

# REPLICATOR DYNAMICS AS THE LARGE-POPULATION LIMIT OF A MULTI-STRATEGY DISCRETE MORAN PROCESS

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✉ M. Morandotti, G. Orlando - Preprint 2025.

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# THE REPLICATOR EQUATION

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## THE EQUATION

$$\begin{cases} \dot{\lambda}_i = \lambda_i \left( (A\lambda)_i - \lambda^T A \lambda \right) & \text{for } i = 1, 2, \dots, M \\ + \text{initial conditions} \end{cases}$$

• Unknown:  $\lambda = \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_M \end{pmatrix} : [0, T] \rightarrow \mathbb{R}^M$

• Parameters:  $A = \begin{pmatrix} a_{11} & a_{12} & \dots & a_{1M} \\ a_{21} & a_{22} & \dots & a_{2M} \\ \vdots & \vdots & \ddots & \vdots \\ a_{M1} & a_{M2} & \dots & a_{MM} \end{pmatrix} \in \mathbb{R}^{M \times M}$

# A SIMPLE OBSERVATION

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$$\dot{\lambda}_i = \lambda_i \left( (A\lambda)_i - \lambda^T A \lambda \right)$$

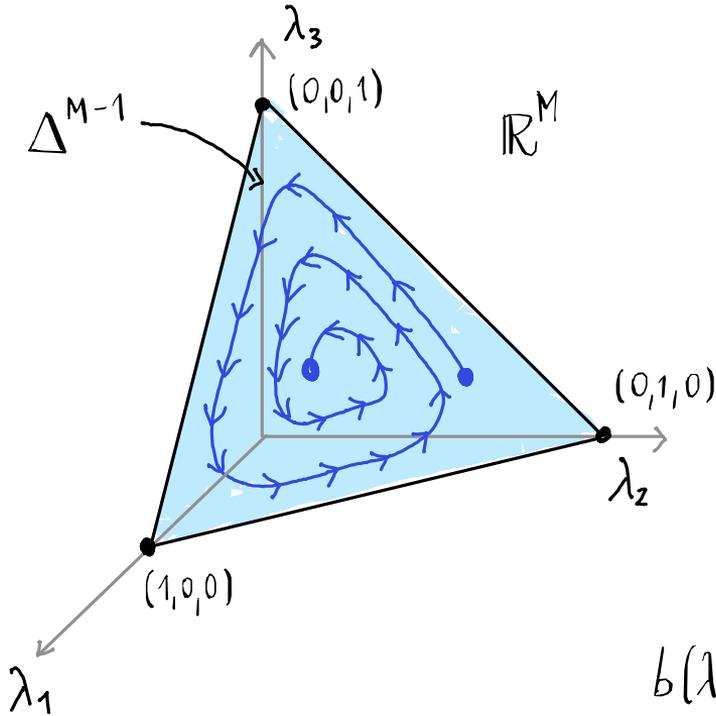
⇓

$$\begin{aligned} \frac{d}{dt} \left( \sum_{i=1}^M \lambda_i \right) &= \sum_{i=1}^M \lambda_i (A\lambda)_i - \left( \sum_{i=1}^M \lambda_i \right) \lambda^T A \lambda \\ &= \lambda^T A \lambda - \left( \sum_{i=1}^M \lambda_i \right) \lambda^T A \lambda = \\ &= \left( 1 - \sum_{i=1}^M \lambda_i \right) \lambda^T A \lambda \end{aligned}$$

⇓

If  $\sum_{i=1}^M \lambda_i = 1$  at time  $t=0$ ,  
then  $\sum_{i=1}^M \lambda_i = 1$  for all times.

# AN EQUATION ON THE SIMPLEX $\Delta^{M-1}$



$$\Delta^{M-1} = \left\{ \lambda \in \mathbb{R}^M : \lambda_i \geq 0 \text{ and } \sum_{i=1}^M \lambda_i = 1 \right\}$$

$$\dot{\lambda}_i = \lambda_i \left( (A\lambda)_i - \lambda^T A \lambda \right)$$

$$\Updownarrow$$

$$\dot{\lambda} = b(\lambda)$$

with  $b : \Delta^{M-1} \rightarrow T\Delta^{M-1}$

$$b(\lambda) = \begin{pmatrix} b_1(\lambda) \\ \vdots \\ b_M(\lambda) \end{pmatrix} = \begin{pmatrix} \lambda_1 \left( (A\lambda)_1 - \lambda^T A \lambda \right) \\ \vdots \\ \lambda_M \left( (A\lambda)_M - \lambda^T A \lambda \right) \end{pmatrix}$$

