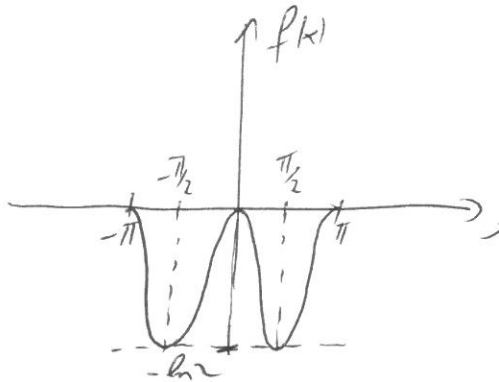


[1]

$$A_n = \int_{-\pi}^{\pi} 2^{-n \sin^2 x} dx = \int_{-\pi}^{\pi} e^{n f(x)} dx \quad \text{with } f(x) = -(\ln 2) \sin^2 x :$$



This f does NOT have a unique global maximum on $[a, b] = [-\pi, \pi]$,

so the Laplace method for almost Gaussian integrals does not

apply directly. However, $\sin^2 x = \frac{1 - \cos(2x)}{2}$ is

periodic by π , so

$$A_n = 2 \int_{-\pi/2}^{\pi/2} e^{n f(x)} dx \quad \text{with the same } f(x).$$

Now on $[a, b] = [-\frac{\pi}{2}, \frac{\pi}{2}]$ there is a unique global

maximum at $x_0 = 0$: $f(x) = -(\ln 2) \sin^2 x$

$$f'(x) = -2(\ln 2) \sin x \cos x = -(\ln 2) \sin(2x)$$

$$f''(x) = -2(\ln 2) \cos(2x)$$

$\Rightarrow A_n \sim f(x_0) = 0$, $f'(x_0) = 0$ as it should be,

$$B := -f''(x_0) = 2 \ln 2.$$

f is also twice differentiable on $[a, b] = [-\frac{\pi}{2}, \frac{\pi}{2}]$, so by the almost Gaussian approximation theorem

$$A_n = 2 \int_a^b e^{n f(x)} dx \sim 2 e^{n A} \sqrt{\frac{2\pi}{n B}} = \underline{\underline{2 \sqrt{\frac{2\pi}{n \ln 2}}}}$$

[2] If the probability space is $(\Omega, \mathcal{F}, \mathbb{P})$ and $Y = \sqrt{X}$, then

$$\mu = Y_* \mathbb{P}, \text{ so } \nu = f_* Y_* \mathbb{P} = (f \circ Y)_* \mathbb{P}.$$

With $g(x) = x^3$, the integral substitution theorem

says

$$\int_{\mathbb{R}} x^3 d\nu(x) = \int_{\mathbb{R}} g d\nu = \int_{\Omega} g \circ (f \circ Y) d\mathbb{P} = \int_{\Omega} \sqrt{X}^4 d\mathbb{P} =$$

$$= \int_{\Omega} X d\mathbb{P} = \mathbb{E}X = \frac{1+2+ \dots + 100}{100} = \underline{\underline{50.5}}$$

[3] With $h(x) = \sqrt{x}$, the integral substitution theorem says that

$$\int_{[0,1]} \sqrt{x} d\nu(x) = \int_{[0,1]} h d(g_* \mu) \stackrel{\substack{\downarrow \\ g'([0,1]) = [1,1] \\ \text{hag, let } h(g(x)) = \sqrt{x^2} = |x|}}{=} \int_{g'([0,1])} h \circ g d\mu$$

$$= \int_{[1,1]} |x| d\mu(x) \stackrel{d\mu(x) = e^{-x} dx}{=} \int_{[-1,1]} |x| e^{-x} dx \stackrel{2 = 2 \cdot 1}{=} \int_{-1}^1 |x| e^{-x} dx =$$

