

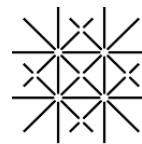
# Influenza: Limited predictability of evolution Ecology of host and pathogen

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**John Huddleston**  
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The Center for  
Molecular Life Sciences

# Human seasonal influenza virus

~ hundreds of million cases / year —► 5-10 % of humans

In constant evolution (especially surface proteins HA & NA)

Generation time ~ 1 week

—► Pop. size ~ 10e6 - 10e7

A/H3N2: HA phylogenetic tree

~ 5e-3 AA mutations / year / site (HA)

—► 2-3 AA changes / year

Variability in the present population

2000

2005

2010

2015

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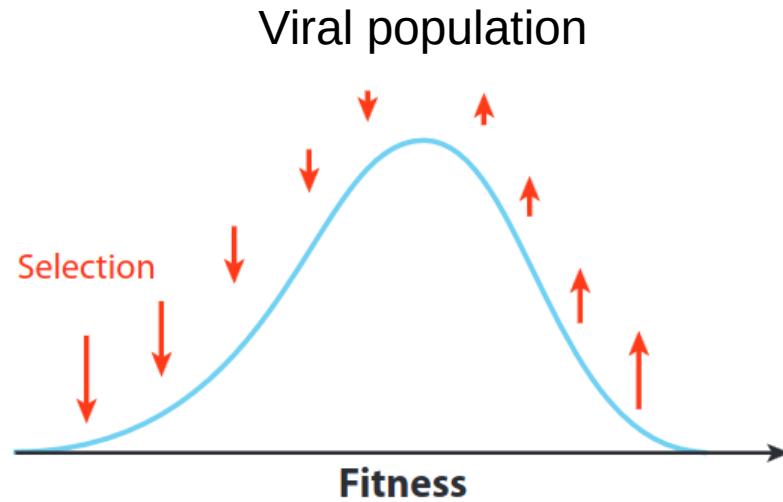
2005

2010

2015

?

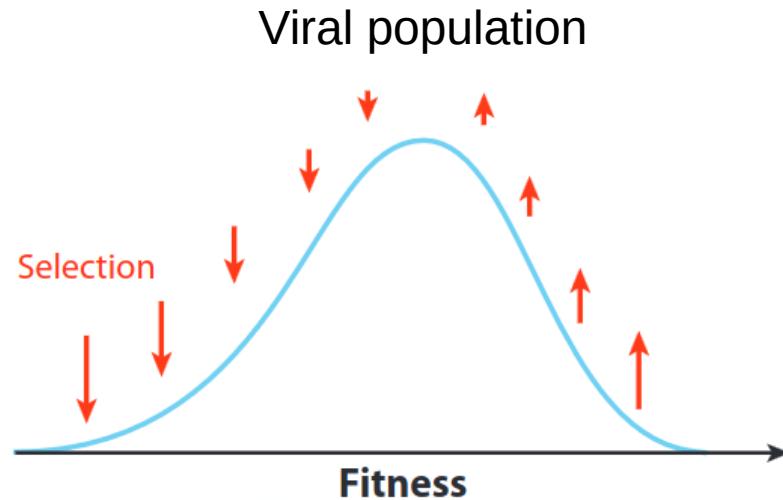
# Traditional approach: travelling fitness wave



- Mutations have a fixed fitness effect
- Fitness determines the fate of a mutant
- Extra-complexity: competition between mutants

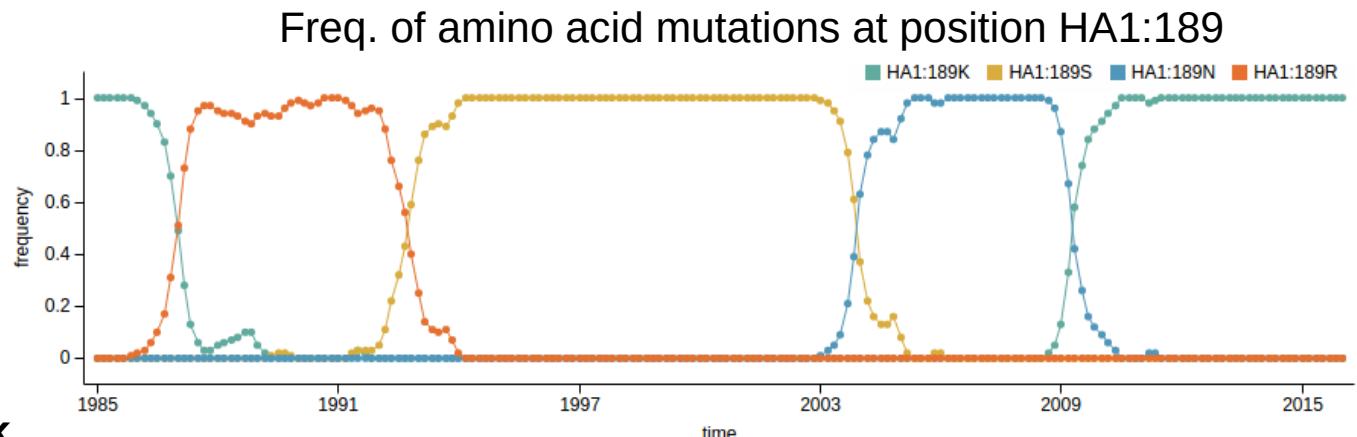
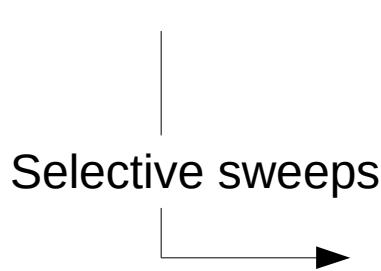
→ **Some degree of predictability**

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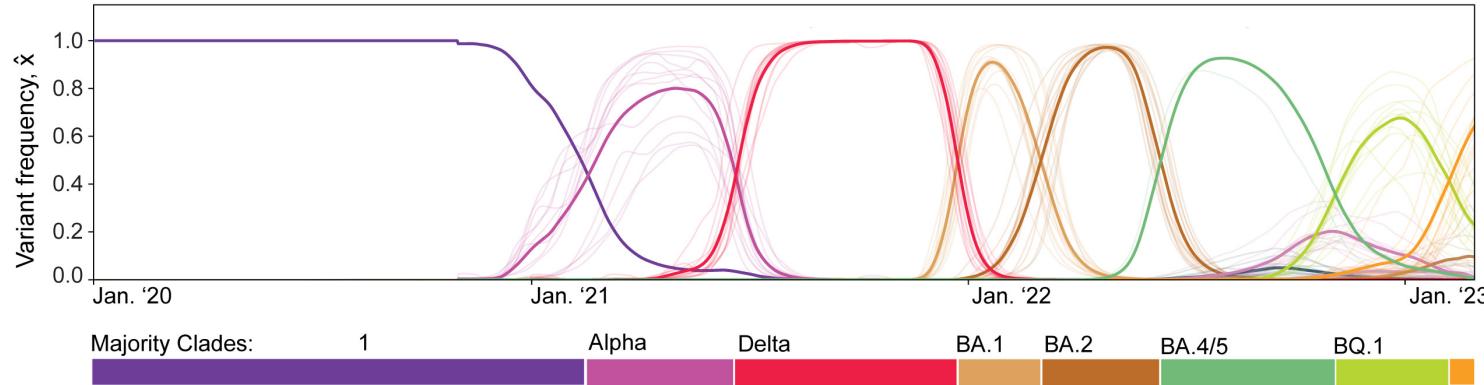
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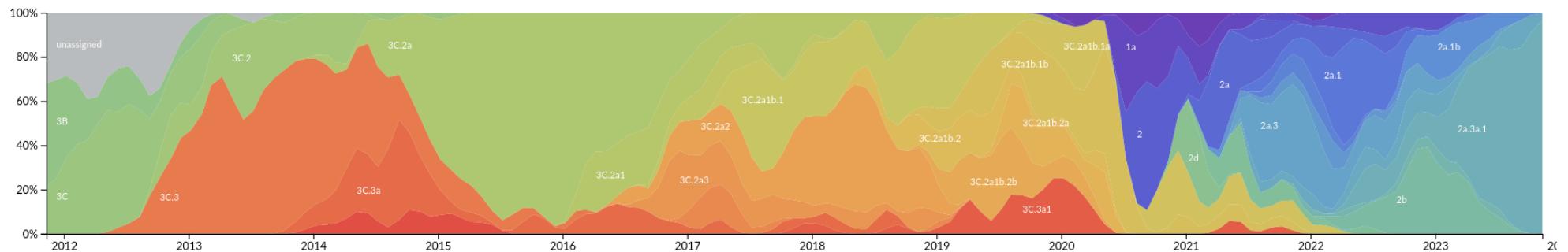
Is this the right way to think  
about the process?

