

Mathematics of evolution

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DARWIN200



12 February 1809 – 12 February 2009

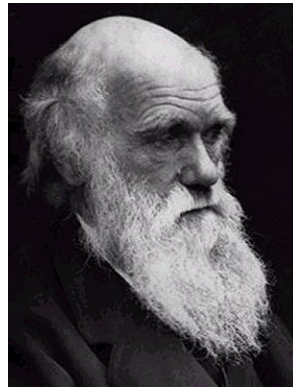
Summary

- (1) A bit of history**
- (2) Fundamentals of evolution**
- (3) Genetic drift**
- (4) Sequences and fitness landscapes**
- (5) Game theory**
- (6) Evolutionary game theory**

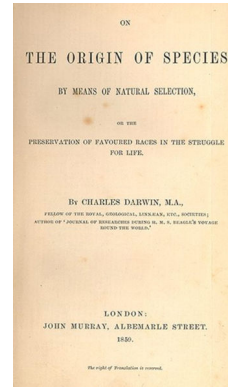
A little bit of history



Lamarck (1744-1829)



Darwin (1809-1882)



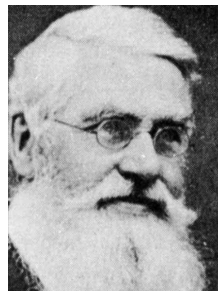
1859



Malthus (1766-1834)



farmer breeding



Wallace (1823-1913)



Beagle (1831-1836)



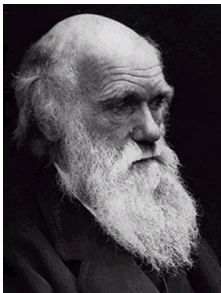
Neodarwinism



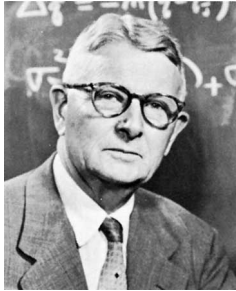
Mendel (1744-1829)



Huxley (1827-1895)



Darwin (1809-1882)



Wright (1889-1988)



Fisher (1890-1962)



Haldane (1892-1964)



Kimura (1924-1994)

population genetics

biology



Morgan (1866-1945)



Dobzhansky (1900-1975)

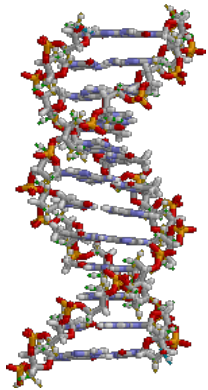


Mayr (1904-2005)

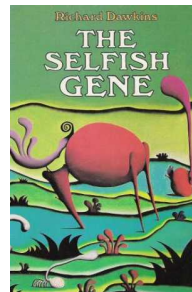
The modern era

selfish genes

evolutionary game theory



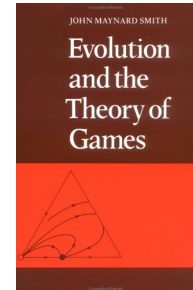
Dawkins (1941-)



1976



Maynard-Smith (1920-2004)



Hamilton (1936-2000)

FUNDAMENTALS OF EVOLUTION

Evolution: building blocks

- Replication
- Selection
- Mutation

Evolution: building blocks

- Replication

- Selection

- Mutation

Replication

Bacterial reproduction:

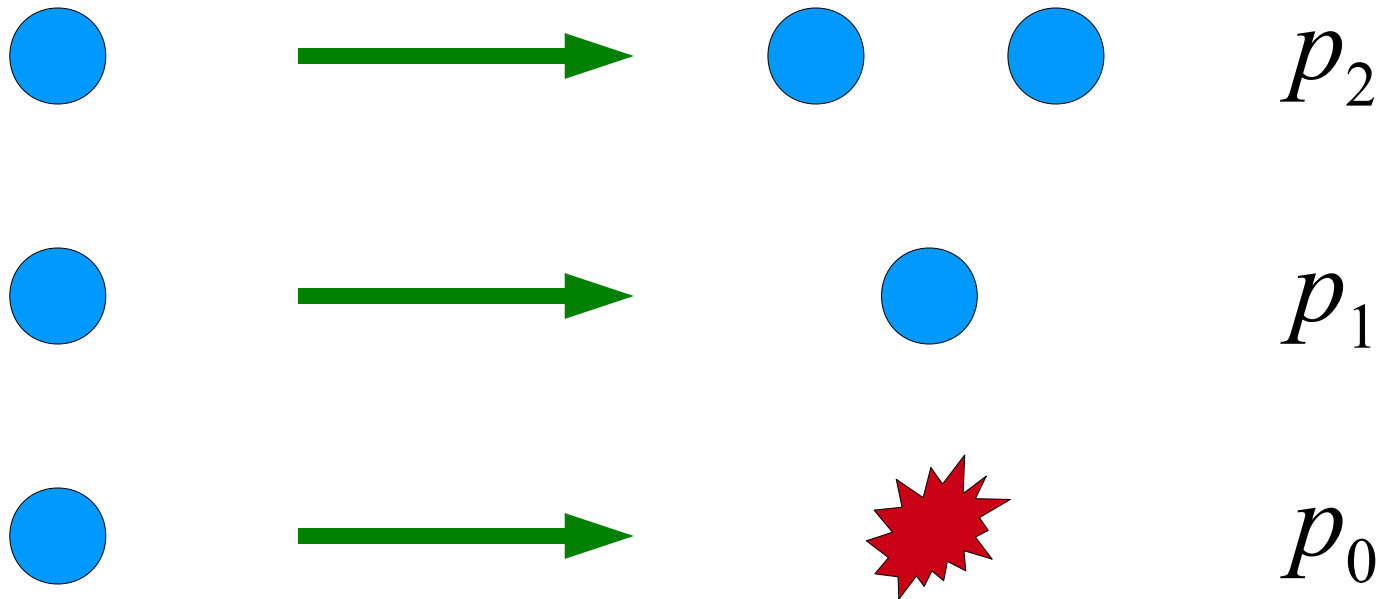
$$x_{t+1} = 2 x_t \quad x_t = 2^t x_0$$

3 divisions / hour = 144 divisions / 2 days

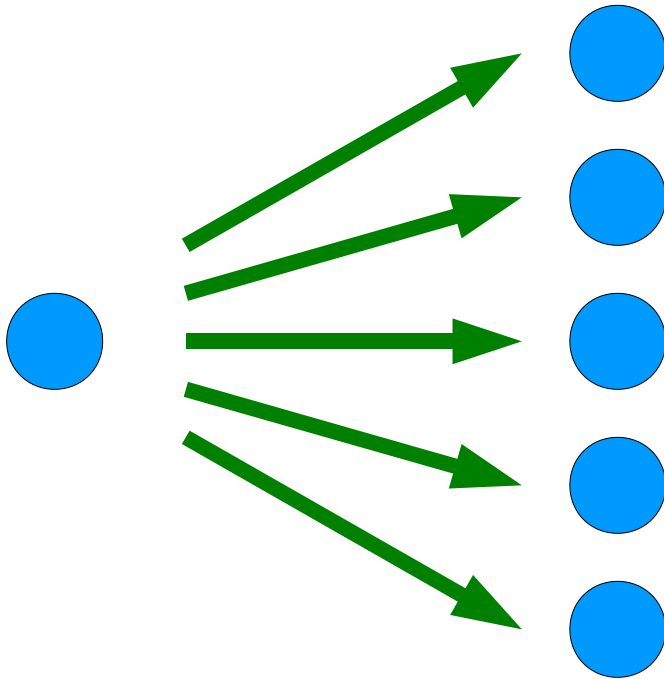
$$2^{144} \approx 2 \times 10^{43} \approx 2 \times 10^{28} \text{ kg} \approx 3000 \text{ earths!}$$

Refining the argument

check every τ secs \ll 20 min



Galton-Watson process



$$P\{X = k\} = p_k$$
$$k = 0, 1, 2, \dots$$

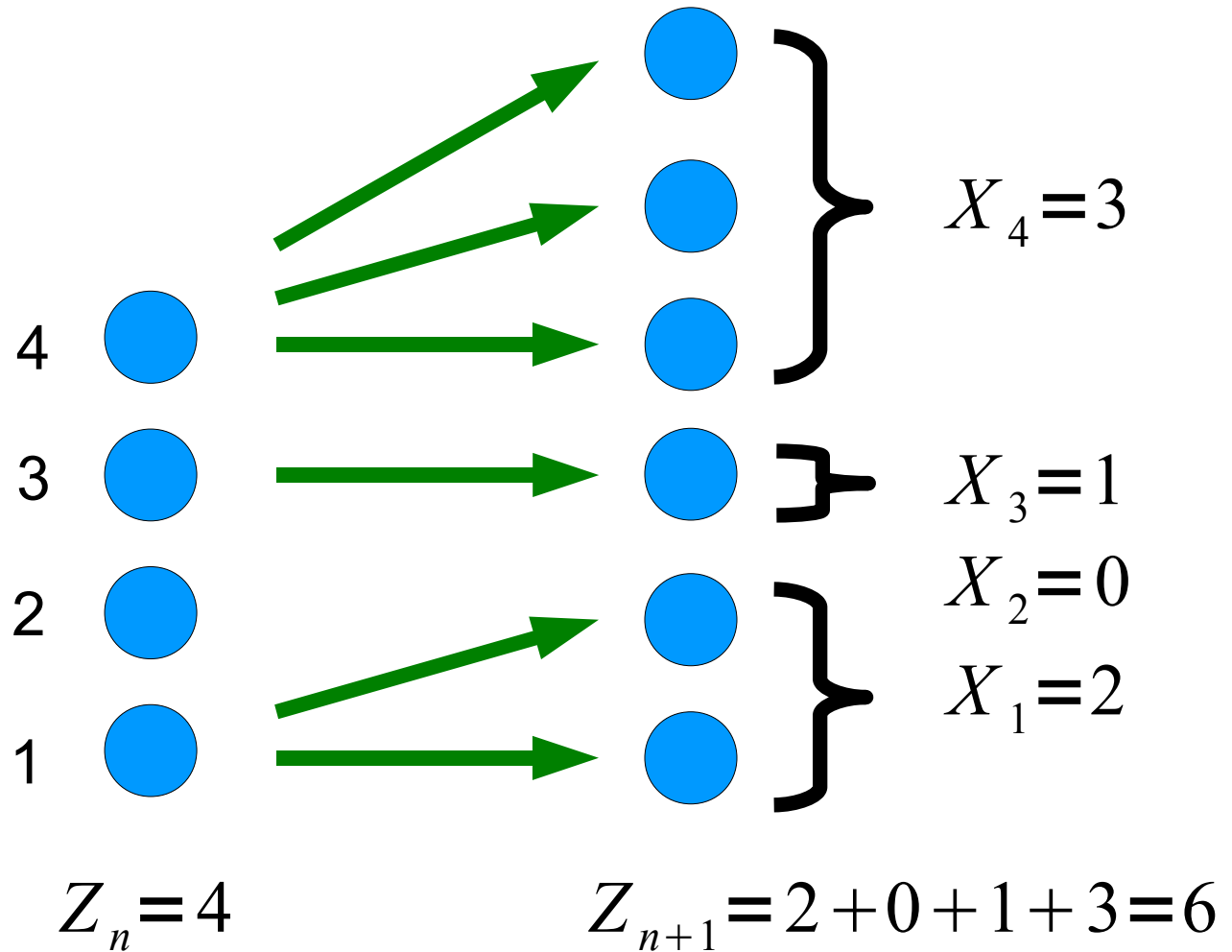
$$F(s) = \sum_{k=0}^{\infty} p_k s^k$$

$$F(1) = 1$$

$$F'(1) = m$$

$$F''(1) = \sigma^2 + m^2 - m$$

Galton-Watson process



Galton-Watson process

$$Z_0 = 1 \quad Z_n = X_1 + X_2 + \cdots + X_{Z_{n-1}} \quad (n > 0)$$

$$\mathbb{P}\{Z_n = k\} = p_k^{(n)} \quad k = 0, 1, 2, \dots$$

$$F_n(s) = \sum_{k=0}^{\infty} p_k^{(n)} s^k$$

Markov process:

$$\mathbb{P}\{Z_{n+1} = k \mid Z_n = j\} = P_{j,k} \quad j, k = 0, 1, 2, \dots$$

Galton-Watson process

$$G_j(s) = \sum_{k=0}^{\infty} P_{j,k} s^k = [F(s)]^j$$

$$F_{n+1}(s) = \sum_{j=0}^{\infty} p_j^{(n)} [F(s)]^j = F_n(F(s))$$

$$F_0(s) = s \qquad F_{n+1}(s) = F(F_n(s))$$

Galton-Watson process

$$F'_n(1) = F'(1)F'_{n-1}(1) = m F'_{n-1}(1)$$

$$m_n = m^n$$

$$\begin{aligned} F''_n(1) &= F''(1)[F'_{n-1}(1)]^2 + F'(1)F''_{n-1}(1) \\ &= F''(1)m^{2n-2} + m F''_{n-1}(1) \end{aligned}$$

$$\sigma_n^2 = \sigma^2 \frac{m^{n-1}(m^n - 1)}{m - 1} \quad m \neq 1$$

$$\sigma_n^2 = n\sigma^2 \quad m = 1$$

Galton-Watson process

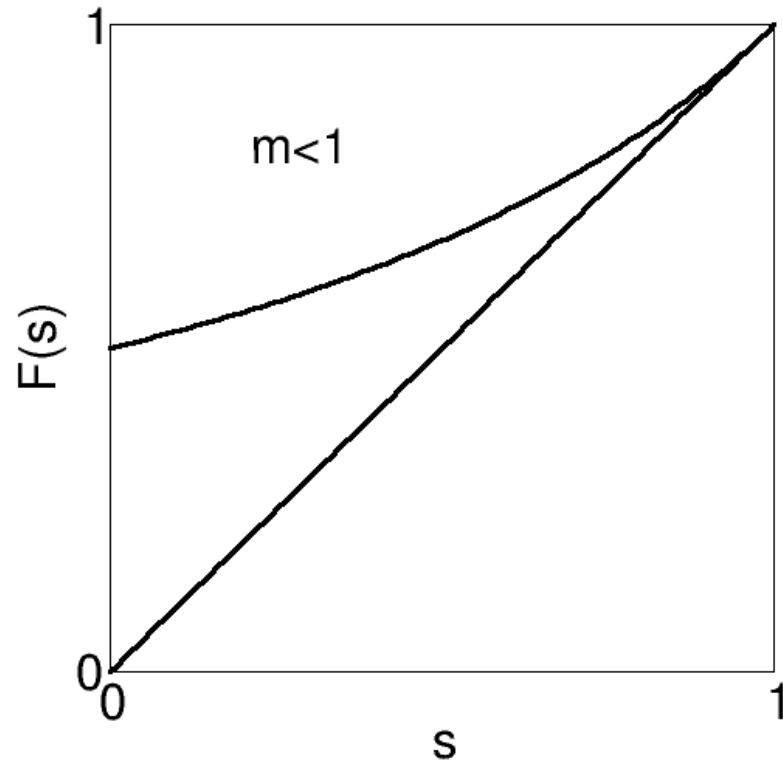
$$F(1) = 1 \quad F(0) = p_0 \quad F'(1) = m$$

$$p_0 + p_1 < 1$$



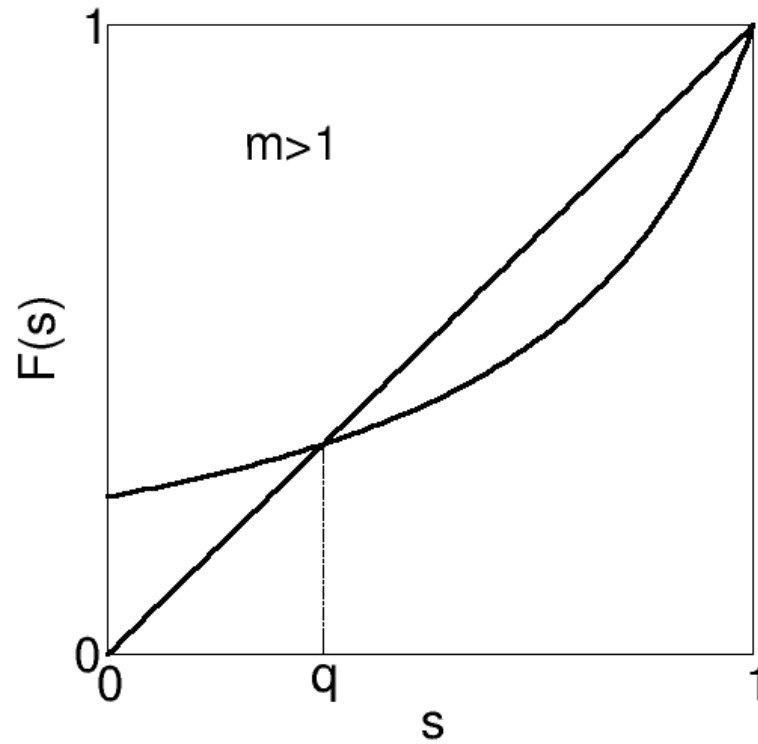
$$F'(s) > 0 \quad F''(s) > 0 \quad s \in [0, 1]$$

Galton-Watson process



subcritical

Galton-Watson process



supercritical

Galton-Watson process

extinction probability:

$$q = \lim_{n \rightarrow \infty} F_n(0)$$

$$F_{n+1}(0) = F(F_n(0)) \quad \Rightarrow \quad q = F(q)$$

$$m \leq 1 \quad \Rightarrow \quad q = 1$$

$$m > 1 \quad \Rightarrow \quad q < 1$$

Bacterial growth revisited

$$\begin{aligned} F(s) &= p_0 + p_1 s + p_2 s^2 \\ &= s + (1-s)(p_0 - p_2 s) \end{aligned}$$

$$m = 1 + p_2 - p_0$$

$$q = 1 \quad p_2 \leq p_0$$

$$q = \frac{p_0}{p_2} \quad p_2 > p_0$$

$$m_n = (1 + p_2 - p_0)^n \approx e^{np_2(1-q)}$$

Continuous Galton-Watson process

$$p_k(\tau) = \tau \lambda p_k + o(\tau) \quad k \neq 1$$

$$p_1(\tau) = 1 - \tau \lambda (1 - p_1) + o(\tau)$$

$$F(s; \tau) = \sum_{k=0}^{\infty} p_k(\tau) s^k = s + \tau \lambda \overbrace{[F(s) - s]}^{U(s)} + o(\tau)$$

$$\lim_{\tau \rightarrow 0} p_k^{(t/\tau)} = p_k(t)$$

$$\lim_{\tau \rightarrow 0} F_{t/\tau}(s) = F(s, t)$$

Continuous Galton-Watson process

$$F_{t/\tau+1}(s) = F(F_{t/\tau}(s); \tau)$$

$$\frac{F_{t/\tau+1}(s) - F_{t/\tau}(s)}{\tau} = \lambda U(F_{t/\tau}(s)) + o(1)$$

$$\frac{\partial F(s, t)}{\partial t} = \lambda U(F(s, t))$$

backward Kolmogorov eq.

Continuous Galton-Watson process

$$F_{t/\tau+1}(s) = F_{t/\tau}(F(s; \tau))$$

$$\frac{F_{t/\tau+1}(s) - F_{t/\tau}(s)}{\tau} = \frac{F_{t/\tau}(s + \lambda\tau U(s) + o(\tau)) - F_{t/\tau}(s)}{\tau}$$

$$\frac{\partial F(s, t)}{\partial t} = \lambda U(s) \frac{\partial F(s, t)}{\partial s}$$

forward Kolmogorov eq.

Evolution of the mean

$$\lim_{s \rightarrow 1} \frac{\partial}{\partial s} F(s, t) = m(t) \quad U'(1) = m - 1 \equiv r / \lambda \quad U(1) = 0$$

$$\frac{\partial}{\partial t} \frac{\partial F(s, t)}{\partial s} = \lambda U'(s) \frac{\partial F(s, t)}{\partial s} + \lambda U(s) \frac{\partial^2 F(s, t)}{\partial s^2}$$

$$\frac{d m(t)}{d t} = r m(t)$$

Malthus law

Bacterial growth again

$$U(s) = (1-s)(p_0 - p_2 s)$$

$$F(s, 0) = s \quad p_2 > p_0 \quad r \equiv \lambda(p_2 - p_0)$$

$$F(s, t) = \frac{p_0(1-s) - (p_0 - p_2 s)e^{-rt}}{p_2(1-s) - (p_0 - p_2 s)e^{-rt}}$$

$$\mathbf{P}\{T_{ext} \leq t\} = p_0(t) = F(0, t) = \frac{p_0 - p_0 e^{-rt}}{p_2 - p_0 e^{-rt}}$$

mean extinction time of realizations that go extinct:

$$\mathbf{E}\{T_{ext}\} = \frac{-\ln(1-q)}{\lambda p_0} = \frac{1}{\lambda p_2} \left[1 + \frac{q}{2} + o(q) \right]$$

Saturation

$$\frac{d m}{d t} = r m \left(1 - \frac{m}{K} \right)$$

carrying capacity



$$m(t) = \frac{K m_0 e^{rt}}{K + m_0 (e^{rt} - 1)}$$

$$\lim_{t \rightarrow \infty} m(t) = K$$

saturation maintains a constant population

Evolution: building blocks

- Replication
- **Selection**
- Mutation

Fitness

fitness: mean number of adult offspring in the next generation (separated generations)

fitness: mean growth rate (mixed generations)

$$\frac{d m}{d t} = r m$$

↑
fitness

Competition

$$\frac{d m_A}{d t} = r_A m_A$$

$$\frac{d m_B}{d t} = r_B m_B$$

$$x = \frac{m_A}{m_A + m_B}$$

$$y = \frac{m_B}{m_A + m_B} = 1 - x$$

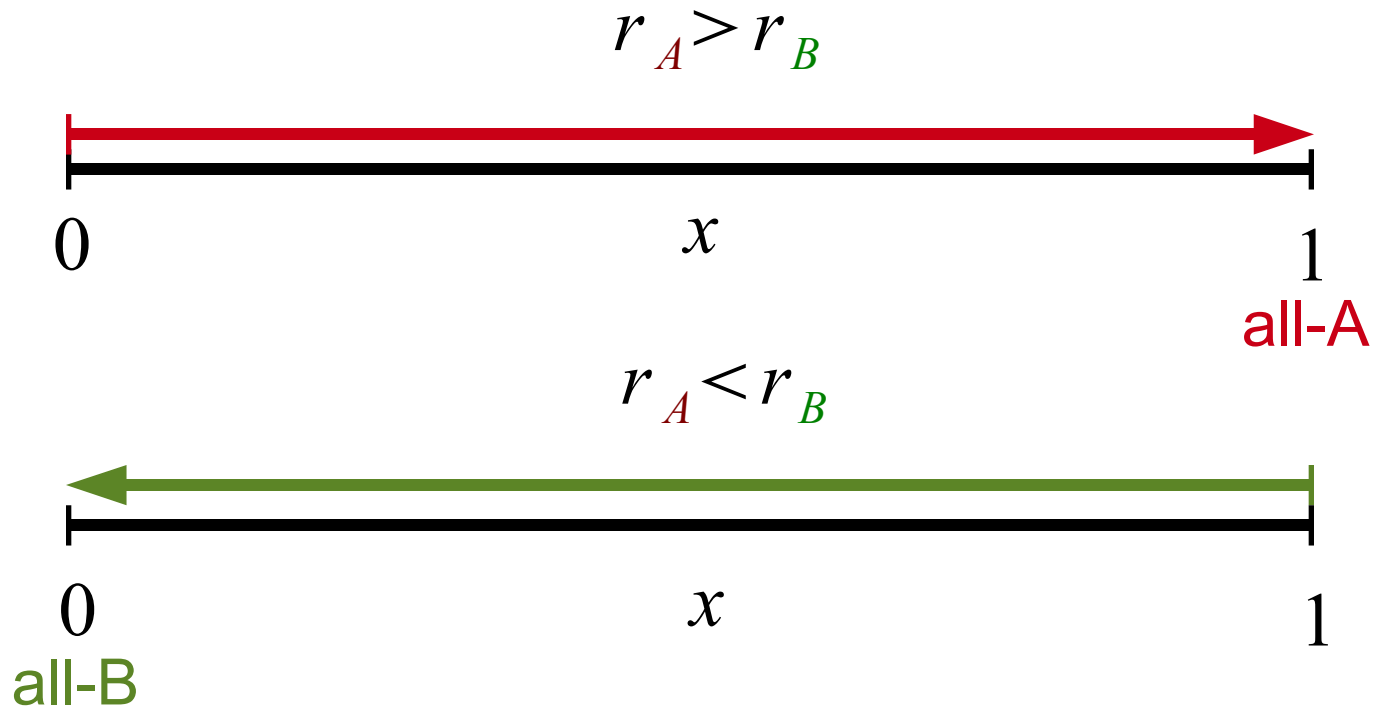
$$\frac{d x}{d t} = x(r_A - \phi)$$

$$\frac{d y}{d t} = y(r_B - \phi)$$

average fitness: $\phi = x r_A + y r_B$

Survival of the fittest

$$\frac{d x}{d t} = x(1-x)(r_A - r_B)$$



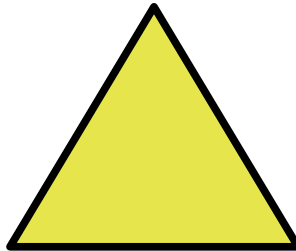
Survival of the fittest

$$\frac{d x_k}{d t} = x_k (f_k - \phi) \quad \phi = \sum_{k=1}^n x_k f_k$$

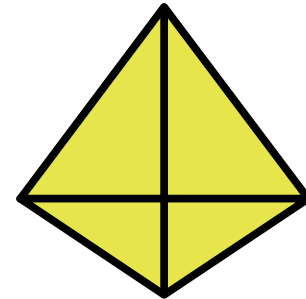
$$\sum_{k=1}^n x_k = 1 \quad \forall t$$



$n=2$



$n=3$



$n=4$

Survival of the fittest

$$\frac{d x_k}{d t} = x_k \sum_{j=1}^n x_j (f_k - f_j)$$

assume $f_k > f_j \quad \forall j \neq k$



$$\lim_{t \rightarrow \infty} x_k(t) = 1 \qquad \lim_{t \rightarrow \infty} x_j(t) = 0 \quad (j \neq k)$$

Fundamental theorem of natural selection

$$\frac{d\phi}{dt} = \sum_{k=1}^n f_k \frac{dx_k}{dt} = \sum_{k=1}^n f_k x_k (f_k - \phi) = \sum_{k=1}^n x_k (f_k - \phi)^2 \equiv \sigma_f^2$$

$$\frac{d\phi}{dt} = \sigma_f^2$$

- Mean fitness never decreases ($\sigma_f^2 \geq 0$)
- The speed of increase is determined by the variation within the population

