# UMR 7083 Fluctuations in cell lineages and population trees Arthur Genthon

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### Abstract

Experiments on growing cells can be carried out either in bulk (population experiments) or in confined geometries that constrain the growth of the colony (e.g. single-lineage experiments). These two setups generate different statistics, as cells with high reproductive success are over-represented in the population, while no such effect occurs in single-lineage experiments. This bias has thus been proposed as a model-independent measure of fitness and selection [1]. We study this bias, akin to fluctuation theorems in stochastic thermodynamics, and derive a series of results analogous to Jarzynski equality, the second law, and fluctuation-dissipation theorems far from equilibrium, which establish general principles of evolution.

# Single-lineage experiments [2]

## **Population experiments** [1]





 $\omega_{\text{back}} = \frac{1}{10}$ 

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**Backward sampling**:  $\omega_{\text{back}}(l) = 1/N(t)$ .

 $\rightarrow$  Over-represents lineages that divided more than average

Forward sampling:  $\omega_{\text{for}}(l) = 2^{-K(l)} / N_0$ .

 $\rightarrow$  Cancels the effect of selection of successful lineages  $\rightarrow$  Reproduces statistics from single lineage experiments

## Flucutation theorem and consequences [4]

The forward-backward (or lineage-population) bias is expressed as a **fluctuation theorem**:

$$p_{\text{back}}(K,t) = p_{\text{for}}(K,t) e^{K \ln 2 - t\Lambda_t}$$
 with  $\Lambda_t = \frac{1}{t} \ln \frac{N(t)}{N_0}$ : population growth rate

Jarzynski equality

$$\Lambda_t = \frac{1}{t} \ln \langle 2^K \rangle_{\text{for}}$$

Population growth rate estimator from the statistics of *L* independent single lineages [3]:



Second law

$$\frac{t}{\langle K \rangle_{\text{back}}} \le \frac{\ln 2}{\Lambda_t} \le \frac{t}{\langle K \rangle_{\text{for}}}$$

When  $t \rightarrow \infty$  (+ dynamical conditions), inequality between mean generation times and population dou-



$$\langle \tau \rangle_{\text{back}} \leq T_d \leq \langle \tau \rangle_{\text{for}}$$

Cells divide faster in populations!

## Fitness and selection [1]

Fitness landscape: captures correlations between a cell trait *s* and the number of divisions:

 $h_t(s) = \Lambda_t + \frac{1}{t} \ln \left[ \frac{p_{\text{back}}(s, t)}{p_{\text{for}}(s, t)} \right]$ 

Strength of selection: change in mean fitness between the ensembles with (backward) and without (forward) selection:

 $\Pi_{\mathcal{S}} = \langle h_t(s) \rangle_{\text{back}} - \langle h_t(s) \rangle_{\text{for}}$ 

Fluctuation-response relations for the selection strength [5]

The strength of selection is bounded by the fluctuations in fitness ( $\sigma(h_t)$ ) and by the  $\chi^2$  distance:

 $\Pi_{\mathcal{S}} \leq \min \left| \sigma_{\text{for}}(h_t) \chi^2(p_{\text{back}}; p_{\text{for}}), \sigma_{\text{back}}(h_t) \chi^2(p_{\text{for}}; p_{\text{back}}) \right|$ 

Case of equallity in the limit of small selection:

 $\Pi_{S} \sim t \sigma^{2}(h_{t})$  (// Fisher's theorem of natural selection)

A lower bound depending on the fluctuations in fitness landscape is also derived:

 $\Pi_{\mathcal{S}} \geq \mathcal{L}_{\mathcal{S}}(\sigma_{\text{for}}(h_t), \sigma_{\text{back}}(h_t))$ 

# Lineage statistics in presence of cell death [7]



## References

[1] T. Nozoe et al. PLoS Genet. (2017). [2] P. Wang et al. Curr. Biol. (2010). [3] Y. Tanouchi et al. Sci. Data (2017). [4] A. Genthon et al. Sci. Rep. (2020). [5] A. Genthon et al. Phys. Rev. Research (2021). [6] Y. Wakamoto et al. Science (2013). [7] A. Genthon et al. arXiv:2305.05406 (2023).