PROBABILITY THEORY II

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Second Semester

List of Symbols

Ω, a sample space.

ω, an element of a sample space.

EX, the expectation of the random variable X.

$\mathrm{Var}X$, the variance of the random variable X.

$N(\mu, \sigma^2)$, a normal distribution with expectation μ and variance σ^2.

$N_n(k)$, the number of paths from $(0,0)$ to (n,k) in a simple random walk.

$N_n^+(k)$, the number of paths from $(0,0)$ to (n,k) through strictly positive values in a random walk.

p_k^X, the probability mass function for a random variable X.

Contents

Chapter 1

RANDOM WALKS AND MISC. RESULTS

January 3rd.

We first start with some initial statements. Let Ω be a countable state space, and let each $\omega \in \Omega$ have a probabiltiy $P(\omega)$ associated with it.

Lemma 1.1. *For random variables X, Y such that $X(\omega) \leq Y(\omega)$ for all $\omega \in \Omega$. Then, $EX \leq EY$.*

Proof. This can easily be seen by summing over all terms via the alternate definition of the expectation,

$$EX = \sum_{\omega \in \Omega} X(\omega)P(\omega) \leq \sum_{\omega \in \Omega} Y(\omega)P(\omega) = EY. \tag{1.1}$$

■

We now state Markov's inequality.

Theorem 1.2 (*Markov's inequality*)**.** *If X is a non-negative randm variable, then for $a > 0$, we have*

$$P(X > a) \leq \frac{EX}{a}. \tag{1.2}$$

Proof. Define an indicator function $I_a(\omega)$ as 1 if $X(\omega) \geq a$, and 0 if otherwise. We then have

$$I_a(\omega) \leq \frac{X(\omega)}{a} \implies P(X \geq a) = EI_a \leq \frac{1}{a}EX. \tag{1.3}$$

■

Remark 1.3. A better upper bound here may be found by starting with $I_a(\omega)X(\omega)$ instead of just $X(\omega)$.

If we have $X \sim N(0,1)$, then we can find an upper bound for its probability density function.

$$P(X > a) = \int_a^\infty \frac{1}{\sqrt{2\pi}} e^{\frac{-x^2}{2}}\,dx \leq \int_a^\infty \frac{1}{\sqrt{2\pi}} \frac{x}{a} e^{\frac{-x^2}{2}}\,dx = \frac{e^{\frac{-a^2}{2}}}{\sqrt{2\pi}a}. \tag{1.4}$$

Note that X here is a random variable over a continuous state space; the previous lemma and Markov's inequality also work here. We are to show them for the continuous case instead of the discrete one.

Proof. Here, we have $0 \leq X(\omega) \leq Y(\omega)$ for all ω in our continuous state space Ω. We see that $\{X > x\} \subseteq \{Y > x\} \implies P(X > x) \leq P(Y > x)$. Integrating both sides gives us $EX \leq EY$. ■

Theorem 1.4 (*Chebyshev's inequality*)**.** *Let X be a random variable with finite mean $\mu = EX$ and finite variance $\sigma^2 = Var(X)$. Then for $a > 0$,*

$$P(|X - \mu| > a) \leq \frac{Var(X)}{a^2}. \tag{1.5}$$

Proof. Start with the proof of Markov's inequality, replacing the indiciator function with one that's unity when $|X-\mu| \geq a$. ■

Example 1.5. Suppose $X_1, X_2, \ldots, X_n$ are n independent and identically distributed random variables, with $EX_i = \mu$ and $\mathrm{Var}X_i = \sigma^2$. If $S_n = \sum X_i$, we then have

$$P(|S_n - n\mu| > a) \leq \frac{\mathrm{Var}S_n}{a^2} = \frac{n\sigma^2}{a^2}. \tag{1.6}$$

If we replace a with $n^{\frac{1}{2}+\varepsilon}$, we then have

$$P(|S_n - n\mu| > n^{\frac{1}{2}+\varepsilon}) \leq \frac{\sigma^2}{n^{2\varepsilon}} \to 0 \text{ as } n \to \infty. \tag{1.7}$$

Proposition 1.6. *If $Var(X) = 0$, then $P(X = EX) = 1$.*

Proof. For all $\varepsilon > 0$, we have

$$P(|X - EX| > \varepsilon) \leq \frac{\mathrm{Var}X}{\varepsilon^2} = 0. \tag{1.8}$$

Define A_n as $\{|X - EX| > \frac{1}{n}\}$. Taking $P(\bigcup A_n) = \lim_{n\to\infty} P(A_n)$, the proof follows. ■

1.1 The Law of Large Numbers

We start by stating the weak law of large numbers.

Theorem 1.7 (*Weak law of large numbers*)**.** *Let $\{X_k\}_{k\geq 1}$ be a sequence of independent and identically distributed random variables with $E|X_i| < \infty$. Let $\mu = EX_i$. Then for any $a > 0$,*

$$\lim_{n\to\infty} P\left(\left|\frac{X_1 + X_2 + \ldots + X_n}{n} - \mu\right| > a\right) = 0. \tag{1.9}$$

Proof. For now, let us assume that Ω is countable. We begin with the case where the variance of X_i, σ^2, is finite. Fix $a > 0$, and let $S_n = X_1 + X_2 + \ldots + X_n$. Then,

$$P\left(\left|\frac{S_n}{n} - \mu\right| > a\right) = P(|S_n - n\mu| > na) \leq \frac{\mathrm{Var}S_n}{n^2a^2} = \frac{n\sigma^2}{n^2a^2} \to 0 \text{ as } n \to \infty. \tag{1.10}$$

We now focus the case when the variance, σ^2, is infinite. Assume that the expected value, μ, is 0; if it were non-zero, we would then instead work with $X_i - \mu$. Let $\delta > 0$; we shall choose a particular δ later. For each n, define n pairs of random variables, $U_1, V_1, \ldots, U_n, V_n$, as $U_k = X_k, V_k = 0$ if $|X_k| \leq \delta n$, and $U_k = 0, V_k = X_k$ if $|X_k| > \delta n$. X_k can be rewritten as $U_k + V_k$. We then have

$$\{|X_1 + \ldots + X_n| \geq na\} \subseteq \{|U_1 + \ldots + U_n| \geq \frac{na}{2}\} \cup \{|V_1 + \ldots + V_n| \geq \frac{na}{2}\} \tag{1.11}$$

$$\implies P\left(|X_1 + \ldots + X_n| \geq na\right) \leq P\left(|U_1 + \ldots + U_n| \geq \frac{na}{2}\right) + P\left(|V_1 + \ldots + V_n| \geq \frac{na}{2}\right). \tag{1.12}$$

We focus on the first term on the right hand side. The U_i's are independently and identically distributed, so

$$P\left(|U_1 + \ldots + U_n| \geq \frac{na}{2}\right) \leq \frac{4E[|U_1 + \ldots + U_n|^2]}{a^2n^2} = \frac{4}{a^2n^2}\left(\mathrm{Var}(U_1 + \ldots + U_n) + (nEU_i)^2\right). \tag{1.13}$$

For the variance, we have

$$\mathrm{Var}(U_1 + \ldots + U_n) = n\mathrm{Var}U_i \leq nEU_i^2 \leq nE[|U_i|\,|U_i|] \leq \delta n^2 E[|U_i|] \tag{1.14}$$

which transforms the previous equation as

$$P\left(|U_1 + \ldots + U_n| \geq \frac{na}{2}\right) \leq \frac{4}{a^2n^2}\left(\delta n^2 E[|U_i|] + (nEU_i)^2\right). \tag{1.15}$$

A lemma (to be proven later) states that $E[|U_i|] = E[|X_i|]$ as $n \to \infty$, and $EU_i = EX_i = 0$ too. So,

$$P\left(|U_1 + \ldots + U_n| \geq \frac{na}{2}\right) \leq \frac{4}{a^2n^2}\left(\delta n^2 E[|U_i|] + (nEU_i)^2\right) \leq \frac{4\delta E[|U_i|]}{a^2} + \frac{4}{a^2}(EU_i)^2. \tag{1.16}$$

For the second term on the right hand side, begin with

$$P(V_1 + \ldots + V_n \neq 0) \leq P(\{V_1 \neq 0\} \cup \ldots \cup \{V_n \neq 0\}) \leq nP(V_i \neq 0) = n \sum_{|x|>\delta n} P(X_i = x)$$

$$\leq n \sum_{|x|>\delta n} \frac{|x|}{\delta n} P(X_i = x) = \frac{1}{\delta} E[|V_i|]. \tag{1.17}$$

The rightmost term here tends to 0 as $n \to \infty$. Now choose δ to be $\frac{\varepsilon a^2}{|6E|X_i||}$, and then choose N to be large enough such that for all $n > N$, both the terms are smaller than $\frac{\varepsilon}{2}$. ■

January 7th.

We now prove the lemma called upon earlier.

Lemma 1.8. *If X is a discrete random variable and takes values $y_1, y_2, \ldots, y_k$, and $E[|X|] < \infty$, then $\lim_{n\to\infty} E[|X| \, 1_{|X|\leq n}] = E[|X|]$.*

Proof. Notice that the terms on the left hand side and right hand side are $\sum_{y_k:|y_k|\leq n}$ and $\sum_{y_k} |y_k| \, P(Y = y_k)$. The condition for convergence may now be applied. ■

The above equation, begin inside absolute braces, must imply that the term $E[X \cdot 1_{|X|\leq n}]$ must also absolutely converge to EX.

1.2 Simple Random Walk

Let $X_1, X_2, \ldots$ be independent and identically distributed random variables, with $X_i = 1$ with probability $\frac{1}{2}$ and $X_i = -1$ with probability $\frac{1}{2}$. Now define $S_0 = 0$ and $S_n = \sum_{i=1}^{n} X_i$. The sequence $(S_n)_{n\geq 0}$ is a *simple random walk*.

Note that $S_0 = k_0 = 0, S_1 = k_1, \ldots, S_n = k_n$ can occur if and only if $|k_i - k_{i+1}| = 1$ for all $0 \leq i \leq n-1$. The sequence $(k_n)_{n\geq 0}$ is a *simple path* of the simple random walk. By the event $\{S_n = k\}$, we are concerned with the event that the random walk visits k at step n. If $(k_n)_{n\geq 0}$ is given we have $X_i = k_i - k_{i-1}$. Because the X_i's are independent and identically distributed, each event $\{X_1 = l_1, X_2 = l_2, \ldots, X_n = l_n\}$, where $l_i = \pm 1$, is equally likely with probability $\frac{1}{2^n}$. Thus,

$$P(S_n = k) = \frac{N_n(k)}{2^n} \tag{1.18}$$

where $N_n(k)$ is defined as the number of distinct of path that start at 0 and end at k at step n. We also define $N_n^+(k)$ to be the number of distinct paths that end at k at step n and stay above the x-axis up to time $n-1$. The probability of the corresponding event is

$$P(\{S_1 > 0, S_2 > 0, \ldots S_{n-1} > 0, S_n = k\}) = \frac{N_n^+(k)}{2^n}. \tag{1.19}$$

Lemma 1.9. *Suppose a, a', b, b' are integers, with $0 \leq a < a'$. Then the number of distinct path from (a, b) to (a', b') depends only on $a' - a = n$ and $b' - b = k$, and is given by $\binom{n}{\frac{n+k}{2}}$.*

Proof. Notice that we need x $+1$'s and y -1's to appear, satisfying $x + y = a' - a$ and $x - y = b' - b$. Solving, we get $x = \frac{n+k}{2}$ and $y = \frac{n-k}{2}$. Thus, the number of paths is given by $\binom{n}{\frac{n+k}{2}}$. ■

Using this lemma, we find that $N_n(k) = \binom{n}{\frac{n+k}{2}}$. The following convention is now followed; if t is not an integer, then $\binom{n}{t} = 0$.

Lemma 1.10 (The *method of images*). *Suppose a, a', b, b' are integers, with $0 \leq a < a'$ and $b, b' > 0$. Then the number of distinct paths from (a, b) to (a', b') that intersect the x-axis is equal to the number of paths from $(a, -b)$ to (a', b').*

Proof. Consider any path $(b = k_0, k_1, \ldots, k_{n-1}, k_n = b')$, from (a, b) to (a', b'), that intersects the x-axis. Let j be the smallest index for which $k_j = 0$. For ease, denote (a, b) by A, (a', b') by A', $(a + j, 0)$ by B, and $(a, -b)$ by A''. Reflect the segment from A to B about the x-axis to obtain a 'mirrored-path' from A'' to B; $(-b = -k_0, -k_1, \ldots, -k_{j-1}, k_j = 0, k_{j+1}, \ldots, k_n = b')$. There is now a one-to-one correspondence between the paths from A to A' that intersect the x-axis, and the paths from A'' to A'. ■

We can now easily compute $N_n^+(k)$; it simply the number of paths from $(1,1)$ to (n,k) that do not intersect the x-axis.

Theorem 1.11 (*Ballot theorem*)**.** *The number of paths that progress from $(0,0)$ to (n,k) through strictly positive values is given by $N_n^+(k) = \frac{k}{n}N_n(k)$.*

Proof. We have

$$\begin{aligned} N_n^+(k) &= \text{ number of paths from } (1,1) \text{ to } (n,k) - \text{ number of such paths that intersect the } x\text{-axis} \\ &= N_{n-1}(k-1) - N_{n-1}(k+1) \\ &= \binom{n-1}{\frac{n+k}{2}-1} - \binom{n-1}{\frac{n+k}{2}} = \frac{k}{n}\binom{n}{\frac{n+k}{2}} = \frac{k}{n}N_n(k). \end{aligned} \tag{1.20}$$

■

Suppose $n = 2\nu$. Define $u_{2\nu}$ to be $P(S_{2\nu} = 0) = \frac{\binom{2\nu}{\nu}}{2^n}$. The question we ask is to compute the probability that the first return to 0, if at all, occurs after step n. It can be found out as

$$\begin{aligned} P(\text{first return to 0...}) &= P(S_1 \neq 0, S_2 \neq 0, \ldots, S_{2\nu} \neq 0) \qquad (1.21) \\ &= P(S_1 > 0, \ldots, S_{2\nu} > 0) + P(S_1 < 0, \ldots, S_{2\nu} < 0) \\ &= 2P(S_1 > 0, \ldots, S_{2\nu} > 0) \\ &= 2 \sum_{k \text{ even}, k>0} P(S_1 > 0, \ldots, S_{2\nu-1} > 0, S_{2\nu} = k) \\ &= \frac{2}{2^{2\nu}} \sum_{k \text{ even}, k>0} N_{2\nu}^+(k) \\ &= \frac{2}{2^{2\nu}} \sum_{k \text{ even}, k>0} N_{2\nu-1}(k-1) - N_{2\nu-1}(k+1) \\ &= \frac{2}{2^{2\nu}} N_{2\nu-1}(1) = u_{2\nu}. \qquad (1.22) \end{aligned}$$

We state this down as a lemma.

