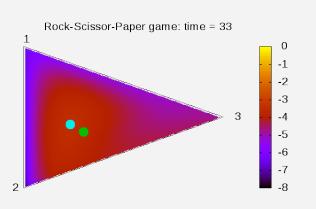
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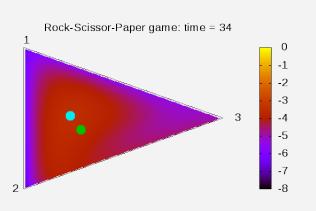
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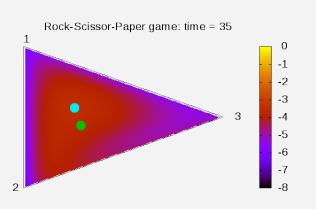
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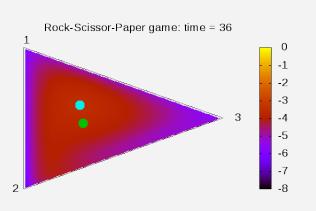
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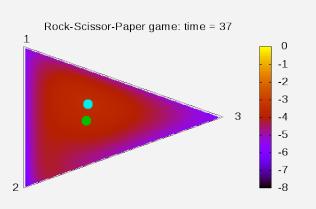
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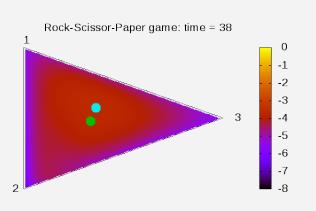
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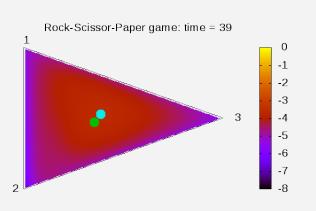
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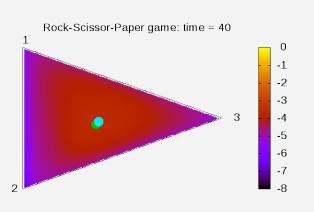
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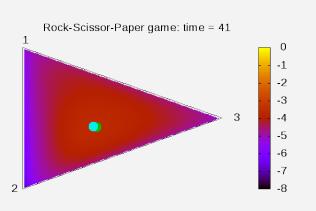
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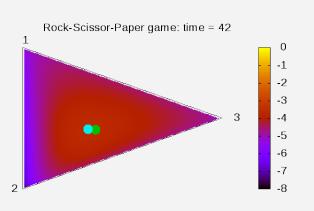
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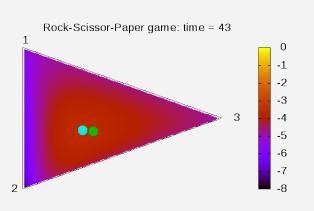
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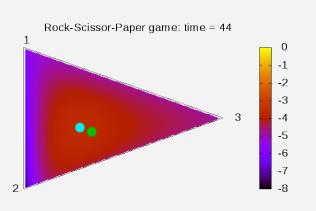
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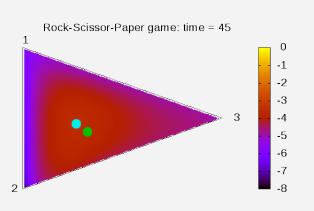
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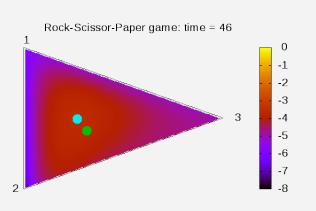
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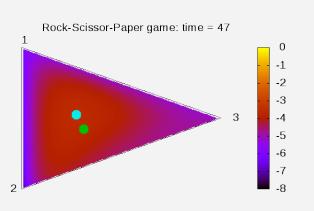
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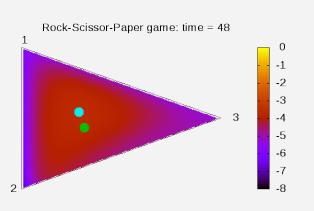
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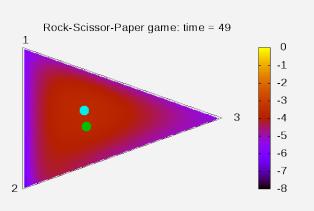
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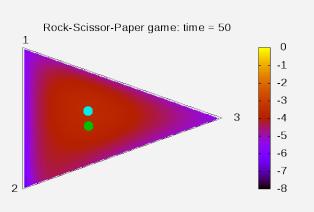
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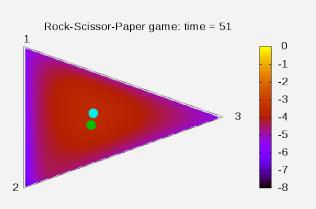
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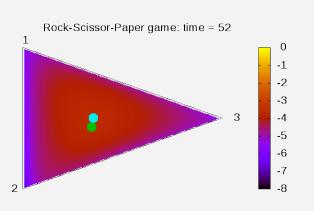
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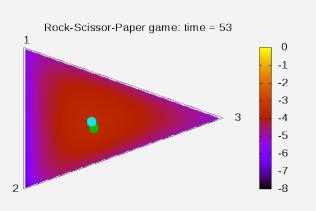
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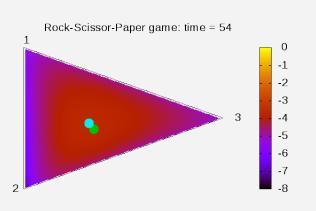
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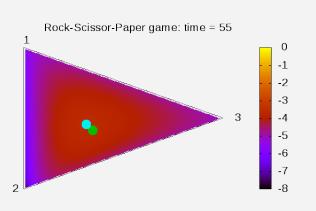
