

### 3 Random signals and probabilistic systems

We have defined stochastic signals<sup>1</sup> in an earlier lecture. A stochastic signal  $X$  is a collection  $(X_t)_{t \in T}$  of random variables indexed by a time variable  $t \in T$ . Depending on the structure of the set  $T$ , we speak of discrete- or continuous-time signals:

- If  $T$  is a subset of the integers  $\mathbb{Z}$ , then  $X$  is a discrete-time stochastic signal.
- If  $T$  is a finite or an infinite interval of the real line  $\mathbb{R}$ , then  $X$  is a continuous-time stochastic signal.

The set  $X$  of possible values each  $X_t$  can take is called the *state space* of the process. If the elements of  $X$  can be put in a one-to-one correspondence with a subset of  $\mathbb{Z}$ , then we say that  $X$  is a *discrete-state* process; otherwise, if  $X$  is a finite or an infinite interval of  $\mathbb{R}$ , we say that  $X$  is a *continuous-state* process. It is important to point out that, even though we are using the word “state,” it does not mean that  $X_t$  is a state variable in the sense that it contains all relevant information about the signal up to time  $t$ .

Another way to view stochastic signals is as follows. We have a probability space  $(\Omega, \mathcal{F}, \mathbf{P})$ , such that each  $X_t$  is a random variable with values in  $X$ , i.e., a function  $X_t : \Omega \rightarrow X$ . This specifies a random variable for each  $t \in T$ . On the other hand, fixing  $\omega \in \Omega$  specifies a function from  $T$  into  $X$  — this function simply assigns the value  $X_t(\omega)$  to each  $t \in T$ . Thus, one can think of  $X$  as a *random function* of  $t$ , where all the randomness is packed into  $\omega$ .

This is best appreciated through examples, so let’s take a look at a few.

**Deterministic signals.** Deterministic signals are a special case of stochastic signals. That is, if  $x : T \rightarrow X$  is a deterministic signal with state space  $X$ , we can just take  $X_t(\omega) = x(t)$  for all  $t \in T$  and all  $\omega \in \Omega$ . Thus, the value of  $X_t$  at each time  $t$  is known and equal to  $x(t)$  — that is,  $X$  is a function of  $t$ . Another way of stating that  $X$  is a deterministic signal is to note that, for any subset  $A$  of the state space  $X$ ,  $\mathbf{P}[X_t \in A]$  takes only two values: 0 if  $x(t) \notin A$  and 1 if  $x(t) \in A$ .

**i.i.d. processes.** Take  $T = \mathbb{Z}_+$  and let  $X_0, X_1, \dots$  be a collection of independent and identically distributed (i.i.d.) random variables. Then  $X = (X_t)_{t \in \mathbb{Z}_+}$  is called an i.i.d. stochastic process, and the common probability distribution of the  $X_t$ ’s is called the (one-time) *marginal distribution* of  $X$ . For example, if each  $X_t$  is a Bernoulli( $p$ ) random variable, then  $X = (X_t)$  records the outcomes of repeated tosses of a coin with bias  $p$ . If we view it as a random function of  $t$ , then the value of this function at any time  $t$  can be only 0 or 1. Moreover, because of independence, for any collection of times  $t_1, t_2, \dots, t_n \in T$  and for any binary values  $x_1, \dots, x_n \in \{0, 1\}$ ,

$$\mathbf{P}[X_{t_1} = x_1, \dots, X_{t_n} = x_n] = \prod_{i=1}^n \mathbf{P}[X_{t_i} = x_i] = \prod_{i=1}^n p^{x_i} (1-p)^{1-x_i}. \quad (3.1)$$

<sup>1</sup>Also known as stochastic processes – we will use both terms in this course.

**Markov processes.** We have already encountered Markov processes before. A Markov process with state space  $X$  is a discrete time process  $X = (X_t)_{t \in \mathbb{Z}_+}$  that can be realized in the form

$$X_{t+1} = f(X_t, U_t), \quad t = 0, 1, 2, \dots$$

where  $U = (U_t)_{t \in \mathbb{Z}_+}$  is an i.i.d. process, and the initial condition  $X_0$  is independent of all the  $U_t$ 's. We have mostly focused on discrete-state Markov processes, but  $X$  can take real values as well.

**Deterministic signals with stochastic parameters.** Let  $A$  and  $\Theta$  be two independent random variables, where  $A \sim \text{Uniform}(0, 1)$  and  $\Theta \in \text{Uniform}(0, 2\pi)$ . Let  $X_t = A \cos(2\pi f t + \Theta)$ ,  $-\infty < t < \infty$ . This is a sinusoidal signal with random amplitude and random phase, and is an example of a *predictable stochastic signal*: if we can observe  $X_t$  over a full period (i.e., any interval of length  $1/2\pi f$ ), then we can reconstruct the entire signal.

### 3.1 Describing stochastic signals

Given a deterministic signal  $x : T \rightarrow \mathbb{R}$ , we can compute its value at any time  $t \in T$ , at least in principle. With a stochastic signal, though, we can only deal in probabilities. Thus, if we have a discrete-state process, we can specify the probabilities  $\mathbf{P}[X_t = x]$  for all  $t \in T$  and all  $x \in X$ ; if we have a continuous-state process, we can specify the probabilities  $\mathbf{P}[a \leq X_t \leq b]$  for any finite or infinite subinterval  $[a, b]$  of the state space  $X$ . It's useful to think about the latter probability as the probability that the graph of the (random) function  $t \mapsto X_t$  will “pass” through the “gate”  $[a, b]$  at time  $t$  – see Figure 1.

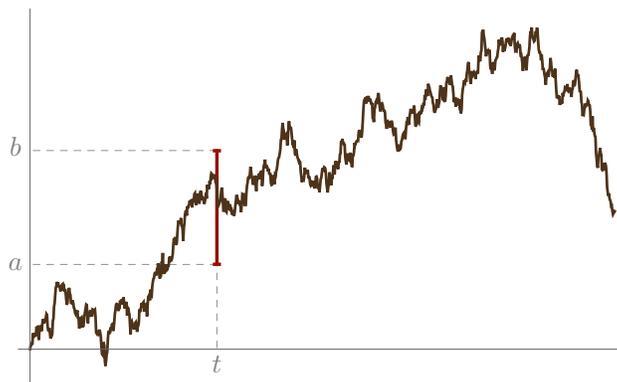


Figure 1: The event  $\{a \leq X_t \leq b\}$ .

If we can do this for every  $t \in T$ , does this give us a complete description of the underlying stochastic signal? The answer is no. To see why, consider the following two discrete-time stochastic processes:

- $X = (X_t)_{t \in \mathbb{Z}_+}$  is an i.i.d. Bernoulli(1/2) process. That is, each  $X_t$  encodes an independent toss of a fair coin.

- $Y = (Y_t)_{t \in \mathbb{Z}_+}$  is a Markov process with binary state space  $X = \{0, 1\}$  with initial state  $Y_0 \sim \text{Bernoulli}(1/2)$  and with one-step transition probabilities  $M(0, 0) = M(1, 1) = 0.7$  and  $M(1, 0) = M(0, 1) = 0.3$ .