~~$$= \int_{-1}^0 -x e^{-x} dx + \int_0^1 x e^{-x} dx = \left[-x e^{-x} - e^{-x} \right]_{-1}^0 + \left[-x e^{-x} + e^{-x} \right]_0^1 = \left[1 - (-e) \right] - \left[\frac{1}{e} + 1 \right] = 2 - \frac{2}{e} \approx 1.2642$$~~

$$= \int_{-1}^0 -x e^{-x} dx + \int_0^1 x e^{-x} dx = \left[x e^{-x} + e^{-x} \right]_{-1}^0 - \left[x e^{-x} + e^{-x} \right]_0^1 =$$

$$= \left\{ 1 - (-e) \right\} - \left\{ \frac{1}{e} + 1 \right\} = \underline{\underline{2 - \frac{2}{e} \approx 1.2642}}$$

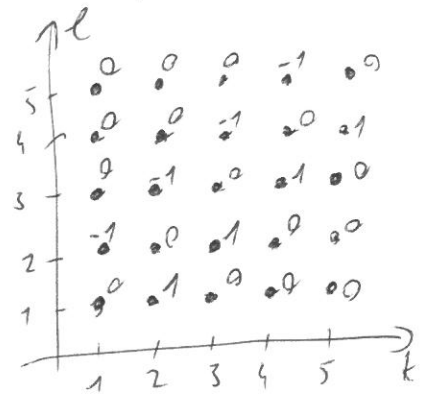
4 a.) This is TRUE by the (Fubini)-Tonelli theorem,

since $a_{k,e}^2 \geq 0$ always, so the sums (which are integrals w.r.t. counting measure) can be exchanged:

$$\sum_{k=1}^{\infty} \sum_{e=1}^{\infty} a_{k,e}^2 = \sum_{e=1}^{\infty} \sum_{k=1}^{\infty} a_{k,e}^2 \xrightarrow[\text{rename } k \leftrightarrow e]{=} \sum_{k=1}^{\infty} \sum_{e=1}^{\infty} a_{e,k}^2$$

b.) This is NOT true in general: for example

$$\text{let } a_{k,e} = \begin{cases} 1, & \text{if } k=e+1 \\ -1, & \text{if } e=k+1 \\ 0 & \text{otherwise} \end{cases}$$



Then $a_{k,e}^3 = a_{k,e}$; $a_{e,k} = -a_{k,e}$

$$\sum_{e=1}^{\infty} a_{k,e}^3 = \sum_{e=1}^{\infty} a_{k,e} = \begin{cases} -1, & \text{if } k=1 \\ 0, & \text{if not} \end{cases}$$

$$\Rightarrow \sum_{k=1}^{\infty} \sum_{e=1}^{\infty} a_{k,e}^3 = -1 \quad \text{and similarly } \sum_{k=1}^{\infty} \sum_{e=1}^{\infty} a_{e,k}^3 = +1$$

$$\xrightarrow[\text{rename } k \leftrightarrow e]{=} \sum_{k=1}^{\infty} \sum_{e=1}^{\infty} a_{e,k}^3 = +1$$



[5] NOT true: Let Y be any non-negative random variable with $EY^2 = A_0$, let $X_n = -\frac{1}{n}Y$ and $X \equiv 0$.

