

$$1) \int_{-\infty}^{\infty} P(x < X \leq x+a) dx = \int_{-\infty}^{\infty} F(x+a) - F(x) dx$$

$$= \lim_{K \rightarrow \infty} \int_{-K}^K F(x+a) - F(x) dx$$

$$= \lim_K \left( \int_{-K}^K F(x+a) dx - \int_{-K}^K F(x) dx \right)$$

$$= \lim_K \left( \int_{-K+a}^{K+a} F(x) dx - \int_{-K}^K F(x) dx \right)$$

$$= \lim_K \left( \int_K^{K+a} F(x) dx - \int_{-K}^{-K+a} F(x) dx \right)$$

$$= \lim_K (a F(K+a) - F(-K+a)) = a$$

Approach using Fubini (covered later).

$$\begin{aligned} \int_{-\infty}^{\infty} P(x < X \leq x+a) dx &= \int_{-\infty}^{\infty} \int_{\Omega} \mathbb{1}_{[x, x+a)}(\omega) dP d\omega \\ &= \int_{\Omega} \int_{-\infty}^{\infty} \mathbb{1}_{[x, x+a)}(\omega) dx dP = E(a) = a. \end{aligned}$$

Q2 a)

$$|Y| = \left| \max_{1 \leq k \leq n} X_k \right| \leq \max_{1 \leq k \leq n} |X_k|$$

$$\leq |X_1| + |X_2| + \dots + |X_n|$$

$$\text{and } E|Y| \leq E|X_1| + \dots + E|X_n| < \infty$$

since  $n$  finite and  $|X_i|$  integrable.

b) This follows from monotonicity of integration

$$X_k \leq \max_{1 \leq j \leq n} X_j = Y$$

$$\text{and so } E(X_k) \leq E(Y)$$

c)

$$\text{Let } X_1 = 0 \quad (\text{constant})$$

$$\text{Let } X_2 = -1 \quad (\text{constant})$$

$$\text{Then } E|X_2| = 1 \quad \text{but}$$

$$Y = \max\{X_1, X_2\} = X_1 \quad \text{and}$$

$$E|Y| = 0.$$

Q3

" $\Rightarrow$ " If  $Y$  is integrable we have

$$|X_k| \leq \max_{1 \leq j \leq n} |X_j| = |Y| \quad \text{and so}$$

$$E|X_k| \leq E|Y|. \quad \text{Now let } Z = |Y|.$$

" $\Leftarrow$ " Assume such  $Z$  exists.

Since  $Y = \max_{1 \leq j \leq n} |X_j|$  the assumption

$$|X_k| \leq Z \quad \text{also implies } |Y| \leq Z.$$

Since  $E(|Y|) \leq E(|Z|) < \infty$ ,  $Y$  is integrable.

Q4.

$$E(m_n^2) = \frac{1}{n} \sum_{k=1}^n E((X_k - \bar{X}_n)^2)$$

$$= \frac{1}{n} \sum_{k=1}^n (E(X_k^2) + E(\bar{X}_n^2) - 2E(X_k \bar{X}_n))$$

$$= E(X_1^2) + E(\bar{X}_n^2) - 2E(X_1 \bar{X}_n)$$

$$= E(X_1^2) + \frac{1}{n^2} E\left(\left(\sum_{k=1}^n X_k\right)^2\right) - 2E\left(X_1 \frac{1}{n} \sum_{k=1}^n X_k\right)$$

$$= E(X_1^2) + \underbrace{\frac{1}{n^2} E\left(\sum_{k=1}^n X_k\right)^2}_{(*)} - 2 \underbrace{E\left(X_1 \frac{1}{n} \sum_{k=1}^n X_k\right)}_{(+)} \quad (\#)$$

$$(*) = E\left(\sum_{k=1}^n X_k^2 + \sum_{k=1}^n \sum_{i \neq k} X_k X_i\right)$$

$$= n E(X_1^2) + n(n-1) E(X_1)^2$$

$$(+)= \frac{1}{n} E\left(X_1^2 + \sum_{k=2}^n X_1 X_k\right) = \frac{1}{n} E(X_1^2) + \frac{n-1}{n} E(X_1)^2$$

$$(\#) = E(X_1^2) + \underbrace{\frac{E(X_1^2)}{n}}_{\dots\dots\dots} + \frac{n-1}{n} E(X_1)^2 - \underbrace{\frac{2}{n} E(X_1^2)}_{\dots\dots\dots} - 2 \frac{n-1}{n} E(X_1)^2$$

$$= E(X_1^2) - \frac{1}{n} E(X_1^2) - \frac{n-1}{n} E(X_1)^2$$

$$= \frac{n-1}{n} \left( E(X_1^2) - E(X_1)^2 \right) = \frac{n-1}{n} \text{Var}(X_1)$$

$\text{Var}(m_n^2)$  calculation similar. Details omitted.

