

# Chapter 6

## Working with the single-locus diffusion model

The formal results in the previous chapter glossed over an important question: what are the benefits of showing that a particular microscopic model is equivalent to the single-locus diffusion,

$$\frac{\partial f}{\partial t} = \underbrace{sf(1-f)}_{\text{selection}} + \underbrace{\mu(1-f) - \nu f}_{\text{mutation}} + \underbrace{\sqrt{\frac{f(1-f)}{N}} \cdot \eta(t)}_{\text{genetic drift}}, \quad (6.1)$$

for some effective parameters  $N$ ,  $s$ ,  $\mu$ , and  $\nu$ ?

One benefit is that it is sometimes possible to speed up simulations of a particular model by replacing it with a different member of the same universality class. This is a common strategy in computational studies. For example, the Poisson sampling step in the serial dilution model is slightly faster to simulate on a computer than the equivalent Binomial sampling step in the Wright-Fisher model — our convergence results show that the faster version will still yield similar predictions when the population size is large.

Similar logic applies for analytical results as well. If one model is analytically tractable, it can provide a “mathematical speedup” for all of the other models

that share the same universality class. In this chapter, we will show that the SDE model in Eq. (6.1) constitutes one such example, enabling analytical results that are difficult or impossible to derive in the original Wright-Fisher model (or our serial dilution model from Chapter 4).

To do so, we will need to develop methods for “integrating” stochastic differential equations like Eq. (6.1). This was trivial in the case of the Gaussian random walk in Section 5.2.1, since the step sizes all had the same mean and variance. The task is more challenging for models like Eq. (6.1) where the sizes depend on the current value of  $f(t)$ . For sufficiently dense sampling of  $f(t)$ , we could generalize our result in Eq. (5.16) to write down a path-integral-like approximation for the probability of the full trajectory,

$$p(f(\delta t), \dots, f(t)|f(0)) \approx \prod_{k=0}^{\frac{t}{\delta t}-1} \frac{e^{-\frac{[\delta f(k \cdot \delta t) - \mu(f(k \cdot \delta t) \cdot \delta t)]^2}{2 \cdot \sigma^2(f(k \cdot \delta t)) \cdot \delta t}}}{\sqrt{2\pi\sigma^2(f(k \cdot \delta t))}}, \quad (6.2)$$

which will be valid if  $\mu(f(t + \delta t)) \approx \mu(f(t))$  and  $\sigma^2(f(t + \delta t)) \approx \sigma^2(f(t))$ . However, this path integral formulation is rarely useful in practice, since we rarely have such fine-grained measurements of  $f(t)$ . Instead, we are often interested in more coarse-grained outcomes: did the mutation fix or go extinct? How much do we expect its frequency to change over a finite time interval? Enumerating and summing over all of the trajectories that could contribute to these outcomes is often as difficult as solving the original SDE itself.

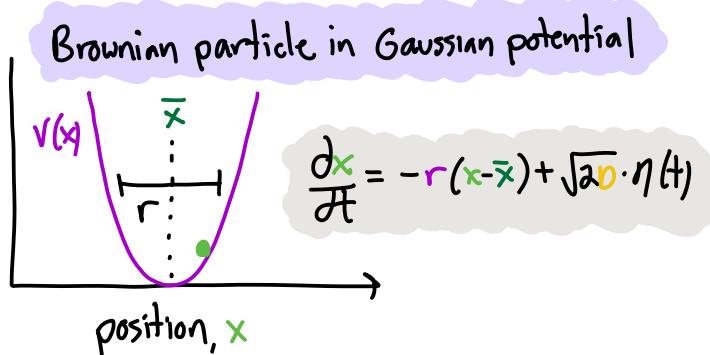
To make progress, we will need to introduce a different methodology for working directly with SDEs like Eq. (6.1). These methods are sometimes known as the *stochastic calculus*. The name may sound intimidating, but we will see that most of these rules can be derived from straightforward applications of the discrete update rule in Eq. (5.35). To illustrate these ideas, it will be helpful to start by considering a simpler SDE that frequently arises in physical settings. We will then show how we can extend these ideas to the single-locus model in Eq. (6.1).

## 6.1 Detour: Brownian particle in a quadratic potential

We will start by considering the simpler problem of a *Brownian particle in a quadratic potential*. This model arises in many different areas of physics, and will turn out to be useful in some evolutionary contexts as well. The goal is to model the position of an ordinary random walker that is subject to a restoring force  $F(x) = -\frac{\partial V(x)}{\partial x}$ . For a quadratic potential, the SDE can be written in the general form,

$$\frac{\partial x}{\partial t} = - \underbrace{r(x - \bar{x})}_{\frac{\partial V}{\partial x}} + \sqrt{2D} \cdot \eta(t) \quad (6.3)$$

where  $\bar{x}$  is the *equilibrium point*,  $r$  is the *restoring force*, and  $D$  is the *diffusion constant* (which is proportional to the temperature  $kT$  in many physical problems).<sup>1</sup> This is the simplest SDE model with non-constant coefficients.