# Clade frequencies: SARS-CoV-2 & Influenza

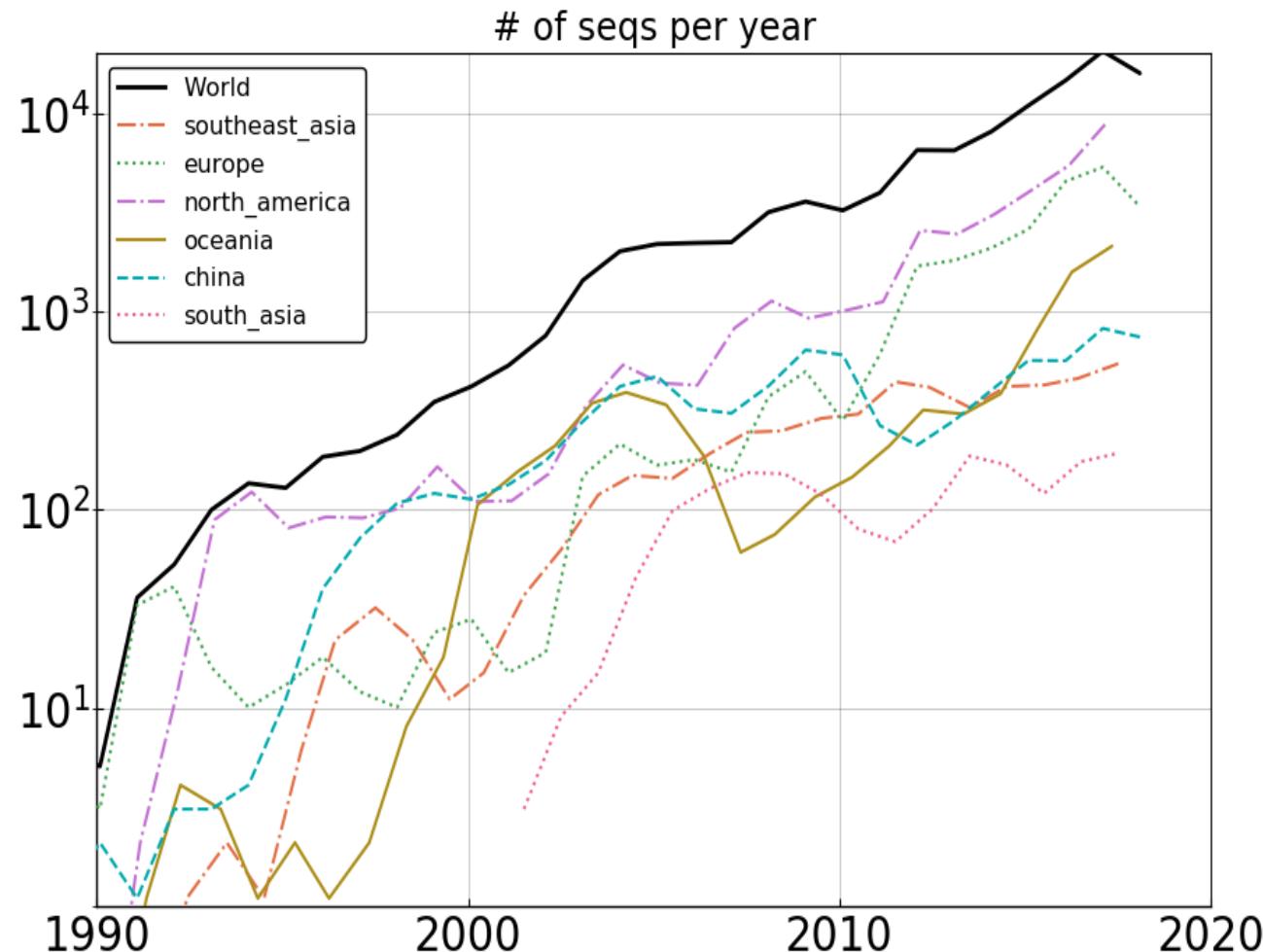
## Covid



## H3N2 Influenza



# Data

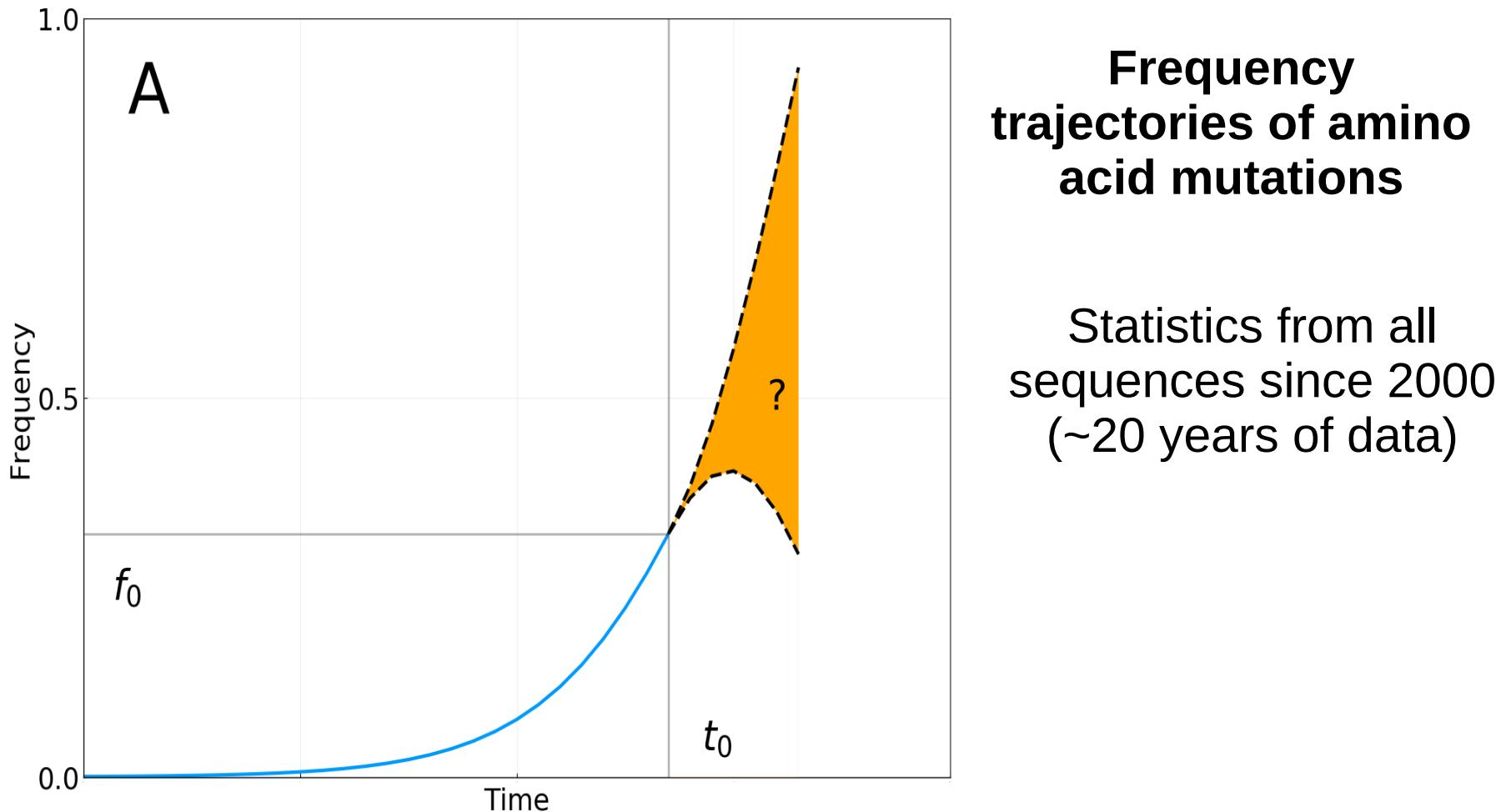


Time-binning of the past sequences by 1 month intervals

→ **Snapshots of the population**

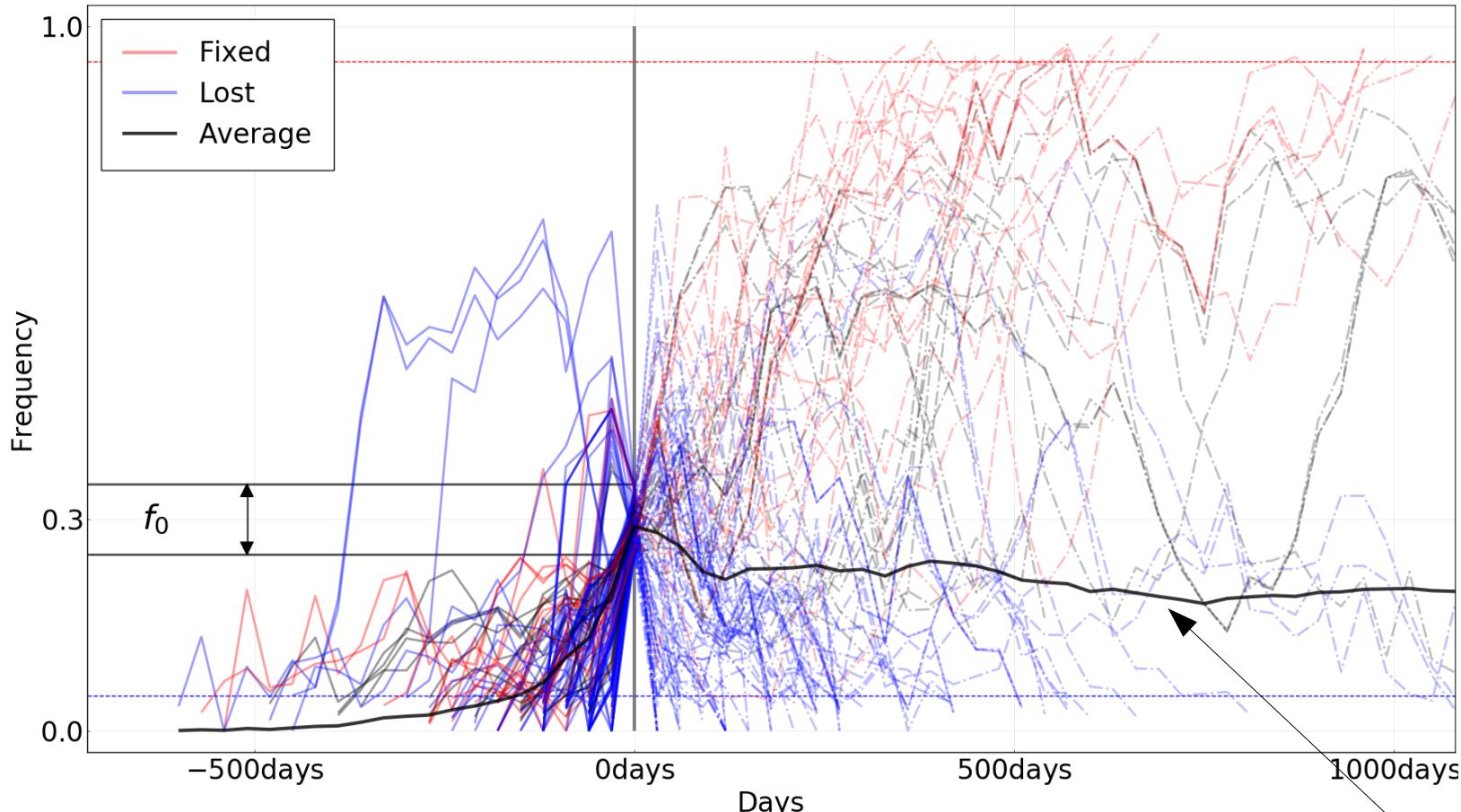
→ **Frequency trajectories**

# Simple analysis: predictability of influenza



# Inertia of trajectories

Influenza H3N2, HA protein



## Mutations:

- Absent in the past
- Seen around  $f_0=30\%$

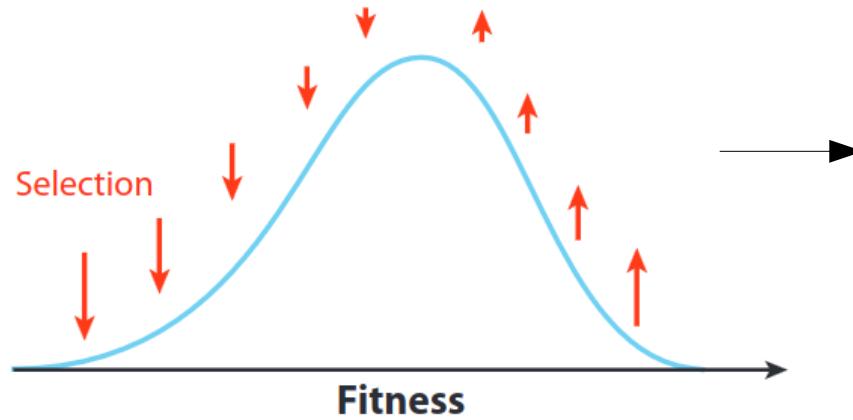
Average

► No inertia

# Using a proxy for fitness

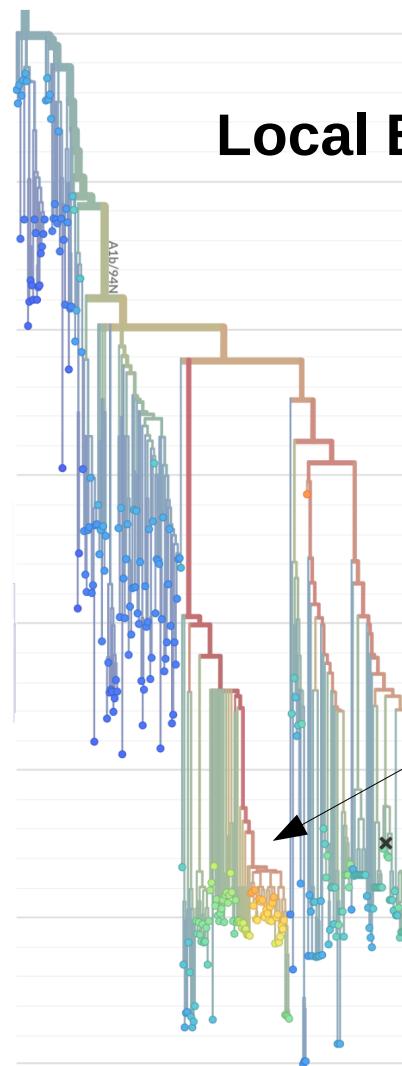
Neher, 2014

Viral population



## Local Branching Index (LBI)

Strains with high fitness have more offsprings

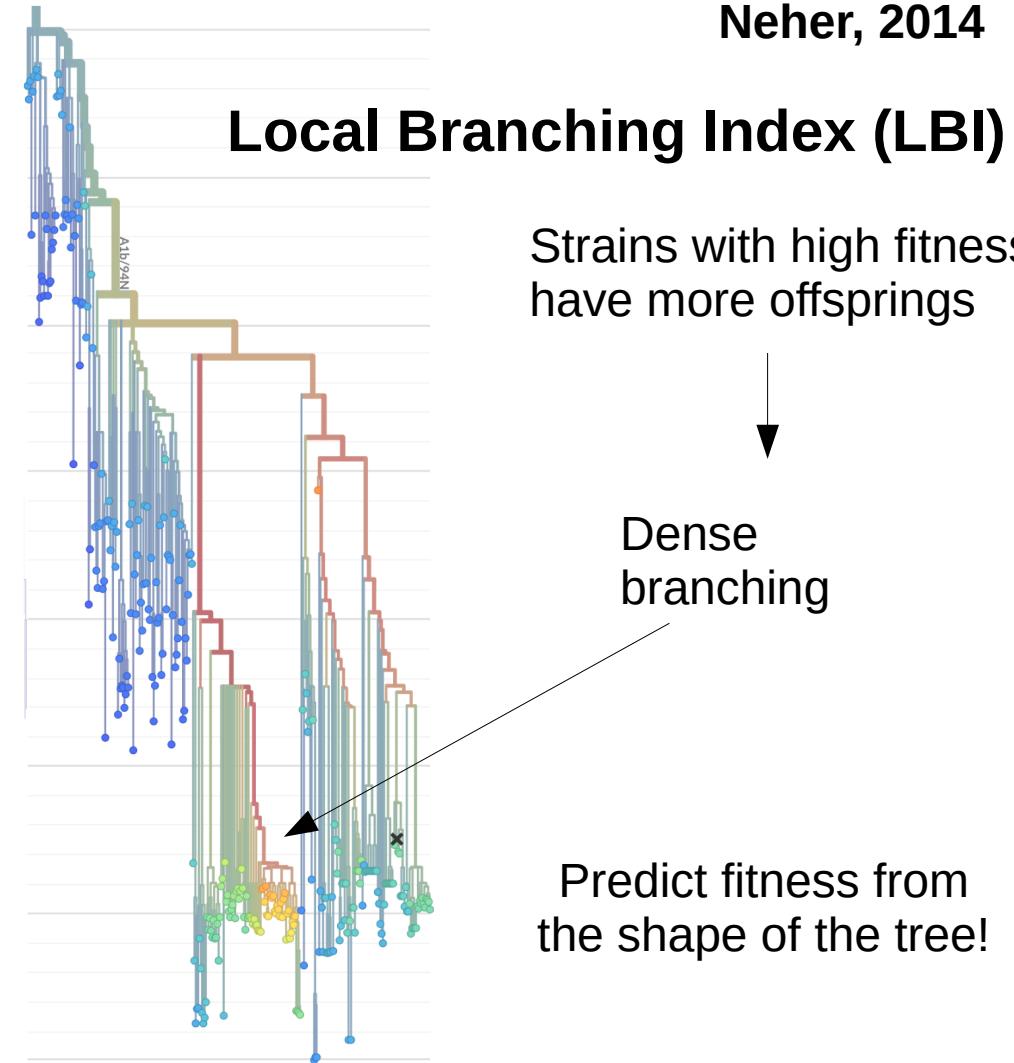
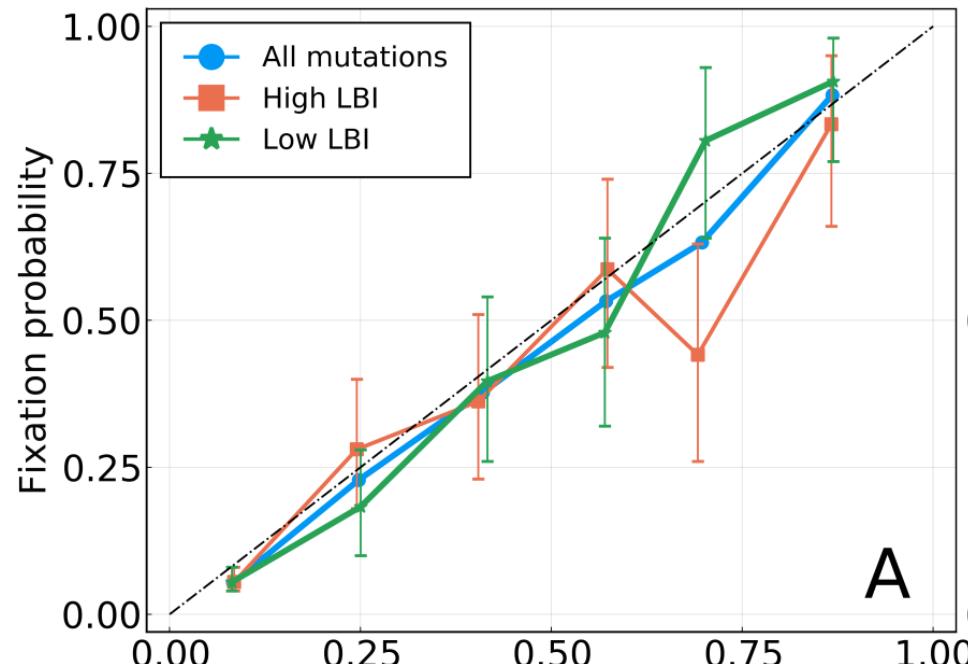


