

226[9] Let  $X_n \in \{1, -1\}$  be a sequence of independent random variables such  $\mathbf{P}(X_n = 1) = p = 1 - q = 1 - \mathbf{P}(X_n = -1)$ . Let  $U$  be the number of terms in the sequence before the first change of sign and  $V$  the further number of terms before the second change of sign. In other words, the sequence  $X_1, X_2, \dots$  of random variables is made up of a number of runs of  $+1$ 's and runs of  $-1$ 's.  $U$  is the length of the first run and  $V$  is the length of the second run.

(a) Show that  $\mathbf{E}(U) = \frac{p}{q} + \frac{q}{p}$  and  $\mathbf{E}(V) = 2$ .

(b) Write down the joint distribution of  $U$  and  $V$  and find  $\mathbf{Cov}(U, V)$  and  $\rho(U, V)$ .

(a.) To compute the expectations, let us determine the pmf's for the individual variables  $U$  and  $V$  following the procedure outlined in lecture. Observe that set of values of  $U$  or  $V$ , the number in the run is  $D_i = \mathbb{N} = \{1, 2, 3, \dots\}$ , the natural numbers. Let  $A_i$  denote the event that  $X_i = 1$ . The idea is to condition on  $A_1$ , the first value. This determines whether the first run is  $+1$ 's or  $-1$ 's. Thus if  $X_1 = 1$  and there are  $u$  in the first run, then  $X_2 = X_3 = \dots = X_u = 1$  and  $X_{u+1} = -1$ , so if  $u \in D_1$ ,

$$f_U(u | A_1) = p^{u-1} q.$$

Similarly, if  $X_1 = -1$ , then

$$f_U(u | A_1^c) = q^{u-1} p.$$

Using the partitioning formula

$$f_U(u) = f_U(u | A_1) \mathbf{P}(A_1) + f_U(u | A_1^c) \mathbf{P}(A_1^c) = p^{u-1} q p + p q^{u-1} q = p^u q + p q^u.$$

It follows that

$$\mathbf{P}(U \geq u) = \sum_{k=u}^{\infty} (p^k q + p q^k) = \frac{p^u q}{1-p} + \frac{p q^u}{1-q} = p^u + q^u.$$

Thus, using Theorem 4.3.11,

$$\mathbf{E}(U) = \sum_{u=1}^{\infty} \mathbf{P}(U \geq u) = \sum_{u=1}^{\infty} (p^u + q^u) = \frac{p}{1-p} + \frac{q}{1-q}.$$

Thus if  $X_1 = 1$  and there are  $u$  in the first run and  $v$  in the second run, then  $X_{u+1} = -1$  and  $X_{u+2} = X_{u+3} = \dots = X_{u+v} = -1$  and  $X_{u+v+1} = 1$ , so if  $v \in D_2$ , and independence of individual  $X_i$ 's,

$$f_V(v | A_1) = p q^{v-1}.$$

Similarly, if  $X_1 = -1$ , then

$$f_V(v | A_1^c) = p^{v-1} q.$$

Using the partitioning formula

$$f_V(v) = f_V(v | A_1) \mathbf{P}(A_1) + f_V(v | A_1^c) \mathbf{P}(A_1^c) = p q^{v-1} p + p^{v-1} q^2 = p^2 q^{v-1} + p^{v-1} q^2.$$

Here is an alternative way to compute the expectation. These formulas involve for  $|z| < 1$ ,

$$\begin{aligned} \sum_{k=1}^{\infty} k z^{k-1} &= \frac{d}{dz} \left( \sum_{k=0}^{\infty} z^k \right) = \frac{d}{dz} \left( \frac{1}{1-z} \right) = \frac{1}{(1-z)^2}; \\ \sum_{k=1}^{\infty} k^2 z^{k-1} &= \sum_{k=1}^{\infty} [(k+1)k - k] z^{k-1} = \frac{d^2}{dz^2} \left( \sum_{k=-1}^{\infty} z^{k+1} \right) - \frac{1}{(1-z)^2} \\ &= \frac{d^2}{dz^2} \left( \frac{1}{1-z} \right) - \frac{1}{(1-z)^2} = \frac{2}{(1-z)^3} - \frac{1}{(1-z)^2} = \frac{1+z}{(1-z)^3}. \end{aligned} \quad (1)$$