Composition-dependent fitness

$$f_k = f_k(x_1, \dots, x_n) \equiv f_k(\mathbf{x})$$

Example: two species

$$r_A(x, y) = r + \alpha_A y$$

$$r_B(x, y) = r + \alpha_B x$$

symbiosis

$$\alpha_A > 0$$

$$\alpha_B > 0$$

competition

$$\alpha_A < 0$$

$$\alpha_B < 0$$

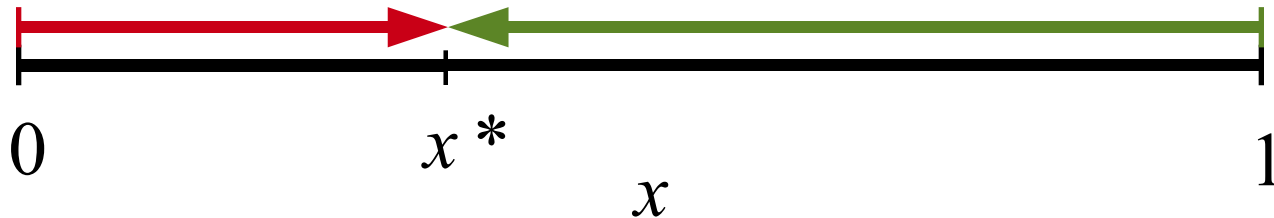
Symbiotic coexistence

$$\frac{d x}{d t} = x(1-x) [\alpha_A - (\alpha_A + \alpha_B) x]$$

$$\alpha_A > 0$$

$$\alpha_B > 0$$

$$x^* = \frac{\alpha_A}{\alpha_A + \alpha_B}$$



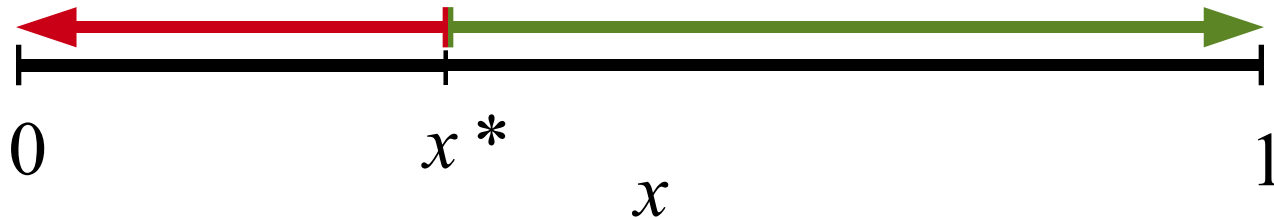
Competitive exclusion

$$\frac{d x}{d t} = x(1-x) [\alpha_A - (\alpha_A + \alpha_B) x]$$

$$\alpha_A < 0$$

$$\alpha_B < 0$$

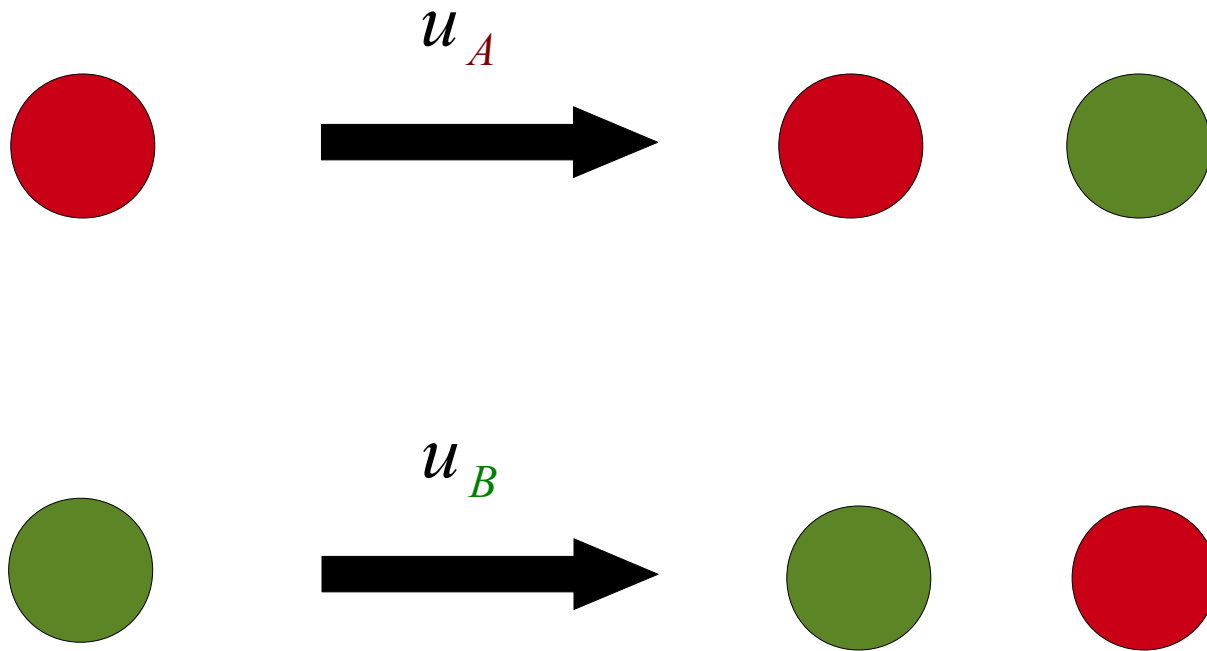
$$x^* = \frac{\alpha_A}{\alpha_A + \alpha_B}$$



Evolution: building blocks

- Replication
- Selection
- **Mutation**

Replication with error



Replication with error

$$\frac{d x}{d t} = x r_A (1 - u_A) + y r_B u_B - \phi x$$

$$\frac{d y}{d t} = x r_A u_A + y r_B (1 - u_B) - \phi y$$

$$\phi = x r_A + y r_B$$

$$\frac{d x}{d t} = x(1-x)(r_A - r_B) + (1-x)r_B u_B - x r_A u_A$$

$x=0$ $x=1$ are not equilibria

Replication with error

$$x^* \approx 1 - \frac{r_A u_A}{r_A - r_B} \quad r_A > r_B$$

$$x^* \approx \frac{r_B u_B}{r_B - r_A} \quad r_A < r_B$$

$$x^* = \frac{u_A}{u_A + u_B} \quad r_A = r_B$$

mutation is the source of variability

Evolution with mutation

mutation matrix $Q = (q_{ij})$ $\mathbf{u} = (1, \dots, 1)$

$$\sum_{j=1}^n q_{ij} = 1 \quad \Leftrightarrow \quad Q \mathbf{u}^T = \mathbf{u}^T$$

$$R = \begin{pmatrix} r_1 & & 0 \\ & \ddots & \\ 0 & & r_n \end{pmatrix}$$

$$W \equiv RQ$$

mutation-selection matrix

$$\frac{d\mathbf{x}}{dt} = \mathbf{x}W - \phi \mathbf{x} \quad \phi = \mathbf{x}W \mathbf{u}^T = \sum_{j=1}^n x_j r_j$$

quasispecies equation

Evolution with mutation

fundamental theorem

may be negative!

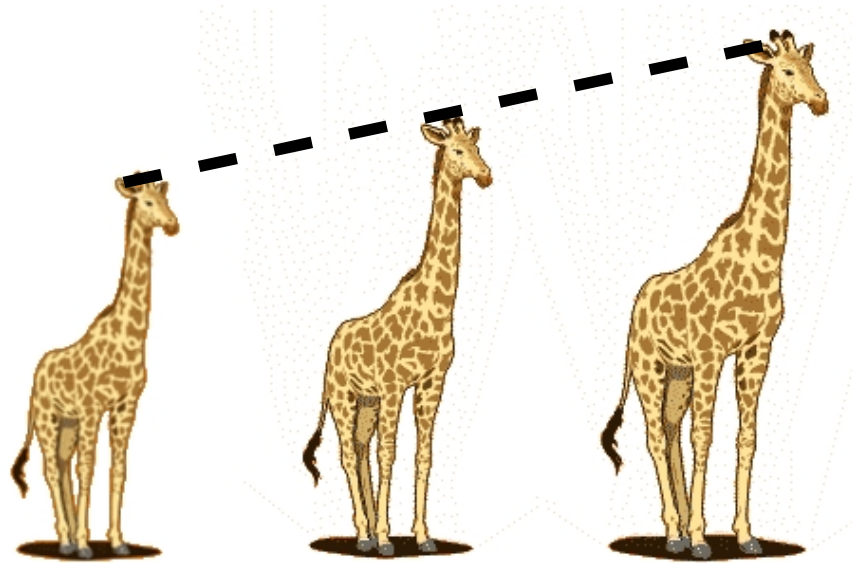
$$\frac{d\phi}{dt} = \frac{d\mathbf{x}}{dt} W \mathbf{u}^T = \mathbf{x} W^2 \mathbf{u}^T - \phi^2 = \mathbf{x} (W - \phi I)^2 \mathbf{u}^T$$

equilibria: $\mathbf{x}^* W = \phi^* \mathbf{x}^*$

if Q is irreducible, ϕ^* is the largest eigenvalue of W

as \mathbf{x}^* normally corresponds to a mixed population,
 ϕ^* need not be the absolute maximum

The paradox of mutation reversion



“classical” theory of inheritance:

$$X_{n+1} = \frac{1}{2} (X_n^{(1)} + X_n^{(2)}) + Z_n \leftarrow N(0, \sigma)$$

The paradox of reversion

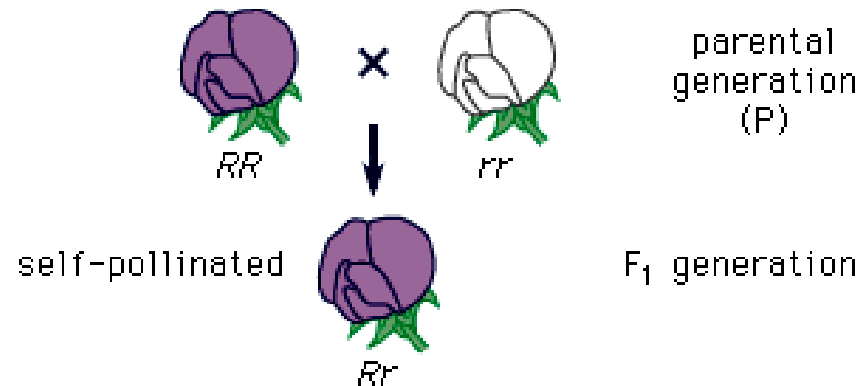
$$\mathbb{P}\{X_n \leq x\} = P_n(x) \quad F_n(q) = \int e^{iqx} dP_n(x)$$

$$\log F_n(q) = iqm_n + \sum_{k=2}^{\infty} \kappa_n^{(j)} \frac{(iq)^j}{j!}$$

$$F_{n+1}(q) = F_n(q/2)^2 e^{-\sigma^2 q^2/2} \quad \Leftrightarrow \quad \begin{cases} m_{n+1} = m_n \\ \sigma_{n+1}^2 = \frac{\sigma_n^2}{2} + \sigma^2 \\ \kappa_{n+1}^{(j)} = \frac{\kappa_n^{(j)}}{2^{j-1}} \quad j > 2 \end{cases}$$

$$\lim_{n \rightarrow \infty} F_n(q) = e^{iqm_1 - \sigma^2 q^2} \quad \Rightarrow \quad \lim_{n \rightarrow \infty} P_n(x) = N(m_1, \sqrt{2}\sigma)$$

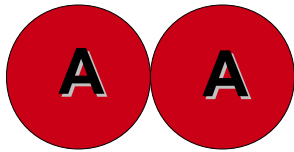
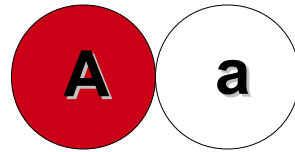
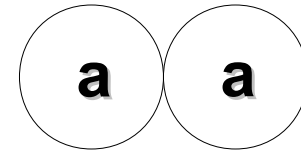
“Quantum” theory of inheritance



		pollen	
		R	r
♀ avules	R	 RR	 Rr
	r	 Rr	 rr

F₂ generation

Hardy-Weinberg law

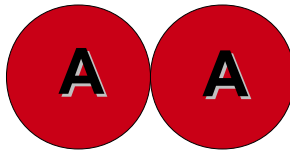
 X_0  Y_0  Z_0 $= 1$

$$X_1 = X_0^2 + X_0 Y_0 + \frac{Y_0^2}{4}$$

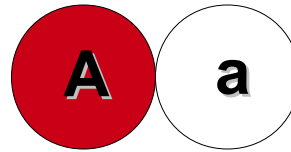
$$Y_1 = X_0 Y_0 + \frac{Y_0^2}{2} + 2 X_0 Z_0 + Y_0 Z_0$$

$$Z_1 = \frac{Y_0^2}{4} + Y_0 Z_0 + Z_0^2$$

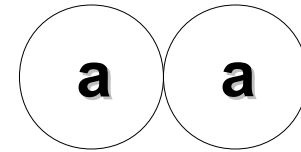
Hardy-Weinberg law



X_0



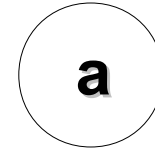
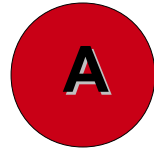
Y_0



Z_0

$$X_1 = \left(X_0 + \frac{Y_0}{2} \right)^2$$
$$Y_1 = 2 \left(X_0 + \frac{Y_0}{2} \right) \left(Z_0 + \frac{Y_0}{2} \right)$$
$$Z_1 = \left(Z_0 + \frac{Y_0}{2} \right)^2$$

Hardy-Weinberg law



p_0

+

q_0

= 1

$$X_1 = p_0^2$$

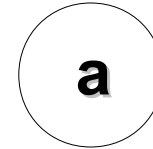
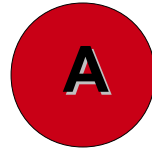
$$p_0 = X_0 + \frac{Y_0}{2}$$

$$Y_1 = 2p_0q_0$$

$$q_0 = Z_0 + \frac{Y_0}{2}$$

$$Z_1 = q_0^2$$

Hardy-Weinberg law



$$p_0 + q_0 = 1$$

$$p_1 = X_1 + \frac{Y_1}{2} = p_0^2 + p_0 q_0 = p_0$$

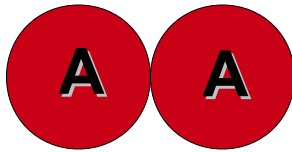
$$X_2 = X_1$$

$$\Rightarrow Y_2 = Y_1$$

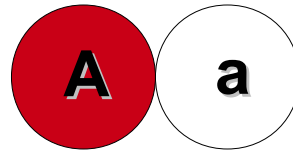
$$q_1 = Z_1 + \frac{Y_1}{2} = q_0^2 + p_0 q_0 = q_0$$

$$Z_2 = Z_1$$

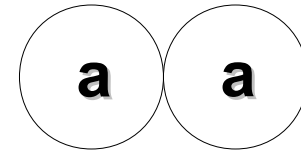
Hardy-Weinberg law



$$X_n = p_0^2$$



$$Y_n = 2p_0q_0$$



$$Z_n = q_0^2$$

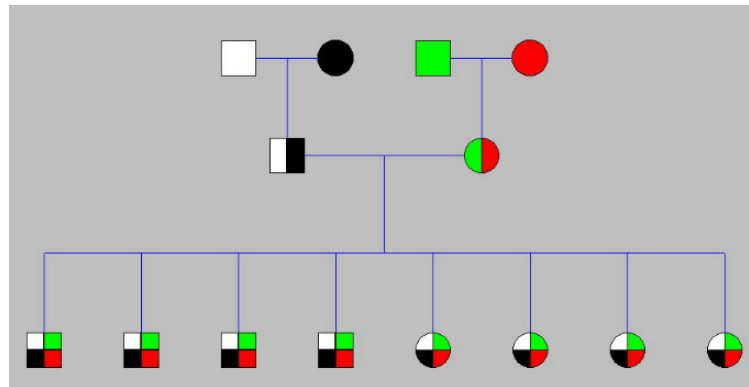
$$p_0 = X_0 + \frac{Y_0}{2}$$

$$q_0 = Z_0 + \frac{Y_0}{2}$$

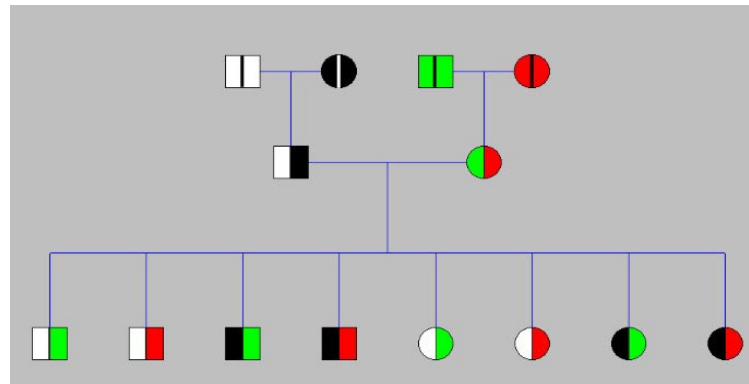
no reversion of the mutant
sustainment of variability

Classical vs. quantum inheritance

pre-Mendel (Galton)



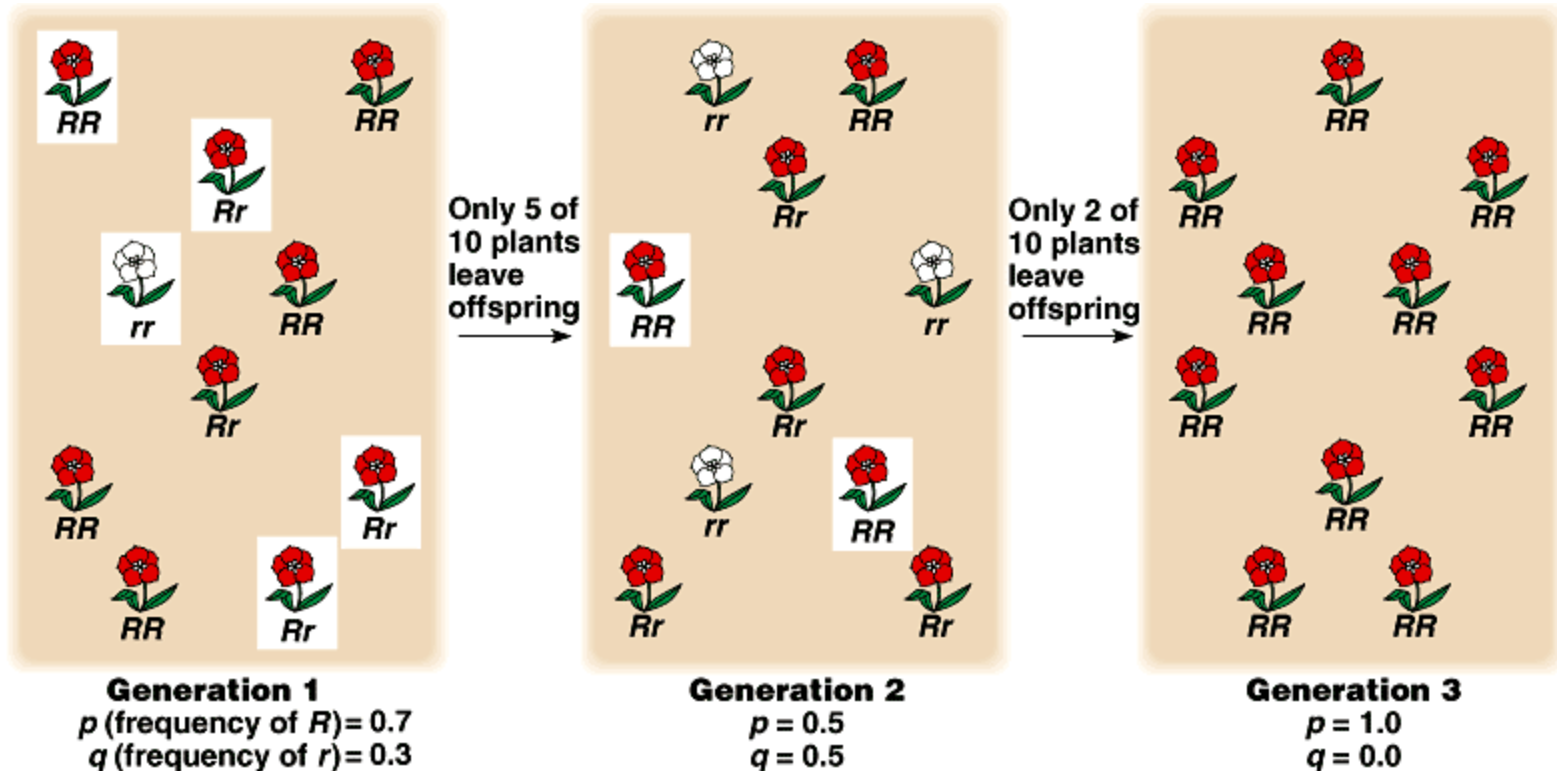
Mendel



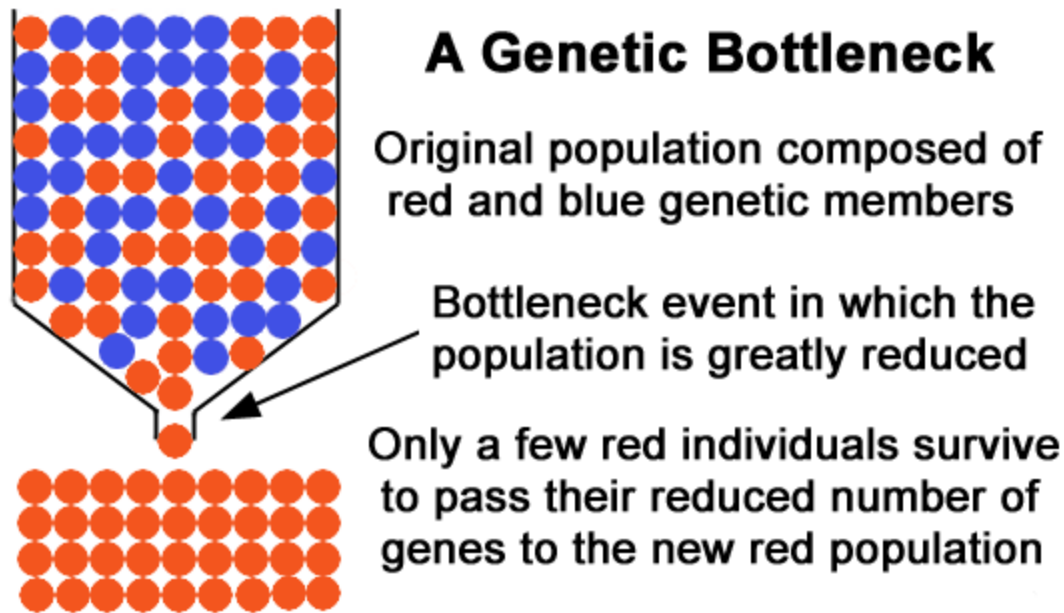
GENETIC DRIFT

Genetic drift

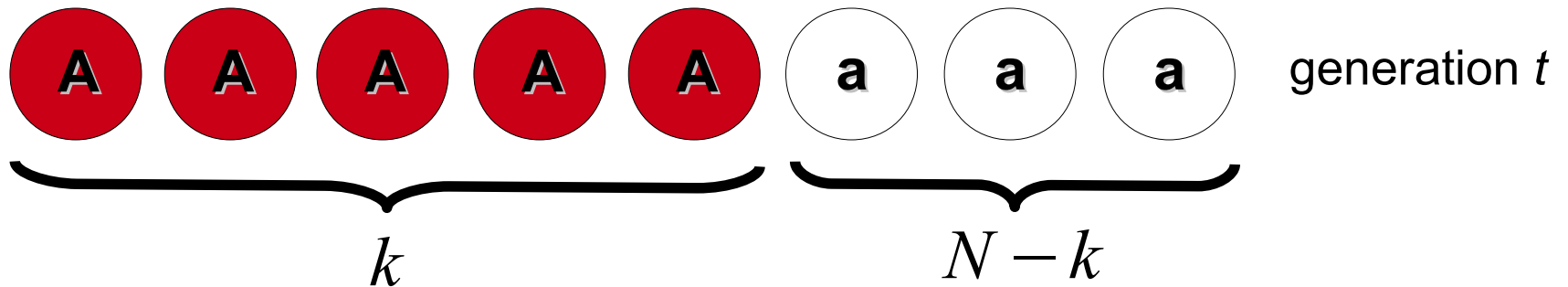
neutral evolution (no selection, no mutation)



Small populations: bottlenecks



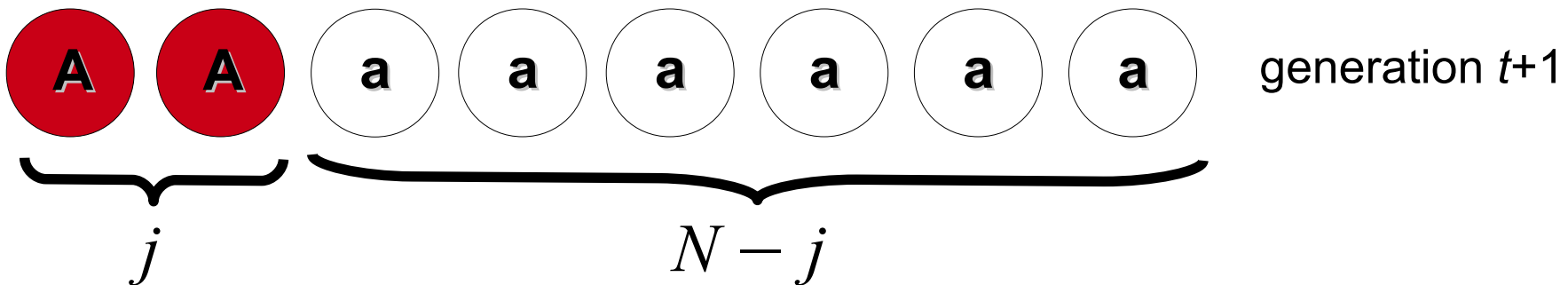
Fisher-Wright model



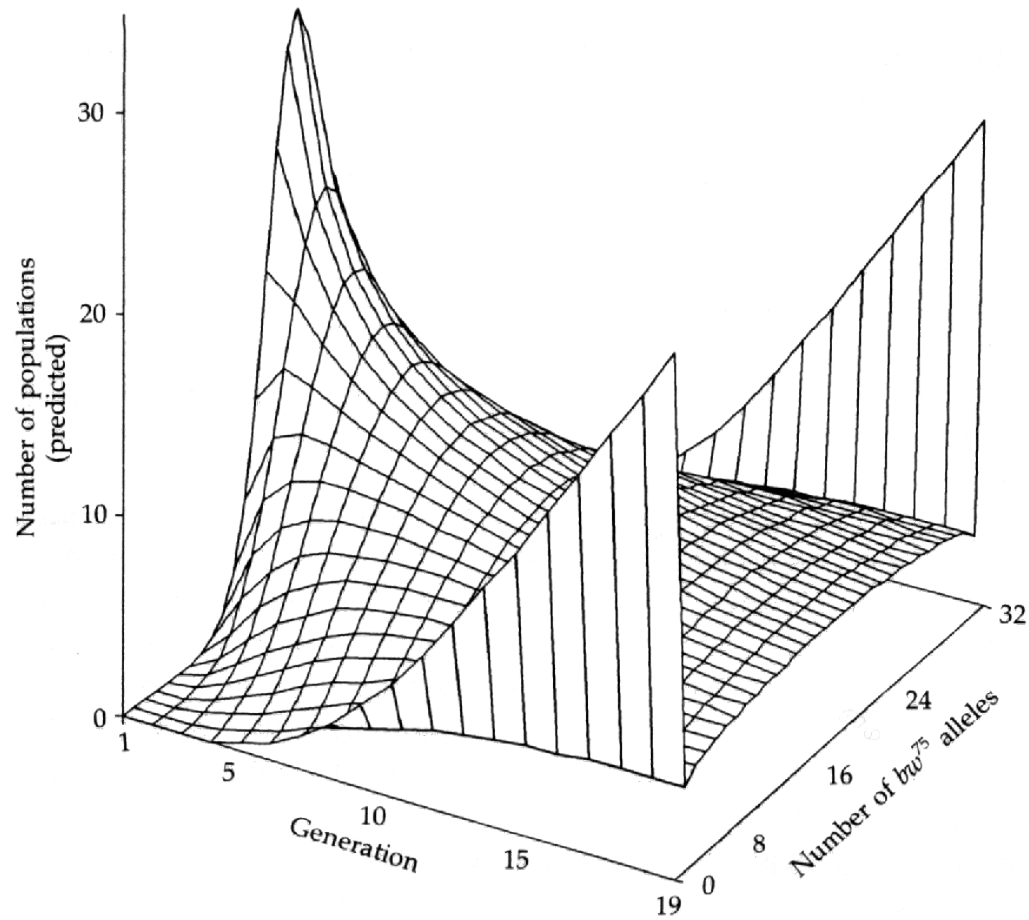
sample with replacement



$$P_{kj} = \binom{N}{j} \left(\frac{k}{N}\right)^j \left(\frac{N-k}{N}\right)^{N-j}$$