Dense  
branching

Predict fitness  
from the shape of the tree!

# Using a proxy for fitness

Neher, 2014



Strains with high fitness have more offsprings

Dense branching

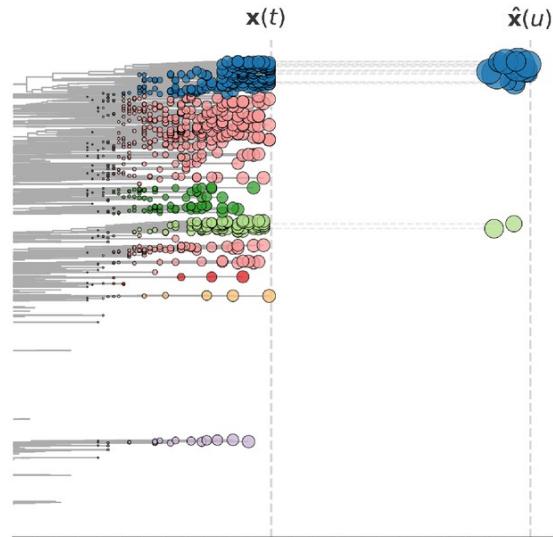
Predict fitness from the shape of the tree!

# Strain level forecast

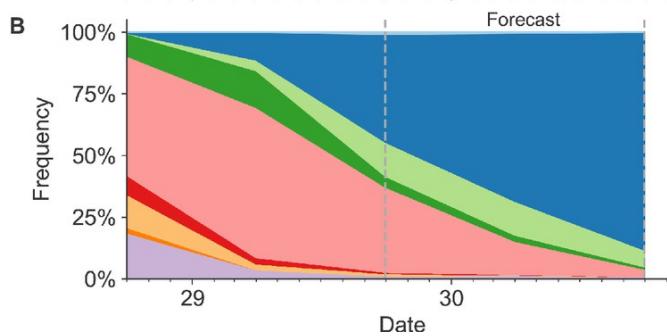
Huddleston et. al. 2020

- Predict a fitness for each strain --> fit model to data (LBI, antigenic novelty, ...)
- Forecast future population 1 year ahead

A



B

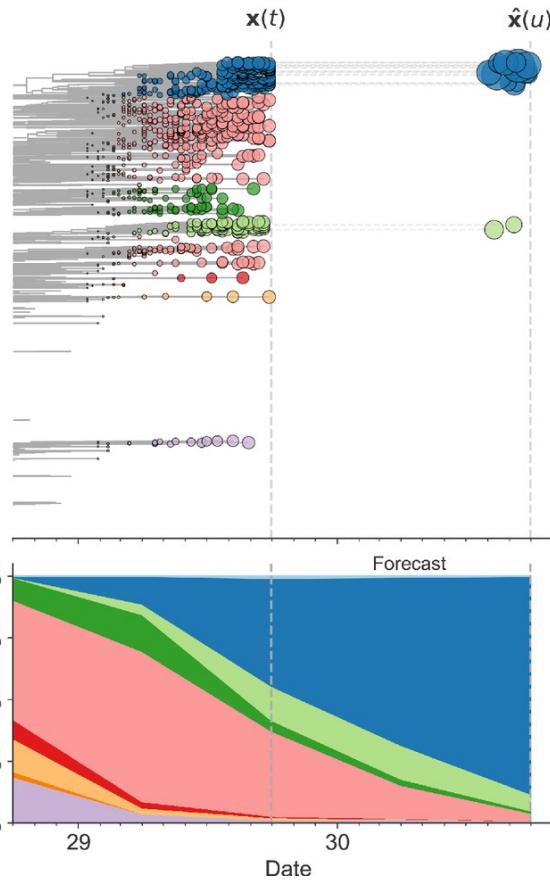


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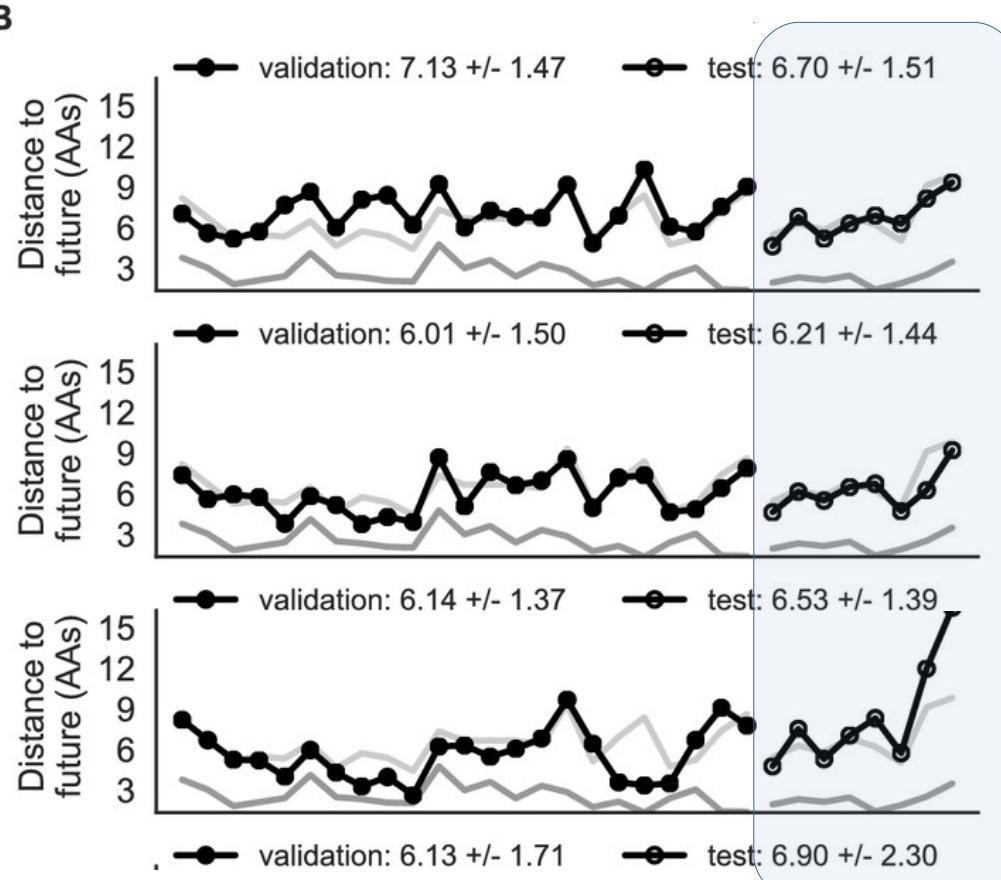
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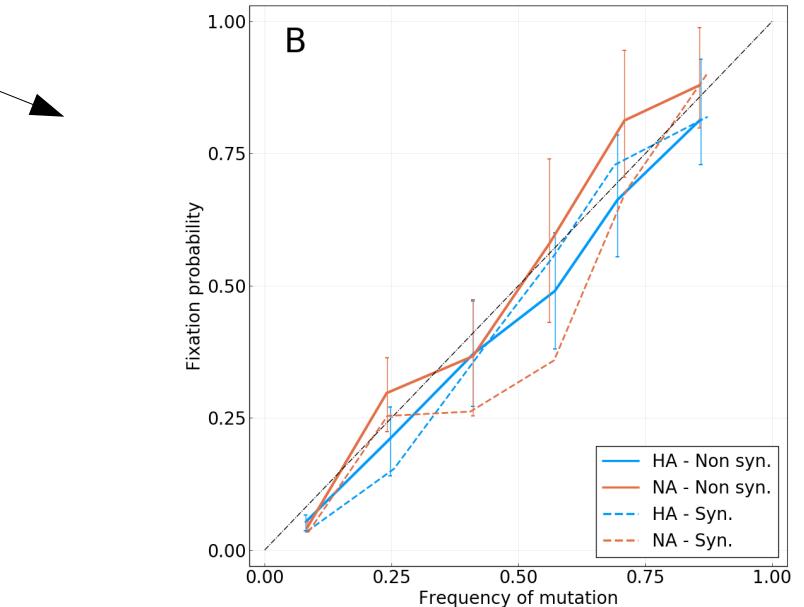
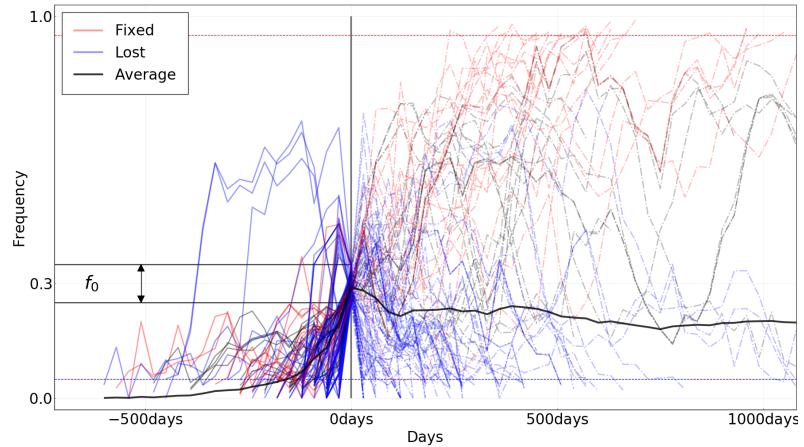
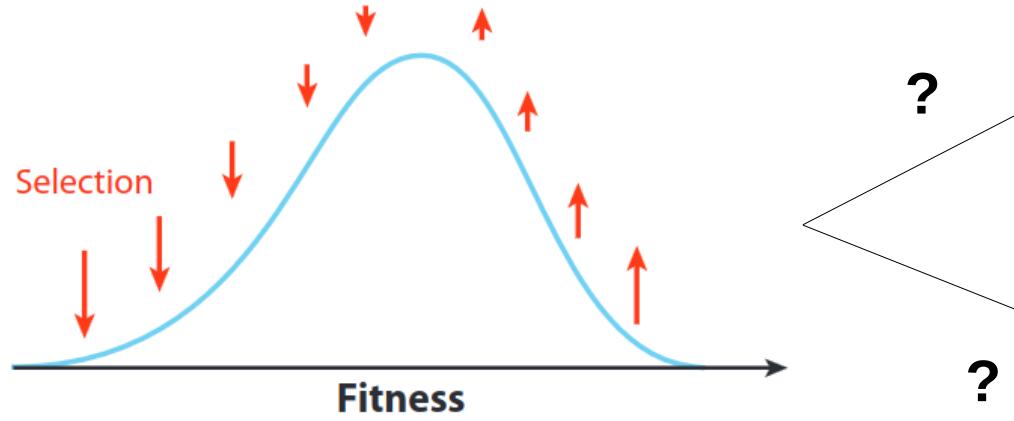
A