We claim that these two processes have the same one-time marginal distributions, i.e.,  $\mathbf{P}[X_t = 0] = \mathbf{P}[Y_t = 0]$  for all  $t$  (since the state space of both processes has only two elements, this is all we need to prove). That is, we claim that  $\mathbf{P}[Y_t = 0] = \frac{1}{2}$  for all  $t$ . From our earlier example of a two-state Markov chain, we know that  $\pi = (1/2, 1/2)$  is an equilibrium distribution of our Markov chain. Since  $X_0 \sim \text{Bernoulli}(1/2)$ , we know that  $X_t \sim \text{Bernoulli}(1/2)$  for all  $t$ . This proves the claim. However, the two processes are very different. If we knew that  $X_{1000} = 0$  and asked for the (conditional) probability that  $X_{1001} = 0$ , we would get the answer  $1/2$  because the  $X_t$ 's correspond to *independent* coin tosses – the outcome of the coin toss at  $t = 1000$  has no effect on the outcome of the coin toss at  $t = 1001$ . On the other hand, for the  $Y$  process we know that  $\mathbf{P}[Y_{1001} = 0 | Y_{1000} = 0] = M(0, 0) = 0.7$ . And, of course, the  $Y_t$ 's are not independent — Markov processes have memory, albeit a very short one.

It turns out that, in order to arrive at a full description of a stochastic signal  $X$ , we must be able to specify all probabilities of the form

$$\mathbf{P}[X_{t_1} = x_1, X_{t_2} = x_2, \dots, X_{t_n} = x_n]$$

for all  $n$ , all  $t_1 < t_2 < \dots < t_n$  and all  $x_1, \dots, x_n \in X$  (for discrete-state stochastic signals) and

$$\mathbf{P}[a_1 \leq X_{t_1} \leq b_1, a_2 \leq X_{t_2} \leq b_2, \dots, a_n \leq X_{t_n} \leq b_n]$$

for all  $n$ , all  $t_1 < t_2 < \dots < t_n$ , and all finite or infinite intervals  $[a_1, b_1], \dots, [a_n, b_n]$  of  $X$  (for continuous-state signals). Of course, it may not be easy to obtain closed-form expressions for these probabilities even for  $n = 2$  — but, as long as we can do this *in principle*, we are done.

In many situations, however, we do not need such a fine-grained description of  $X$ . For example, if  $X$  has a continuous state space, we may want to know what value  $X_t$  will take “on average” and how much we can expect it to fluctuate around this average value. This is encoded in the first two moments of  $X_t$ : the mean  $m_X(t) \triangleq \mathbf{E}[X_t]$  and the variance  $\sigma_X^2(t) \triangleq \text{Var}[X_t]$ . We can also talk about *correlations* between the values of  $X$  at different times. This information is encoded in the *autocorrelation function*<sup>2</sup>

$$R_X(s, t) \triangleq \mathbf{E}[X_s X_t], \quad \forall s, t \in T$$

and in the *autocovariance function*

$$C_X(s, t) \triangleq \mathbf{E}[(X_s - m_X(s))(X_t - m_X(t))] = \mathbf{E}[X_s X_t] - m_X(s)m_X(t) = R_X(s, t) - m_X(s)m_X(t).$$

Later on, we will also be looking at two signals at a time, say,  $X = (X_t)$  and  $Y = (Y_t)$ , where  $X$  is the input and  $Y$  is the output of some system. Then we may want to look at the *crosscorrelation*

$$R_{XY}(s, t) \triangleq \mathbf{E}[X_s Y_t]$$

and the *crosscovariance*

$$C_{XY}(s, t) \triangleq \mathbf{E}[(X_s - m_X(s))(Y_t - m_Y(t))] = R_{XY}(s, t) - m_X(s)m_Y(t).$$

<sup>2</sup>The Greek prefix “auto” means “self.” So, this is fancyspeak for “self-correlation.”

### 3.2 Random walk

We can spend all the time in the world on definitions and generalities, but the best way of appreciating key concepts is in the context of examples. This way, we will reinforce the already introduced definitions and motivate some new ones. Our first example is the *random walk*.

Formally, a random walk is a discrete-time stochastic signal  $X = (X_t)_{t \in \mathbb{Z}_+}$  with the deterministic initial condition  $X_0 = 0$  (this is imposed mostly for technical convenience) and with the update rule

$$X_{t+1} = X_t + U_t, \quad t = 0, 1, 2, \dots \quad (3.2)$$

where  $U = (U_t)_{t \in \mathbb{Z}_+}$  is some i.i.d. stochastic signal. In other words,  $X$  describes a randomly moving particle, which at each time  $t$  undergoes a displacement of random length and random direction (left or right) from its current position  $X_t \in \mathbb{R}$ . Thus,  $X$  is a Markov process because it can be realized in the form

$$X_{t+1} = f(X_t, U_t)$$

with  $f(x, u) = x + u$ , such that the initial condition  $X_0$  is independent of  $U = (U_t)$ .

A random walk has another important property: it has *independent increments*. To see what this means, fix two times  $0 \leq s < t$  and write

$$X_t - X_0 = (X_t - X_s) + (X_s - X_0).$$

Here,  $X_t - X_0$  is the net displacement of the particle at time  $t$ , and  $X_t - X_s$  is the net displacement of the particle between times  $s$  and  $t$ . Now, iterating (3.2), we can write

$$X_t - X_0 = \sum_{r=0}^{t-1} U_r$$

for every  $t$ . Therefore,

$$X_t - X_s = (X_t - X_0) - (X_s - X_0) = \sum_{r=0}^{t-1} U_r - \sum_{r=0}^{s-1} U_r = \sum_{r=s}^{t-1} U_r.$$

This tells us that  $X_s - X_0$  is a function of  $U_0, \dots, U_{s-1}$ , while  $X_t - X_s$  is a function of  $U_s, \dots, U_{t-1}$ . Since  $U$  is an i.i.d. process, and independence is preserved by grouping, we see that the increments  $X_t - X_s$  and  $X_s - X_0$  are indeed independent. Thus, a random walk is a Markov process with independent increments.

We can easily compute first- and second-order moments of a random walk. Let  $\mu = \mathbf{E}[U_0]$  and  $\sigma^2 = \text{Var}[U_0]$  denote the common mean and variance of the  $U_t$ 's. Then, by linearity of expectation, we have

$$m_X(t) = \mathbf{E}[X_t] = \mathbf{E}\left[\sum_{r=0}^{t-1} U_r\right] = \sum_{r=0}^{t-1} \mathbf{E}[U_r] = t\mu,$$

so the mean  $m_X(t)$  increases linearly with  $t$  if  $\mu > 0$ , stays at zero if  $\mu = 0$ , and decreases linearly with  $t$  if  $\mu < 0$ . For the variance, we have

$$\sigma_X^2(t) = \text{Var}[X_t] = \text{Var}\left[\sum_{r=0}^{t-1} U_r\right].$$

Since the variance of a sum of independent random variables is the sum of the variances, we can write

$$\sigma_X^2(t) = \sum_{r=0}^{t-1} \text{Var}[U_r] = t\sigma^2.$$

Thus, the variance of  $X_t$  grows linearly with  $t$ . The mean  $m_X(t)$  tells us where on average we expect to find the particle at time  $t$ , and the standard deviation  $\sigma_X(t) = \sigma\sqrt{t}$  tells us the range of fluctuations of  $X_t$ . The same reasoning can be used to compute the means and the variances of the increments of  $X$ . First, let's compute the mean: for  $s < t$ ,

$$\mathbf{E}[X_t - X_s] = \mathbf{E}[X_t] - \mathbf{E}[X_s] = m_X(t) - m_X(s) = (t - s)\mu.$$