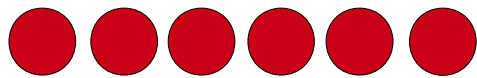


Fisher-Wright model

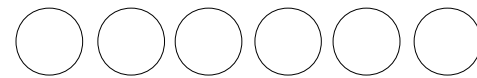


Fisher-Wright model

two absorbing states:



$$k = N$$



$$k = 0$$

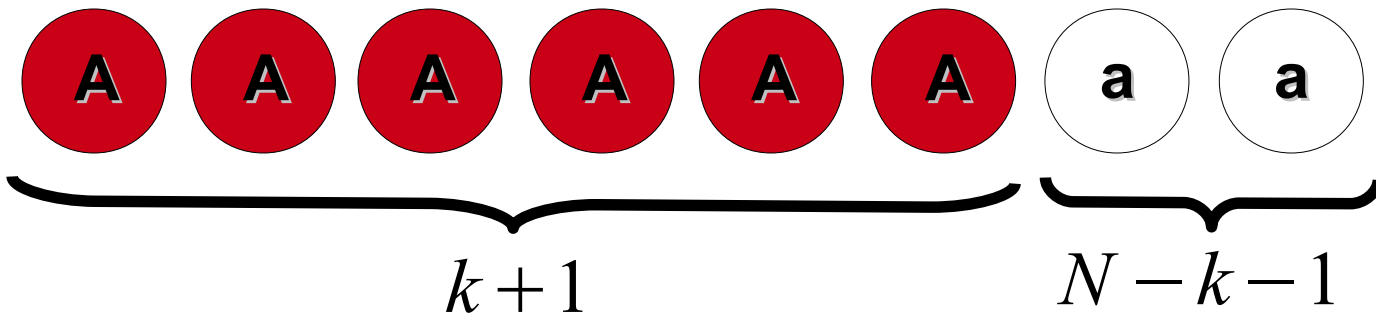
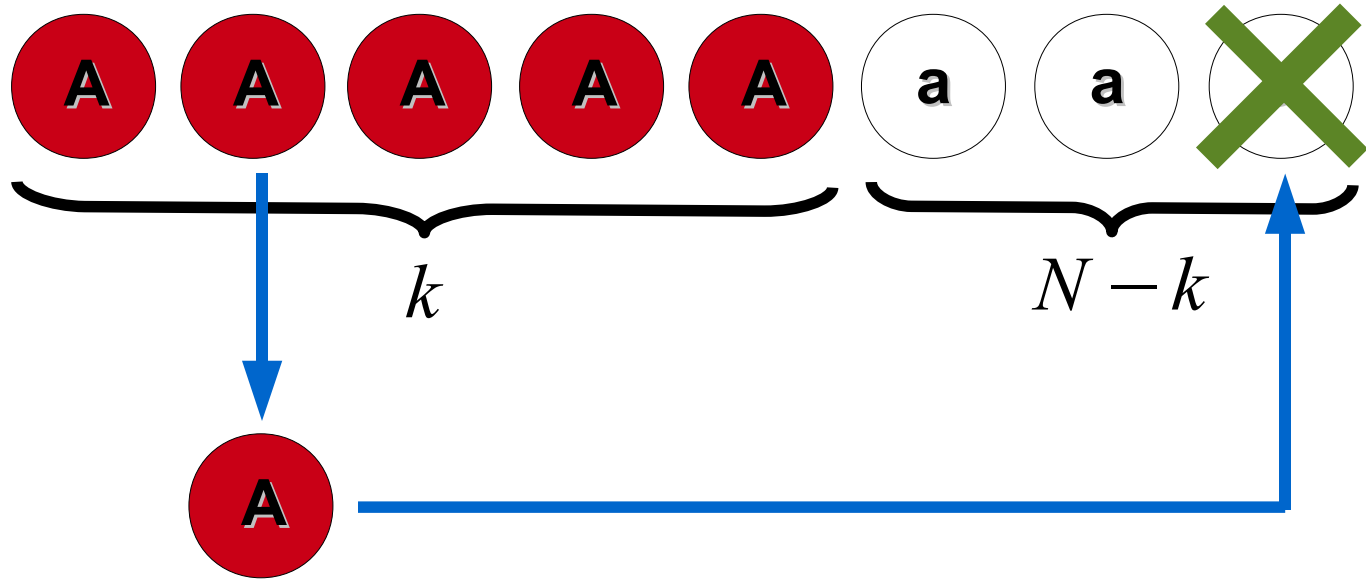
$$\pi_i = \mathbb{P} \left\{ \lim_{t \rightarrow \infty} X_t = N \mid X_0 = i \right\}$$

$$\pi_i = \sum_{j=0}^N P_{ij} \pi_j \quad \pi_0 = 0 \quad \pi_N = 1$$

$$\mathbb{E} \{ X_{t+1} \mid X_t = k \} = k \quad \Rightarrow$$

$$\pi_i = \frac{i}{N}$$

Moran model



Moran model

$$P_{k, k \pm 1} = \frac{k(N - k)}{N^2}$$

$$P_{k, k} = \frac{(N - k)^2 + k^2}{N^2}$$

$$P_{k, j} = 0 \quad \text{if } |k - j| > 1$$

birth-death process with
two absorbing states

Birth-death processes

$$q_0 = 1 \quad q_j = \prod_{k=1}^j \frac{P_{k,k-1}}{P_{k,k+1}} \quad Q_i = \sum_{j=0}^{i-1} q_j$$

if absorption

$$\pi_i = \mathbf{P} \left\{ \lim_{t \rightarrow \infty} X_t = N \mid X_0 = i \right\}$$
$$t_{ij} = \sum_{n=0}^{\infty} (P^n)_{ij} \quad T = P T + I \quad t_{0j} = t_{Nj} = 0$$

if ergodic

$$w = w P$$

Birth-death processes

two absorbing states (0 & N)

$$\pi_i = \frac{Q_i}{Q_N}$$
$$t_{ij} = \frac{Q_N (1 - \pi_i) \pi_j}{q_j P_{j,j+1}} \quad \text{if } j \leq i$$
$$t_{ij} = \frac{Q_N \pi_i (1 - \pi_j)}{q_j P_{j,j+1}} \quad \text{if } j > i$$

one absorbing state (N)

$$t_{ij} = \frac{Q_N - Q_i}{q_j P_{j,j+1}} \quad \text{if } j \leq i$$
$$t_{ij} = \frac{Q_N - Q_j}{q_j P_{j,j+1}} \quad \text{if } j > i$$

no absorbing state

$$w_i = \frac{(q_i P_{i,i+1})^{-1}}{\sum_{j=0}^N (q_j P_{j,j+1})^{-1}}$$

Moran model

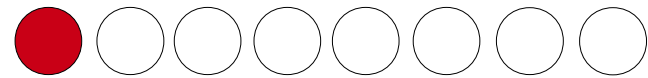
$$q_i = 1 \quad Q_i = i \quad \pi_i = \frac{i}{N}$$

$$t_{ij} = N \left(\frac{N-i}{N-j} \right) \quad \text{if } j \leq i \quad t_{ij} = N \left(\frac{i}{j} \right) \quad \text{if } j > i$$

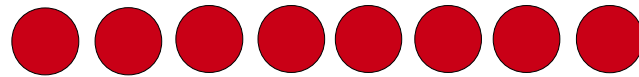
mean absorption time

$$t_i = \sum_{j=1}^{N-1} t_{ij} = O(N)$$

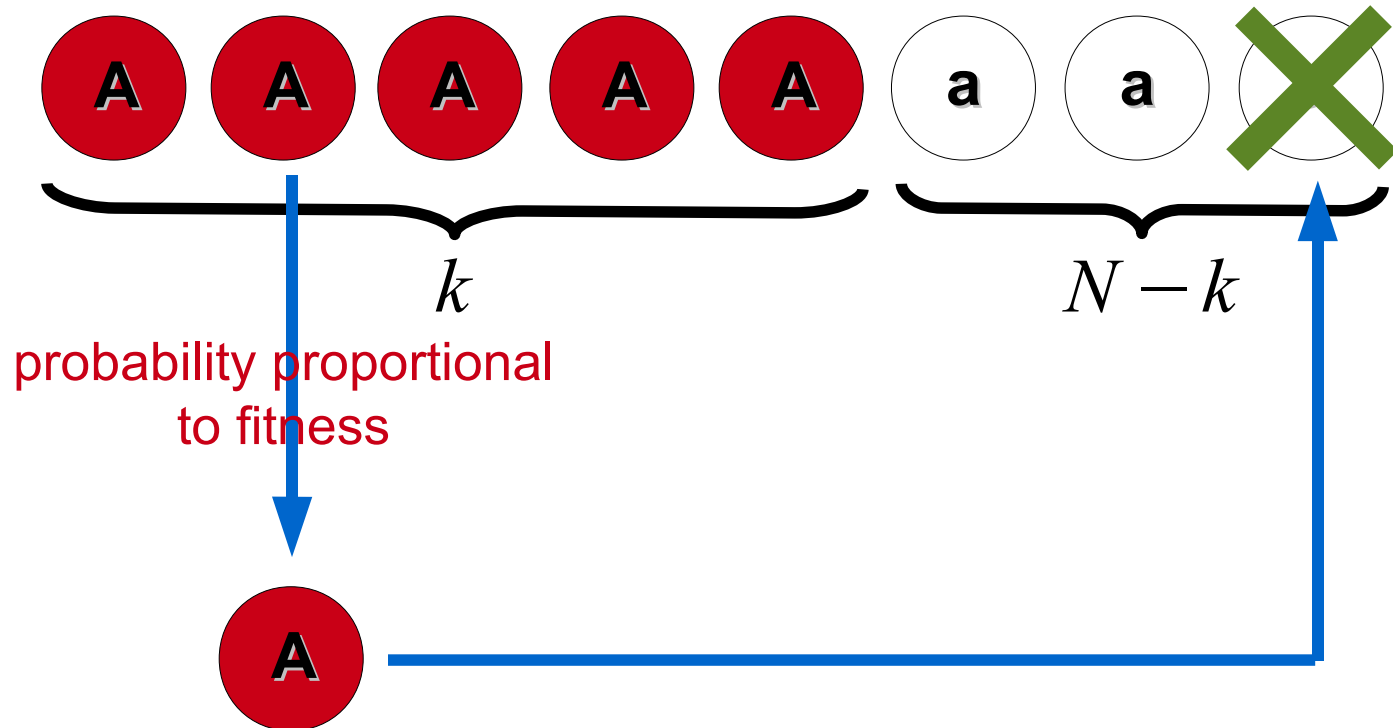
Fixation of a mutant allele



$$\pi_1 = \frac{1}{N}$$



Genetic drift under selection



Genetic drift under selection

$$P_{k,k+1} = \frac{N-k}{N} \frac{k f_A}{k f_A + (N-k) f_a}$$

$$P_{k,k-1} = \frac{k}{N} \frac{(N-k) f_a}{k f_A + (N-k) f_a}$$

$$\frac{P_{k,k-1}}{P_{k,k+1}} = \frac{f_a}{f_A} \equiv r^{-1}$$

$$\pi_i = \frac{1 - r^{-i}}{1 - r^{-N}}$$

Fixation of a mutant allele under selection

$$\rho_A = \frac{1 - r^{-1}}{1 - r^{-N}} \qquad \rho_a = \frac{1 - r}{1 - r^N}$$

- If $r > 1$ selection favors **A** over neutral case
- If $r < 1$ selection favors **a** over neutral case

Diffusion approximation

$$\mathbf{w}(t+1) = \mathbf{w}(t)P$$

master equation

$$w_i(t+1) - w_i(t) = \sum_j w_j(t) P_{ji} - w_i(t) \sum_j P_{ij}$$

birth-death process

$$\Delta w_i(t) = \sum_{\pm} \left[w_{i\pm 1}(t) P_{i\pm 1, i} - w_i(t) P_{i, i\pm 1} \right]$$

Diffusion approximation

$$x \equiv \frac{i}{N} \quad w_i(t) \equiv N f(x, t) \quad \Delta t \equiv (\Delta x)^2 = \frac{1}{N^2}$$

$$a(x) \equiv P_{i,i+1} - P_{i,i-1} \quad b(x) \equiv P_{i,i+1} + P_{i,i-1}$$

forward Kolmogorov (Fokker-Planck) equation

$$\frac{\partial f(x, t)}{\partial t} = -N \frac{\partial}{\partial x} [a(x) f(x, t)] + \frac{1}{2} \frac{\partial^2}{\partial x^2} [b(x) f(x, t)]$$

Diffusion approximation

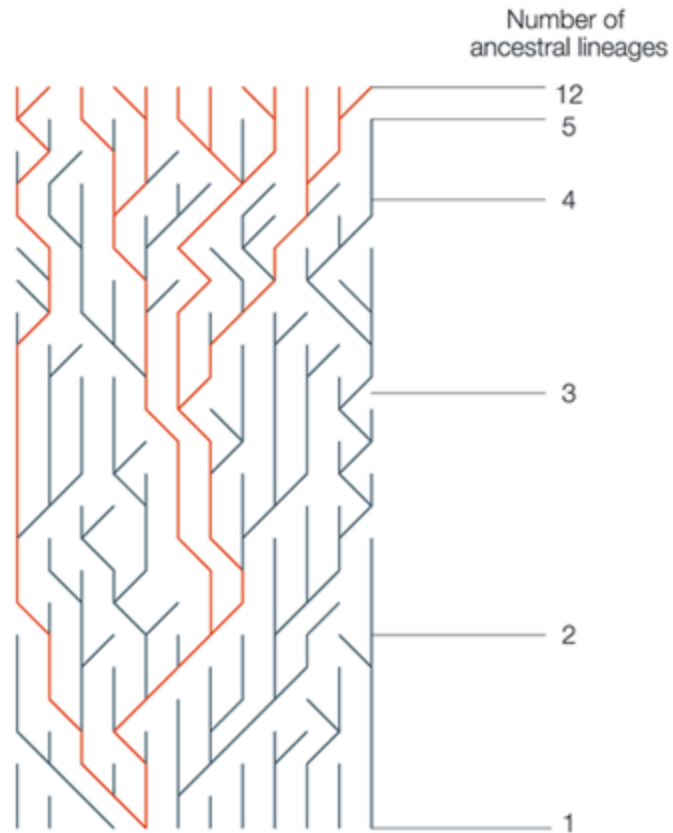
absorption probability

$$0 = -N a(x) \pi'(x) + \frac{1}{2} b(x) \pi''(x)$$

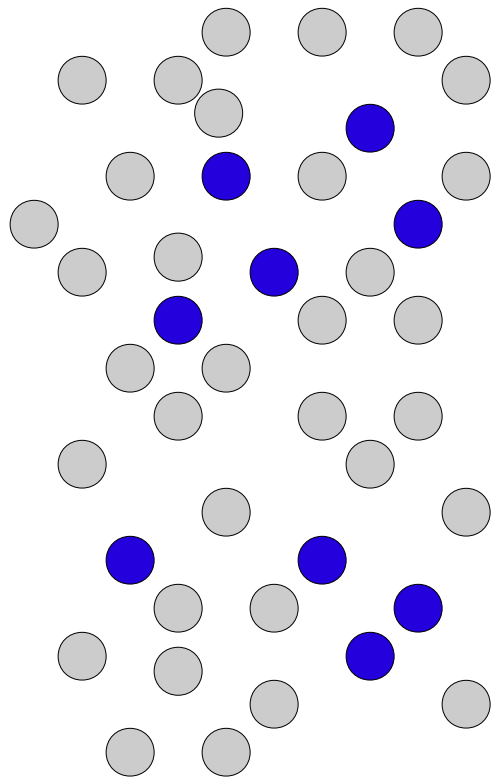
mean absorption time

$$-1 = -N a(x) \tau'(x) + \frac{1}{2} b(x) \tau''(x)$$

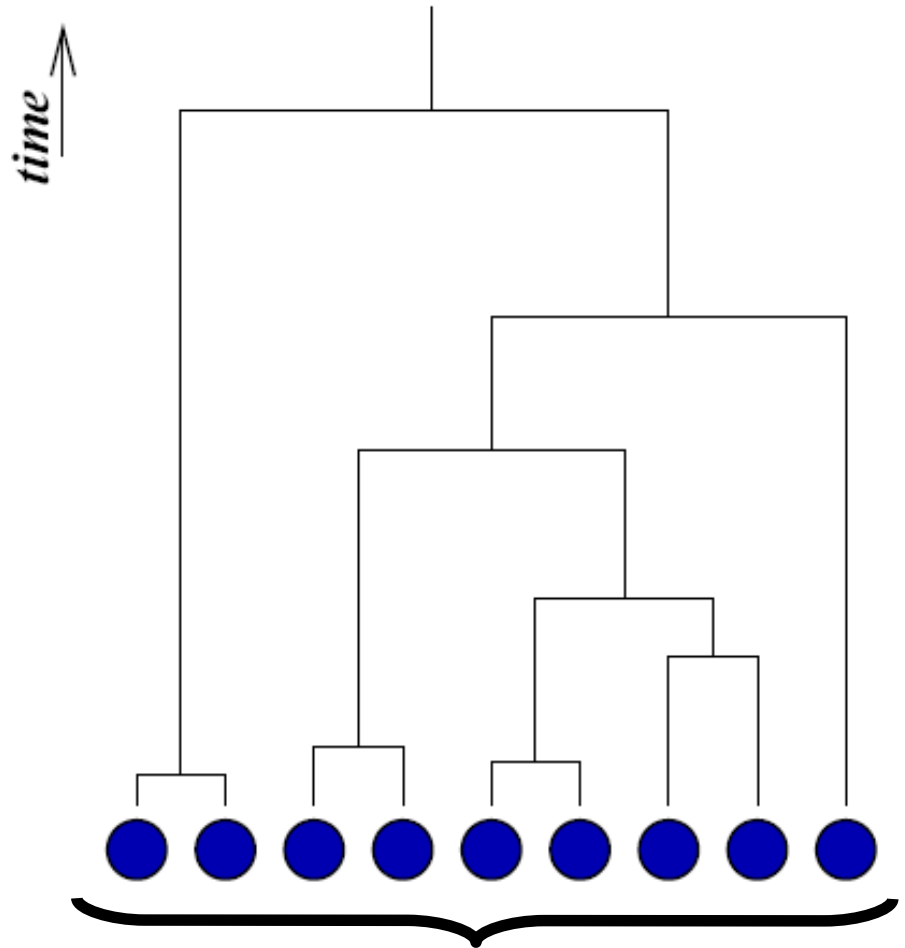
The coalescent



The coalescent

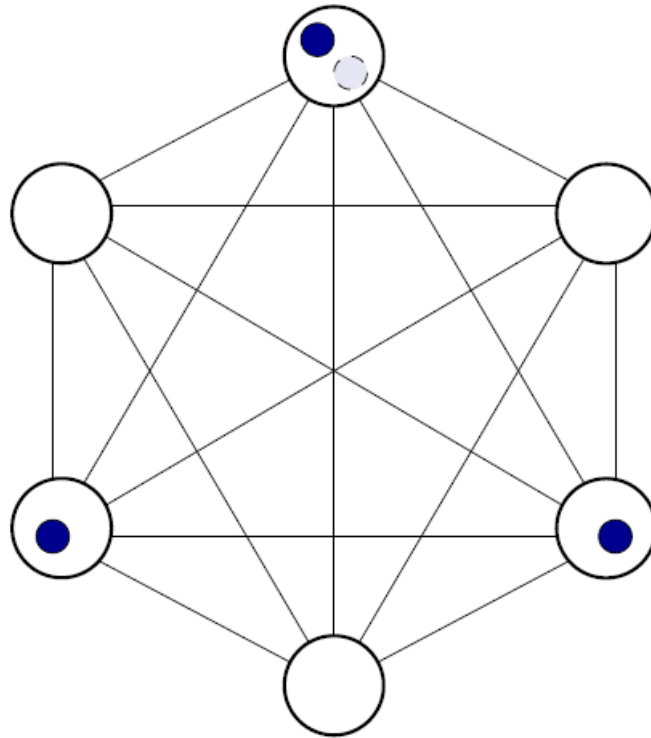


population N



sample n

The coalescent



The coalescent

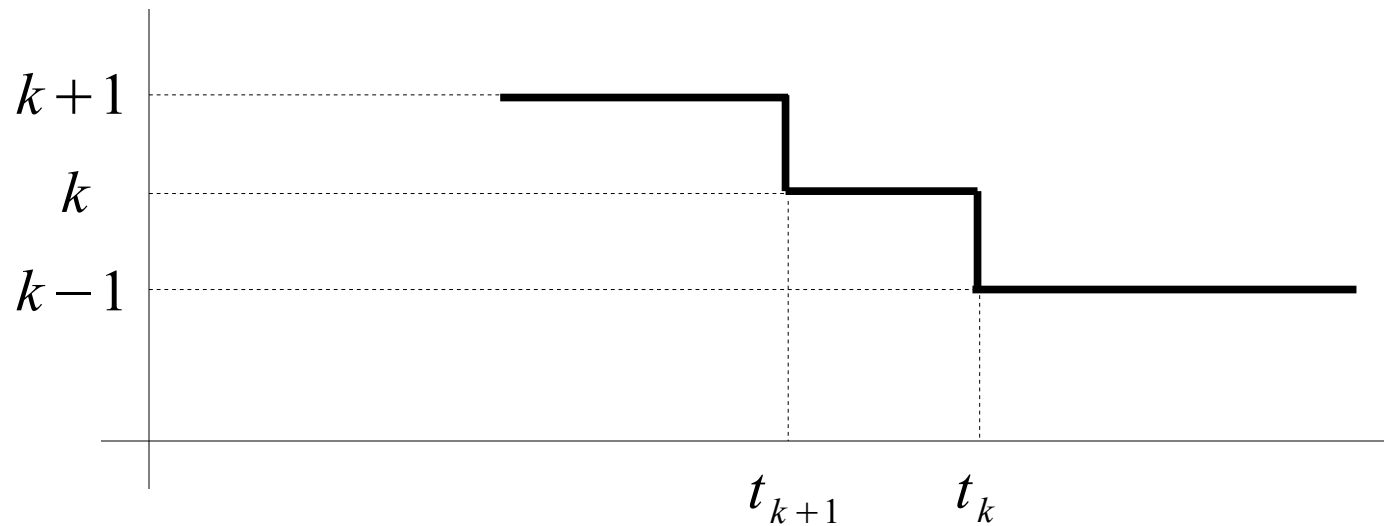
$$\mathbb{P}\{j-1, t+\delta t \mid j, t\} = \frac{j(j-1)}{2} \delta t$$
$$1 < j \leq n$$

Wright-Fisher: $\delta t = \frac{1}{N} \quad n \ll N$

Moran: $\delta t = 1 \quad n \leq N$

$$\mathbb{P}\{n, t \mid n, 0\} = \exp\left\{-\frac{n(n-1)}{2} t\right\}$$

Distribution of branching times



$$\Pi(t_n, t_{n-1}, \dots, t_k) = \prod_{j=k}^n \exp \left\{ -\frac{j(j-1)}{2} (t_l - t_{l+1}) \right\}$$

$(t_{k+1} \equiv 0)$

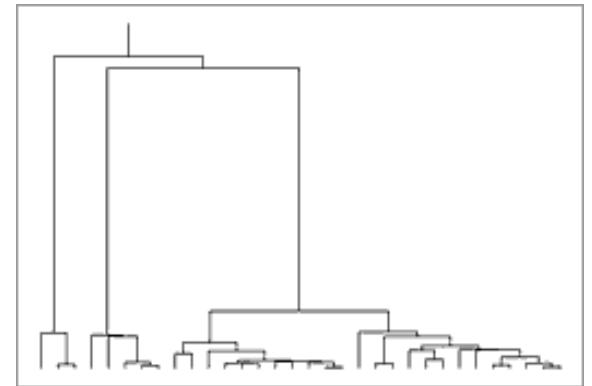
Expected times

$$\mathbb{E}\{t_{j \rightarrow j-1}\} = \frac{2}{j(j-1)}$$

$$\mathbb{E}\{t_{n \rightarrow m}\} = 2 \sum_{j=m+1}^n \frac{1}{j(j-1)} = 2 \left(\frac{1}{m} - \frac{1}{n} \right)$$

$$T_{\text{MRCA}} \equiv \mathbb{E}\{t_{n \rightarrow 1}\} = 2 \left(1 - \frac{1}{n} \right) \approx 2$$

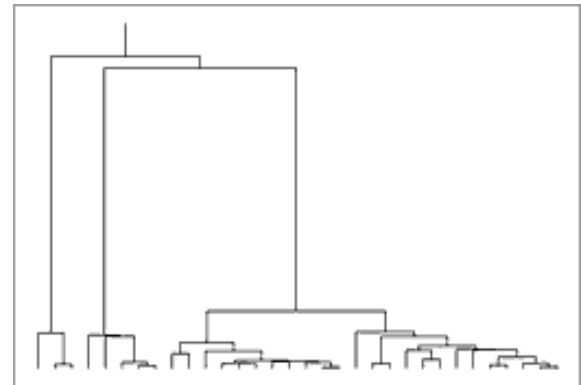
Most Recent Common Ancestor



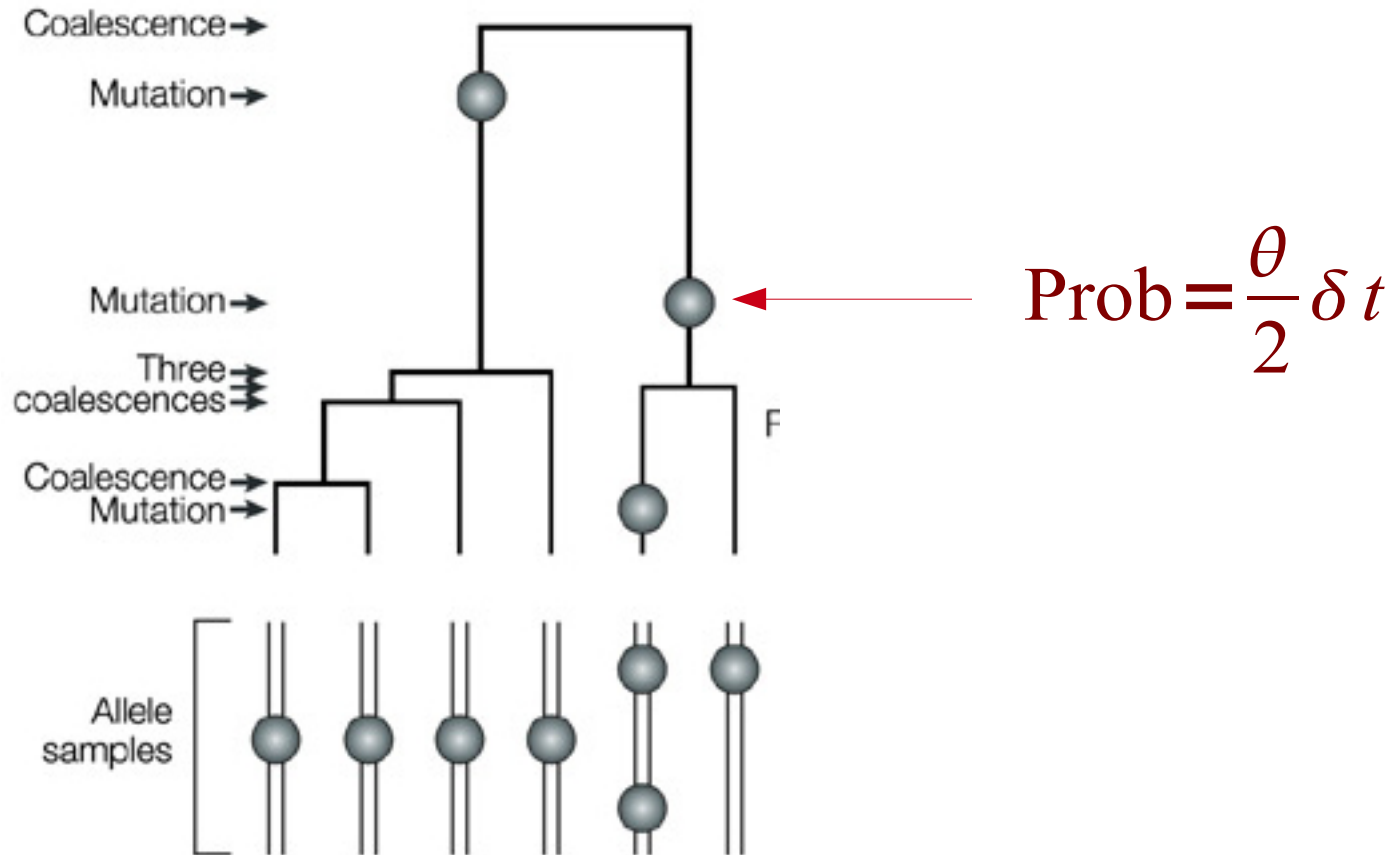
Variances

$$\text{Var}\{t_{j \rightarrow j-1}\} = \frac{4}{j^2 (j-1)^2}$$

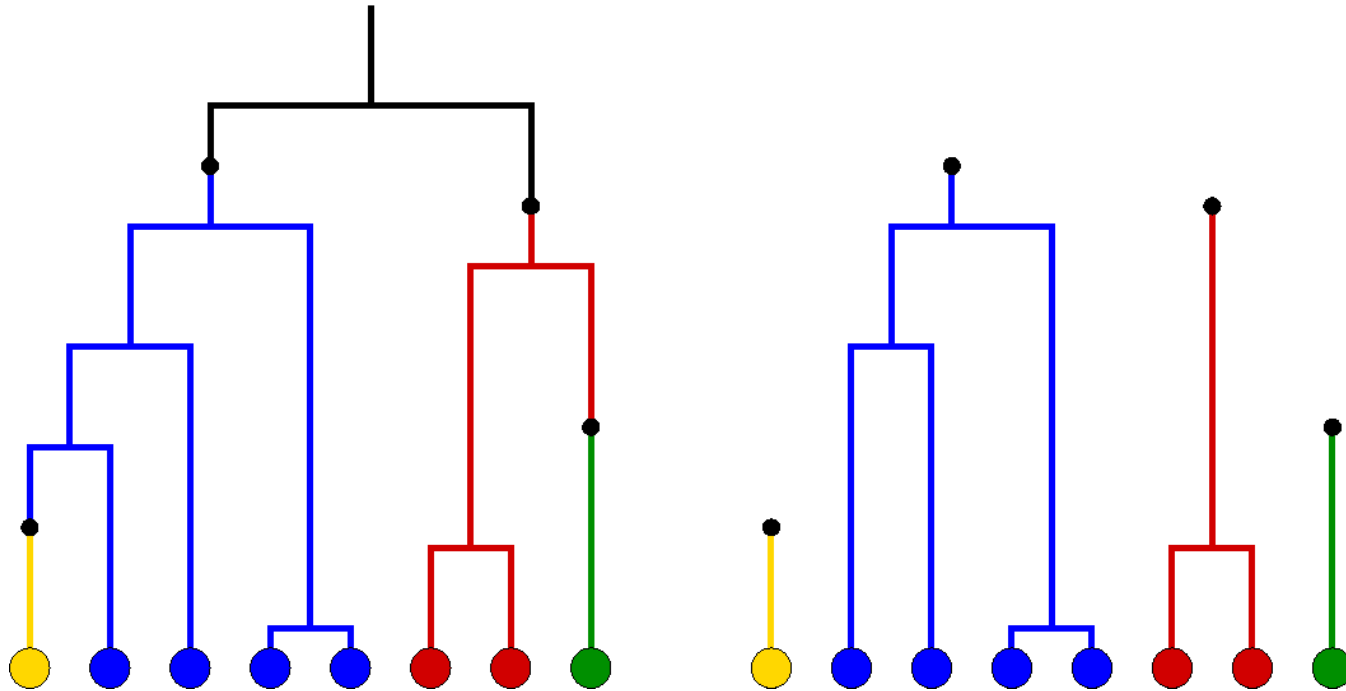
$$\text{Var}\{t_{n \rightarrow 1}\} = 4 \sum_{j=1}^{n-1} \frac{1}{j^2 (j+1)^2} \approx 1.16$$