Lemma 1.12 (*Basic lemma*)**.** *For n even, the probability that the first return to 0, if at all, occurs after step n is the same as the probability that the location at step n is 0. For n odd, it is the probability that the location at step $n-1$ is 0.*

We ask another question; for a fixed n, where does the random walk achieve its first maximum upto time n? For this, denote by M_n the index m at which the walk $S_0, S_1, \ldots, S_n$, over n steps, achieves its maximum for the first time.

For $0 < m < n$, $M_n = m$ if and only if $S_m > S_0,\ S_m > S_1, \ldots, S_m > S_{m-1}$ and $S_m \geq S_{m+1},\ S_m \geq S_{m+2}, \ldots, S_m \geq S_n$. Notice that the first of these two conditions depends only on $X_1, X_2, \ldots, X_m$, and the second condition depends only on $X_{m+1}, X_{m+2}, \ldots, X_n$. So, $P(M_n = m) = P(S_m > S_0,\ S_m > S_1, \ldots, S_m > S_{m-1}) \cdot P(S_m \geq S_{m+1},\ S_m \geq S_{m+2}, \ldots, S_m \geq S_n)$.

The key idea here is to consider the *reversed walk*; define a new walk with $X_1' = X_m,\ X_2' = X_{m-1}, \ldots, X_m' = X_1$. Also define $S_k' = X_1' + \ldots + X_k'$. From here, we can deduce that $S_m > S_{m-i}$ is true if and only if $X_m + \ldots + X_{m-i} > 0$ is true, which is true if and only if $S_i' > 0$ is true. So, $P(S_m > S_0,\ S_m > S_1, \ldots, S_m > S_{m-1}) = P(S_1' > 0,\ S_2' > 0, \ldots, S_m' > 0)$. If we now define $S_k'' = X_{m+1} + \ldots + X_{m+k}$, we have

$$\begin{aligned} P(S_m \geq S_{m+1},\ S_m \geq S_{m+2}, \ldots, S_m \geq S_n) &= P(X_{m+1} \leq 0,\ X_{m+1} + X_{m+2} \leq 0, \ldots, X_{m+1} + \ldots + X_n \leq 0) \\ &= P(S_1'' \leq 0,\ S_2'' \leq 0, \ldots, S_{n-m}'' \leq 0) \\ &= P(S_1'' \geq 0,\ S_2'' \geq 0, \ldots, S_{n-m}'' \geq 0) \end{aligned}$$

The first of the terms discussed, $P(S_1' > 0,\ S_2' > 0, \ldots, S_m' > 0)$, can be computed for $m = 2\nu, 2\nu+1$; it is simply $\frac{1}{2}u_{2\nu}$. For the latter of these terms, we introduce a new random variable $\tilde{X}$ which has the same distribution as the X_i's and is independent. Also define $\tilde{S}_i$ to be $\tilde{X} + X_1 + \ldots + X_{i-1}$ and $\tilde{S}_0$ to be 0.

We then have

$$\begin{aligned}\frac{1}{2}P(S_0 \geq 0, \ldots, S_{n-m} \geq 0) &= P(\tilde{X} = 1) \cdot P(S_0 \geq 0, \ldots, S_{n-m} \geq 0) \\ &= P(\tilde{X} = 1, S_0 \geq 0, S_0 \geq 0, \ldots, S_{n-m} \geq 0) \\ &= P(\tilde{S_1} = 1, \tilde{S_2} > 0, \ldots, \tilde{S_{n-m+1}} > 0) \\ &= P(S_1 > 0, S_2 > 0, \ldots, S_{n-m+1} > 0). \end{aligned} \tag{1.23}$$

Thus, we get

$$P(M_n = m) = \frac{1}{2}u_{2k}u_{2\nu-2k} \tag{1.24}$$

where m is of the form $2k$ or $2k+1$, and n is of the form 2ν, with $1 < k < \nu$.

January 10th.

Plugging in $m = 0$, we get $P(M_n = 0) = P(S_1 \leq 0, \ldots, S_{2\nu} \leq 0) = \frac{1}{2}u_{2\nu}$. For $m = n$, we have $P(M_n = n) = P(S_1 \leq 0, \ldots, S_{2\nu} \leq 0) = \frac{1}{2}u_{2\nu}$. Let us first compute u_{2k}.

$$\begin{aligned} u_{2k} = P(2k = 0) = \frac{\binom{2k}{k}}{2^{2k}} &= \frac{(2k)!}{(k!)^2 2^{2k}} \\ \sim \frac{(2k)^{2k+\frac{1}{2}}e^{-2k}\sqrt{2\pi}}{(\sqrt{2\pi}k^{k+\frac{1}{2}}e^{-k})^2 2^{2k}} &= \frac{1}{\sqrt{\pi k}}. \end{aligned} \tag{1.25}$$

For $0 < a < b < 1$, we have

$$\begin{aligned} P(an \leq M_n \leq bn) &= \sum_{m=an}^{bn} P(M_n = m) = \sum_{k=a\nu}^{b\nu} u_{2k}u_{2\nu-2k} \\ &\sim \sum_{k=a\nu}^{b\nu} \frac{1}{\sqrt{\pi k}} \frac{1}{\sqrt{\pi(\nu-k)}} = \sum_{k=a\nu}^{b\nu} \frac{1}{\nu\sqrt{\pi\frac{k}{\nu}}\sqrt{\pi(1-\frac{k}{\nu})}} \\ &\to \frac{1}{\pi}\int_a^b \frac{dx}{\sqrt{x(1-x)}} = \frac{2}{\pi}(\arcsin\sqrt{b} - \arcsin\sqrt{a}). \end{aligned} \tag{1.26}$$

In fact, this is the *arcsin law for maxima*; for $0 \leq t \leq 1$, we have

$$\lim_{n\to\infty} P\left(\frac{M_n}{n} \leq t\right) = \frac{2}{\pi}\arcsin\sqrt{t}. \tag{1.27}$$

If we look at this as a cumulative density funtion, the probability density function becomes $\frac{d}{dt}\frac{2}{\pi}\arcsin\sqrt{t} = \frac{1}{\pi\sqrt{t(1-t)}}$.

We are now interested in $\tilde{M_n}$, the last time when maximum up to time n is attained. We can just look at the walk backwards again; in this case, we get

$$P(\frac{\tilde{M_n}}{n}) = P\left(\frac{n-\tilde{M_n}}{n} \leq t\right) \to \frac{2}{\pi}\arcsin\sqrt{t}. \tag{1.28}$$

We now ask the probability that the random walk of $n = 2\nu$ steps last visit 0 at time $2k$. We denote by K_n the location of the last return to 0 in a walk of n steps. Now look at

$$\begin{aligned} \alpha_{2k,2\nu} &= P(K_n = 2k) = P(S_{2k} = 0, S_{2k+1} \neq 0, \ldots, S_{2\nu} \neq 0) \\ &= P(S_{2k} = 0) \cdot P(X_{2k+1} \neq 0, \ldots, X_{2k+1} + \ldots + X_{2\nu} \neq 0) \\ &= P(S_{2k} = 0) \cdot P(S_1 \neq 0, \ldots, S_{2\nu-2k} \neq 0) = u_{2k}u_{2\nu-2k}. \end{aligned} \tag{1.29}$$

We can also state an *arcsin law for last visit* here; for $0 < t < 1$

$$\lim_{n\to\infty} P(K_n \leq tn) = \frac{2}{\pi}\arcsin\sqrt{t}. \tag{1.30}$$

If we set the an additional limit that says t tends to 0, replacing t by an arbitrary $\varepsilon > 0$, we have

$$\lim_{n\to\infty} P(K_n = 0) = 0. \tag{1.31}$$

Given enough time, a simple random walk must return to 0.

Denote by f_{2n} the probability that the first return to 0 occurs at time $2n$.

$$\begin{aligned} f_{2n} &= P(S_1 \neq 0, \ldots, S_{2n-1} \neq 0, S_{2n} = 0) \\ &= P(S_1 \neq 0, \ldots, S_{2n-1} \neq 0) - P(S_1 \neq 0, \ldots, S_{2n} \neq 0) \\ &= P(S_1 \neq 0, \ldots, S_{2n-2} \neq 0) - P(S_1 \neq 0, \ldots, S_{2n} \neq 0) \\ &= u_{2n-2} - u_{2n} = \frac{1}{2n-1} u_{2n}. \end{aligned} \tag{1.32}$$

Lemma 1.13. *With the usual notation,*

$$u_{2n} = f_2 u_{2n-2} + f_4 u_{2n-4} + \ldots + f_{2n} u_0. \tag{1.33}$$

Proof. We have

$$\begin{aligned} P(S_{2n} = 0) &= \sum_{k=1}^{n} P(S_{2n} = 0, \text{ first return at } 2k) \\ &= \sum_{k=1}^{n} P(\text{first return at 2k}) \cdot P(S_{2n} = 0 \mid \text{first return at 2k}) \\ \implies P(S_n = 0) &= \sum_{k=1}^{n} f_{2k} u_{2n-2k}. \end{aligned} \tag{1.34}$$

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Theorem 1.14. *The probability that in the time interval* 0 *to* $n = 2\nu$*, the random walk spends* $2k$ *amount of time on the positive side and* $2\nu - 2k$ *amount of time on the negative side is* $\alpha_{2k,2\nu}$*.*

Corollary 1.15. *For* $0 < t < 1$*,*

$$P(\textit{random walk spends less than tn time on positive side}) \to \frac{2}{\pi} \arcsin \sqrt{t}. \tag{1.35}$$

Proof. This is the proof of the theorem. We introduce $b_{2k,2\nu}$; it is defined as the probability that the random walk of length 2ν and $2k$ sides above the x-axis. We need to show that $b_{2k,2\nu} = \alpha_{2k,2\nu}$. We have

$$b_{2\nu,2\nu} = P(S_1 \geq 0, S_2 \geq 0, \ldots, S_{2\nu} \geq 0) = u_{2\nu}, \tag{1.36}$$

$$b_{0,2\nu} = P(S_1 \leq 0, \ldots, S_{2\nu} \leq 0) = u_{2\nu}. \tag{1.37}$$

We are left to prove it for $1 \leq k \leq \nu - 1$. Assume that exactly $2k$ out of 2ν time are spent above the x-axis, with $1 \leq k \leq \nu - 1$. Suppose first return to 0 occurs at time $2r < 2\nu$. We deal in cases.

- Case I: $2r$ time units upto first return are on the positive side. Then, $r \leq k \leq \nu - 1$. The time from $2r$ to 2ν has to be above the x-axis, $2k - 2\nu$ time. The number of such paths is $(\frac{1}{2} 2^{2r} f_{2r})(2^{2\nu-2r} b_{2k-2r,2\nu-2r})$.
- The $2r$ time units upto the first return are on the negative side. The nubmer of such paths is $(\frac{1}{2} 2^{2r} f_{2r})(2^{2\nu-2r} b_{2k,2\nu-2r})$. Also, $\nu - r \geq k$.

Thus, we have

$$b_{2k,2\nu} = \frac{1}{2} \sum_{r=1}^{k} f_{2r} b_{2k-2r,2\nu-2r} + \frac{1}{2} \sum_{r=1}^{\nu-k} f_{2r} b_{2k,2\nu-2r}. \tag{1.38}$$

We now proceed with induction on ν. We have already shown this for $\nu = 1$; assume that this is true for $\nu \leq V - 1$. By induction,

$$\begin{aligned} b_{2k,2V} &= \frac{1}{2} \sum_{r=1}^{k} f_{2r} \alpha_{2k-2r,2V-2r} + \frac{1}{2} \sum_{r=1}^{V-k} f_{2r} \alpha_{2k,2V-2r} \\ &= \frac{1}{2} u_{2V-2k} \sum_{r=1}^{k} f_{2r} u_{2k-2r} + \frac{1}{2} u_{2k} \sum_{r=1}^{V-k} f_{2r} u_{2V-2k-2r} \\ &= u_{2k} u_{2\nu-2k} = \alpha_{2k,2\nu}. \end{aligned} \tag{1.39}$$

■

January 17th.

Theorem 1.16 (*Weirstrass's polynomial approximation.*). *Let $f : [0,1] \to \mathbb{R}$ be a continuous function. Then for every $\varepsilon > 0$, there is a polynomial P, dependent on f and ε, such that*

$$|f(x) - P(x)| < \varepsilon \text{ for all } x \in [0,1]. \tag{1.40}$$

Remark 1.17. Any continuous function $f : [0,1] \to \mathbb{R}$ is bounded and uniformly continuous. This fact will be useful in proving the previous theorem.