Now, to compute the variance we write

$$\text{Var}[X_t - X_s] = \text{Var}\left[\sum_{r=s}^{t-1} U_r\right] = \sum_{r=s}^{t-1} \text{Var}[U_r] = (t - s)\sigma^2,$$

once again using the fact that the  $U_r$ 's are independent. We can also compute the autocorrelation function: Fix  $s < t$ . Then

$$\begin{aligned} R_X(s, t) &= \mathbf{E}[X_s X_t] \\ &= \mathbf{E}[(X_s - X_0)(X_t - X_0)] \\ &= \mathbf{E}[(X_s - X_0)(X_t - X_s + X_s - X_0)] \\ &= \mathbf{E}[(X_s - X_0)(X_t - X_s)] + \mathbf{E}[(X_s - X_0)^2]. \end{aligned}$$

Since  $X$  has independent increments, we can write

$$\mathbf{E}[(X_s - X_0)(X_t - X_s)] = \mathbf{E}[X_s - X_0]\mathbf{E}[X_t - X_s] = s\mu \cdot (t - s)\mu = s(t - s)\mu^2.$$

Also,

$$\mathbf{E}[(X_s - X_0)^2] = \mathbf{E}[X_s^2] = \sigma_X^2(s) + m_X^2(s) = s\sigma^2 + s^2\mu^2.$$

Putting everything together, we write

$$R_X(s, t) = s(t - s)\mu^2 + s\sigma^2 + s^2\mu^2 = st\mu^2 + s\sigma^2.$$

On the other hand, if  $t \leq s$ , then we obtain

$$R_X(s, t) = st\mu^2 + t\sigma^2.$$

Expressed more succinctly, the autocorrelation function of our random walk  $X$  is given by

$$R_X(s, t) = st\mu^2 + \sigma^2 \min(s, t). \quad (3.3)$$

The autocovariance is then given by

$$C_X(s, t) = R_X(s, t) - m_X(s)m_X(t) = \sigma^2 \min(s, t). \quad (3.4)$$

Next, we will use random walks as building blocks of two important types of continuous-time stochastic signals: the Wiener process and the Poisson process.

### 3.3 The Wiener process

Recall our example of the symmetric random walk on the integers: at time  $t = 0$  a particle starts at  $x = 0$  and, at each time  $t = 1, 2, \dots$  it hops either one step to the left or one step to the right with equal probability. This is a random walk whose increments are sums of independent Rademacher random variables (remember that a Rademacher random variable takes values  $\pm 1$  with probability  $\frac{1}{2}$ ). Now suppose that the particle hops every  $\tau$  seconds, and each hop is  $\pm h$  meters. This gives us a *continuous-time* stochastic process  $X = (X_t)_{t \in \mathbb{R}_+}$  that can be described in terms of an i.i.d. Rademacher sequence  $U = (U_k)_{k \in \mathbb{Z}_+}$  as follows:

$$X_t = 0, \quad \text{for } 0 \leq t < \tau \quad (3.5)$$

and

$$X_t = h(U_0 + \dots + U_{n-1}), \quad \text{if } n\tau \leq t < (n+1)\tau \text{ for } n = 1, 2, \dots \quad (3.6)$$

A typical path of  $X$  is shown in Figure 2.

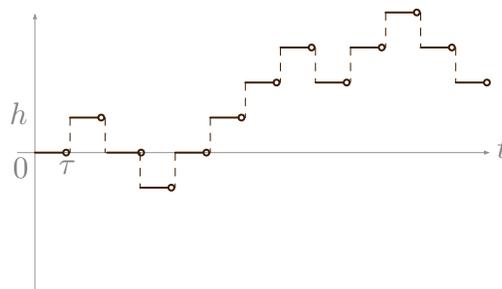


Figure 2: A continuous-time interpolation of a random walk.

We will now consider the case when both the times between hops and the sizes of hops become infinitesimally small, i.e., when  $\tau \rightarrow 0$  and  $h \rightarrow 0$ . The continuous-time stochastic signal that results in the limit is known as the *Wiener process* or as the *Brownian motion*.

The Wiener process has a rich history. In 1828, the English botanist Robert Brown noticed a curious thing: when he looked through his microscope at some particles of pollen suspended in

water, he noticed that the particles were constantly and irregularly moving. At first, he attributed this to the pollen somehow being alive, but he repeated the same experiment with inanimate particles (such as sawdust) and observed the same result. No one could explain this phenomenon until the early 1900's, when Albert Einstein in 1905 and, independently of him, Marian Smoluchowski in 1906 came up with an explanation based on the atomic hypothesis and gave a mathematical description of this Brownian motion of particles in water. The explanation was as follows: Imagine a vessel containing water at room temperature. If the atomic hypothesis is false, then water is a smooth continuous medium, and, by symmetry, we should not expect the pollen particles to move around. On the other hand, if the atomic hypothesis is true, then water is not a continuous fluid but consists of discrete molecules,<sup>3</sup> and these molecules will be undergoing constant random agitation due to heat. If we suspend pollen in the water, then its particles will be kicked around by the randomly moving water molecules. This is what Robert Brown saw when he looked in his microscope. Both Einstein and Smoluchowski assumed that each such kick is delivered by a different molecule, and that the random motions of different molecules are independent. Now, a particle of pollen is immense compared to a molecule of water, so each kick will be very weak; moreover, being so tiny compared to pollen particles, the water molecules will move very fast, so the time between different kicks will be very short. Our stochastic process  $X$  defined in (3.5) and (3.6) is a simplified model of Brownian motion of a single particle, where we assume that the motion takes place in one dimension. Einstein's model made some concrete quantitative predictions, which were verified experimentally by Jean Perrin. For this work, Perrin was awarded the Nobel Prize in physics in 1926. After Perrin's experiments, the atomic hypothesis, first advanced by John Dalton in the early 1800's, was finally settled.

It should be pointed out that neither Einstein nor Smoluchowski were mathematically rigorous in their derivations (and that wasn't the point). The first rigorous analysis of Brownian motion was published by Norbert Wiener in 1921, hence the name "Wiener process." These days, the Wiener process is ubiquitous in stochastic modeling. Apart from the Brownian motion, it is used in physics to model random diffusion phenomena, in engineering to describe thermal noise in electric conductors, and in finance to model fluctuations of stock prices. In fact, the same mathematical model was used by Louis Bachelier in 1900 (before Einstein and Smoluchowski) to model the fluctuations in prices of stock options on the Paris exchange. We will come back to some of these uses of the Wiener process later in the course.