In the absence of noise ( $D = 0$ ), the solution to Eq. (6.3) is given by the deterministic function,

$$x_{\text{det}}(t) = \bar{x} + [x(0) - \bar{x}]e^{-rt}. \quad (6.4)$$

---

<sup>1</sup>If you're curious where this equation comes from, you can think of it as an instantaneous balance between a conservative force  $F(x) = -\frac{\partial V(x)}{\partial x}$  and a viscous drag force  $F_{\text{drag}} = -\gamma \frac{\partial x}{\partial t}$  when the inertia of the particle is small. This explains why the SDE depends on the first derivative of  $x(t)$  rather than the second derivative that you might expect from Newtonian mechanics. For simplicity, we have absorbed the drag coefficient  $\gamma$  into the definition of  $V(x)$  in Eq. (6.3).

This shows that the position of the particle approaches the equilibrium point  $\bar{x}$  at an exponential rate  $r$ . How does this picture change in the presence of noise?

One way to approach this question is to focus on the moments of  $x(t)$ , e.g. the mean  $\langle x(t) \rangle$ . We can calculate this quantity by recalling that our SDE notation is shorthand for the discrete update rule in Eq. (5.23). For the SDE in Eq. (6.3), the corresponding update rule is

$$x(t + \delta t) = x(t) - r[x(t) - \bar{x}]\delta t + \sqrt{2D \cdot \delta t} \cdot Z_t, \quad (6.5)$$

where  $Z_t$  is a Gaussian random variable  $\langle Z_t \rangle = 0$  and  $\langle Z_t^2 \rangle = 1$ . Taking the average of both sides, we find that

$$\begin{aligned} \langle x(t + \delta t) \rangle &= \langle x(t) - r[x(t) - \bar{x}]\delta t + \sqrt{2D \cdot \delta t} \cdot Z_t \rangle \\ &= \langle x(t) \rangle - r[\langle x(t) \rangle - \bar{x}] \delta t + 0 \end{aligned} \quad (6.6)$$

where we have exploited the linearity of the expectation and the fact that  $\langle Z_t \rangle = 0$ . This is now a *deterministic* update rule for the mean position  $\langle x(t) \rangle$ . Taking differences and dividing by  $\delta t$  yields

$$\frac{\langle x(t + \delta t) \rangle - \langle x(t) \rangle}{\delta t} = -r[\langle x(t) \rangle - \bar{x}] \quad (6.7)$$

which reduces to

$$\frac{\partial \langle x(t) \rangle}{\partial t} = -r[\langle x(t) \rangle - \bar{x}] \quad (6.8)$$

in the limit that  $\delta t$  is small. We've now reduced our stochastic differential equation to an *ordinary differential equation* for  $\langle x(t) \rangle$ . The solution is given by

$$\langle x(t) \rangle - \bar{x} = [x(0) - \bar{x}] e^{-rt} \quad (6.9)$$

which is equivalent to the deterministic solution in Eq. (6.4). Thus, in this particular example, the average value of  $x(t)$  is unchanged by the addition of noise.

What about the spread around this average value? When  $x(0) = \bar{x} = 0$ , the variance in the position is given by the second moment,  $\langle x(t)^2 \rangle$ . We can calculate this quantity using the same basic procedure that we used for the mean:

**Step 1:** We can start by using the update rule in Eq. (6.5) to write down an expression for  $x(t + \delta t)^2$ ,

$$x(t + \delta t)^2 = \left[ x(t) - rx(t)\delta t + \sqrt{2D\delta t}Z_t \right]^2 \quad (6.10)$$

Taking the average of both sides yields:

$$\langle x(t + \delta t)^2 \rangle = \left\langle \left[ x(t) - rx(t)\delta t + \sqrt{2D\delta t}Z_t \right]^2 \right\rangle \quad (6.11)$$

**Step 2:** We can then expand the terms in the right hand side as a power series in  $\delta t$ . This yields

$$\begin{aligned} \langle x(t + \delta t)^2 \rangle &= \left\langle x(t)^2 - 2rx(t)^2\delta t + 2x(t)\sqrt{D\delta t}Z_t + 2DZ_t^2\delta t + \dots \right\rangle \\ &= \langle x(t)^2 \rangle - 2r\langle x(t)^2 \rangle\delta t + 2D\delta t + \dots \end{aligned} \quad (6.12)$$

where we have used the fact that  $\langle Z_t \rangle = 0$  and  $\langle Z_t^2 \rangle = 1$ .