B



# Limited predictability

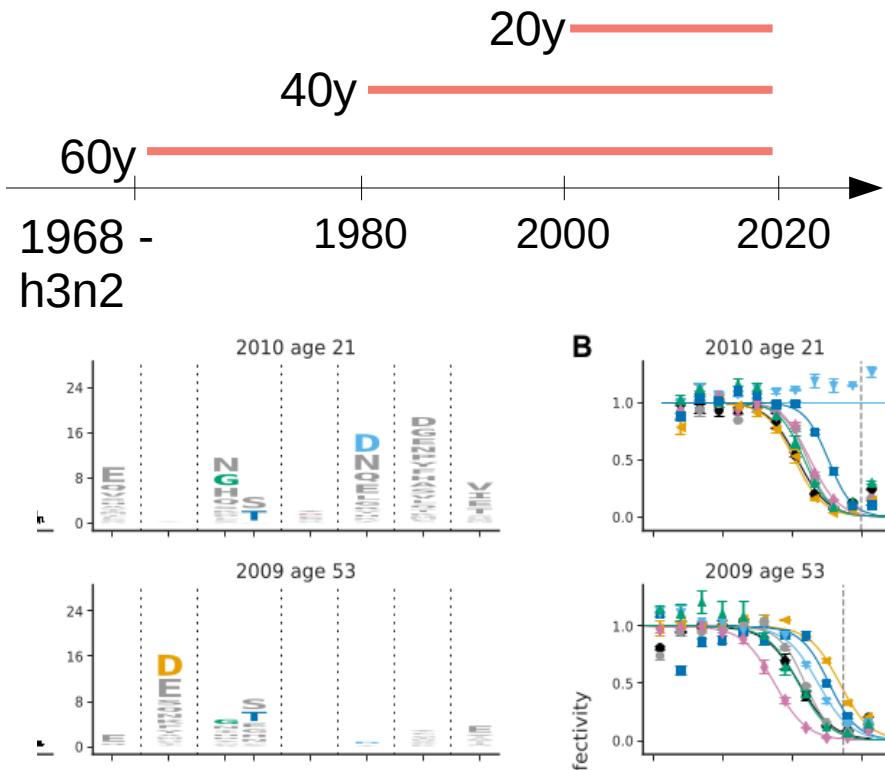


Qualitative difference between  
model and observations

# Adaptive immunity and expiring fitness

## Adaptation is driven by immunity

- Most adaptive mutations escape immunity
- They only escape a fraction of the host population



## Adaptive immunity of hosts

- fitness advantage expires before fixation
- “ecology”: organisms shape their environment

→ Model hosts' immunity explicitly

[Lee et. al., eLife 2019]

# Susceptible – Infected model

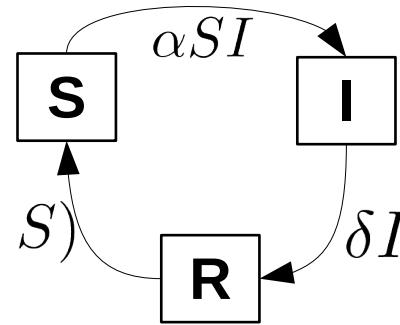
One viral strain

$$\dot{S} = -\alpha SI + \gamma(1 - S)$$

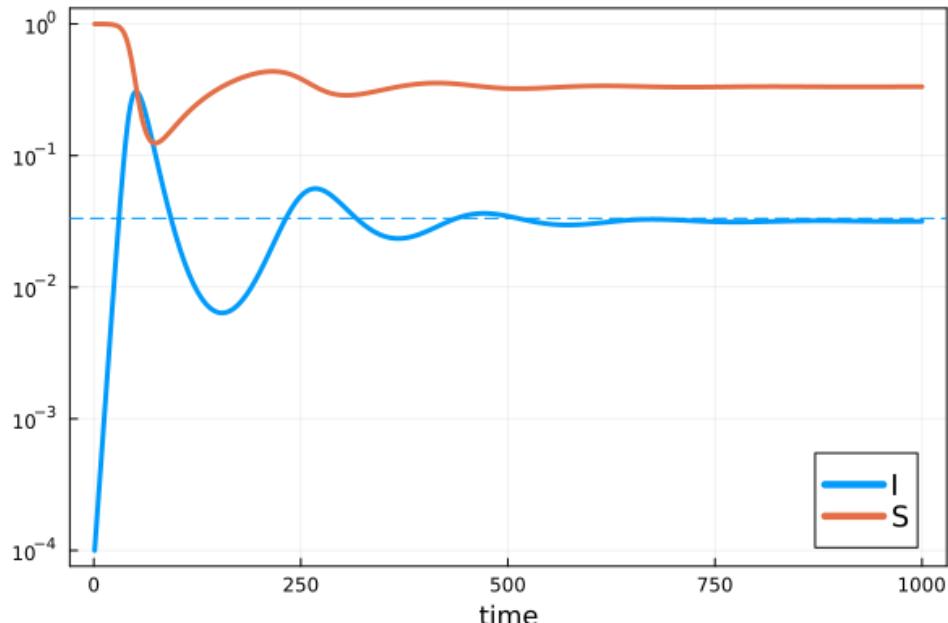
$$\dot{I} = \alpha SI - \delta I$$

Host population

$$S + I + R = 1$$



Initially naive pop.



$$I_{eq} = \frac{\gamma}{\delta}(1 - \delta\alpha^{-1})$$

# SI model

Two strains: wild-type and mutant

$$\dot{S}^a = -\alpha S^a \sum_{b \in \{wt, m\}} K^{ab} I^b + \gamma(1 - S^a)$$

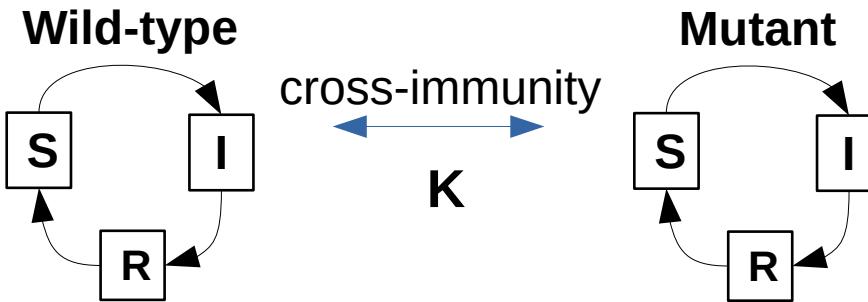
$$\dot{I}^a = \alpha S^a I^a - \delta I^a$$



Equilibrium

$$S = \frac{\delta}{\alpha}$$

$$I = \frac{\gamma}{\delta} (1 - \delta/\alpha) \mathbf{K}^{-1} \vec{1}$$



cross-immunity

$$K = \begin{bmatrix} 1 & b \\ f & 1 \end{bmatrix}$$

immune to wt after  
infection by mut.

immune to mut after  
infection by wt

- No notion of “fitness”
- Mutant is **different**, not better

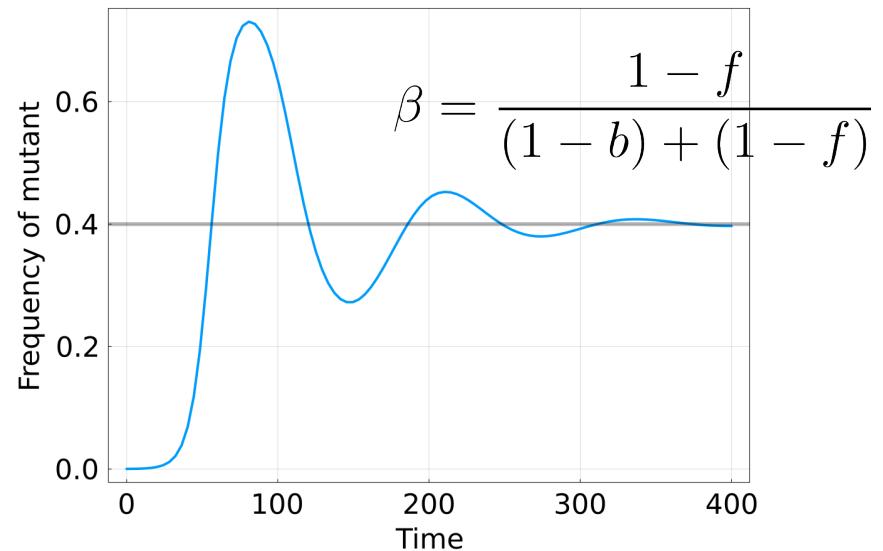
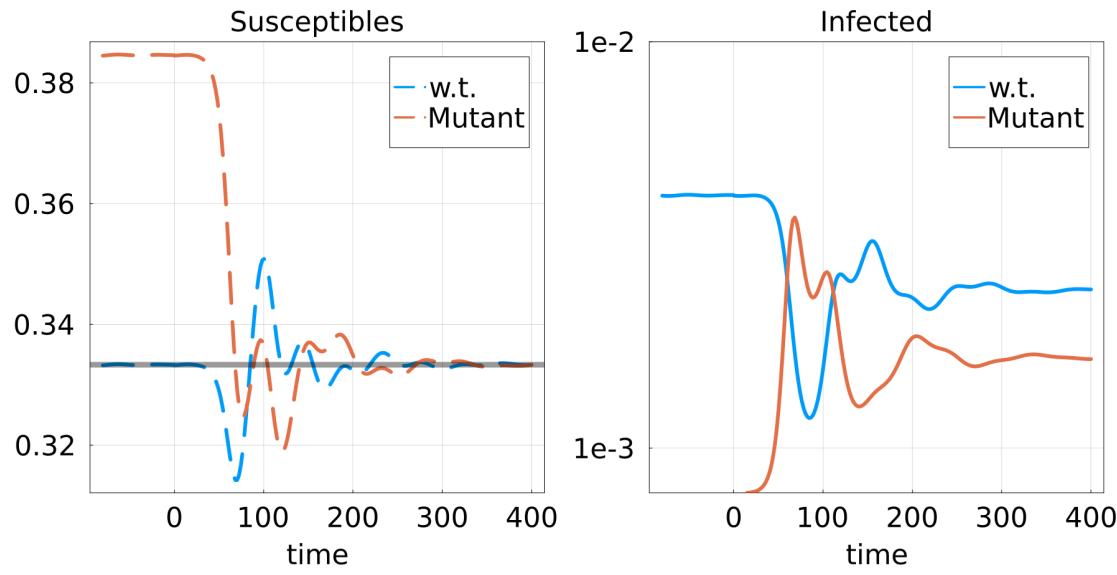
# Partial sweep with SI model

