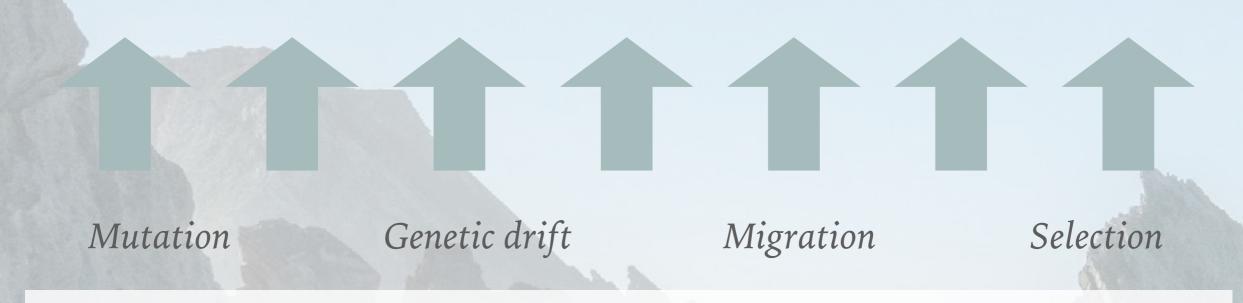
# POSITIVE AND NEGATIVE SELECTION (AND RELATED PROBLEMS)

**CLAUDIA BANK** 



#### **Evolutionary Dynamics @ IGC:**

- How do populations adapt to challenging environments?
  E.g., how does drug resistance evolve?
- ► Which processes drive speciation & diversification?
- What is the role of interactions in evolution?

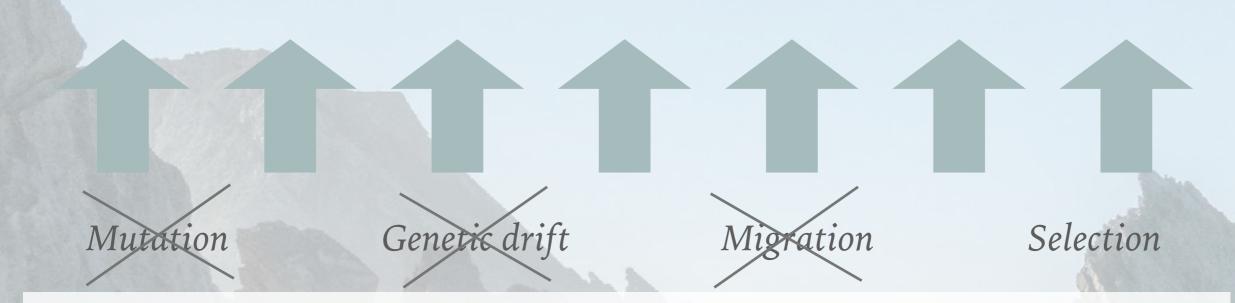


#### What we do

- Study evolutionary processes using simple models
- Evaluate these models using empirical and simulated data
- Use modeling to inform experimental design a priori

#### **Evolutionary Dynamics @ IGC:**

- How do populations adapt to challenging environments?
  E.g., how does drug resistance evolve?
- ► Which processes drive speciation & diversification?
- What is the role of interactions in evolution?



#### What we do

- Study evolutionary processes using simple models
- Evaluate these models using empirical and simulated data
- Use modeling to inform experimental design a priori

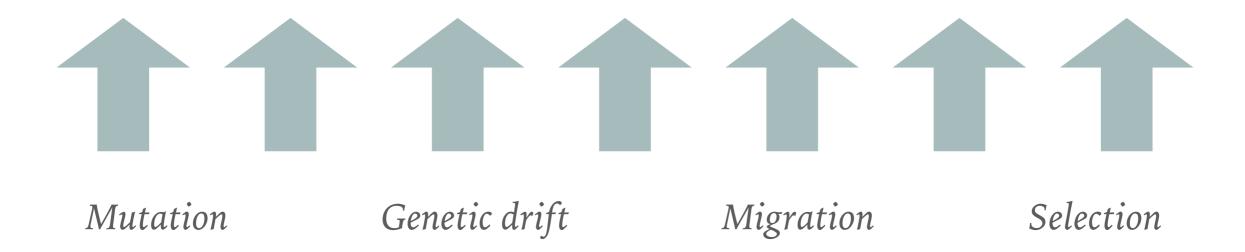
It may be said that natural selection is daily and hourly scutinising, throughout the world, every variation, even the slightest; rejecting that which is bad, preserving and adding up all that is good; silently and insensibly working, whenever and wherever opportunity offers, at the improvement of each organic being in relation to its organic and inorganic conditions of life. We see nothing of these slow changes in progress, until the hand of time has marked the long lapse of ages.

- Darwin, 1859

It may be said that natural selection is daily and hourly scutinising, throughout the world, every variation, even the slightest; rejecting that which is bad, preserving and adding up <u>all</u> that is good; silently and insensibly working, whenever and wherever opportunity offers, at the improvement of each organic being in relation to its organic and inorganic conditions of life. We see nothing of these slow changes in progress, until the hand of time has marked the long lapse of ages.

- Darwin, 1859

If you were to write a book about evolution, what would you introduce first, and why?



# NATURAL SELECTION REQUIRES

. . . . . . . . . . . . . . . . . . .

. . . . . . . . . .

- ► Variation
- ► Inheritance
- Differential reproductive success

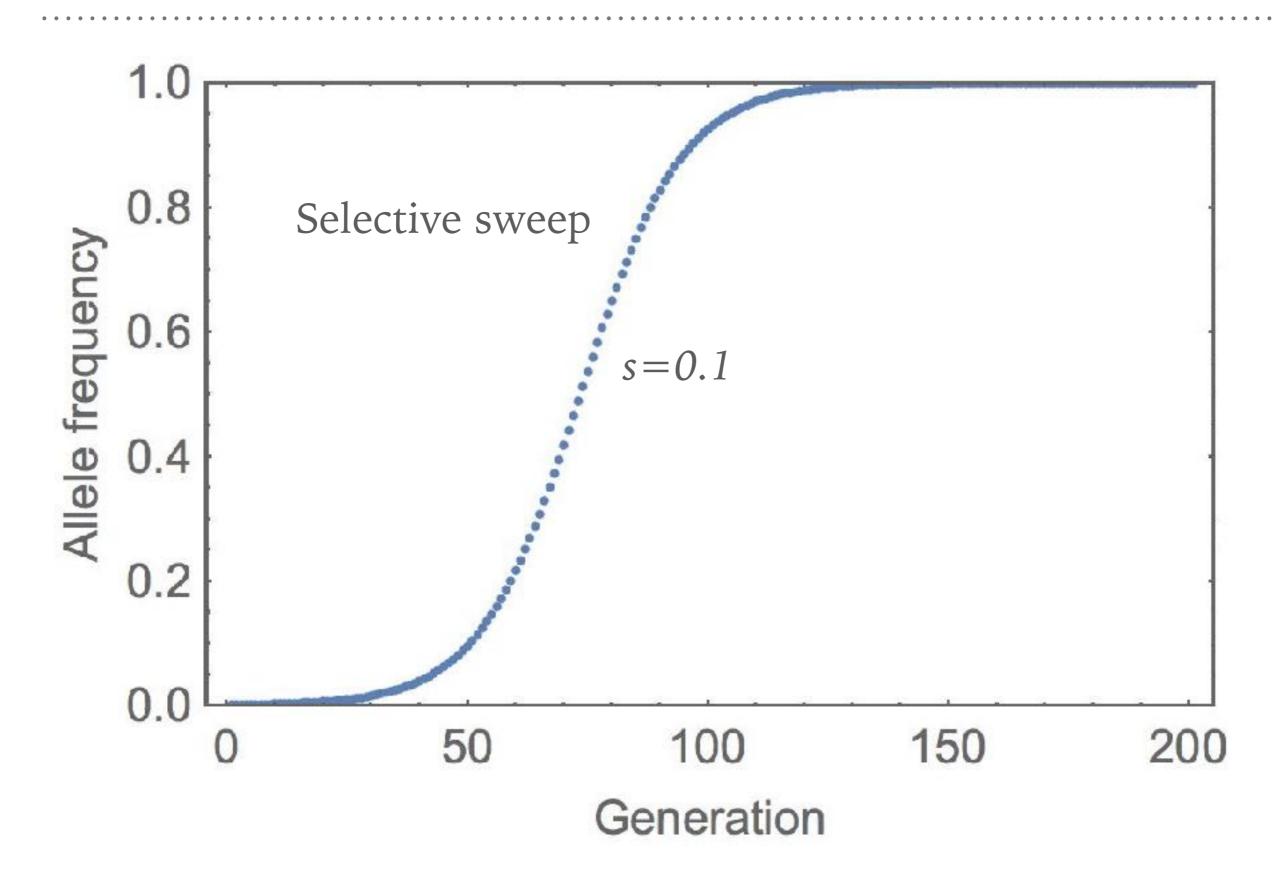
Although many processes shape evolution, natural selection is special because it creates complex, functioning organisms. All other processes tend to degrade what has been built up by natural selection, simply because these processes act at random with respect to function.

-Barton et al., Evolution (textbook)

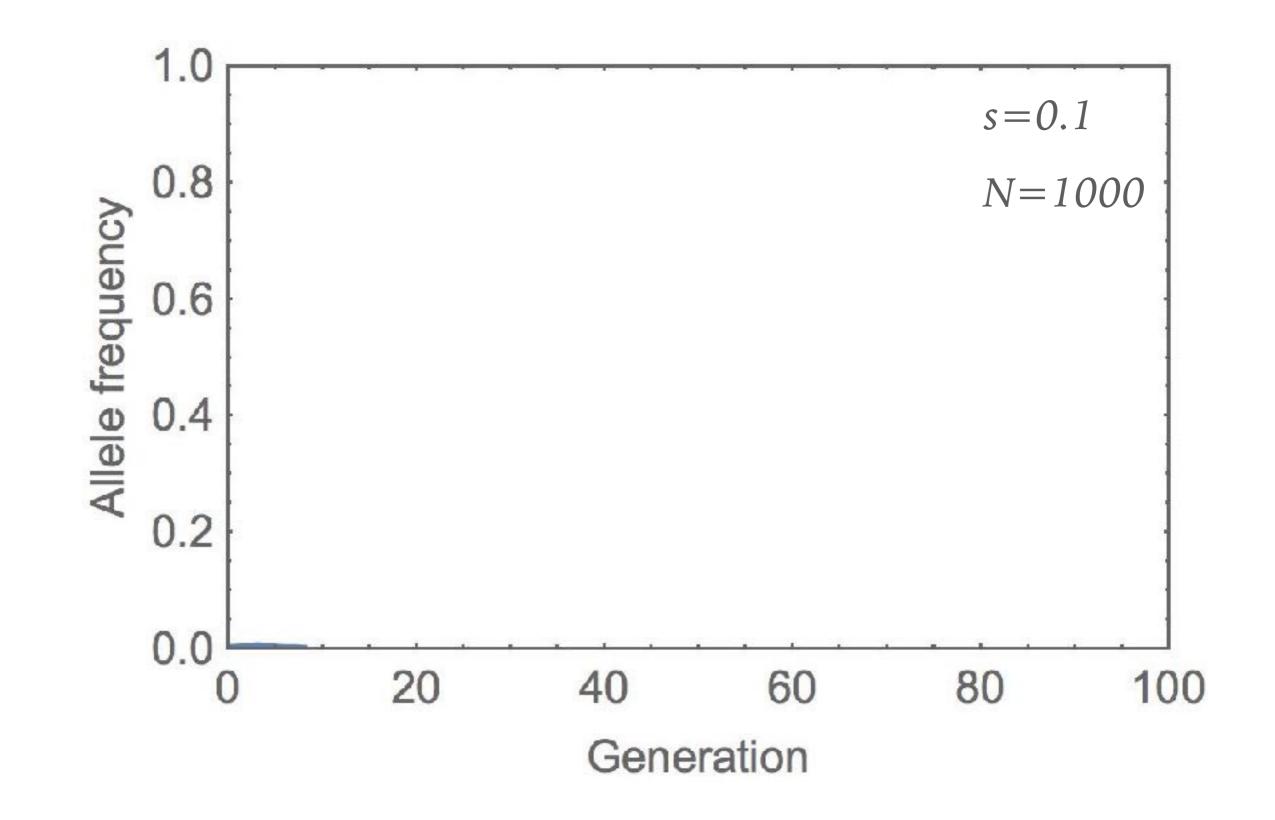
# WHAT WE WANT TO KNOW ABOUT SELECTION

- How big/small are adaptive steps?
- What are the proportions of beneficial, neutral, and deleterious mutations?
- How do mutational effects change dependent on the environment?
- How do mutational effects change dependent on the genetic background? (I.e., what is the role of epistasis?)
- What is the role of selection vs. other evolutionary processes in shaping genomes?
- How can we infer the contribution of selection to molecular evolution?

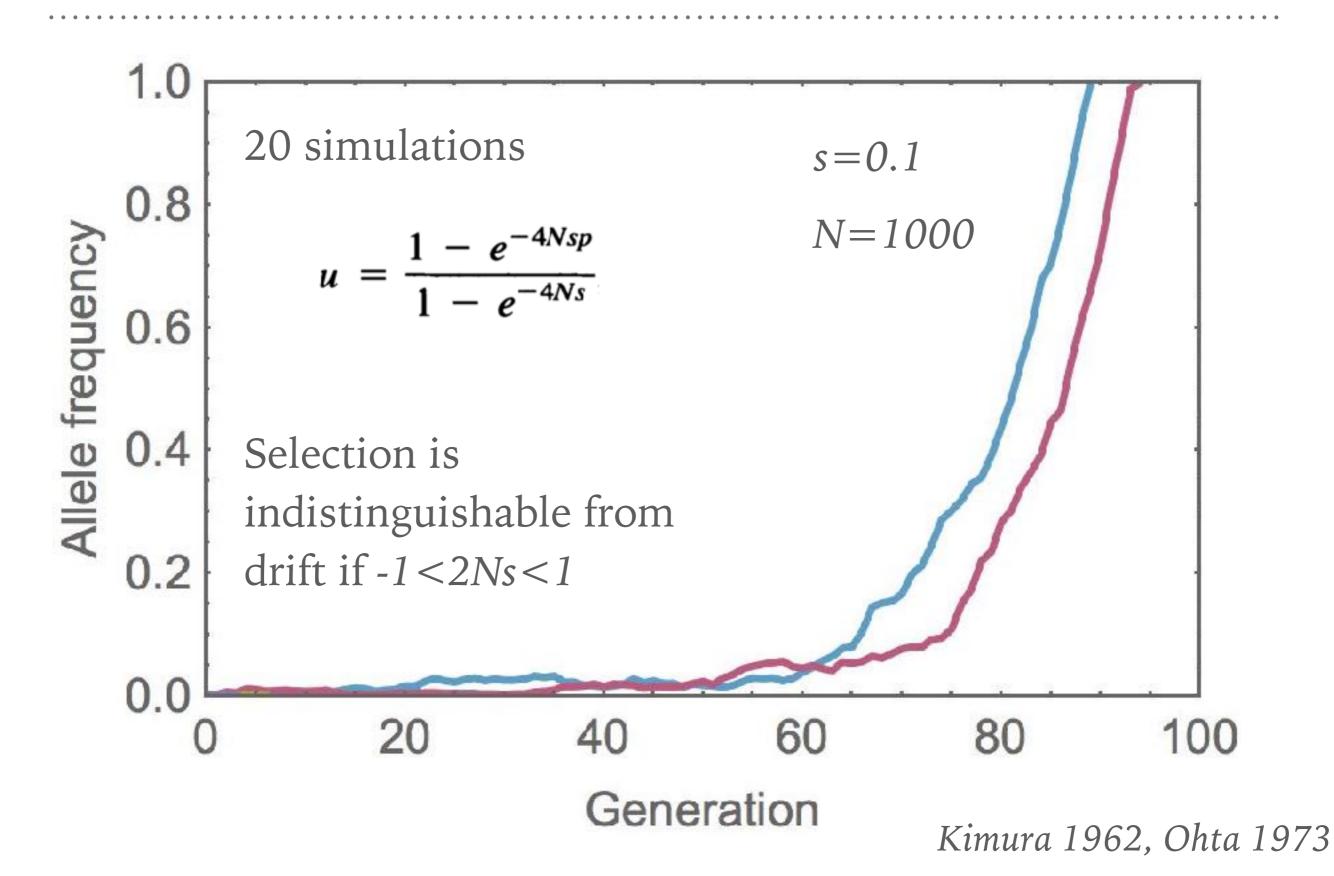
#### THEORETICALLY, SELECTION IS THE "EASIEST" EVOLUTIONARY FORCE



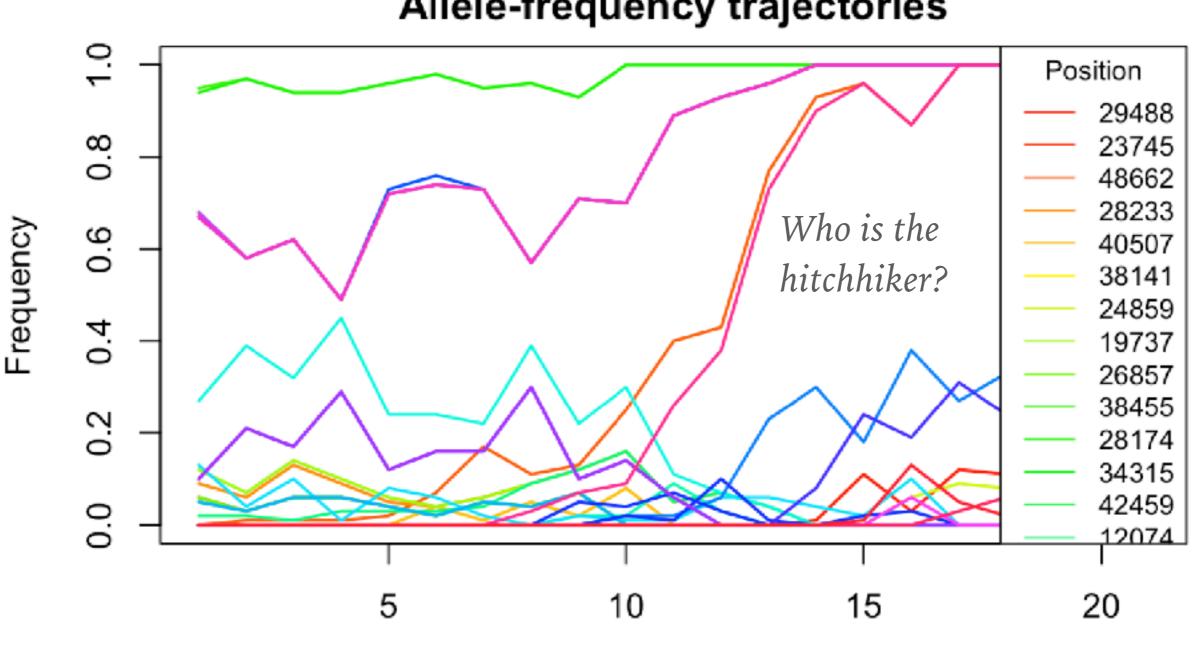
#### BUT THEN, GENETIC DRIFT COMES ALONG