Thus, using (1),

$$\begin{aligned} \mathbf{E}(V) &= \sum_{v \in D_2} v f_V(v) = \sum_{v=1}^{\infty} v (p^2 q^{v-1} + p^{v-1} q^2) \\ &= p^2 \sum_{v=0}^{\infty} v q^{v-1} + q^2 \sum_{v=0}^{\infty} v p^{v-1} = \frac{p^2}{(1-q)^2} + \frac{q^2}{(1-p)^2} = 2. \end{aligned}$$

(b.) The joint probability is also gotten by conditioning on  $A_1$ . Let  $(u, v) \in D_1 \times D_2$  and  $f(u, v) = \mathbf{P}(U = u \text{ and } V = v)$ . Thus if  $X_1 = 1$  and the length of the first run is  $u$  and the length of the second run is  $v$ , then  $X_2 = \dots = X_u = 1$ ,  $X_{u+1} = X_{u+2} = \dots = X_{u+v} = -1$  and  $X_{u+v+1} = 1$ , so if  $v \in D_2$ , and independence of individual  $X_i$ 's,

$$f(u, v \mid A_1) = p^{u-1} q^v p = p^u q^v.$$

Similarly, if  $X_1 = -1$ , then

$$f(u, v \mid A_1^c) = q^{u-1} p^v q = p^v q^u.$$

Using the partitioning formula

$$f(u, v) = f_V(u, v \mid A_1) \mathbf{P}(A_1) + f(u, v \mid A_1^c) \mathbf{P}(A_1^c) = p^u q^v p + p^v q^u q = p^{u+1} q^v + p^v q^{u+1}.$$

Let us check the marginal probabilities.

$$\begin{aligned} f_U(u) &= \sum_{v \in D_2} f(u, v) = \sum_{v=1}^{\infty} (p^{u+1} q^v + p^v q^{u+1}) = \frac{p^{u+1} q}{1-q} + \frac{p q^{u+1}}{1-p} = p^u q + p q^u; \\ f_V(v) &= \sum_{u \in D_1} f(u, v) = \sum_{u=1}^{\infty} (p^{u+1} q^v + p^v q^{u+1}) = \frac{p^2 q^v}{1-p} + \frac{p^v q^2}{1-q} = p^2 q^{v-1} + p^{v-1} q^2. \end{aligned}$$

To compute the further expectations, using (1),

$$\begin{aligned} \mathbf{E}(U^2) &= \sum_{u=1}^{\infty} u^2 f_U(u) = \sum_{u=1}^{\infty} u^2 (p^u q + p q^u) = \frac{p q (1+p)}{(1-p)^3} + \frac{p q (1+q)}{(1-q)^3} = \frac{p(1+p)}{q^2} + \frac{q(1+q)}{p^2} \\ \mathbf{E}(V^2) &= \sum_{v=1}^{\infty} v^2 f_V(v) = \sum_{v=1}^{\infty} v^2 (p^2 q^{v-1} + p^{v-1} q^2) = \frac{p^2 (1+q)}{(1-q)^3} + \frac{q^2 (1+p)}{(1-p)^3} = \frac{1+q}{p} + \frac{1+p}{q} \\ \mathbf{E}(UV) &= \sum_{u=1}^{\infty} \sum_{v=1}^{\infty} uv f(u, v) = \sum_{u=1}^{\infty} \sum_{v=1}^{\infty} uv (p^{u+1} q^v + p^v q^{u+1}) = \frac{p^2 q + p q^2}{(1-p)^2 (1-q)^2} = \frac{1}{q} + \frac{1}{p}. \end{aligned}$$

The variances are

$$\mathbf{Var}(U) = \mathbf{E}(U^2) - \mathbf{E}(U)^2 = \frac{p(1+p)}{q^2} + \frac{q(1+q)}{p^2} - \left(\frac{p}{q} + \frac{q}{p}\right)^2;$$

$$\mathbf{Var}(V) = \mathbf{E}(V^2) - \mathbf{E}(V)^2 = \frac{1+q}{p} + \frac{1+p}{q} - 4;$$

$$\mathbf{Cov}(U, V) = E(UV) - \mathbf{E}(U)\mathbf{E}(V) = \frac{1}{q} + \frac{1}{p} - \frac{2p}{q} - \frac{2q}{p} = \frac{p+q-2p^2-2q^2}{pq}.$$