Now let us return to analyzing the process  $X$ . As already mentioned, we will pass to the limit as  $h, \tau \rightarrow 0$ . However, we cannot treat these time and space parameters as independent. Let's see why. From (3.6), we can compute the variance of  $X_t$ : if  $n\tau \leq t < (n+1)\tau$ , then

$$\begin{aligned}\text{Var}[X_t] &= \text{Var}[h(U_0 + \dots + U_{n-1})] \\ &= h^2 \text{Var}[U_0 + \dots + U_{n-1}] \\ &= nh^2,\end{aligned}$$

where we have used the fact that the Rademacher random variables  $U_k$  are independent, and each has unit variance. Now, if  $\tau$  is very small, then  $n = \lfloor t/\tau \rfloor \approx t/\tau$ , so we can approximate  $\text{Var}[X_t] \approx$

<sup>3</sup>Today, every schoolchild knows that matter consists of atoms. The atomic hypothesis was still a matter of controversy in the early XX century.

$th^2/\tau$ . Now, what is the physical meaning of  $\text{Var}[X_t]$ ? It is the mean-square net displacement of the particle at time  $t$ . It is reasonable to assume on physical grounds that the mean-square displacement per unit time is constant, so we will let both  $h$  and  $\tau$  tend to zero, while keeping the ratio  $D \triangleq h^2/\tau$  constant.

Now our task is to examine the distribution of  $X_t$  and to see what happens as  $\tau \rightarrow 0$  (we no longer need to worry about  $h$  separately, because it is given by  $\sqrt{\tau D}$ ). When  $\tau$  is very small, we will keep things simple and just assume that  $t = n\tau$  for some  $n \in \mathbb{Z}_+$ . So, we are interested in the probability  $\mathbf{P}[X_t = mh] = \mathbf{P}[X_{n\tau} = mh]$  for some  $n \in \mathbb{Z}_+$  and some integer  $m$  — i.e., the probability that, at time  $t$ , the particle will have undergone a net displacement of  $mh$ . Now,  $m$  can be positive or negative, but the set of values it can take is constrained. Indeed, since  $t = n\tau$ , the particle made a total of  $n$  hops, each of size  $\pm h$ . The directions of the hops are determined by the random signs of  $U_0, \dots, U_{n-1}$ . Suppose that there were  $k$  hops to the right and  $n - k$  hops to the left, where  $k \in \{0, 1, \dots, n\}$ . Then the net displacement (in units of  $h$ ) at time  $t = n\tau$  is  $k - (n - k) = 2k - n$ . Hence, for  $t = n\tau$ ,  $m$  can only take values in the set

$$\{2k - n : k = 0, 1, \dots, n\} = \{-n, 2 - n, 4 - n, \dots, n - 2, n\}.$$

Since we are concerned with the net displacement of the particle after  $n$  hops, it does not matter when the particle hopped left and when it hopped right, as long as the end result is the same. For example, the path in Figure 2 was generated by the following pattern of hops: RLLRRRLRLL. There are  $\binom{n}{k}$  patterns of signs for  $U_0, \dots, U_{n-1}$ , so that exactly  $k$  are positive and  $n - k$  are negative, and each sign is equally likely. Therefore, we arrive at the following:

$$\mathbf{P}[X_{n\tau} = mh] = \begin{cases} \frac{1}{2^n} \binom{n}{\frac{m+n}{2}}, & \text{if } m = -n, 2 - n, \dots, n - 2, n \\ 0, & \text{otherwise} \end{cases}. \quad (3.7)$$

When  $\mathbf{P}[X_{n\tau} = mh]$  is nonzero, it can be expressed in terms of the *binomial distribution*, which arises in the following way. Suppose we have a coin with bias  $p$ , and we toss it  $n$  times. The outcome of the  $i$ th toss is described by an independent Bernoulli( $p$ ) random variable  $B_i$ , taking the value 1 with probability  $p$  and 0 with probability  $1 - p$ . Thus,  $Z = \sum_{i=1}^n B_i$  is the number of times the coin comes up HEADS in  $n$  tosses. It can take values in the set  $\{0, 1, \dots, n\}$  with probabilities

$$\mathbf{P}[Z = k] = \binom{n}{k} p^k (1 - p)^{n-k}, \quad k = 0, 1, \dots, n$$

and is referred to as the *binomial random variable* with parameters  $n$  and  $p$ . Symbolically, we write  $Z \sim \text{Binom}(n, p)$  to denote this fact. In particular, examining our expression for  $\mathbf{P}[X_{n\tau} = mh]$  in (3.7), we can write

$$\mathbf{P}[X_{n\tau} = mh] = \mathbf{P}\left[\text{Binom}(n, 1/2) = \frac{m+n}{2}\right] \quad (3.8)$$

whenever this probability is nonzero. Now, we are interested in the limit  $\tau \rightarrow 0$ , which corresponds to letting  $n = t/\tau$  approach infinity. So, we need to see what happens to the right-hand side of (3.8) in this limit.

To that end, we will use a remarkable asymptotic expression for the binomial distribution, called the *DeMoivre–Laplace theorem*.<sup>4</sup> Imagine repeatedly tossing a coin with bias  $p$  and recording  $Z$ , the number of HEADS in  $n$  tosses. We know that  $Z \sim \text{Binom}(n, p)$ , and thus  $\mathbf{E}[Z] = np$  and  $\text{Var}[Z] = np(1-p)$ . That is, on average we expect the proportion of HEADS in  $n$  tosses to be somewhere around  $p$ , and the standard deviation  $\sqrt{np(1-p)}$  gives us an idea of the fluctuations of  $Z$  around its mean. Suppose we repeat such an experiment a large number of times (say,  $N$ ) and let  $Z_j$  be the number of HEADS out of  $n$  tosses in the  $j$ th experiment. Then, if for each  $k \in \{0, 1, \dots, n\}$  we plot the number of times  $j \in \{1, \dots, N\}$  when  $Z_j$  took the value  $k$ , we would end up with a nice bell-shaped plot with the peak around  $k = np$  and with rapid decay of the height of the plot for  $|k - np| > \sqrt{np(1-p)}$ . The DeMoivre–Laplace theorem expresses this quantitatively and says the following: for all sufficiently large values of  $n$  and for all  $|k - np| \leq \sqrt{np(1-p)}$ ,

$$\binom{n}{k} p^k (1-p)^{n-k} \simeq \frac{1}{\sqrt{2\pi np(1-p)}} \exp\left(-\frac{(k - np)^2}{2np(1-p)}\right). \quad (3.9)$$

In our case,  $p = 1/2$  and  $k = \frac{m+n}{2}$ , so, for  $n$  large and for  $|m| \leq \sqrt{n}$ , Eq. (3.9) gives

$$\mathbf{P}[X_{n\tau} = mh] \simeq \frac{1}{\sqrt{n\pi/2}} \exp\left(-\frac{m^2}{2n}\right). \quad (3.10)$$

Now, in the limit  $\tau \rightarrow 0$ , we will obtain a continuous-time stochastic signal  $W = (W_t)_{t \in \mathbb{R}_+}$ , which is our Wiener process. Unlike  $X$ , whose state space is discrete and consists of integer multiples of  $h$ , the state space of  $W$  will be the entire real line. Hence, as we pass to the limit of  $\tau \rightarrow \infty$ , the probability mass function  $\mathbf{P}[X_t = mh]$  will become a *probability density function*  $f_t(x)$  of  $W_t$  — that is, by definition,  $f_t(x)dx \approx \mathbf{P}[x \leq W_t \leq x + dx]$ , where  $dx$  denotes an infinitesimally small change in  $x$ . More formally,

$$f_t(x) = \lim_{\delta \rightarrow 0} \frac{\mathbf{P}[x \leq W_t < x + \delta]}{\delta}.$$