5) First note that

$$X > n \Rightarrow \frac{n}{X} < 1 \text{ whenever } X \neq 0$$

Hence

$$\mathbb{E}\left(\frac{n}{X} I_{X>n}\right) = \int \frac{n}{X} I_{X>n} dP < \int 1 I_{X>n} dP \\ = 1 - F_X(n). \quad \text{But } F_X(n) \rightarrow 1 \text{ as } n \rightarrow \infty$$

giving the first statement.

For the second, we note that

$$\frac{X \cdot I_{X>n}}{n} \leq \frac{n}{n} = 1. \quad \text{Since } \mathbb{E}(|I|) = 1 < \infty$$

we may use the DCT to the seq.

$$Y_n = \frac{X \cdot I_{X>n}}{n} \quad \text{which converges pointwise} \\ \text{to } 0 \text{ as } Y_n = \frac{X(\omega) \cdot I(\omega)}{n} \leq \frac{X(\omega)}{n} \rightarrow 0.$$

$$\text{So } Y_n \rightarrow 0 \quad \text{and} \quad \lim_{n \rightarrow \infty} \mathbb{E}(Y_n) = \mathbb{E}(0) = 0. \quad \square$$

G.)

a) Let  $t \in [-\theta, \theta]$ . Then, there exists  $p \in [0, 1]$  s.t.  $t = p(-\theta) + (1-p)\theta$

Since  $X$  is non-negative, for any fixed  $X \geq 0$

$t \mapsto e^{Xt}$  is convex. Thus,

$$e^{Xt} \leq p e^{-\theta X} + (1-p) e^{\theta X}.$$

Using monotonicity,

$$\begin{aligned} \mathbb{E}(e^{Xt}) &\leq p \mathbb{E}(e^{-\theta X}) + (1-p) \mathbb{E}(e^{\theta X}) \\ &\leq \mathbb{E}(e^{-\theta X}) + \mathbb{E}(e^{\theta X}) < \infty \end{aligned}$$

Hence there exists such  $C > 0$ .

b) Let  $f(t, X): \mathbb{R} \rightarrow \mathbb{R}_0^+$  be measurable.

Assume that  $f$  is uniformly differentiable wrt.  $t$  on a neighbourhood  $(t_0 - a, t_0 + a)$ . We first show,

assuming  $\mathbb{E}\left(\left|\frac{\partial}{\partial t} f(t, X)\right|_{t=t_0}\right) < \infty$ , that

$$\frac{\partial}{\partial t} \mathbb{E}(f(t, X)) \Big|_{t=t_0} = \mathbb{E}\left(\frac{\partial}{\partial t} f(t, X) \Big|_{t=t_0}\right).$$

The LHS can be expressed as

$$\lim_{n \rightarrow \infty} \frac{\mathbb{E}(f(t_0 + a_n, X)) - \mathbb{E}(f(t_0, X))}{a_n},$$

where  $|a_n| < a$  is any seq. such that  $a_n \rightarrow 0$

This gives

$$\lim_{n \rightarrow \infty} \mathbb{E} \left( \frac{f(t_0 + a_n, X) - f(t_0, X)}{a_n} \right)$$

$$= \lim_{n \rightarrow \infty} \mathbb{E} \left( \left. \frac{\partial}{\partial t} f(t, X) \right|_{t=t_0} + \delta_n \right), \text{ where the error}$$

$$\delta_n \rightarrow 0 \text{ as } n \rightarrow \infty. \text{ Since } \mathbb{E} \left( \left| \frac{\partial}{\partial t} f(t, X) \right| \right) < \infty$$

this is bounded. Applying the DCT gives

$$\left. \frac{\partial}{\partial t} \mathbb{E}(f(t, X)) \right|_{t=t_0} = \lim_{n \rightarrow \infty} \mathbb{E} \left( \left. \frac{\partial}{\partial t} f(t, X) \right|_{t=t_0} + \delta_n \right) = \mathbb{E} \left( \left. \frac{\partial}{\partial t} f(t, X) \right|_{t=t_0} \right)$$

The argument can be repeated for all  $t_0$  in an open interval and hence we may differentiate under the expectation, assuming integrability. Hence,

$$\frac{d^k}{dt^k} M_X(t) = \mathbb{E} \left( \frac{d^k}{dt^k} e^{tX} \right) = \mathbb{E} (X^k e^{tX}),$$

provided the latter is integrable. But

$$\mathbb{E} (X^k e^{tX}) < \mathbb{E} (e^{kX} e^{tX}) = \mathbb{E} (e^{(t+k)X}) < \infty$$

by assumption

□

c) To compute the  $k$ -th moment, we consider  $\left. \frac{d^k}{dt^k} M_X(t) \right|_{t=0} = \mathbb{E}(X^k e^{tX}) \Big|_{t=0} = \mathbb{E}(X^k)$ .