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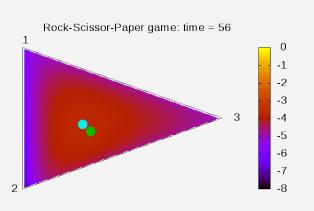
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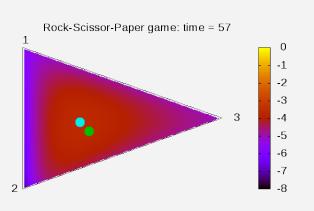
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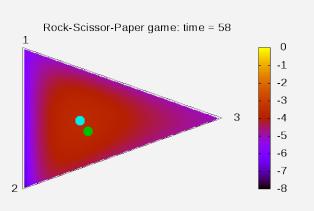
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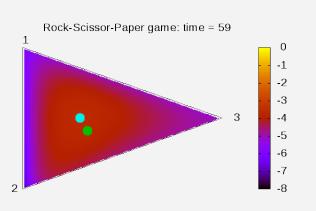
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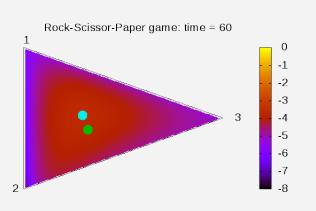
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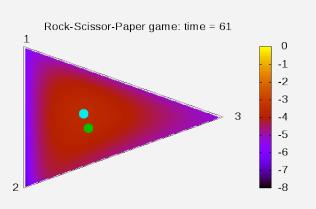
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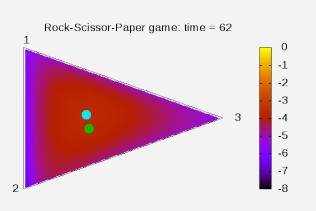
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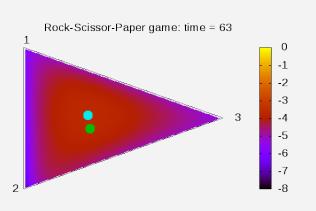
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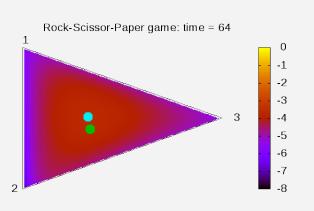
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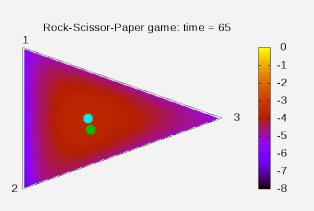
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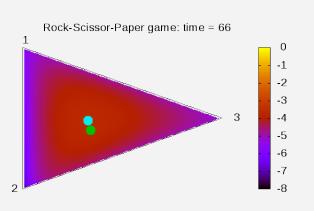
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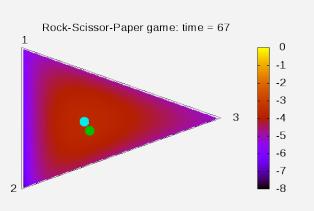
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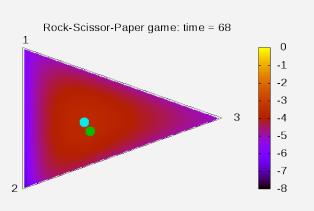
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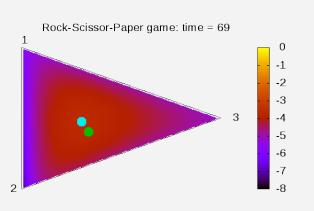
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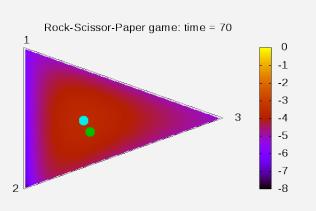
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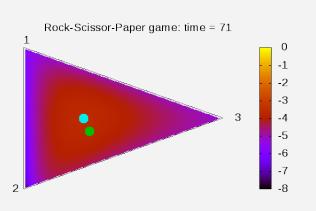
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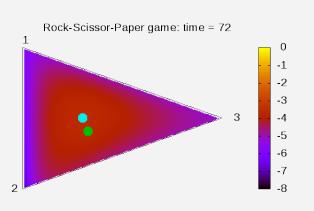
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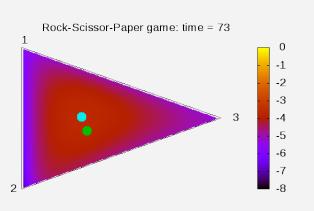
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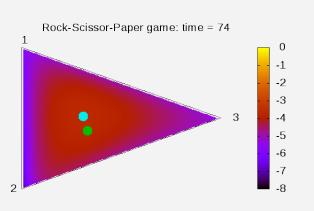
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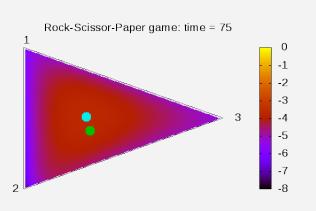
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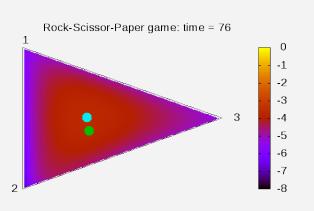
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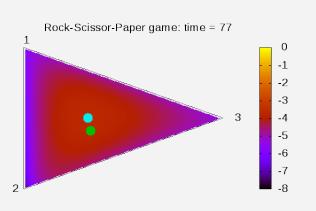
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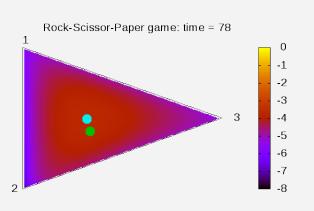