# BUT THEN, GENETIC DRIFT COMES ALONG



#### **OR LINKAGE**



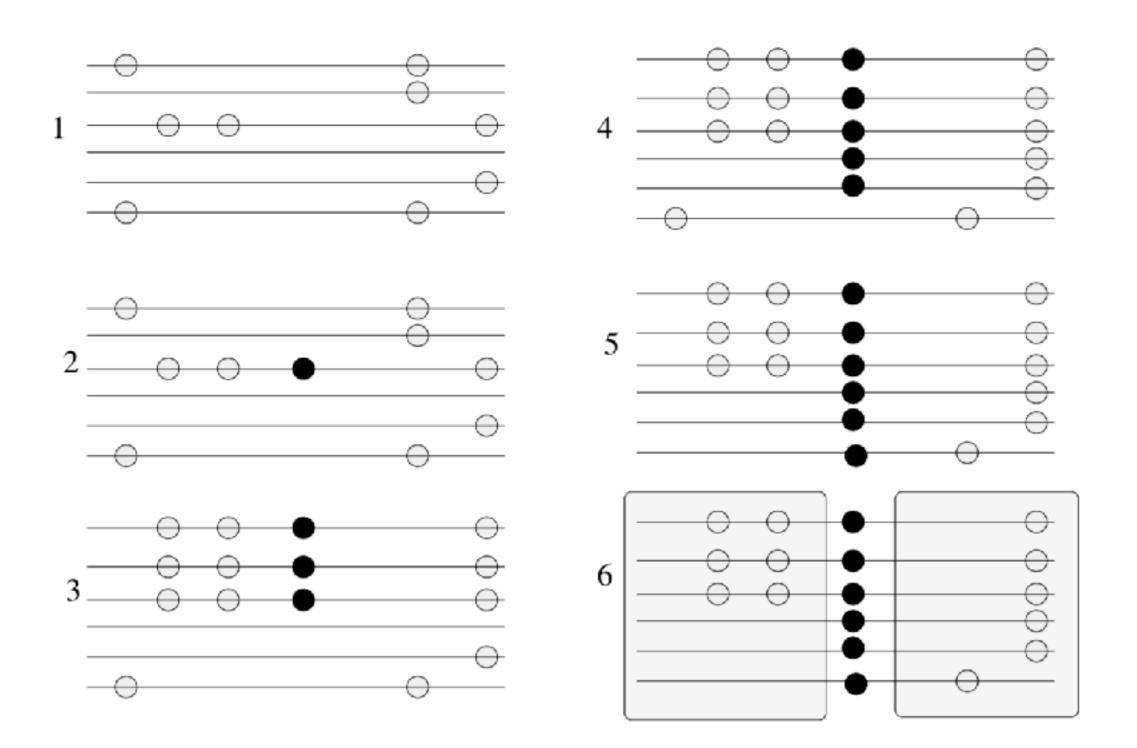
Allele-frequency trajectories

Time point

#### OR POPULATION STRUCTURE, OR EPISTASIS, OR [ADD YOUR FAVORITE HERE]

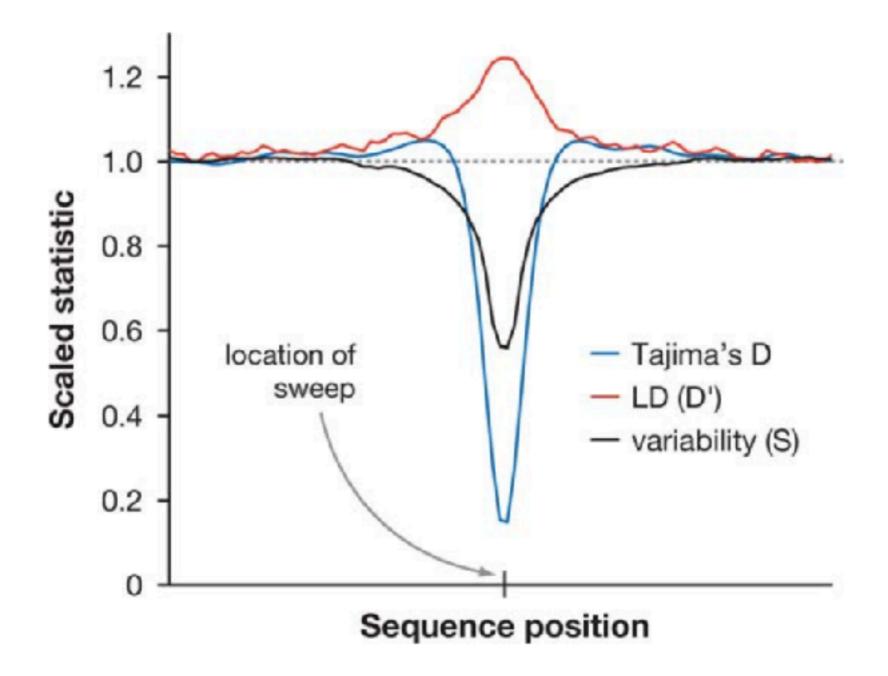
 Keep in mind that selection operates on phenotypic differences among individuals in a population; it does not act on a genotype, much less an allele.

#### **SELECTION LEAVES TRACES IN GENOMES**



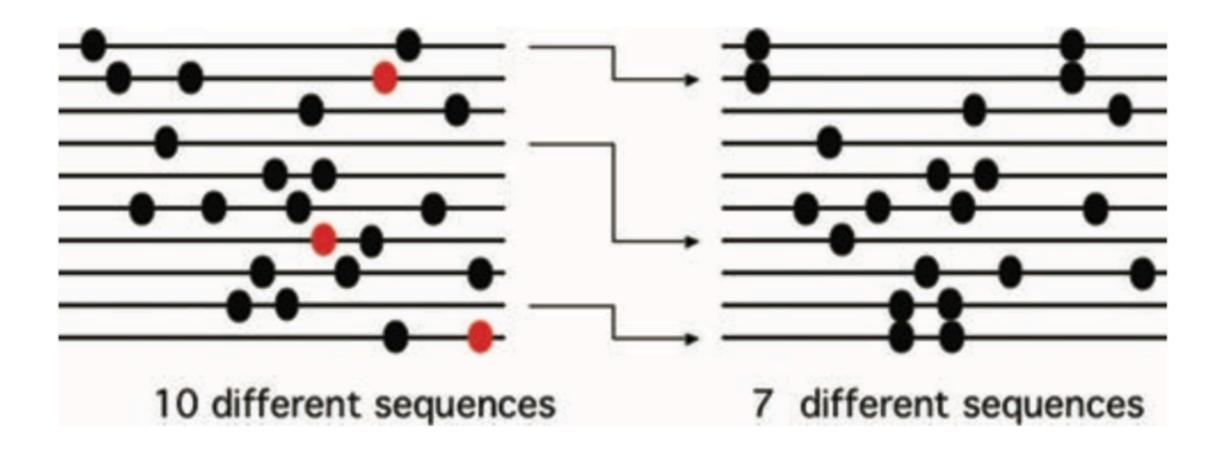
Pavlidis and Alachiotis 2017

#### TRACES OF A SELECTIVE SWEEP



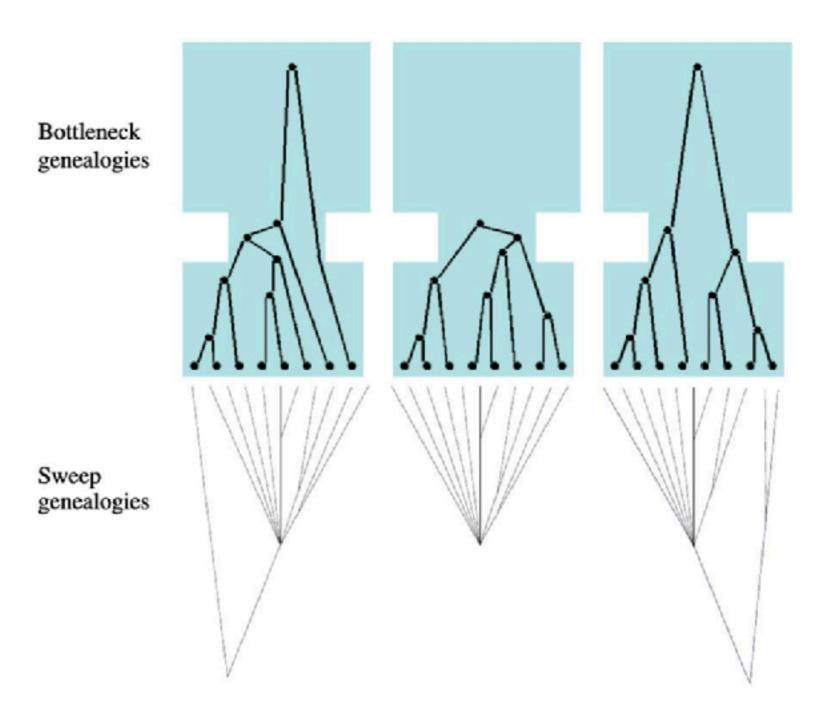
Nielsen 2005

#### TRACES OF BACKGROUND SELECTION



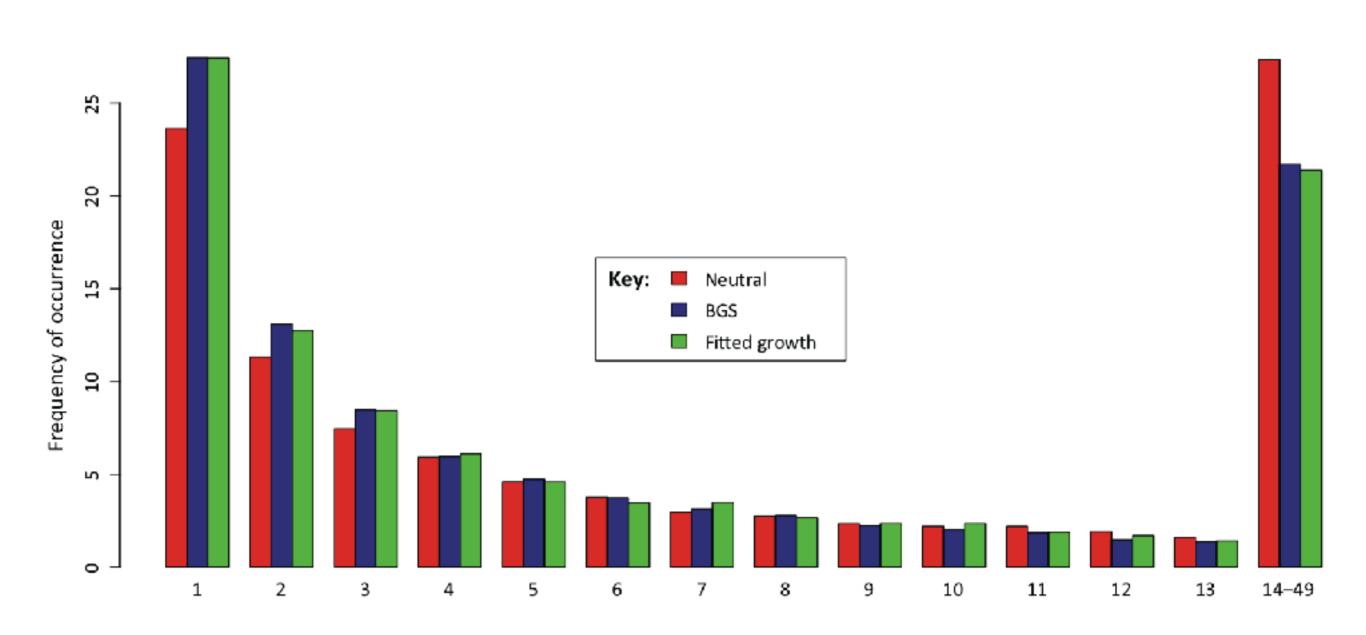
Charlesworth 2013

#### BUT IT IS DIFFICULT TO DISTINGUISH SELECTION FROM DEMOGRAPHY



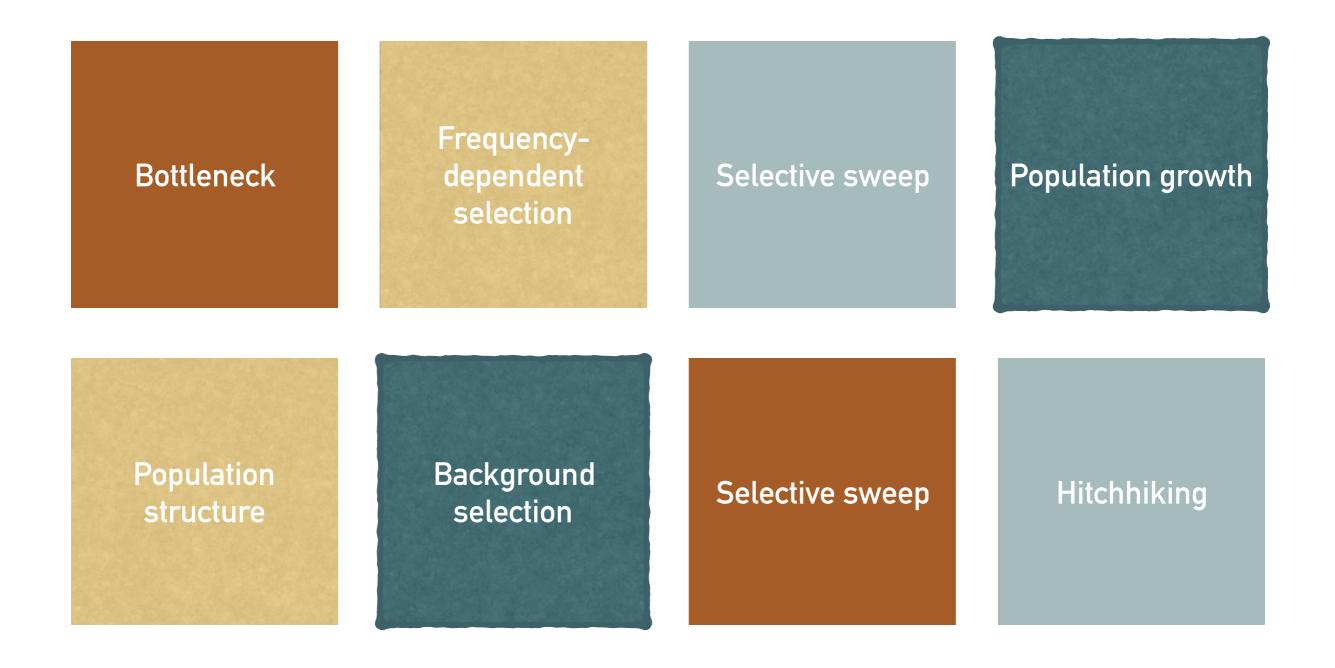
Pavlidis and Alachiotis 2017

#### BUT IT IS DIFFICULT TO DISTINGUISH SELECTION FROM DEMOGRAPHY



Bank et al. 2014

## **SELECTION VS DEMOGRAPHY MEMORY**



# **PROGRESS IN POPULATION-GENETIC SELECTION INFERENCE**

- genome-wide data and additional information
- ► Haplotype data and statistics
- Many (orthogonal) inference methods can be used in parallel (SFS-based, haplotype based, comparative)
- Two-step approach: infer demography from putatively neutral regions, then use the inferred demographic model for selection scan (e.g., Pavlidis et al. 2013) - joint inference in the future?xs
- ► Use simulations to validate results
- ► Use info from experimental evolution
  - Obtain time-serial data for increased statistical power

Bank et al. 2014

# WHAT WE WANT TO KNOW ABOUT SELECTION

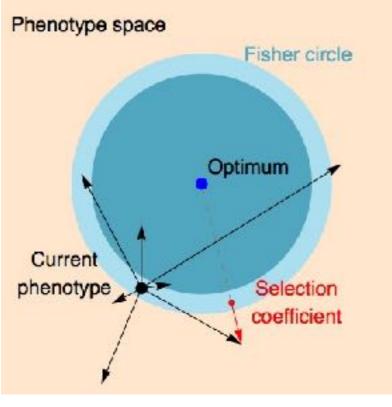
- How big/small are adaptive steps?
- What are the proportions of beneficial, neutral, and deleterious mutations?
- How do mutational effects change dependent on the What do we expect adaptation to be like THEORETICALLY?
  - background? (I.e., what is the role of epistasis?)
- What is the role of selection vs. other evolutionary processes in shaping genomes?
- How can we infer the contribution of selection to molecular evolution?

