From branching Brownian motion to regularized unbalanced optimal transport

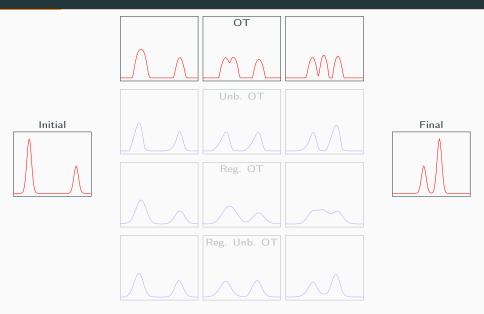
Aymeric Baradat

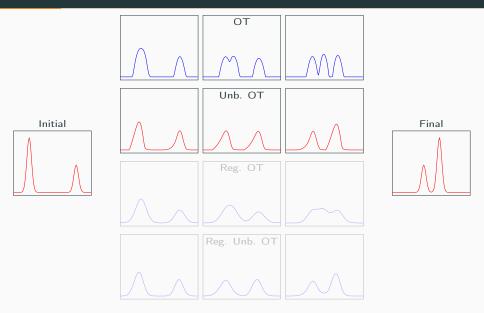
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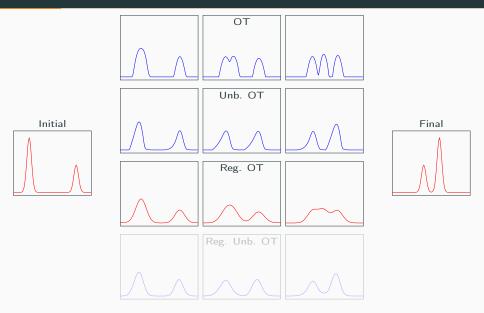
Work in progress in collaboration with Hugo Lavenant, from Bocconi University in Milan.

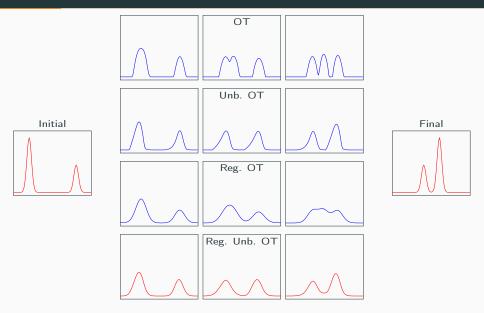




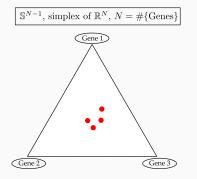




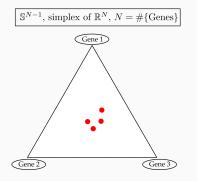




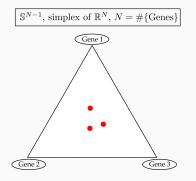
Can we describe quantitatively the process of specialization of the cells of an individual during its development?



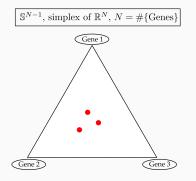
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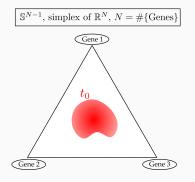
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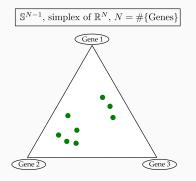
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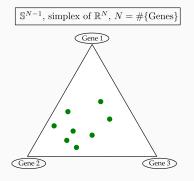
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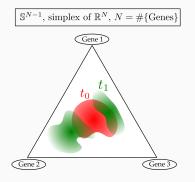
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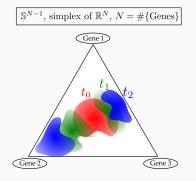
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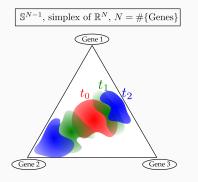


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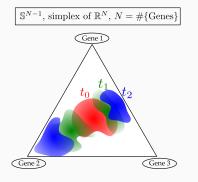
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<u>Question</u>: How to interpolate between these different intensities? Schiebinger & *al.* 2019 (Cell), Lavenant & *al.* 2021 (preprint).