Now, for a fixed value of  $\tau$ ,  $\mathbf{P}[X_{n\tau} = mh] = \mathbf{P}[mh \leq X_{n\tau} < (m+2)h]$  — since  $m$  can take the values  $\{-n, -n+2, \dots, n-2, n\}$ , any two possible values of  $X_{n\tau}$  are at least  $2h$  apart. So, if we fix  $t$  and  $x$ , let  $\tau = t/n$ ,  $h = \frac{x}{m} = \sqrt{\frac{tD}{n}}$ , and  $\delta = 2h$ , and then take the limit as  $n \rightarrow \infty$ , then we will obtain

$$\begin{aligned} f_t(x) &= \lim_{n \rightarrow \infty} \frac{\mathbf{P}[mh \leq X_{n\tau} < (m+2)h]}{2h} \\ &= \lim_{n \rightarrow \infty} \frac{1}{2h\sqrt{n\pi/2}} \exp\left(-\frac{m^2}{2n}\right) \\ &= \lim_{n \rightarrow \infty} \frac{1}{\sqrt{2\pi nh^2}} \exp\left(-\frac{m^2}{2n}\right) \\ &= \frac{1}{\sqrt{2\pi Dt}} \exp\left(-\frac{x^2}{2Dt}\right), \end{aligned}$$

<sup>4</sup>For a detailed derivation, see Chapter 7, Section 2 in W. Feller, *An Introduction to Probability Theory and Its Applications*, vol. 1, John Wiley & Sons, New York, 1950.

where we have used (3.10). This shows that the marginal distribution of  $W_t$  is Gaussian with mean 0 and variance  $Dt$ .

Moreover, let us again return to our process  $X = (X_t)_{t \in \mathbb{R}_+}$  for fixed finite values of  $h$  and  $\tau$ . Then, using (3.6), for any three times  $r \leq s \leq t$  we can write

$$X_r = h(U_0 + \dots + U_{\lfloor r/\tau \rfloor - 1})$$

and

$$\begin{aligned} X_t - X_s &= h(U_0 + \dots + U_{\lfloor t/\tau \rfloor - 1}) - h(U_0 + \dots + U_{\lfloor s/\tau \rfloor - 1}) \\ &= h(U_{\lfloor s/\tau \rfloor} + \dots + U_{\lfloor t/\tau \rfloor - 1}). \end{aligned}$$

Since  $\lfloor r/\tau \rfloor - 1 < \lfloor s/\tau \rfloor$ , we see that  $X_r$  and the increment  $X_t - X_s$  are functions of two disjoint subsets of the  $U_k$ 's, which are independent. Therefore,  $X_t - X_s$  is independent of all  $\{X_r\}_{r=0}^{s-1}$ , so  $X$  has independent increments. Passing to the limit as  $\tau \rightarrow 0$ , we see that the Wiener process  $W$  also has independent increments: for any three times  $r \leq s \leq t$ , the increments  $W_t - W_s$  and  $W_s - W_r$  are independent. Another immediate observation that follows from (3.6) is that, for  $s \leq t$ ,  $X_t - X_s$  has the same distribution as  $X_{t-s}$ . Therefore, the same holds in the limit for the Wiener process: The increment  $W_t - W_s$  has the same distribution as  $W_{t-s}$ , which, as we have already seen, is Gaussian with mean 0 and variance  $D(t-s)$ . We then say that  $W$  has *stationary increments*: the distribution of  $W_t - W_s$  depends only on  $t-s$ , and therefore the increment  $W_{t+r} - W_{s+r}$  has the same distribution as  $W_t - W_s$  for any  $r \in \mathbb{R}$ , such that  $s+r \geq 0$ .

Before moving on, let us summarize the three key properties of the Wiener process  $W = (W_t)_{t \geq 0}$ :

1.  $W_0 = 0$  (zero initial condition)
2. For any three times  $0 \leq r \leq s \leq t$ ,  $W_t - W_s$  is independent of  $W_r$  (independent increments)
3. For any  $0 \leq s \leq t$ ,  $W_t - W_s \sim N(0, D(t-s))$  (stationary Gaussian increments)

Another key property of the Wiener process (which we will not prove) is that we can always perform the passage to the limit in such a way that its sample paths are continuous functions of  $t$ . Then it can also be proved that they are nowhere differentiable. A typical sample path of a Wiener process is shown in Figure 1. Finally, the Wiener process is Markov in the sense that, for any  $t \geq 0$ , the future of the process, i.e.,  $(W_s)_{s \geq t}$  is determined by  $W_t$  only, and not by the entire past  $(W_s)_{s \leq t}$ . You can easily convince yourselves of this by looking at the discrete-time random-walk approximations (for finite values of  $\tau$  and  $h$ ) — and we know that these processes are Markov. In general, the definition of a continuous-time Markov process is a bit technical, but we can state it as follows: Consider a continuous-time stochastic process  $X = (X_t)_{t \in T}$ . For any increasing sequence of “sampling times”  $t_0 < t_1 < \dots$  in  $T$ , we can define a discrete-time process  $Y = (Y_k)_{k \in \mathbb{Z}_+}$  by taking  $Y_k = X_{t_k}$ . Then we say that  $X$  is Markov if the sampled process  $Y$  is Markov for any choice of the sampling instants.

Let us apply this criterion to the Wiener process. For any sequence of sampling instants  $t_0 < t_1 < \dots$ , we can write

$$Y_{k+1} = Y_k + (Y_{k+1} - Y_k) = W_{t_k} - W_0 + W_{t_{k+1}} - W_{t_k}.$$

Since  $W$  has independent increments,  $Y_k = W_{t_k} - W_0$  and  $W_{t_{k+1}} - W_{t_k}$  are independent. In particular,  $Y_0 = W_{t_0} - W_0$  is independent of  $Y_1 - Y_0, Y_2 - Y_1$ , etc. Moreover,  $W_{t_{k+1}} - W_{t_k} \sim N(0, D(t_{k+1} - t_k))$ . Now, for each  $k$  define a function

$$f_k(y, u) \triangleq y + \sqrt{D(t_{k+1} - t_k)}u,$$

and let  $U = (U_k)_{k \in \mathbb{Z}_+}$  be a sequence of i.i.d.  $N(0, 1)$  random variables, which are also independent of  $Y_0 = X_{t_0}$ . Then we can realize  $Y$  using the imperative model

$$Y_{k+1} = f_k(Y_k, U_k).$$

Thus,  $Y$  is a *time-inhomogeneous* Markov process. Since this can be done for any sequence of sampling instants, we see that the Wiener process is, indeed, Markov.

### 3.4 The Poisson process

The Wiener process is a good and tractable model for stochastic phenomena involving the net additive effect of many small independent random variables. However, there are many situations where we are observing discrete events happening at random times, and would like to keep track of the number of events at each time  $t$ . For example, an event could be the arrival of a packet at a router, or the click of a Geiger counter, or the arrival of a customer to a service center. In the context of Poisson processes, it is customary to refer to these events as *arrivals*. In order to keep track of the total number of arrivals at each time  $t$ , we introduce the notion of a *counting function*. A counting function is a function  $n : \mathbb{R}_+ \rightarrow \mathbb{Z}_+$  with the following properties:

- $n(0) = 0$ ;
- $n$  is nondecreasing (i.e., if  $s \leq t$ , then  $n(s) \leq n(t)$ );
- for any two times  $s < t$ ,  $n(t) - n(s) \leq 1$ .