# **ADAPTATION VS ADAPTATIONS**

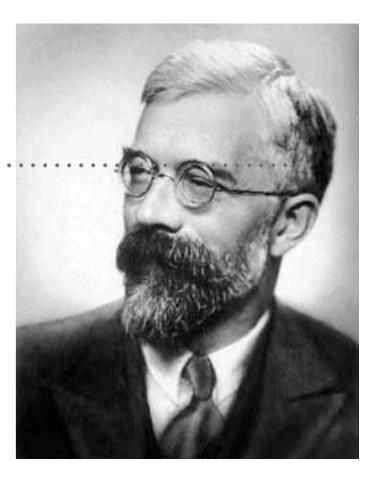
- Adaptation: the process of increasing (mean) fitness of a population in an environment
- An adaptation: a trait that increases its carrier's fitness in a specific environment, and that has spread bc of of the direct action of natural selection for its function

# TWO MODELS OF ADAPTATION

#### FISHER'S GEOMETRIC MODEL



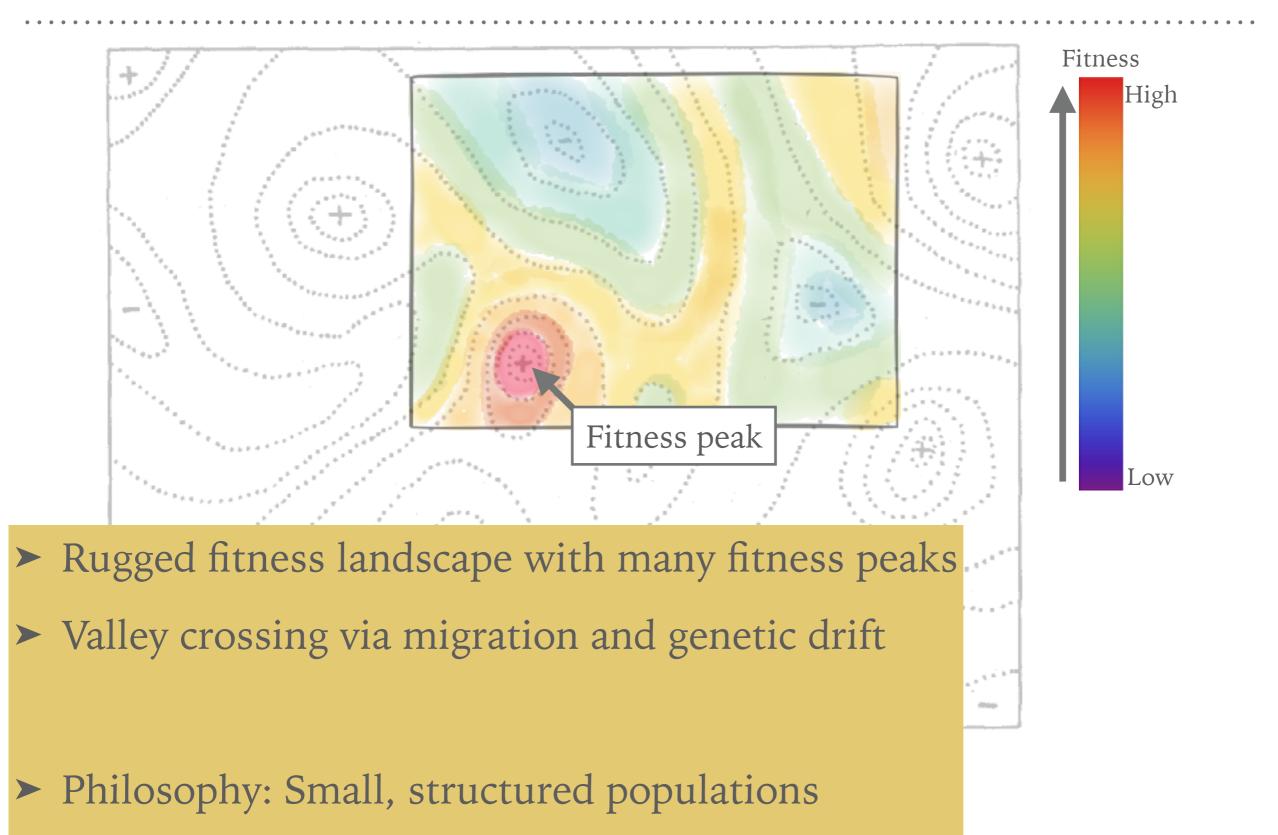
Fisher, 1930



More challenging environment
 => more beneficial mutations

Philosophy: Large populations, a single fitness optimum

### WRIGHT'S SHIFTING BALANCE



Wright, 1932

Which team are you on, Team Fisher or Team Wright, and why?

## WHAT WE WANT TO KNOW ABOUT SELECTION

- ► How big/small are adaptive steps?
- What are the proportions of beneficial, neutral, and deleterious mutations?
- How do mutational effects change dependent on the environment?

➤ What is the shape of the distribution of fitness effects (DFE)?

#### ESTIMATES OF MEAN BENEFICIAL EFFECT SIZE FROM POLYMORPHISM DATA

- ► s=0.002 (Li and Stephan 2006; Jensen et al. 2008)
- ► s=0.01 (MacPherson et al. 2008)
- ► s=0.00001 (Andolfatto 2007)

> For known phenotype: s=0.102 (Linnen et al. 2009)

# AN EXPERIMENTAL APPROACH TO THE DFE: DEEP MUTATIONAL SCANNING

 Systematic high-throughout sampling of hundreds of chosen mutations (including those that are strongly deleterious)



Deep mutational scanning results in a (almost "evolution-free") snapshot of the DFE

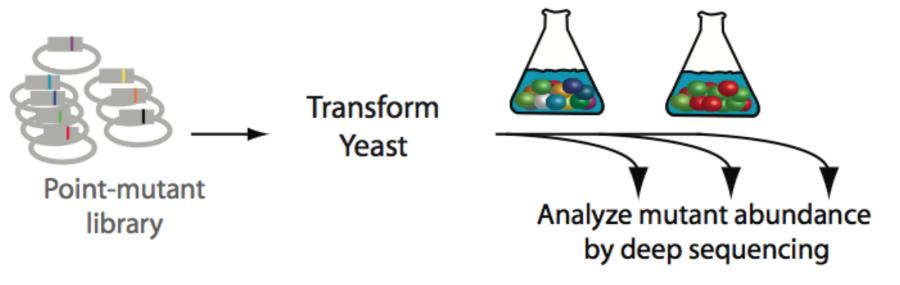
 Genetic background is precisely controlled (minimized potential for secondary mutations)



Ryan Hietpas



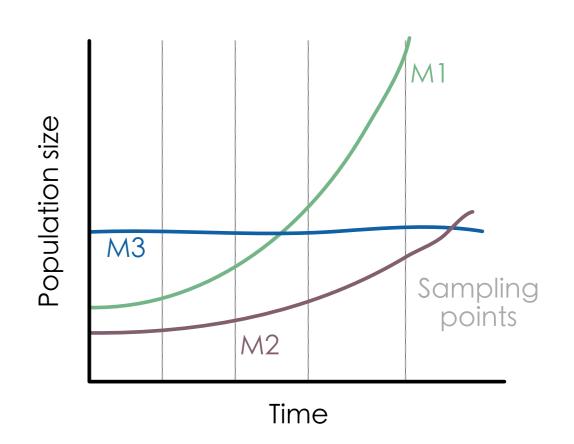
Jeff Jensen



Hietpas, Jensen & Bolon, PNAS, 2011

## DEEP MUTATIONAL SCANNING FROM A MODELER'S POINT OF VIEW

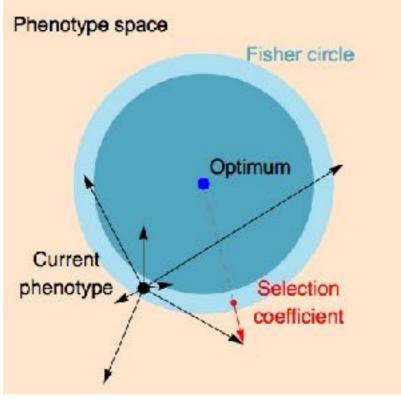
- Exponential growth of hundreds of mutants, each with its own growth rate/selection coefficient
- Sequencing corresponds to multinomial sampling of mutants independently at each sampling time



► <1% fitness differences detectable

# For the "Fisherians": the shape of the DFE across environments

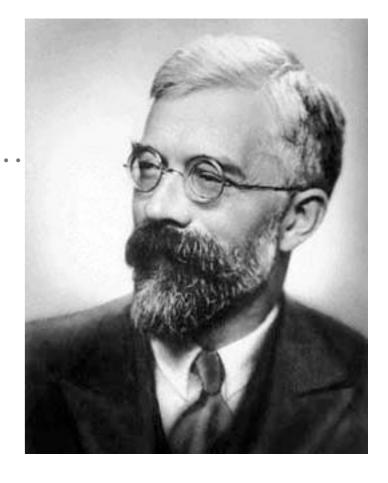
### FISHER'S GEOMETRIC MODEL



*Fisher, 1930* 

Hypotheses:

- Relocation of the optimum or the current phenotype in a new environment can increase the distance to the optimum and hence the potential for beneficials.
- The distribution of beneficial mutations is bounded or exponential.



#### THE SHAPE OF THE DFE IN CHALLENGING ENVIRONMENTS

#### The data set

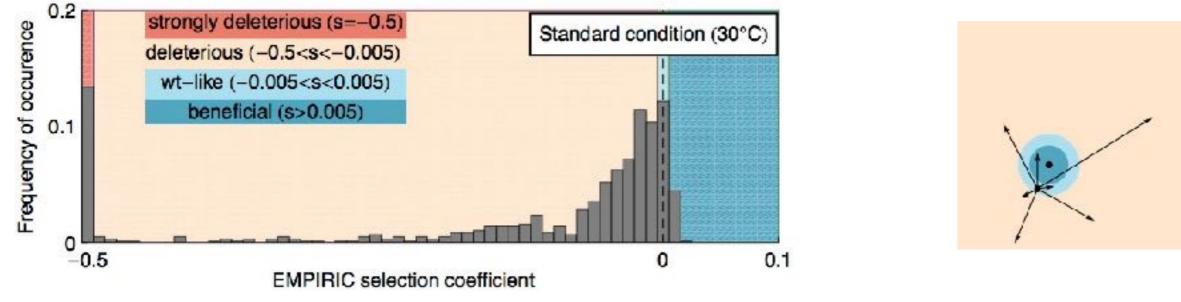
- 9 aa region from Hsp90 (aa positions 582-590) in Saccharomyces cerevisiae
- - 6 environments:

30°C	30°C+0.5M NaCl
36°C	36°C+0.5M NaCl
25°C	25°C+0.5M NaCl

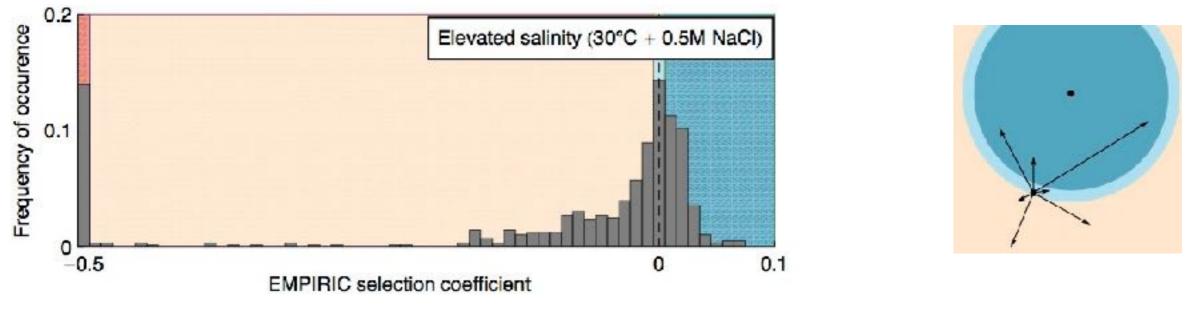
Relative growth of wt:
 Fitness data for every possible co don åt each aa position (i.e. this anne 560 nightions per en vironment) 0,63 0,3

Data obtained by Ryan Hietpas @ UMassMed

#### The shape of the full DFE



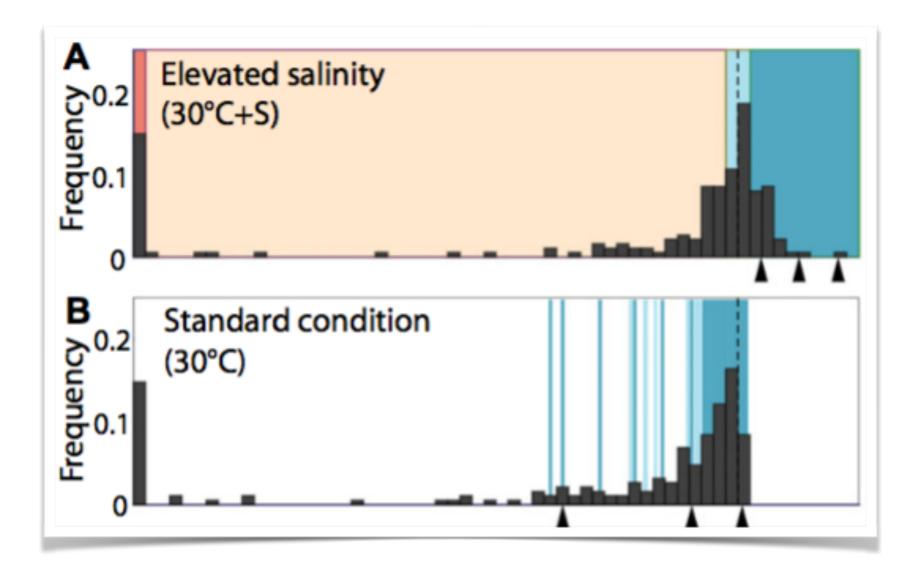
Bimodal DFE, few beneficials - close to optimum



Increased number of beneficials, increased variance - far from optimum

Hietpas, Bank et al. 2013

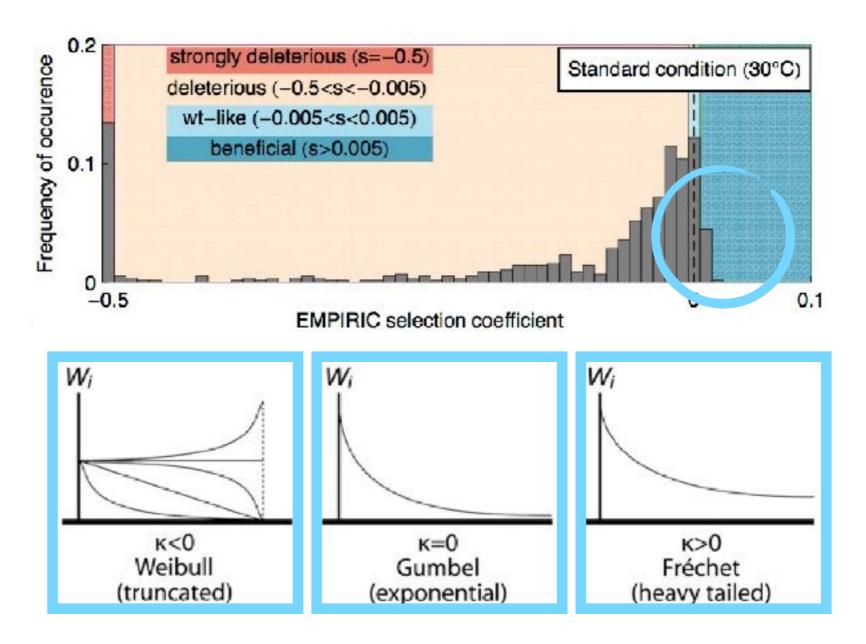
#### **COSTS OF ADAPTATION**



#### THE SHAPE OF THE BENEFICIAL TAIL OF THE DFE

#### HOW PREDICTABLE IS ADAPTIVE EVOLUTION?

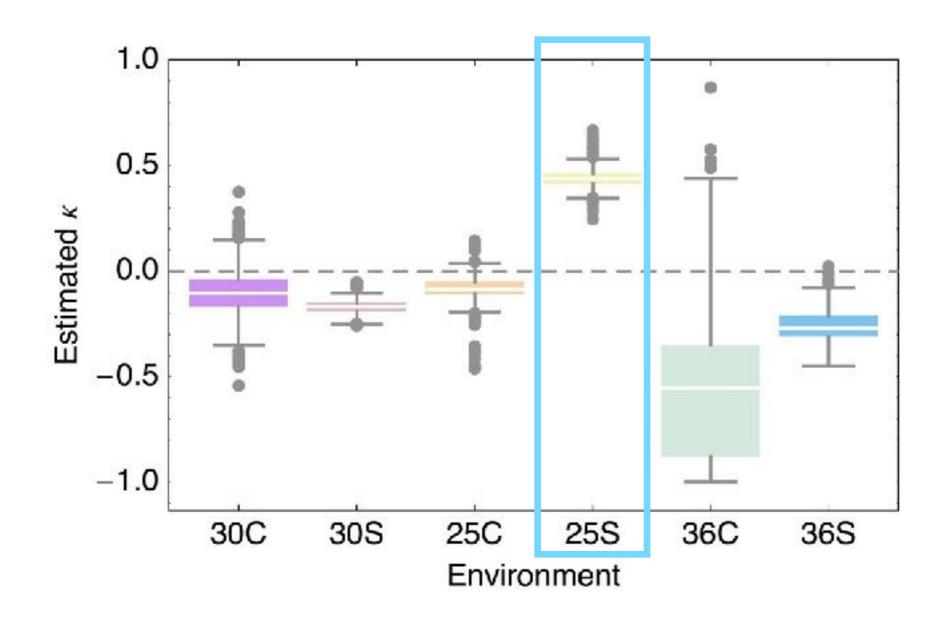
- Fit Generalized
   Pareto distribution to
   beneficial tail
- Kappa parameter
   determines tail shape
  - Unbounded DFE, highly unpredictable mutational effects
  - Not captured by FGM