Proof. Start with $X_1, X_2, \dots$ which are independent and identically disitributed Bernoulli random variables, $\mathrm{Ber}(x)$. Let $S_n = X_1 + X_2 + \ldots + X_n$. From the weak law of large numbers, we know that $\frac{S_n}{n}$ is approximately x. We can expect that $f(x)$ will also be approximately $f(\frac{S_n}{n})$. We now have

$$\begin{aligned} f_n(x) = Ef(\frac{S_n}{n}) &= \sum_{j=0}^{n} f(\frac{j}{n}) P(S_n = j) \\ &= \sum_{j=0}^{n} f(\frac{j}{n}) \binom{n}{j} x^j (1-x)^{n-j}. \end{aligned} \tag{1.41}$$

This is now a polynomial; we wish to see how close this is to f. Define A_δ to be $\{j : \left|\frac{j}{n} - x\right| \leq \delta\}$

$$\begin{aligned} |f_n(x) - f(x)| &= \left| \sum_{j=0}^{n} \left(f(\frac{j}{n}) - f(x) \right) \right| P(S_n = j) \\ &= \left| \sum_{j \in A_\delta} \left(f(\frac{j}{n}) - f(x) \right) + \sum_{j \notin A_\delta} \left(f(\frac{j}{n}) - f(x) \right) \right| P(S_n = j) \\ &\leq \sum_{j \in A_\delta} \left| f(\frac{j}{n}) - f(x) \right| P(S_n = j) + \sum_{j \notin A_\delta} \left| f(\frac{j}{n}) - f(x) \right| P(S_n = j). \end{aligned} \tag{1.42}$$

We have two terms to deal with now. For the first term, choose $\delta > 0$ such that $|x - y| < \delta \implies |f(x) - f(y)| < \varepsilon$; this δ can be chosen since f is uniformly continuous. Similarly, also choose $M = \sup_{x \in [0,1]} |f(x)|$. M is finite since f is bounded. Thus, we have

$$\sum_{j \in A_\delta} \left| f(\frac{j}{n}) \right| P(S_n = j) \leq \sum_{j \in A_\delta} \varepsilon P(S_n = j) \leq \varepsilon \tag{1.43}$$

and

$$\sum_{j \notin A_\delta} \leq 2MP(\left|\frac{S_n}{n} - x\right| > \delta) \leq 2M \frac{\mathrm{Var}(S_n)}{n^2 \delta^2} = \frac{2Mnx(1-x)}{n^2\delta^2}. \tag{1.44}$$

Combining the two, and choosing n large enough, we have

$$|f_n(x) - f(x)| \leq \varepsilon + \frac{2Mx(1-x)}{n\delta^2} \leq \varepsilon + \frac{M}{2n\delta^2} \leq 2\varepsilon. \tag{1.45}$$

■

1.3 Erdös-Renyi Random Graph

We first discuss the setup; start with n vertices of an empty graph. For any pair of points (i, j), with $i \neq j$, join these vertices with an edge with probability p independently for all such pairs. Such a graph is denoted by $G_{n,p}$.

A collection of three points $S = \{i, j, k\}$ form a triangle if $G_{n,p}$ has the edges $\{i, j\}$, $\{j, k\}$, and $\{i, k\}$. We question the probability that such a graph has no formed triangles. Can we find $p = p_n$ such that triangles begin to appear at p_n? Let S be any set of three vertices. Define X_S to be the indicator function; 1 if S forms a triangle, and 0 otherwise. We note that $X_S \sim \mathrm{Ber}(p^3)$. We note that

$$EX_S = p^3,\ \mathrm{Var}X_S = p^3(1-p^3) \leq p^3.$$

Denote by N the number of triangles in the graph $G_{n,p}$. Clearly,

$$N = \sum_{S:|S|=3} X_S,\ EN = \binom{n}{3} p^3 < n^3p^3,\ \mathrm{Var}N = \sum_S \mathrm{Var}X_S + \sum_S \sum_{T\neq S} \mathrm{Cov}(X_S X_T) \leq n^3p^3 + n^4p^5$$

ALso, $P(N \geq 1) \leq EN < n^3p^3$. If $p = p_n << \frac{1}{n}$, then $P(N \geq 1) \to 0$ as $n \to \infty$. We discuss this for $p >> \frac{1}{n}$. We have

$$P(N=0) \leq P(|N - EN| \geq EN) \leq \frac{\mathrm{Var}N}{(EN)^2} \leq \frac{(n^3p^3 + n^4p^5)}{\frac{n^6p^6}{100}} \leq \frac{100}{n^3p^3} + \frac{100}{n(np)} \to 0. \tag{1.46}$$

We can state this as a theorem.

Theorem 1.18. *Consider G_{n,p_n}. Let E be the event that the graph is triangle free. We then have*

$$P(E) \to \begin{cases} 0 & \text{if } \frac{p_n}{\frac{1}{n}} \to \infty, \\ 1 & \text{if } \frac{p_n}{\frac{1}{n}} \to 0. \end{cases} \tag{1.47}$$

Now suppose that $\underset{\to}{np_n} C > 0$ as $n \to \infty$. Then we have

$$N \approx \mathrm{Poisson}\left(\frac{C^3}{6}\right). \tag{1.48}$$

January 21st.

Remark 1.19. For this next 'game', we will think of X_i's as the winnings in game i and μ to be the entrance fees for a game.

Definition 1.20. Suppose that $X_1, X_2, \ldots$ are independent, but not necessarily identically distributed. Let $S_n = X_1 + \ldots + X_n$. We say a game with accumulated entrance fees $\{\alpha_n, n \geq 1\}$ is fair if

$$P(\left|\frac{S_n}{\alpha_n} - 1\right| > \varepsilon) \to 0 \tag{1.49}$$

for all $\varepsilon > 0$.

Using this definition of 'fair', we look at an example.

Example 1.21. This is the St. Petersburg's paradox. This is the game; toss a coin repeatedly until the first head is observed. If this head occurs at the k^{th} toss, the amount paid out is $X = 2^k$. Let us find a fair accumulated entrance fees. In this case,

$$EX = \sum_{k=1}^{\infty} \frac{1}{2^k} 2^k = \infty. \tag{1.50}$$

Suppose we play this game n times. We are to find a fair accumulated sum $\{\alpha_n\}$ such that

$$P(|S_n - \alpha_n| > \varepsilon\alpha_n) \to 0. \tag{1.51}$$

To find this, we will define

$$U_j = X_j 1_{\{X_j \leq a_n\}},$$
$$V_j = X_j 1_{\{X_j > a_n\}}.$$

a_n shall be determined later. Note that $S_n = X_1 + \ldots + X_n = U_1 + \ldots + U_n + V_1 + \ldots V_n$. Then,

$$P(|S_n - \alpha_n| > \varepsilon\alpha_n) \leq P(|U_1 + \ldots + U_n - \alpha_n| > \frac{1}{2}\varepsilon\alpha_n) + P(|V_1 + \ldots + V_n| > \frac{1}{2}\varepsilon\alpha_n). \tag{1.52}$$

We first bound the second term on the right hand side. We have

$$P(|V_1 + \ldots + V_n| > \frac{1}{2}\varepsilon\alpha_n) \le P(\bigcup_{i=1}^{n}\{V_i \neq 0\}) \le nP(V_1 \neq 0) = nP(X_1 > a_n) \tag{1.53}$$

$$= \sum_{2^k > a_n} P(X = 2^k) \le \frac{2n}{a_n}. \tag{1.54}$$

Thus, we will require that $a_n >> n$. Also,

$$EU_1 = \sum_{k \le \log_2 a_n} 2^k \cdot 2^{-k} = \lfloor \log_2 a_n \rfloor \,,\ \mathrm{Var} U_1 \le E[U_1^2] = \sum_{k \le \log_2 a_n} (2^k)^2 \cdot 2^{-k} = 2^{\lfloor \log_2 a_n \rfloor + 1} - 1 < 2a_n. \tag{1.55}$$

$\frac{1}{n}(U_1 + \ldots + U_n) \approx EU_j = \lfloor \log_2 a_n \rfloor$, so we should choose

$$\alpha_n = nEU_j = n \lfloor \log_2 a_n \rfloor \,. \tag{1.56}$$

This gives us

$$P(|U_1 + \ldots + U_n - \alpha_n| > \frac{1}{2}\varepsilon\alpha_n) \le \frac{n(2a_n)}{\frac{1}{4}\varepsilon^2\alpha_n^2}. \tag{1.57}$$

Thus, we have another condition where we require that $\frac{na_n}{\alpha_n^2} \to 0$. The conditions we require are

$$\frac{n}{a_n} \to 0 \text{ and } \frac{na_n}{n^2(\log_2 a_n)^2} \to 0.$$

The sequence $\{a_n\}$ defined as $a_n = n\log_2 n$ satisfies these properties. The sequnce α_n is thus

$$\alpha_n = n\log_2 a_n = n\log_2 n + n\log_2\log_2 n. \tag{1.58}$$

Chapter 2

GENERATING FUNCTIONS

January 24th.

Definition 2.1. For a sequence $\{a_n\}_{n\geq 0}$, the *generating function* of $\{a_n\}$ is given as

$$A(s) = \sum_{n=0}^{\infty} a_n s^n \tag{2.1}$$

for some $-s_0 < s < s_0$.

For this probability course, we will be interested in a particular form; for a random variable X that takes values $k = 0, 1, \ldots$, the function we look at is

$$\sum_{k=0}^{\infty} P(X = k)s^k \text{ for } -1 \leq s \leq 1. \tag{2.2}$$

Suppose we have two sequences $\{a_n\}$ and $\{b_n\}$ with generating functions $A(s)$ and $B(s)$, respectively. If we define a new sequence $\{c_n\}$ as

$$c_n = a_0 b_n + a_1 b_{n-1} + \ldots + a_{n-1} b_1 + a_n b_0 \text{ for all } n \geq 0, \tag{2.3}$$

then the sequence $\{c_n\}$ is termed the *convolution* of the sequences $\{a_n\}$ and $\{b_n\}$, and we shall denote it as

$$\{c_n\} = \{a_n\} * \{b_n\}.$$

Note that this convolution operation is both associative and commutative. We are now interested in finding the generating function of $\{c_n\}$. We have

$$\begin{aligned}
C(s) &= \sum_{n=0}^{\infty} c_n s^n = \sum_{n=0}^{\infty} \left(\sum_{k=0}^{n} a_k b_{n-k} \right) s^n \\
&= \sum_{n=0}^{\infty} \sum_{k=0}^{n} a_k s^k b_{n-k} s^{n-k} = \sum_{k=0}^{\infty} \sum_{m=0}^{\infty} a_k s^k b_m s^m \\
\implies C(s) &= \left(\sum_{k=0}^{\infty} a_k s^k \right) \cdot \left(\sum_{m=0}^{\infty} b_m s^m \right) = A(s) \cdot B(s).
\end{aligned} \tag{2.4}$$

We state this down as a theorem.

Theorem 2.2. $C(s) = A(s) \cdot B(s)$ *when* $\{c_n\} = \{a_n\} * \{b_n\}$.

Suppose X takes values in $\mathbb{Z}_+ = \{0, 1, \ldots\}$. Denote $P(X = k)$ as p_k. The generating function is, thus,

$$\mathcal{P}(s) = \sum_{k=0}^{\infty} p_k s^k = E[s^X].$$

Also,

$$\mathcal{P}(1) = 1, \tag{2.5}$$

$$\mathcal{P}'(1) = \sum_{k=1}^{\infty} kp_k s^{k-1}|_{s=1} = EX. \tag{2.6}$$

Also note that

$$E[X^2] = \sum_{k=0}^{\infty} k^2 p_k = \sum k(k-1)p_k + \sum kp_k = \mathcal{P}''(1) + \mathcal{P}'(1) \tag{2.7}$$

which gives us the variance of X a

$$\mathrm{Var}X = E[X^2] - (EX)^2 = \mathcal{P}''(1) + \mathcal{P}'(1) - (\mathcal{P}'(1))^2. \tag{2.8}$$

The individual probabilities of $X = k$ may also be found as

$$p_k = P(X = k) = \frac{1}{k!} \cdot \frac{d^k}{ds^k}\mathcal{P}(s)|_{s=0}. \tag{2.9}$$

Now suppose that X and Y are two independent variables, taking values in $\mathbb{Z}_+$. Let $Z = X + Y$. We ask the probability that Z equals k. We can find this as

$$P(Z = k) = \sum_{m=0}^{k} P(X = m, Y = k - m) = \sum_{m=0}^{k} P(X = m) \cdot P(Y = k - m). \tag{2.10}$$

Therefore, denoting $p_k^{(X)}$ to be the probability mass function of X, we have

$$\{p_k^{(Z)}\} = \{p_k^{(X)}\} * \{p_k^{(Y)}\} \implies \mathcal{P}^{(Z)}(s) = \mathcal{P}^{(X)}(s) \cdot \mathcal{P}^{(Y)}(s). \tag{2.11}$$

There is an easier way to see the last equation; we could have started with $Es^Z = E[s^X \cdot s^Y] = E[s^X]E[s^Y]$.

If we have $S_n = X_1 + X_2 + \ldots + X_n$, where the X_i's are independently distributed taking values in $\mathbb{Z}_+$, it can be shown that

$$\{p_k^{(S_n)}\} = \{p_k^{(X)}\}^{n*} \tag{2.12}$$

Example 2.3. Let us compute the generating function of $X \sim \mathrm{Bin}(n, p)$. We have

$$\mathcal{P}(s) = \sum_{k=0}^{\infty} P(X = k)s^k = \sum_{k=0}^{n} \binom{n}{k} p^k (1-p)^{n-k} s^k = ((1-p) + ps)^n. \tag{2.13}$$

This is the generating function of the binomial distribution. Clearly,

$$EX = \mathcal{P}'(1) = np,$$
$$\mathrm{Var}X = \mathcal{P}''(1) + \mathcal{P}'(1) - (\mathcal{P}'(1))^2 = n(n-1)p^2 + np - n^2p^2 = np(1-p).$$

Note that using this generating function, we can also show that $\mathrm{Bin}(n, p) + \mathrm{Bin}(m, p) = \mathrm{Bin}(m + n, p)$ when the former terms are independent.

Example 2.4. We look at $X \sim \mathrm{Poisson}(\lambda)$. We have

$$\mathcal{P}(s) = \sum_{k=0}^{\infty} e^{-\lambda} \frac{\lambda^k}{k!} s^k = e^{-\lambda} \sum_{k=0}^{\infty} \frac{(\lambda s)^k}{k!} = e^{-\lambda + \lambda s}. \tag{2.14}$$

For this, we can als verify $EX = \mathrm{Var}X = \lambda$. We can also show that $\mathrm{Poisson}(\lambda) + \mathrm{Poisson}(\mu) = \mathrm{Poisson}(\lambda + \mu)$ when the former terms are independent.