Coalescent with mutations



Coalescent with mutations



$$\mathbb{P}\{j-1, t+\delta t \mid j, t\} = \frac{j(j-1)}{2} \delta t + j \frac{\theta}{2} \delta t = \frac{j(j+\theta-1)}{2} \delta t$$

Expected times

$$\mathbb{E}\{t_{j \rightarrow j-1}\} = \frac{2}{j(j+\theta-1)}$$

$$\mathbb{E}\{t_{n \rightarrow 1}\} = \frac{2}{\theta} + 2 \sum_{j=2}^n \frac{1}{j(j+\theta-1)} \quad T_{\text{MRCA}}(\theta) = 2 \sum_{j=1}^n \frac{1}{j(j+\theta-1)}$$

$$\theta < 2 \quad \Rightarrow \quad T_{\text{MRCA}}(\theta) > T_{\text{MRCA}}$$

$$\theta = 2 \quad \Rightarrow \quad T_{\text{MRCA}}(\theta) = T_{\text{MRCA}} + O\left(\frac{1}{n^2}\right)$$

$$\theta > 2 \quad \Rightarrow \quad T_{\text{MRCA}}(\theta) < T_{\text{MRCA}}$$

Number of different types

$$P\{\text{mutation} \mid j \rightarrow j-1\} = \frac{\theta j/2}{j(j+\theta-1)/2} = \frac{\theta}{j+\theta-1}$$

$$E\{\text{different types in sample}\} = \sum_{j=1}^n \frac{\theta}{j+\theta-1}$$

$$P\{k \text{ types in sample}\} = \frac{\left[\begin{matrix} n \\ k \end{matrix} \right] \theta^k}{S_n(\theta)} \quad 1 \leq k \leq n$$

unsigned Stirling
numbers of first kind



$$S_n(\theta) = \theta(\theta+1)\cdots(\theta+n-1) \\ = \sum_{k=1}^n \left[\begin{matrix} n \\ k \end{matrix} \right] \theta^k$$

$$\left[\begin{matrix} n+1 \\ k \end{matrix} \right] = n \left[\begin{matrix} n \\ k \end{matrix} \right] + \left[\begin{matrix} n \\ k-1 \end{matrix} \right]$$

$$\left[\begin{matrix} n \\ 0 \end{matrix} \right] = 0 \quad \left[\begin{matrix} n \\ n \end{matrix} \right] = 1$$

$n > 0$

Cycles in permutations

$$\begin{pmatrix} 1 & 2 & 3 & 4 & 5 \\ 2 & 5 & 4 & 3 & 1 \end{pmatrix} = (1 \ 2 \ 5)(3 \ 4) = (3 \ 4)(1 \ 2 \ 5) = (3 \ 4)(5 \ 1 \ 2)$$

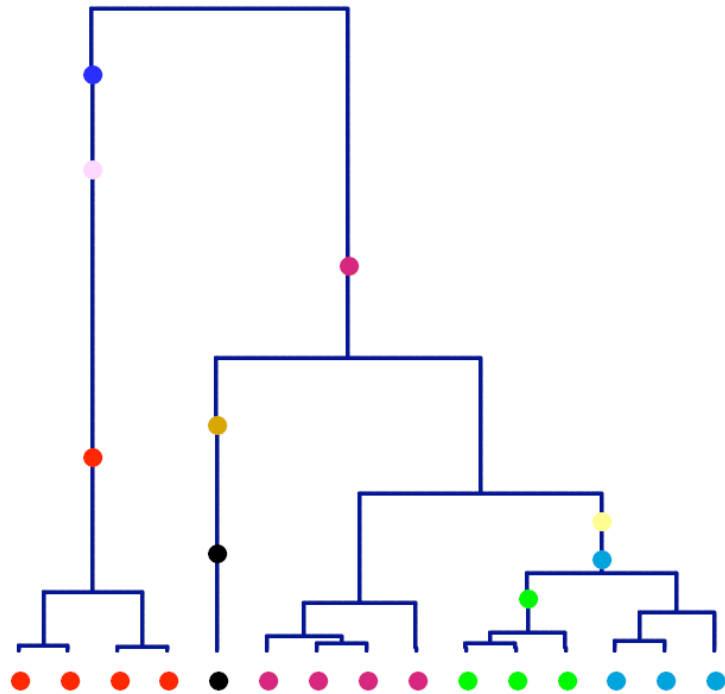
there are $\begin{bmatrix} n \\ k \end{bmatrix}$ permutations of n elements into k cycles

permutations of n elements into c_1 cycles with 1 element, c_2 cycles with 2 elements, etc.

$$\frac{n!}{1^{c_1} \cdots n^{c_n} c_1! \cdots c_n!} \quad \sum_{j=1}^n j c_j = n \quad \sum_{j=1}^n c_j = k$$

Ewens' sampling formula

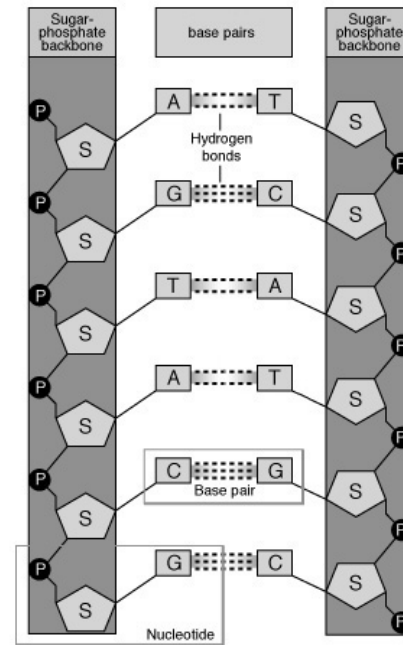
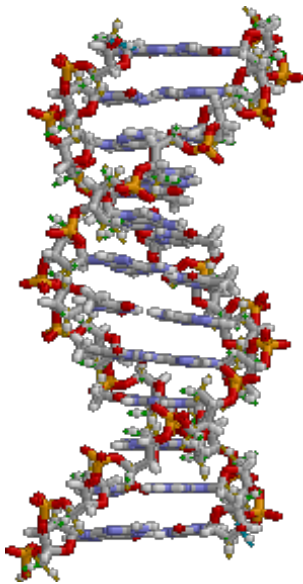
$$P\left\{c_1, \dots, c_n \mid \sum_{j=1}^n j c_j = n\right\} = \prod_{j=1}^n \left[\frac{j}{\theta + j - 1} \frac{(\theta/j)^{c_j}}{c_j!} \right]$$



Sample configuration of alleles 4 A_1 , 1 A_2 , 4 A_3 , 3 A_4 , 3 A_5

**SEQUENCES
AND
FITNESS LANDSCAPES**

Sequences: DNA



Chromosomes

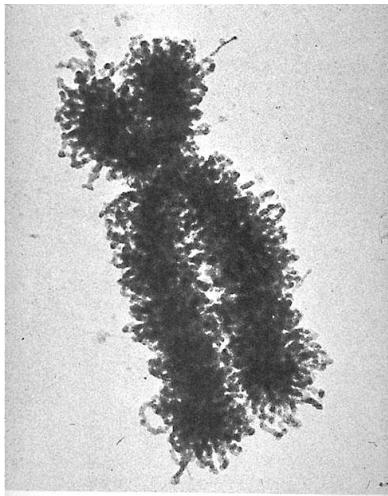
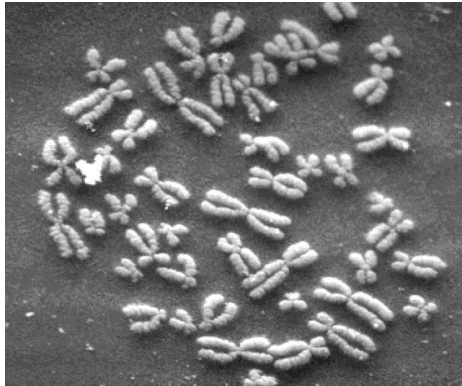
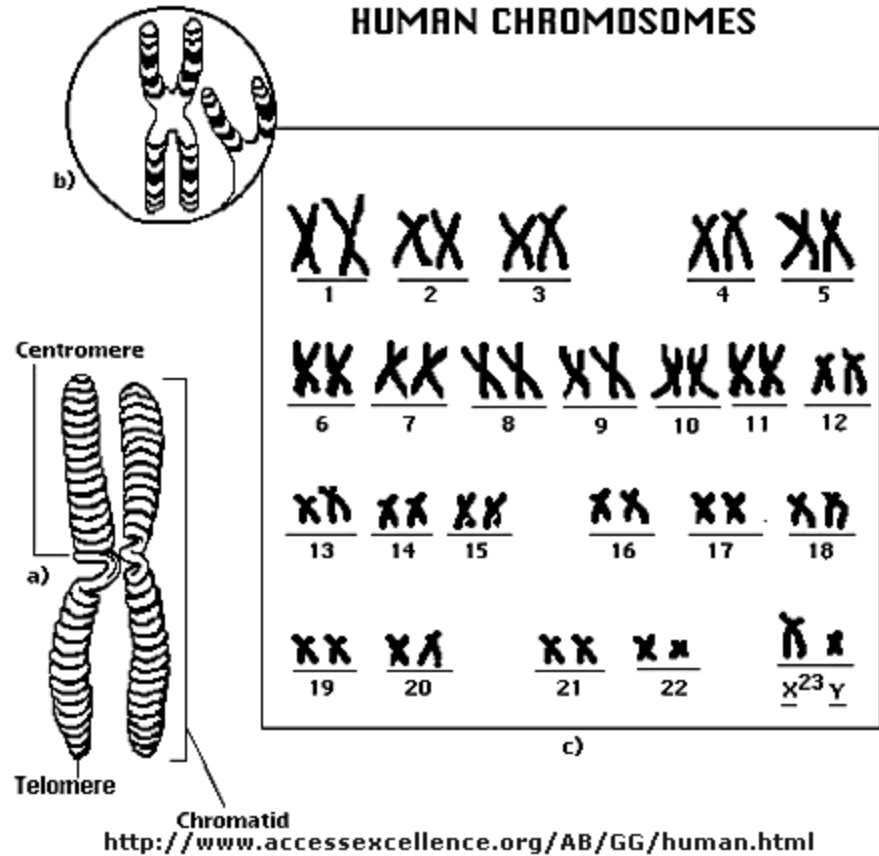
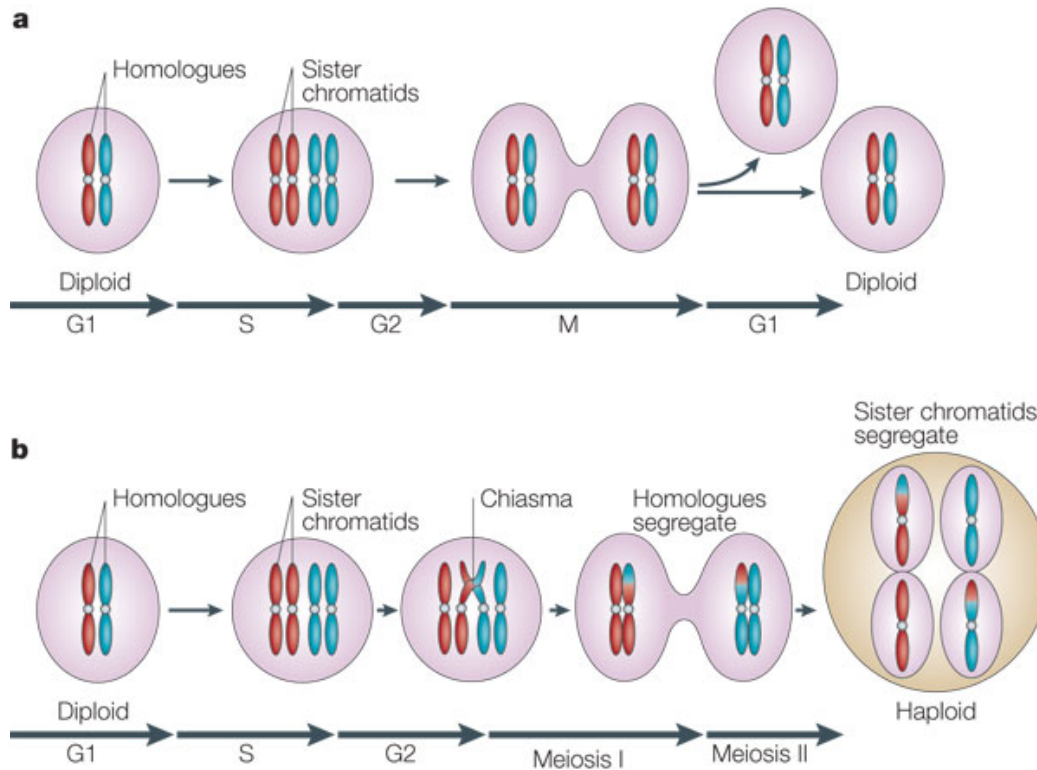


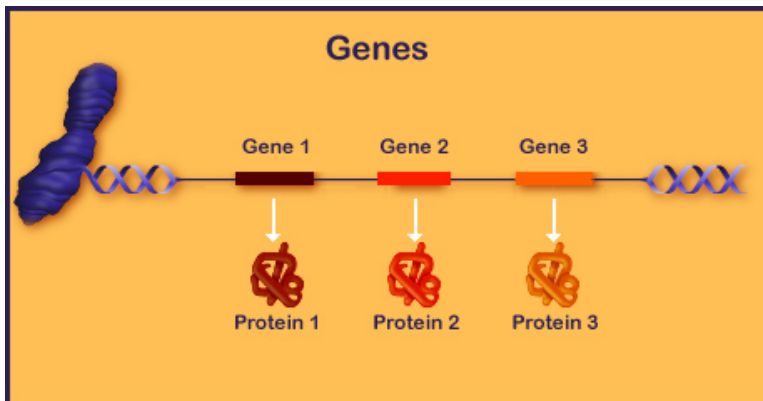
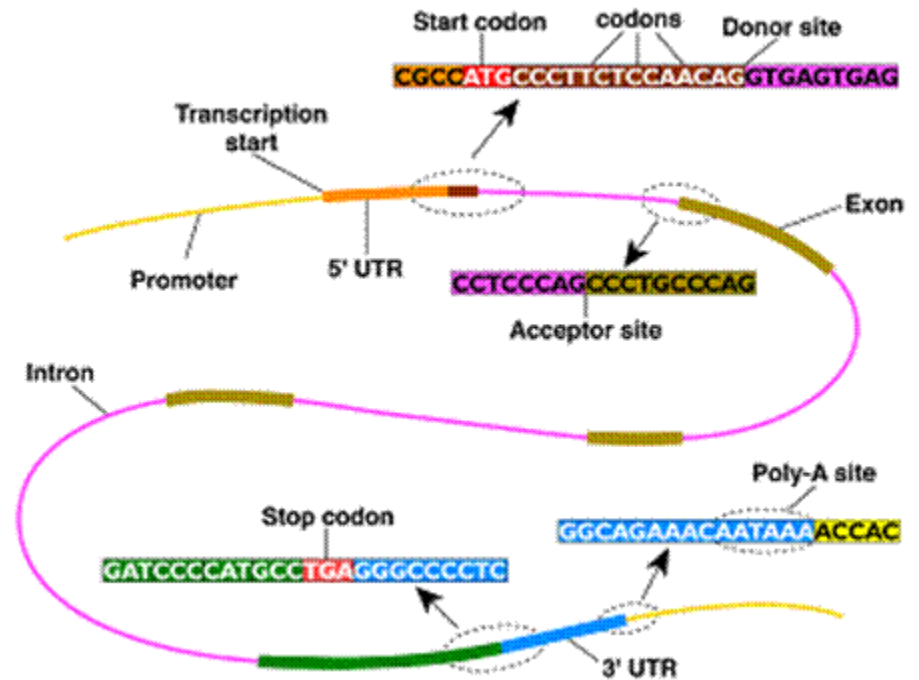
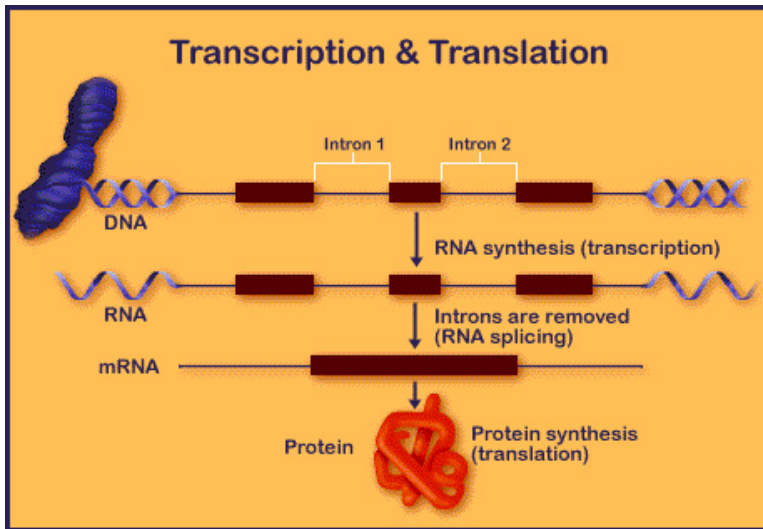
FIGURE 1-14
An electron micrograph of a human chromosome.
Chromosome XII from a HeLa cell culture. (Courtesy
of Dr. E. Du Praw.)



Mitosis & meiosis



Genes



Transcription: genetic code



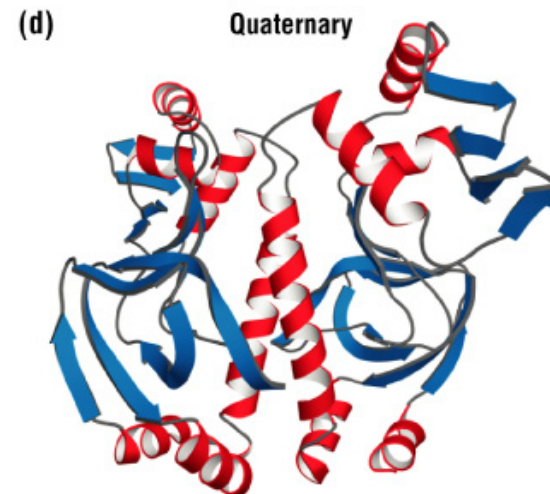
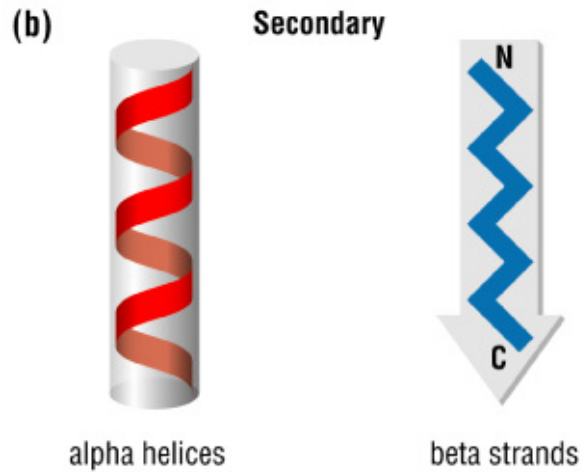
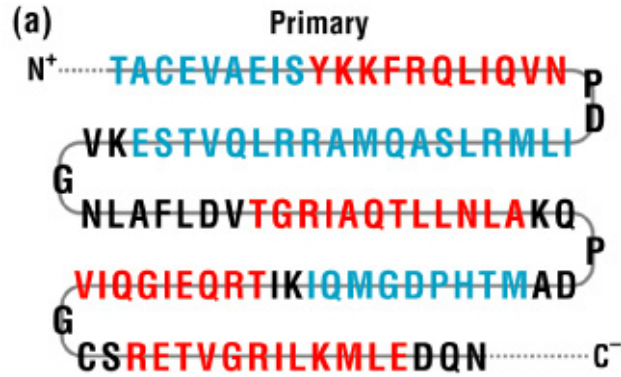
G
 C
 U
 A
 C
 G
 G
 A
 G
 C
 U
 U
 C
 G
 G
 A
 G
 C
 U
 A
 G

Codon 1
 Codon 2
 Codon 3
 Codon 4
 Codon 5
 Codon 6
 Codon 7

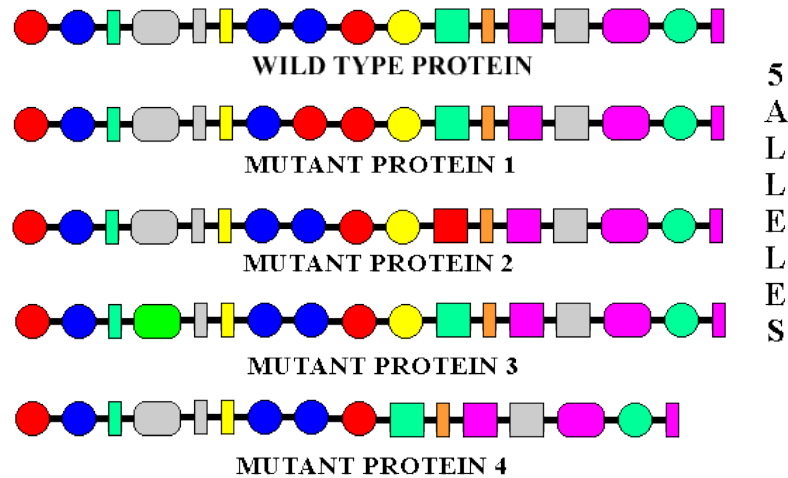
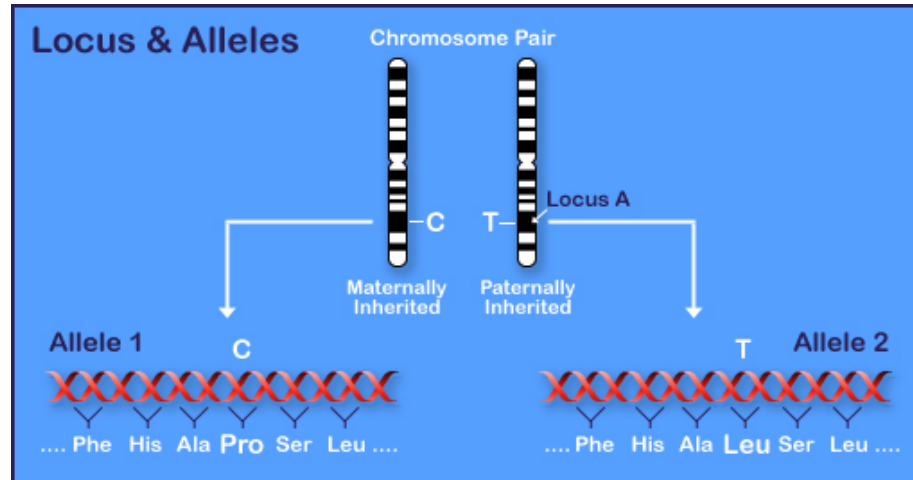
mRNA
Ribonucleic acid

		Second Base				
		U	C	A	G	
U	U	UUU Phe	UCU Ser	UAU Tyr	UGU Cys	U
	U	UUC	UCC	UAC	UGC	C
	A	UUA Leu	UCA	UAA Stop	UGA Stop	A
	U	UUG	UCG	UAG Stop	UGG Trp	G
C	U	CUU Leu	CCU Pro	CAU His	CGU Arg	U
	C	CUC	CCC	CAC	CGC	C
	A	CUA	CCA	CAA Gln	CGA	A
	U	CUG	CCG	CAG	CGG	G
A	U	AUU Ile	ACU Thr	AAU Asn	AGU Ser	U
	C	AUC	ACC	AAC	AGC	C
	A	AUA	ACA	AAA Lys	AGA Arg	A
	U	AUG Met / Start	ACG	AAG	AGG	G
G	U	GUU Val	GCU Ala	CAU Asp	GGU Gly	U
	C	GUC	GCC	GAC	GGC	C
	A	GUA	GCA	GAA Glu	GGA	A
	U	GUG	GCG	GAG	GGG	G