(note:  $\sum_{i=1}^M b_i(\lambda) = 0$ )

# IT'S AN EVOLUTIONARY GAME

Strategies:  $u = \{u_1, u_2, \dots, u_M\}$

$$\lambda = \begin{pmatrix} \lambda_1 \\ \vdots \\ \lambda_M \end{pmatrix} : [0, 1] \rightarrow \Delta^{M-1}$$

$A =$

	$u_1$	$u_2$	...	$u_M$
$u_1$	$a_{11}$	$a_{12}$	...	$a_{1M}$
$u_2$	$a_{21}$	$a_{22}$	...	$a_{2M}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
$u_M$	$a_{M1}$	$a_{M2}$	...	$a_{MM}$

REPLICATOR EQUATION:

$$\dot{\lambda}_i = \lambda_i \left( \underbrace{(A\lambda)_i}_{\text{blue}} - \underbrace{\lambda^T A \lambda}_{\text{red}} \right)$$

$\rightarrow (A\lambda)_i = \sum_{j=1}^M a_{ij} \lambda_j$

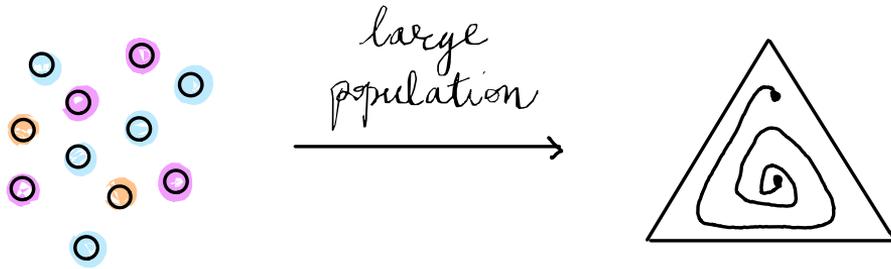
$\rightarrow \lambda^T A \lambda = \sum_{i=1}^M \lambda_i (A\lambda)_i$

INTERPRETATION:  $u_i$  tends to replicate if its expected payoff is better than the average one.

# QUESTION

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Can we derive rigorously the  
REPLICATOR EQUATION  
from a finite population game?



ANSWER: yes.

# THE (UNIFORM) MORAN PROCESS

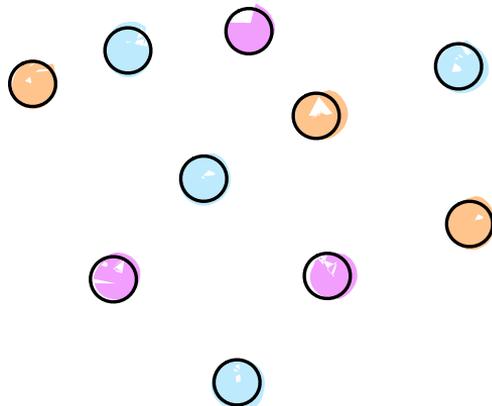
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POPULATION:  $N$  agents  $\{1, 2, \dots, N\}$ ,  $n$ : agent

STRATEGIES:  $M$  strategies  $\mathcal{U} = \{u_1, u_2, \dots, u_M\}$

PROPORTIONS:  $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_M)^T \in \Delta^{M-1}$

$$\lambda_i = \frac{\#\{\text{agents with strategy } u_i\}}{N}$$



Legend:

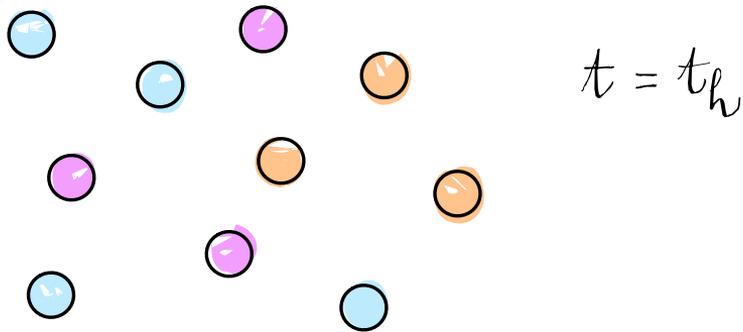
● =  $u_1$

● =  $u_2$

● =  $u_3$

# THE (UNIFORM) MORAN PROCESS

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## BIRTH-DEATH PROCESS:

- An agent is selected randomly uniformly to replicate its strategy:

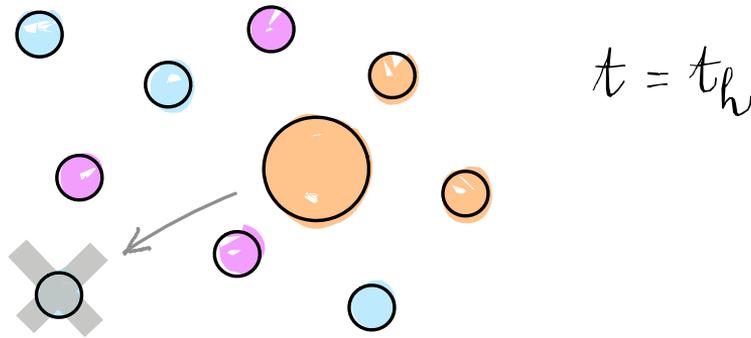
$$P(n \text{ selected for replication}) = \frac{1}{N}$$

- An agent is selected randomly uniformly to abandon its strategy:

$$P(n' \text{ selected to die}) = \frac{1}{N}$$

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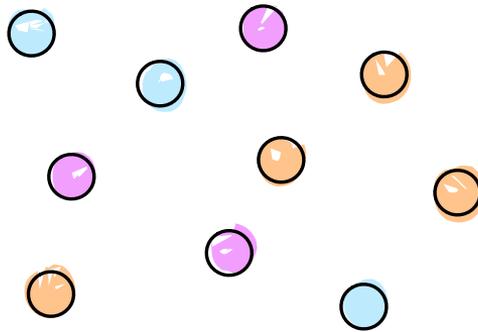
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# THE (UNIFORM) MORAN PROCESS

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$$t = t_{h+1}$$

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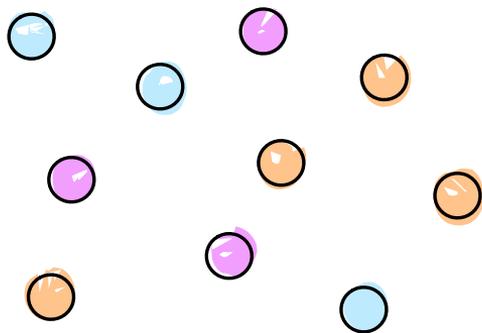
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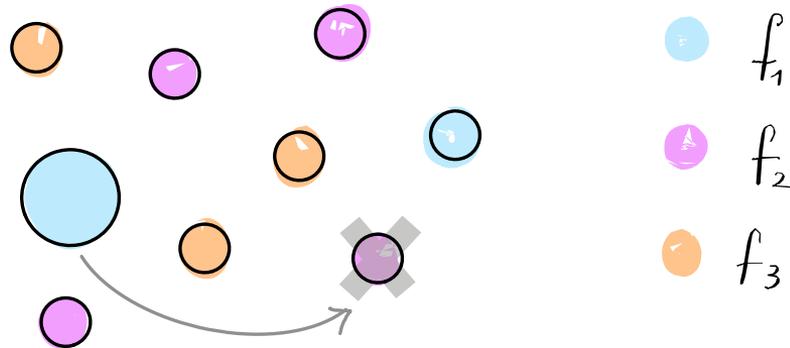
DISCRETE MARKOV CHAIN:

State at step  $t_n$ :  $(\lambda_1, \dots, \lambda_i, \dots, \lambda_j, \dots, \lambda_M)$   
 $= \lambda$

State at time  $t_{n+1}$ :  $(\lambda_1, \dots, \lambda_i + \frac{1}{N}, \dots, \lambda_j - \frac{1}{N}, \dots, \lambda_M)$   
 $= \lambda + \frac{1}{N}(e_i - e_j)$

with probability  $\lambda_i \lambda_j$

# FITNESS IN A MORAN PROCESS



BIRTH-DEATH PROCESS:

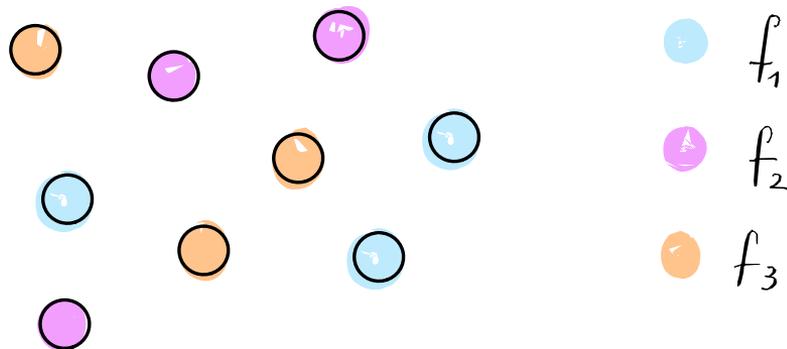
- $P(n \text{ with } u_i \text{ selected for replication}) = \frac{\frac{1}{N} f_i}{\sum_{j=1}^M \lambda_j f_j}$

$$P(u_i \text{ replicator}) = \frac{\lambda_i f_i}{\sum_{l=1}^M \lambda_l f_l}$$

- death as before (uniform)

Note: if all  $f_i = 1$ ,  
then it is  
uniform

# FITNESS IN A MORAN PROCESS



DISCRETE MARKOV CHAIN:

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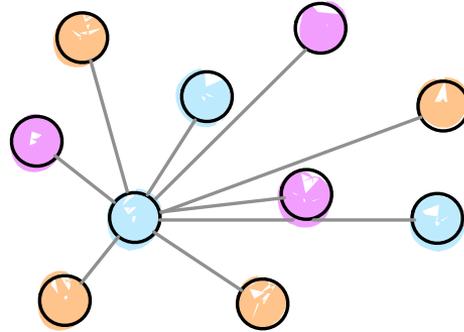
$$= \lambda + \frac{1}{N}(e_i - e_j)$$

with probability

$$\frac{\lambda_i f_i \lambda_j}{\sum_{\ell=1}^M \lambda_\ell f_\ell}$$

# PAYOFFS IN A MORAN PROCESS

	$u_1$	$u_2$	...	$u_M$
$u_1$	$a_{11}$	$a_{12}$	...	$a_{1M}$
$u_2$	$a_{21}$	$a_{22}$	...	$a_{2M}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$
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An agent  $n$  with strategy  $u_i$  has an expected payoff

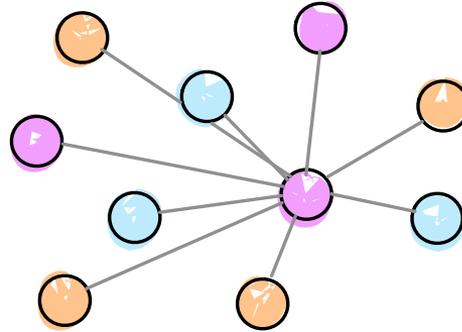
$$\pi_i = \sum_{\substack{j=1 \\ j \neq i}}^M a_{ij} \frac{\#\{w/\text{strategy } u_j\}}{N-1} + a_{ii} \frac{\#\{w/\text{strategy } u_i\} - 1}{N-1}$$

$$\approx (A\lambda)_i$$

↑  
for  $N \gg 1$

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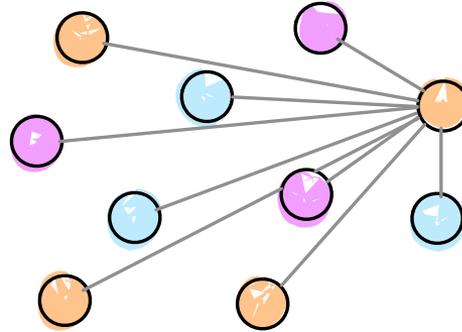
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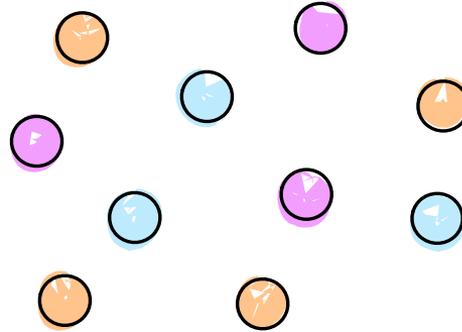
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# PAYOFFS IN A MORAN PROCESS

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An agent  $n$  with strategy  $u_i$  has fitness