One **wild-type** virus, one **mutant**

$$K = \begin{bmatrix} 1 & b \\ f & 1 \end{bmatrix} \quad (b = 0.7, f = 0.8)$$

**cross-immunity**

Initially, no mutant  $I^{mut} = 0$  - At  $t = 0$ , introduce mutant



# Immune groups: regularize the dynamics

Hosts split into **M** immune groups, with different cross-immunity

Mutant is adaptive in group 1

Very close to w.t. in other groups

$$K_1 = \begin{bmatrix} 1 & b \\ f & 1 \end{bmatrix}$$

$$K_{i>1} = \begin{bmatrix} 1 & 1 - \varepsilon \\ 1 - \varepsilon & 1 \end{bmatrix}$$

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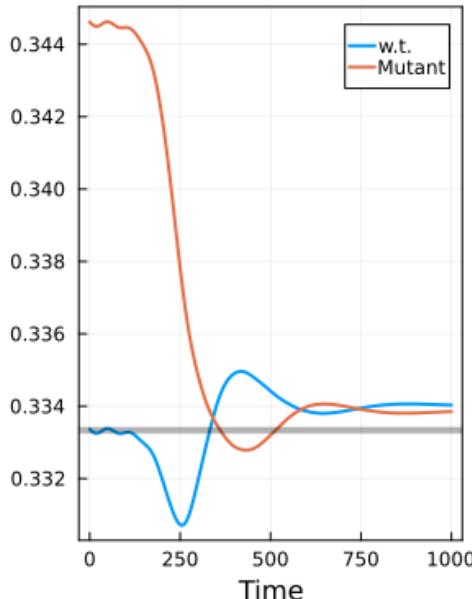
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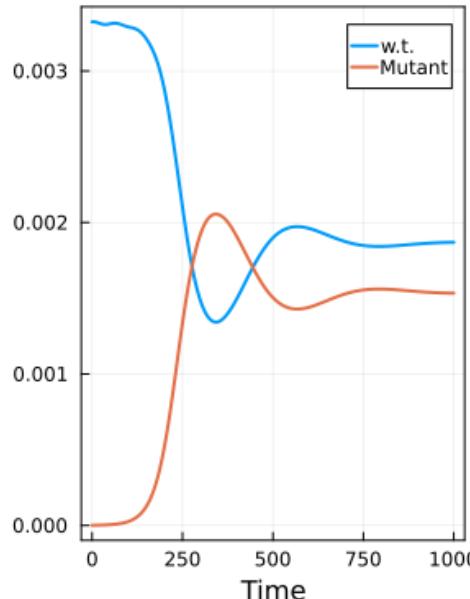
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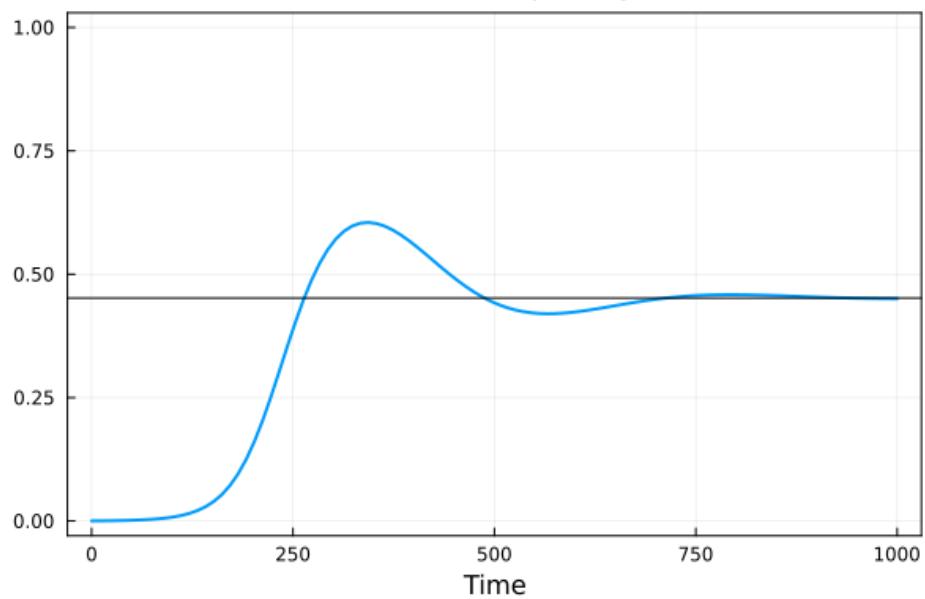
Susceptibles (all groups)



Infectious (all groups)



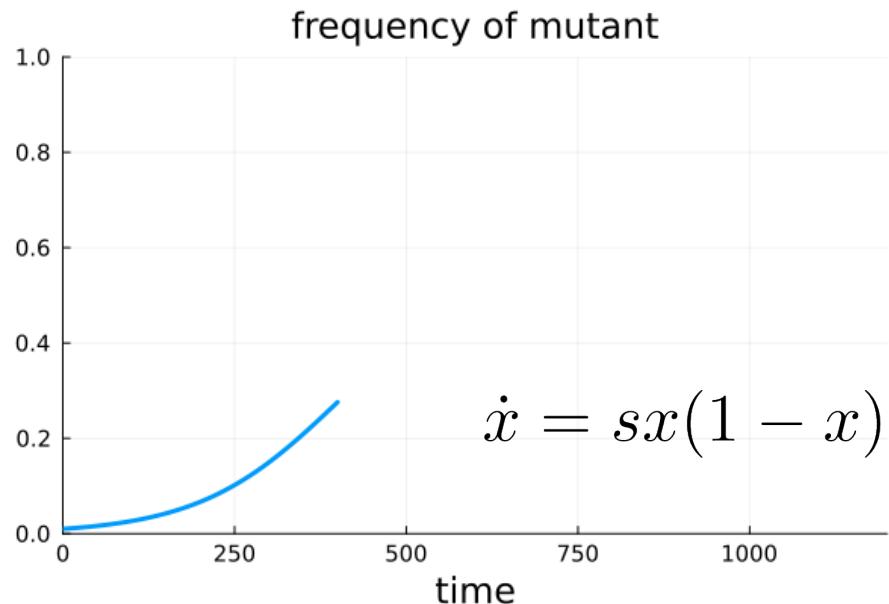
Mutant frequency



# Adaptive immunity and expiring fitness

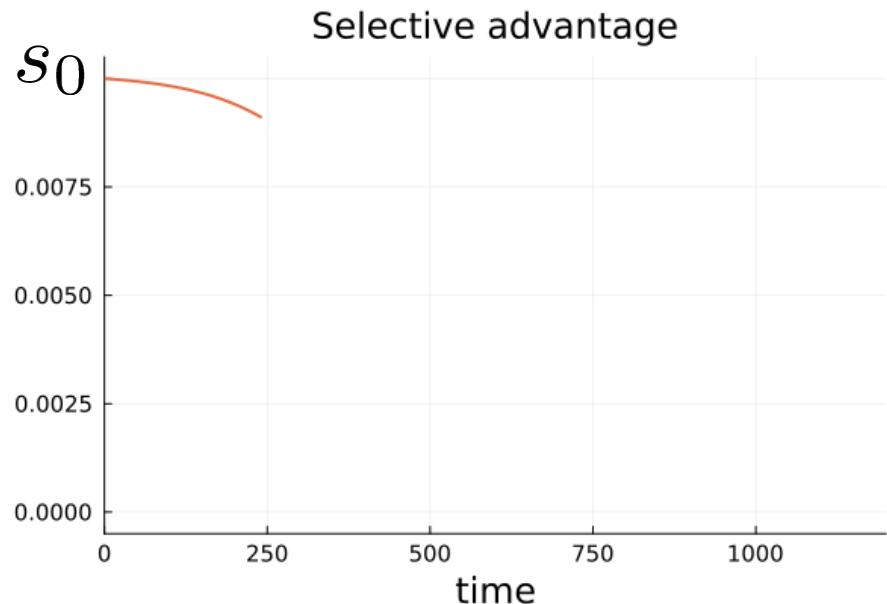
## Adaptation is driven by immunity

- Most adaptive mutations escape immunity
- They only escape a fraction of the host population



## Adaptive immunity of hosts

- fitness advantage expires before fixation
- “ecology”: organisms shape their environment