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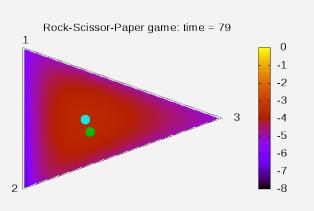
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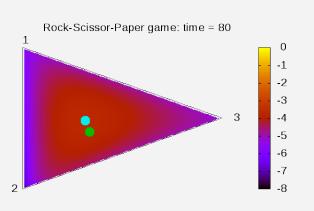
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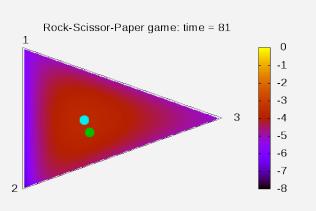
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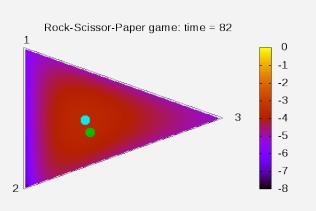
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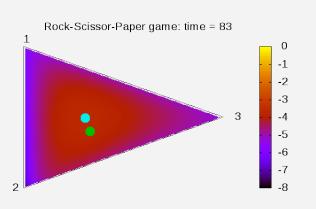
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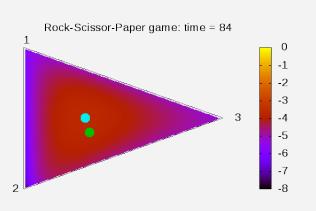
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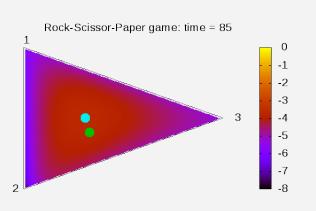
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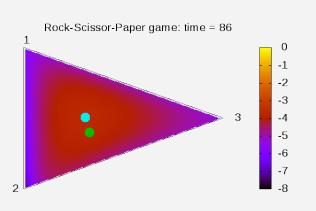
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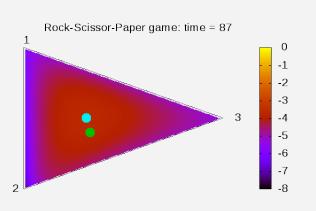
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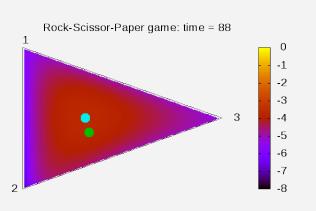
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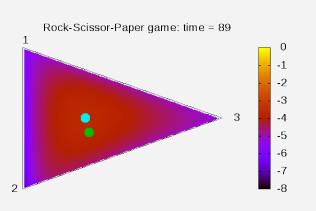
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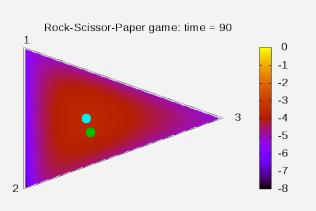
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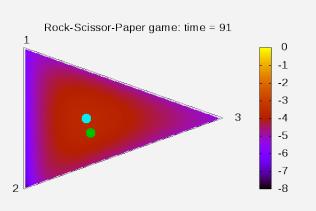
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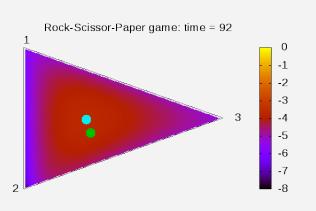
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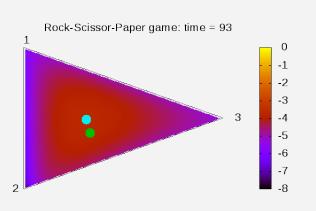
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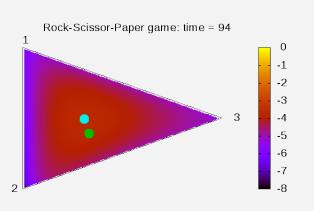
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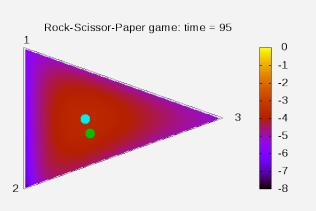
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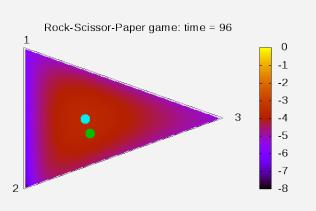
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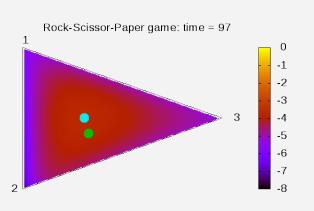
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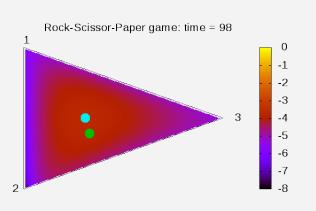
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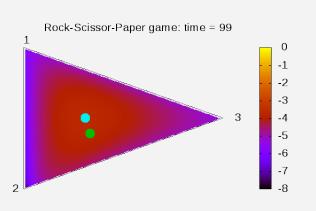
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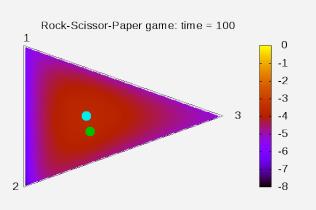
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Transition matrix for two types