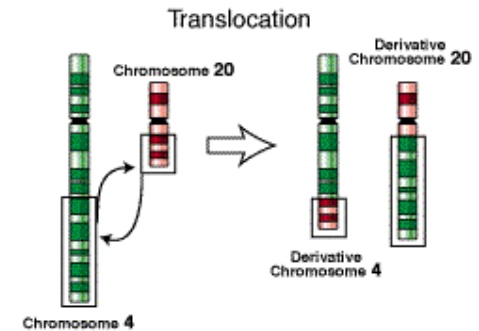
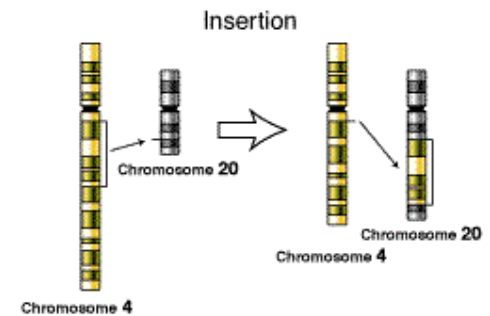
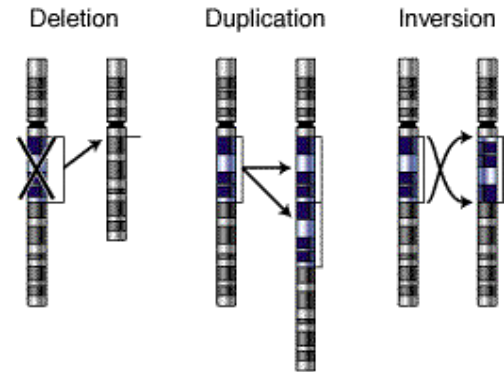
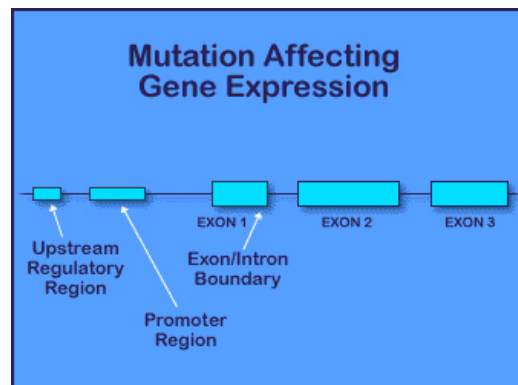
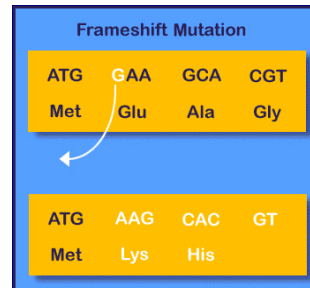
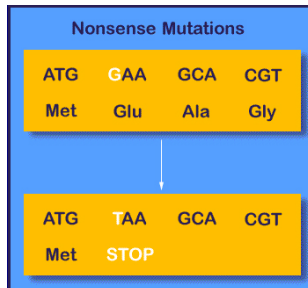
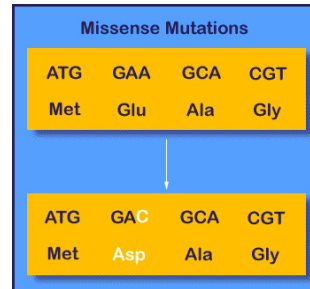
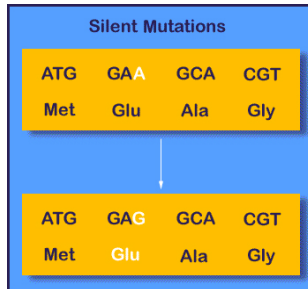
Proteins



Locus & alleles



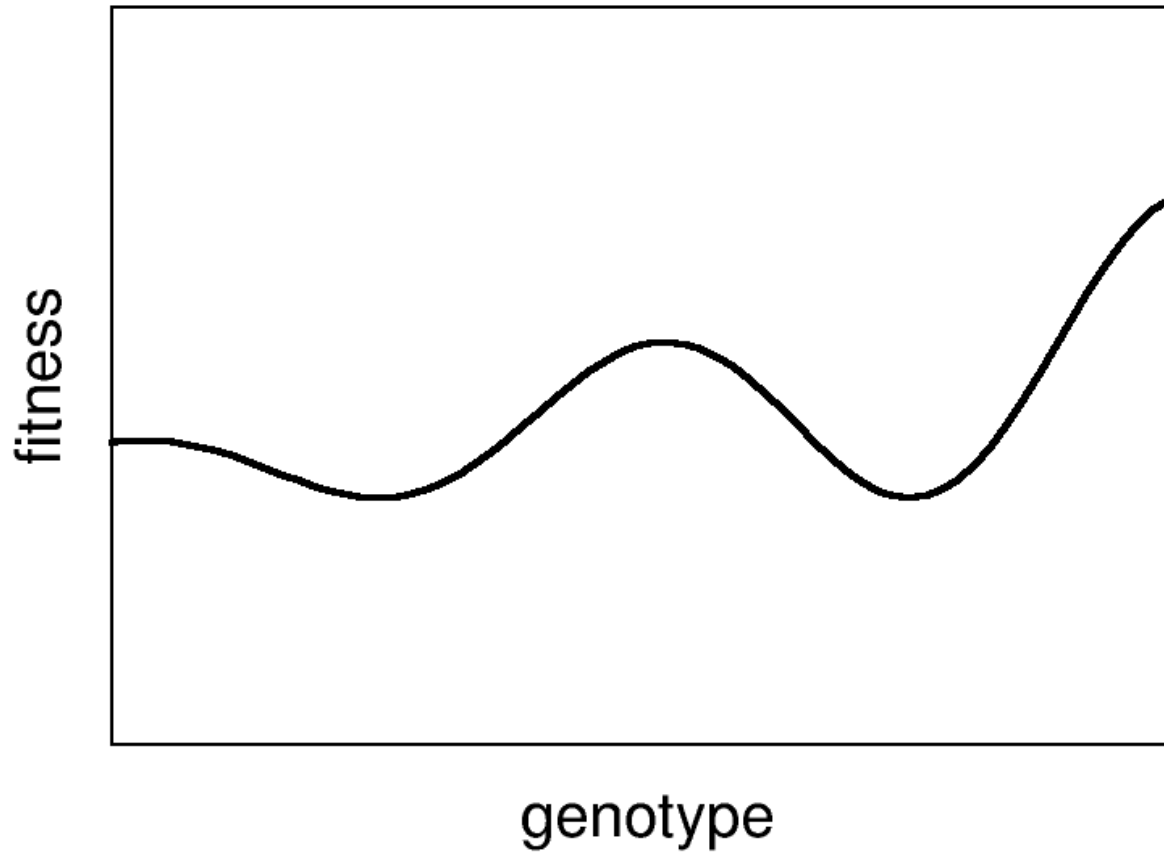
Types of mutation



Fitness landscapes

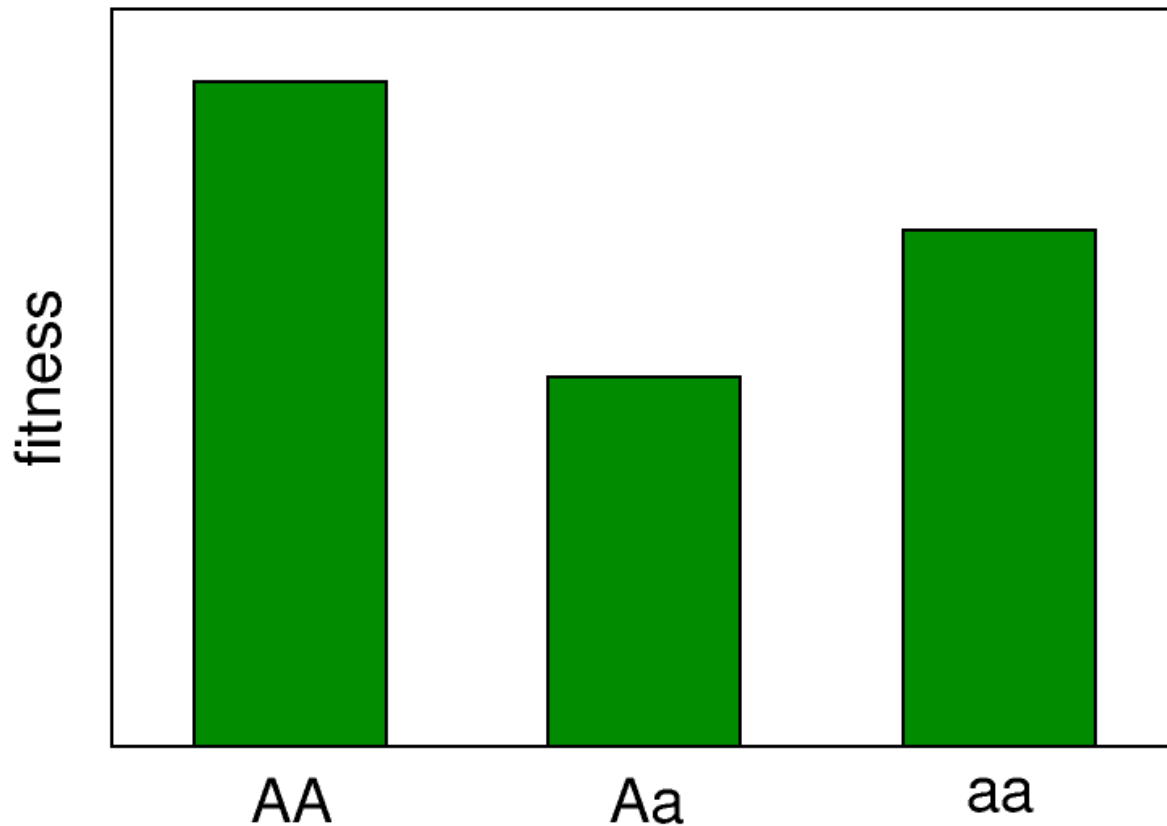
- Metaphor introduced by Wright (1932)
- Representation of fitness of individuals or population
- Key points:
 - Fitness is affected by environment (external factors)
 - Fitness depends on phenotype, which is determined by genotype (permanent factor)

Fitness landscapes



Working example:

1 locus, 2 alleles, random mating



Working example:

1 locus, 2 alleles, random mating

$$x = [A] \quad y = [a]$$

Hardy-Weinberg law:

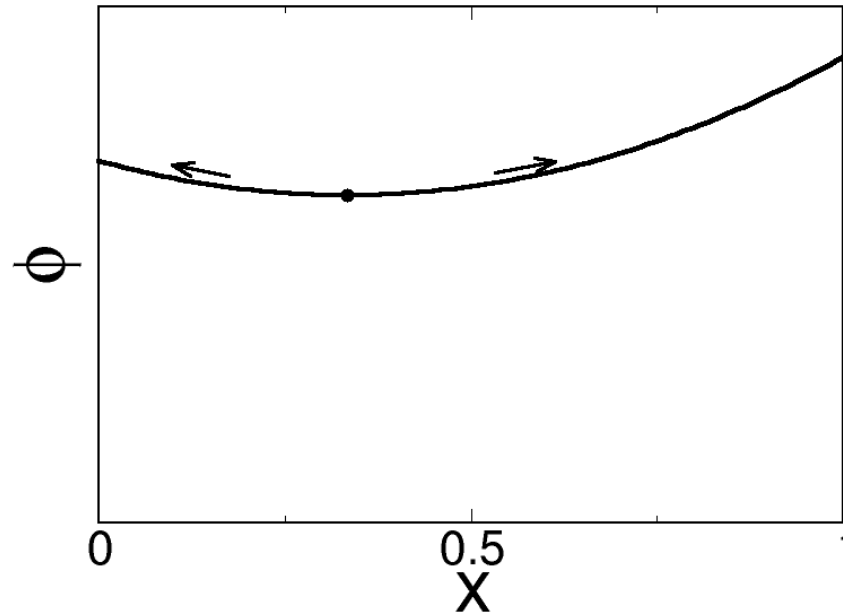
$$[AA] = x^2 \quad [Aa] = 2xy \quad [aa] = y^2$$

$$f_A(x) = f_{AA}x + f_{Aa}y \quad f_a(x) = f_{Aa}x + f_{aa}y$$

$$\phi(x) = f_{AA}x^2 + f_{Aa}2xy + f_{aa}y^2$$

Working example:

1 locus, 2 alleles, random mating

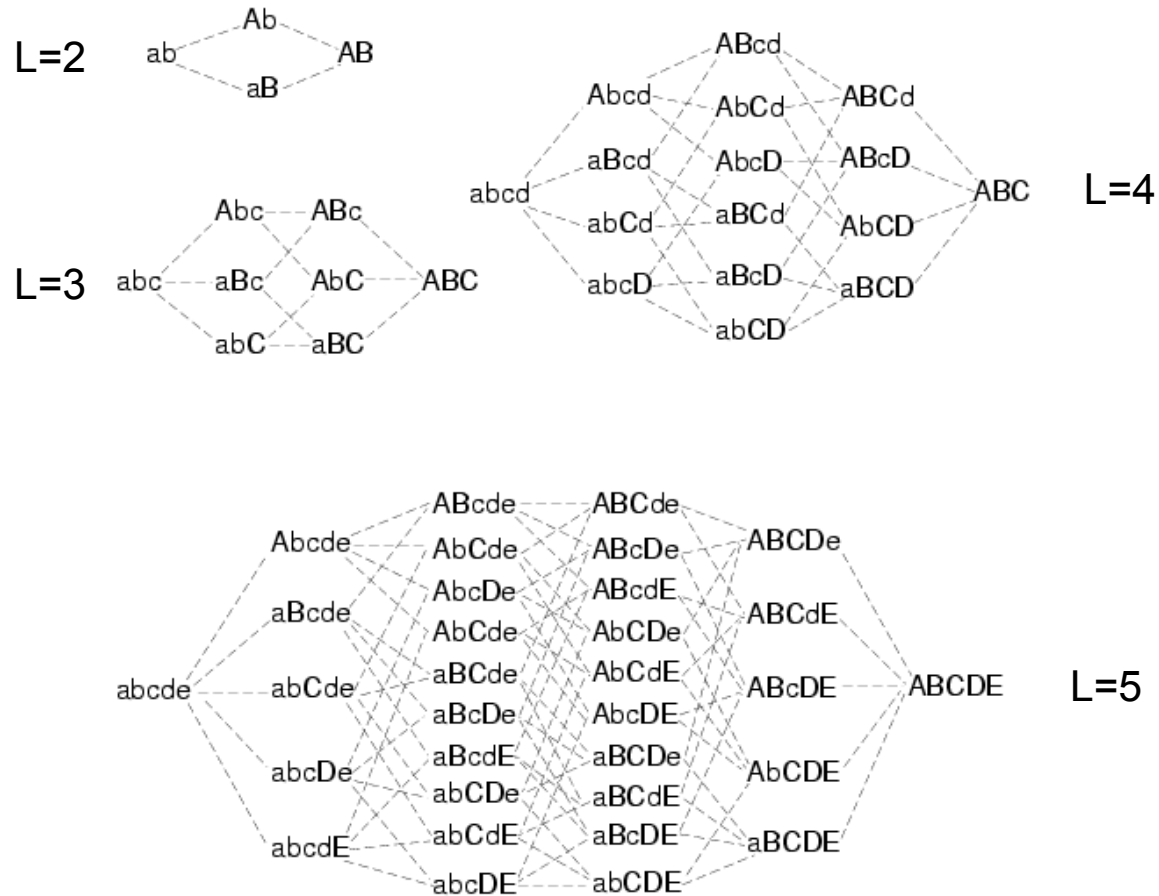


$$\frac{d x}{d t} = x y [f_A(x) - f_a(x)] = \frac{1}{2} x y \frac{d \phi(x)}{d x}$$

Remarks

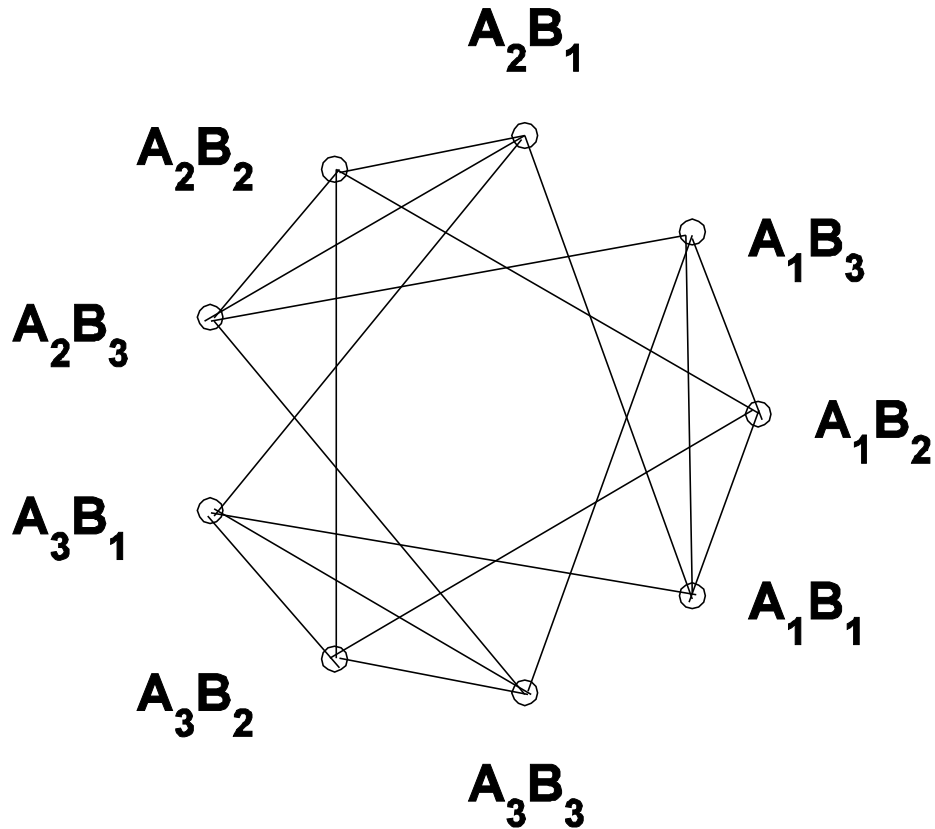
- First representation is a fundamental one:
 - Individuals sit at their genotypic positions
 - Population at every position changes in time
- Second representation is not because:
 - Depends on evolution law
 - Assumes maximization of mean fitness (not always true; e.g. mutations)
 - Can't be generalized to multilocus models

Genotype space



vertices of L-dimensional hypercubes

Genotype space



different genotypes for L loci and A alleles:

$$G = A^L$$

dimensionality (number of nearest neighbors):

$$D = L(A - 1)$$

e.g. $L=100$, $A=2$:

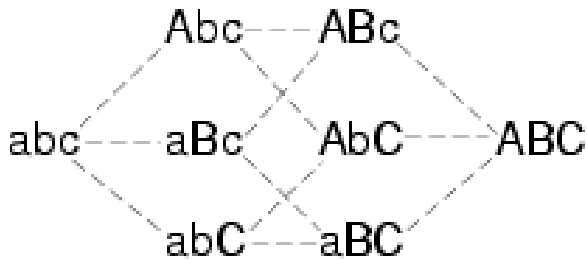
$$D = 100 \quad G \approx 10^{30}$$

$L=2$ (loci), $A=3$ (alleles)

Hamming distance

$$\mathbf{s}^a = s_1^a s_2^a \cdots s_L^a$$
$$\mathbf{s}^b = s_1^b s_2^b \cdots s_L^b$$

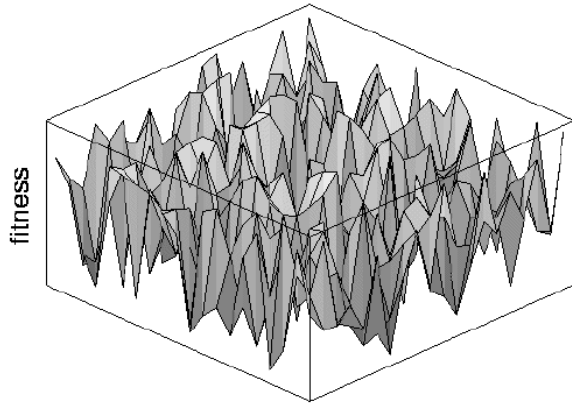
$$d(\mathbf{s}^a, \mathbf{s}^b) = \sum_{i=1}^L \delta(s_i^a, s_i^b)$$



$$d(\text{abc}, \text{aBC}) = 2$$

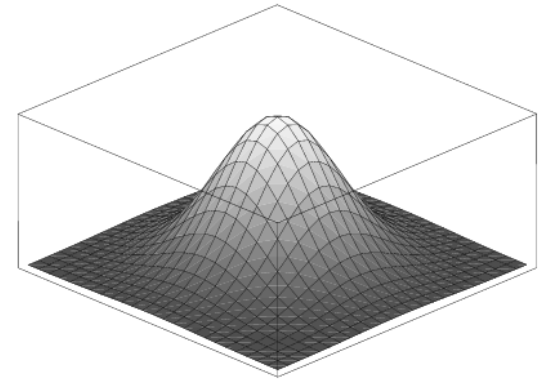
$$d(\text{Abc}, \text{aBC}) = 3$$

The metaphor



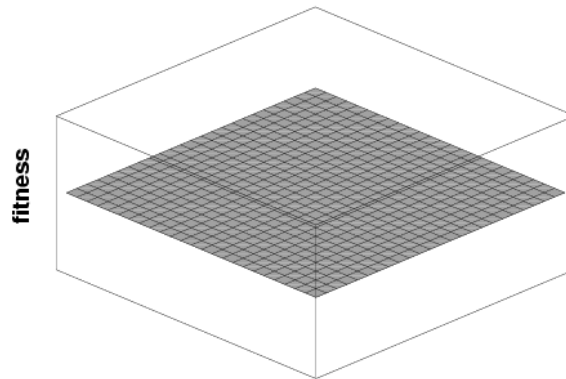
genotype space

rugged (Wright)



genotype space

Fujijama (Fisher)



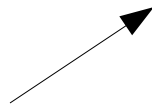
genotype space

flat (Kimura)

Quasispecies

ATTGGAAATGCCGCAATTTACGGGA
ACTTGCAAATTCGCAAATTCGGGG
AGTTGGAAC TTCCGCAATTCCTCGGGA
ACTTGGA CATTCCGATATTCCTCGGGA
GGTTGGAAATACCCAATTTTCGGGA
ACTTTGAAATTCGCAACGGTCGGGA
ACATGGAAATTCGCAATTTTCGGGA

ACTTGGAAATTCGCAATTTTCGGGA

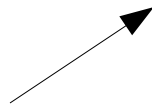


consensus sequence

Quasispecies

11001010100110011011000100
10001110101110011111100101
11001010001110011010100100
10001011101110101010100100
01001010100111011011100100
10000010101110011100100100
10101010101110011011100100

10001010101110011011100100



consensus sequence

Quasispecies equation

$$Q = (q_{ij}) \quad \mathbf{u} = (1, \dots, 1) \quad Q \mathbf{u}^T = \mathbf{u}^T$$

$$F = \begin{pmatrix} f_1 & & 0 \\ & \ddots & \\ 0 & & f_n \end{pmatrix} \quad W \equiv FQ$$

$$\frac{d \mathbf{x}}{d t} = \mathbf{x} W - \phi \mathbf{x} \quad \phi = \mathbf{x} W \mathbf{u}^T = \sum_{j=1}^n x_j f_j$$

Point mutations

probability of a point mutation: $\mu \ll 1$

$$q_{ij} = \mu^{d_{ij}} (1 - \mu)^{n - d_{ij}} \quad d_{ij} \text{ Hamming distance}$$

$$i, j = 0, \dots, n \quad (n \equiv 2^L - 1)$$

$$f_0 > 1 = f_1 = f_2 = \dots = f_n$$

$$x_0 = x \quad x_1 + x_2 + \dots + x_n = 1 - x$$

$$\frac{d \mathbf{x}}{d t} = \mathbf{x} W - \phi \mathbf{x} \quad \phi = \mathbf{x} W \mathbf{u}^T = \sum_{j=1}^n x_j f_j$$

Error catastrophe

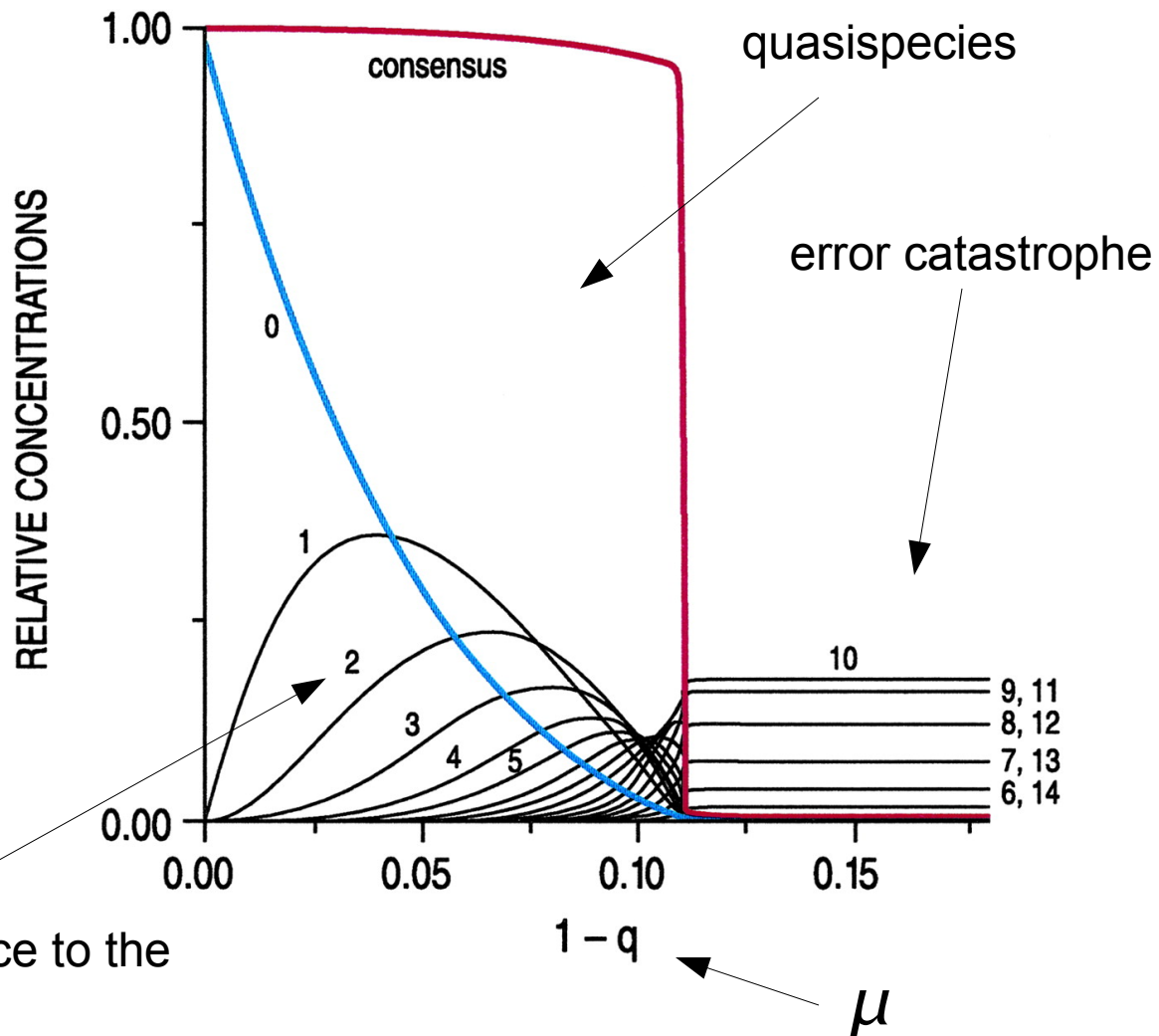
$$\frac{dx_i}{dt} = \sum_{j=0}^n x_j f_j q_{ji} - \phi x_i \quad \phi = f x + 1 - x$$

$$\frac{dx}{dt} = x \left[\underbrace{f(1-\mu)^L}_{\approx e^{-\mu L}} - 1 - (f-1)x \right] + O(\mu)$$