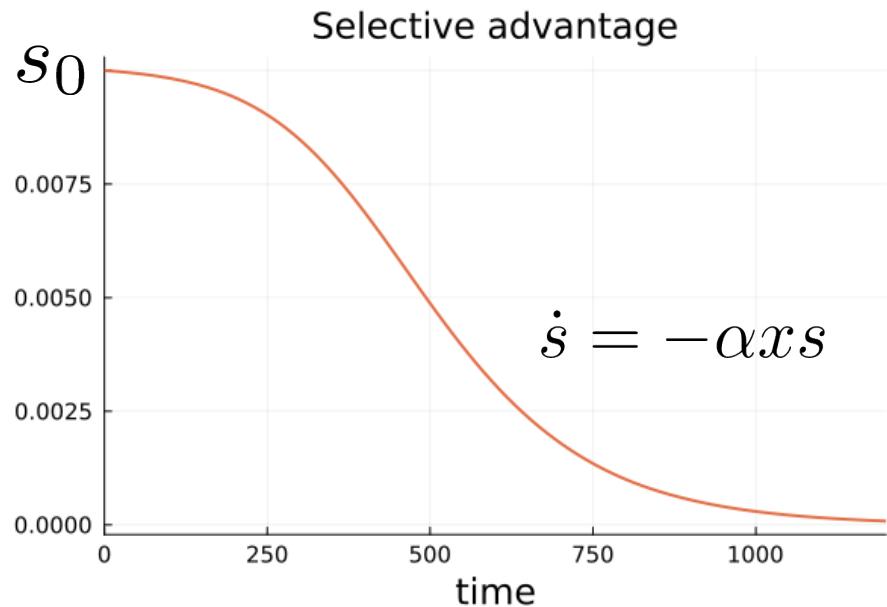
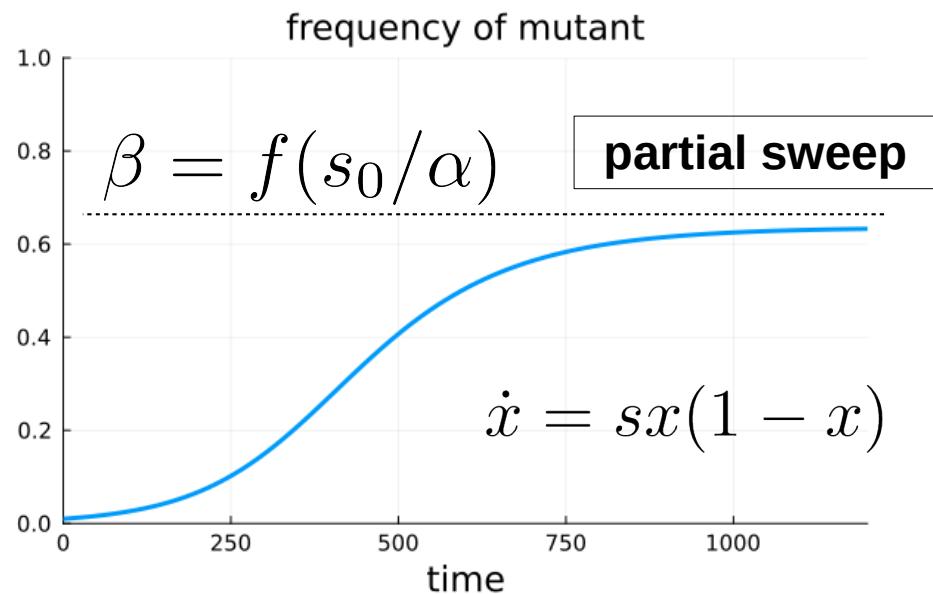
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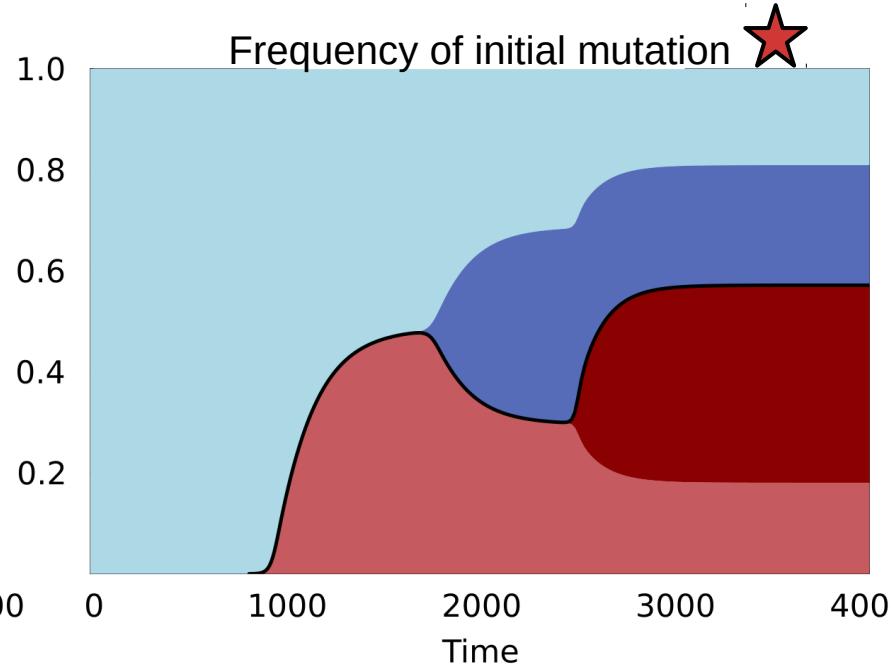
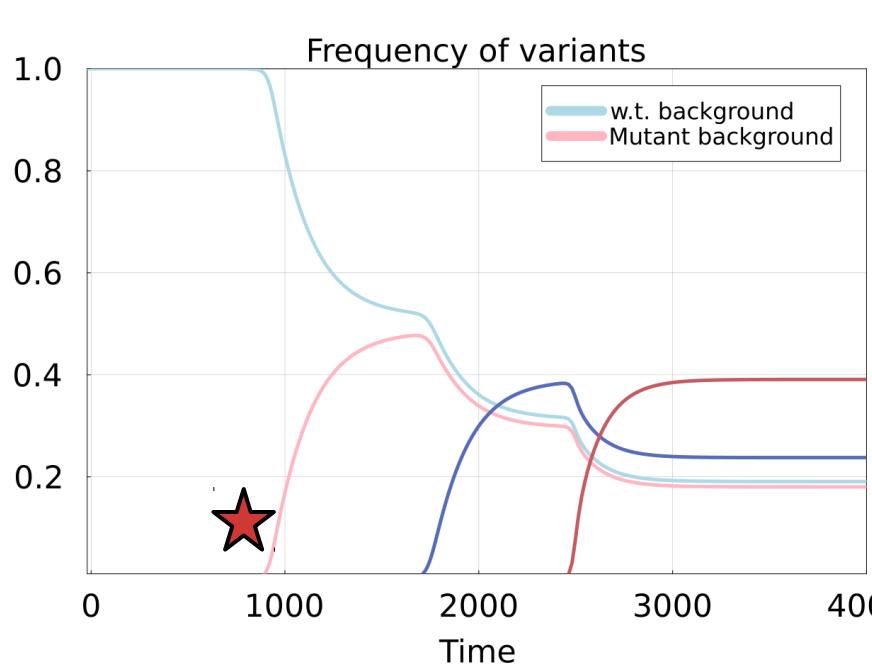
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Used to model covid evolutionary dynamics [Meijers et. al., Cell 2023]

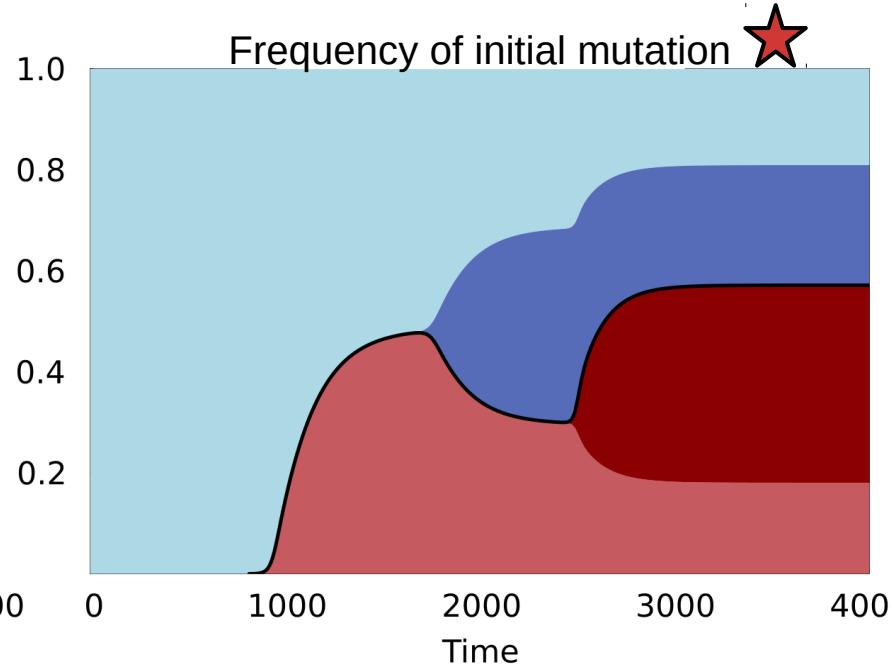
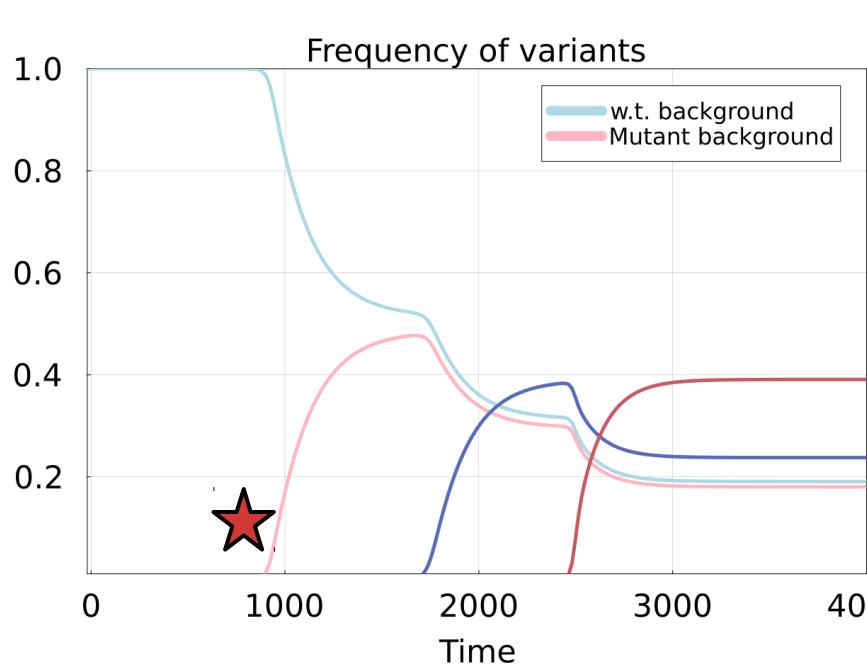
# Evolution with partial sweeps

New variants appear at rate  $\rho$



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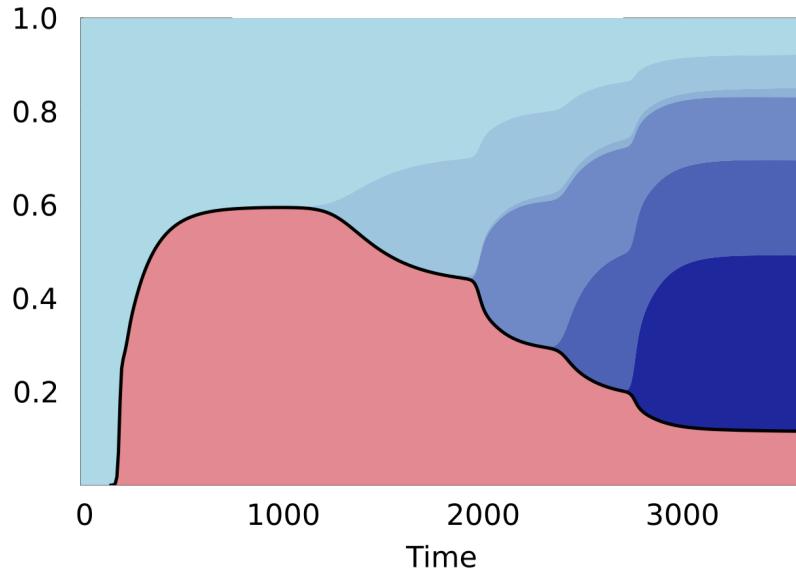
Limit case: non overlapping partial sweeps

$$x_{t+1} = x_t + \begin{cases} \beta(1 - x_t) & \text{with prob. } x_t, \\ -\beta x_t & \text{with prob. } 1 - x_t, \end{cases}$$

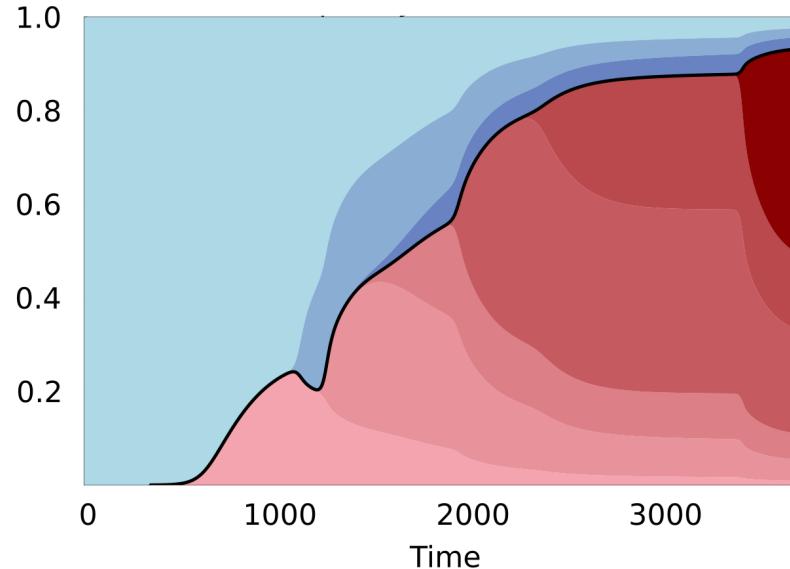
# Evolution with partial sweeps

New variants appear at rate  $\rho$

Mutant vanishes (“sweeps”)



Mutant fixes (“sweeps”)