From Beisel et al., Genetics, 2007

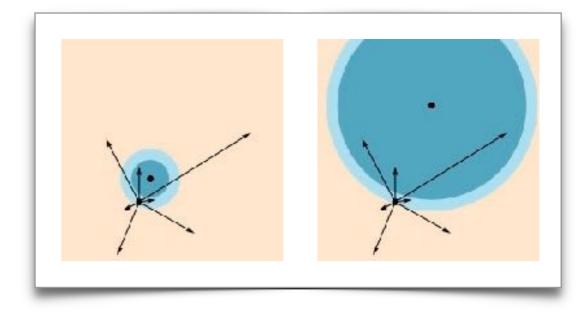
#### TAIL SHAPE PARAMETER IN CHALLENGING ENVIRONMENTS

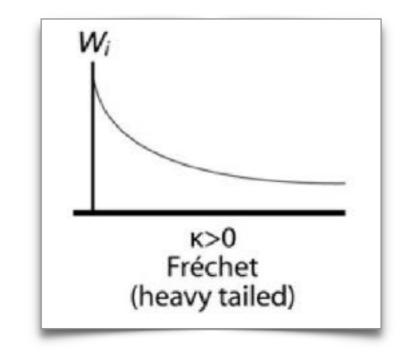
S. cerevisiae EMPIRIC data from Hsp90



### **SUMMARY – TEAM FISHER**

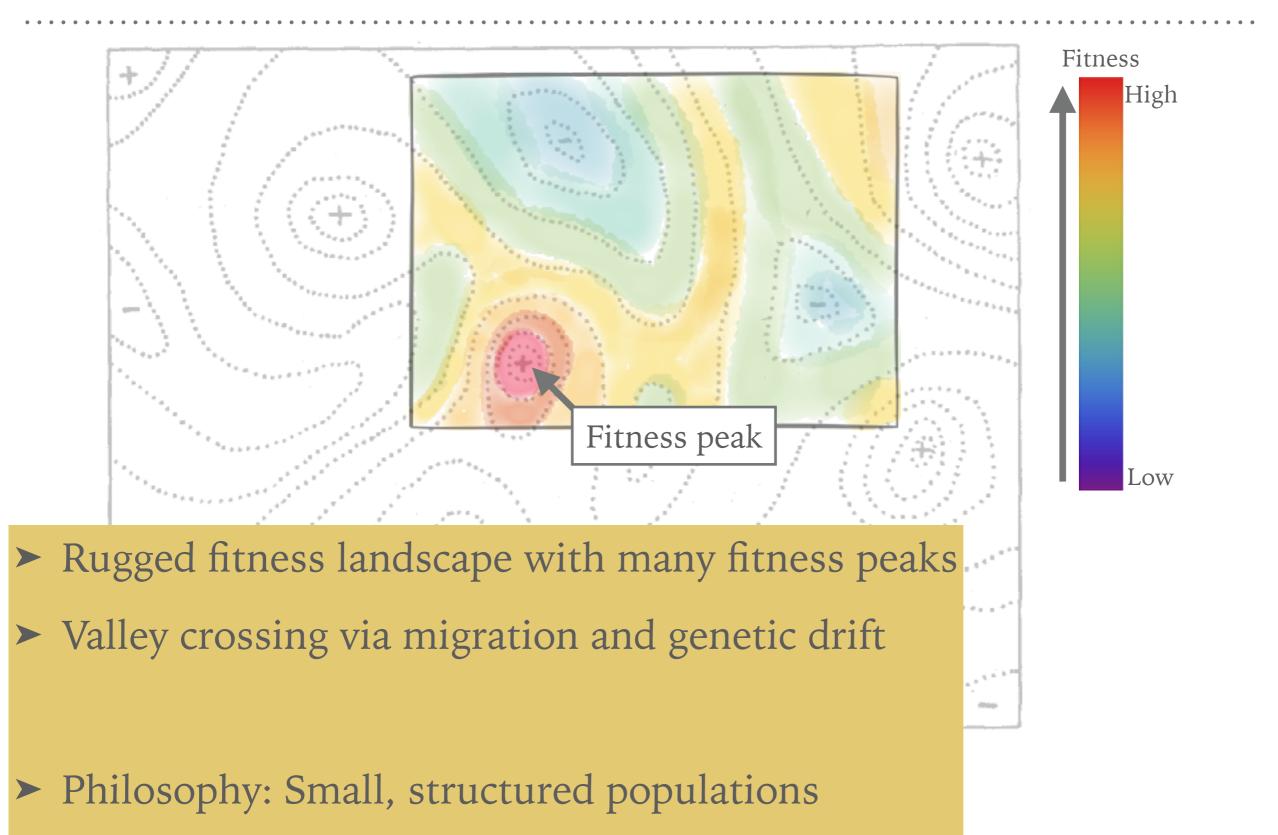
- In response to a novel environmental challenge the number and size of beneficial mutations increases, and costs of adaptation are observed - in agreement with predictions from Fisher's geometric model when the optimum is displaced.
- Following severe environmental challenges, the step size of adaptive mutations might be highly unpredictable.





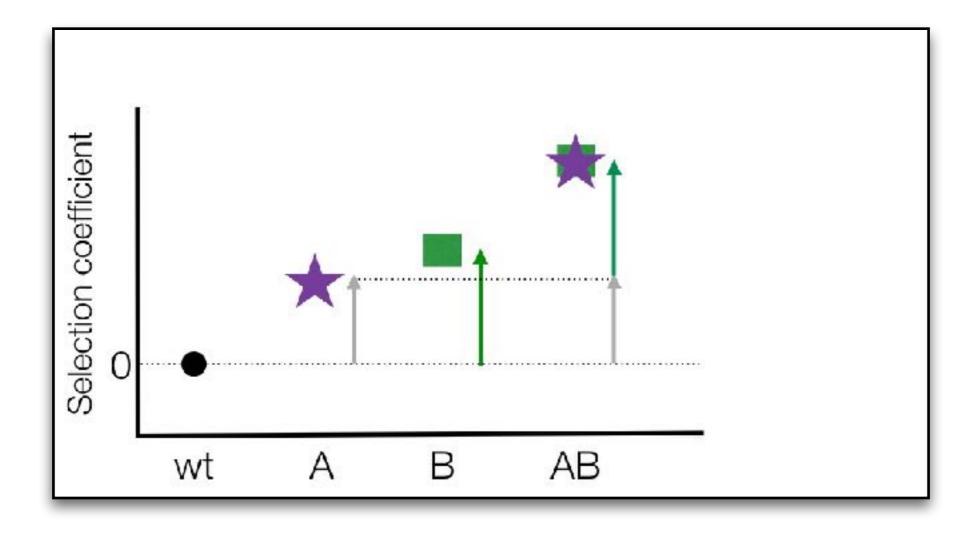
But what about epistasis? (Spoiler: this is the part for the "Wrightians")

#### WRIGHT'S SHIFTING BALANCE



Wright, 1932

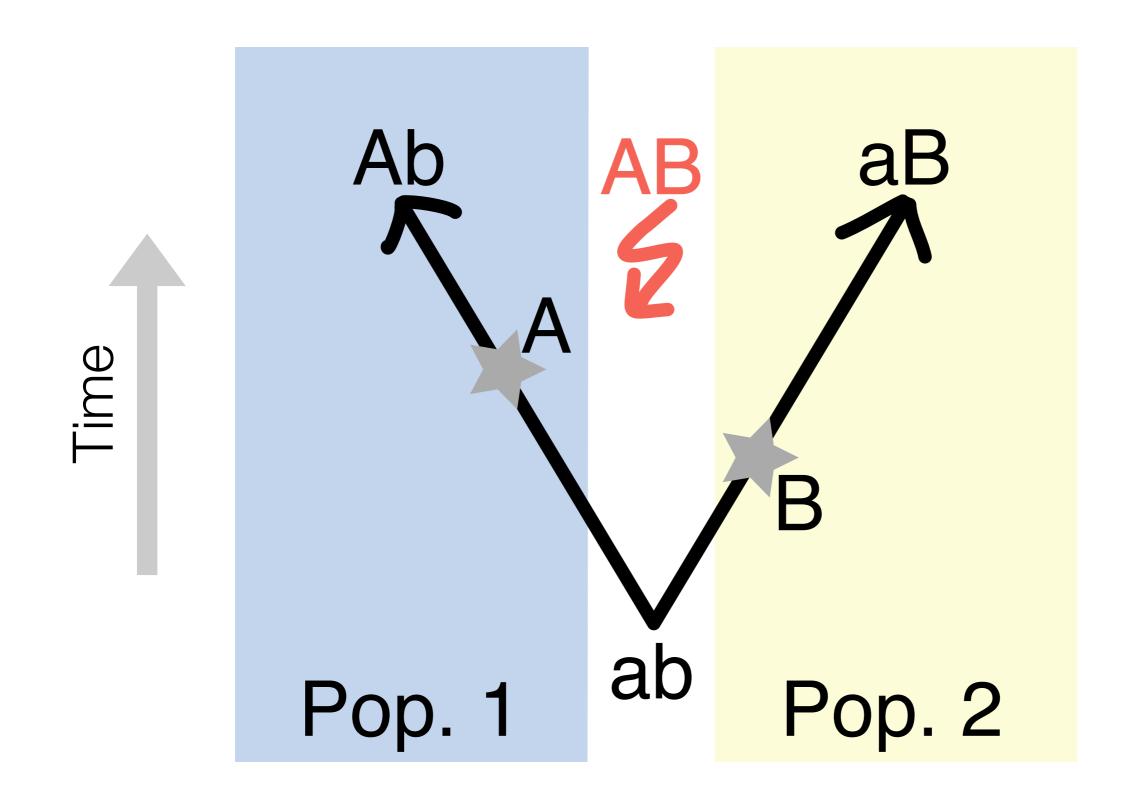
#### WHAT IS EPISTASIS?



#### WHY SHOULD WE CARE?

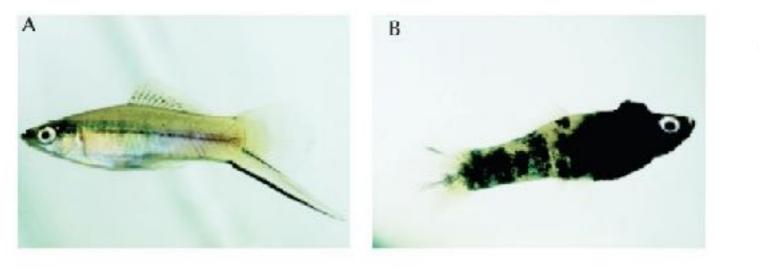
- epistasis creates non-random associations between loci (LD)
- Ruggedness of fitness landscape is a determinant of predictability/repeatability of evolution
- accumulation of epistatic alleles is basis of the most widely accepted model for allopatric speciation

#### THE DOBZHANSKY-MULLER MODEL

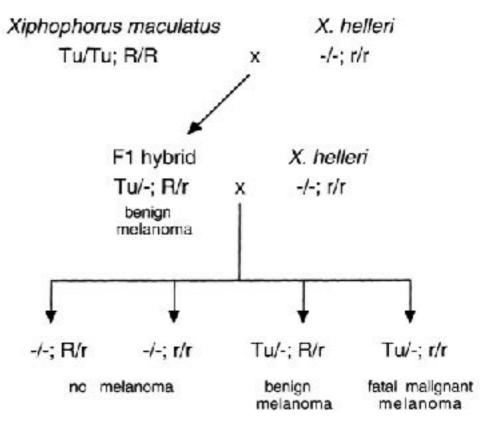


#### WHAT IS THE EVIDENCE?



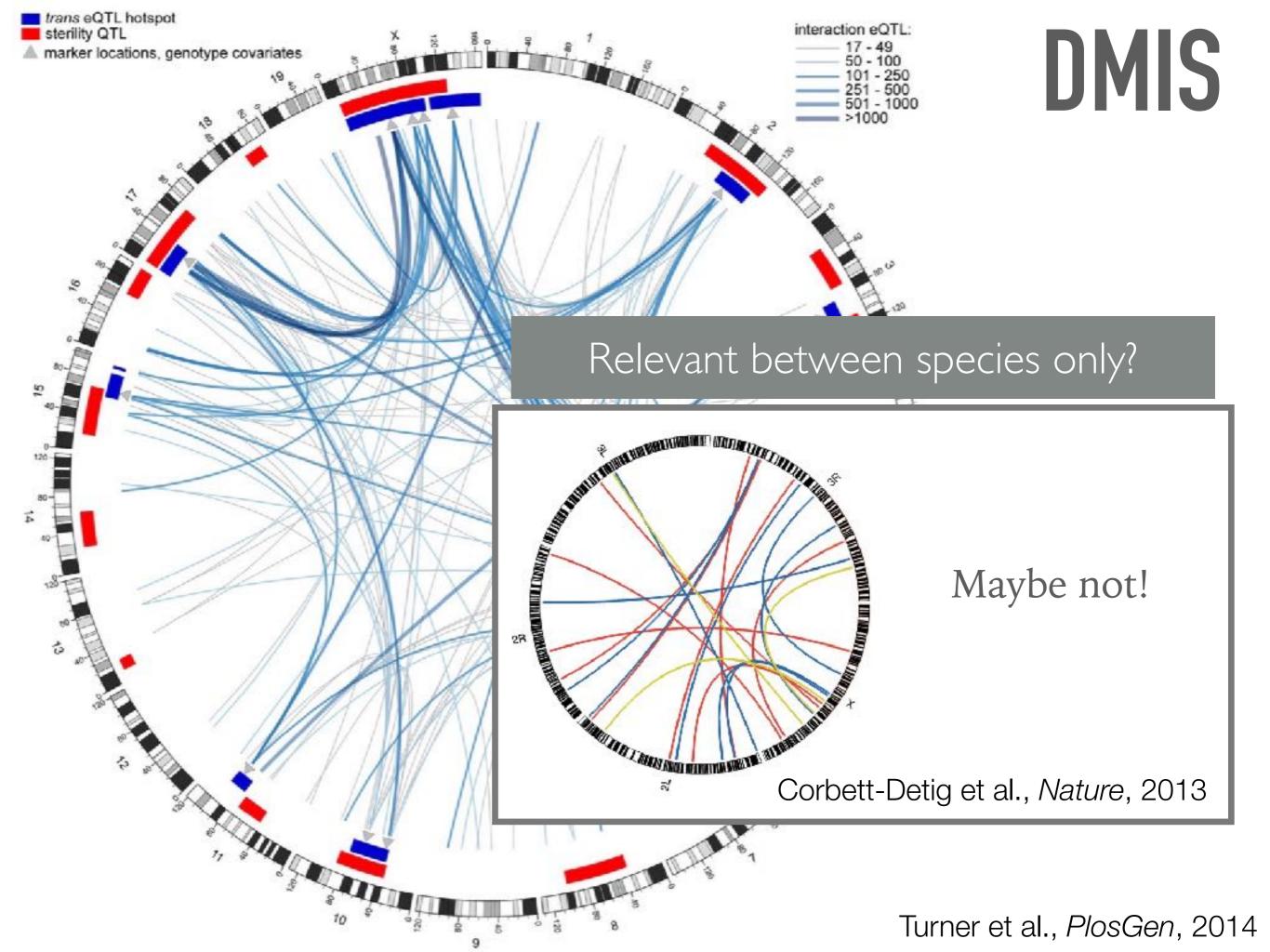


Orr & Presgraves, Bioessays, 2000

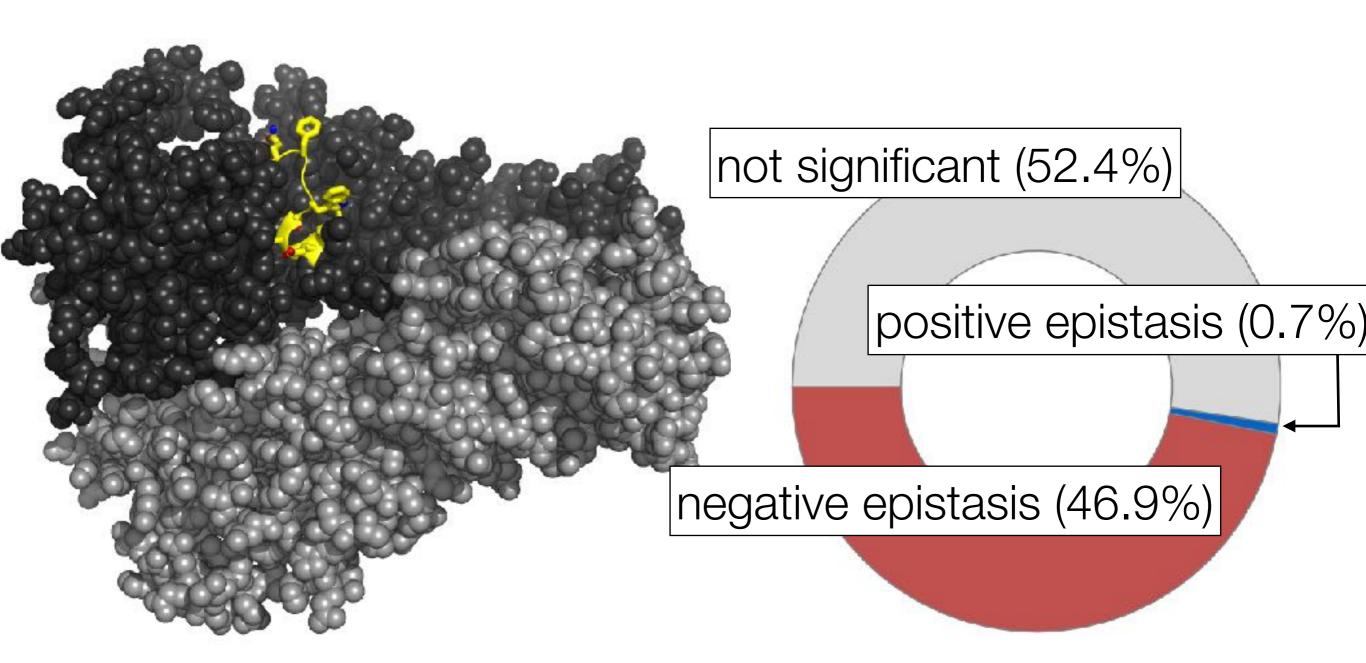


- sexual selection on tumor gene
- interaction with promoter of repressor gene
- ongoing gene flow