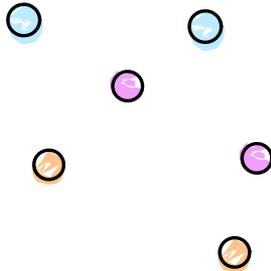
$$f_i = (1-w) \cdot 1 + w \underbrace{\pi_i}_{\text{expected payoff}} \quad w \in [0, 1]$$

# AIM

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Limit for:

- Large population :  $N \rightarrow +\infty$
- Small time steps :  $\tau = t_{h+1} - t_h \rightarrow 0$
- Weak selection :  $w \rightarrow 0$

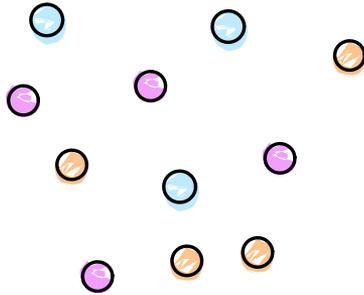


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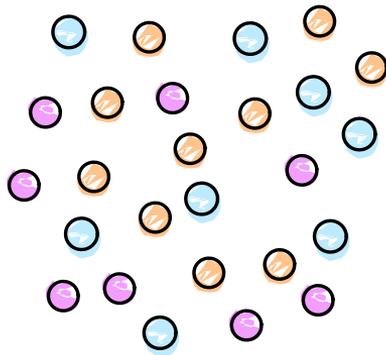


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Sequences:

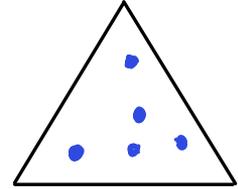
- $\tau_k \rightarrow 0$
- $N_k = \tau_k^{-\alpha} \rightarrow +\infty$
- $w_k = \tau_k^{\beta} \rightarrow 0$

# EULERIAN SPECIFICATION

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INTERPOLATION:

$$\lambda^k(t) = \lambda^k(t_h) + \frac{t - t_h}{\tau_k} (\lambda^k(t_{h+1}) - \lambda^k(t_h))$$

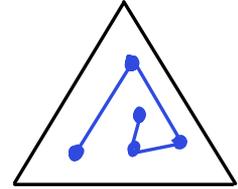


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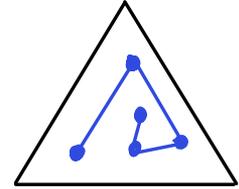


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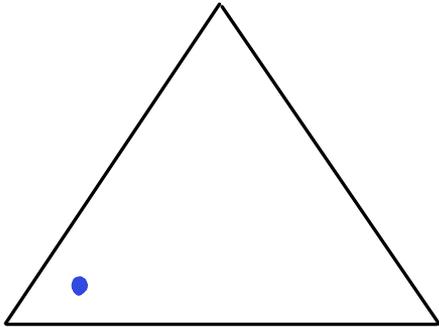
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RANDOM PATH:

$$\lambda^k : (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow C([0, T]; \Delta^{M-1})$$

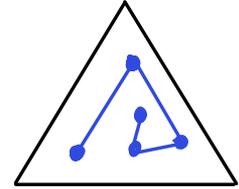


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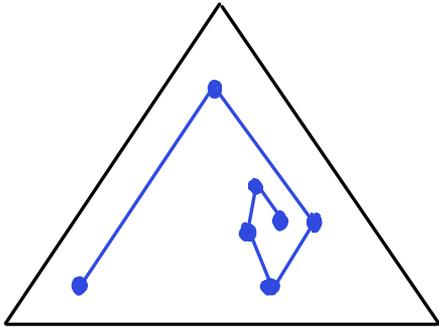
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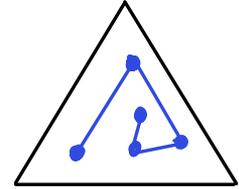


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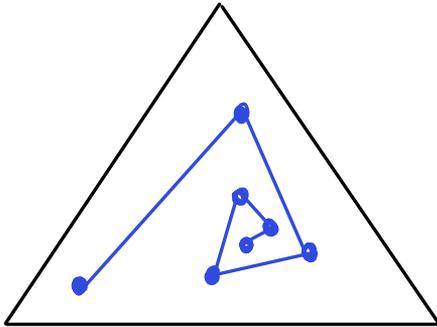
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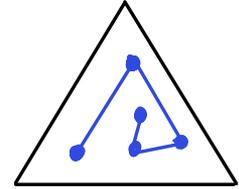