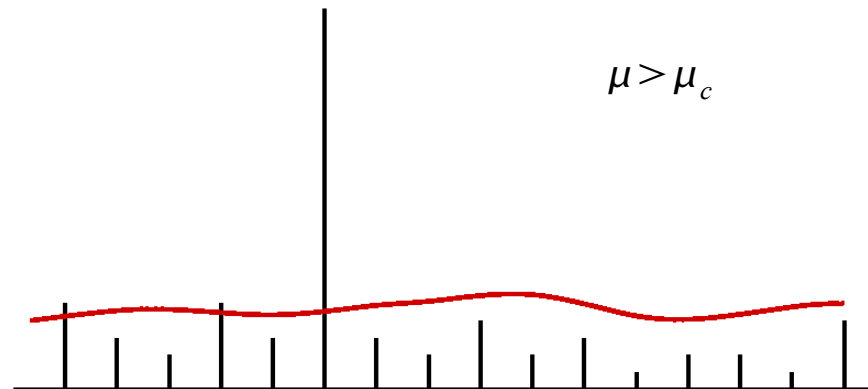
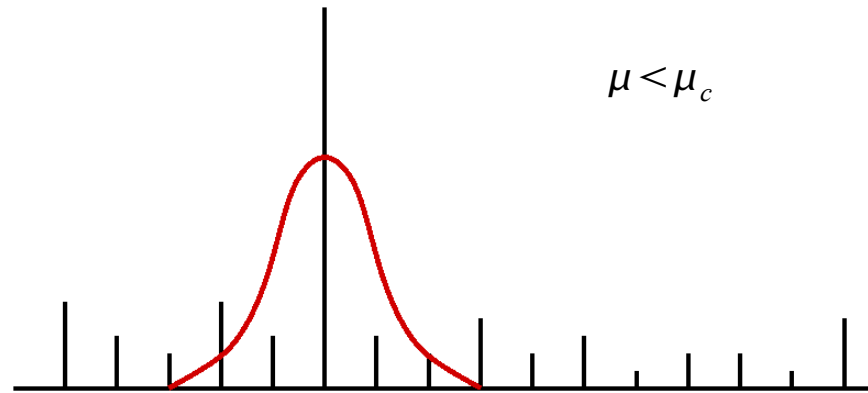
$$x^* \approx \frac{f}{f-1} e^{-L\mu} \quad \text{if } \mu < \frac{\log f}{L}$$

$$x^* = O(\mu) \quad \text{if } \mu > \frac{\log f}{L}$$

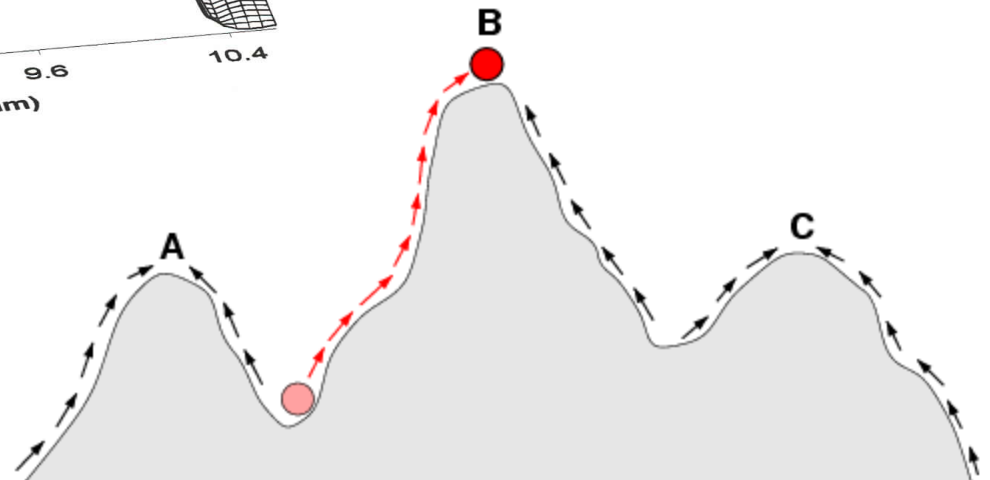
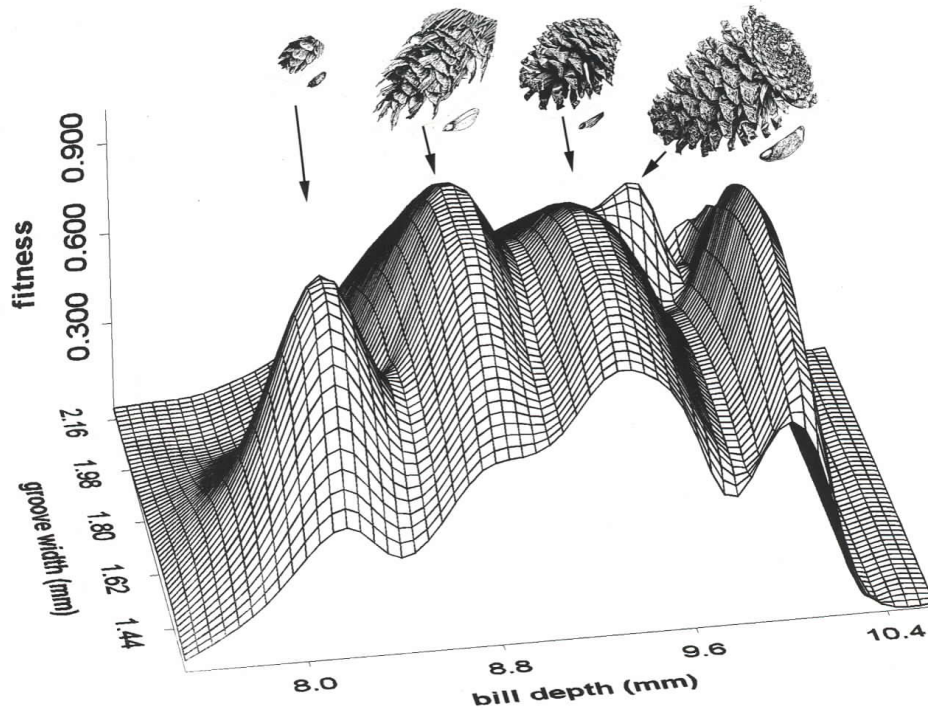
Error catastrophe



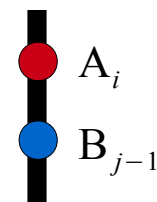
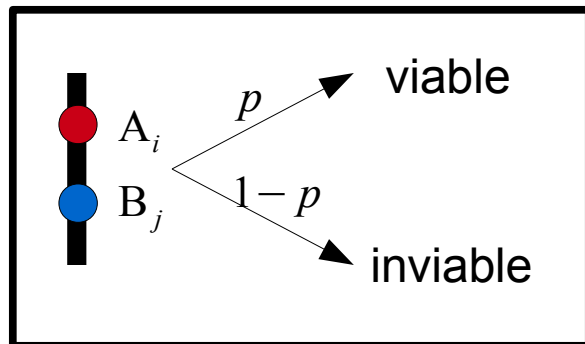
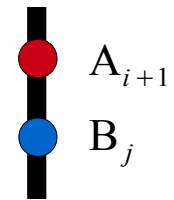
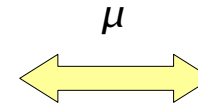
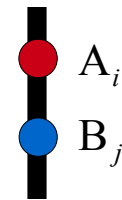
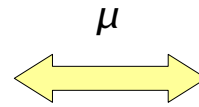
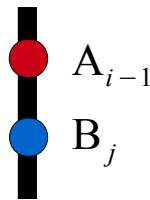
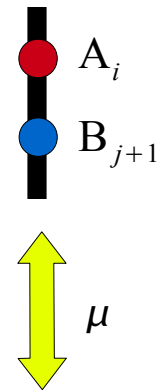
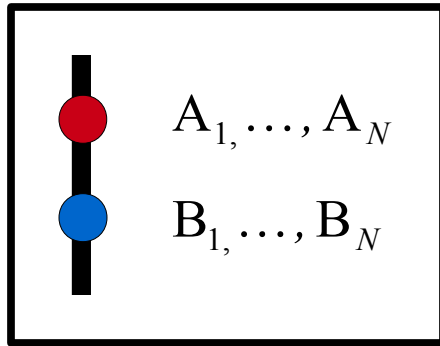
Error catastrophe



Speciation in rough landscapes



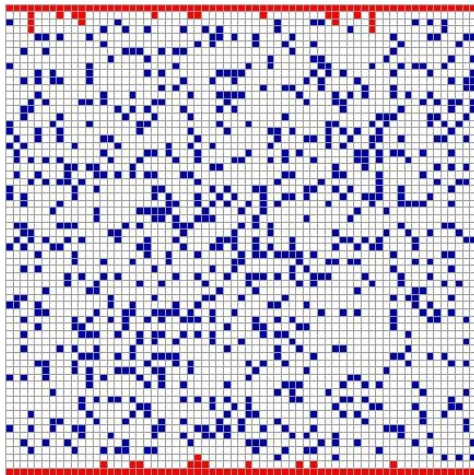
Russian roulette model



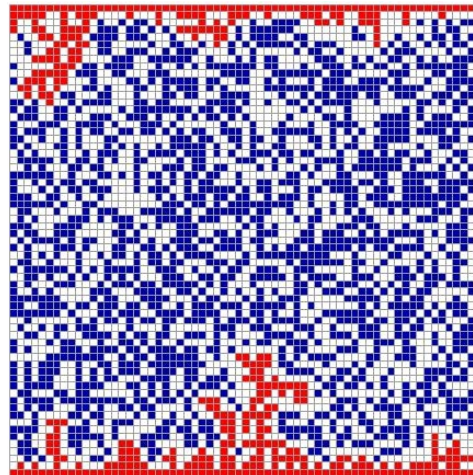
Russian roulette model

2D site percolation

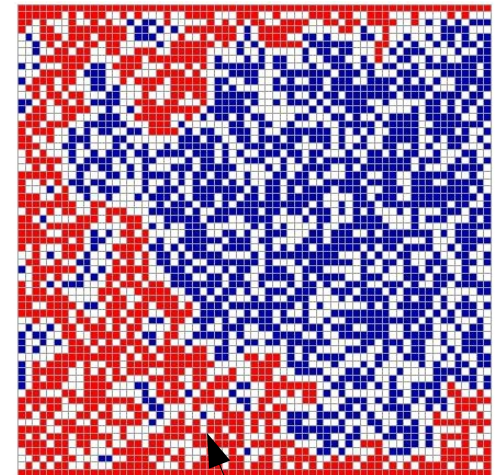
$p=0.2$



$p=0.51$



$p=0.594$



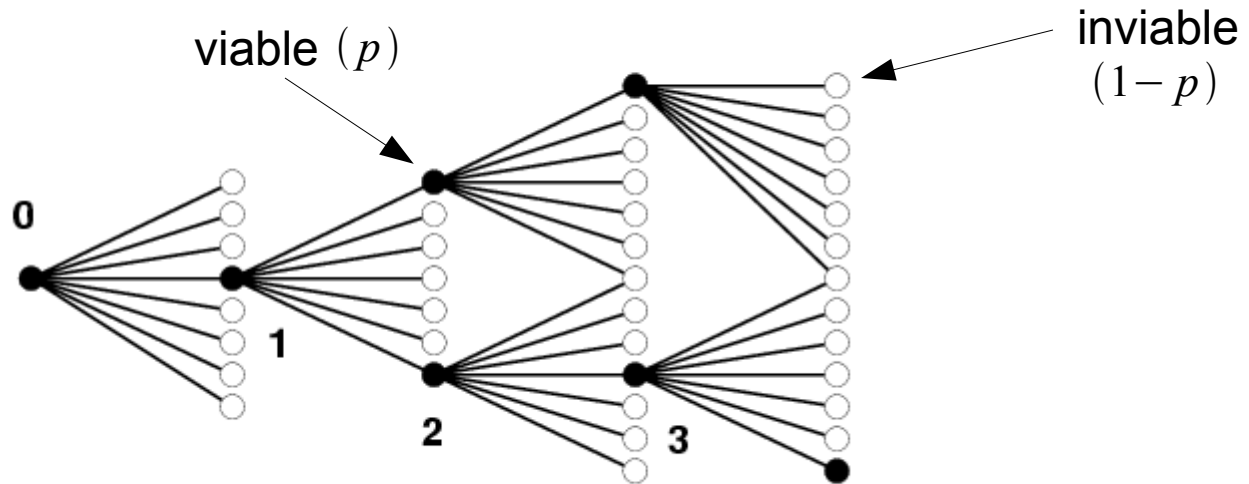
size=65x65

$p_c = 0.592746$

neutral network

Russian roulette for sequences

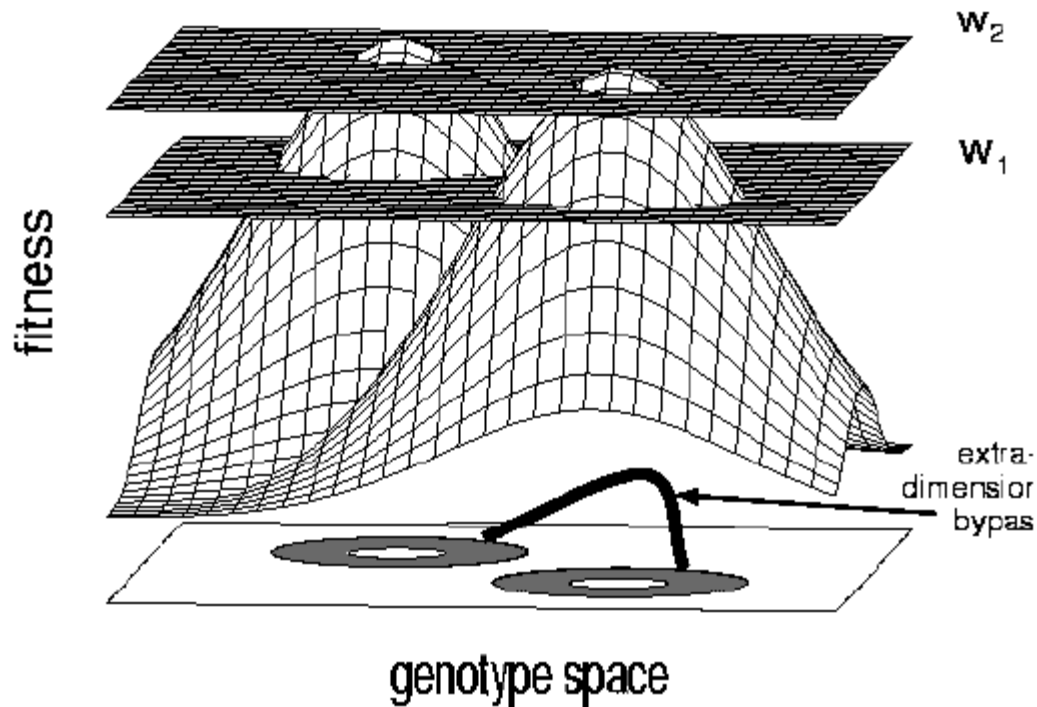
$$D = L(A - 1) \quad L \gg 1$$



branching process $p_k = \binom{D-1}{k} p^k (1-p)^{D-1-k}$

$$E\{k\} = (D-1)p \quad \Leftrightarrow \quad p_c = \frac{1}{D-1} \approx \frac{1}{D}$$

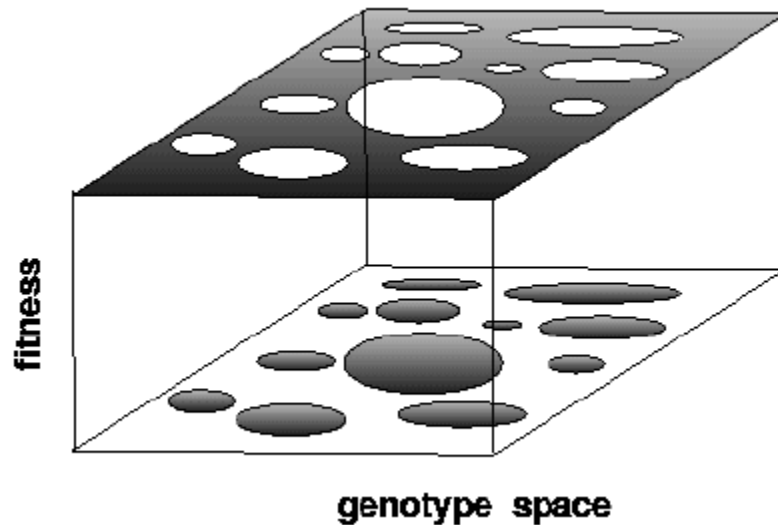
More general rugged landscapes



$$\int_{w_1}^{w_2} f(w) d w > \frac{1}{D} \Rightarrow \text{quasi-neutral network}$$

↑
fitness distribution

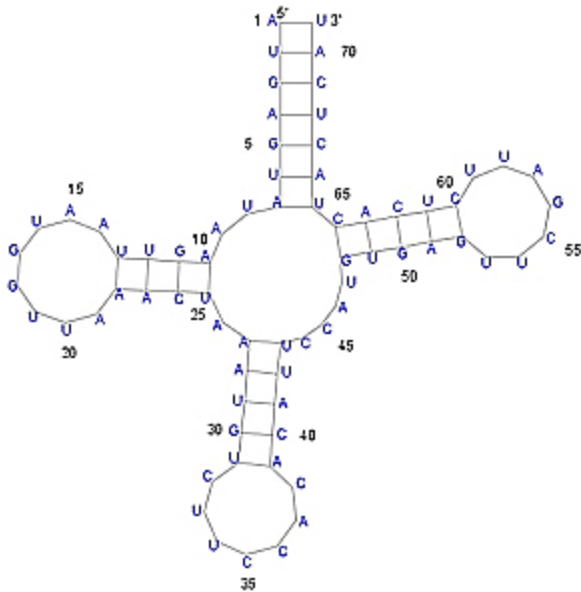
New metaphor of fitness landscapes



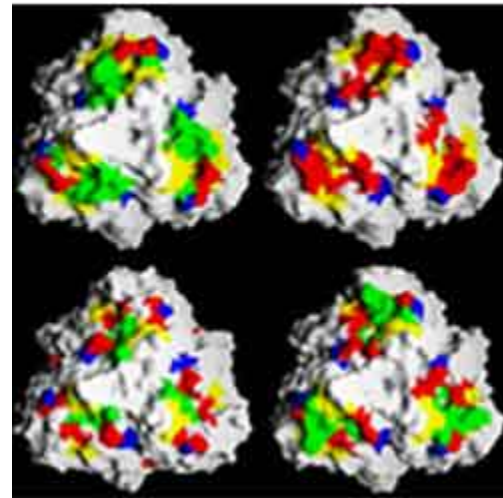
most evolutionary steps are neutral (*Kimura*)

Neutral networks

WORD \rightarrow WORE \rightarrow GORE \rightarrow GONE \rightarrow GENE



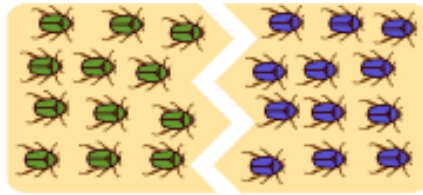
RNA



proteins

Speciation

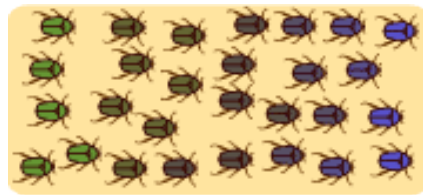
speciation proceeds mostly through random drift



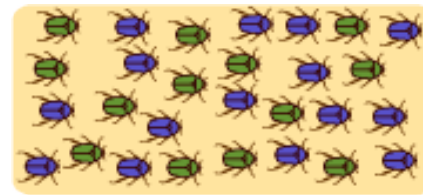
allopatric



peripatric

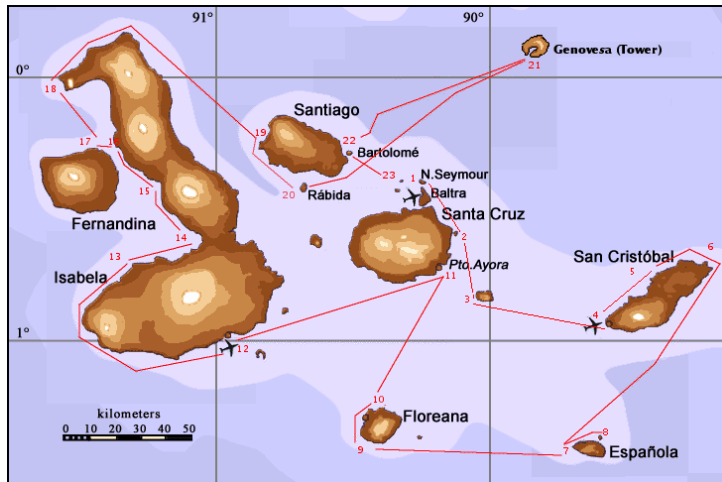


parapatric



sympatric

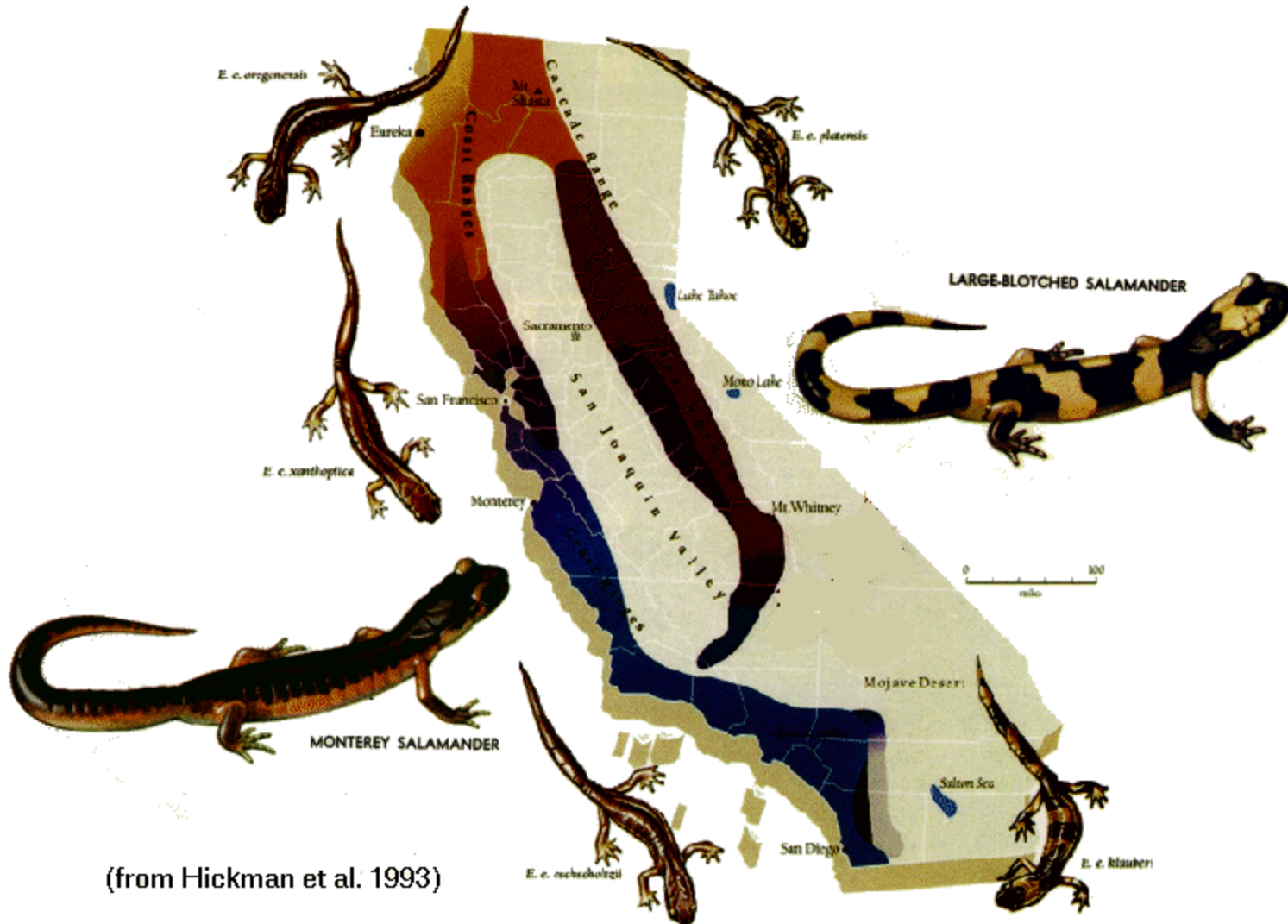
Allopatric speciation



Adaptive radiation in Galapagos finches



Paratric speciation



(from Hickman et al. 1993)

GAME THEORY

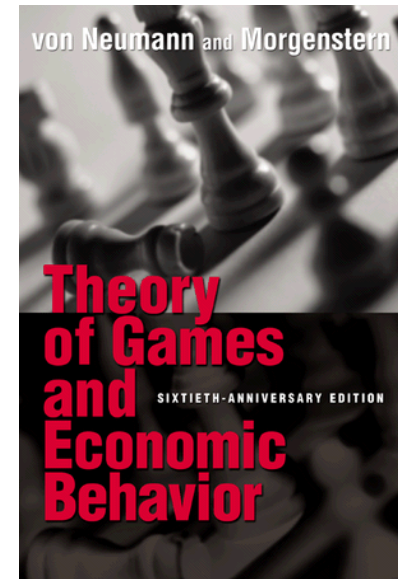
Game theory



Von Neumann
(1903-1957)



Morgenstern
(1902-1977)



1944

Game

- Players $i = 1, \dots, N$
- Set of strategies S_i , $|S_i| = n_i$
- Strategy profile

$$\mathbf{s} = (s_1, \dots, s_N) \in \mathbf{S} \equiv S_1 \times \dots \times S_N$$

- Payoff (utility) functions

$$W_i : \mathbf{S} \rightarrow \mathbb{R}$$

$$\mathbf{s} \rightarrow W_i(\mathbf{s}) \quad i = 1, \dots, N$$

Two-player games

$$\mathbf{W}^{(1)} = \{ W_1(s_1, s_2) \}_{\{s_i \in \mathcal{S}_i\}}$$

$$\mathbf{W}^{(2)} = \{ W_2(s_2, s_1) \}_{\{s_i \in \mathcal{S}_i\}}$$

$$\mathbf{W}^{(1)} =$$

a11	a12	a13
a21	a22	a23

$$\mathbf{W}^{(2)} =$$

b11	b12
b21	b22
b31	b32

symmetric game

$$\mathbf{W}^{(1)} = \mathbf{W}^{(2)}$$

Zero-sum games

one player's gain is the other player's loss
matching pennies



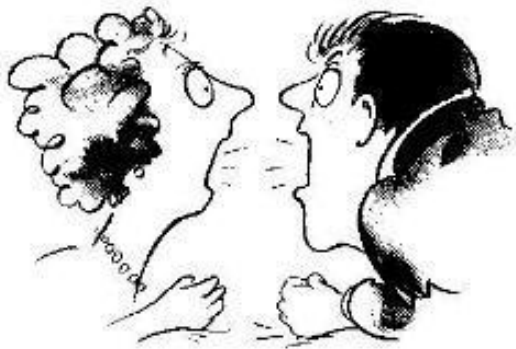
= player

≠ player

	1	2
1	1,-1	-1,1
2	-1,1	1,-1

Coordination games

doing the same as the other player
battle of the sexes



		him	
		opera	soccer
her	opera	2,1	0,0
	soccer	0,0	1,2

Coordination games

doing the same as the other player
stag-hunt



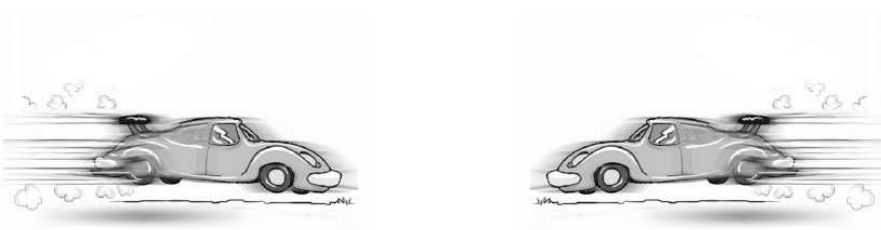
hunter 1

hunter 2

	stag	hare
stag	3,3	0,2
hare	2,0	1,1

Anti-coordination games

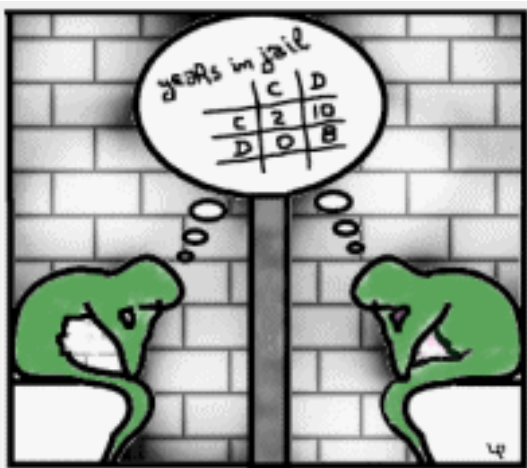
doing the opposite to the other player
chicken / snowdrift



		player 2	
		stay	quit
player 1	stay	-1,-1	2,0
	quit	0,2	0,0

Dilemmatic games

prisoner's dilemma



prisoner 1

prisoner 2

	coop.	defect
coop.	3,3	0,4
defect	4,0	1,1

Principle of perfect rationality

Every player will always aim at maximizing its payoff

Common knowledge



Dominated strategies

		player 2		
		L	M	R
player 1	U	2,2	1,1	4,0
	D	1,2	4,1	3,5

Dominated strategies

		player 2		
		L	M	R
player 1	U	2, 2	1, 1	4,0
	D	1, 2	4, 1	3,5

Dominated strategies

		player 2		
		L	M	R
player 1	U	2,2	1,1	4,0
	D	1,2	4,1	3,5

Dominated strategies

		player 2		
		L	M	R
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	D	1,2	4,1	3,5