#### Scarpino et al., MBE, 2013



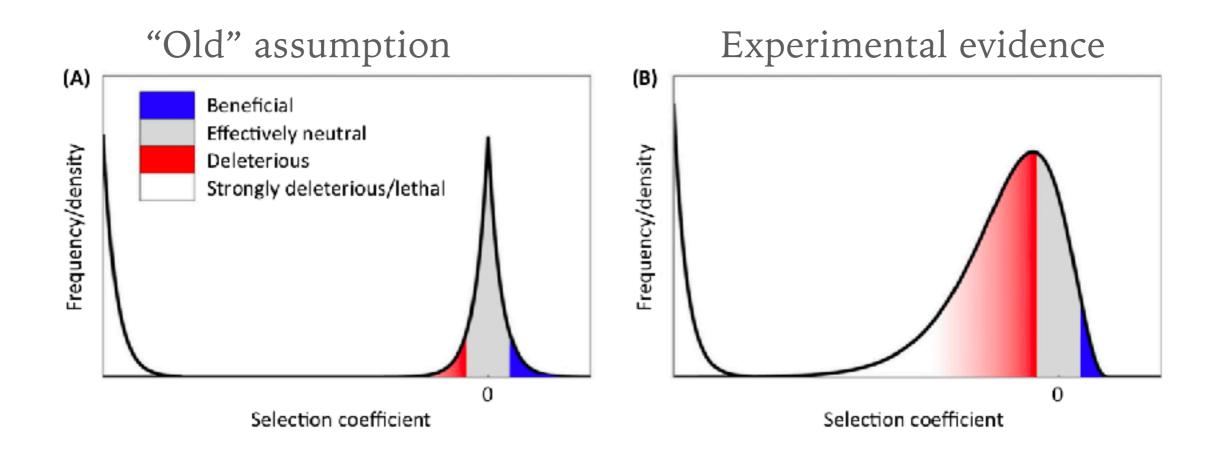
#### PAIRWISE EPISTASIS WITHIN A PROTEIN



Bank et al. 2015

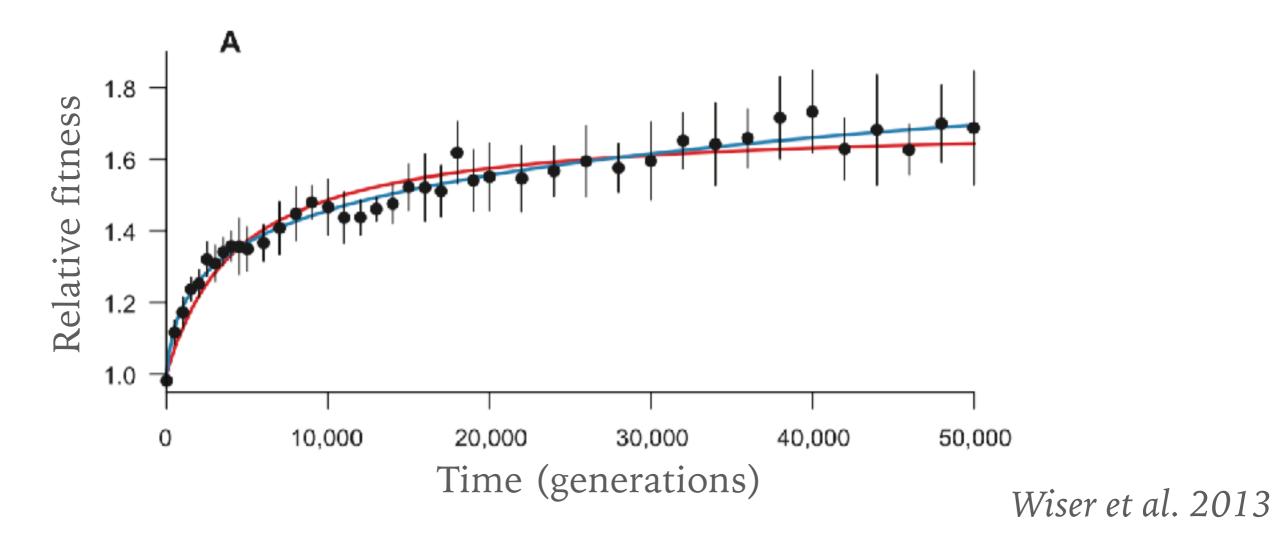
#### SYNOPSIS OF PART 1

- Selection is both simple and difficult, but certainly important
- DFE looks different than what has been assumed in most studies
- Epistasis seems to be common



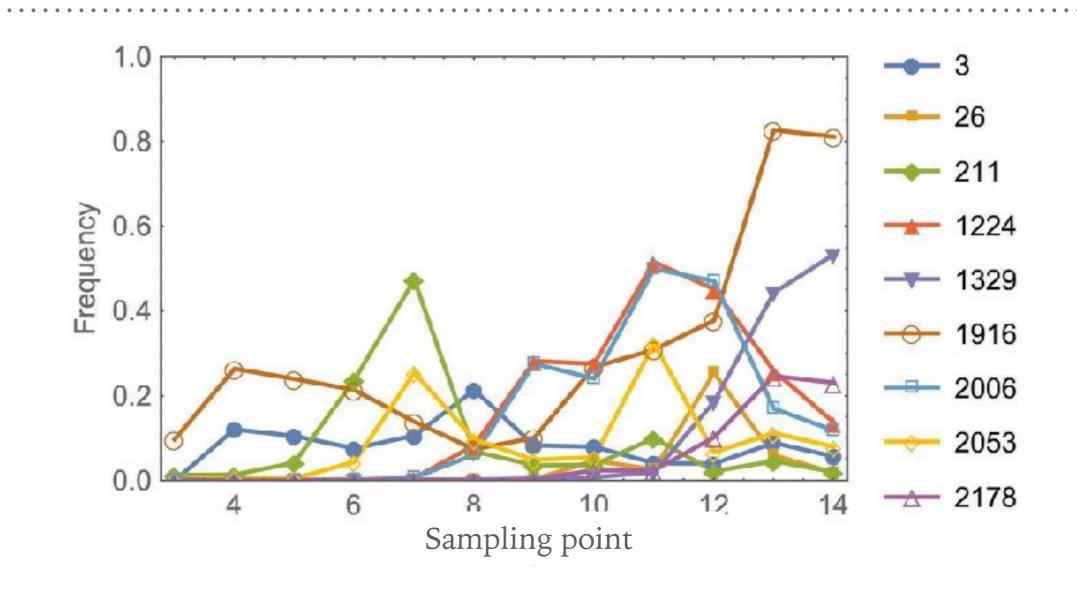
#### FISHER OR WRIGHT?

- From an ecological point of view, frequent bottlenecks seem likely.
- But adaptation is also miraculous in constant environments with high population sizes how is that possible?



# SERIAL SNP DATA

#### CAN WE ESTIMATE SELECTION COEFFICIENTS FROM TRAJECTORIES?

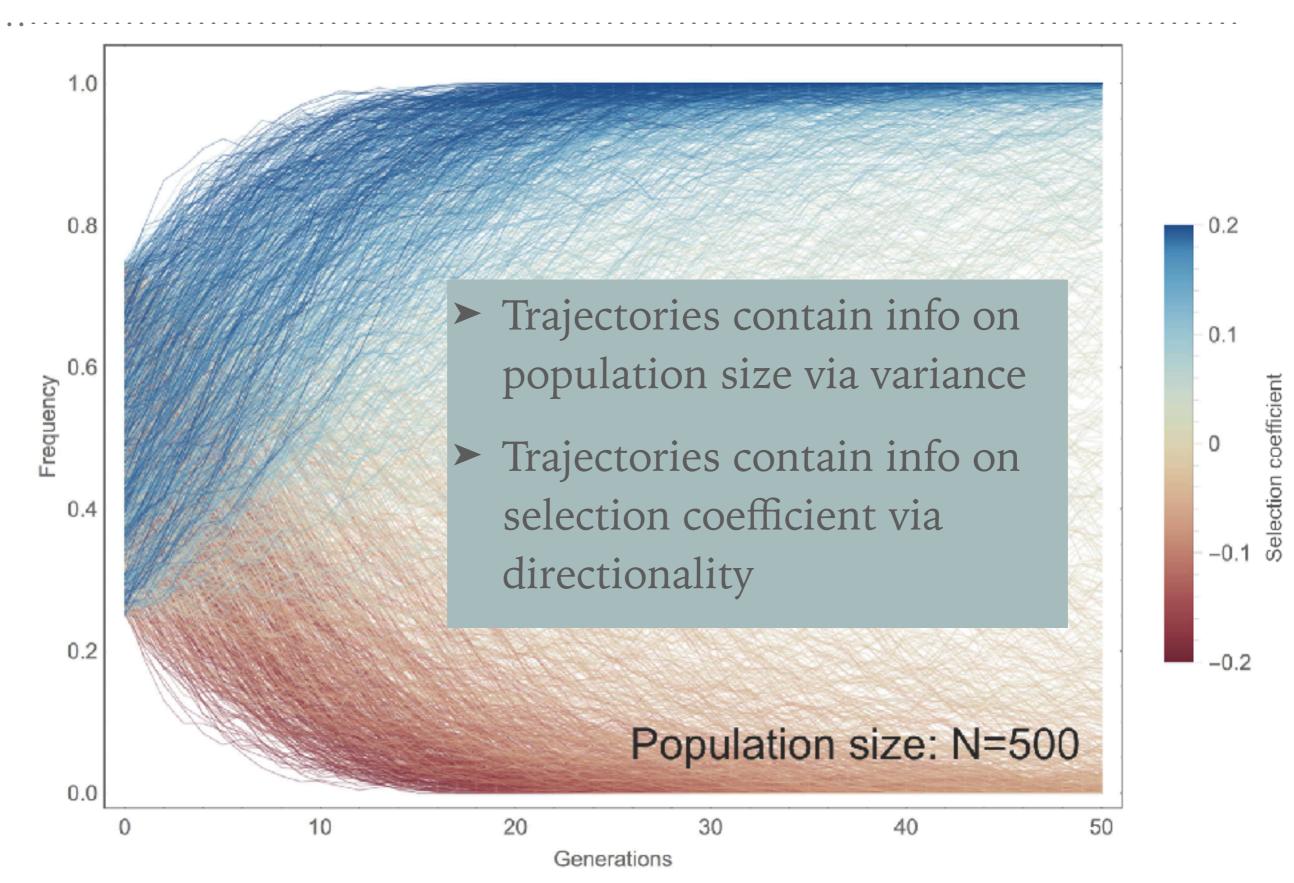


Output: allele-frequency trajectories of mutants along the genome

#### WFABC\*

\*Foll, Poh et al. 2014, Foll, Shim et al. 2014

#### THE WRIGHT-FISHER MODEL



#### SUMMARY STATISTICS FOR WFABC

$$Fs = \frac{(x-y)^2}{z(1-z)} \text{ and } Fs' = \frac{1}{t} \frac{Fs[1-1/(2\tilde{n})] - 2/\tilde{n}}{(1+Fs/4)[1-1/(n_y)]}$$

► *x*, *y*: minor allele frequencies at two consecutive time points

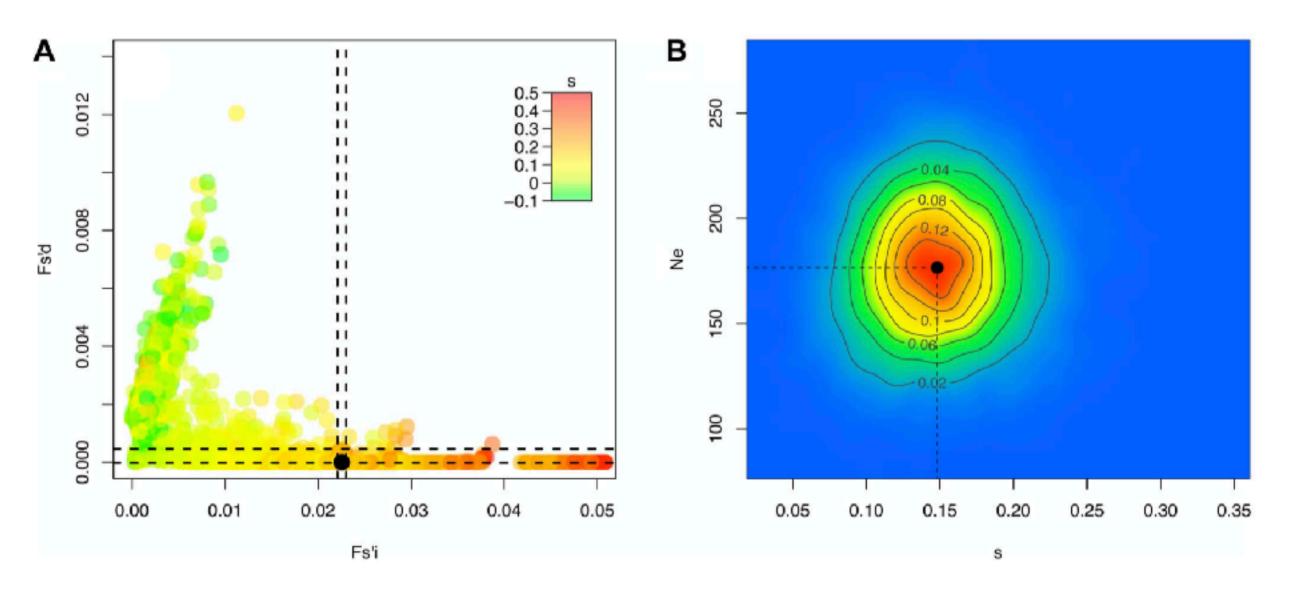
- ► z=(x-y)/2
- ▶  $\tilde{n}$ : harmonic mean of sample sizes  $n_x$  and  $n_y$
- ► *t* generations between sampling points
- ► *Fs*' is averaged over sites and times

$$N_e = 1/Fs' \text{ or } N_e = 1/(2Fs')$$

Jorde & Ryman 2007

#### SUMMARY STATISTICS FOR WFABC

U(X<sub>i</sub>) = (Fsd<sub>i</sub>, Fsi<sub>i</sub>): for each single trajectory split *Fs*' into *Fsd*' and *Fsi*' prime to determine the directional components in the trajectory.