The expressions may be simplified using

$$p^2 + q^2 = p^2 + 2pq + q^2 - 2pq = (p+q)^2 - 2pq = 1 - 2pq; \quad (2)$$

$$p^2 - q^2 = (p+q)(p-q) = p-q. \quad (3)$$

The variance of  $U$  may be simplified using (2) and (3),

$$\begin{aligned} \mathbf{Var}(U) &= \frac{p^3(p+q+p) + q^3(p+q+q)}{p^2q^2} - \left(\frac{p^2+q^2}{pq}\right)^2 \\ &= \frac{2p^4 + p^3q + pq^3 + 2q^4 - p^4 - 2p^2q^2 - q^4}{p^2q^2} \\ &= \frac{(p^4 - 2p^2q^2 + q^4) + pq(p^2 + q^2)}{p^2q^2} \\ &= \frac{(p^2 - q^2)^2 + pq(p^2 - 2pq + q^2) + 2p^2q^2}{p^2q^2} \\ &= 2 + \frac{(p-q)^2}{pq} + \frac{(p-q)^2}{p^2q^2}. \end{aligned}$$

The variance of  $V$  may be simplified

$$\begin{aligned} \mathbf{Var}(V) &= \frac{p+2q}{p} + \frac{2p+q}{q} - 4 = \frac{pq + 2q^2 + 2p^2 + pq - 4pq}{pq} \\ &= \frac{2pq + 2(p^2 - 2pq + q^2)}{pq} = 2 + \frac{2(p-q)^2}{pq}. \end{aligned}$$

Thus  $\mathbf{Var}(V) < \mathbf{Var}(U)$  unless  $p = q = \frac{1}{2}$ .

The covariance may be simplified using (2)

$$\begin{aligned} \mathbf{Cov}(U, V) &= \frac{p+q-2p^2-2q^2}{pq} = \frac{1-2(p^2+q^2)}{pq} = \frac{1-2(1-2pq)}{pq} = \frac{4pq-1}{pq} \\ &= \frac{4pq - (p+q)^2}{pq} = -\frac{(p-q)^2}{pq}. \end{aligned}$$

The correlation coefficient is thus

$$\begin{aligned} \rho(U, V) &= \frac{\mathbf{Cov}(U, V)}{\sqrt{\mathbf{Var}(U)} \cdot \sqrt{\mathbf{Var}(V)}} \\ &= \frac{-(p-q)^2}{\sqrt{\left(2pq + (p-q)^2 + \frac{(p-q)^2}{pq}\right) (2pq + 2(p-q)^2)}}. \end{aligned}$$

I doubt that the text's answer is correct since neither variance has  $(p-q)^2$  as a factor.

226[25] Let  $X$  and  $Y$  be independent geometric variables so that for  $m \geq 0$ ,

$$f_X(m) = \mathbf{P}(X = m) = (1 - \lambda)\lambda^m, \quad f_Y(m) = \mathbf{P}(Y = m) = (1 - \mu)\mu^m,$$

where  $0 < \lambda, \mu < 1$ .

(a) If  $\lambda \neq \mu$ , show that

$$\mathbf{P}(X + Y = n) = \frac{(1 - \lambda)(1 - \mu)}{\lambda - \mu} (\lambda^{n+1} - \mu^{n+1}).$$

Find  $\mathbf{P}(X = k \mid X + Y = n)$ .

(b) Find the distribution of  $Z = X + Y$  if  $\lambda = \mu$ , and show that in this case,

$$\mathbf{P}(X = k \mid X + Y = n) = \frac{1}{n + 1}.$$

These geometric rv's are defined for  $m \in D = \{0, 1, 2, \dots\}$ . Since the variables are assumed independent, their joint pmf is the product

$$f(x, y) = f_X(x) f_Y(y) = (1 - \lambda)(1 - \mu) \lambda^x \mu^y.$$

(a.) The pmf of the sum of independent variables is given by the convolution formula Theorem 5.4.11. We observe that the sum is a finite geometric sum.

$$\begin{aligned} f_Z(z) &= \sum_{x=0}^z f_X(x) f_Y(z-x) \\ &= \sum_{x=0}^z (1 - \lambda)(1 - \mu) \lambda^x \mu^{z-x} \\ &= (1 - \lambda)(1 - \mu) \mu^z \sum_{x=0}^z \left(\frac{\lambda}{\mu}\right)^x \\ &= (1 - \lambda)(1 - \mu) \mu^z \frac{1 - \left(\frac{\lambda}{\mu}\right)^{z+1}}{1 - \frac{\lambda}{\mu}} \\ &= (1 - \lambda)(1 - \mu) \frac{\mu^{z+1} - \lambda^{z+1}}{\mu - \lambda}. \end{aligned}$$