Since  $n$  takes nonnegative integer values, these three conditions imply that the graph of a counting function looks like Figure 3. When we look at Figure 3, we see that any counting function is specified by the list of “timestamps”  $t_1, t_2, \dots$ , such that  $n$  is constant on the intervals  $[t_i, t_{i+1})$ , and  $n(t_{i+1}) = n(t_i) + 1$  for all  $i$  (we also set  $t_0 = 0$ , and then  $n(t_1) = n(t_0) + 1 = n(0) + 1 = 1$ ). Each timestamp corresponds to a new arrival.

Now let us construct a *stochastic* counting function by letting the timestamps be random. We will do this in the following way. Let us carve the time axis  $T = \mathbb{R}_+$  into slots of length  $1/n$ . We assume that, when arrivals happen, they happen at the end of each slot (i.e., at times  $t = 1/n, 2/n, 3/n, \dots$ ), that at most one arrival can happen at each time, and that the arrivals in nonoverlapping slots are independent and happen with probability  $p$ . Thus, we end up with a sequence  $U = (U_k)_{k \in \mathbb{Z}_+}$  of i.i.d. Bernoulli( $p$ ) random variables, where  $U_k = 1$  if an arrival happened at  $t = (k + 1)/n$  and 0 otherwise. In this way,  $\sum_{k=0}^{m-1} U_k$  is the total number of arrivals in slots 1 through  $m$ . Thus, the total number of arrivals at time  $t = 1$  is given by

$$N^{(n)} = \sum_{k=0}^{n-1} U_k = U_0 + \dots + U_{n-1}$$

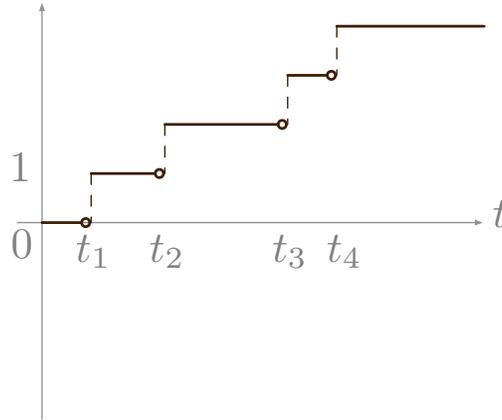


Figure 3: The graph of a counting function.

(we are using the superscript  $(n)$  to remind us of the “temporal resolution parameter”  $n$ ). Since  $U_k \stackrel{\text{i.i.d.}}{\sim} \text{Bernoulli}(p)$ ,  $N^{(n)} \sim \text{Binom}(n, p)$ . Thus, for any  $k \in \{0, 1, \dots, n\}$ ,

$$\mathbf{P}[N^{(n)} = k] = \binom{n}{k} p^k (1-p)^{n-k}.$$

We will now take the continuous-time limit, just as we had done with the Wiener process. We do this by letting  $n$ , the number of slots in the unit interval  $[0, 1]$ , go to infinity. However, we will pass to the limit in such a way that the average number of arrivals per unit time remains constant. Since  $\mathbb{E}[N^{(n)}] = np$ , we require that  $p = \lambda/n$ , where  $\lambda \geq 0$  is the given *rate of arrivals* (since  $p$  cannot exceed 1,  $n$  must be larger than  $\lambda$ ). Thus, in the limit  $n \rightarrow \infty$ , the random variables  $N^{(n)}$  will converge to an integer-valued random variable  $N$ , such that, for any  $k \in \mathbb{Z}_+$ ,

$$\begin{aligned} \mathbf{P}[N = k] &= \lim_{\substack{n \rightarrow \infty \\ p = \lambda/n}} \mathbf{P}[\text{Binom}(n, p) = k] \\ &= \lim_{n \rightarrow \infty} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k}. \end{aligned} \quad (3.11)$$

So, now we have to compute the limit in (3.11). This is actually not too difficult, provided we rearrange things in just the right way. Since  $k$  stays fixed and  $n$  is allowed to grow, we separate out the terms involving  $k$  only:

$$\begin{aligned} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} &= \frac{n!}{(n-k)!k!} \frac{\lambda^k}{n^k} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k} \\ &= \frac{\lambda^k}{k!} \frac{n!}{(n-k)!n^k} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k}. \end{aligned}$$

Therefore,

$$\begin{aligned} \lim_{n \rightarrow \infty} \binom{n}{k} \left(\frac{\lambda}{n}\right)^k \left(1 - \frac{\lambda}{n}\right)^{n-k} &= \frac{\lambda^k}{k!} \lim_{n \rightarrow \infty} \frac{n!}{(n-k)!n^k} \left(1 - \frac{\lambda}{n}\right)^n \left(1 - \frac{\lambda}{n}\right)^{-k} \\ &= \frac{\lambda^k}{k!} \cdot \lim_{n \rightarrow \infty} \frac{n!}{(n-k)!n^k} \cdot \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n \cdot \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^{-k} \end{aligned}$$

Each of the three limits above is easy to evaluate:

$$\begin{aligned} \lim_{n \rightarrow \infty} \frac{n!}{(n-k)!n^k} &= \lim_{n \rightarrow \infty} \frac{n}{n} \frac{n-1}{n} \dots \frac{n-k+1}{n} = 1 \\ \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^n &= e^{-\lambda} \\ \lim_{n \rightarrow \infty} \left(1 - \frac{\lambda}{n}\right)^{-k} &= 1. \end{aligned}$$

Putting everything together, we obtain

$$\mathbf{P}[N = k] = \frac{e^{-\lambda} \lambda^k}{k!}, \quad (3.12)$$

i.e., the total number of arrivals  $N$  by time  $t = 1$  has the Poisson distribution with parameter  $\lambda$  — we write  $N \sim \text{Pois}(\lambda)$  to denote this fact. Now, we are interested in the number of arrivals at any time  $t$ , so let's denote it by  $N_t$ . Exactly the same reasoning as before, but applied to the interval  $[0, t]$ , yields the following analog of (3.12):

$$\mathbf{P}[N_t = k] = \frac{e^{-\lambda t} (\lambda t)^k}{k!}. \quad (3.13)$$

That is,  $N_t \sim \text{Pois}(\lambda t)$  for every  $t \geq 0$ , and, in particular,  $N = N_1$ . The limiting stochastic signal  $N = (N_t)_{t \geq 0}$  is called the *Poisson process* with rate  $\lambda$ .