Example 2.5. We look at $X \sim \mathrm{Geo}(p)$. Denote $1 - p$ as q. The generating function is given as

$$\mathcal{P}(s) = \sum_{k=0}^{\infty} pq^k s^k = \frac{p}{1 - qs}. \tag{2.15}$$

As an extension, let X_k denote the number of failures between the $(k-1)^{\text{th}}$ and k^{th} successes. If we denote $S_r = X_1 + X_2 + \ldots + X_r$, we find that $S_r \sim \text{NB}(p, r)$. From direct computation, we know that

$$P(S_r = k) = \binom{r+k-1}{k} q^k p^r \text{ for } k = 0, 1, \ldots$$

Let us compute this in another way; S_r is the sum of independent geomtric random variables with parameter p. We have

$$\mathcal{P}^{(S_r)}(s) = \left(\frac{p}{1-qs}\right)^r = p^r(1-qs)^{-r} = p^r \sum_{k=0}^{\infty} \binom{-r}{k} (-qs)^k \tag{2.16}$$

which tells us that

$$P(S_r = k) = p^r \binom{-r}{k} (-q)^k. \tag{2.17}$$

2.1 Random Walks, with Generating Functions

Here, we consider the paths that have a right step with probability p and a left step with probability $q = 1-p$. We first look at the waiting time for the first gain, that is, the event $\{S_1 \le 0, S_2 \le 0, \ldots, S_{n-1} \le 0, S_n = 1\}$ (Event $(*)$). Denote the probability of this event by ϕ_n, and its generating function by $\Phi(s)$. Note that $\phi_0 = 0$ and $\phi_1 = p$ lead to trivial cases. We focus on $n > 1$.

We must have $S_1 = -1$ (Event (1)). Denote, by $\nu < n$, the first return to 0 (Event (2)). ν only depends on $X_0, X_1, \ldots, X_\nu$. We need another $n - \nu$ steps to reach 1; this depends on $X_{\nu+1}, X_{\nu+2}, \ldots, X_n$ (Event (3)). For some $n > 1$, Event $(*)$ occurs if and only Event (1) $\cap$ Event (2) $\cap$ Event (3) occurs for some $\nu < n$. The point here is that the three events are independent. For some fixed $\nu < n$,

$$P(\text{Event (1)}) = q,\ P(\text{Event (2)}) = \phi_{\nu-1},\ P(\text{Event (3)}) = \phi_{n-\nu}. \tag{2.18}$$

Thus,

$$\phi_n = \sum_{\nu=2}^{n-1} q\phi_{\nu-1}\phi_{n-\nu}. \tag{2.19}$$

We have

$$\Phi(s) - ps = \sum_{n=2}^{\infty} \phi_n s^n = q\sum_{n=2}^{\infty} (\phi_1\phi_{n-2} + \ldots + \phi_{n-2}\phi_1)s^n = qs\sum_{n=1}^{\infty} \phi_n^{2*} s^n = qs(\Phi(s))^2 \tag{2.20}$$

$$\implies \Phi(s) - ps = qs(\Phi(s))^2. \tag{2.21}$$

This is a standard quadratic; solving gives us

$$\Phi(s) = \frac{1 \pm \sqrt{1-4pqs^2}}{2qs}. \tag{2.22}$$

The solution with the '+' is rejected; if it was valid, then plugging in $s < 1$ would give us $\Phi(s) > 1$, which is impossible. We expand this using the binomial theorem,

$$\Phi(s) = \frac{1}{2qs}\left(1 - \sum_{k=0}^{\infty} \binom{\frac{1}{2}}{k} (-4pqs^2)^k\right) = \sum_{k=1}^{\infty} \binom{\frac{1}{2}}{k} \frac{(-1)^{k-1}(4pq)^k}{2q} s^{2k-1} \tag{2.23}$$

which tells us that

$$\phi_{2k-1} = \frac{(-1)^{k-1}}{2q}\binom{\frac{1}{2}}{k}(4pq)^k,\ \phi_{2k} = 0. \tag{2.24}$$

Thus,

$$\Phi(1) = \sum \phi_n = \frac{1-\sqrt{1-4pq}}{2q} = \frac{1-|p-q|}{2q} = \begin{cases} \frac{p}{q} & \text{if } p < q, \\ 1 & \text{if } p \ge q. \end{cases}$$

This gives the probability that, at some point of the random walk, the displacement 1 is reached.

Similarly, for displacement S_n, we have

$$P(S_n \leq 0 \ \forall n) = \begin{cases} \frac{q-p}{p} & \text{if } p < q, \\ 0 & \text{if } p \geq q. \end{cases}$$

January 28th.

Recall that we used u_k denote the probability that the random walk returns to zero at step k. For unequal left-right step probabilities,

$$u_k = P(S_k = 0) = \begin{cases} 0 & \text{if } k \text{ is odd,} \\ \binom{2k}{k} p^n q^n & \text{if } k = 2n. \end{cases}$$

Thus, the generating function for this is

$$U(s) = \sum_{n=0}^{\infty} u_{2n} s^{2n} = \sum_{n=0}^{\infty} \binom{2n}{n} (pqs^2)^n = \sum_{n=0}^{\infty} \binom{-\frac{1}{2}}{n} (-4pqs^2)^n = \frac{1}{\sqrt{1-4pqs^2}}. \tag{2.25}$$

Denote, by f_{2n}, the probability that the first return to zero occurs at step $2n$, for some $n \geq 1$. In fact, it consists of subevents; if $X_1 = 1$, denote it by f_{2n}^+ and if $X_1 = -1$, denote it by f_{2n}^-. If we also recall the definition of our ϕ_n,

$$f_{2n}^- = P(X_1 = -1, S_2 < 0, S_3 < 0, \ldots, S_{2n-1} < 0, S_{2n} = 0) = q\phi_{2n-1}. \tag{2.26}$$

The generating function of $\{f_{2n}^-\}$ will be given as

$$F^-(s) = \sum_{n=1}^{\infty} f_{2n}^- s^{2n} = q \sum_{n=1}^{\infty} \phi_{2n-1} s^{2n} = qs \sum_{n=1}^{\infty} \phi_{2n-1} s^{2n-1} = qs\Phi(s) = \frac{1}{2}(1 - \sqrt{1-4pqs^2}). \tag{2.27}$$

It can be shown that f_{2n}^+ is just f_{2n}^- with the probabilities reversed (check!). The generating function of $\{f_{2n}^+\}$ is given as

$$F^+(s) = \sum_{n=0}^{\infty} f_{2n}^+ s^{2n} = \frac{1}{2}(1 - \sqrt{1-4pqs^2}). \tag{2.28}$$

Adding both of these, we get

$$F(s) = F^+(s) + F^-(s) = 1 - \sqrt{1-4pqs^2} = 1 - \sum_{n=0}^{\infty} \binom{\frac{1}{2}}{n} (-4pqs^2)^n \tag{2.29}$$

$$\implies f_{2n} = (-1)^{n+1} \binom{\frac{1}{2}}{n} (4pq)^n. \tag{2.30}$$

$F(1)$ gives us the probability that walk eventually returns to zero,

$$F(1) = \sum_{n=0}^{\infty} f_{2n} = 1 - \sqrt{1-4pq} = 1 - |p-q|. \tag{2.31}$$

$F'(1)$ gives us the expected time of return to zero,

$$F'(s) = -\frac{1}{2}(1-4pqs^2)^{-\frac{1}{2}}(-8pqs). \tag{2.32}$$

If $p = q = \frac{1}{2}$, then

$$F'(1) = \lim_{s \to 1^-} F'(s) = \infty.$$

The basic lemma can be proved using the generating functions.

2.2 Simple Random Walks in Higher Dimensions

Consider the walk in the dimension d. A walker starts at the origin in the lattice $\mathbb{Z}^d$. The random variables $X_1, X_2, \ldots$ are independent and identically distributed with probabilities

$$P(X_i = -e_d) + \ldots + P(X_i = -e_2) + P(X_i = -e_1) + P(X_i = e_1) = P(X_i = e_2) + \ldots + P(X_i = e_d) = \frac{1}{2d}.$$

for all valid i. The random walk here is defined as $S_n = X_1 + \ldots + X_n$. We ask the probabilitiy that S_n returns to the origin. Denote by u_{2n} the probability that $S_{2n} = 0$, and denote by f_{2n} the probability that the first return to the origin occurs at time $2n$. By conditioning,

$$u_{2n} = \sum_{k=0}^{n} f_{2k} u_{2n-2k}. \tag{2.33}$$

If $U(s)$ and $F(s)$ are the appropriate generating functions, then we can show that

$$U(s) - 1 = F(s)U(s) \implies U(s) = \frac{1}{1 - F(s)}. \tag{2.34}$$

Both $U(s)$ and $F(s)$ are covergent for $|s| < 1$. For each N,

$$\sum_{n=0}^{N} u_{2n} \leq \lim_{s \to 1^-} U(s) \leq \sum_{n=0}^{\infty} u_{2n}. \tag{2.35}$$

Lemma 2.6. *A random walk on $\mathbb{Z}^d$ return to the origin with probability 1 if and only if $\sum u_{2n} = \infty$.*

Proof. Suppose $F(1) < 1$. Then, $\lim s \to 1^- U(s) < \infty$ and, consequently, $\sum_{n=0}^{\infty} u_{2n} < \infty$. The converse can be proved by reversing the steps. ∎

The lemma tells us that to see the probability that the random walk returns to the origin, we only need to compute $\sum_{n=0}^{\infty} u_{2n}$.

For $d = 2$, we need the number of e_i jumps to be equal to the number of $-e_i$ jumps for $i = 1, 2$. We have

$$\begin{aligned} u_{2n} &= \frac{1}{4^{2n}} \sum_{j=0}^{n} \binom{2n}{j} \binom{2n-j}{j} \binom{2n-2j}{n-j} \binom{n-j}{n-j} = \frac{1}{4^{2n}} \binom{2n}{n} \sum_{j=0}^{n} \binom{n}{j}^2 = \frac{1}{4^{2n}} \binom{2n}{n}^2 \\ &\sim \frac{2}{2\pi} \frac{n^{4n+1}}{n^{4n+2}} = \frac{1}{\pi n}. \end{aligned} \tag{2.36}$$

Since this is any asymptotic relationship, $u_{2n} \geq \frac{(1-\varepsilon)}{\pi n}$ for large n. Thus, we can show $\sum u_{2n} = \infty$.

For $d = 3$,

$$\begin{aligned} u_{2n} &= \frac{1}{6^{2n}} \sum_{j,k=0; j+k \leq n}^{n} \frac{(2n)!}{j! j! k! k! (n-j-k)! (n-j-k)!} = \frac{1}{6^{2n}} \sum_{j,k=0l j+k \leq n}^{\infty} \frac{(2n)!}{(j!)^2 (k!)^2 ((n-j-k)!)^2} \\ &= \frac{1}{2^{2n}} \binom{2n}{n} \sum_{j,k; j+k \leq n} \left(\frac{n!}{j! k! (n-j-k)!} \frac{1}{3^n} \right)^2. \end{aligned} \tag{2.37}$$

$\frac{1}{2^{2n}} \binom{2n}{n}$ behaves asymptotically as $\frac{1}{\sqrt{\pi n}}$. For the rest of the term,

$$\sum_{j,k; j+k \leq n} \left(\frac{n!}{j! k! (n-j-k)!} \frac{1}{3^n} \right)^2 \leq t_n \sum_{j,k; j+k \leq n} \frac{n!}{j! k! (n-j-k)!} \frac{1}{3^n} \tag{2.38}$$

where $t_n = \max_{j,k; j+k \leq n} \frac{n!}{j! k! (n-j-k)!}$. The maximum is attained roughly when $j, k \approx \frac{n}{3}$. Also, the summation behaving as the upper bound is just unity. Thus,

$$\sum_{j,k; j+k \leq n} \left(\frac{n!}{j! k! (n-j-k)!} \frac{1}{3^n} \right)^2 \leq t_n \approx \frac{n!}{((\frac{n}{3})!)^3 3^n} \sim \frac{C}{n} \tag{2.39}$$

for some constant C. Therefore,

$$u_{2n} \leq \frac{C^*}{n^{\frac{3}{2}}} \implies \sum u_{2n} < \infty \implies F(1) < 1. \tag{2.40}$$

Theorem 2.7 (*Polya*)**.** *A random walk in 1 or 2 dimensions will always return to the origin with probability 1. A random walk in more than 2 dimensions has a positive probability of never returning to the origin.*

2.3 .

January 31st.
Recall that in the first course, we studied that if $X_n \sim \text{Bin}(n, p_n)$ with $np_n \to \lambda$ as $n \to \infty$, then

$$\lim_{n\to\infty} P(X_n = k) = P(\text{Poisson}(\lambda) = k) \text{ for } k \geq 0. \tag{2.41}$$

We now extend upon this idea.

Theorem 2.8 (*Continuity theorem*)**.** *Suppor for each n the sequence $a_{0,n}, a_{1,n}, \dots$ is a probability distribution, that is,*

$$a_{k,n} \geq 0 \textit{ for all } k \textit{ and } \sum_{k=0}^{\infty} a_{k,n} = 1. \tag{2.42}$$

Let $A^{(n)}(s)$ denote the generating function for $\{a_{k,n}\}_{k\geq 0}$, that is,

$$A^{(n)}(s) = \sum_{k=0}^{\infty} a_{k,n} s^k \textit{ for all } n. \tag{2.43}$$

*Then $a_k = \lim_{n\to\infty} a_{k,n}$ exists for all k (*statement $\star$*) if and only if $A(s) = \lim_{n\to\infty} A^{(n)}(s)$ exists for all $0 < s < 1$ (*statement $\star\star$*). In this case, $A(s) = \sum_{k=0}^{\infty} a_k s^k$.*

Proof. Assume statement $\star$. Thus, $|a_{k,n} - a_k| \leq 1$ for all n large enough. If we now fix $0 < s < 1$, then for some K and a fixed $\varepsilon > 0$, we have

$$\begin{aligned}
\left|A^{(n)}(s) - A(s)\right| &= \left|\sum_{k=0}^{\infty} a_{k,n} s^k - \sum_{k=0}^{\infty} a_k s^k\right| && (2.44)\\
&= \left|\sum_{k=0}^{K} a_{k,n} s^k + \sum_{k=K+1}^{\infty} a_{k,n} s^k - \sum_{k=0}^{K} a_k s^k - \sum_{k=K+1}^{\infty} a_k s^k\right| \\
&\leq \left|\sum_{k=0}^{K} a_{k,n} s^k - \sum_{k=0}^{K} a_k s^k\right| + \left|\sum_{k=K+1}^{\infty} (a_{k,n} - a_k) s^k\right| \\
&\leq \left|\sum_{k=0}^{K} a_{k,n} s^k - \sum_{k=0}^{K} a_k s^k\right| + \frac{s^{K+1}}{1-s}. && (2.45)
\end{aligned}$$

We can choose K such that the second term becomes less than ε, and we can choose N such that for all $n \geq N$, the first term becomes smaller than ε. Therefore, the entire term becomes less than 2ε.