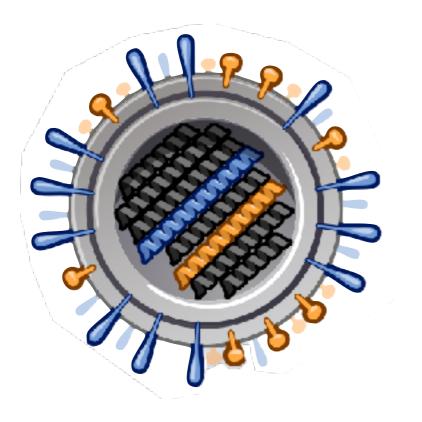


Foll, Poh et al. 2014

# WFABC – A SOFTWARE TO INFER EFFECTIVE POPULATION SIZE AND SELECTION FROM TIME-SERIAL DATA

- ► Input: allele-frequency trajectories (min. 3 time points)
- wfabc\_1: Infer effective population size from whole data set
- wfabc\_2: Infer selection coefficient from individual trajectories
- ► ABC method. Output: posterior probabilities

Developed by Matthieu Foll; Foll, Poh et al. 2014, Foll, Shim et al. 2014



# **OSELTAMIVIR (TAMIFLU)**

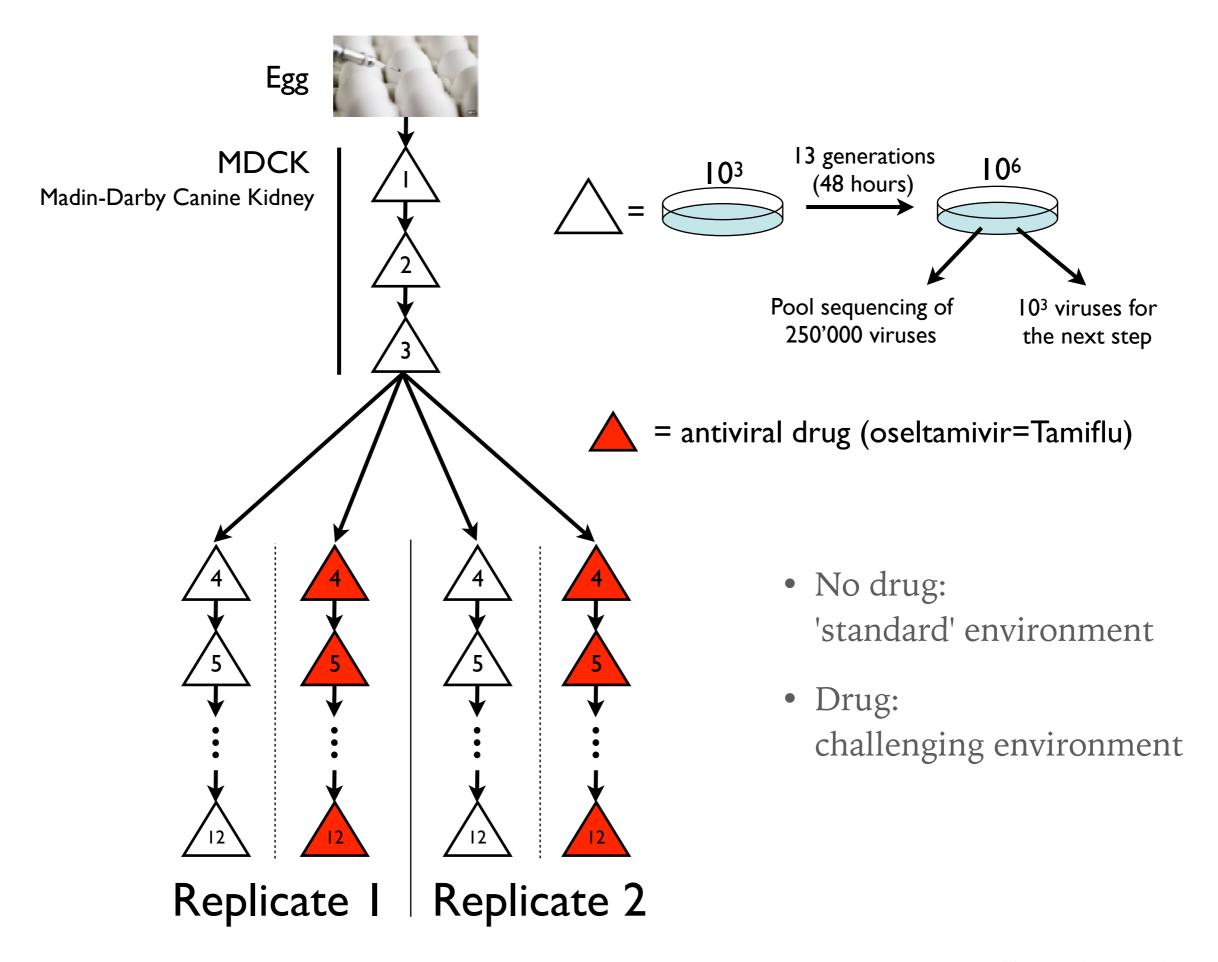
- competitive inhibitor of neuraminidase: prevents viral particles from being released by infected cells
- Resistance by single mutation in NA spread rapidly in natural populations

## INFLUENZA

- responsible for 150,000-200,000 deaths each year
- high motivation to develop effective vaccines and treatments

### FAVIPIRAVIR

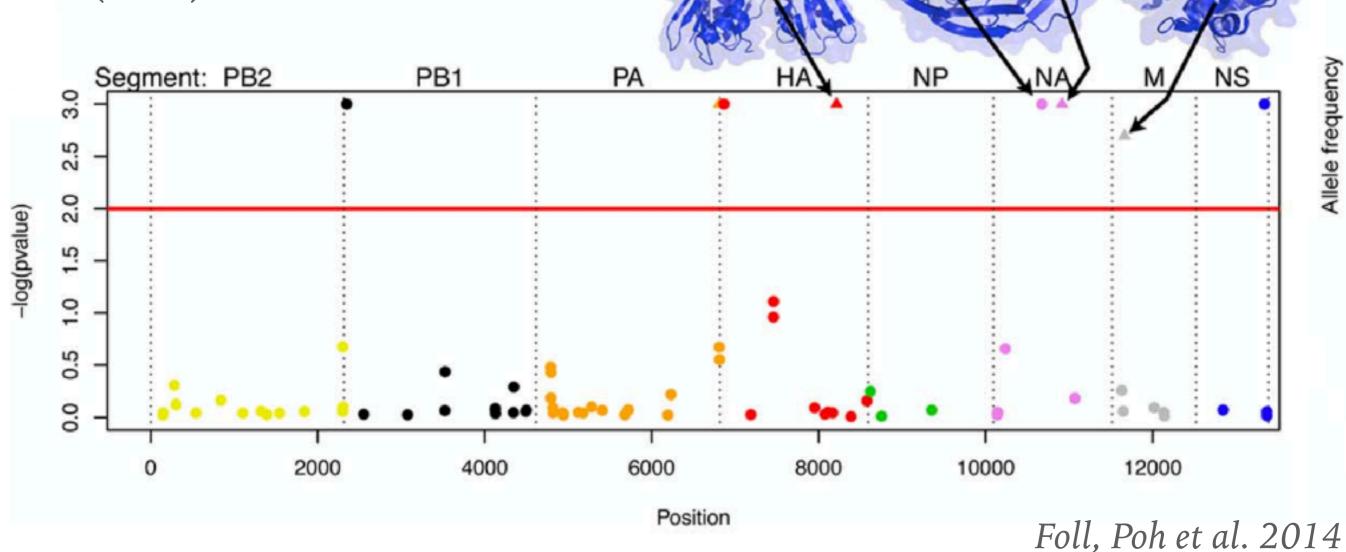
- increases mutation rate by interfering with viral RNAdependent RNA polymerase - lethal mutagenesis
- Approved in Japan, in trials in USA



Foll, Poh et al. 2014

#### **Results:**

- resistance evolves quickly
- characterization of all observed mutations (DFE)

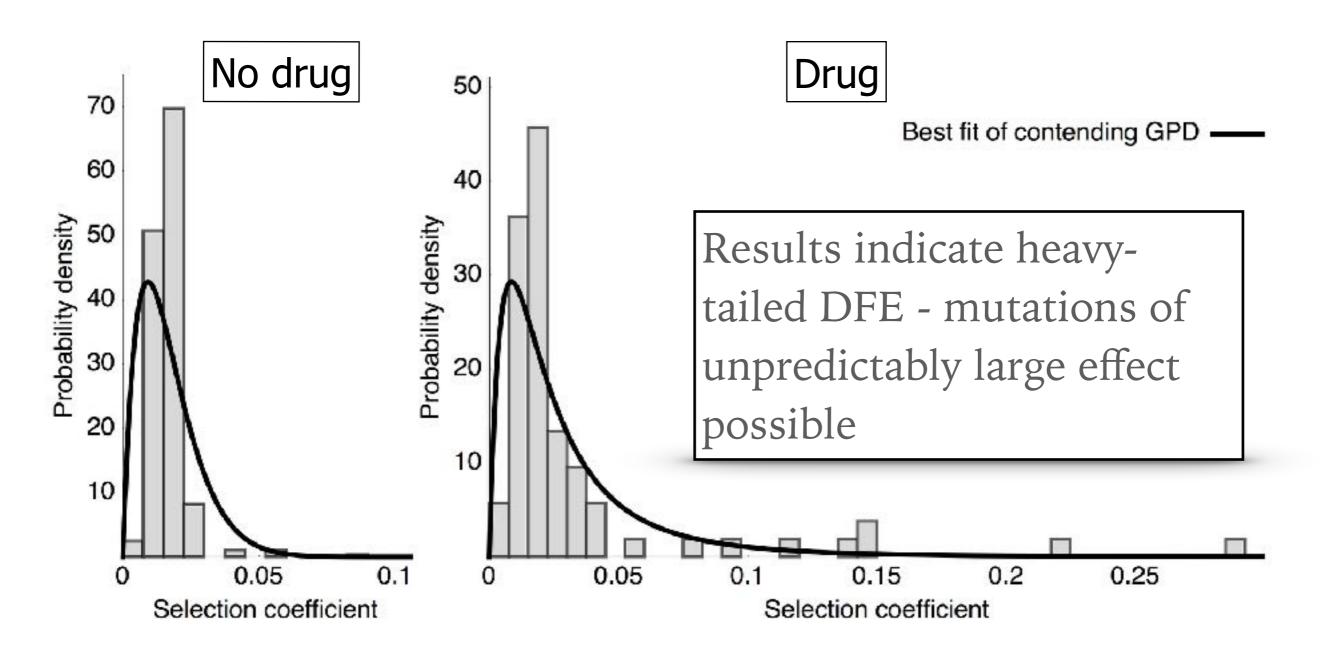


Position

Oseltamivir

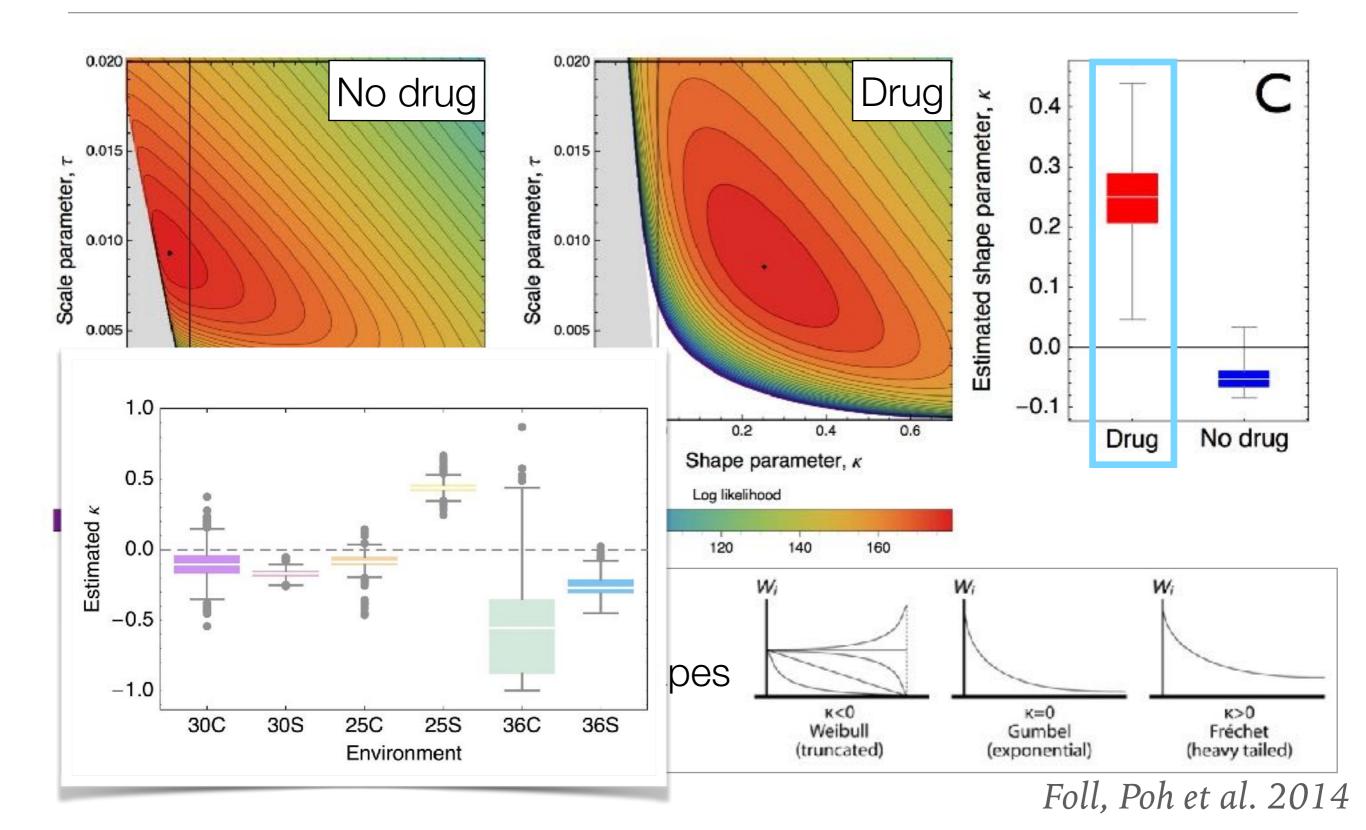
MI

#### SHAPE OF THE DFE (OF MUTATIONS THAT REACH >2% FREQUENCY)



Foll, Poh et al. 2014

#### Tail shape parameter in challenging environments



#### **EXPERIMENTAL EVOLUTION OF INFLUENZA VIRUS**

- Useful approach to study (resistance) evolution, both from a medical and an evolutionary point of view
- Artificial setup allows us to monitor various aspects of the dynamics - bottleneck size, absolute growth rate, genomewide allele frequencies, cell culture quality - a great testing ground for population-genetic methods

#### FINALLY SOMETHING ABOUT NEGATIVE SELECTION

#### WHAT MAKES MUTATION-RATE ENHANCERS EXCITING

# MEDICALLY

- could be used against a range of different viruses
- resistance is assumed to be difficult to achieve

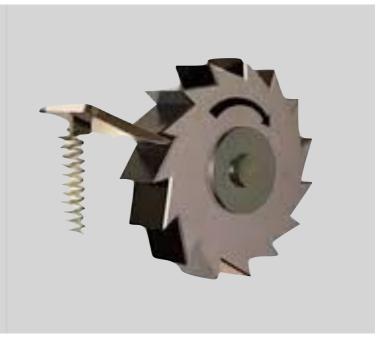
### EVOLUTIONARILY

- existing body of theory on the potential effects of high mutation rates
- proposed mechanisms of extinction versus rapid adaptation potential for validation?

#### MUTATIONAL MELTDOWN/LETHAL MUTAGENESIS

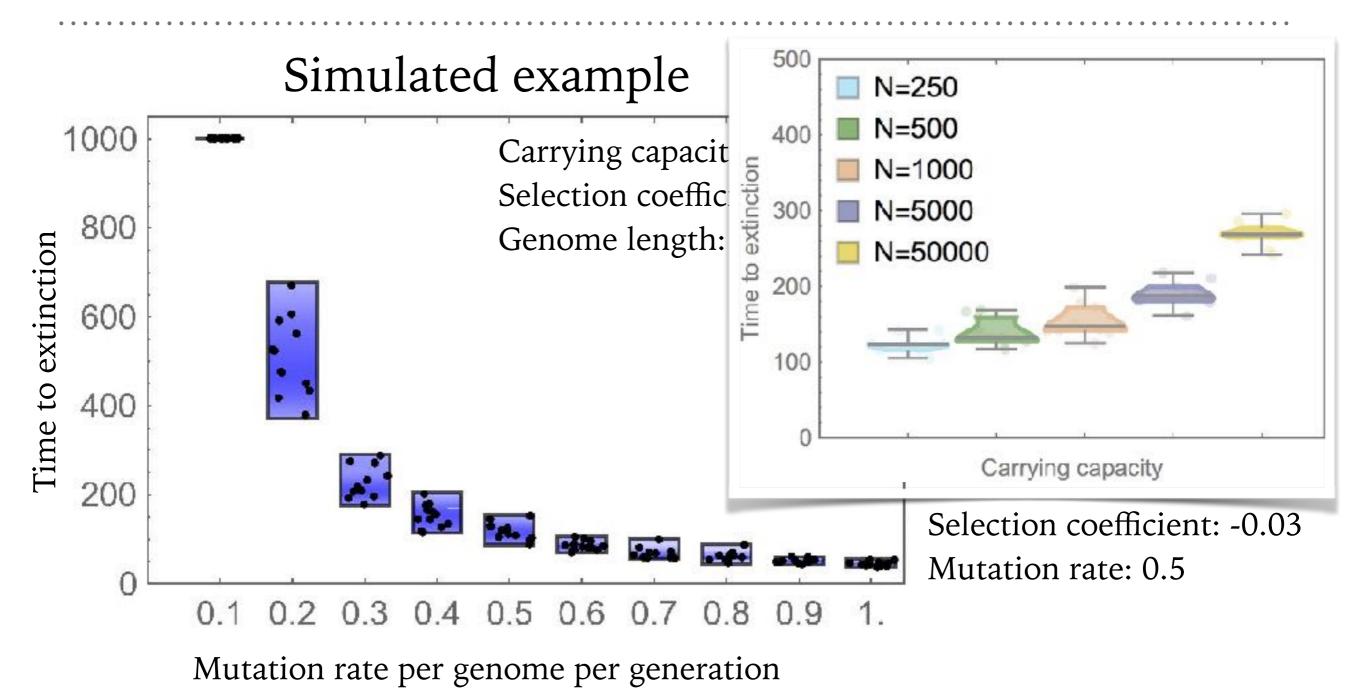
a population goes extinct because it accumulates too many deleterious mutations (such that the absolute growth rate becomes <1) - this can be caused by mutation pressure or random genetic drift (or both)

> Muller's ratchet: the step-wise loss of the fittest genotype due to accumulation of deleterious mutations in asexual populations