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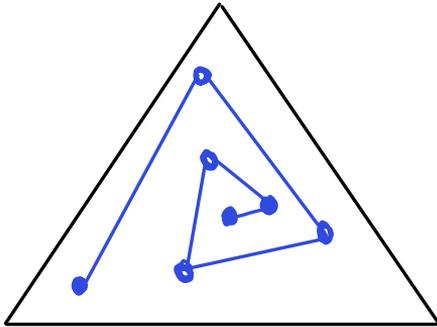
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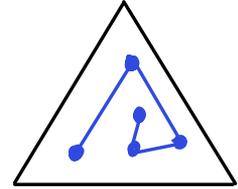


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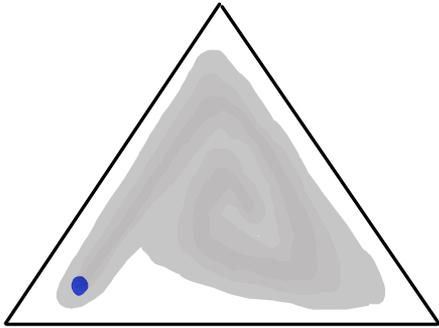
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LAW:

$$\Lambda^k = \lambda^k_{\#} \mathbb{P} \in \mathcal{P}(C([0, T]; \Delta^{M-1}))$$

$$\Lambda_t^k = \lambda^k(t)_{\#} \mathbb{P} \in \mathcal{P}(\Delta^{M-1})$$

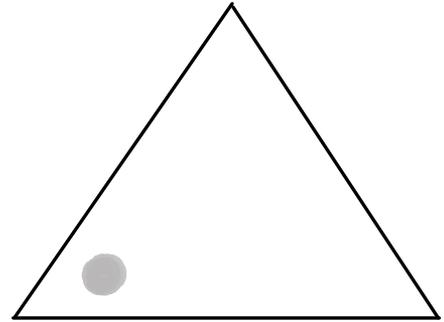
evolution of  $\Lambda_t^k$ ?

# DISCRETE PDE

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$$\partial_t \Lambda_t^K + \operatorname{div}(b \Lambda_t^K) \approx 0$$

where  $b_i(\lambda) = (A\lambda)_i - \lambda^T A \lambda$



THEOREM: For every test function  $\phi \in C_c^\infty([0, T] \times \Delta^{M-1})$

$$\int_0^T \int_{\Delta^{M-1}} \partial_t \phi(t, \lambda) d\Lambda_t^K(\lambda) dt + \frac{w_K}{\tau_K N_K} \int_0^T \int_{\Delta^{M-1}} D\phi(t, \lambda) b(\lambda) d\bar{\Lambda}_t^K(\lambda) dt =$$

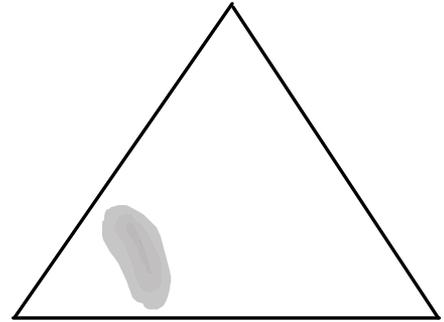
$$= \underbrace{- \int_{\Delta^{M-1}} \phi(0, \lambda) d\Lambda_0^K(\lambda)}_{\text{initial datum term}} + \underbrace{\text{"small" error}}_{\text{depending on } \tau_K, N_K, w_K!}$$

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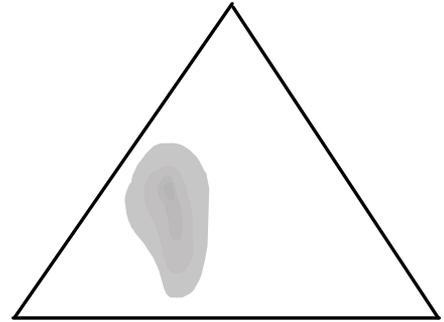
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initial datum term