For the converse, assume statement $\star\star$. $A(s)$ is monotonic in s; $A(0) = \lim_{s\to 0^-} A(s)$. We sandwich as follows—

$$\begin{aligned}
a_{0,n} \leq A^{(n)}(s) &\leq a_{0,n} + \frac{s}{1-s} \\
\implies A^{(n)}(s) - \frac{s}{1-s} &\leq a_{0,n} \leq A^{(n)}(s).
\end{aligned}$$

Letting n grow to infinity,

$$A(s) - \frac{s}{1-s} \leq \liminf_{n\to\infty} a_{0,n} \leq \limsup_{n\to\infty} a_{0,n} \leq A(s). \tag{2.46}$$

If $s \to 0$, note that $\lim_{n\to\infty} a_{0,n} = A(0)$. Now define

$$B^{(n)}(s) = \frac{A^{(n)}(s) - a_{0,n}}{s} \to \frac{A(s) - A(0)}{s} \to A'(0). \tag{2.47}$$

Working similarly,

$$a_{1,n} \le B^{(n)}(s) \le a_{1,n} + \frac{s}{1-s} \tag{2.48}$$

$$\implies B^{(n)}(s) - \frac{s}{1-s} \le a_{1,n} \le B^{(n)}(s). \tag{2.49}$$

If we again proceed as shown, we will get $B(0) = \lim_{n\to\infty} a_{1,n}$ and $a_{1,n} \to A'(0) = a_1$. Thus, induction is in play here. ■

Example 2.9. Let us work with the binomial distribution example given before. We have $X_n \sim \text{Bin}(n, p_n)$ with $np_n \to \lambda$. We have

$$A^{(n)}(s) = \sum_{k=0}^{\infty} P(X_n = k)s^k = ((1-p_n) + p_n s)^n = (1 + p_n(s-1))^n$$
$$\implies \lim_{n\to\infty} A^{(n)}(s) = \lim_{n\to\infty} \left(1 + \frac{np_n}{n}(s-1)\right)^n = e^{\lambda(s-1)} = E[s^{\text{Poisson}(\lambda)}]. \tag{2.50}$$

Thus, we have shown the prior statement.

Example 2.10. We have $X_1^{(n)}, X_2^{(n)}, \dots, X_n^{(n)}$ independent, with $X_i^{(n)} \sim \text{Ber}(p_i^{(n)})$ for $1 \le i \le n$. Let $S_n = X_1^{(n)} + X_2^{(n)} + \dots X_n^{(n)}$. We have

$$E[s^{S_n}] = \prod_{i=1}^{n} E[s^{X_i^{(n)}}] = \prod_{i=1}^{n} \left((1-p_i^{(n)}) + p_i^{(n)} s\right) = \exp\left(\ln \prod_{i=1}^{n}(\dots)\right). \tag{2.51}$$

Assume that $\lim_{n\to\infty} \sum_{i=1}^{n} p_i^{(n)} = \lambda$ and $\lim_{n\to\infty} \max_i p_i^{(n)} = 0$. Thus,

$$\exp\left(\sum_{i=1}^{n} \ln(1 + p_i^{(n)}(s-1))\right) = \exp\left(\sum_{i=1}^{n} p_i^{(n)}(s-1) - \frac{(p_i^{(n)}(s-1))^2}{2} + \dots\right)$$
$$= \exp\left((s-1)\sum_{i=1}^{n} p_{i=1}^{n} - \sum_{i=1}^{n} o(p_i^{(n)}(s-1))\right) \tag{2.52}$$
$$\to e^{\lambda(s-1)}. \tag{2.53}$$

Example 2.11. Let $X^{(n)} \sim \text{NB}(r_n, p)_n$, the number of successes before the r_n^{th} success in trials with success probability p_n. Let $p_n \to 1$ and $r_n \to \infty$ such that $r_n(1-p_n) \to \lambda$, where λ is fixed. We would then have $P(X^{(n)} = k) \to P(\text{Poisson}(\lambda) = k)$.

2.4 Gambler's Ruin

We take a look at a gambler, who has starting capital z. His probability of a success $(+1)$ is p, and of a failure (-1) is q. We ask the probability q_z that the gambler reaches 0 before a when he starts at capital z. Note that q_z satisfies

$$q_z = pq_{z+1} + qq_{z-1} \text{ for } 1 < z < a-1 \text{ (statement } \star\text{)}, \text{ with } q_0 = 1,\ q_a = 0 \text{ (statement } \star\star\text{)}. \tag{2.54}$$

We look at two cases, beginning with the case when $p \neq q$. Note that $q_z = 1$ for $1 \le z \le a-1$ solves for statement $\star$, ignoring statement statement $\star\star$ and ignoring probaility for now. $q_z = (\frac{q}{p})^z$ for $1 \le z \le a-1$ also solves for statement $\star$. Therefore, $A + B(\frac{q}{p})^z$ solves statement $\star$. Now, we plug in the boundary conditions given by statement $\star\star$. Solving the equations $A + B = 1$ and $A + B(\frac{q}{p})^a = 0$ gives us

$$B = \frac{1}{1-(\frac{q}{p})^a},\ A = 1 - \frac{1}{1-(\frac{q}{p})^a}. \tag{2.55}$$

Plugging this in, gives us

$$q_z = \frac{(\frac{q}{p})^a - (\frac{q}{p})^z}{(\frac{q}{p})^a - 1}. \tag{2.56}$$

Note that we were working the case when $p \neq q$. For $p = q$, this solution does not work.

We work the case for when $p = q = \frac{1}{2}$. Again, $q_z = 1$ for $1 \leq z \leq a-1$ satisfies statement $\star$. We also find that $q_z = z$ for $1 \leq z \leq a-1$ also satisfies this statement. Hence, we look for $A + Bz$ which satisfies boundary condition given by statement $\star\star$. Solving, this gives us

$$q_z = 1 - \frac{z}{a}. \tag{2.57}$$

Note that we are yet to show $p_z + q_z = 1$. If we instead focus on a *second* gambler playing against our gambler, we would have a gambler with capital $a - z$, and probability of success q and probability of failure p. Replacing z by $a - z$ and q by p and p by q in our formed equations would give us $p_z + q_z = 1$.

Let us intuitively look at our equations with a table of examples.

p	q	z	a	q_z
0.45	0.55	9	10	0.21
0.45	0.55	90	100	0.866
0.45	0.55	99	100	0.182
0.5	0.5	9	10	0.1
0.5	0.5	90	100	0.1
0.5	0.5	99	100	0.01

Table 2.1: Probability of ruin (q_z) given initial parameters.

Note that the expected net gain is given by

$$(a - z)(1 - q_z) - zq_z = a(1 - q_z) - z. \tag{2.58}$$

If we plug in this into our first three rows of our table, we would have $-1.1,\ -77,\ -18$. If one is gambling under such condition, we must start with big capital z and low target $a - z$.

2.4.1 Duration of the Game

We look at D_z, the expected duration of a game starting at z; the expected time before the gambler hits a or 0. The linear recurrance satisfied here is

$$D_z = pD_{z+1} + qD_{z-1} + 1 \text{ with boundary conditions } D_0 = 0,\ D_a = 0. \tag{2.59}$$

For $p \neq q$,

$$D_z = \frac{z}{q-p} - \frac{a}{q-p}\left(\frac{1 - (\frac{q}{p})^z}{1 - (\frac{q}{p})^n}\right). \tag{2.60}$$

For $p = q = \frac{1}{2}$,

$$D_z = z(a - z). \tag{2.61}$$

Chapter 3

JOINT CONTINUOUS DISTRIBUTIONS

3.1 Introduction

February 4th.

Recall that $X : \Omega \to \mathbb{R}$ is *continuous random variable* if it has a probability density function $f_X : \mathbb{R} \to \mathbb{R}_{\geq 0}$. In this case, if $A \subseteq \mathbb{R}$, then

$$P(X \in A) = \int_A f_X(x)dx. \tag{3.1}$$

For a minute dx,

$$P(X \in [x, x + dx]) \approx f_X(x)dx. \tag{3.2}$$

Two random variables X and Y are termed *jointly continuous* if there exists a function $f : \mathbb{R}^2 \to R$ such that for $A \subseteq \mathbb{R}^2$,

$$P((X,Y) \in A) = \iint_A f(x,y)dxdy. \tag{3.3}$$

In this case, f is termed the *joint probability density function* of X and Y. In particular, if $B, C \subseteq \mathbb{R}$, then

$$P(X \in C,\ Y \in B) = P((X,Y) \in C \times B) = \int_B \int_C f(x,y)dxdy. \tag{3.4}$$

The *joint cumulative density function* is given as

$$F(a,b) = P(X \leq a,\ Y \leq b) = P((X,Y) \in (-\infty, a] \times (-\infty, b]) = \int_{-\infty}^{b} \int_{-\infty}^{a} f(x,y)dxdy. \tag{3.5}$$

There is, again, joint analagous versions of the single random variables cases;

$$\frac{\partial^2}{\partial a \partial b} F(a,b) = f(a,b) \tag{3.6}$$

and

$$P(X \in [a, a + da],\ Y \in [b, b + db]) \approx f(a,b)dadb. \tag{3.7}$$

Note that (X,Y) being jointly continuous implies that both X and Y are continuous. Indeed, if $A \subseteq \mathbb{R}$, then

$$P(X \in A) = P(X \in A,\ Y \in \mathbb{R}) = \int_A \int_{\mathbb{R}} f(x,y)dydx = \int_A f_X(x)dx. \tag{3.8}$$

In this case, the inner intergral becomes the probability density funciton of X.

Example 3.1. We are given the joint probability density function of X and Y as

$$f(x,y) = \begin{cases} 2e^{-x}e^{-2y} & \text{if } 0 < x < \infty,\ 0 < y < \infty, \\ 0 & \text{if otherwise.} \end{cases}$$

We are to compute $P(X > 1, Y < 1)$, $P(X < Y)$ and $P(X < a)$. This is left as an exercise.

Example 3.2. Suppose (X, Y) represents a random points inside a circle of radius R. The probability density function is given by

$$f(x,y) = \begin{cases} \frac{1}{\pi R^2} & \text{if } x^2 + y^2 \leq R^2, \\ 0 & \text{if otherwise.} \end{cases}$$

Compute f_X, f_Y and f_D where $D = \sqrt{X^2 + Y^2}$.

We call X and Y indepedent if, for $A, B \subseteq \mathbb{R}$,

$$P(X \in A, Y \in B) = P(X \in A) \cdot P(Y \in B). \tag{3.9}$$

If we take $A = (-\infty, a], B = (-\infty, b]$, then

$$F(a,b) = F_X(a)F_Y(b) \implies f(a,b) = f_X(a)f_Y(b).$$

In fact, all three conditions are equivalent. Note that everything discussed so far may be extended to more than two random variables. If $A \subseteq \mathbb{R}^n$ and $(X_1, X_2, \ldots, X_n)$ are jointly continuous, then

$$P((X_1, X_2, \ldots, X_n) \in A) = \int \cdots \int_A f(x_1, x_2, \ldots, x_n) dx_1 \cdots dx_n \tag{3.10}$$

where $f : \mathbb{R}^n \to \mathbb{R}_{\geq 0}$.

Example 3.3 (*Buffin's needle problem*)**.** Suppose we have a table of width D and length sufficient. We throw a needle of length $L \leq D$ randomly (and necessarily) on this table. We are to find the probability that the needle will hand over either side of the table separated by width D. Denote by X the distance of the midpoint of the needle from the nearest edge, and denote by θ the angle is subtends with respect to the vertical.

Note that $X \in [0, \frac{D}{2}]$, and $\theta \in [0, \frac{\pi}{2}]$. By the procedure, one can assume these are independent. We look at the probability that the length of half the needle is greater than the length of the hypotenuse determined by X and θ—

$$P(\frac{L}{2} > \frac{X}{\cos\theta}) = \int_0^{\frac{\pi}{2}} \int_0^{\frac{L}{2}\cos\theta} \frac{2}{D} \cdot \frac{2}{\pi} dx d\theta = \frac{2L}{D\pi} \int_0^{\frac{\pi}{2}} \cos\theta d\theta = \frac{2L}{D\pi}. \tag{3.11}$$

Proposition 3.4. *The jointly continuous random variables X and Y are independent if and only the probability density function can be factored into functions of x and y respectively.*

Suppose that X and Y are independent and jointly continuous random variables. Then $f(x,y) = f_X(x)f_Y(y)$. Let us compute the cumulative density function of $X + Y$.

$$P(X+Y \leq a) = \int_{-\infty}^{\infty} \int_{-\infty}^{a-x} f_X(x)f_Y(y) dy dx = \int_{-\infty}^{\infty} f_X(x)F_Y(a-x) dx = \int_{-\infty}^{\infty} f_Y(y)F_X(a-y) dy. \tag{3.12}$$

Differentiating to give the probability density function of $X + Y$,

$$\frac{d}{da} F_{X+Y}(a) = \int_{-\infty}^{\infty} f_X(x)f_Y(a-x) dx = \int_{-\infty}^{\infty} f_X(a-y)f_Y(y) dy. \tag{3.13}$$

This is the convolution of f_X and f_Y.

February 11th.