Let $P(x, t, N, \Delta t)$ be the probability of at time t there are xN, $x = 0, \frac{1}{N}, \ldots, 1$, mutants in a population of fixed size N evolving with time steps of order Δt .

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and M is a stochastic matrix.

This implies that $\mathcal{P}(\kappa\Delta t)=\mathsf{M}^{\kappa}\mathcal{P}(0)$.
Discrete and Continuous Models

Spectral theory

Theorem

$$\lim_{\kappa \to \infty} \mathbf{M}^{\kappa} = \begin{pmatrix} 1 & 1 - F_1 & \cdots & 1 - F_N \\ 0 & 0 & \cdots & 0 \\ & & \vdots & \\ 0 & F_1 & \cdots & F_N \end{pmatrix} .$$

where the F_n satisfy $F_n=\sum_{m=0}^N\Theta_N\left(rac{n}{N} orac{m}{N}
ight)F_m$, with $F_0=0$ and $F_N=1$.

In particular, any stationary state will be concentrated at the endpoints. If 1 denotes the vector $(1,1,\ldots,1)^\dagger$, $\mathbf{F}=(F_0,F_1,\ldots,F_N)^\dagger$ and if $\langle\cdot,\cdot,\rangle$ denotes the usual inner product, then we have that $\langle \mathbf{P}(t),\mathbf{1}\rangle=\langle \mathbf{P}(0),\mathbf{1}\rangle$ and $\langle \mathbf{P}(t),\mathbf{F}\rangle=\langle \mathbf{P}(0),\mathbf{F}\rangle$.

General idea: 2 types

We look for a differential equation that approximates the discrete evolution of P when $N \to \infty$ and $\Delta t \to 0$.

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The limit function $p = \lim_{N \to \infty, \Delta t \to 0} \frac{P}{1/N}$ is such that

$$\begin{split} p\left(x\pm\frac{1}{N},t\right) &= p(x,t)\pm\frac{1}{N}\partial_{x}p(x,t) + \frac{1}{2N^{2}}\partial_{x}^{2}p(x,t) + \mathcal{O}(N^{-3}),\\ p\left(x,t+\Delta t\right) &= p(x,t) + (\Delta t)\,\partial_{t}p(x,t) + \mathcal{O}\left((\Delta t)^{2}\right). \end{split}$$

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lacksquare The time-step is such that $arepsilon(\Delta t)=N^{-\mu}$

Formal asymptotic: Wright-Fisher process for two types

Using all these assumptions, we find the asymptotic expansion:

$$\partial_t \rho = -\frac{1}{\left(\Delta t\right)^{1-\nu}} \partial_x \left(x(1-x) \left(\psi^{(\mathbb{A})}(x) - \psi^{(\mathbb{B})}(x) \right) \rho \right) + \frac{1}{2N\Delta t} \partial_x^2 \left(x(1-x)\rho \right) .$$

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or the replicator-diffusion equation

$$\partial_t p = \frac{\varepsilon}{2} \partial_x^2 \left(x(1-x)p \right) - \partial_x \left(x(1-x) \left(\psi^{(\mathbb{A})}(x) - \psi^{(\mathbb{B})}(x) \right) p \right) .$$

Formal asymptotic: Wright-Fisher process for two types

The invariants become the following conservation laws:

$$\frac{\mathrm{d}}{\mathrm{d}t}\int_0^1 p(x,t)\,\mathrm{d}x=0, \qquad \frac{\mathrm{d}}{\mathrm{d}t}\int_0^1 \phi(x)p(x,t)\,\mathrm{d}x=0,$$

where ϕ satisfies

$$\frac{\varepsilon}{2}\phi'' + \left(\psi^{(\mathbb{A})}(x) - \psi^{(\mathbb{B})}(x)\right)\phi' = 0, \quad \phi(0) = 0, \quad \phi(1) = 1.$$

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This implies:

$$\phi(x) = \frac{\int_0^x \exp\left[-\frac{2}{\varepsilon} \int_0^{x'} \left(\psi^{(\mathbb{A})}(x'') - \psi^{(\mathbb{B})}(x'')\right) dx''\right] dx'}{\int_0^1 \exp\left[-\frac{2}{\varepsilon} \int_0^{x'} \left(\psi^{(\mathbb{A})}(x'') - \psi^{(\mathbb{B})}(x'')\right) dx''\right] dx'}.$$

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If we start from the initial condition $ho^{\mathrm{I}}=\delta_{\mathsf{x_0}}$, then the fixation probability

The Kimura equation

The equation

$$\partial_t f = \frac{\varepsilon}{2} x (1-x) \partial_x^2 f + \gamma x (1-x) \partial_x f$$
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with boundary condition given by f(0, t) = 0 and f(1, t) = 1 is known as the Kimura equation.

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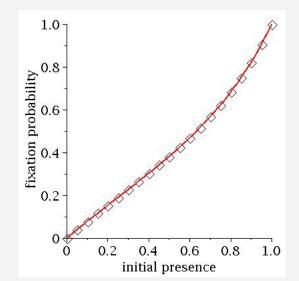
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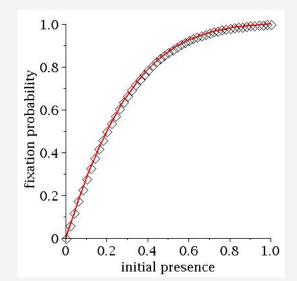
The final state is the final fixation probability: $\lim_{t\to\infty} f(x,t) = \phi(x)$.