What other properties does this process have? For starters, each path of this process is a counting function. This shows that the random variables  $N_t$  are certainly not independent. Indeed, if  $t > s$ , then we know that  $N_t \geq N_s$ , since the number of arrivals by time  $t$  is at least as large as the number of arrivals by an earlier time  $t$ . However, by referring to our discrete-time approximation, we can easily convince ourselves that the increment  $N_t - N_s$  is independent of all  $N_r$ ,  $r \leq s$ , just like with the Wiener process. Moreover, the increment  $N_t - N_s$  corresponds to zeroing out the arrival counter at time  $s$  and then counting the arrivals between time  $s$  and time  $t$ . By symmetry, these arrivals are generated by exactly the same process that had generated the arrivals in the interval  $[0, s]$ , so  $N_t - N_s$  has a Poisson distribution with parameter  $\lambda(t - s)$ . Moreover, exactly the same argument as in the case of the Wiener process shows that, for any  $s \leq t$  and any  $r$  such that  $s + r \geq 0$ ,  $N_{t+r} - N_{s+r}$  has the same distribution as  $N_{t-s}$ , namely  $\text{Pois}(\lambda(t - s))$ . This shows that the Poisson process has stationary increments. Summarizing, the Poisson process has the following properties:

1.  $N_0 = 0$  (zero initial condition)

2. For any three times  $0 \leq r \leq s \leq t$ ,  $N_t - N_s$  is independent of  $N_r$  (independent increments)
3. For any  $0 \leq s \leq t$ ,  $N_t - N_s \sim \text{Pois}(0, \lambda(t - s))$  (stationary Poisson increments)

Exactly the same reasoning as for the Wiener process also shows that  $N$  is a Markov process.

Figure 4 shows the typical path of a Poisson process. As we already noted above, it is a counting function with random timestamps  $T_1, T_2, \dots$ . If we assemble the timestamps into a discrete-time process  $T = (T_k)_{k \in \mathbb{Z}_+}$  with  $T_0 = 0$ , then the knowledge of  $T$  suffices to reconstruct  $N$ :  $N_t = 0$  for  $t \in [0, T_1)$ , the value of  $N_t$  is constant on the intervals  $[T_i, T_{i+1})$ , and increases by one at each  $T_i$ .

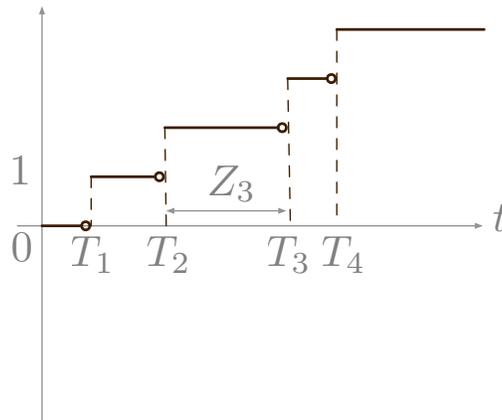


Figure 4: A sample path of a Poisson process.

The process  $T$  is called a *Poisson point process* — its sample path is a discrete collection of points on the half-axis  $\mathbb{R}_+$ , with the following properties:

- For every interval  $[a, b] \subset \mathbb{R}_+$ , define the random variable

$$N(a, b) \triangleq |\{k : T_k \in [a, b]\}|,$$

i.e., the number of points  $T_i$  that lie in  $A$ . Then  $N(a, b) \sim \text{Pois}(\lambda(b - a))$ . This is obvious in light of the fact that the number of points  $T_i$  in  $[a, b]$  is exactly the increment  $N_b - N_a$ .

- If the intervals  $(a, b)$  and  $(c, d)$  are nonoverlapping, then  $N(a, b)$  and  $N(c, d)$  are independent.

The random variables  $T_k$  are obviously dependent, because, for one, they must form a strictly increasing sequence:  $T_1 < T_2 < T_3 < \dots$ . However, let us define, for each  $k \in \{1, 2, \dots\}$ ,  $Z_k \triangleq T_k - T_{k-1}$ . We claim that the  $Z_k$ 's are independent, and each has the exponential distribution with parameter  $\lambda$ , i.e.,

$$\mathbf{P}[Z_k \leq t] = \begin{cases} 0, & t < 0 \\ 1 - e^{-\lambda t}, & t \geq 0 \end{cases}$$

(we then write  $Z_k \stackrel{\text{i.i.d.}}{\sim} \text{Exp}(\lambda)$ ). To see this, let us first analyze  $Z_1 \equiv T_1$ . We are interested in its cdf,  $F_{Z_1}(t) = \mathbf{P}[Z_1 \leq t]$ . Now, if the event  $\{Z_1 \leq t\} = \{T_1 \leq t\}$  occurs, then there must have been at least

one arrival by time  $t$ , so  $N_t \geq 1$ . Conversely, if the event  $\{N_t \geq 1\}$  occurs, then the time  $T_1$  of the first arrival cannot be larger than  $t$  (for otherwise we would have had  $N_t = 0$ ). Consequently, the events  $\{T_1 \leq t\}$  and  $\{N_t \geq 1\}$  are equivalent, and therefore

$$\begin{aligned} \mathbf{P}[Z_1 \leq t] &= \mathbf{P}[N_t \geq 1] \\ &= 1 - \mathbf{P}[N_t = 0] \\ &= 1 - \mathbf{P}[\text{Pois}(\lambda t) = 0] \\ &= 1 - e^{-\lambda t}. \end{aligned}$$

This shows that  $Z_1 \sim \text{Exp}(\lambda)$ . Now, what about  $Z_2$ ? Reasoning as before, imagine that we zero out the arrival counter at time  $T_1$ . Since the Poisson process  $N$  has independent increments, the time that elapses before the next arrival after  $T_1$  has the same distribution as  $T_1$ , and is independent of  $T_1$ . Thus,  $Z_2$  is independent of  $Z_1$ , and also has  $\text{Exp}(\lambda)$  distribution. Incidentally, this shows that the discrete-time process  $T = (T_k)_{k \in \mathbb{Z}_+}$  is a random walk, since

$$T_{k+1} = T_k + Z_k,$$

where  $Z_k \sim \text{Exp}(\lambda)$  is independent of  $T_k$ . Just like  $T$ ,  $Z$  fully describes the counting function  $N$ : since  $Z_1 = T_1$ , we know the time of the first arrival; since  $T_2 = T_1 + Z_2$ , we know the time of the second arrival; etc.

### 3.5 Stationarity: weak and strong

As we have seen, both the Wiener process and the Poisson process have *stationary increments*. For example, if  $W = (W_t)_{t \geq 0}$  is a Wiener process, then, for any two times  $0 \leq s \leq t$  and for any  $r \geq -s$ , the distribution of the increment  $W_t - W_s$  is the same as the distribution of the increment  $W_{t+r} - W_{s+r}$ , namely Gaussian with mean 0 and variance  $D(t-s)$ . Thus, the statistical properties of the increments of  $W$  are unaffected by time shifts.