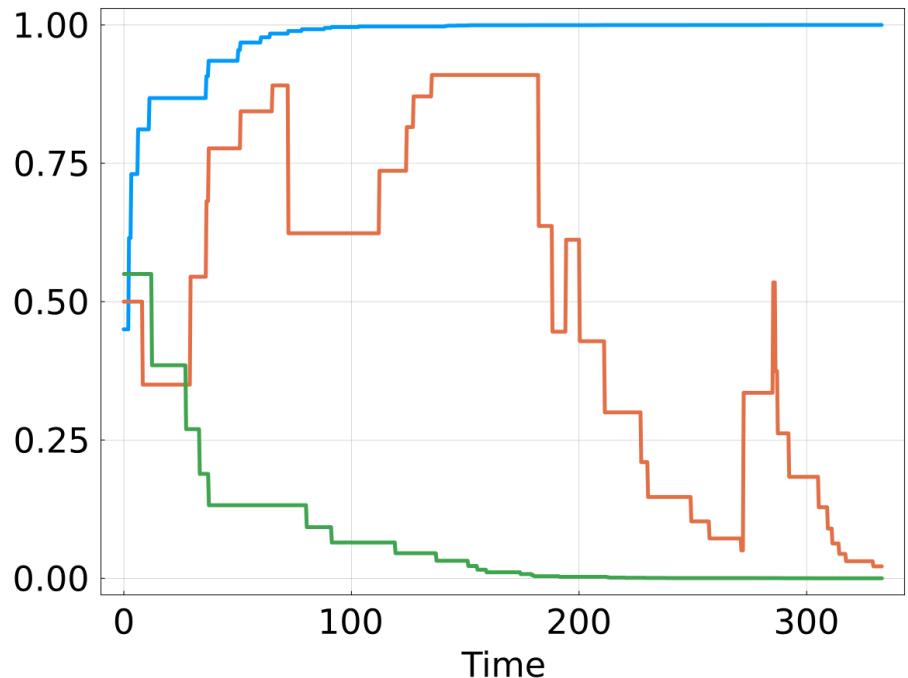
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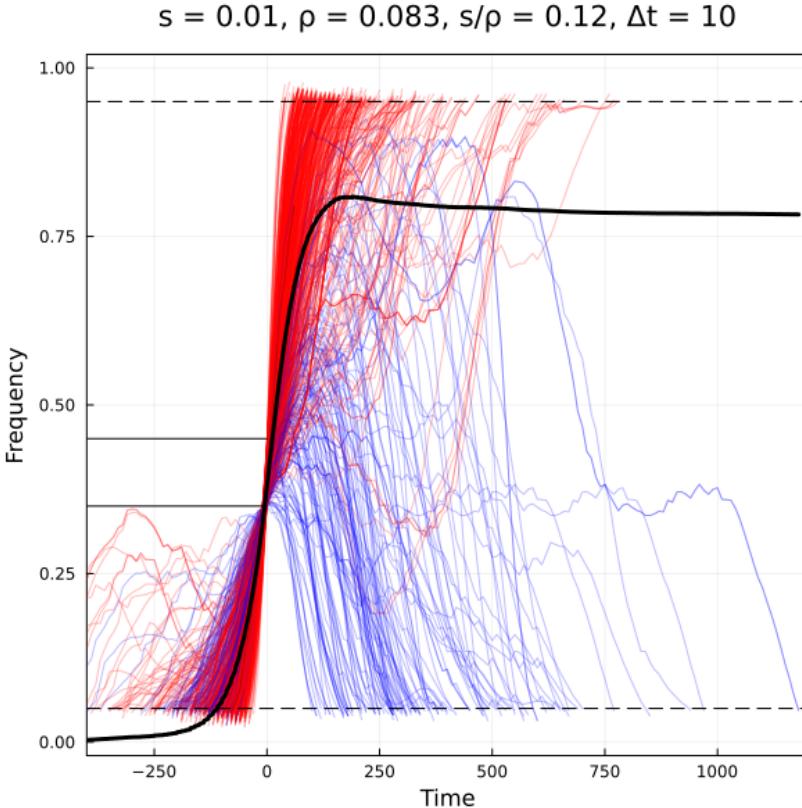
$\langle \Delta x \rangle = 0 \rightarrow \text{Low predictability}$



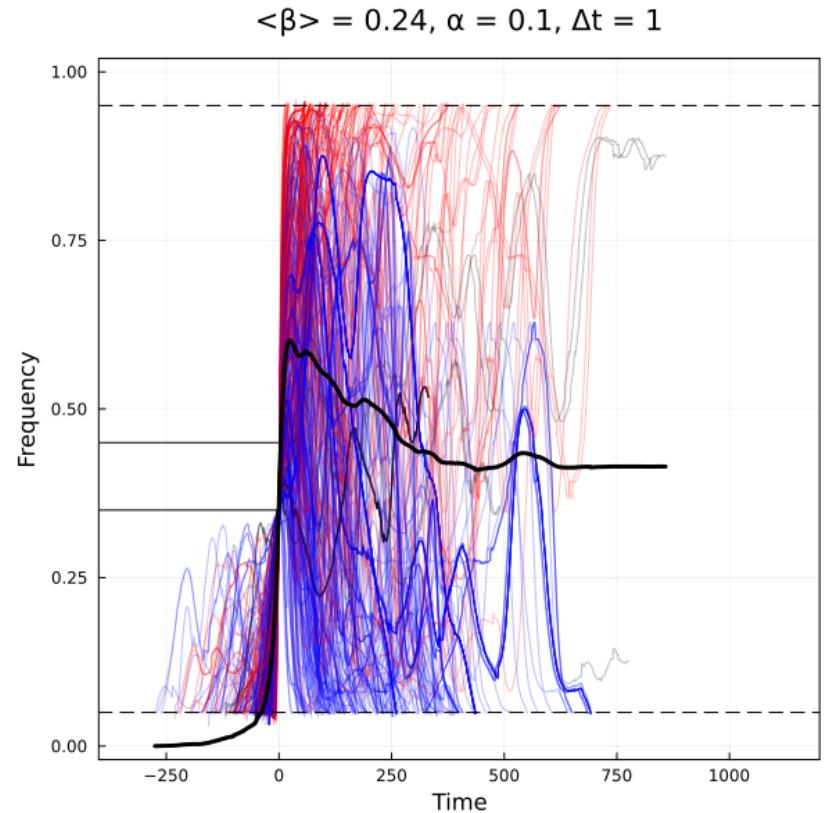
# Inertia of frequency trajectories

Simulation of a viral population (Wright-Fisher style)

## Fixed fitness effects

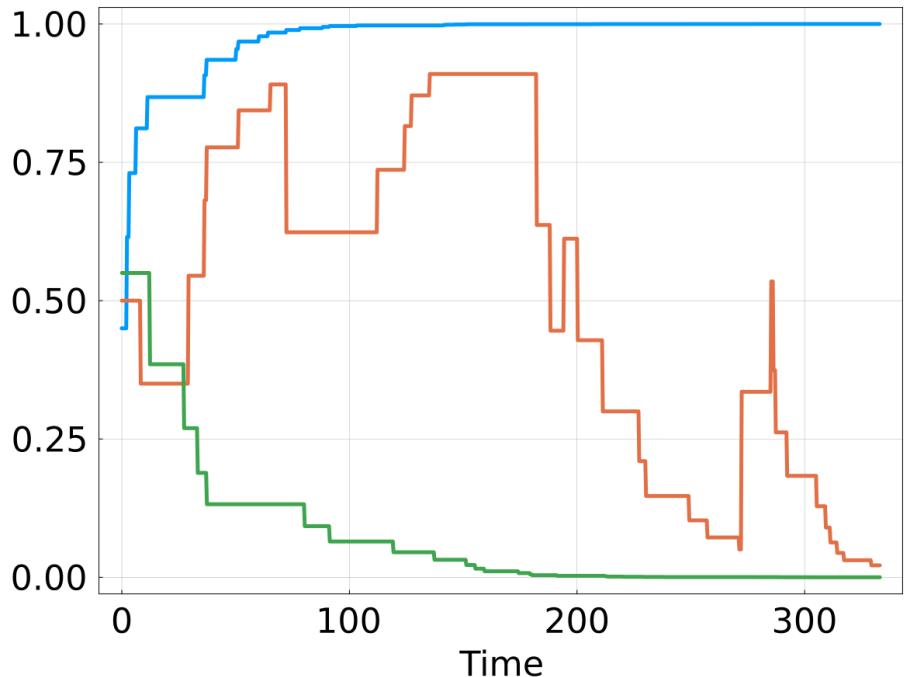


## Expiring fitness



# Evolution with partial sweeps

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$\langle \Delta x \rangle = 0 \rightarrow \text{Low predictability}$

**Timescales**

$$\langle \Delta x^2 \rangle = \rho \langle \beta^2 \rangle x(1 - x)$$

**Analogy with neutral evolution**

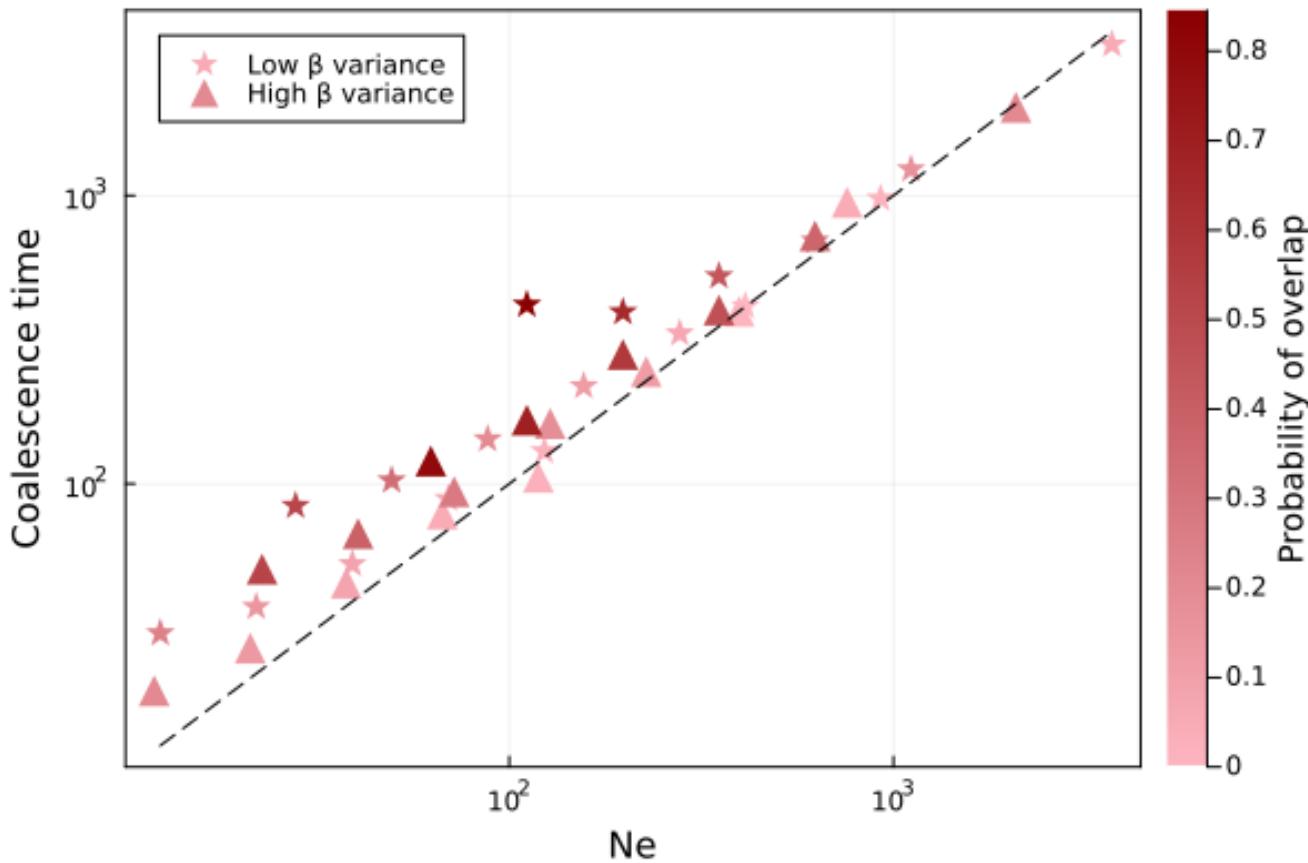
$$\text{timescale } N_e^{-1} = T^{-1} \sim \rho \langle \beta^2 \rangle$$

$$\rho^{-1} \sim 15 \quad (\sim 4 \text{ partial sweeps/year})$$

$$\beta \sim 0.3 \rightarrow T \sim 150 \sim 3y$$

$$\text{H3N2 influenza} \rightarrow T_{MRCA} \sim 6y$$

# Time to Most Recent Common Ancestor



$$N_e^{-1} = T^{-1} \sim \rho \langle \beta^2 \rangle$$

Simulate a population (Wright-Fisher) with

- different distributions for  $\beta$
- different values for  $\rho$

# Summary

H3N2Influenza:

- **Predictability** of evolution is surprisingly low
- Travelling wave models

**Partial sweeps**

- **Adaptation** of host immunity
- Fitness advantage of mutant **expires** before full sweep
- Modeled by a multi-strain Susceptible-Infected model

Evolution with **partial sweeps**

- Driven by fitness
- Low predictability
- Qualitatively closer to data

**Thank you!**

# Summary

H3N2Influenza:

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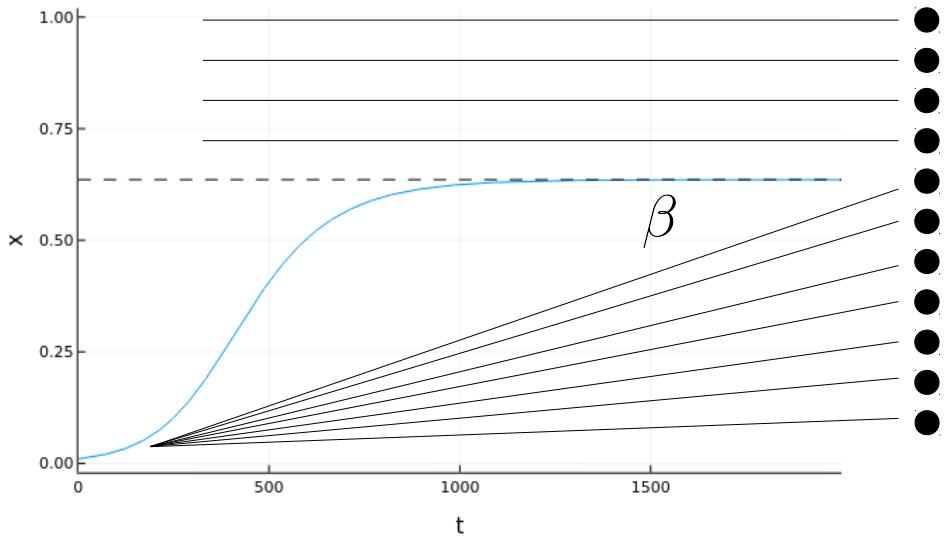
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# Shape of the phylogeny: multiple mergers

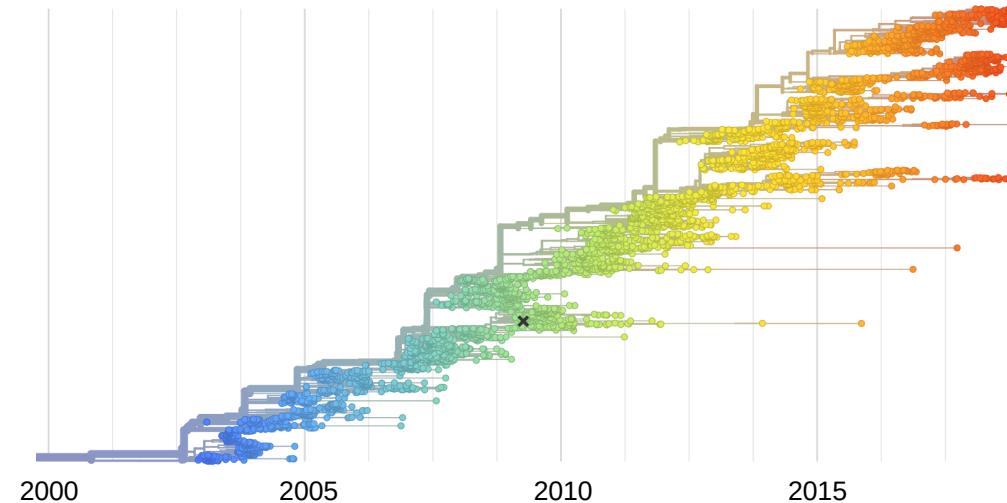


- Multiple mergers
- Ladder-like phylogenies

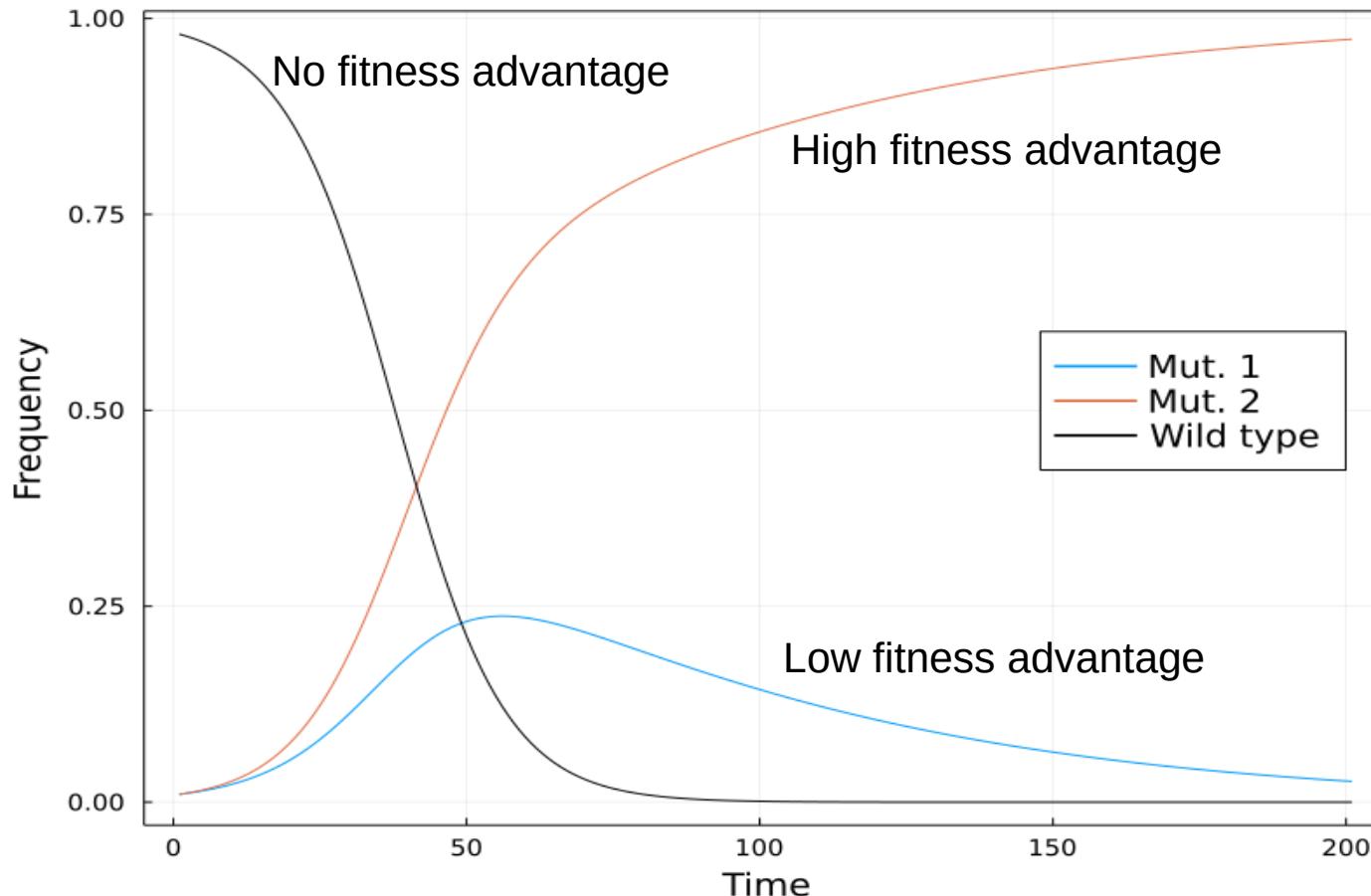
Rate of  $k$ -coalescence among  $n$  lineages

$$\Lambda_n(k) = \rho \binom{n}{k} \beta^k (1 - \beta)^{n-k}$$

Lambda coalescent



# Is this expected? Clonal interference



Adaptive mutations appearing on different individuals



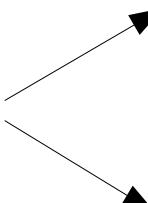
**Competition**

# Genetic linkage: toy model

Simulate a population

Simple fitness landscape  $f(\vec{s}) = \sum_{i=1}^L h_i s_i$

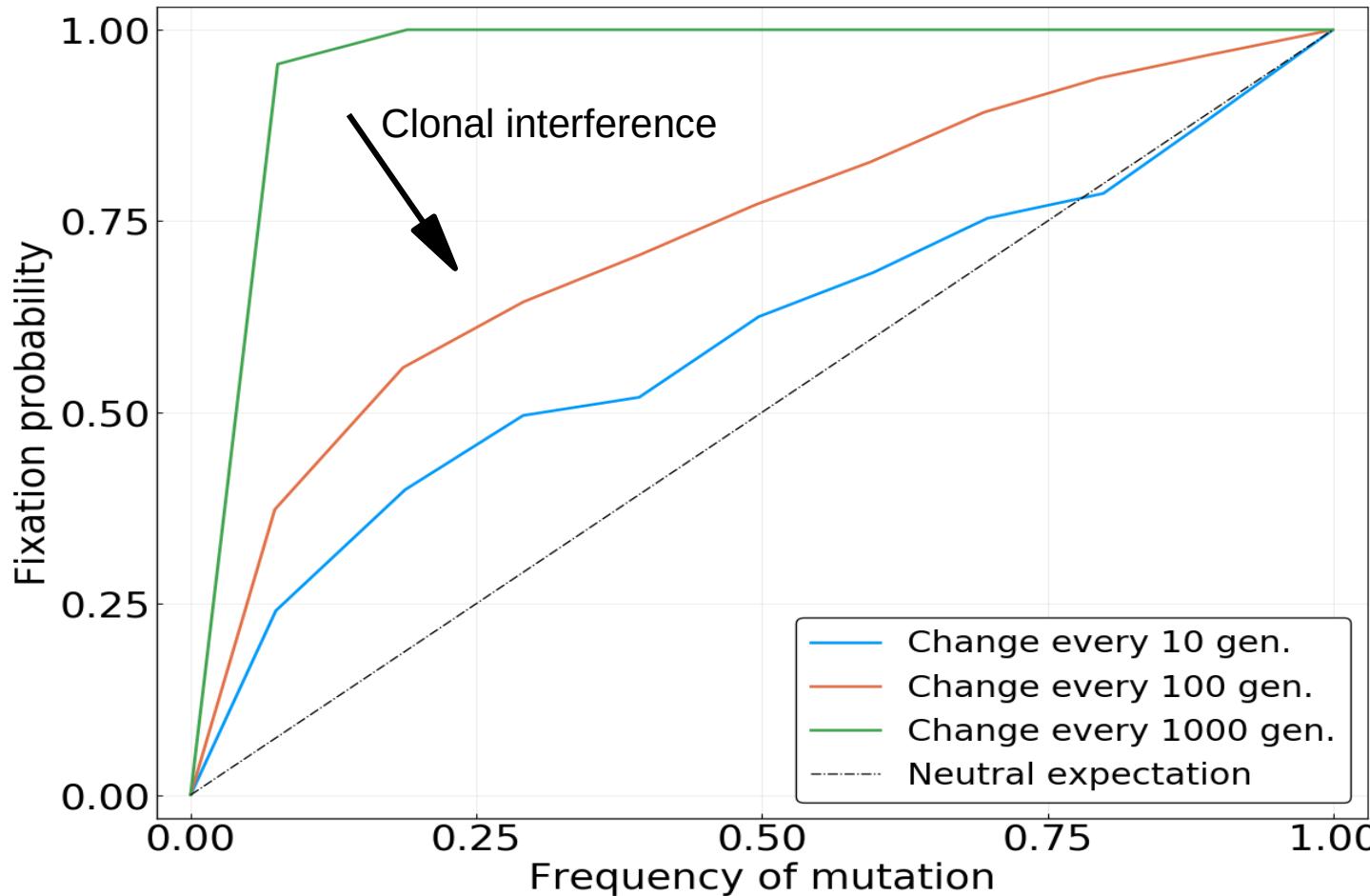
Change the fitness landscape periodically



Slow rate of change  
**Clean sweeps**

High rate of change  
**Clonal interference**

# Genetic linkage: toy model



Sweep time ~400 generations  
(vs ~3 years for flu)

**It's hard to mimic neutrality!**