**Step 3:** We can then rewrite this expression as a difference equation:

$$\frac{\langle x(t + \delta)^2 \rangle - \langle x(t)^2 \rangle}{\delta t} = -2r\langle x(t) \rangle + 2D + \dots \quad (6.13)$$

where the higher-order terms are all larger powers of  $\delta t$ . When  $\delta t$  is small, this yields an ordinary differential equation for the second moment

$$\frac{\partial \langle x(t)^2 \rangle}{\partial t} = -2r\langle x(t)^2 \rangle + 2D \quad (6.14)$$

The first term is exactly what we'd expect by applying the chain rule to the deterministic solution,

$$\frac{\partial[x_{\text{det}}(t)^2]}{\partial t} = 2x_{\text{det}}(t) \cdot \partial_t x_{\text{det}}(t) = -2rx_{\text{det}}(t)^2 \quad (6.15)$$

The second term in Eq. (6.14) is a new contribution that arises purely from the addition of noise. This term arose from taking the average of two correlated noise terms, each of which was  $\propto \sqrt{\delta t}$ . In this way, we see that SDEs require us to generalize the ordinary chain rule from calculus (this is often known as *Ito's formula*).

At long times, the variance approaches the steady-state value

$$\frac{\partial \langle x(t)^2 \rangle}{\partial t} = 0 \implies \langle x(t)^2 \rangle = \frac{D}{r} \quad (6.16)$$

which constitutes a balance between the diffusive noise  $D$  and the deterministic restoring force  $r$ . Larger values of  $D$  (or smaller values of  $r$ ) lead to larger deviations from  $\bar{x}$ , while smaller values of  $D$  (or larger values of  $r$ ) lead to a tighter distribution.

One can repeat the steps above to calculate higher moments of  $x(t)$ . In this case, it is also possible to calculate the entire distribution of  $x(t)$  at long times. We can do this by turning to the Fokker-Planck representation of the SDE (Section 5.2.3). For a general SDE of the form

$$\frac{\partial x}{\partial t} = -\frac{\partial V(x)}{\partial x} + \sqrt{2D} \cdot \eta(t), \quad (6.17)$$

the corresponding Fokker-Planck equation is

$$\frac{\partial p(x, t)}{\partial t} = -\frac{\partial}{\partial x} \left[ -\frac{\partial V}{\partial x} \cdot p(x, t) \right] + \frac{\partial^2}{\partial x^2} [Dp(x, t)]. \quad (6.18)$$

At long times, we expect that the time derivatives will vanish ( $\partial_t p = 0$ ), so that

the steady-state distribution will satisfy

$$0 = -\frac{\partial}{\partial x} \left[ -\frac{\partial V}{\partial x} \cdot p(x, t) \right] + \frac{\partial^2}{\partial x^2} [Dp(x, t)] \quad (6.19)$$

The solution is given by the so-called **Boltzmann distribution**

$$p(x) \propto e^{-\frac{V(x)}{D}}, \quad (6.20)$$

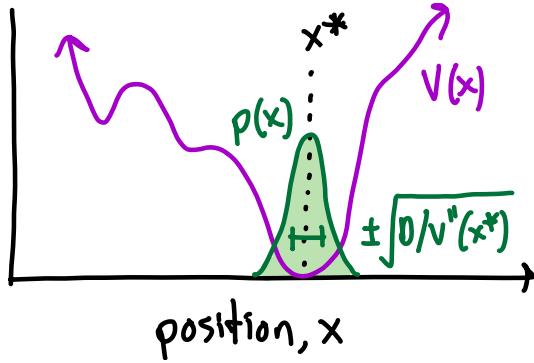
which you might recognize from a course in equilibrium statistical mechanics. In the Boltzmann distribution, the most likely position of the particle is the one with the lowest value of  $V(x)$ . This will often occur at a local minimum of  $V(x)$ , where

$$\frac{\partial V}{\partial x} \Big|_{x=x^*} = 0, \quad \frac{\partial^2 V(x)}{\partial x^2} \Big|_{x=x^*} > 0 \quad (6.21)$$

If we expand around this point, the Boltzmann distribution approaches the Gaussian form,

$$p(x) \propto e^{-\frac{V(x^*)+V'(x^*)(x-x^*)+\frac{V''(x^*)}{2}(x-x^*)^2+\dots}{D}} \propto e^{-\frac{V''(x^*)}{2D}(x-x^*)^2} \quad (6.22)$$

with mean  $\langle x \rangle = x^*$  and variance  $\sigma^2 = D/V''(x^*)$ . This approximation is exact in the case of our quadratic potential, where  $x^* = \bar{x}$  and  $V''(x) = r$ . Thus, we can think about the quadratic potential as describing the generic behavior of a Brownian particle near a local energy minimum. This will be a “Case I” distribution according to our terminology in Section 2.2.1: the particle will stay close to its deterministic expectation ( $x^*$ ) with some fuzziness due to noise ( $\pm \sqrt{D/V''(x^*)}$ ).