This property turns out to be rather useful, so we abstract it into a definition: A stochastic signal  $X = (X_t)_{t \in T}$  is (*strongly*) *stationary* if, for any  $n \in \mathbb{N}$ , any finite sequence of times  $t_1, t_2, \dots, t_n \in T$ , and any  $r \in \mathbb{R}$ , such that  $t_1 + r, \dots, t_n + r \in T$ ,

$$(X_{t_1}, X_{t_2}, \dots, X_{t_n}) \stackrel{d}{=} (X_{t_1+r}, X_{t_2+r}, \dots, X_{t_n+r}) \quad (3.14)$$

(the notation  $U \stackrel{d}{=} V$  means that the random quantities  $U$  and  $V$  have the same distribution). When  $X$  has a discrete state space  $\mathcal{X}$ , the stationarity condition (3.14) means that

$$\mathbf{P}[X_{t_1} = x_1, X_{t_2} = x_2, \dots, X_{t_n} = x_n] = \mathbf{P}[X_{t_1+r} = x_1, X_{t_2+r} = x_2, \dots, X_{t_n+r} = x_n]$$

for all  $x_1, \dots, x_n \in \mathcal{X}$ ; when  $X$  has a continuous state space  $\mathcal{X}$ , (3.14) means that

$$\mathbf{P}[a_1 \leq X_{t_1} \leq b_1, \dots, a_n \leq X_{t_n} \leq b_n] = \mathbf{P}[a_1 \leq X_{t_1+r} \leq b_1, \dots, a_n \leq X_{t_n+r} \leq b_n]$$

for all subintervals  $[a_1, b_1], \dots, [a_n, b_n]$  of  $\mathcal{X}$ . This definition covers discrete and continuous time. For example, any i.i.d. process  $X = (X_k)_{k \in \mathbb{Z}_+}$  is strongly stationary.

However, for many purposes, strong stationarity is too much to ask for. Instead, we consider the following weaker notion: Let  $X = (X_t)_{t \in T}$  be a stochastic signal with a continuous state space  $X$ . Then we say that  $X$  is *weakly stationary* (and write WS, for short) if it has the following two properties:

1. The mean function  $m_X(t) = \mathbf{E}[X_t]$  is constant as a function of  $t$ :

$$m_X(t) = \mu, \quad \forall t \in T. \quad (3.15)$$

2. For any two times  $s, t \in T$  and any  $r \in \mathbb{R}$  such that  $s + r \in T$  and  $t + r \in T$ ,

$$R_X(s, t) = R_X(s + r, t + r). \quad (3.16)$$

Here,  $R_X(s, t) = \mathbf{E}[X_s X_t]$  is the autocorrelation function of  $X$ .

This property is much weaker than strong stationarity: one can easily construct examples of stochastic signals that are very nonstationary in the sense of (3.14), yet are weakly stationary. (Of course, any strongly stationary process with a continuous state space is also weakly stationary.) Now let us examine some implications of weak stationarity. While the definition applies to any  $T$ , we will focus on the easy case when  $T$  is closed under addition and subtraction: if  $s, t \in T$ , then  $s + t \in T$  and  $s - t \in T$ . Then  $0 \in T$ . In that case, from (3.15) we get  $\mu = \mathbf{E}[X_0]$ , and from (3.16) with  $r = -t$  we get

$$\mathbf{E}[X_t^2] = R_X(t, t) = R_X(0, 0) = \mathbf{E}[X_0^2].$$

Thus,  $\mathbf{E}[X_t^2] = \sigma^2$  for some  $\sigma \geq 0$ . Now, if we use (3.16) with  $r = -s$  and  $r = -t$ , we have

$$R_X(s, t) = R_X(0, t - s) \quad \text{and} \quad R_X(t, s) = R_X(0, s - t).$$

Since  $R_X(s, t) = R_X(t, s)$ , we conclude that  $R_X(s, t)$  depends only on  $\tau = t - s$ . Thus, for a weakly stationary stochastic process  $X = (X_t)_{t \in T}$ , we can overload the notation and write its autocorrelation function as  $R_X(\tau)$ . This really means that

$$R_X(\tau) = \mathbf{E}[X_t X_{t+\tau}] = \mathbf{E}[X_t X_{t-\tau}], \quad \forall t, \tau \in T$$

and, in particular, implies that  $R_X(\tau) = R_X(-\tau)$ .

Before moving on, let us look at an example. Let  $A, B$  be two jointly distributed real-valued random variables, and consider the following stochastic signal  $X = (X_t)_{t \in \mathbb{R}}$ :

$$X_t = A \cos \omega t + B \sin \omega t \quad (3.17)$$

(here,  $\omega$  is a deterministic angular frequency, not to be confused with a generic element of some probability space  $(\Omega, \mathcal{F}, \mathbf{P})$ ). This is an example of a deterministic signal with stochastic parameters. What are the conditions on  $A$  and  $B$  for this signal to be weakly stationary? We claim that  $X$  is weakly stationary if and only if the following three conditions are satisfied:

1.  $\mathbf{E}[A] = \mathbf{E}[B] = 0$  (both  $A$  and  $B$  have zero mean).

2.  $\text{Var}[A] = \text{Var}[B] = \sigma^2$  ( $A$  and  $B$  have the same variance).
3.  $\mathbf{E}[AB] = 0$  ( $A$  and  $B$  are uncorrelated).

We will only prove the statement that if  $X$  is WS, then  $A$  and  $B$  have to satisfy the above conditions; the converse will be a homework problem. So, suppose that  $X$  is WS. Then

$$m_X(t) = \mathbf{E}[X_t] = \mathbf{E}[A \cos \omega t + B \sin \omega t] = \mathbf{E}[A] \cos \omega t + \mathbf{E}[B] \sin \omega t,$$

and the only way for  $m_X(t)$  to be a constant is to have  $\mathbf{E}[A] = \mathbf{E}[B] = 0$ , because otherwise it will depend on  $t$ . This proves Item 1. Now, again by the WS assumption,  $\mathbf{E}[X_t^2] = R_X(0)$  must be a constant. Since  $X_0 = A$  and  $X_{\pi/2\omega} = B$ , we have  $\mathbf{E}[X_0^2] = \mathbf{E}[A^2] = \text{Var}[A]$  and  $\mathbf{E}[X_{\pi/2\omega}^2] = \mathbf{E}[B^2] = \text{Var}[B]$  (we have used the fact that both  $A$  and  $B$  have zero mean). Thus,  $\text{Var}[A] = \text{Var}[B] = \sigma^2$  for some  $\sigma \geq 0$ . This proves Item 2. Finally, for any  $t, \tau \in T$  we write

$$\begin{aligned} R_X(t, t + \tau) &= \mathbf{E}[X_t X_{t+\tau}] \\ &= \mathbf{E}[(A \cos \omega t + B \sin \omega t)(A \cos \omega(t + \tau) + B \sin \omega(t + \tau))] \\ &= \mathbf{E}[A^2] \cos \omega t \cos \omega(t + \tau) + \mathbf{E}[B^2] \sin \omega t \sin \omega(t + \tau) \\ &\quad + \mathbf{E}[AB](\cos \omega t \sin \omega(t + \tau) + \sin \omega t \cos \omega(t + \tau)) \\ &= \sigma^2 \cos \omega \tau + \mathbf{E}[AB] \sin \omega(2t + \tau), \end{aligned}$$

where we have used trigonometric identities and the fact that  $\mathbf{E}[A^2] = \mathbf{E}[B^2] = \sigma^2$ . We see that, unless  $\mathbf{E}[AB] = 0$ ,  $R_X(t, t + \tau)$  will depend on both  $t$  and  $\tau$ , which would violate the assumption that  $X$  is WS. This proves Item 3.

As we will soon learn, weak stationarity is preserved by linear time invariant (LTI) systems: if  $X = (X_t)_{t \in \mathbb{R}}$  is a WS input to an LTI system, then the output  $Y = (Y_t)_{t \in \mathbb{R}}$  is also WS, and its mean and correlation functions can be explicitly computed from those of  $X$  and from the impulse response of the system.