Dominated strategies

		player 2		
		L	M	R
player 1	U	2,2	1,1	4,0
	D	1,2	4,1	3,5

Dominated strategies

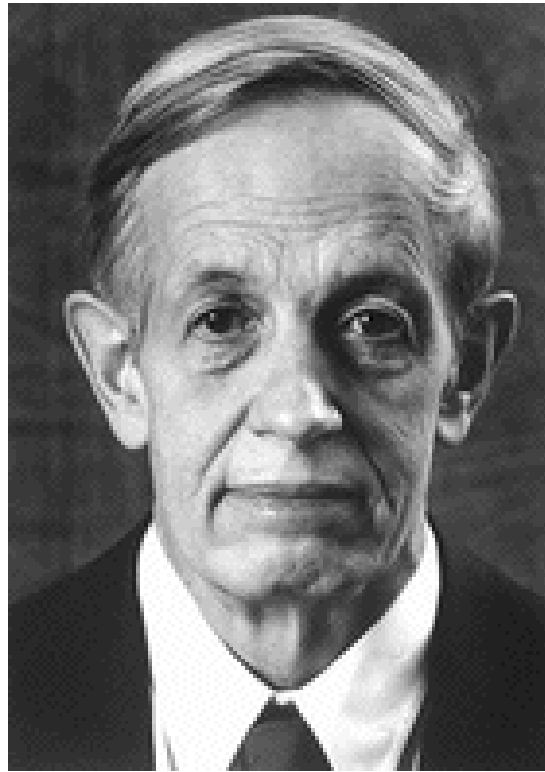
		player 2		
		L	M	R
player 1	U	2,2	1,1	4,0
	D	1,2	4,1	3,5

Dominated strategies

player 2

	L	M	R
player 1 U	2,2	1,1	4,0
D	1,2	4,1	3,5

Nash equilibria



Nash (1928-)

Master thesis: 1949 - Nobel Prize in Economics: 1994

Nash equilibria in pure strategies

$$W_i(\mathbf{s}^*) \geq W_i(s_i, \mathbf{s}_{-i}^*) \quad \forall s_i \in S_i \quad \forall i = 1, \dots, N$$

↑
NEPS

- Games may have 0, 1 or more than 1 NEPS
- Iterative elimination of dominated strategies leads to a NEPS when it converges

Zero-sum games

one player's gain is the other player's loss
matching pennies



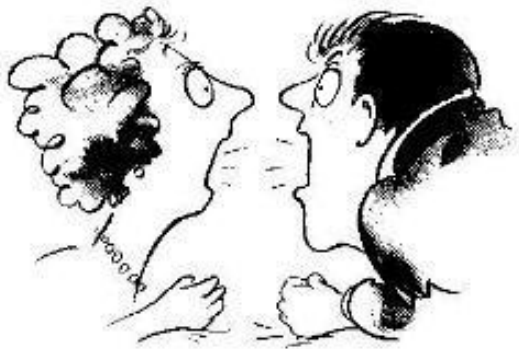
= player

≠ player

	1	2
1	1,-1	-1,1
2	-1,1	1,-1

Coordination games

doing the same as the other player
battle of the sexes



		her	
		opera	soccer
him	opera	2,1	0,0
	soccer	0,0	1,2

Coordination games

doing the same as the other player
stag-hunt



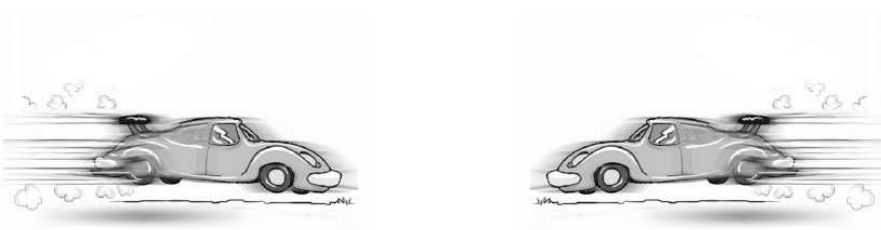
Pareto dominant

risk dominant

		hunter 2	
		stag	hare
hunter 1	stag	3,3	0,2
	hare	2,0	1,1

Anti-coordination games

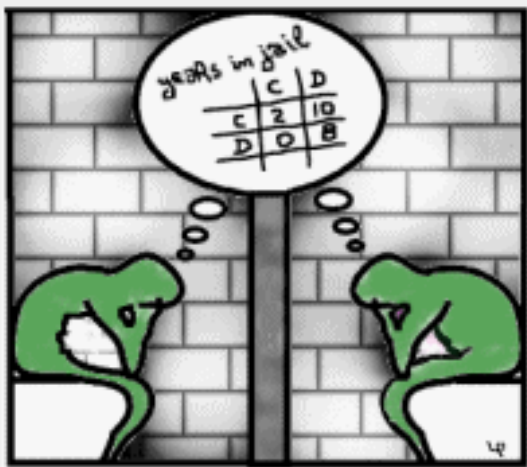
doing the opposite to the other player
chicken / snowdrift



		player 2	
		stay	quit
player 1	stay	-1,-1	2,0
	quit	0,2	0,0

Dilemmatic games

prisoner's dilemma



prisoner 1

prisoner 2

maximizes welfare

	coop.	defect
coop.	3,3	0,4
defect	4,0	1,1

Mixed strategies

$$p_i : S_i \rightarrow [0, 1] \quad \sum_{s \in S_i} p_i(s) = 1$$

$$\mathbf{p} = (p_1, \dots, p_N)$$

$$W_i(\mathbf{p}) = \sum_{s_1 \in S_1} \cdots \sum_{s_N \in S_N} p_1(s_1) \cdots p_N(s_N) W_i(s_1, \dots, s_N)$$

Nash equilibria

$$W_i(\mathbf{p}^*) \geq W_i(p_i, \mathbf{p}_{-i}^*) \quad \forall p_i \text{ mixed strategy}$$
$$\forall i = 1, \dots, N$$

NE

Every finite game has at least one NE
(Nash (1950) PNAS **36**, 48)

Fundamental theorem

$$W_i(s_i, \mathbf{p}_{-i}^*) = W_i(\mathbf{p}^*) \quad \forall p_i^*(s_i) > 0$$

Example

		player 2	
		L	R
player 1	U	1,1	0,4
	D	0,2	2,1

$$p_1^* = \alpha \mathbf{U} + (1 - \alpha) \mathbf{D} \quad p_2^* = \beta \mathbf{L} + (1 - \beta) \mathbf{R}$$

$$W_1(\mathbf{U}, p_2^*) = W_1(\mathbf{D}, p_2^*) \Leftrightarrow \beta = 2(1 - \beta) \Leftrightarrow \beta = \frac{2}{3}$$

Example

		player 2	
		L	R
player 1	U	1,1	0,4
	D	0,2	2,1

$$p_1^* = \alpha \mathbf{U} + (1 - \alpha) \mathbf{D} \quad p_2^* = \frac{2}{3} \mathbf{L} + \frac{1}{3} \mathbf{R}$$

$$W_2(p_1^*, \mathbf{L}) = W_2(p_2^*, \mathbf{R}) \Leftrightarrow \alpha + 2(1 - \alpha) = 4\alpha + (1 - \alpha)$$
$$\Leftrightarrow \alpha = \frac{1}{4}$$

Example

		player 2	
		L	R
player 1	U	1,1	0,4
	D	0,2	2,1

$$p_1^* = \frac{1}{4} \mathbf{U} + \frac{3}{4} \mathbf{D} \quad p_2^* = \frac{2}{3} \mathbf{L} + \frac{1}{3} \mathbf{R}$$

Matching pennies



$$p_i^* = \frac{1}{2} \mathbf{1} + \frac{1}{2} \mathbf{2}$$

≠ player

= player

	1	2
1	1,-1	-1,1
2	-1,1	1,-1

Stag-hunt



$$p_i^* = \frac{1}{2} \mathbf{S} + \frac{1}{2} \mathbf{H}$$

hunter 2

hunter 1

	stag	hare
stag	3,3	0,2
hare	2,0	1,1

Chicken / snowdrift



$$p_i^* = \frac{2}{3} \mathbf{S} + \frac{1}{3} \mathbf{Q}$$

player 2

		player 2	
		stay	quit
player 1	stay	-1,-1	2,0
	quit	0,2	0,0

EVOLUTIONARY GAME THEORY

Games and evolution

NATURE VOL. 246 NOVEMBER 2 1973

The Logic of Animal Conflict

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Conflicts between animals of the same species usually are of "limited war" type, not causing serious injury. This is often explained as due to group or species selection for behaviour benefiting the species rather than individuals. Game theory and computer simulation analyses show, however, that a "limited war" strategy benefits individual animals as well as the species.

In a typical combat between two male animals of the same species, the winner gains mates, dominance rights, desirable territory, or other advantages that will tend toward transmitting its genes to future generations at higher frequency than the loser's genes. Consequently, one might expect that natural selection would develop maximally effective weapons and fighting styles for a "total war" strategy of battles between males to the death. But instead, widespread conflicts are typically of a "limited war" type, involving inefficient weapons or ritualized tactics that seldom cause serious injury to either contestant. For example, in many snake species the males fight each other by writhing without using their fangs! In male deer (*Odocoileus hemionus*) the bucks fight furiously but harmlessly by crashing or pushing antlers against antlers, while they retreat from attacking side on opponent's nose, exposing the unprotected side of its body. And in the Arabian oryx (*Oryx oryx*) the extremely long, backward-pointing horns are so inefficient for combat that in order for two males to fight they are forced to kneel down with their heads between their knees to direct their horns forward. (For additional examples, see Collins', Davies', Hingston', Huxley *et al.*, Lorenz' and Wynne-Edwards').

How can one explain such oddities as snakes that wrestle with each other, deer that refuse to strike "total wars", and animals that kneel down to fight?

The accepted explanation for the conventional nature of combat is that if no conventional methods extend, many individuals would be injured, and this would reduce against the survival of the species (see, for example, Huxley's). The difficulty with this type of explanation is that it appears to assume the operation of "group selection". Although the current role of group selection as an agent producing adaptations in a single life-form is still debated as a major special circumstance¹⁻³. Consequently it seems to us that group selection cannot by itself account for the complex anatomical and behavioral adaptations for limited conflict found in so many species, but there must also be individual selection for them, which means that a "limited war" strategy must be differentially advantageous for individuals.

We consider simple formal models of conflict situations,

and ask what strategy will be favoured under individual selection. We first consider conflict in species possessing offensive weapons capable of inflicting serious injury on other members of the species. Then we consider conflict in species where serious injury is impossible, so that victory goes to the contestant who fights longest. For each model, we seek a strategy that will be stable under natural selection; that is, we seek an "evolutionarily stable strategy" or ESS. The concept of an ESS is fundamental to our argument; it has been derived in part from the theory of games, and in part from the work of MacArthur⁴ and of Hamilton⁵ on the evolution of the sex ratio. Roughly, an ESS is a strategy such that if most of the members of a population adopt it, then a "mutant" strategy that would give higher reproductive fitness.

A Computer Model

A main reason for using computer simulation was to test whether it is possible even in theory for individual selection to account for "limited war" behaviour.

We consider a species that possesses offensive weapons capable of inflicting serious injuries. We assume that there are two categories of conflict tactics: "conventional" tactics, C, which are similar to some serious injury, and "dangerous" tactics, D, which are likely to injure the opponent seriously if they are employed for long. Thus in the snake example, writhing involves C tactics and use of fangs would be D tactics. In many species, C tactics are limited to threat displays at a distance, without any physical fighting. We consider a conflict between two individuals to consist of a series of alternate "moves". At each move, a contestant can employ C or D tactics, or retreat, R. If a contestant employs D tactics, there is a fixed probability that his opponent will be seriously injured: a contestant who is seriously injured always retreats. If a contestant retreats, the contest is at an end and his opponent is the winner. A possible conflict between contestants A and B can be represented in this way:

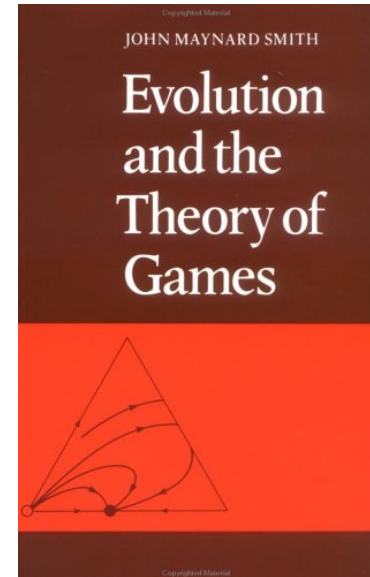
A's move C C C C C C C C C C C C C C C C D

B's move C C C C C C C C C C C C C C C C R

If a contestant plays D on the first move of a contest, or plays D in response to C by his opponent, this is called a "probe" or a "provocation". A probe made after the opening move is said to "result" in a contest from C to D level. A contestant who plays D in reply to a probe is said to "retaliate". In the example shown above, A probes on his first move and retaliates on move 2. Retaliation after the first probe, but retreats after the second, leaving A the winner. At the end of a contest there are "pay-offs" to each contestant. The pay-offs are taken as measures of the contribution the contest has made to the reproductive success of the individual. They take account of these factors: the advantages of winning as compared with losing, the disadvantages of being seriously injured, and the disadvantage of wasting time and energy in the contest.



Maynard-Smith (1920-2004)



1982







Nature, 1973

New setup

	classic GT	evolut. GT
players	rational	irrational
strategies	chosen from a set	inherited (phenotypes)
interaction	all at once	random sampling of population
equilibria	Nash equilibria	Evolutionary Stable Strategies

Hawk & doves

Hawk-Dove Model: Costs and Benefits of Fighting over Resources

Payoff* to...	...in fights against:	
	hawk	dove
hawk	 Hawk wins 50% of fights; is injured in 50% of fights. Payoff: $(V-D)/2$	 Hawk always wins; dove flees. Payoff: V
dove	 Dove never wins; is never injured. Payoff: 0	 Dove wins 50% of fights; is never injured; wastes time. Payoff: $V/2 - T$

* V = fitness value of winning resources in fight

D = fitness costs of injury

T = fitness costs of wasting time

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Nash equilibrium

if $V > D + 2T$

$$p_i^* = \mathbf{H}$$

if $V < D + 2T$

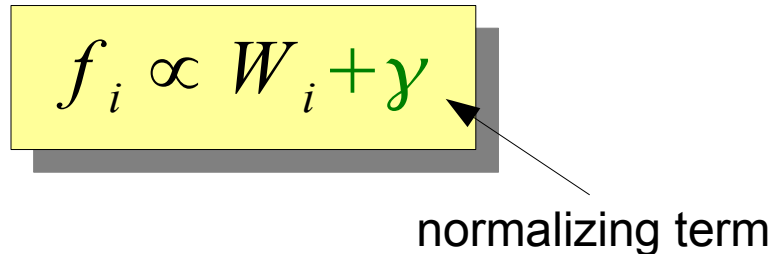
$$p_i^* = \frac{V}{D + 2T} \mathbf{H} + \frac{D + 2T - V}{D + 2T} \mathbf{D}$$

Connection with evolution

- Species interact by playing games
- Fitness increases with game payoffs
- Simplest setting:

$$f_i \propto W_i + \gamma$$

normalizing term



Hawk & doves

$$[\text{hawks}] = x \quad [\text{doves}] = 1 - x$$

$$f_h(x) = W_{hh}x + W_{hd}(1 - x)$$

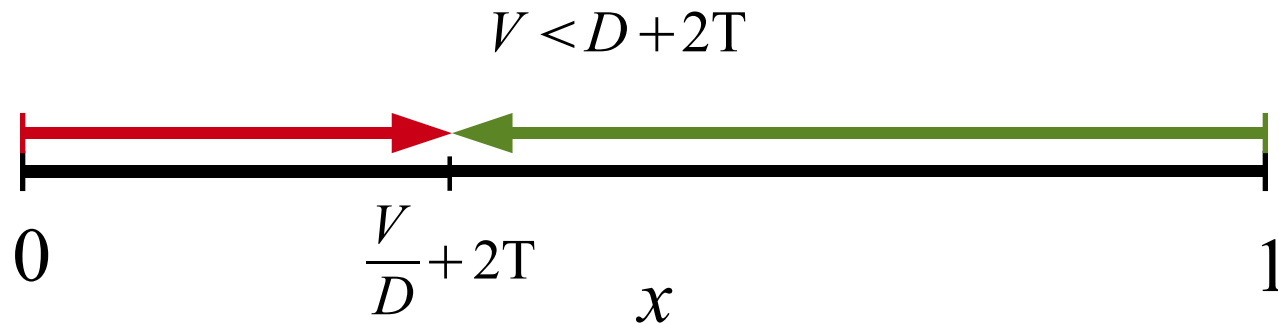
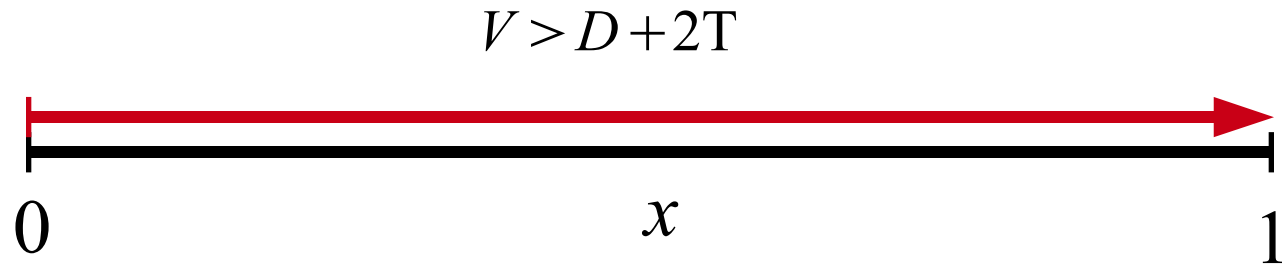
$$f_d(x) = W_{dh}x + W_{dd}(1 - x)$$

$$f_h(x) = \frac{V - D}{2}x + V(1 - x)$$

$$f_d(x) = \left(\frac{V}{2} - T \right) (1 - x)$$

Hawk & doves

$$\frac{dx}{dt} = x(1-x)(f_h(x) - f_d(x)) = \frac{1}{2}x(1-x)[V - (D + 2T)x]$$



Replicator dynamics

$$\begin{aligned} f_i(\mathbf{x}) &= W_i(\mathbf{x}) \\ &= \sum_{j_2=1}^S \cdots \sum_{j_n=1}^S x_{j_2} \cdots x_{j_n} \overbrace{W(i, j_2, \dots, j_n)}^{n\text{-player game's payoff}} \\ \phi(\mathbf{x}) &= \sum_{i=1}^S x_i W_i(\mathbf{x}) \end{aligned}$$

number of species

fraction of population

$$\frac{d x_i}{d t} = x_i [f_i(\mathbf{x}) - \phi(\mathbf{x})]$$

Equilibria

$$\frac{d x_i}{d t} = x_i [f_i(\mathbf{x}) - \phi(\mathbf{x})]$$

$$x_i = 0 \quad \text{or} \quad f_i(\mathbf{x}) = \phi(\mathbf{x})$$



mixed-strategies Nash equilibria

Equilibria

$$x_i [f_i(\mathbf{x}) - \phi(\mathbf{x})] = 0$$



$$x_i = 0 \quad \text{or} \quad f_i(\mathbf{x}) = \phi(\mathbf{x})$$



mixed-strategies Nash equilibria

2 species

$$W = \begin{matrix} & \begin{matrix} \text{A} & \text{B} \end{matrix} \\ \begin{pmatrix} a & b \\ c & d \end{pmatrix} & \begin{matrix} \text{A} \\ \text{B} \end{matrix} \end{matrix}$$

$$f_A(x) = ax + b(1-x)$$

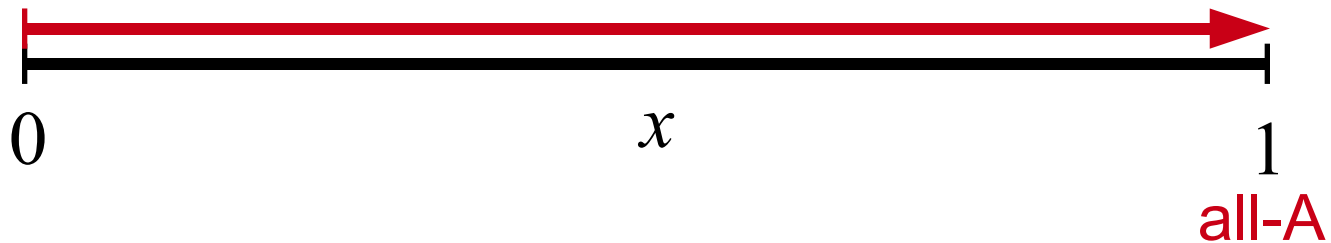
$$f_B(x) = cx + d(1-x)$$

$$\frac{dx}{dt} = x(1-x)[(b-d) - (b-d+c-a)x]$$

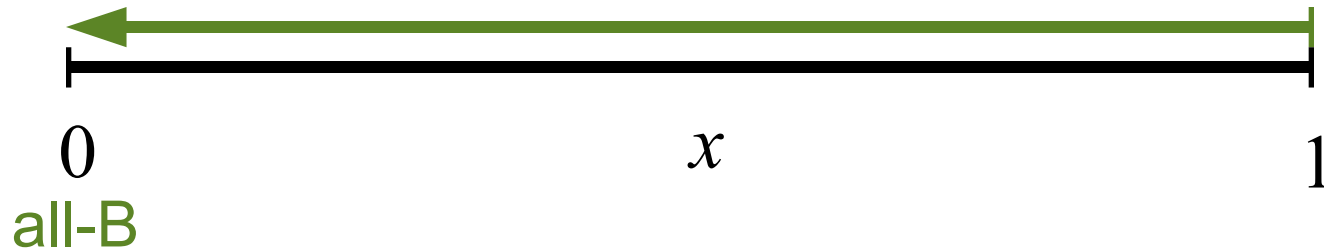
2 species

$(b-d)(c-a) < 0 \iff$ 1 species dominates

$$(b-d) > 0$$

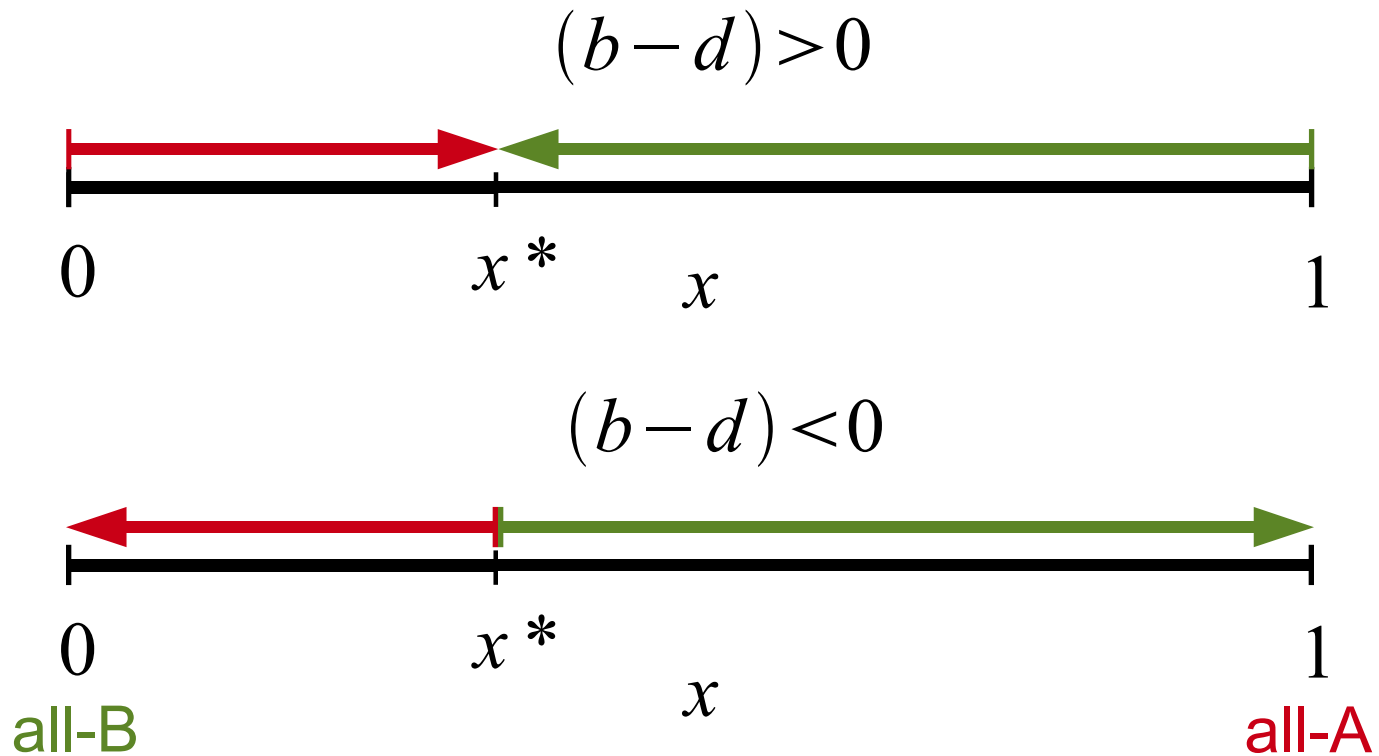


$$(b-d) < 0$$

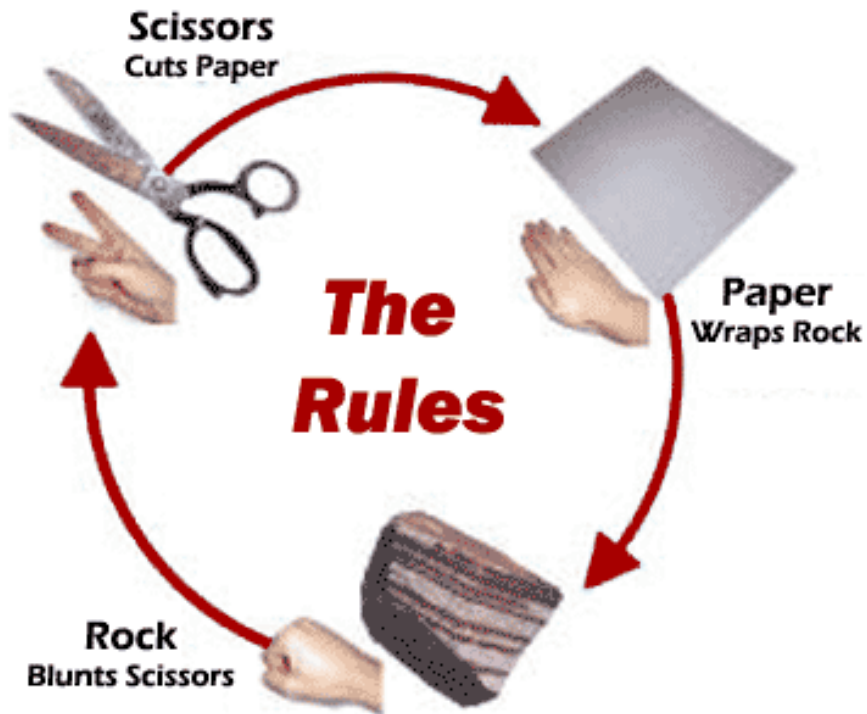


2 species

$$(b-d)(c-a) > 0 \quad \Leftrightarrow \quad x^* = \frac{b-d}{b-d+c-a}$$



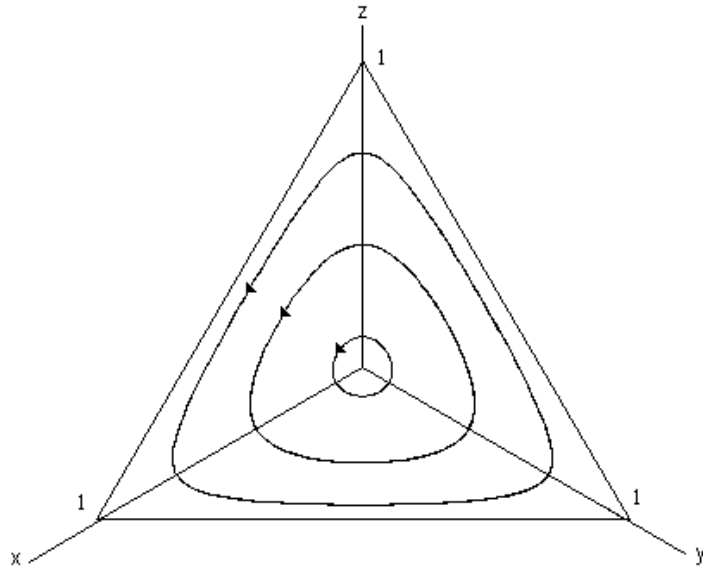
3 species: Rock-Paper-Scissors



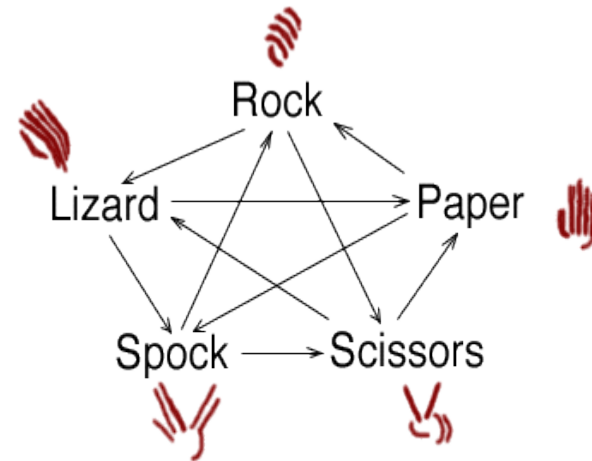
Dynamics of RPS

$$W = \begin{matrix} & \mathbf{R} & \mathbf{P} & \mathbf{S} \\ \begin{pmatrix} 0 & -1 & 1 \\ 1 & 0 & -1 \\ -1 & 1 & 0 \end{pmatrix} & \mathbf{R} \\ & \mathbf{P} \\ & \mathbf{S} \end{matrix} \quad \phi = 0$$