Observing that  $x = k$  and  $x + y = n$  implies  $x = k$  and  $y = n - k$ , the conditional probability is gotten using the usual formula for  $0 \leq k \leq n$ ,

$$\begin{aligned} \mathbf{P}(X = k \mid Z = n) &= \frac{\mathbf{P}(X = k \text{ and } Z = n)}{\mathbf{P}(Z = n)} = \frac{\mathbf{P}(X = k \text{ and } Y = n - k)}{\mathbf{P}(Z = n)} \\ &= \frac{f(k, n - k)}{f_Z(n)} = \frac{\lambda^k \mu^{n-k} (\lambda - \mu)}{\lambda^{n+1} - \mu^{n+1}}. \end{aligned}$$

(b.) In case  $\lambda = \mu$ ,

$$\begin{aligned} f_Z(z) &= \sum_{x=0}^z f_X(x) f_Y(z-x) \\ &= \sum_{x=0}^z (1 - \lambda)^2 \lambda^x \lambda^{z-x} \\ &= (z + 1)(1 - \lambda)^2 \lambda^z. \end{aligned}$$

The conditional probability is for  $0 \leq k \leq n$ ,

$$\begin{aligned} \mathbf{P}(X = k \mid Z = n) &= \frac{\mathbf{P}(X = k \text{ and } Z = n)}{\mathbf{P}(Z = n)} = \frac{\mathbf{P}(X = k \text{ and } Y = n - k)}{\mathbf{P}(Z = n)} \\ &= \frac{f(k, n - k)}{f_Z(n)} = \frac{(1 - \lambda)^2 \lambda^n}{(n + 1)(1 - \lambda)^2 \lambda^n} = \frac{1}{n + 1}. \end{aligned}$$

[A.] Two cards are chosen at random without replacement from a standard deck. Let  $X$  denote the number of kings and  $Y$  the number of clubs. Find the joint pmf  $f(x, y)$ ,  $\mathbf{Cov}(X, Y)$  and  $\rho(X, Y)$ .

The sample space  $\Omega$  is the set of combinations of 52 cards taken two at a time. Thus  $|\Omega| = \binom{52}{2} = 1326$ . Both  $X$  and  $Y$  take values in  $D_i = \{0, 1, 2\}$ . The pairs take values in  $D_1 \times D_2$ . If  $X = x$  and  $Y = y$  then  $f(x, y) = \mathbf{P}(X = x \text{ and } Y = y)$ . There are  $52 - 16 = 36$  cards that are neither kings nor clubs. If  $X = 0$  and  $Y = 0$  both cards are neither king nor club. If instead  $Y = 1$  then one card is a club that isn't a king and the other is neither king nor club. If also  $Y = 2$  both cards are clubs but neither is a king.

$$\begin{aligned} f(0, 0) &= \frac{\binom{36}{2}}{\binom{52}{2}} = \frac{36 \cdot 35}{52 \cdot 51} = \frac{105}{221}, & f(0, 1) &= \frac{12 \cdot 36}{\binom{52}{2}} = \frac{12 \cdot 36 \cdot 2}{52 \cdot 51} = \frac{72}{221} \\ f(0, 2) &= \frac{\binom{12}{2}}{\binom{52}{2}} = \frac{12 \cdot 11}{52 \cdot 51} = \frac{11}{221} \end{aligned}$$

If  $X = 1$  there is one king. For  $Y = 0$  the king can't be a club so there are three remaining kings. The second card cannot be king nor club, so there are 36 choices. For  $Y = 1$  there is one king and one club. Either one card is the king of clubs and the other neither king nor club or one is a non-club king and the other is a non-king club. If also  $Y = 2$  then one of the cards is a king of clubs and the other is another club so

$$\begin{aligned} f(1, 0) &= \frac{3 \cdot 36}{\binom{52}{2}} = \frac{3 \cdot 36 \cdot 2}{52 \cdot 51} = \frac{18}{221}, & f(1, 1) &= \frac{1 \cdot 36 + 3 \cdot 12}{\binom{52}{2}} = \frac{72 \cdot 2}{52 \cdot 51} = \frac{12}{221}, \\ f(1, 2) &= \frac{1 \cdot 12}{\binom{52}{2}} = \frac{12 \cdot 2}{52 \cdot 51} = \frac{2}{221} \end{aligned}$$