## 6.2 Back to the single-locus model

We can now try to use the same techniques to analyze the single-locus model in Eq. (6.1). This model has two key differences from the Brownian particle example above:

1. The effective diffusion coefficient now depends on the current value of  $f(t)$ . This means that the strength of noise will vary for different parts of the mutation trajectory.
2. The selection term in the deterministic portion of the SDE is now a *non-linear* function of  $f(t)$ .

These may seem like small differences, but we will see that they can have a profound effect on the dynamics of the resulting mutation trajectories.

## 6.3 Dynamics of the mean and variance

For example, if we want to calculate the average mutation frequency  $\langle f(t) \rangle$ , starting from a given frequency  $f(0)$ , we can repeat the procedure above starting

from the analogous discrete update rule:

$$\begin{aligned} f(t + \delta t) &= f(t) + sf(t)[1 - f(t)]\delta t + \mu(1 - f)\delta t \\ &\quad - \nu f\delta t + \sqrt{\frac{f(t)[1 - f(t)]\delta t}{N}} \cdot Z_t. \end{aligned} \quad (6.23)$$

Taking the average of both sides, we find that

$$\begin{aligned} \langle f(t + \delta t) \rangle &= \langle f(t) \rangle + s [\langle f(t) \rangle - \langle f(t)^2 \rangle] \delta t \\ &\quad + \mu(1 - \langle f(t) \rangle) \delta t - \nu \langle f(t) \rangle \delta t \end{aligned} \quad (6.24)$$

or in differential form,

$$\frac{\partial \langle f \rangle}{\partial t} = s[\langle f \rangle - \langle f^2 \rangle] + \mu(1 - \langle f \rangle) - \nu \langle f \rangle. \quad (6.25)$$

Note that the selection term contains a contribution from the *second* moment  $\langle f(t)^2 \rangle$ , rather than the first moment squared. Thus, in contrast to the example in the previous section, we will generally need to know the behavior of the second moment  $\langle f(t)^2 \rangle$  to calculate the dynamics of the mean frequency  $\langle f(t) \rangle$ .

We can repeat the same procedure to derive a corresponding equation for the second moment  $\langle f(t)^2 \rangle$ . In this case we find that

$$\frac{\partial \langle f^2 \rangle}{\partial t} = \underbrace{2s \cdot \langle f \cdot f(1 - f) \rangle}_{\text{from deterministic part (chain rule)}} + \underbrace{\frac{f(1 - f)}{N}}_{\text{collision of correlated stochastic terms}} + \dots \quad (6.26)$$

where we have omitted the contributions from the mutation terms. This equation depends on the first and second moments of  $f(t)$ , but it also has a contribution from the third moment  $\langle f(t)^3 \rangle$ . An analogous calculation shows that the third moment depends on the fourth moment, and so on. In this case, we say that the **the moment hierarchy does not close** (also known as “**moment bell**”). This effect will always occur when we are dealing with nonlinear SDEs.

Since the non-linearities are ultimately caused by the selection term in Eq. (6.1), one approach is to restrict our attention to scenarios where natural selection is absent ( $s = 0$ ). In this ***neutral limit***, the moment equations do close, and one can derive exact solutions for the dynamics of the mean and variance of the mutation trajectory. (You will carry out this calculation yourself in Problem 3 of Homework 2). Much of the classical population genetics literature has focused this limit, and a sophisticated set of mathematical tools (collectively known as the ***neutral theory***) have been developed for analyzing this case. We will revisit this topic later in the course when we talk about multi-site genomes. For the rest of this chapter, we will continue to consider cases where natural selection is present.