Fixation probability for homogeneous populations



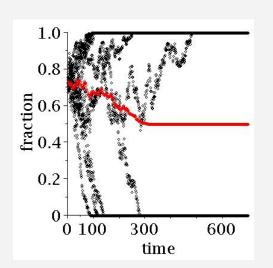
Fixation probability for N=20 and pay-off matrix $\begin{pmatrix} 1 & 3 \\ 4 & 2 \end{pmatrix}$. The red line indicates the function $\phi(x)$ for $\varepsilon=0.1125157473$.

Fixation probability for homogeneous populations



Fixation probability for N=50 and pay-off matrix $\begin{pmatrix} 9 & 4 \\ 2 & 2 \end{pmatrix}$. The red line indicates the function $\phi(x)$ for $\varepsilon=0.04315862961$.

Time evolution in the Wright-Fisher process



Number of individuals of the first type, for the Wright-Fisher process with pay-off matrix given by simulations with initial conditions of 220/300 individuals of the first type. The red line indicates the evolution of the mean.

Rigorous asymptotic: the replicator-diffusion equation for two types

Let $\mathcal{BM}^+([0,1])$ denote the positive Radon measures in [0,1].

Theorem

For a given $p^I \in \mathcal{BM}^+([0,1])$, there exists a unique (weak) solution p, with $p \in L^\infty\left([0,\infty); \mathcal{BM}^+([0,1])\right)$ and such that p satisfies the conservations laws. The solution can be written as $p(x,t) = r(x,t) + a(t)\delta_0 + b(t)\delta_1$, where $r \in C^\infty\left(\mathbb{R}^+; C^\infty([0,1])\right)$ is a classical (regular) solution to the replicator diffusion equation without boundary conditions, and δ_y denotes the singular measure supported at y. We also have that a(t) and b(t), belong to $C([0,\infty)) \cap C^\infty(\mathbb{R}^+)$. For large time, we have that $\lim_{t\to\infty} r(x,t) = 0$, uniformly, and that a(t) and b(t), the transient extinction and fixation probabilities, respectively, are monotonically increasing functions. Moreover, we have that

$$\lim_{t\to\infty} p(\cdot,t) = \pi_0[p^{\mathrm{I}}]\delta_0 + \pi_1[p^{\mathrm{I}}]\delta_1,$$

with respect to the Radon metric. Finally, the convergence rate is exponential.

Rigorous asymptotic: the replicator-diffusion equation for two types

Theorem

Let $p(x,t,N,\Delta t)$ be the solution of the finite population dynamics (of population N, time step $\Delta t=1/N$), with initial conditions given by $p^0(x,N,\Delta t)=p^0(x), x=0,1/N,2/N,\cdots,1$, for p^0 as in the previous theorem. Assume also the weak-selection limit, with $\nu=\frac{1}{2}$. Let $p_{\rm cont}(x,t)$ be the solution of the continuous model, with initial condition given by $p^0(x)$. If we write p_i^n for the i-th component of $p(x,t,N,\Delta t)$ in the n-th iteration, we have, for any $t^*>0$, that

$$\lim_{N \to \infty} p_{xN}^{tN^2} = p_{\text{cont}}(x, t), \quad x \in [0, 1], \quad t \in [0, t^*].$$

From the discrete to the continuous

We look for a simpler model for intermediate populations.

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Diffusion to the vertexes of the simplex (pure states)

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Diffusion to the vertexes of the simplex (pure states)

Let the n-1-dimensional simplex be

$$S^{n-1} := \{ \mathbf{x} \in \mathbf{R}^n | |\mathbf{x}| := \sum_{i=1}^n x_i = 1, x_i \ge 0, \forall i = 1, \dots, n \}.$$

From the discrete to the continuous

We consider the discrete evolution $(|\mathbf{y}| = \sum_i y_i)$

$$ho_N(\mathsf{x},t+\Delta t) = \sum_{|\mathsf{y}|=1} \Theta_N(\mathsf{y} o \mathsf{x})
ho_N(t,\mathsf{y}) = \sum_{|\mathsf{y}|=0} \Theta_N(\mathsf{x}-\mathsf{y} o \mathsf{x})
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We assume the weak selection principle $\phi^{(i)}(\mathbf{y}) = 1 + \frac{\psi^{(i)}(\mathbf{y})}{N}$, and then $\bar{\phi}(\mathbf{y}) = 1 + \frac{\bar{\psi}(\mathbf{y})}{N}$.