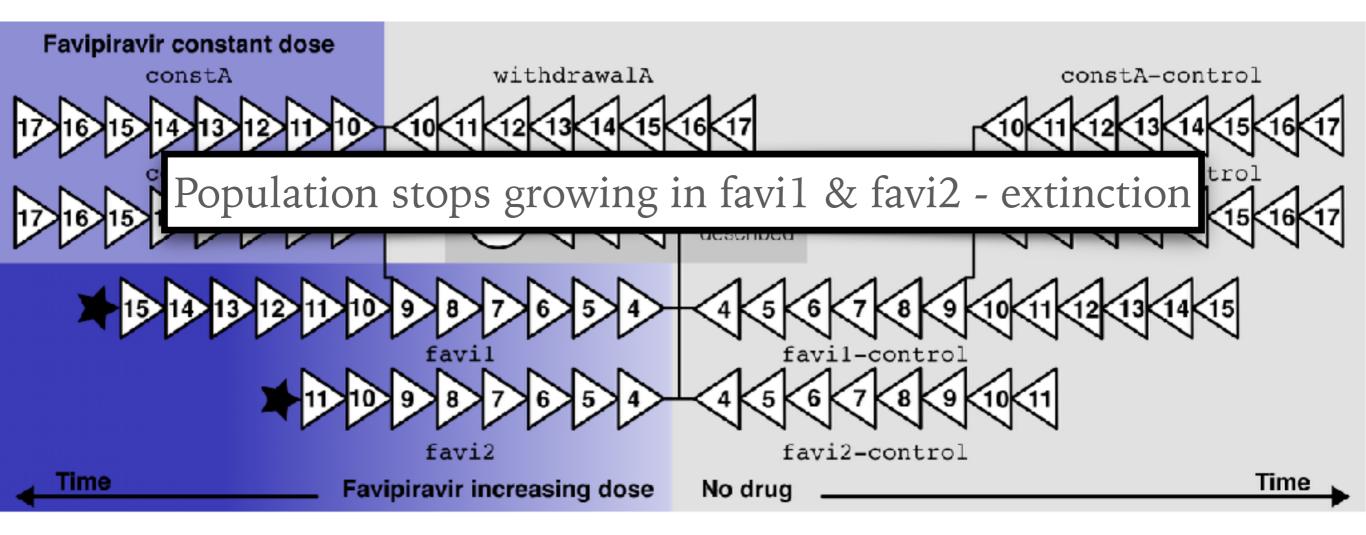
E.g., Lynch et al., 1990, Evolution

#### MUTAGENIC DRUGS AGAINST RNA VIRUS INFECTIONS



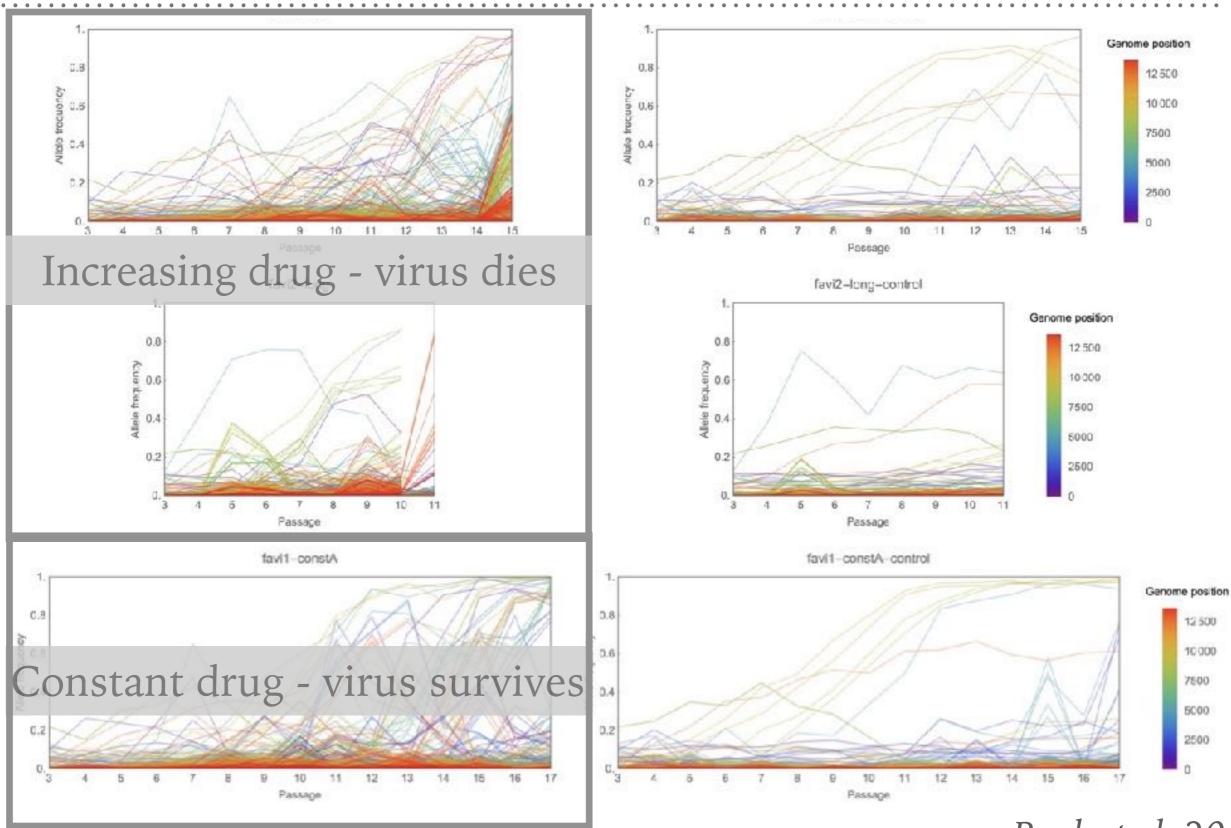
Mutagenic drug favipiravir approved for use against influenza in Japan and discussed as promising candidate drug against various RNA viruses.

#### **EXPERIMENTAL APPROACH**

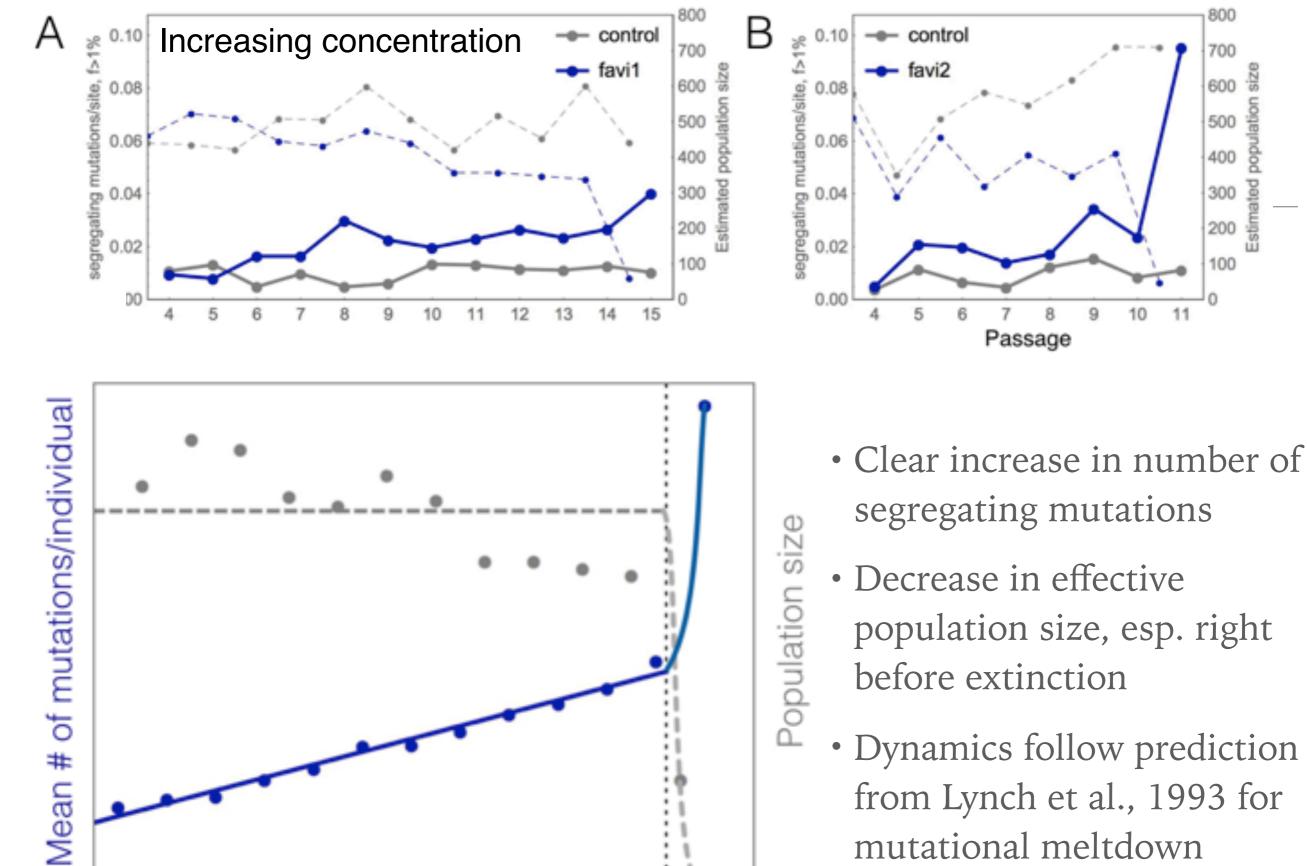


- Describe evolutionary dynamics under different drug treatments
- study potential for resistance mutations

#### INFLUENZA A LABORATORY EVOLUTION UNDER MUTAGENIC DRUG TREATMENT



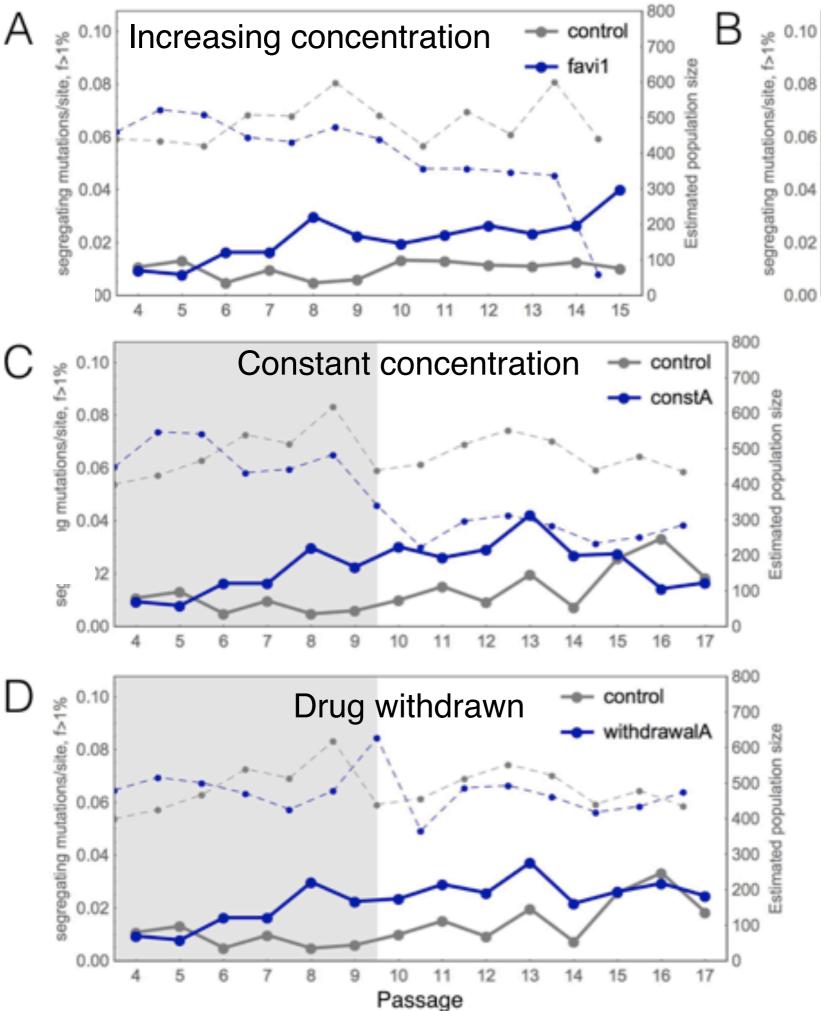
Bank et al. 2016



before extinction

Dynamics follow prediction from Lynch et al., 1993 for mutational meltdown

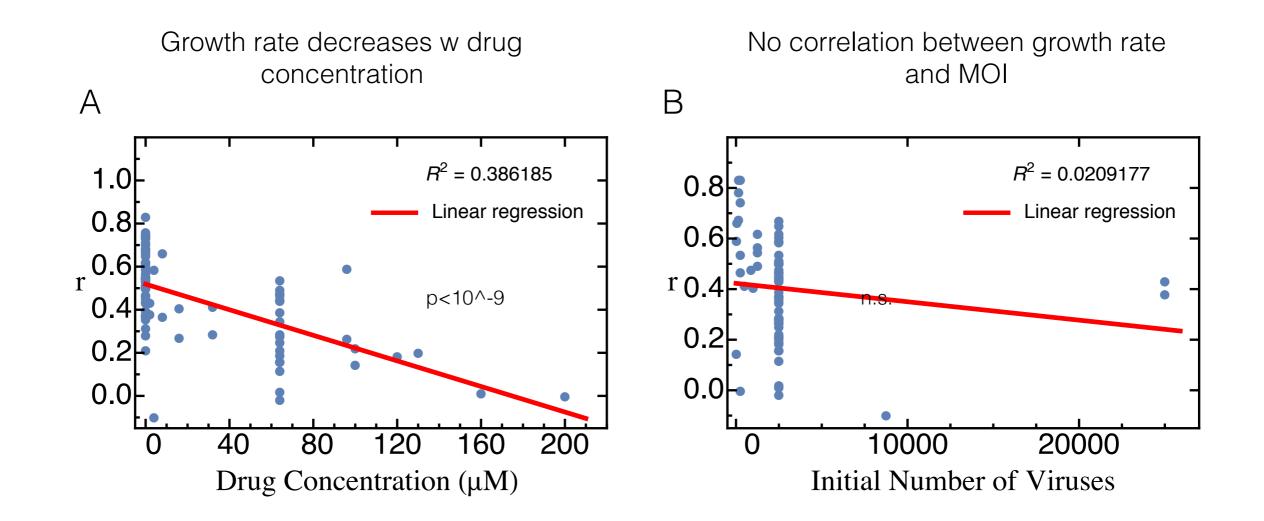
Generations



800 control 700 favi2 size 600 population 500 400 Estimated 300 200 100 0 10 11 9 8 5 Passage

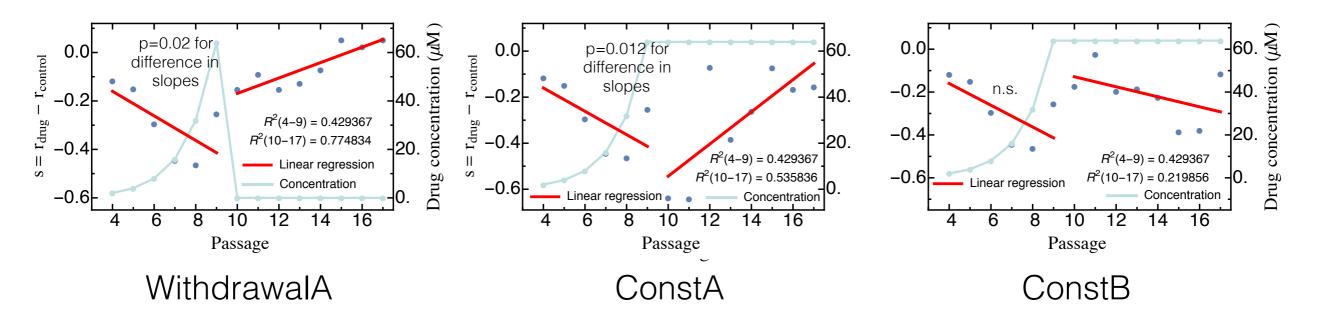
- Immediate recovery of effective population size but not # of segregating mutations in withdrawal
- survival of population at constant dose, but at low effective pop. size

#### Absolute growth rates



• obtained via MOI and virus output

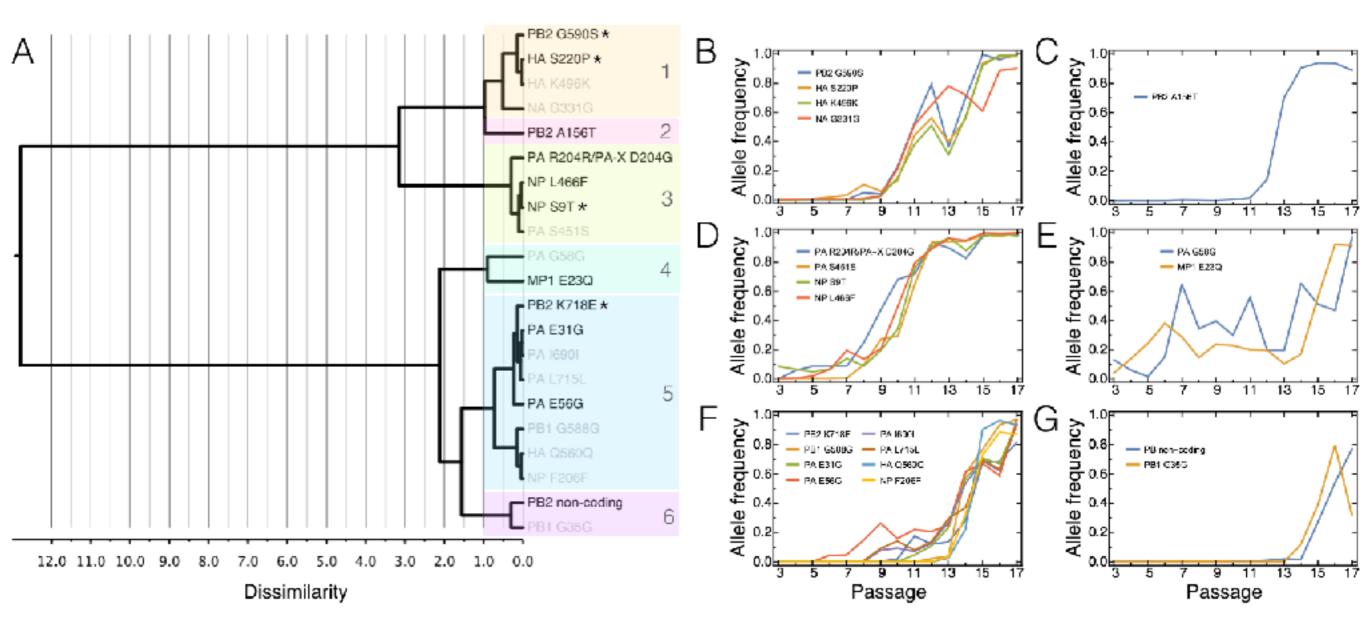
#### Absolute growth rates



- recovery of growth rate in withdrawal
- evidence for evolving recovery on constA resistance?
- indeed greatest number of (and most compelling evidence for) adaptations in constA!