## 6.4 Stationary distribution

We can also try to derive an analogue of the stationary distribution in Eq. (6.20). The Fokker-Planck equation for the single-locus model in Eq. (6.1) is given by

$$\begin{aligned} \frac{\partial p(f, t)}{\partial t} &= -\frac{\partial}{\partial f} [(sf(1-f) + \mu(1-f) - \nu f) p(f, t)] \\ &\quad + \frac{\partial^2}{\partial f^2} \left[ \frac{f(1-f)}{2N} \cdot p(f, t) \right] \end{aligned} \tag{6.27}$$

In this case, one can show<sup>2</sup> that the stationary distribution ( $\partial_t p \approx 0$ ) can be written in the general form,

$$p(f) \propto f^{-1}(1-f)^{-1} e^{-2N\Lambda(f)}, \tag{6.28}$$

where the function  $\Lambda(f)$  is defined by

$$\Lambda(f) = -[sf + \mu \log f + \nu \log(1-f)] \tag{6.29}$$

---

<sup>2</sup>For example, one can verify that this is a solution by substituting it into Eq. (6.27).

Equation (6.28) can be viewed as the frequency-space analogue of the Boltzmann distribution in Eq. (6.20). The function  $\Lambda(f)$  plays the role of the potential function  $V(x)$ . This analogy goes beyond the Boltzmann-like form of Eq. (6.28): the  $\Lambda(f)$  function has the special property that

$$\frac{\partial \Lambda(f)}{\partial f} = -\frac{1}{f(1-f)} \left( \frac{\partial f}{\partial t} \right)_{\text{det}}, \quad (6.30)$$

where  $(\partial f / \partial t)_{\text{det}}$  is the deterministic portion of the SDE in Eq. (6.27). Thus, in the absence of noise, the deterministic dynamics of  $f(t)$  will act to decrease the value of  $\Lambda(f)$ :

$$\left( \frac{d\Lambda(f(t))}{dt} \right)_{\text{det}} = \frac{\partial \Lambda}{\partial f} \left( \frac{\partial f}{\partial t} \right)_{\text{det}} = -\frac{1}{f(1-f)} \left( \frac{\partial f}{\partial t} \right)_{\text{det}}^2 \leq 0 \quad (6.31)$$

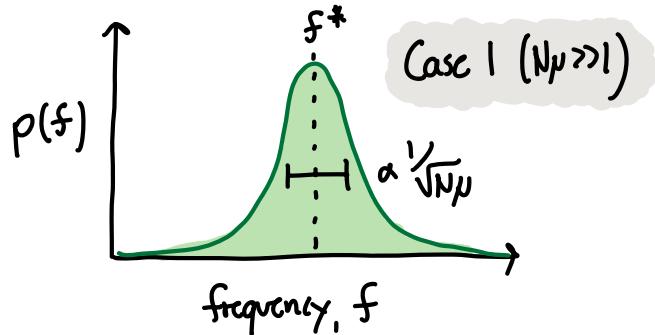
similar to the classical minimization of the potential energy. Conversely, the inverse population size  $1/2N$  constitutes the analogue of the diffusion coefficient (or temperature) in Eq. (6.20), which parameterizes the overall strength of noise. Large values of  $N$  will tend to amplify the importance of the energy function  $\Lambda(f)$ , while small values of  $N$  will make it less important.

For the specific form of  $\Lambda(f)$  in Eq. (6.29), the stationary distribution reduces to

$$p(f) \propto f^{2N\mu-1} (1-f)^{2N\nu-1} e^{2Ns f}, \quad (6.32)$$

This is a celebrated result known as ***mutation-selection-drift-balance*** (originally derived by Sewall Wright in the 1930's). It describes the long-term distribution of the mutation's frequency under the joint action of natural selection, mutation, and genetic drift. The shape of this distribution will strongly depend on the values of the compound parameters  $N\mu$  and  $N\nu$ .

**Case 1 (“fuzzy noise”).** When  $N\mu, N\nu \gg 1$ , the stationary distribution in Eq. (6.32) becomes strongly peaked around a characteristic frequency  $f^*$ , which minimizes the potential energy function  $\Lambda(f)$ .



This minimum occurs when

$$\frac{\partial \Lambda}{\partial f} = f^{-1}(1-f)^{-1} \left( \frac{\partial f}{\partial t} \right)_{\text{det}} = 0 \quad (6.33)$$