From the discrete to the continuous

We consider the discrete evolution $(|\mathbf{y}| = \sum_i y_i)$

$$\rho_N(\mathbf{x},t+\Delta t) = \sum_{|\mathbf{y}|=1} \Theta_N(\mathbf{y}\to\mathbf{x}) \rho_N(t,\mathbf{y}) = \sum_{|\mathbf{y}|=0} \Theta_N(\mathbf{x}-\mathbf{y}\to\mathbf{x}) \rho_N(t,\mathbf{x}-\mathbf{y}) \,.$$

We assume the weak selection principle $\phi^{(i)}(\mathbf{y}) = 1 + \frac{\psi^{(i)}(\mathbf{y})}{N}$, and then $\bar{\phi}(\mathbf{y}) = 1 + \frac{\bar{\psi}(\mathbf{y})}{N}$. This implies that

$$\begin{split} \left(\frac{y_{i}\phi^{(i)}}{\bar{\phi}}\right)^{Nx_{i}} &\approx & \exp\left\{Nx_{i}\left[\log y_{i} + \log\left(1 + \frac{\psi^{(i)}(\mathbf{y})}{N}\right)\left(1 - \frac{\bar{\psi}(\mathbf{y})}{N} + \frac{\bar{\psi}^{2}(\mathbf{y})}{N^{2}}\right)\right]\right\} \\ &\approx & y_{i}^{Nx_{i}}\exp\left[x_{i}\left(\psi^{(i)}(\mathbf{y}) - \bar{\psi}\left(\mathbf{y}\right)\right) + \frac{x_{i}\bar{\psi}}{N}\left(\bar{\psi}(\mathbf{y}) - \psi^{(i)}(\mathbf{y})\right)\right] \;. \end{split}$$

From the discrete to the continuous

Using the Stirling formula $x! \approx \sqrt{2\pi x} x^x e^{-x}$ we write

$$\frac{N!}{(Nx_1)!(Nx_2)!\cdots(Nx_n)!}\approx \frac{(2\pi)^{\frac{1-n}{2}}}{N^{n-1}}\frac{N^{\frac{n-1}{2}}}{(x_1x_2\cdots x_n)^{\frac{1}{2}}x_1^{x_1N}x_2^{x_2N}\cdots x_n^{x_nN}}.$$

From the discrete to the continuous

Finally, we have

$$\Theta_{\text{N}}(\mathbf{y} \rightarrow \mathbf{x}) \approx \frac{1}{\text{N}^{n-1}} \Lambda(\mathbf{y}, \mathbf{x}, \text{N}^{-\frac{1}{2}}) \left(1 + \Xi(\mathbf{y}, \mathbf{x}, \text{N}^{-\frac{1}{2}}) + o(\text{N}^{-1})\right) \; , \label{eq:theta_N}$$

where

$$\begin{split} & \Lambda(\mathbf{y}, \mathbf{x}, z) := \frac{(2\pi)^{\frac{1-n}{2}} z^{1-n}}{(x_1 x_2 \cdots x_n)^{\frac{1}{2}}} \prod_{i=1}^n \left(\frac{y_i}{x_i}\right)^{\frac{x_i}{z^2}} \\ & \Xi(\mathbf{y}, \mathbf{x}, z) := \sum_{i=1}^n \left[x_i \left(\psi^{(i)}(\mathbf{y}) - \bar{\psi}(\mathbf{y}) \right) + z^2 x_i \bar{\psi}(\mathbf{y}) \left(\bar{\psi}(\mathbf{y}) - \psi^{(i)}(\mathbf{y}) \right) \right] \ . \end{split}$$

Note that Ξ is associated to the drift generated by the fitness; i.e., if $\psi^{(i)}(\mathbf{y})$ is constant, then $\Xi(\mathbf{y},\mathbf{x},N)=0$.

From the discrete to the continuous

We introduce the new variables $au_i = y_i \sqrt{N}$ and $z = \frac{1}{\sqrt{N}}$.

Lemma

For large N (and then small z) the neutral transition probability Λ scales as

$$\Lambda(\mathbf{x}-z\boldsymbol{\tau},\mathbf{x},z)\approx\frac{(2\pi)^{\frac{1-n}{2}}z^{1-n}}{(x_1x_2\cdots x_n)^{\frac{1}{2}}}\exp\left(-\frac{1}{2}\mathcal{Q}(\boldsymbol{\tau},\boldsymbol{\tau})\right),$$

where \mathcal{Q} is a quadratic form with associated eigenvalues $\lambda_1,\cdots,\lambda_{n-1}$. These eigenvalues are the eigenvalues of the matrix $\mathbf{F}=(F_{ij})$, $i,j=1,\cdots,n-1$, such that $F_{ii}=x_i^{-1}+x_n^{-1}$ and $F_{ij}=x_n^{-1}$, for $i\neq j$, i.e., $\lambda_1\cdots\lambda_{n-1}=(x_1\cdots x_n)^{-1}$. This implies that

$$\int_{\mathbb{R}^{n-1}} \exp\left(-\frac{1}{2}\mathcal{Q}(\boldsymbol{\tau},\boldsymbol{\tau})\right) \mathrm{d}\boldsymbol{\tau} = (2\pi)^{\frac{n-1}{2}} \sqrt{x_1 \cdots x_n} \; .$$

From the discrete to the continuous

Lemma

For large N (and then small z) the neutral transition probability Λ has the following first moments:

$$\begin{split} z^{n-1} & \int \Lambda(\mathbf{x}, \mathbf{x} + z \boldsymbol{\tau}, z) \mathrm{d} \boldsymbol{\tau} = \int \Lambda(\mathbf{x}, \mathbf{x} + \mathbf{y}, z) \mathrm{d} \mathbf{y} = 1 \ , \\ z^n & \int \tau_i \Lambda(\mathbf{x}, \mathbf{x} + z \boldsymbol{\tau}, z) \mathrm{d} \boldsymbol{\tau} = 0 \ , \\ z^{n+1} & \int \tau_i \tau_j \Lambda(\mathbf{x}, \mathbf{x} + z \boldsymbol{\tau}, z) \mathrm{d} \boldsymbol{\tau} = \mathrm{o}(z^3) + z^2 \times \left\{ \begin{array}{l} (-x_i x_j) & \text{if } i \neq j \ , \ i, j \leq n-1 \ , \\ x_i (1 - x_i) & \text{if } i = j \leq n-1 \ . \end{array} \right. \end{split}$$