If  $X = 2$  and  $Y = 0$  both cards are kings but neither is the king of clubs. If instead  $Y = 1$  then there are two kings, one being the king of clubs. If also  $Y = 2$  then it is impossible that both cards are kings and both cards are clubs.

$$f(2, 0) = \frac{\binom{3}{2}}{\binom{52}{2}} = \frac{3 \cdot 2}{52 \cdot 51} = \frac{1}{442}, \quad f(2, 1) = \frac{3}{\binom{52}{2}} = \frac{3 \cdot 2}{52 \cdot 51} = \frac{1}{442}, \quad f(2, 2) = 0.$$

The joint pmf is collected in Figure 1.

The marginal probabilities are the row and column sums of the joint pmf. For  $x \in D_1$  or  $y \in D_2$ ,

$$f_X(x) = \sum_{y \in D_2} f(x, y); \quad f_Y(y) = \sum_{x \in D_1} f(x, y).$$

The marginal probabilities are also given in Figure 1.

The variables  $X$  and  $Y$  are not independent, for example because

$$f(2, 2) = 0 \neq \frac{1}{221} \cdot \frac{13}{221} = f_X(2)f_Y(2).$$

	$x = 0$	$x = 1$	$x = 2$	$f_Y(y)$
$y = 0$	$\frac{105}{221}$	$\frac{18}{221}$	$\frac{1}{442}$	$\frac{247}{442} = \frac{19}{34}$
$y = 1$	$\frac{72}{221}$	$\frac{12}{221}$	$\frac{1}{442}$	$\frac{169}{442} = \frac{13}{34}$
$y = 2$	$\frac{11}{221}$	$\frac{2}{221}$	0	$\frac{13}{221} = \frac{1}{17}$
$f_X(x)$	$\frac{188}{221}$	$\frac{32}{221}$	$\frac{1}{221}$	1

Figure 1: Table of joint pmf and marginal probabilities.

The expected values are

$$\begin{aligned} \mathbf{E}(X) &= \sum_{x \in D_1} x f_X(x) = \frac{0 \cdot 188 + 1 \cdot 32 + 2 \cdot 1}{221} = \frac{34}{221} = \frac{2}{13}; \\ \mathbf{E}(Y) &= \sum_{y \in D_2} y f_Y(y) = \frac{0 \cdot 19 + 1 \cdot 13 + 2 \cdot 2}{34} = \frac{17}{34} = \frac{1}{2}; \\ \mathbf{E}(X^2) &= \sum_{x \in D_1} x^2 f_X(x) = \frac{0^2 \cdot 188 + 1^2 \cdot 32 + 2^2 \cdot 1}{221} = \frac{36}{221}; \\ \mathbf{E}(Y^2) &= \sum_{y \in D_2} y^2 f_Y(y) = \frac{0^2 \cdot 19 + 1^2 \cdot 13 + 2^2 \cdot 2}{34} = \frac{21}{34}; \\ \mathbf{E}(XY) &= \sum_{(x,y) \in D_1 \times D_2} xy f(x,y) = \frac{1 \cdot 1 \cdot 24 + 1 \cdot 2 \cdot 4 + 2 \cdot 1 \cdot 1}{442} = \frac{34}{442} = \frac{1}{13}. \end{aligned}$$

The variances and covariances are from their computational formulas,

$$\begin{aligned} \mathbf{Var}(X) &= \mathbf{E}(X^2) - \mathbf{E}(X)^2 = \frac{36}{221} - \frac{2^2}{13^2} = \frac{400}{2873}; \\ \mathbf{Var}(Y) &= \mathbf{E}(Y^2) - \mathbf{E}(Y)^2 = \frac{21}{34} - \frac{1^2}{2^2} = \frac{25}{68}; \\ \mathbf{Cov}(X, Y) &= \mathbf{E}(XY) - \mathbf{E}(X) \mathbf{E}(Y) = \frac{1}{13} - \frac{2}{13} \cdot \frac{1}{2} = 0. \end{aligned}$$

Thus  $X$  and  $Y$  are uncorrelated, since the correlation coefficient is

$$\rho(X, Y) = \frac{\mathbf{Cov}(X, Y)}{\sqrt{\mathbf{Var}(X)} \sqrt{\mathbf{Var}(Y)}} = 0.$$