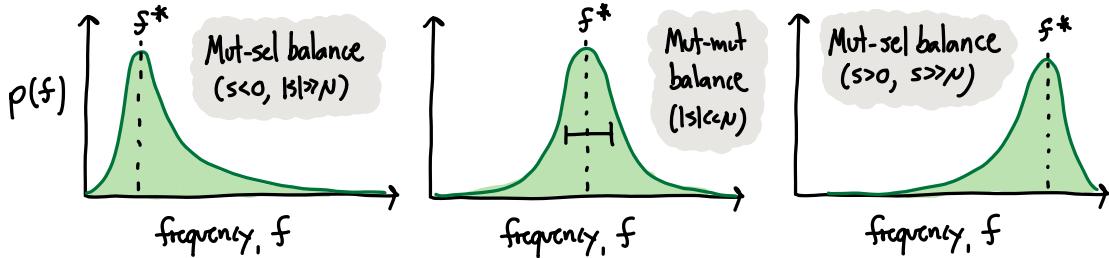
which implies that it is an equilibrium solution of the deterministic dynamics,

$$\left( \frac{\partial f}{\partial t} \right)_{\text{det}} = sf^*(1-f^*) + \mu(1-f^*) - \nu f^* = 0 \quad (6.34)$$

This point is often known as *deterministic mutation-selection balance* (or just *deterministic mutation balance* if  $s = 0$ ), since it is independent of genetic drift. We can use the quadratic formula to solve for  $f^*$  as a function of  $s$ ,  $\mu$ , and  $\nu$ . However, it can be more instructive to examine its leading-order behavior in different asymptotic limits. Using the dominant balance methods in Chapter 2, one can show that

$$f^* \approx \begin{cases} \frac{\mu}{|s|} & \text{if } s < 0 \text{ and } |s| \gg \mu, \nu, \\ \frac{\mu}{\mu+\nu} & \text{if } |s| \ll \mu, \nu, \\ 1 - \frac{\nu}{s} & \text{if } s > 0 \text{ and } s \gg \mu, \nu. \end{cases} \quad (6.35)$$

Each of these cases has a simple heuristic interpretation:



The first case represents a balance between forward mutations and negative selection ( $s < 0$ ), which pins the mutant strain at a small but nonzero frequency. This equilibrium frequency is larger for higher mutation rates, and smaller for larger fitness costs. The second case represents a balance between forward and back mutations, leading to a mixture of mutant and wildtype at intermediate frequencies. The last case represents a balance between positive selection and back mutation, which pins the *wildtype* population at a small but nonzero frequency. Stronger positive selection pushes the mutant closer to fixation, but while higher rates of back mutation push it down.

If we expand around  $f^*$ , the stationary distribution again approaches a Gaussian form,

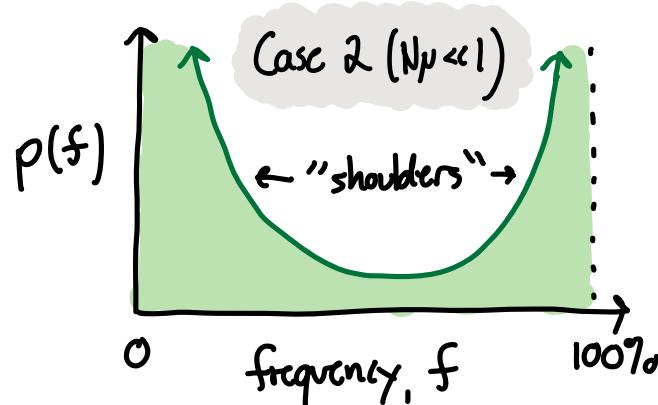
$$p(f) \propto f^{*-1} (1 - f^*)^{-1} e^{-2N\Lambda(f^*) - N\Lambda''(f^*)(f - f^*)^2} \quad (6.36)$$

which has a variance equal to

$$\sigma_f^2 = \frac{1}{2N\Lambda''(f^*)} = \frac{[f^*(1 - f^*)]^2}{2N [\mu(1 - f^*)^2 + \nu f^{*2}]} \quad (6.37)$$

Our Gaussian expansion assumed that this spread is small compared to the peak frequency  $f^*$ . Plugging in our expression for  $f^*$  in Eq. (6.35), we see that this will be true when  $N\mu \gg 1$  and  $N\nu \gg 1$ , which is exactly the regime we are considering. In this case, we can think of genetic drift as inducing a small amount of spread around the deterministic expectation for  $f(t)$  (“fuzzy noise” according to our classification system in Chapter 2).

**Case 2 (“jagged noise”).** In the opposite case, where  $N\mu, N\nu \ll 1$ , the  $f^{-1}(1-f)^{-1}$  prefactor in Eq. (6.32) causes the stationary distribution to adopt a **U-shaped form** that is qualitatively different from the case above.