From the discrete to the continuous

$$\int p(\mathbf{x}, t + \Delta t) g(\mathbf{x}) d\mathbf{x} \approx \iint \Theta_N(\mathbf{x} - \mathbf{y} \to \mathbf{x}) p(\mathbf{x} - \mathbf{y}, t) N^{n-1} g(\mathbf{x}) d\mathbf{x} d\mathbf{y}$$

$$\approx \frac{1}{z^{n-1}} \iint \Theta_{\frac{1}{z^2}}(\mathbf{x} - z\boldsymbol{\tau} \to \mathbf{x}) p(\mathbf{x} - z\boldsymbol{\tau}, t) g(\mathbf{x}) d\boldsymbol{\tau} d\mathbf{x}$$

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From the discrete to the continuous

$$\int \rho(\mathbf{x}, t + \Delta t) g(\mathbf{x}) d\mathbf{x} \approx \iint \Theta_N(\mathbf{x} - \mathbf{y} \to \mathbf{x}) \rho(\mathbf{x} - \mathbf{y}, t) N^{n-1} g(\mathbf{x}) d\mathbf{x} d\mathbf{y}$$

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$$= z^{n-1} \iint \left[1 + \Xi(\mathbf{x}, \mathbf{x} + z\tau, z) \right] \Lambda(\mathbf{x}, \mathbf{x} + z\tau, z) \rho(\mathbf{x}, t) g(\mathbf{x} + z\tau) d\tau d\mathbf{x}$$

$$\approx z^{n-1} \iint \left[1 + z \sum_{i=1}^{n} \tau_i \left(\psi^{(i)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) + o(z^3) \right] \Lambda(\mathbf{x}, \mathbf{x} + z\tau, z) \rho(\mathbf{x}, t)$$

$$\times \left[g(\mathbf{x}, t) + z \sum_{j=1}^{n-1} \tau_j \partial_{x_j} g(\mathbf{x}) + \frac{z^2}{2} \sum_{k,l=1}^{n-1} \tau_k \tau_l \partial_{x_k x_k}^2 g(\mathbf{x}) \right] d\tau d\mathbf{x}$$

$$\begin{split} &\int \rho(\mathbf{x},t+\Delta t)g(\mathbf{x})\mathrm{d}\mathbf{x} \\ &\approx z^{n-1} \iint \Lambda(\mathbf{x},\mathbf{x}+z\boldsymbol{\tau},z)\rho(\mathbf{x},t)g(\mathbf{x})\mathrm{d}\boldsymbol{\tau}\mathrm{d}\mathbf{x} \\ &+z^n \iint \rho(\mathbf{x},t) \left[\sum_{i=1}^n \left(\psi^{(i)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) \tau_i + \sum_{j=1}^{n-1} \tau_j \partial_{x_j} g(\mathbf{x}) \right] \Lambda(\mathbf{x},\mathbf{x}+z\boldsymbol{\tau},z)\mathrm{d}\boldsymbol{\tau}\mathrm{d}\mathbf{x} \\ &+z^{n+1} \iint \rho(\mathbf{x},t) \left[\sum_{k,l=1}^{n-1} \frac{\tau_k \tau_l}{2} \partial_{x_k x_l}^2 g(\mathbf{x}) + \sum_{i=1}^n \sum_{j=1}^{n-1} \partial_{x_j} g(\mathbf{x}) (\psi^{(i)}(\mathbf{x}) - \bar{\psi}(\mathbf{x})) \tau_i \tau_j \right] \\ &\times \Lambda(\mathbf{x},\mathbf{x}+z\boldsymbol{\tau},z)\mathrm{d}\boldsymbol{\tau}\mathrm{d}\mathbf{x} \ . \end{split}$$

$$\int \rho(\mathbf{x}, t + \Delta t) g(\mathbf{x}) d\mathbf{x}$$

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$$+ z^{n} \iint \rho(\mathbf{x}, t) \left[\sum_{i=1}^{n} \left(\psi^{(i)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) \tau_{i} + \sum_{j=1}^{n-1} \tau_{j} \partial_{x_{j}} g(\mathbf{x}) \right] \Lambda(\mathbf{x}, \mathbf{x} + z\tau, z) d\tau d\mathbf{x}$$

$$+ z^{n+1} \iint \rho(\mathbf{x}, t) \left[\sum_{k,l=1}^{n-1} \frac{\tau_{k} \tau_{l}}{2} \partial_{x_{k} x_{l}}^{2} g(\mathbf{x}) + \sum_{i=1}^{n} \sum_{j=1}^{n-1} \partial_{x_{j}} g(\mathbf{x}) (\psi^{(i)}(\mathbf{x}) - \bar{\psi}(\mathbf{x})) \tau_{i} \tau_{j} \right]$$

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$$+ z^2 \int g(\mathbf{x}) \left[\frac{1}{2} \sum_{k=1}^{n-1} \partial_{x_k}^2 \left(x_k (1 - x_k) \rho(\mathbf{x}, t) \right) - \frac{1}{2} \sum_{k,l=1, k \neq l}^{n-1} \partial_{x_k x_l}^2 \left(x_k x_l \rho(\mathbf{x}, t) \right) - \sum_{i=1}^{n-1} \partial_{x_j} \left(x_i \left(\psi^{(j)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) \rho(\mathbf{x}, t) \right) \right] d\mathbf{x} .$$