Suppose we have $U_1, U_2, \ldots, U_n$ which are independent and have the distribution Uniform$(0,1)$. From $\{1, 2, \ldots, n\}$, if we choose a subset of size k, then each subset of size k has probability $\frac{1}{\binom{n}{k}}$. We will generate $I_1, I_2, \ldots, I_n$, where exactly k of them are 1. I_1 is defined as

$$I_1 = \begin{cases} 1 & \text{if } U_1 < \frac{k}{n}, \\ 0 & \text{if otherwise.} \end{cases} \tag{3.14}$$

Once $I_1, I_2 < \ldots, I_i$ are determined, we can define

$$I_{i+1} = \begin{cases} 1 & \text{if } U_{i+1} < \frac{k-(I_1+I_2+\ldots+I_i)}{n-1}, \\ 0 & \text{if otherwise.} \end{cases} \tag{3.15}$$

Notice that if $I_1 + I_2 + \ldots + I_i = k$, then $I_{i+1}, I_{i+2}, \ldots = 0$. Note that $P(I_1 = 1) = \frac{k}{n}$, and

$$P(I_{i+1} = 1 | I_1, I_2, \ldots, I_i) = \frac{k - \sum_{r=1}^{i} I_r}{n-i}, \text{ for } 1 < i \leq n. \tag{3.16}$$

If we do induction on $k+n$, we know the case $k+n=2$ to be true ($k=1, n=1$). We assume for all the cases $k+n \leq l$, and suppose that $k+n = l+1$. Consider any subset of size k, say, $i_1 \leq i_2 \leq \ldots \leq i_k$.

- Case I, where $i_1 = 1$. Here,

$$\begin{aligned} & P(I_{i_1} = I_{i_2} = \ldots = I_{i_k} = 1, I_j = 0 \text{ otherwise}) \\ = & P(I_1 = 1) \cdot P(I_{i_2} = \ldots = I_{i_k} = 1, I_j = 0 \text{ otherwise} | I_1 = 1) \\ = & \frac{k}{n} \frac{1}{\binom{n-1}{k-1}} = \frac{1}{\binom{n}{k}}. \end{aligned}$$

- Case II, where $i_1 > 1$. In this case,

$$\begin{aligned} & P(I_{i_1} = 0, I_{i_2} = \ldots = I_{i_k} = 1, I_j = 0 \text{ otherwise}) \\ = & P(I_1 = 0) \cdot P(I_{i_2} = \ldots = I_{i_k} = 1, I_j = 0 \text{ otherwise} | I_1 = 0) \\ = & \left(1 - \frac{k}{n}\right) \frac{1}{\binom{n-1}{k}} = \frac{1}{\binom{n}{k}}. \end{aligned}$$

3.2 Some Distributions

3.2.1 Gamma Random Variable

We have $X \sim \text{Gamma}(t, \lambda)$ where $\lambda > 0$ and $t > 0$. The probability density function is defined as

$$f_X(x) = \frac{\lambda e^{-\lambda y} (\lambda y)^{t-1}}{\Gamma(t)} \text{ for } 0 < y < \infty. \tag{3.17}$$

Here, Γ is the gamma function.

Proposition 3.5. *If* $X \sim \text{Gamma}(s, \lambda)$ *and* $Y \sim \text{Gamma}(t, \lambda)$, *then* $X + Y \sim \text{Gamma}(s+t, \lambda)$.

Proof. Via convolution, we know that

$$\begin{aligned} f_{X+Y}(a) &= \int_0^a f_X(a-y) f_Y(y) dy \\ &= \frac{1}{\Gamma(t)\Gamma(s)} \int_0^a \lambda e^{-\lambda(a-y)} (\lambda(a-y))^{t-1} \lambda e^{-\lambda y} (\lambda y)^{s-1} dy \\ &= \frac{\lambda e^{-\lambda a} (\lambda a)^{s+t-1}}{\Gamma(t+s)} \frac{\Gamma(t+s)}{\Gamma(t)\Gamma(s)} \int_0^a \frac{(a-y)^{t-1} y^{s-1}}{a^{s+t-1}} dy \\ &= \frac{\lambda e^{-\lambda a} (\lambda a)^{s+t-1}}{\Gamma(t+s)} \frac{\Gamma(t+s)}{\Gamma(t)\Gamma(s)} \int_0^1 (1-u)^{t-1} u^{s-1} du. \end{aligned}$$

If we integrate this probability distribution function, we must have

$$\int_0^\infty f_{X+Y}(a) da = 1 \tag{3.18}$$

$$\implies \frac{\Gamma(s+t)}{\Gamma(s)\Gamma(t)} \int_0^1 (1-u)^{t-1} u^{s-1} du = 1. \tag{3.19}$$

This gives rise to the Beta function, defined as $\int_0^1 (1-u)^{t-1} u^{s-1} du = B(t,s) = \frac{\Gamma(s)\Gamma(t)}{\Gamma(s+t)}$. ■

One corollary that can be inferred from here is that if $X_1, X_2, \dots, X_n$ are independent Gamma(t_i, λ) distributions, then $\sum_{i=1}^n X_i \sim \text{Gamma}(\sum_{i=1}^n t_i, \lambda)$. We also notice that $X \sim \text{Exp}(\lambda) = \text{Gamma}(1, \lambda)$. If we take the X_i's to be all the exponential distribution, then $S_n = X_1 + X_2 + \dots + X_n \sim \text{Gamma}(n, \lambda)$. The density of S_n is given by

$$g_n(y) = \frac{\lambda(\lambda y)^{n-1} e^{-\lambda y}}{\Gamma(n)} = \frac{\lambda(\lambda y)^{n-1} e^{-\lambda y}}{(n-1)!} \text{ for } 0 < y < \infty \tag{3.20}$$

with the cumulative distribution function

$$G_n(y) = \frac{1}{(n-1)!} \int_0^y \lambda(\lambda a)^{n-1} e^{-\lambda a} da. \tag{3.21}$$

Example 3.6. Suppose we have buses that each take time $X_i \sim \text{Exp}(\lambda)$. Suppose we fix a time t, and define $N(t)$ to be the number of buses seen up to time t. We ask the probability $P(N(t) = n)$.

$$\begin{aligned} P(N(t) = n) &= P(X_1 + X_2 + \dots + X_n \leq t, X_1 + X_2 + \dots + X_{n+1} > t) \qquad (3.22) \\ &= P(X_1 + \dots + X_n \leq t) - P(X_1 + \dots + X_n \leq t, X_1 + \dots + X_{n+1} \leq t) \\ &= P(X_1 + \dots + X_n \leq t) - P(X_1 + \dots + X_{n+1} \leq t) \\ &= G_n(t) - G_{n+1}(t) = e^{-\lambda t} \frac{(\lambda t)^n}{n!}. \qquad (3.23) \end{aligned}$$

Notice that there is a unique k for which $S_{k-1} < t \leq S_k$. Define X_k to be $S_k - S_{k-1}$.

Proposition 3.7. *The X_k satisfying $S_{k-1} < t \leq S_k$ has density*

$$v_t(x) = \begin{cases} \lambda^2 x e^{-\lambda x} & \text{if } 0 < x \leq t, \\ \lambda(1 + \lambda t) e^{-\lambda x} & \text{if } x > t. \end{cases} \tag{3.24}$$

Proof. Let k denote the index for which $S_{k-1} < t \leq S_k$. Define $L_t = S_k - S_{k-1}$. Let us first compute the cumulative distribution function.

- Case I, when $x < t$. Note that $L_t \leq x \iff$ there exist n, y such that $t - x \leq y < t$, $S_n = y$, $t - y \leq X_{n+1} \leq x$.

$$\begin{aligned} P(L_t \leq x) &= \sum_{n=1}^\infty \int_{t-x}^t \int_{t-y}^x f_{S_n, X_{n+1}}(y, z) dz dy \\ &= \sum_{n=1}^\infty \int_{t-x}^t \int_{t-y}^x g_n(y) f_{X_{n+1}}(z) dz dy \\ &= \sum_{n=1}^\infty \int_{t-x}^t g_n(y) [e^{-\lambda(t-y)} - e^{-\lambda x}] dy \\ &= \lambda \int_{t-x}^t [e^{-\lambda(t-y)} - e^{-\lambda y}] dy. \qquad (3.25) \end{aligned}$$

- Case II, when $x > t$. Note that

$$\{L_t \leq x\} = \{t < S_1 \leq x\} \cup \bigcup_{n=1}^\infty \{\text{bus } n \text{ arrives at } y < t \text{ and } t - y < X_{n+1} \leq x\}. \tag{3.26}$$

These are all disjoint events. $P(t < S_1 \leq x) = e^{-\lambda t} - e^{-\lambda x}$, and

$$P(\text{bus } n \text{ arrives at } y < t \text{ and } t - y < X_{n+1} \leq x) = \int_0^t \int_{t-y}^x g_n(y) f_{X_{n+1}}(z) dz dy. \tag{3.27}$$

Adding up the probabilities of the disjoint events, we have

$$\begin{aligned} P(L_t \leq x) &= e^{-\lambda t} - e^{-\lambda x} + \sum_{n=1}^\infty \int_0^t g_n(y) [e^{-\lambda(t-y)} - e^{-\lambda x}] dy \\ &= e^{-\lambda t} - e^{-\lambda x} + \lambda \int_0^t [e^{-\lambda(t-y)} - e^{-\lambda x}] dy \\ &= e^{-\lambda t} - e^{-\lambda x} + 1 - e^{-\lambda t} - \lambda t e^{-\lambda x}. \qquad (3.28) \end{aligned}$$

■

3.3 Conditional Distribution

February 25th.

Let X and Y hae a joint probability density function given by $f(x,y)$. The *conditional probability density function* of X given $Y = y$ is

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} \tag{3.29}$$

and it is defined for $f_Y(y) > 0$. The motivation behind defining this is as follows—

$$f_{X|Y}(x|y)dx = \frac{f(x,y)dxdy}{f_Y(y)dy} = \frac{P(x \le X \le x+dx, y \le Y \le y+dy)}{P(y \le Y \le y+dy)} = P(x \le X \le x+dx | y \le Y \le y+dy). \tag{3.30}$$

If one is given the conditional probability density function, we can do the following computation as well,

$$P(X \in A | Y = y) = \int_A f_{X|Y}(x|y)dx. \tag{3.31}$$

We can also make sense of a *conditional cumulative distribution function* of X given $Y = Y$.

$$F_{X|Y}(a|y) = P(X \le a | Y = y) = \int_{-\infty}^{a} f_{X|Y}(x|y)dx \tag{3.32}$$

Remark 3.8. If X and Y are independent, then the joint density factorizes into the product of the marginals which results in

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = \frac{f_X(x)f_Y(y)}{f_Y(y)} = f_X(x). \tag{3.33}$$

Example 3.9. Suppose the joint density of X and Y is given as

$$f(x,y) = \begin{cases} e^{-\frac{x}{y}}e^{-y}y^{-1} & \text{if } 0 < x < \infty, 0 < y < \infty \\ 0 & \text{if otherwise.} \end{cases} \tag{3.34}$$

Let us compute $P(X > 1 | Y = y)$ for $0 < y < \infty$.

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = \frac{e^{-\frac{x}{y}}e^{-y}}{y\int_0^\infty \frac{e^{-\frac{x}{y}}e^{-y}}{y}dx} = \frac{1}{y}e^{-\frac{x}{y}} \text{ for } 0 < x < \infty. \tag{3.35}$$

Thus,

$$P(X > 1 | Y = y) = \int_1^\infty \frac{1}{y}e^{-\frac{x}{y}}dx = e^{-\frac{1}{y}}. \tag{3.36}$$

3.3.1 The t-distribution

Suppose we have $Y \sim \chi_n^2 \equiv \text{Gamma}(\frac{n}{2}, \frac{1}{2})$ and $Z \sim N(0,1)$ with both independent. Then the *t-distribution* with n degrees of freedom is defined as

$$T = \frac{Z}{\sqrt{Y/n}} = \sqrt{n}\frac{Z}{\sqrt{Y}}. \tag{3.37}$$

If a $Y = y$ is fixed, then $T = \sqrt{\frac{n}{y}}Z \sim N(0, \frac{n}{y})$. Thus,

$$f_{T|Y}(t|y) = \frac{1}{\sqrt{2\pi\frac{n}{y}}}e^{-\frac{1}{2}\frac{t^2y}{n}} \tag{3.38}$$

$$\implies f_{T,Y}(t,y) = f_{T|Y}(t|y)f_Y(y) = \frac{1}{\sqrt{2\pi\frac{n}{y}}}e^{-\frac{1}{2}\frac{t^2y}{n}}\left(\frac{e^{-\frac{y}{2}}y^{\frac{n}{2}-1}}{2^{\frac{n}{2}}\Gamma(\frac{n}{2})}\right) \text{ for } t \in \mathbb{R}, y > 0. \tag{3.39}$$

Thus, the probability density function for T can be found out as

$$f_T(t) = \int_0^\infty f_{T|Y}(t|y)dy = \int_0^\infty \frac{1}{\sqrt{2\pi n}} \cdot \frac{e^{-\frac{1}{2}(1+\frac{t^2}{n})y} y^{\frac{n-1}{2}}}{2^{\frac{n}{2}}\Gamma(\frac{n}{2})} dy. \tag{3.40}$$

If we let $c = \frac{1}{2}(1 + \frac{t^2}{n})$ and make the change of variable from x to cy, the intergral transforms as

$$\frac{c^{-\frac{n+1}{2}}}{\sqrt{\pi n} 2^{\frac{n+1}{2}} \Gamma(\frac{n}{2})} \int_0^\infty e^{-x} x^{\frac{(n-1)}{2}} dx = \frac{\Gamma(\frac{n+1}{2})}{\sqrt{\pi n}\Gamma(\frac{n}{2})} \left(1 + \frac{t^2}{n}\right)^{-\frac{n+1}{2}}. \tag{3.41}$$

Note that as $n \to \infty$,

$$f_T(t) \to \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}}. \tag{3.42}$$

3.3.2 The Bivariate Normal Distribution

Five parameters are used here— $\mu_x, \mu_y \in \mathbb{R}$, $\sigma_x, \sigma_y > 0$, and $-1 < \rho < 1$. The joint probability density function is given by

$$f(x, y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)}\left(\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho\left(\frac{(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}\right)\right)\right). \tag{3.43}$$

We find the conditional density of X given $Y = y$.

$$\begin{aligned}
f_{X|Y}(x|y) &= \frac{f(x,y)}{f_Y(y)} = c_1(y) f(x,y) && (3.44)\\
&= c_2(y) \exp\left(-\frac{1}{2(1-\rho^2)}\left(\left(\frac{x-\mu_x}{\sigma_x}\right)^2 - 2\rho\frac{x(y-\mu_y)}{\sigma_x\sigma_y}\right)\right)\\
&= c_2(y) \exp\left(-\frac{1}{2(1-\rho^2)\sigma_x^2}\left(x^2 - 2x\mu_x + \mu_x^2 - 2\frac{\rho\sigma_x}{\sigma_y}x(y-\mu_y)\right)\right)\\
&= c_3(y) \exp\left(-\frac{1}{2(1-\rho^2)\sigma_x^2}\left(x^2 - 2x(\mu_x + \rho\frac{\sigma_x}{\sigma_y}(y-\mu_y))\right)\right)\\
&= c_4(y) \exp\left(-\frac{1}{2(1-\rho^2)\sigma_x^2}\left(x - \left(\mu_x + \rho\frac{\sigma_x}{\sigma_y}(y-\mu_y)\right)\right)^2\right). && (3.45)
\end{aligned}$$

The integral of the last term must be 1, so we can conclude that it is the probability density function must be that of the normal distribution.

$$X|Y = y \sim N\left(\mu_x + \rho\frac{\sigma_x}{\sigma_y}(y-\mu_y), \sigma_x^2(1-\rho^2)\right), \tag{3.46}$$

$$Y|X = x \sim N\left(\mu_y + \rho\frac{\sigma_y}{\sigma_x}(x-\mu_x), \sigma_y^2(1-\rho^2)\right). \tag{3.47}$$

Note that X and Y are independent if and only if $\rho = 0$. Also,

$$f_X(x) = \frac{f(x,y)}{f_{Y|X}(y|x)} = \frac{1}{\sqrt{2\pi\sigma_x^2}} \exp\left(-\frac{1}{2\sigma_x^2}(x-\mu_x)^2\right). \tag{3.48}$$

3.4 Order Statistics

February 28th.