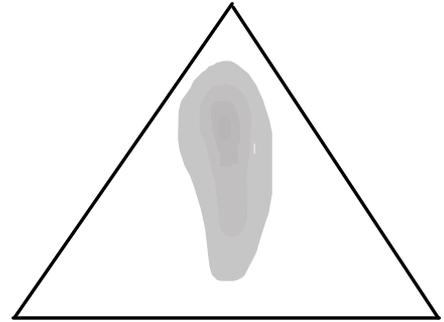
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$$\partial_t \Lambda_t^K + \operatorname{div}(b \Lambda_t^K) \approx 0$$

where  $b_i(\lambda) = (A\lambda)_i - \lambda^T A \lambda$



THEOREM: For every test function  $\phi \in C_c^\infty([0, T] \times \Delta^{M-1})$

$$\int_0^T \int_{\Delta^{M-1}} \partial_t \phi(t, \lambda) d\Lambda_t^K(\lambda) dt + \frac{w_K}{\tau_K N_K} \int_0^T \int_{\Delta^{M-1}} D\phi(t, \lambda) b(\lambda) d\bar{\Lambda}_t^K(\lambda) dt =$$

$$= \underbrace{- \int_{\Delta^{M-1}} \phi(0, \lambda) d\Lambda_0^K(\lambda)}_{\text{initial datum term}} + \underbrace{\text{"small" error}}_{\text{depending on } \tau_K, N_K, w_K!}$$

initial datum term

depending on  $\tau_K, N_K, w_K!$

# THE "SMALL" ERROR

Recall the term  $\frac{w_k}{\tau_k N_k} = \frac{\tau_k^\beta}{\tau_k \tau_k^{-\alpha}} = \tau_k^{\alpha+\beta-1} \approx 1$

$$\begin{aligned} \text{"small" error} &= O\left(\frac{w_k}{\tau_k N_k^2} \|D\phi\|_\infty\right) \checkmark \\ &+ O\left(\frac{w_k^2}{\tau_k N_k} \|D\phi\|_\infty\right) \checkmark \\ &+ O\left(\frac{1}{\tau_k N_k^2} \|D^2\phi\|_\infty\right) \end{aligned}$$

$$\frac{1}{\tau_k N_k^2} = \frac{1}{\tau_k \tau_k^{-2\alpha}} = \tau_k^{2\alpha-1}$$

ASSUMPTIONS:  $\begin{cases} \alpha + \beta = 1 \\ \alpha > \frac{1}{2} \end{cases}$

# COMPACTNESS ?

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AIM: Letting  $\tau_k \rightarrow 0$ ,  $N_k = \tau_k^{-\alpha} \rightarrow +\infty$ ,  $W_k = \tau_k^\beta \rightarrow 0$   
under the assumptions  $\alpha + \beta = 1$ ,  $\alpha > \frac{1}{2}$  and  
passing to the limit

$$\partial_t \Lambda_t^k + \operatorname{div}(b \Lambda_t^k) \approx 0 \xrightarrow{k \rightarrow +\infty} \partial_t \Lambda_t + \operatorname{div}(b \Lambda_t) = 0$$

CAVEAT: The statement is void without compactness

REMARK: •  $t \mapsto \Lambda_t^k \in \mathcal{P}(\Delta^{M-1})$   
•  $(\mathcal{P}(\Delta^{M-1}), \mathcal{W}_1)$  is compact

IF  $t \mapsto \Lambda_t^k$  equicontinuous, THEN use Arzela-Ascoli.

# COMPACTNESS ?

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## EQUICONTINUITY?

$$\alpha + \beta = 1, \alpha > 1/2$$

A rough estimate:  $|\lambda^k(t_{h+1}) - \lambda^k(t_h)| \leq \frac{\sqrt{2}}{N_k}$  a.s.

$$\begin{aligned} \Rightarrow \int_{\Delta^{M-1}} \psi(\lambda) d(\Lambda_{t_{h+1}}^k - \Lambda_{t_h}^k)(\lambda) &= \\ &= \mathbb{E} \left[ \psi(\lambda^k(t_{h+1})) - \psi(\lambda^k(t_h)) \right] \leq \\ &\leq \mathbb{E} \left[ |\lambda^k(t_{h+1}) - \lambda^k(t_h)| \right] \leq \frac{\sqrt{2}}{N_k} = C \tau_k^\alpha \end{aligned}$$

$$\Rightarrow \mathcal{W}_1(\Lambda_{t_{h+1}}^k, \Lambda_{t_h}^k) \leq C \tau_k^\alpha$$

# COMPACTNESS ?

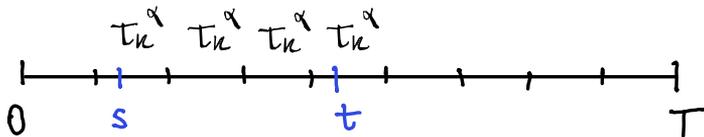
## EQUICONTINUITY?