This U-shaped distribution has a pair of peaks at  $f = 0$  and  $f = 1$ , with “**shoulders**” that fall off as  $\sim 1/f$  and  $\sim 1/(1-f)$  respectively. The relative heights of the shoulders are (roughly) controlled by the exponential factor  $e^{2Ns_f}$ , which increases by a factor of  $e^{2Ns}$  between  $f \approx 0$  and  $f \approx 1$ . It is clear that these U-shaped distributions cannot be interpreted as a small perturbation away from the deterministic expectation above — even when the population size is very large. As long as the corresponding mutation rates are small enough that  $N\mu < 1$ , then genetic drift will always play a non-negligible role. Interestingly, we will see in later chapters that empirical mutation frequency distributions (e.g. in humans) are often of the U-shaped variety, suggesting that this will be an important case to consider when we are interested in making connections to data.

## 6.5 Extinction and fixation probabilities

While the stationary distributions were more analytically tractable than the moment equations in Section 6.3, they raise several natural questions that are difficult to answer from these formal solutions alone. What’s going on “behind

the scenes” to generate the stationary distributions above? i.e. what do the individual mutation trajectories look like? What do the “shoulders” of the U-shaped distribution correspond to? And perhaps most importantly, how long does it take for the population to reach this long-term steady-state? Will it ever be relevant in practice (e.g. when making comparisons with data)?

We can start to gain some insight into these questions by considering a final stationary distribution scenario. If we consider a single-locus model in the absence of new mutations ( $\mu = \nu = 0$ ),

$$\frac{\partial f}{\partial t} = sf(1-f) + \sqrt{\frac{f(1-f)}{N}}\eta(t) \quad (6.38)$$

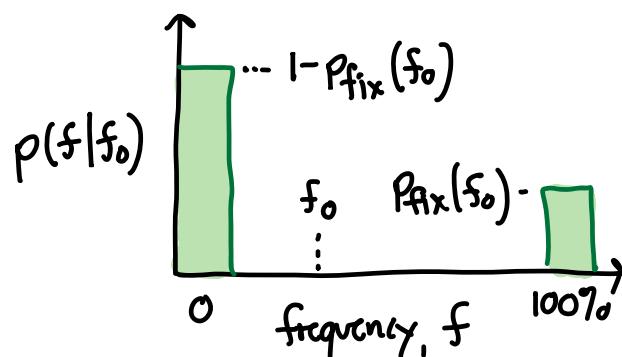
then at long times we know that the mutation must either fix or go extinct. The stationary distribution will therefore consist of two spikes at  $f = 0$  and  $f = 1$ :

$$p(f|f_0) = p_{\text{fix}}(f_0) \cdot \delta(f - 1) + (1 - p_{\text{fix}}(f_0)) \cdot \delta(f) \quad (6.39)$$

whose relative heights are specified by a single number

$$p_{\text{fix}}(f_0) = \Pr[f(\infty) = 1 | f(0) = f_0] \quad (6.40)$$

that depends on the initial frequency  $f_0$ .



This number can be interpreted as the *fixation probability* of a mutation that started at an initial frequency  $f_0$ . The dependence on the initial condition is

critical — in the absence of further mutations, a mutant that started at 100% frequency will remain there 100% of the time, while a mutant with  $f_0 = 0$  is guaranteed to stay extinct. Due to this dependence on the initial condition, the stationary distribution in Eq. (6.39) is capturing a fundamentally out-of-equilibrium process, even though it is phrased in terms of a long-term equilibrium measurement.

The Fokker-Planck equation is not very useful for discrete distributions like Eq. (6.39), since the derivatives with respect to  $f$  are not really well-defined. However, the generating function,

$$H(z, t) \equiv \langle e^{-zf(t)} \rangle = \int e^{-zf} p(f, t|f_0) df, \quad (6.41)$$

is still very useful in this case. Since the generating function is just a moment of  $f(t)$ , we can derive a (deterministic) equation for  $H(z, t)$  using the same approach we used for  $\langle f(t) \rangle$  and  $\langle f(t)^2 \rangle$  in Section 6.3.

**Deriving an equation of motion for  $H(z, t)$ .** Using the infinitesimal version of Eq. (6.38),

$$f(t + \delta t) = f(t) + sf(t)[1 - f(t)]\delta t + \sqrt{\frac{f(t)[1 - f(t)]\delta t}{N}} Z_t \quad (6.42)$$

we can express the generating function in the next timestep as

$$\begin{aligned} H(z, t + \delta t) &\equiv \left\langle e^{-z f(t+\delta t)} \right\rangle \\ &= \left\langle e^{-z \left[ f(t) + sf(t)[1 - f(t)]\delta t + \sqrt{\frac{f(t)[1-f(t)]\delta t}{N}} Z_t \right]} \right\rangle \end{aligned} \quad (6.43)$$