Let $\rho_0, \rho_1 \in \mathcal{M}_+(\mathbb{T}^d)$. Our optimization problem reads

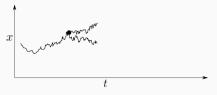
Among those fields $\rho = \rho(t, x)$, v = v(t, x), r = r(t, x) satisfying: $\begin{cases}
\partial_t \rho + \operatorname{div}(\rho v) = \frac{\nu}{2} \Delta \rho + \rho r, \\
\rho|_{t=0} = \rho_0, \quad \rho|_{t=1} = \rho_1,
\end{cases}$ find the ones minimizing:

$$\int_0^1 \int \left\{ \frac{1}{2} |v(t,x)|^2 + \Psi(r(t,x)) \right\} \rho(t,\mathrm{d}x) \,\mathrm{d}x \,\mathrm{d}t.$$

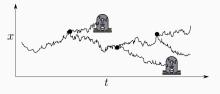
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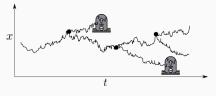
Question: How to chose Ψ ?



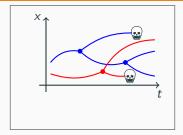


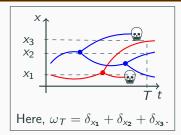


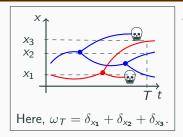
We choose the model of **branching Brownian motion**: each particle of diffusivity $\nu > 0$ has a random lifetime of law $\mathcal{E}xp(\lambda)$, $\lambda > 0$. When it dies, it gives birth to $k \in \mathbb{N}$ particles with probability $p_k \in [0, 1]$.



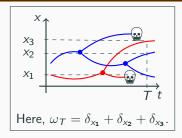
<u>Remark</u>: λ and **p** could depend on t and x: $\lambda(t, x) dt$ represents the probability for a particle in (t, x) to die between t and t+dt. Then, $p_k(t, x)$ is the probability that it is replaced by k particles.



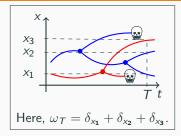




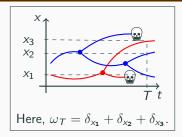
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- $R \in \mathcal{P}(\Omega)$: law of BBM of parameters ν , λ and $\mathbf{p} = (p_k)_k$, of initial law $R_0 \in \mathcal{P}(\mathcal{M}_{\delta}(\mathbb{T}^d))$.



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Fixing the marginals $ho_0,
ho_1 \in \mathcal{M}_+(\mathbb{T}^d)$, our minimization problem reads:

Among those $P \in \mathcal{P}(\Omega)$ satisfying for all $A \in \mathcal{B}(\mathbb{T}^d)$: $\mathbb{E}_P[\omega_0(A)] = \rho_0(A)$ and $\mathbb{E}_P[\omega_1(A)] = \rho_1(A)$. find the ones minimizing $H(P|R) := \mathbb{E}_R\left[\frac{\mathrm{d}P}{\mathrm{d}R}\log\frac{\mathrm{d}P}{\mathrm{d}R}\right] = \mathbb{E}_P\left[\log\frac{\mathrm{d}P}{\mathrm{d}R}\right]$.

Equivalence of the models

RUOT

Branching Schrödinger

R BBM of initial law R_0 , of parameter ν , λ and **p**. Find $P \in \mathcal{P}(\Omega)$ s.t.

$$E_P[\omega_i(A)] = \frac{\rho_i}{A}, \quad i = 0, 1,$$

minimizing H(P|R).

Equivalence of the models

RUOT

Let $\nu > 0$ and Ψ a function. Find (ρ, ν, r) s.t. $\begin{cases} \partial_t \rho + \operatorname{div}(\rho \nu) = \frac{\nu}{2} \Delta \rho + \rho r, \\ \rho|_{t=0} = \rho_0, \quad \rho|_{t=1} = \rho_1, \\ \\ \text{minimizing} \\ \int_0^1 \int \left\{ \frac{|\nu|^2}{2} + \Psi(r) \right\} \rho \, \mathrm{dx} \, \mathrm{dt}. \end{cases}$ Branching Schrödinger

R BBM of initial law R_0 , of parameter ν , λ and \boldsymbol{p} . Find $P \in \mathcal{P}(\Omega)$ s.t. $E_P[\omega_i(A)] = \rho_i(A), \quad i = 0, 1,$ minimizing H(P|R).

Main result (BL): If Ψ is defined via its Legendre transform by:

$$\Psi^*(s) = \nu \lambda \sum p_k \left\{ e^{(k-1)\frac{s}{\nu}} - 1 \right\},\,$$

The minimum in RUOT is the l.s.c. relaxation of the infimum in Branching Schrödinger, up to an initial term.

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<u>A counter-example to equality</u>: In RUOT, we can connect 0 to $\rho_1 \neq 0$. In branching Schrödinger it is not possible.

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