Hence the  $k$ -th moment is given by the  $k$ -th derivative of  $M_X(t)$  at 0. In particular, under these conditions it exists.

7) Let  $X_n$  be the length of stick after the  $n$ -th breaking.  $X_0 = 1$ ,  $X_1 \sim U[0, 1]$ ,  $X_2 \sim U[0, X_1]$ ,  $X_3 \sim U[0, X_2]$ , ...

We note that we can equivalently write

$$X_0 = 1, X_1 = Z_1, X_2 = Z_1 Z_2, X_3 = Z_1 Z_2 Z_3,$$

where  $Z_k \sim U[0, 1]$ . Then,

$$X_n = \prod_{i=1}^n Z_i \quad \text{and} \quad \log X_n = \sum_{j=1}^n \log Z_j$$

$$\text{Now } \mathbb{E}(|\log^4 Z_i|) = \int_0^1 \underbrace{\log^4 x}_u \underbrace{\frac{dx}{dx}}_{dv}$$

$$du = 4 \log^3(x) \cdot \frac{1}{x} dx$$

$$v = x$$

$$= x \log^4 x \Big|_0^1 - \int_0^1 4 \log^3(x) dx = 0 - 4x \log^3 x \Big|_0^1 + \int_0^1 12 \log^2(x) dx$$

$$= \dots = 24 < \infty$$



So it has fourth moment and we

can apply the LLN:

$$\lim_{n \rightarrow \infty} \frac{\log X_n}{n} = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \log Z_i \rightarrow \mathbb{E}(\log Z_1)$$

$$= \int_0^1 \log x \, dx = (x \log x - x) \Big|_0^1 = -1.$$

8)

Using the hint,

$$\begin{aligned} \mathbb{E}(X) &= \mathbb{E}(X I_{X \geq \lambda \mathbb{E}X} + X I_{X < \lambda \mathbb{E}X}) \\ &= \mathbb{E}(X I_{X \geq \lambda \mathbb{E}X}) + \mathbb{E}(X I_{X < \lambda \mathbb{E}X}) \\ &\leq \mathbb{E}(X I_{X \geq \lambda \mathbb{E}X}) + \lambda \mathbb{E}(X) \end{aligned}$$

$$\Rightarrow \mathbb{E}(X)(1-\lambda) \leq \mathbb{E}(X I_{X \geq \lambda \mathbb{E}X})$$

$$\stackrel{\text{C.S.}}{\leq} \sqrt{\mathbb{E}(X^2) \mathbb{E}(I_{X \geq \lambda \mathbb{E}X}^2)} = \sqrt{\mathbb{E}(X^2)} \sqrt{P(X \geq \lambda \mathbb{E}X)}$$

$$\Rightarrow \mathbb{E}(X^2) P(X \geq \lambda \mathbb{E}X) \geq (1-\lambda)^2 \mathbb{E}(X)^2$$

$$\Rightarrow P(X \geq \lambda \mathbb{E}X) \geq (1-\lambda)^2 \frac{\mathbb{E}(X)^2}{\mathbb{E}(X^2)}$$

(This is known as the Paley - Zygmund ineq.)

g) a) Let  $X_k = \begin{cases} 1 & \text{if dots at position } k \text{ and } k+1 \text{ are red} \\ 0 & \text{otherwise} \end{cases}$

For each  $1 \leq k < n$ ,  $P(X_k = 0) = p_n^2$

Note however that  $X_k, X_{k+1}$  are not independent.

Further,  $P_n = \sum_{k=1}^{n-1} X_k$ .

$$\text{Now } E(P_n) = E\left(\sum_{k=1}^{n-1} X_k\right) = \sum_{k=1}^{n-1} E X_k = (n-1) p_n^2$$

b)  $q_n = P(P_n > 0) = P(P_n \geq 1) \leq E(P_n) \quad (\text{Markov})$

Combining with a) gives  $q_n \leq (n-1) p_n^2$

Assuming  $\sqrt{n} p_n \rightarrow 0$  gives  $p_n \leq \varepsilon / \sqrt{n}$  for all

$\varepsilon > 0$  for large enough  $n$ , and  $p_n^2 \leq \frac{\varepsilon}{n}$

Thus  $q_n \leq \frac{(n-1)\varepsilon^2}{n} \leq \varepsilon^2$ . Since  $\varepsilon > 0$  was arbitrary

the desired conclusion follows.

c) We assume there exists a sequence  $n_k$  and

$$\varepsilon > 0 \text{ s.t. } \sqrt{n_k} p_{n_k} \geq \varepsilon \Rightarrow p_{n_k}^2 \geq \frac{\varepsilon^2}{n_k}$$

As noted above  $X_k$  and  $X_{k+1}$  are not independent.