Expanding the right hand side in powers of  $\delta t$ , we obtain

$$H(z, t + \delta t) \approx \left\langle e^{-zf(t)} [1 - zsf(t)[1 - f(t)]\delta t - \sqrt{\frac{f(t)[1 - f(t)]\delta t}{N}} Z_t + \frac{z^2 f(1 - f) Z_t^2}{2N} \delta t] \right\rangle \quad (6.44)$$

$$\begin{aligned} H(z, t + \delta t) &\approx \left\langle e^{-zf(t)} [1 - zsf(t)[1 - f(t)]\delta t - \sqrt{\frac{f(t)[1 - f(t)]\delta t}{N}} Z_t + \frac{z^2 f(1 - f) Z_t^2}{2N} \delta t] \right\rangle \\ &\approx \langle e^{-zf(t)} \rangle - \left( zs - \frac{z^2}{2N} \right) \langle f(t)[1 - f(t)]e^{-zf(t)} \rangle \delta t \end{aligned} \quad (6.45)$$

where we have exploited the linearity of the expectation and the fact that  $Z_t$  is an independent random variable with  $\langle Z_t \rangle = 0$  and  $\langle Z_t^2 \rangle = 1$ . Note that the second term can be rewritten in terms of the generating function by taking derivatives with respect to the (deterministic) variable  $z$ :

$$\langle f(1 - f)e^{-zf} \rangle = - \left\langle \left( \frac{\partial}{\partial z} + \frac{\partial^2}{\partial z^2} \right) e^{-zf} \right\rangle = - \left( \frac{\partial H}{\partial z} + \frac{\partial^2 H}{\partial z^2} \right) \quad (6.46)$$

Substituting this result into Eq. (6.45), we obtain a partial differential equation for the moment generating function,

$$\frac{\partial H(z, t)}{\partial t} = \left[ sz - \frac{z^2}{2N} \right] \left[ \frac{\partial H(z, t)}{\partial z} + \frac{\partial^2 H(z, t)}{\partial z^2} \right]. \quad (6.47)$$

We could have also derived this equation by taking the Laplace transform of the Fokker-Planck equation in Eq. (5.49), emphasizing that these two formulations are equivalent representations of  $p(f, t)$ . We can see any discreteness in the probability density will still produce a continuous dependence on  $z$ , so Eq. (6.47) is still well-defined even for spiky distributions like Eq. (6.39).

**Back to the fixation probability.** The PDE in Eq. (6.47) are still difficult to solve in the general case. However, there is a particular value of the dummy variable  $z$  where the dynamics greatly simplify. We note that if we take  $z^* = 2Ns$ , then the prefactor on the right hand side of Eq. (6.47) vanishes, so that

$$\frac{\partial H(z^*, t)}{\partial t} = 0 \implies H(z^*, t) = \text{const} \quad (6.48)$$

This allows us to connect the value of  $H(z^*, t)$  at the initial and final timepoints. If the mutation frequency starts at  $f = f_0$ , then

$$H(z^*, 0) = \langle e^{-z^* f_0} \rangle = e^{-z^* f_0} \quad (6.49)$$

while at the final timepoint Eq. (6.39) yields

$$H(z^*, \infty) = \langle e^{z^* f(\infty)} \rangle = p_{\text{fix}} e^{-z^* \cdot 1} + (1 - p_{\text{fix}}) e^{-z^* \cdot 0} \quad (6.50)$$

Equating these two equations yields an expression for the **fixation probability**,

$$p_{\text{fix}} = \frac{1 - e^{-z^* f_0}}{1 - e^{z^*}} = \frac{1 - e^{-2Ns f_0}}{1 - e^{-2Ns}}. \quad (6.51)$$

This is a celebrated result (sometimes known as the “**Kimura formula**”) that describes how the ultimate fate of a mutation depends on its fitness advantage  $s$ , the population size  $N$ , and its initial frequency  $f_0$ .

We can see that the first two parameters always enter through their product  $Ns$ . This signals that fixation emerges from a battle between the forces of natural selection and genetic drift. There will be two characteristic regimes that depend on the overall magnitude of  $Ns$ :

**Weak-selection regime.** When  $N|s| \ll 1$ , the fixation probability reduces to the neutral limit,

$$p_{\text{fix}} \approx f_0, \quad (6.52)$$

where mutations fix in proportion to their initial frequencies. This tells us that the neutral behavior from Chapter 4 applies not just in the extreme case where  $s = 0$ , but rather for any value of  $|s| \ll 1/N$ . In this weak selection regime, genetic drift will always dominate over natural selection.

**Strong-selection regime.** In the opposite case, where  $N|s| \gg 1$ , the fate of the mutation will strongly depend on the sign of  $s$  and the relative value of  $f_0$ . There are three characteristic regimes:

TODO: switch to old notes.