Suppose we have $X_1, X_2, \ldots, X_n$ independent and identically distributed continuous random variables with common probability density function f and cumulative distribution function F. We order the X_i's in such a way that $X_{(1)} < X_{(2)} < \ldots < X_{(n)}$. These are termed the *order statistics* corresponding to $X_1, X_2, \ldots, X_n$, and $X_{(k)}$ is termed the k^{th} order statistic. Note that $X_{(1)}, X_{(2)}, \ldots, X_{(n)}$ takes the values $x_1 \leq x_2 \leq \ldots \leq x_n$ if and only if for some permutation $(i_1, i_2, \ldots, i_n)$ of $(1, 2, \ldots, n)$ we have $X_1 = x_{i_1}, X_2 = x_{i_2}, \ldots, X_n = x_{i_n}$. Also, for sufficiently small $\varepsilon > 0$,

$$\begin{aligned} &P\left(x_{i_1} - \frac{\varepsilon}{2} < X_1 < x_{i_1} + \frac{\varepsilon}{2}, x_{i_2} - \frac{\varepsilon}{2} < X_2 < x_{i_2} + \frac{\varepsilon}{2}, \ldots, x_{i_n} - \frac{\varepsilon}{2} < X_n < x_{i_n} + \frac{\varepsilon}{2}\right) \\ &\approx \varepsilon^n f(x_{i_1}) f(x_{i_2}) \cdots f(x_{i_n}) = \varepsilon^n f(x_1) f(x_2) \cdots f(x_n). \end{aligned} \tag{3.49}$$

Therefore, for $x_1 < x_2 < \ldots < x_n$, we have

$$\begin{aligned} &P\left(x_1 - \frac{\varepsilon}{2} < X_{(1)} < x_1 + \frac{\varepsilon}{2}, x_2 - \frac{\varepsilon}{2} < X_{(2)} < x_2 + \frac{\varepsilon}{2}, \ldots, x_n - \frac{\varepsilon}{2} < X_{(n)} < x_n + \frac{\varepsilon}{2}\right) \\ &\approx n! \varepsilon^n f(x_1) \ldots f(x_n) &(3.50) \\ &\implies f_{(X_{(1)}, X_{(2)}, \ldots, X_{(n)})}(x_1, x_2, \ldots, x_n) = n! f(x_1) f(x_2) \cdots f(x_n). &(3.51) \end{aligned}$$

Example 3.10. Three people are distributed on a 1 mile long rong, uniformly. Fix $d \leq \frac{1}{2}$. We are to find the probability that no two people are less distance d apart. Note that the probability density function is $f_{(X_{(1)}, X_{(2)}, X_{(3)})}(x_1, x_2, x_3) = 6$ for $0 \leq x_1 < x_2 < x_3 \leq 1$. The probability is then given us

$$P(X_{(2)} - X_{(1)} \geq d, X_{(3)} - X_{(2)} \geq d) = \int_0^1 \int_{x_1+d}^1 \int_{x_2+d}^1 6 dx_3 dx_2 dx_1 = (1 - 2d)^3. \tag{3.52}$$

The marginal density of $X_{(k)}$ is given as $f_{X_{(k)}}(y_k) =$

$$\int \cdots \int_{x_1 < \ldots < x_{k-1} < y_k < x_{k+1} < \ldots < x_n} f_{(X_{(1)}, \ldots, X_{(n)})}(x_1, \ldots, x_{k-1}, y_k, x_{k+1}, \ldots, x_n) dx_1 \cdots dx_{k-1} dx_{k+1} \cdots dx_n. \tag{3.53}$$

If we note that

$$F_{(X_n)}(y) = P(X_{(n)} \leq y) = P(X_1 \leq y, \ldots, X_n \leq y) = [F(y)]^n \tag{3.54}$$

then

$$f_{X_{(n)}}(y) = n[F(y)]^{n-1} f(y). \tag{3.55}$$

Similarly,

$$1 - F_{X_{(1)}}(y) = P(X_{(1)} > y) = P(X_1 > y, X_2 > y, \ldots, X_n > y) = [1 - F(y)]^n \tag{3.56}$$

gives us

$$f_{X_{(1)}}(y) = n[1 - F(y)]^{n-1} f(y). \tag{3.57}$$

For the other marginal densities, we work as follows—

$$\begin{aligned} F_{X_{(k)}}(y) = P(X_{(k)} \leq y) &= P(\text{at least } k \text{ of } X_1, \ldots, X_n \leq y) \\ &= \sum_{j=k}^{n} P(\text{exactly } j \text{ of } X_1, \ldots, X_n \leq y) \\ &= \sum_{j=k}^{n} \binom{n}{j} F(y)^j (1 - F(y))^{n-j}. \end{aligned} \tag{3.58}$$

Differentiating this to find the probability density function is a tedious task. We work around this. Note that for $X_{(k)}$ to attain the value y_k, one of the $X_1, \ldots, X_k$ should equal y_k, $k - 1$ should be less than y_k, and $n - k$ should be greater than y_k. For a fixed partition to satisfy these conditions, we have

$$P(X_{i_1}, X_{i_2}, \ldots, X_{i_{k-1}} < y_k, X_{l_1} = y_k, X_{j_1}, X_{j_2}, \ldots, X_{j_{n-k}} > y) = F(y)^{k-1} f(y) (1 - F(y))^{n-k}. \tag{3.59}$$

Thus, we can choose any partition in the above mentioned way to get

$$f_{X_{(k)}}(y) = \binom{n}{k-1, n-k, 1} F(y)^{k-1} f(y) (1 - F(y))^{n-k}. \tag{3.60}$$

For $i < j$ the joint density function of $(X_{(i)}, X_{(j)})$, $f_{X_{(i)}X_{(j)}}(y_i, y_j)$ exists for $y_i < y_j$. From the same intuitive reasoning as before, we have

$$f_{X_{(i)}X_{(j)}}(y_i, y_j) = \binom{n}{i-1, 1, j-i-1, 1, n-j} F(y_i)^{i-1} f(y_i)(F(y_j) - F(y_i))^{j-i-1} f(y_j)(1 - F(y_j))^{n-j}. \tag{3.61}$$

Example 3.11. We are the find the cumulative distribution function of $R = X_{(n)} - X_{(1)}$, the range of the X_i's. We simply have

$$\begin{aligned} P(R \le a) = P(X_{(n)} - X_{(1)} \le a) &= \iint_{x_n - x_1 \le a} f_{X_{(1)}X_{(n)}}(x_1, x_n) dx_1 dx_n \qquad (3.62) \\ &= \int_{-\infty}^{\infty} \int_{x_1}^{x_1 + a} \frac{n!}{(n-2)!} [F(x_n) - F(x_1)]^{n-2} f(x_1) f(x_n) dx_n dx_1 \end{aligned}$$

Making the substitution $y = F(x_n) - F(x_1)$ with $dy = f(x_n)dx_n$ will help compute the function. The computation is left as an exercise to the reader.

March 4th.

Let $X_1, X_2, \dots, X_n$ be independent and identically distributed as $\text{Exp}(\alpha)$. These will denote the service times of n counters in a post office, commencing at time 0. Thus, $X_{(i)}$ will denote the time of the i^{th} discharge. We have

$$P(X_{(1)} > t) = P(X_1 > t, \dots, X_n > t) = \prod_{i=1}^{n} P(X_i > t) = e^{-n\alpha t} \implies X_{(1)} \sim \text{Exp}(n\alpha). \tag{3.63}$$

Also,

$$P(X_{(n)} \le t) = P(X_1 \le t, \dots, X_{(n)} \le t) = \prod_{i=1}^{n} P(X_i \le t) = (1 - e^{-\alpha t})^n.$$

Intuitively, from the memoryless property of the exponential distribution, we can infer a proposition.

Proposition 3.12. *The n variables $X_{(1)}, X_{(2)} - X_{(1)}, \dots, X_{(n)} - X_{(n-1)}$ are independent, and the density of $X_{(k+1)} - X_{(k)}$ is $(n-k)\alpha e^{-(n-k)\alpha t}$.*

Proof. We show the case for $n = 3$. The proof can then be generalized. We have

$$f_{X_{(1)}X_{(2)}X_{(3)}}(z_1, z_2, z_3) = 6 f_{X_1, X_2, X_3}(z_1, z_2, z_3) = 6\alpha^3 e^{-\alpha} e^{-\alpha(z_1 + z_2 + z_3)}. \tag{3.64}$$

Also,

$$\begin{aligned} P(X_{(1)} > t_1, X_{(2)} - X_{(1)} > t_2, X_{(3)} - X_{(2)} > t_3) &= 6 \int_{t_1}^{\infty} \alpha e^{-\alpha z_1} \int_{z_1 + t_2}^{\infty} \alpha e^{-\alpha z_2} \int_{z_2 + t_3}^{\infty} \alpha e^{-\alpha t_3} dz_3 dz_2 dz_1 \\ &= e^{-\alpha t_3} e^{-2\alpha t_2} e^{-3\alpha t_1}. \qquad (3.65) \end{aligned}$$

Therefore, $X_{(1)} \sim \text{Exp}(3\alpha)$, $X_{(2)} - X_{(1)} \sim \text{Exp}(2\alpha)$, and $X_{(3)} - X_{(2)} \sim \text{Exp}(\alpha)$. ∎

We ask a few questions; suppose A and B are currently being served at the office, and a third clerk C enters. The probability that C leaves last is one-half due to the memoryless property of the exponential distribution. To find the total time spent by C, we have $T = X_{(1)} + Z$, where Z is the distriution of C's time spent being served. The distribution of T is given as

$$f(t) = \int_{\mathbb{R}} f_{X_{(1)}}(x) f_Z(t - x) dx = \int_0^t 2\alpha e^{-2\alpha x} \alpha e^{-\alpha(t - x_1)} dx = 2\alpha e^{-\alpha t}(1 - e^{-\alpha t}).$$

Let us also compute the distribution of the time of last departure, $\tilde{T}$. Note that C enters only when one of A or B is served. The first discharge has distribution $Z \sim \text{Exp}(2\alpha)$. When C enters, we have 2 independent $\text{Exp}(\alpha)$ random variables, where the last discharge is given as $X_{(2)}$. Note that X_1, X_2 are independent of Z. From the previous quesiton, we know that $X_{(2)} = X_{(2)} - X_{(1)} + X_{(2)}$ has distribution

$\text{Exp}(2\alpha) + \text{Exp}(\alpha)$, and density $2\alpha e^{-\alpha t}(1 - e^{-\alpha t})$. Therefore, the distribution of $\tilde{T}$ matches that of $Z + X_{(2)}$. Integrating gives us

$$f_{\tilde{T}}(\tilde{t}) = 4\alpha(e^{-\alpha\tilde{t}} - e^{-2\alpha\tilde{t}} = \alpha\tilde{t}e^{-2\alpha\tilde{t}}). \tag{3.66}$$

Moving away from the exponential distribution, let us consider $X_1, X_2, \ldots, X_n$ to be independent and identically distributed to Unif[0, 1]. Note that $X_{(1)}, X_{(2)}, \ldots, X_{(n)}$ partition the interval $[0, 1]$ into subintervals of length $l_1 = X_{(1)}, l_2 = X_{(2)} - X_{(1)}, \ldots, l_n = X_{(n)} - X_{(n-1)}$. The lengths $l_1, l_2, \ldots, l_n$ are not independent since they have to satisfy $\sum l_i = 1$. The distributions of l_i's turn out to be identical.

As another exercise, let X_1, X_2 be independent and randomly chosen uniformly on the unit circle. Let $r(x, y)$ denote the clockwise circular distance from points x to y on the unit circle. Note that $r(X_1, X_2)$ has the same distribution as $r(X_2, X_1)$, computed as Unif[0, 1].

3.5 Joint Distribution of Functions of Random Variables

March 7th.

Suppose (X_1, X_2) has joint probability density function $f_{X_1X_2}$, and suppose $Y_1 = g_1(X_1, X_2)$ and $Y_2 = g_2(X_1, X_2)$ for some functions g_1, g_2. We assume that g_1 and g_2 satisfy the following conditions:

- The equations $y_1 = g_1(x_1, x_2)$ and $y_2 = g_2(x_1, x_2)$ can be uniquely solves for x_1 and x_2 in terms of y_1 and y_2, say, $x_1 = h_1(y_1, y_2)$ and $x_2 = h_2(y_1, y_2)$.