From the discrete to the continuous

Imposing $\Delta t = z^2 = \frac{1}{N}$, we have

$$\partial_{t} \rho = \frac{1}{2} \sum_{k=1}^{n-1} \partial_{x_{k}}^{2} \left(x_{k} (1 - x_{k}) \rho(\mathbf{x}, t) \right) - \frac{1}{2} \sum_{k,l=1, k \neq l}^{n-1} \partial_{x_{k} x_{l}}^{2} \left(x_{k} x_{l} \rho(\mathbf{x}, t) \right) - \sum_{j=1}^{n-1} \partial_{x_{j}} \left(x_{j} \left(\psi^{(j)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) \rho(\mathbf{x}, t) \right)$$

We call this equation the replicator-diffusion equation:

$$\partial_t \rho = \frac{1}{2} \sum_{i,j=1}^{n-1} \partial_{x_i x_j}^2 \left(D_{ij} \rho \right) - \sum_{i=1}^{n-1} \partial_{x_i} (\Omega_i \rho) .$$

The replicator equation appears...

The replicator-diffusion equation is given by

$$\partial_t p = \frac{1}{2} \sum_{k=1}^{n-1} \partial_{x_k}^2 \left(x_k (1 - x_k) p(\mathbf{x}, t) \right)$$

$$- \frac{1}{2} \sum_{k,l=1, k \neq l}^{n-1} \partial_{x_k x_l}^2 \left(x_k x_l p(\mathbf{x}, t) \right) - \sum_{j=1}^{n-1} \partial_{x_j} \left(x_j \left(\psi^{(j)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) p(\mathbf{x}, t) \right)$$

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$$\frac{1}{\varepsilon}\partial_{t}\rho = \frac{1}{2}\sum_{k=1}^{n-1}\partial_{x_{k}}^{2}\left(x_{k}(1-x_{k})\rho(\mathbf{x},t)\right) \\
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This equation is equivalent to the replicator dynamics.

Mixed states fade away...

Theorem

Let p be the solution of replicator-diffusion equation. Then, $p^{\infty} := \lim_{t \to \infty} p(\cdot,t)$, is a linear combination of Dirac-deltas supported at the vertexes of the simplex.

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We change variables and re-write the replicator-diffusion equation as

$$\partial_t u = \frac{1}{\omega} \nabla \cdot \left[\omega \left(\frac{1}{2} D \nabla u - \mathbf{B} u \right) \right] ,$$

where $u=\mathrm{e}^{-\theta}p/\lambda$, $\omega=\mathrm{e}^{\theta}/\lambda$, with $\lambda=x_1x_2\cdots x_n$ and $\nabla\theta$ and \mathbf{B} are associated to the Hodges decomposition of the drift part.

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$$\frac{1}{2}\partial_t \int u^2 \omega dV = \int_{S^n} \nabla \cdot \left[\omega \left(\frac{1}{2} D \nabla u - \mathcal{B} u \right) \right] u \, dV < -\alpha \int_{S^n} u^2 \omega \, dV.$$

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Then

$$\int p^2 e^{-\theta} \lambda dx = \int u^2 \omega dx \stackrel{t \to \infty}{\to} 0 ,$$

and, together with the conservation laws $\partial_t \int \phi_i p \mathrm{d}x = 0$, $i = 1, \ldots, n$ we have that p concentrates on the zeros of λ , i.e., the boundary of the simplex.

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$$p^{\infty} = \sum_{v \in V} c_v \delta_v ,$$

where V is the set of all vertexes of the simplex S^n .

The replicator equation appears...

Theorem

Let p_0 be the solution of the replicator-diffusion equation, with $\varepsilon=0$ and let p_{ε} be a solution to replicator-diffusion equation, with $\varepsilon>0$. Then, there exits a C such that, for $\tau\leq C$, we have

$$||p_{\varepsilon}(\cdot,\tau)-p_0(\cdot,\tau)||_{\infty}\leq C\varepsilon.$$

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Define $w_{\varepsilon}=p_{\varepsilon}-p_0$, and

$$\partial_{t}w_{\varepsilon} = \frac{\varepsilon}{2} \sum_{i,j=1}^{n-1} \partial_{ij} \left(D_{ij} w_{\varepsilon} \right) - \sum_{i=1}^{n-1} \partial_{x_{i}} \left(\Omega_{i} w_{\varepsilon} \right) + \frac{\varepsilon}{2} \sum_{i,j=1}^{n-1} \partial_{x_{i} x_{j}} \left(D_{ij} p_{0} \right) , \quad w_{\varepsilon}|_{t=0} = 0$$

General fitness function and n types

The dual of the replicator-diffusion equation generalizes the Kimura equation for *n* types and general fitness:

$$\partial_t f = \frac{\varepsilon}{2} \sum_{k=1}^{n-1} x_k (1 - x_k) \partial_k^2 f - \frac{1}{2} \sum_{k,l=1; k \neq l}^{n-1} x_k x_l \partial_{kl}^2 f + \sum_{j=1}^{n-1} x_j \left(\psi^{(j)}(\mathbf{x}) - \bar{\psi}(\mathbf{x}) \right) \partial_j f$$

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The function f gives the fixation probability of a given type. The precise type will be fixed by the boundary conditions imposed to f.

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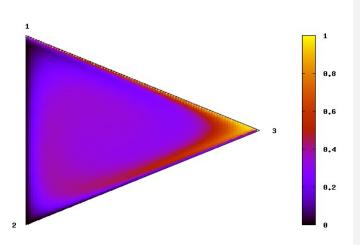
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Fixation probability of a Paper in the Rock-Scissor-Paper game.



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