However,  $X_k$  and  $X_{k+2}$  are independent. We can thus

bound  $P(P_{n_k} > 0)$  below by

$$P(P_n > 0) \geq P\left(\sum_{j=1}^{\lfloor \frac{n-1}{2} \rfloor} X_{2j} > 0\right)$$

$$= 1 - P(X_{2j} = 0 : 1 \leq j \leq \lfloor \frac{n-1}{2} \rfloor)$$

$$= 1 - \prod_{j=1}^{\lfloor \frac{n-1}{2} \rfloor} P(X_{2j} = 0) \quad (\text{independence})$$

$$= 1 - (1 - p_n^2)^{\lfloor \frac{n-1}{2} \rfloor} \geq 1 - (1 - p_n^2)^{n_k}$$

$$= 1 - \exp(n_k \log(1 - p_n^2))$$

$$\geq 1 - \exp(-n_k p_n^2) \geq 1 - \exp(-\varepsilon^2) > 0.$$

This proves our claim.

□

10)

a)

$$X_H = \begin{cases} 0 & \omega \in \{TTT\} \\ 1 & \omega \in \{HTT, THT, TTH\} \\ 2 & \omega \in \{TTH, HTH, HHT\} \\ 3 & \omega \in \{HHH\} \end{cases}$$

b)

$$Y = \begin{cases} 0, \omega \in \{HTT, THT, TTH\} \\ 1, \omega \in \{TTT, TTH, HTH, HHT\} \\ 4, \omega \in \{HHH\} \end{cases}$$

$$E = \{HTT, THT, TTH, HHH\}$$

We get  $\sigma(E) = \{\emptyset, \Omega, E, E^c\}$

$$\sigma(X) = \{\emptyset, \Omega, \{TTT\}, \{HHH\}, \{TTT, HHH\}, \dots\}$$

$$\sigma(Y) = \{\emptyset, \Omega, \{HHH\}, \{HTT, THT, TTH\}, \dots\}$$

$Z = E(X | E)$  must be constant on  $E$  and  $E^c$  by measurability. Hence  $Z = \begin{cases} a & \omega \in E \\ b & \omega \in E^c \end{cases}$

$$\text{and } \int_E Z dP = P(E)a = \int_E X dP = 1 \cdot P(\{HTT, THT, TTH\}) + 3 \cdot P(\{HHH\})$$

$$\Rightarrow a \cdot \frac{4}{8} = 1 \cdot \frac{3}{8} + 3 \cdot \frac{1}{8} \Rightarrow a = \frac{6}{4} = \frac{3}{2}$$

$$\text{Similarly } b \cdot \frac{4}{8} = 0 \cdot \frac{1}{8} + 2 \cdot \frac{3}{8} \Rightarrow b = \frac{6}{4} = \frac{3}{2}$$

$$\text{So } Z(\omega) = \frac{3}{2}.$$

For  $Z = E(X | Y)$ , we must have  $Z$  constant

on  $\{HHH\}$ ,  $\{HTT, THT, TTH\}$ , and  $\{TTT, TTH, HTH, HHT\}$

This gives

$$Z = \begin{cases} 3 & \omega \in \{HHH\} \\ 1 & \omega \in \{HTT, THT, TTH\} \\ \frac{3}{2} & \omega \in \{TTT, TTH, HTH, HHT\} \end{cases}$$

For  $Z = E(Y | X)$  we get

$$Z(\omega) = \begin{cases} 1 & \omega \in \{TTT\} \\ 0 & \omega \in \{HTT, THT, TTH\} \\ 1 & \omega \in \{TTH, HTH, HHT\} \\ 4 & \omega \in \{HHH\} \end{cases} = Y(\omega)$$

$$\text{Since } \int_{\{TTT\}} Z = Z(TTT) P(TTT) = \int_{\{TTT\}} Y = Y(\{TTT\}) P(TTT)$$

$$\int_{\{HTT, THT, TTH\}} Z = 0 \cdot P(HTT, \dots, TTH) = \int_{\{HTT, \dots, TTH\}} Y = 0$$

$$\int_{\{TTH, HTH, HHT\}} Z = 1 \cdot P(TTH, \dots, HHT) = \int_{\{TTH, \dots, HHT\}} Y = 1 \cdot P(TTH, \dots, HHT)$$