# CAN VIRUSES ADAPT TO MUTAGENIC DRUG TREATMENTS?

- "Adaptation" in this context means survival/persistence of a pathogen or other health threat despite exposure to drug, immune system, novel environments, etc.
- By which mechanisms can viruses escape from mutagenic drug treatment? Can we detect the signatures of such adaptation? What are the dangers of mutagenic drugs?
- An example of evolutionary rescue: an adaptation spreads in a population that is otherwise doomed to extinction due to a change in the environment



- similarity between trajectories indicates hitchhiking/ joint selection
- WFABC candidates in constA provide focal set, which then can be refined
- clusters indicate potential "adaptation story"

Data set	# candidates		Increased # mutations?	Indication of recovery?	Reduced Ne?
favi1	5	yes	yes	no	yes
favi2	3	yes	yes	no	yes
constA	18	no	yes	yes	yes
constB	6	no	yes	unclear	yes
withdrawalA	1	no	yes	yes	no

#### Mechanism is working Drug challenges populations

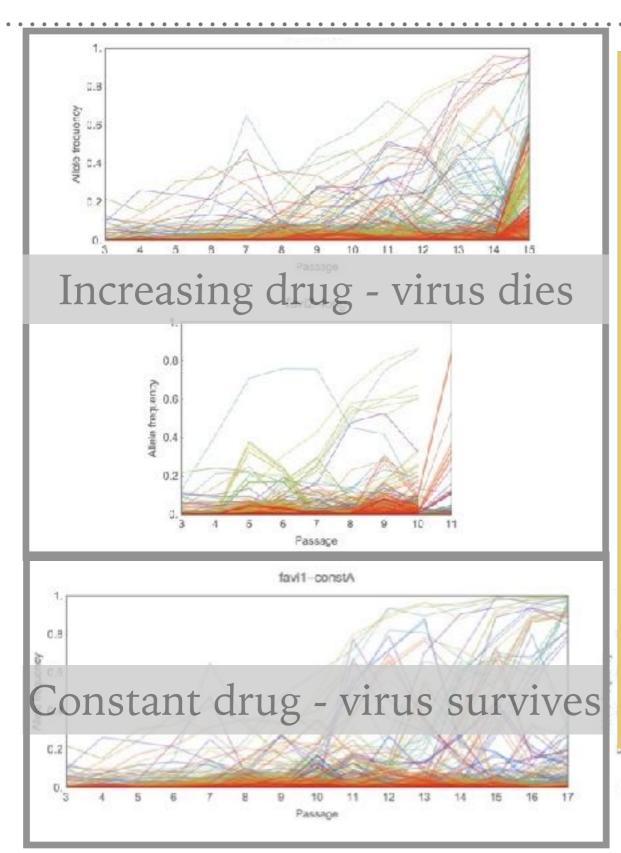
Data set	# candidates	Extinction observed?	Increased # mutations?	Indication of recovery?	Reduced Ne?
favi1		yes	yes meltdov	no	yes
favi2	3	yes	yes	no	yes
constA	18	no	yes	yes	yes
constB	6	no	yes	unclear	yes
withdrawalA	1	no	yes	yes	no

Data set	# candidates	Extinction observed?	Increased # mutations?	Indication of recovery?	Reduced Ne?
favi1	5	yes	yes	no	yes
favi2	3	yes	yes	no	yes
constA	18	no	yes	yes	yes
Resis constB	stance ev				

# SUMMARY/CONCLUSION OF THE STUDY

- We observe mutational meltdown in action i.e., the drug is effective in favi1 & favi2.
- We see potential for resistance evolution (à la evolutionary rescue?) under constant doses of favipiravir i.e., drug doses have to be sufficiently high for success, otherwise the increase in mutation rate may even allow for a speedup of adaptation
- Novel time-serial approaches enable the identification of candidates, which can be tested functionally in the future.

### WHERE'S THE CATCH?



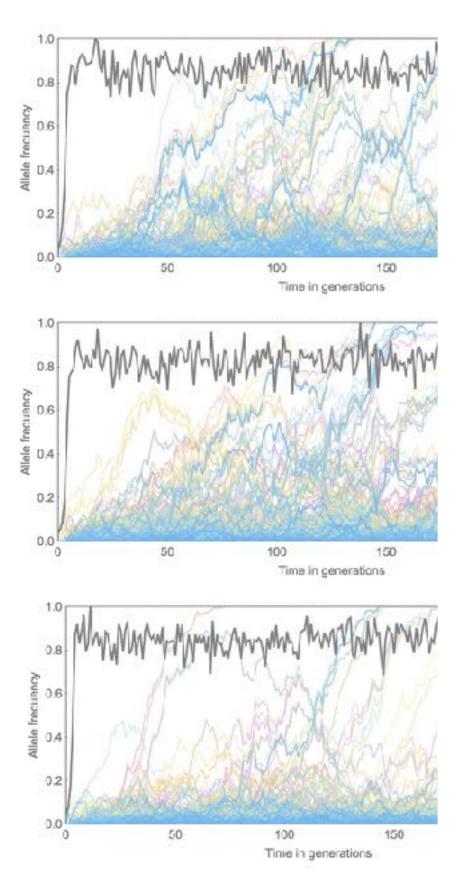
How can the virus adapt to the drug? What is the signature of different adaptation mechanisms?

- How good are our methods for detection of candidate loci?
- How informative are allele frequencies?
- Validate the results with simulations!

2500

Bank et al., 2016, Evolution

#### SIMULATE EVOLUTION OF A CLONAL POPULATION WITH HIGH MUTATION RATES



#### POTENTIAL MECHANISMS OF RESCUE FROM INCREASED MUTATION RATES

- "traditional" beneficial mutations that increase growth rate: only a temporary fix because they will not stop the ratchet
- > a mutation rate modifier that reduces the mutation rate below the critical level: evolution of drug resistance
- a modifier of the fitness distribution, i.e. a mutation that changes mutational effects genome-wide: evolution of drug tolerance

Important to note: both weaker and stronger effects of (deleterious) mutations can slow down the ratchet (Gordo & Charlesworth 2000)

Tolerance could be the most dangerous mechanism of adaptation to mutagenic drugs because it allows the virus to propagate at high mutation rates, which may allow rare/unseen/complex beneficial mutations to invade subsequently.

### **TODAY'S QUESTIONS**

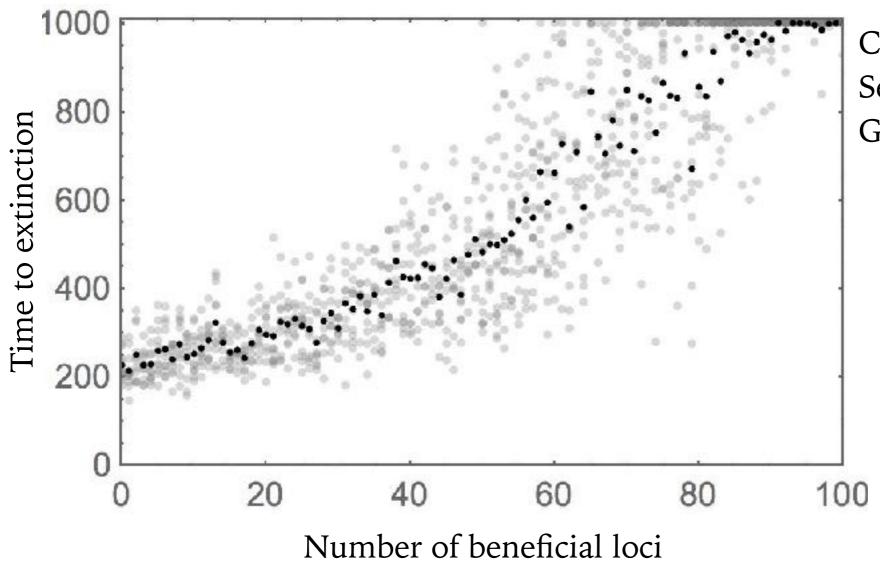
- How does the availability of "traditional" beneficials prolong extinction times?
- ► When does a mutation rate modifier invade?
- In which conditions does a modifier of the distribution of fitness effects (DFE) invade?

## **SIMULATION DETAILS**

- ► Genome with *L* di-allelic loci [1000]
- Carrying capacity C of the clonal population [250], initial population size C<sub>0</sub> [invasion size: 10]
- ► Initial absolute growth rate *R* [2]
- Arbitrary distribution of fitness effects [-0.05; multiplicative]
- > Mutation rate  $\mu$  per genome per generation [0.3]
- Record haplotypes in each generation, stop if no extinction has occurred after 1000 generations (transmission/immune reaction)
- I loci with "adaptive" mutations; either beneficial, mutation rate modifier, or DFE modifier

For now: focus on extinction time & "rescue" probability -Later: compare trajectories

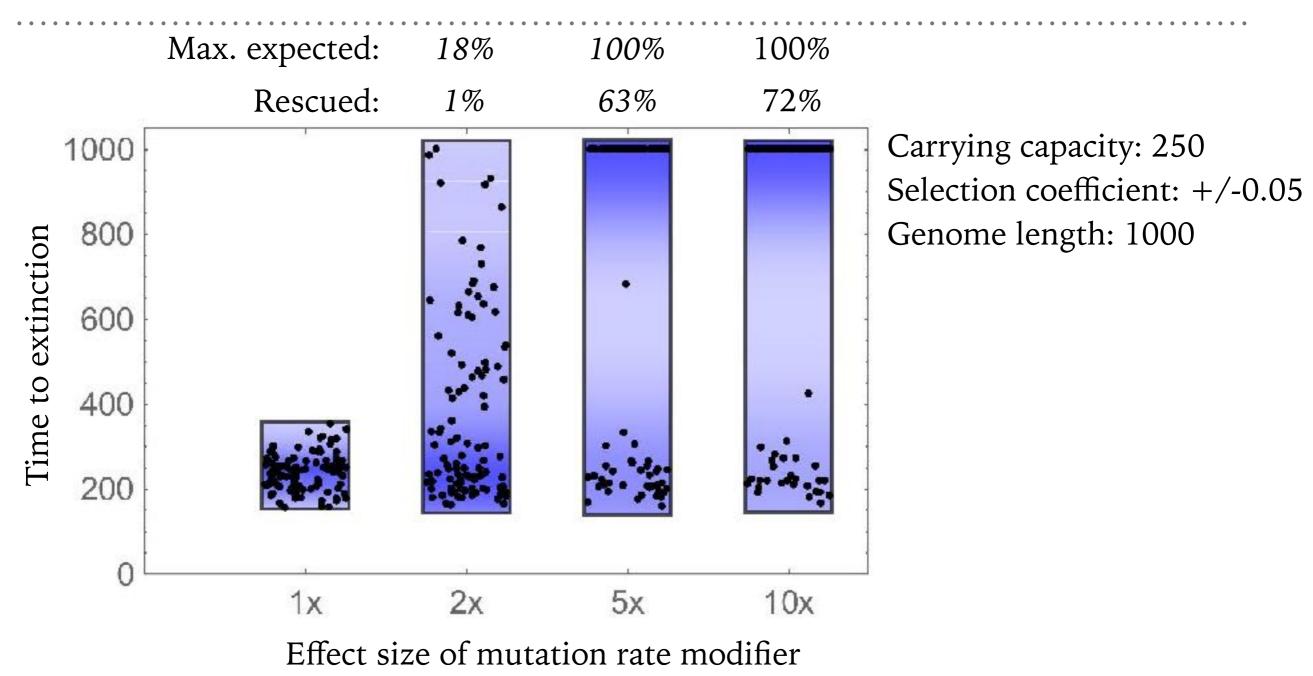
# **EXTINCTION TIMES WITH BENEFICIAL MUTATIONS**



Carrying capacity: 250 Selection coefficient: +/-0.05 Genome length: 1000

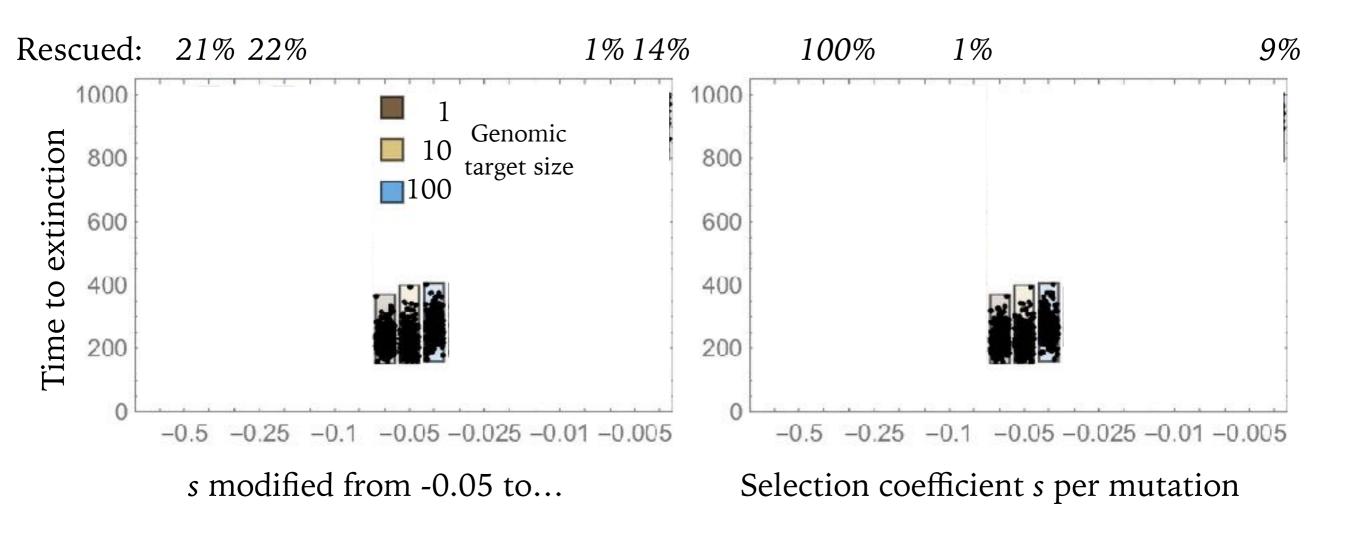
- Many beneficials necessary to allow for significantly prolonged time to extinction.
- Clonal interference impedes efficient spread of multiple beneficials and increases variance in extinction times.

# **INVASION OF A MUTATION RATE MODIFIER**



Mutation rate modifier of sufficient strength readily invades and rescues the population with high probability.

#### **INVASION OF A DFE MODIFIER**



Both types of modifiers can invade; "chaperone" modifier invades easily but rarely rescues; "negative" modifier only invades under specific conditions but then rescues reliably.

#### CONCLUSIONS

- Extinction process is rather deterministic over a large range of the parameter space.
- Many available beneficials are needed to prolong the extinction time (e.g., to successful transmission of the virus).
- If available, mutation rate modifiers readily invade and make the population resistant to mutagenic treatment.
- DFE modifiers in both directions can invade and make the virus tolerant to high mutation rates. This is possibly the most dangerous adaptation mechanism, because it could modify virus evolution also in absence of the drug.

#### www.evoldynamics.org

#### ACKNOWLEDGEMENTS



Alex Blanckaert

**COLLABORATORS** 



Inês Fragata

#### Hermina Ghenu



Marco Louro

FUNDING



Mark Schmitz

#### Maria João Amorim, IGC Thomas Bataillon, Aarhus University Daniel Bolon, Pam Cote, Ryan Hietpas, UMass Medical School Roger Butlin, University of Sheffield Mónica Bettencourt-Dias, IGC Isabel Gordo, IGC Jeffrey Jensen, Arizona State University Rees Kassen, University of Ottawa Jonna Kulmuni, Helsinki University David Liberles, Temple University Sebastian Matuszewski, EPFL Vitor Sousa, University of Lisbon Alex Wong, Carleton University