$$\alpha + \beta = 1, \alpha > 1/2$$

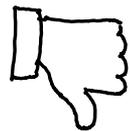
A rough estimate:  $|\lambda^k(t_{h+1}) - \lambda^k(t_h)| \leq \frac{\sqrt{2}}{N_k}$  a.s.

$$\begin{aligned} \Rightarrow \int_{\Delta^{M-1}} \psi(\lambda) d(\Lambda_{t_{h+1}}^k - \Lambda_{t_h}^k)(\lambda) &= \\ &= \mathbb{E}[\psi(\lambda^k(t_{h+1})) - \psi(\lambda^k(t_h))] \leq \\ &\leq \mathbb{E}[|\lambda^k(t_{h+1}) - \lambda^k(t_h)|] \leq \frac{\sqrt{2}}{N_k} = C \tau_k^\alpha \end{aligned}$$

$$\Rightarrow W_1(\Lambda_{t_{h+1}}^k, \Lambda_{t_h}^k) \leq C \tau_k^\alpha$$



$$\frac{|t-s|}{\tau_k} \tau_k^\alpha$$



# COMPACTNESS !

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IDEA: Prove it directly.

- up to a subsequence,  $\Lambda_t^\kappa \xrightarrow{\mathcal{W}_1} \Lambda_t$  for every  $t \in [0, T] \cap \mathbb{Q}$ .
- given  $s, t \in [t_n, t_{n+1}] \cap \mathbb{Q}$ :

$$\begin{aligned} & \int_{\Delta^{M-1}} \phi(\lambda) d(\Lambda_t^\kappa - \Lambda_s^\kappa)(\lambda) \approx \\ & \approx |t-s| \frac{w_\kappa}{\tau_\kappa N_\kappa} \int_{\Delta^{M-1}} D\phi(\lambda) b(\lambda) d\Lambda_{t_n}^\kappa(\lambda) + \\ & + \mathcal{O}\left(\frac{w_\kappa^2}{\tau_\kappa N_\kappa} \|D\phi\|_\infty\right) + \mathcal{O}\left(\frac{w_\kappa}{\tau_\kappa N_\kappa^2} \|D\phi\|_\infty\right) + \mathcal{O}\left(\frac{1}{\tau_\kappa N_\kappa^2} \|D^2\phi\|_\infty\right) \end{aligned}$$

passing to the limit

$$\int_{\Delta^{M-1}} \phi(\lambda) d(\Lambda_t - \Lambda_s) \lesssim |t-s| \Rightarrow \mathcal{W}_1(\Lambda_t, \Lambda_s) \lesssim |t-s|.$$

# MAIN RESULT

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**THEOREM:** Let  $\tau_k \rightarrow 0$ ,  $N_k = \tau_k^{-\alpha}$ ,  $w_k = \tau_k^\beta$  with  $\alpha + \beta = 1$  and  $\alpha > 1/2$ . Let  $\lambda^k: (\Omega, \mathcal{F}, \mathbb{P}) \rightarrow C([0, T]; \Delta^{M-1})$  be the random path generated by the discrete Moran process with population of size  $N_k$ , payoff matrix  $A$  and payoff weight  $w_k$ . Let  $\Lambda_t^k \in \mathcal{P}(\Delta^{M-1})$  be the law of  $\lambda^k(t)$ . Then  $\Lambda_t^k \xrightarrow{w_k} \Lambda_t$  uniformly in  $t \in [0, T]$ , where  $\Lambda_t$  is the unique solution to:

$$\partial_t \Lambda_t + \operatorname{div}(b \Lambda_t) = 0 \quad + \quad \text{initial datum } \Lambda_0$$

Moreover,  $\Lambda_t = \Psi(t, \cdot) \# \Lambda_0$ , where  $\Psi(t, \cdot)$  is the flow of the vector field  $b$ , i.e.,  $\Psi(t, \lambda_0)$  is the solution to

$$\dot{\lambda}(t) = b(\lambda(t)) \quad + \quad \lambda(0) = \lambda_0$$

THANK YOU  
FOR THE ATTENTION

## ESSENTIAL LITERATURE:

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- ▣ F.A.C.C. Chalub, M.O. Souza. Theoretical Population Biology (2009)
- ▣ L. Ambrosio, M. Fornasier, M. Morandotti, G. Savaré. CPAM (2021)