$$\prod_{i=1}^3 x_i = c \leq \frac{1}{9}$$



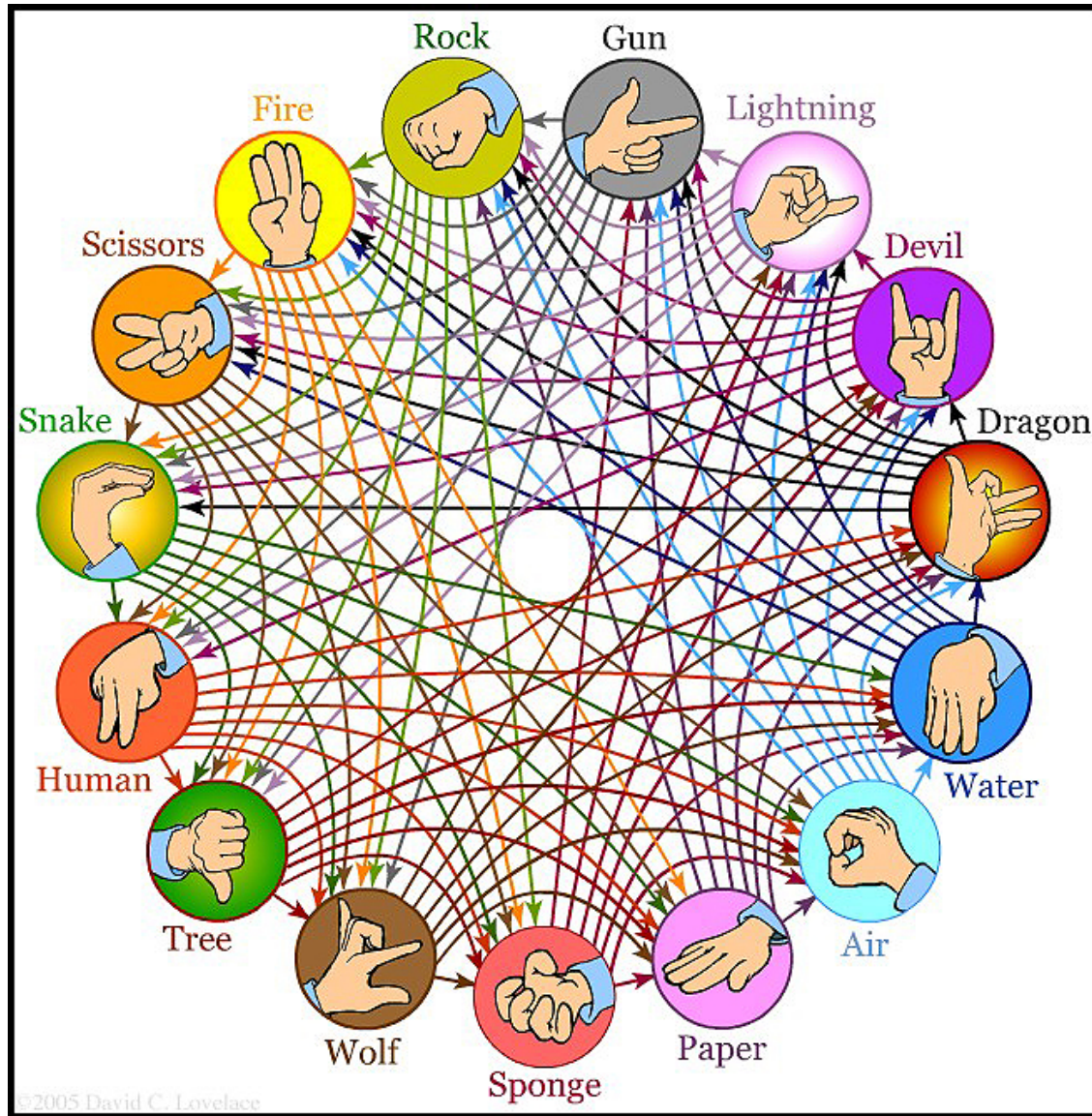
Some "variants"



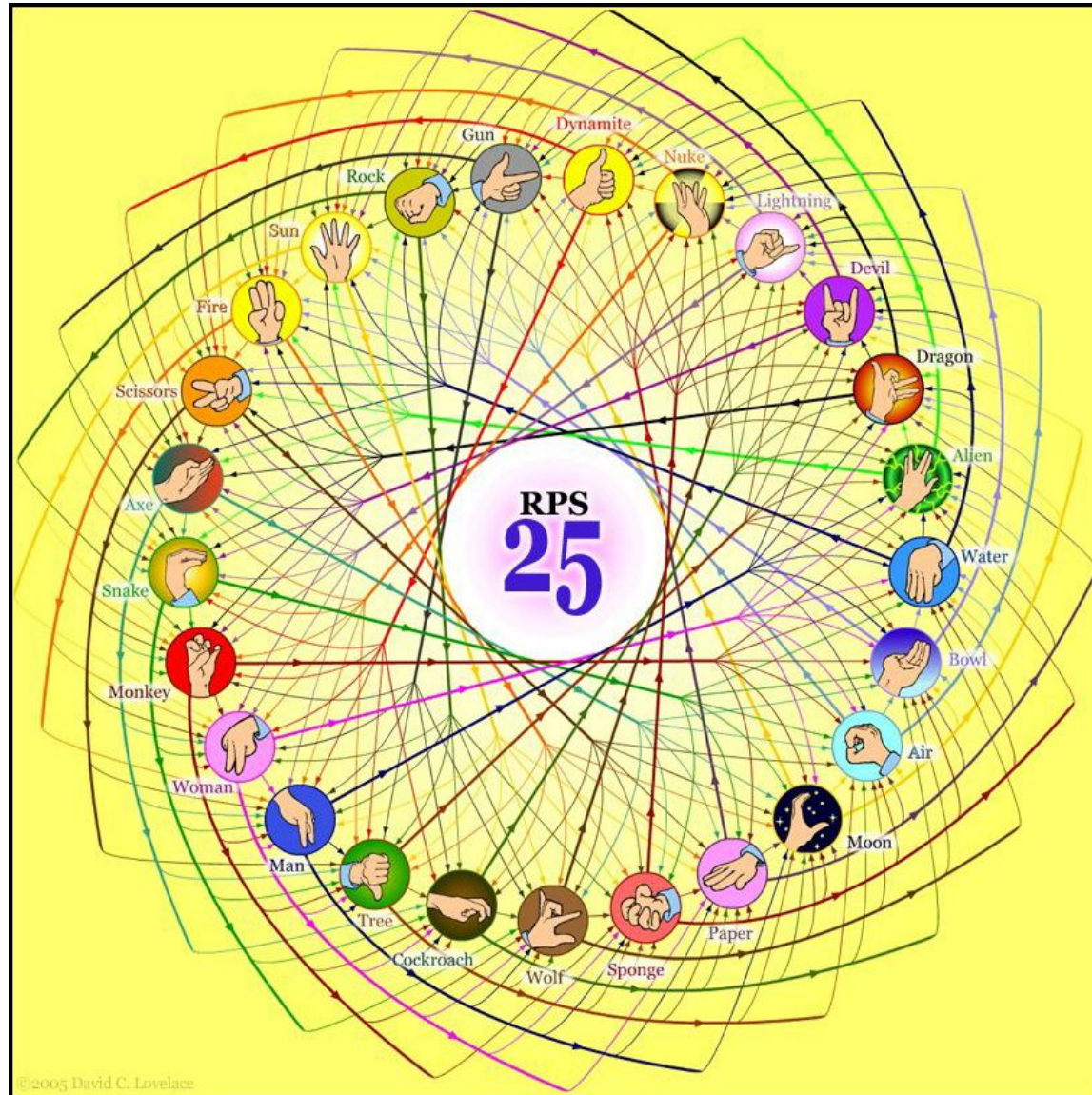
Scissors cuts Paper covers Rock crushes
Lizard poisons Spock smashes Scissors
decapitates Lizard eats Paper disproves
Spock vaporizes Rock crushes Scissors.

$$\prod_{i=1}^{2n+1} x_i = c$$

Some "variants"

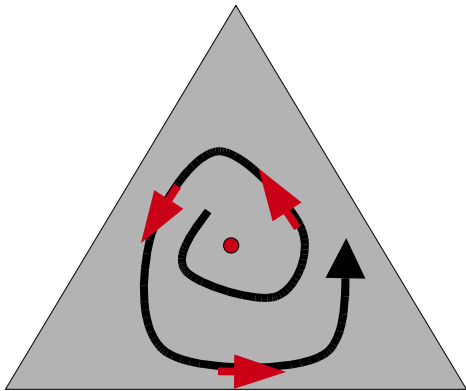


Some "variants"

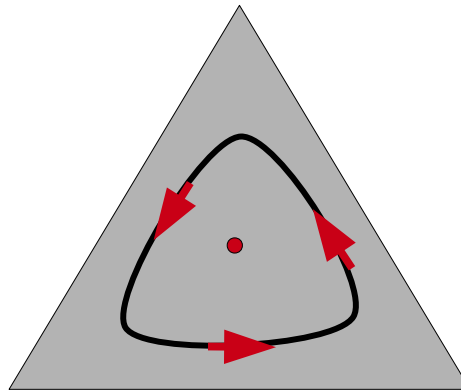


Generalized RPS

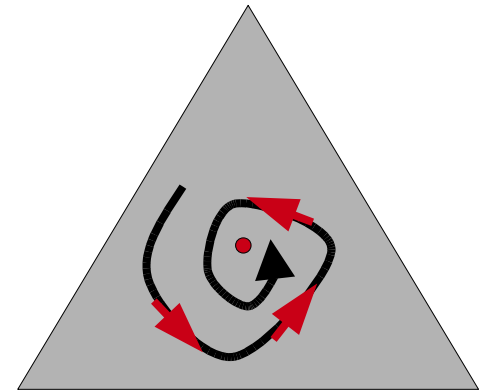
$$W = \begin{matrix} & \mathbf{R} & \mathbf{P} & \mathbf{S} \\ \begin{pmatrix} 0 & -a_2 & b_3 \\ b_1 & 0 & -a_3 \\ -a_1 & b_2 & 0 \end{pmatrix} & \mathbf{R} \\ & \mathbf{P} \\ & \mathbf{S} \end{matrix}$$



$$|W| < 0 \\ (a_1 a_2 a_3 > b_1 b_2 b_3)$$

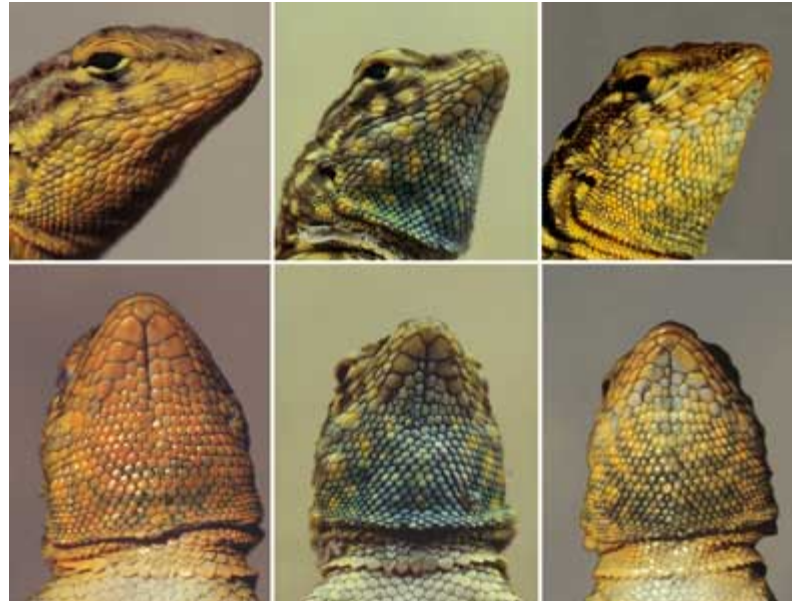


$$|W| = 0 \\ (a_1 a_2 a_3 = b_1 b_2 b_3)$$



$$|W| > 0 \\ (a_1 a_2 a_3 < b_1 b_2 b_3)$$

A live RSP: *Uta stansburiana*



A

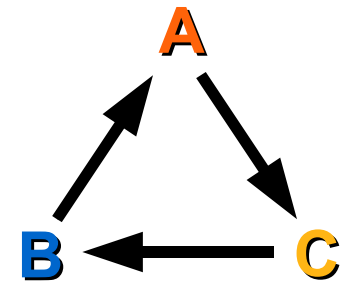
B

C

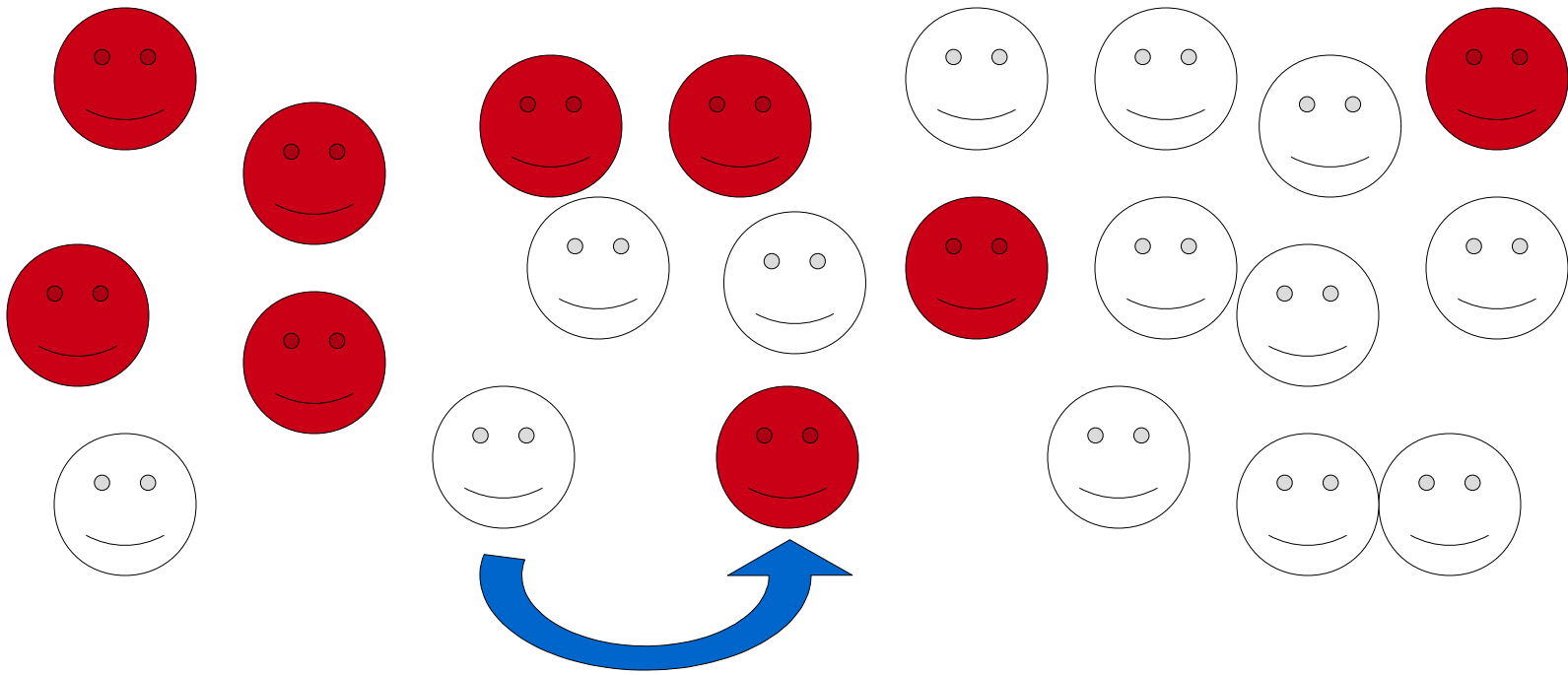
A monogamous, jelous

B polygamous

C sneaky mating

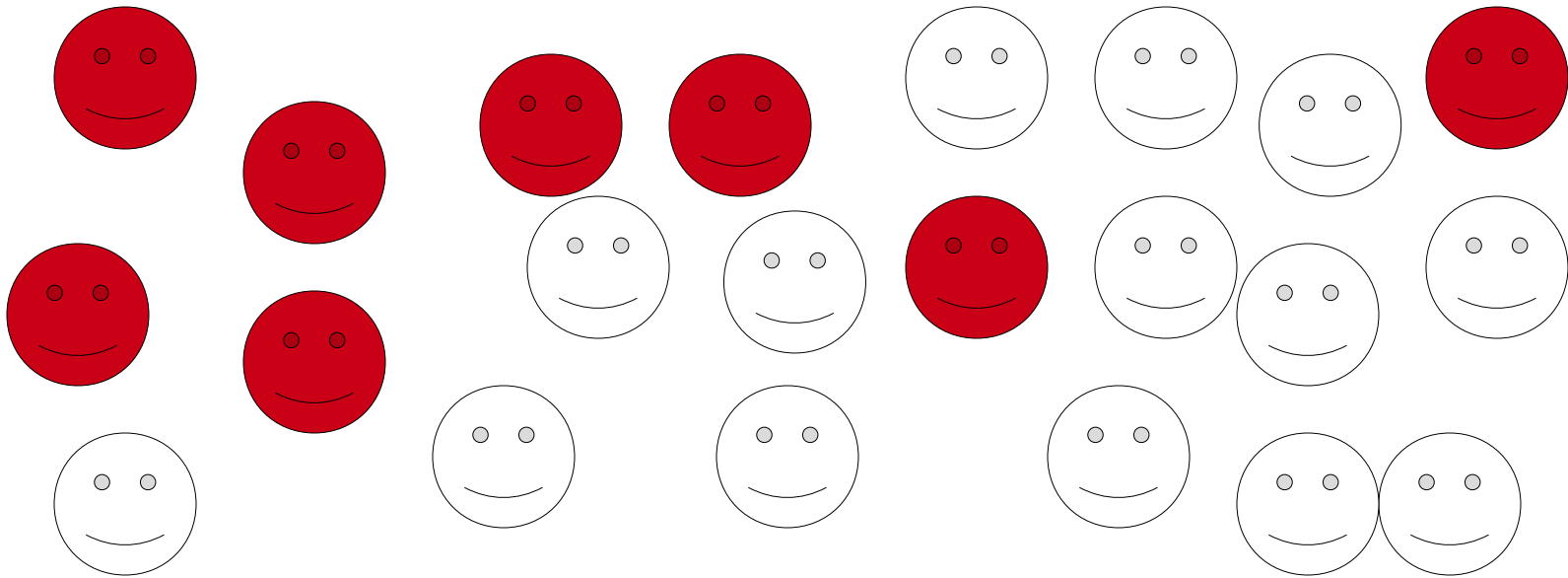


Social dynamics: imitation



$$T_{j \rightarrow i} \equiv f_{ij}(\mathbf{x})$$

Social dynamics: imitation



$$\frac{d x_i}{d t} = \sum_{j=1}^n \left[f_{ij}(\mathbf{x}) - f_{ji}(\mathbf{x}) \right] \underbrace{x_i x_j}_{\text{meeting probability}}$$

meeting probability

Social dynamics: imitation

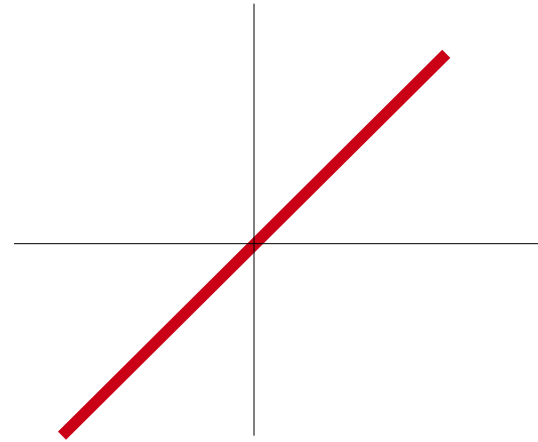
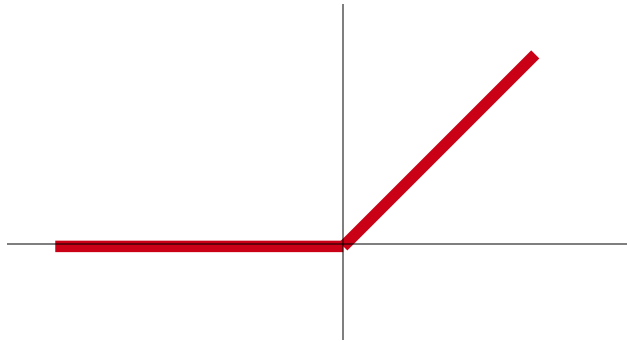
Assumptions:

- $f_{ij}(\mathbf{x}) = F((W \mathbf{x})_i, (W \mathbf{x})_j)$
- $F(u, v) = \phi(u - v)$
- $\psi(z) = \phi(z) - \phi(-z)$

$$\frac{d x_i}{d t} = x_i \sum_{j=1}^n \psi[(W \mathbf{x})_i - (W \mathbf{x})_j] x_j$$

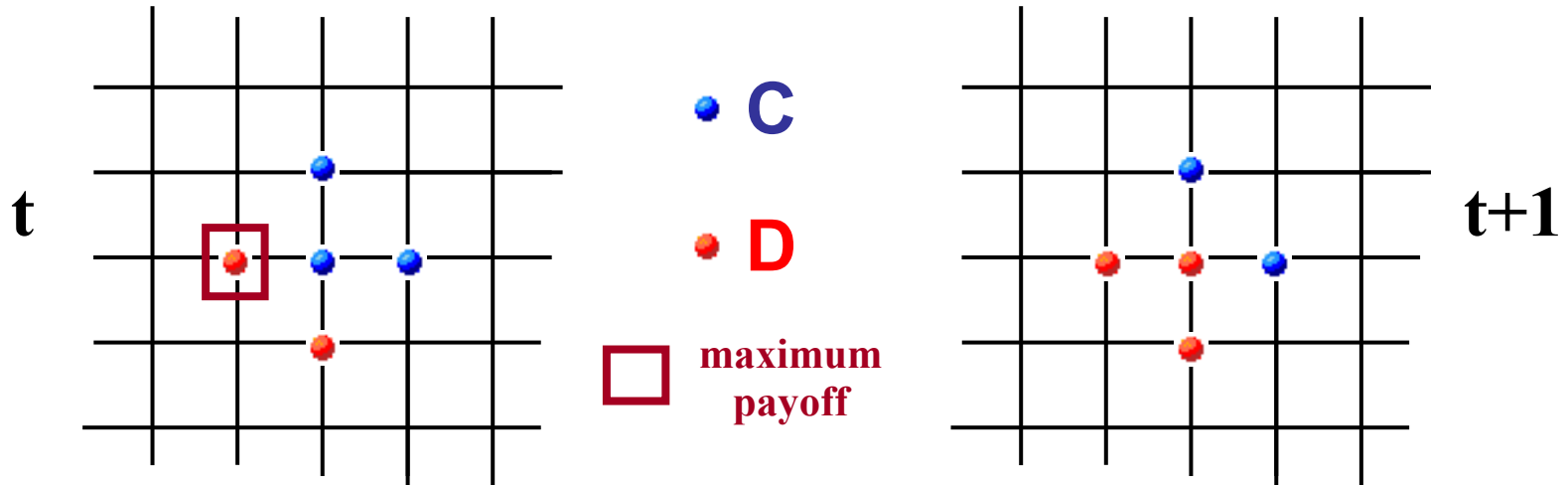
Social dynamics: imitation

$$\phi(z) = (z)_+ \quad \Rightarrow \quad \psi(z) = z$$

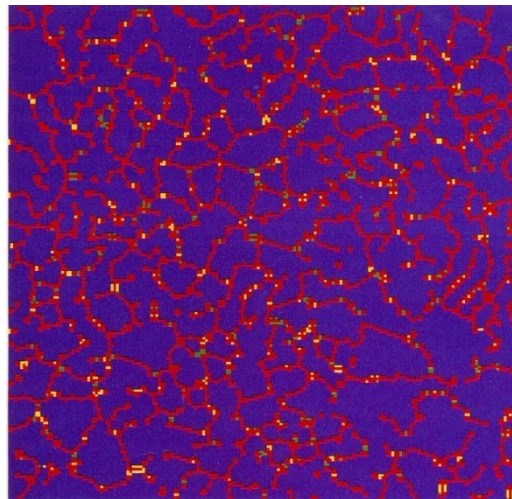


$$\frac{d x_i}{d t} = x_i [(W \mathbf{x})_i - \mathbf{x}^T W \mathbf{x}]$$

Spatial prisoner's dilemma



C → C
D → D
C → D
D → C



M. A. Nowak and R. M. May
Nature **359**, 826 (1992)

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