- g_1 and g_2 have continuous partial derivatives at all (x_1, x_2) and the determinant of the *Jacobian matrix* is

$$J(x_1, x_2) = \det \begin{pmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} \end{pmatrix} = \frac{\partial g_1}{\partial x_1}\frac{\partial g_2}{\partial x_2} - \frac{\partial g_1}{\partial x_2}\frac{\partial g_2}{\partial x_1} \neq 0. \tag{3.67}$$

Then (Y_1, Y_2) has the joint density

$$f_{Y_1Y_2}(y_1, y_2) = f_{X_1X_2}(x_1, x_2) \left|J(x_1, x_2)\right|^{-1} \tag{3.68}$$

where $x_1 = h_1(y_1, y_2)$ and $x_2 = h_2(y_1, y_2)$. The proof of this comes from multivariate analysis.

Remark 3.13. The above can be extended to more than 2 random variables. Suppose that we have the probability density function $f_{X_1X_2\ldots X_n}(x_1, x_2, \ldots, x_n)$ and we have $Y_1 = g_1(X_1, X_2, \ldots, X_n), Y_2 = g_2(X_1, X_2, \ldots, X_n), \ldots, Y_n = g_n(X_1, X_2, \ldots, X_n)$. We have to assume that all the g_i's have continuous partial derivatives, and we have to assume that

$$J(x_1, x_2, \ldots, x_n) = \det \begin{pmatrix} \frac{\partial g_1}{\partial x_1} & \cdots & & \frac{\partial g_1}{\partial x_n} \\ \vdots & \ddots & & \vdots \\ \frac{\partial g_n}{\partial x_1} & \cdots & \frac{\partial g_n}{\partial x_n} \neq 0 \text{ for all } (x_1, x_2, \ldots, x_n). \end{pmatrix} \tag{3.69}$$

We also suppose that that $y_1 = g_1(x_1, \ldots, x_n), \ldots, y_n = g_n(x_1, \ldots, x_n)$ has a unique solution given by $x_1 = h_1(y_1, \ldots, y_n), \ldots, x_n = h_n(y_1, \ldots, y_n)$. The joint density function of $(Y_1, \ldots, Y_N)$ is then given by

$$f_{Y_1Y_2\ldots Y_n}(y_1, y_2, \ldots, y_n) = f_{X_1X_2\ldots X_n}(x_1, x_2, \ldots, x_n) \left|J(x_1, \ldots, x_n)\right|^{-1} \tag{3.70}$$

where $x_i = h_i(y_1, \ldots, y_n)$.

3.5.1 Conditional Expectation and Variance

Let (X, Y) have a joint probability density function $f(x, y)$, and suppose $g : \mathbb{R}^2 \to \mathbb{R}$ is a function.

Proposition 3.14. *The expectation of $g(X, Y)$ is given as*

$$E[g(X, Y)] = \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} g(x, y)f(x, y)dydx.$$

Remark 3.15. By this proposition, if we pick $g(x,y) = x$ for all $(x,y) \in \mathbb{R}^2$, we get

$$EX = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f(x,y) dy dx = \int_{-\infty}^{\infty} x f_X(x) dx.$$

Proof. Assume that $g(x,y) \geq 0$ for all $(x,y) \in \mathbb{R}^2$. We have

$$\begin{aligned} E[g(X,Y)] &= \int_0^{\infty} P(g(X,Y) > t) dt \\ &= \int_0^{\infty} \left(\iint_{\{(x,y):g(x,y)>t\}} f(x,y) dy dx \right) dt \\ &= \iint \int_0^{g(x,y)} f(x,y) dt dy dx \\ &= \iint g(x,y) f(x,y) dy dx. \end{aligned} \tag{3.71}$$

For a general g, we simply work with $g = g^+ - g^-$ where $g^+(x,y) = \max\{g(x,y), 0\}$ and $g^-(x,y) = \max\{-g(x,y), 0\}$. ■

If (X,Y) have a joint probability density function $f(x,y)$, then it can be shown that $E[X+Y] = EX + EY$.

Example 3.16. Suppose $X, Y \sim \text{Unif}[0,L]$. We compute $E|X-Y|$. Noting that the joint probability density function is $f(x,y) = \frac{1}{L^2}$ for all $(x,y) \in [0,L] \times [0,L]$, we have

$$\begin{aligned} E|X-Y| &= \int_0^L \int_0^L \frac{|x-y|}{L^2} dy dx = \frac{1}{L^2} \int_0^L \left(\int_0^x (x-y) dy + \int_x^L (y-x) dy \right) \\ &= \frac{1}{L^2} \int_0^L \left(\frac{x^2}{2} + \frac{(L-x)^2}{2} \right) dx = \frac{L}{3}. \end{aligned} \tag{3.72}$$

Recall that the conditional density of X given $Y = y$ is given as

$$f_{X|Y}(x|y) = \frac{f_{XY}(x,y)}{f_Y(y)}$$

provided that $f_Y(y) > 0$.

Definition 3.17. The conditional expectation is given as

$$E[X|Y=y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|y) dx$$

provided that $f_Y(y) > 0$.

Example 3.18. We compute $E[X|Y=y]$ for $f(x,y) = \frac{e^{-\frac{x}{y}} e^{-y}}{y}$ for $x, y > 0$. It can be shown that the marginal density $f_Y(y)$ is $f_Y(y) = e^{-y}$. Thus, the conditional density is

$$f_{X|Y}(x|y) = \frac{f(x,y)}{f_Y(y)} = \frac{e^{-\frac{x}{y}} e^{-y}}{y e^{-y}} = \frac{1}{y} e^{-\frac{x}{y}}. \tag{3.73}$$

The conditional expectation is then given as

$$E[X|Y=y] = \int_0^{\infty} \frac{x e^{-\frac{x}{y}}}{y} dx = y.$$

It can be shown that

$$E[g(X)|Y=y] = \int g(x) f_{X|Y}(x|y) dx. \tag{3.74}$$

Proposition 3.19. *We have*

$$EX = E[E[X|Y]].$$

Proof. Since $E[X|Y=y] = \int x f_{X|Y}(x|y)dx$ is a function of y, we have

$$\begin{aligned}E[E[X|Y]] &= \int_{-\infty}^{\infty} f_Y(y)\left(\int_{-\infty}^{\infty} x f_{X|Y}(x|y)dx\right)dy = \int_{-\infty}^{\infty} f_Y(y)\int_{-\infty}^{\infty} x\frac{f(x,y)}{f_Y(y)}dxdy \\ &= \int_{-\infty}^{\infty}\int_{-\infty}^{\infty} x f(x,y)dydx = \int_{-\infty}^{\infty} x f_X(x)dx = EX.\end{aligned}$$

■

The conditional variance is also given as

$$\text{Var}(X|Y=y) = E[X^2|Y=y] - (E[X|y=y])^2 = \int x^2 f_{X|Y}(x|y)dx - \left(\int x f_{X|Y}(x|y)dx\right)^2. \tag{3.75}$$

Also recall the conditional variance formula—

$$\begin{aligned}\text{Var}(X) &= E[(X-EX)^2] = E[(X - E[X|Y] + E[X|Y] - EX)^2] \\ &= E[(X-E[X|Y])^2 + (E[X|Y]-EX)^2 + 2(X-E[X|Y])(E[X|Y]-EX)] \\ &= E[\text{Var}(X|Y)] + \text{Var}(E[X|Y]) + 0.\end{aligned} \tag{3.76}$$

Example 3.20. We look at the bivariate normal distribution. The probability density function is given by

$$f(x,y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}}\exp\left(-\frac{1}{2(1-\rho^2)}\left(\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho\frac{(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}\right)\right). \tag{3.77}$$

It can be shown that the correlation between X and Y is indeed ρ, that is, $\frac{E(XY)-\mu_x\mu_y}{\sigma_x\sigma_y} = \rho$. $E(XY)$ is computed by considering $E(XY) = E[E[XY|Y]]$.

Example 3.21. Suppose (S,R) has the following distributions; $R|S=s \sim N(s,1)$ and $S \sim N(\mu,\sigma^2)$. We wish to compute $E[S|R=r]$ and $\text{Var}(S|R=r)$. The former can be found out by first computing

$$f_{S|R}(s|r) = \frac{f_{S,R}(s,r)}{f_R(s)} = \frac{f_{R|S}(r|s)f_S(s)}{f_R(r)}. \tag{3.78}$$

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For random variables X and Y which are jointly distributed, the following hold true:

- $E[(X-a)^2] \geq E[(X-EX)^2]$,
- $E[(Y-g(X))^2] \geq E[(Y-E[Y|X])^2]$.

The best predictor of Y using X is $E[Y|X]$.

Example 3.22. Suppose X is a continuous random variable that we wish to discretize. We first fix an increasing set of numbers $\ldots < a_{-2} < a_{-1} < a_0 < a_1 < a_2 < \ldots$ such that $\lim_{i\to\infty} a_i = \infty$ and $\lim_{i\to-\infty} a_i = -\infty$. Let Y be a random variable taking the value y_i when $a_i < X \leq a_{i+1}$. We wish to choose y_i that minimizes $E[(X-Y)^2]$. For these optimal y_i's one can also show that $EY = EX$ and $\text{Var}Y = \text{Var}X - E[(X-Y)^2]$.

Start with

$$\begin{aligned}E[(X-Y)^2] &= \sum_i E[(X-Y)^2|a_i < X \leq a_{i+1}]P(a_i < X \leq a_{i+1}) \\ &= \sum_i E[(X-y_i)^2|a_i < X \leq a_{i+1}]P(a_i < X \leq a_{i+1}).\end{aligned} \tag{3.79}$$

It is enough to minimize $E[(X-y_i)^2|a_i < X \le a_{i+1}]$. y_i is then computed to be

$$y_i = E[X|a_i < X \le a_{i+1}] = \frac{E[X \cdot 1_{\{a_i < X \le a_{i+1}\}}]}{P(a_i < X \le a_{i+1})} = \frac{\int_{a_i}^{a_{i+1}} x f_X(x)dx}{\int_{a_i}^{a_{i+1}} f_X(x)dx}. \tag{3.80}$$

To show that the expectations of Y and X are equal, we have

$$EY = \sum_i y_i P(Y = y_i) = \sum_i E[X|a_i < X \le a_{i+1}]P(a_i < X \le a_{i+1}) = EX. \tag{3.81}$$

Define a random variable I to be $I = i$ if $a_i < X \le a_{i+1}$. Then

$$\mathrm{Var}X = \mathrm{Var}(E[X|I]) + E[\mathrm{Var}(X|I)] \tag{3.82}$$

can be used. We can compute $E[X|I]$ as $y_I = Y$ and $\mathrm{Var}(X|I)$ as $E[(X-Y)^2|I]$. Thus, the variance equality follows.

Chapter 4

CONVERGENCE OF RANDOM VARIABLES

4.1 Types of Convergence

We being with a probability space (Ω, P), and define a sequence of random variables $X_n : \Omega \to \mathbb{R}$ for $n \geq 1$ and also have another $X : \Omega \to \mathbb{R}$.

Definition 4.1. We first discuss the notion of *almost sure convergence*. A sequence of random variables X_n converges almost surely to X, that is, $X_n \xrightarrow{\text{a.s.}} X$ if

$$P(\{\omega : X_n(\omega) \to X(\omega)\}) = 1.$$

Example 4.2. Suppose that $(\Omega, P) = ([0,1], \text{Unif})$. Suppose that q_n is an enumeration of the rationals in $[0,1]$. We define $X(\omega) = 1$ and $X_n(\omega) = 1$ if $\omega \in [0,1]\backslash\{q_n\}$ and 0 otherwise. We find that

$$A = \{\omega : X_n(\omega) \to X(\omega)\} = [0,1] \tag{4.1}$$

since for any rational ω, further enough terms lead to $X_n(\omega) = 1$ and for any irrational ω, we always have $X_n(\omega) = 1$. Thus, $P(A) = 1$.

Example 4.3. As a continuation to the previous example, if we define the sequence of random variables as

$$X_n(\omega) = \begin{cases} 0 \text{ if } \omega \in \{q_1, \ldots, q_n\}, \\ 1 \text{ if otherwise,} \end{cases} \tag{4.2}$$

we find that $\{\omega : X_n(\omega) \to X(\omega)\} = [0,1] \setminus \mathbb{Q}$. The sequence converges to 0 for rational ω. But, in our probability space, $P([0,1] \setminus \mathbb{Q}) = 1$.

Example 4.4. If we define the sequence of random variables as $X_n = n1_{[0,\frac{1}{n}]}$, we find that $X_n \xrightarrow{\text{a.s.}} 0$. However, $EX_n = 1$ and $E[0] = 0$. The expectation is not preserved in almost sure convergence

Definition 4.5. We discuss the notion of *convergence in probability*. We say that a sequence of random variables X_n converges in probability to X, that is, $X_n \xrightarrow{p} X$ if for every $\varepsilon > 0$,

$$P(|X_n - X| > \varepsilon) \to 0.$$

To show that a sequence of random variables X_n converges in probability to X, it is enough to show that $P(|X_n - X| > \frac{1}{k}) \to 0$ for all $k \geq 1$.

Theorem 4.6. *$X_n \xrightarrow{a.s.} X$ implies $X_n \xrightarrow{p} X$.*

Proof. We have

$$\begin{aligned}\{\omega : X_n(\omega) \to X(\omega)\} &= \{\omega : \text{ for all } k \geq 1, \exists N \text{ such that for all } n \geq N, |X_n(\omega) - X(\omega)| \leq \frac{1}{k}\} \\ &= \bigcap_{k\geq 1} \bigcup_{N} \bigcap_{n\geq N} \{|X_n - X| \leq \frac{1}{k}\}. \end{aligned} \tag{4.3}$$

The probability of this set is 1 due to almost sure convergence. Since the intersection of these events has a probability of 1, each inside event must also have a probability of 1; thus,

$$P(\bigcup_{N} \bigcap_{n\geq N} \{|X_n - X| \leq \frac{1}{k}\}) = 1. \tag{4.4}$$

We note that $\bigcap_{n\geq N}\{|X_n - X| \leq \frac{1}{k}\}$ are events increasing in N. Therefore,

$$P(\bigcap_{n\geq N} \{|X_n - X| \leq \frac{1}{k}\}) \to 1 \implies P(|X_n - X| \leq \frac{1}{k}) \to 1. \tag{4.5}$$

■

However, the converse is not true.

Appendices

Chapter A

Appendix

Extra content goes here.

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