Then X_n is monotone increasing in n

• $X_n \rightarrow X$ strongly so $X_n \Rightarrow X$ as well

• but $E(X_n^2) = -A_0$ for every n

and $E(X^2) = 0$, so $E(X_n^2) \not\rightarrow E(X^2)$

Remark: The statement is true if we assume

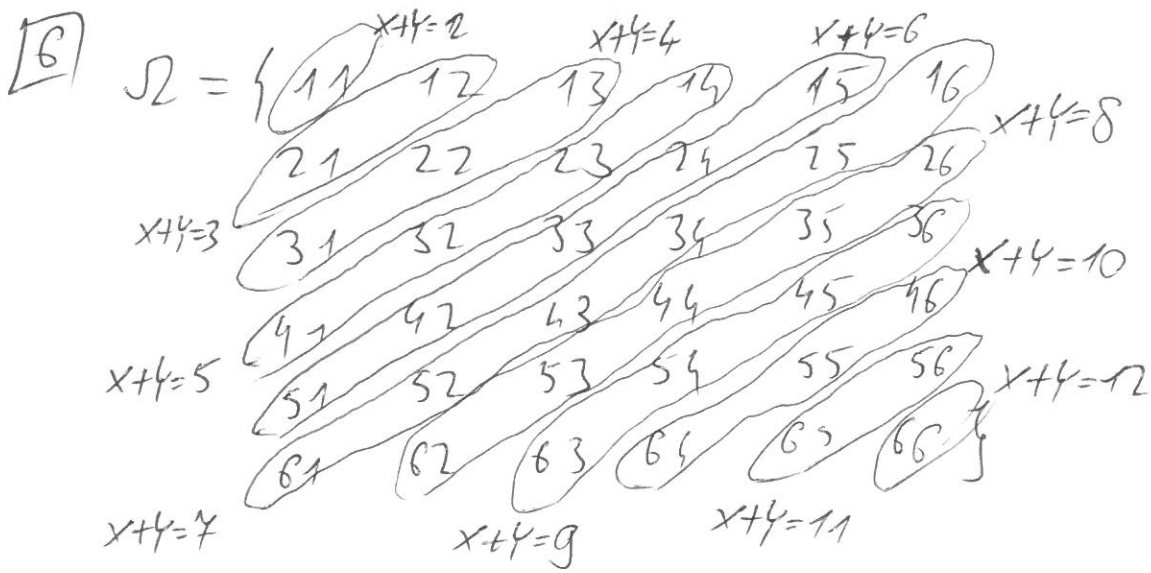
$X_n \geq 0$. Then $X_\infty = \lim_{n \rightarrow \infty} X_n$ exists surely

by monotonicity, and the monotone convergence

theorem ensures $E(X_n^2) \rightarrow E(X_\infty^2)$.

More over, $X_n \rightarrow X_\infty$ strongly implies $X_n \Rightarrow X_\infty$,

so $X_\infty \sim X$, so $E(X_\infty^2) = E(X^2)$



It's easy to see the conditional distribution of X under the condition $\{X+Y=k\}$ (which has positive probability if $k \in \{2, 3, 4, \dots, 12\}$):

k	2	3	4	5	6
conditional distribution of X assuming $x+y=k$	$X \equiv 1$	$\text{Uni}(\{1, 2\})$	$\text{Uni}(\{1, 2, 3\})$	$\text{Uni}(\{1, 2, 3, 4\})$	$\text{Uni}(\{1, \dots, 5\})$

	7	8	9	10	11	12
	$\text{Uni}(\{1, \dots, 6\})$	$\text{Uni}(\{2, \dots, 6\})$	$\text{Uni}(\{3, \dots, 6\})$	$\text{Uni}(\{4, 5, 6\})$	$\text{Uni}(\{5, 6\})$	$X \equiv 6$

\Rightarrow

k	2	3	4	5	6	7
$E(X^2 X+Y=k)$	1^2	$\frac{1^2+2^2}{2}$	$\frac{1^2+2^2+3^2}{3}$	$\frac{1^2+2^2+3^2+4^2}{4}$	$\frac{1^2+2^2+3^2+4^2+5^2}{5}$	$\frac{1^2+\dots+6^2}{6}$

$E(X^2 | G)$ on the set

$\{X+Y=k\}$	8	9	10	11	12
	$\frac{2^2+\dots+6^2}{5}$	$\frac{3^2+4^2+5^2+6^2}{4}$	$\frac{4^2+5^2+6^2}{3}$	$\frac{5^2+6^2}{2}$	6^2

[6] continued

For those, who like formulas:

$$E(X^2|g) = \begin{cases} \frac{\int_{e=1}^{x+y-1} e^2}{x+y-1}, & \text{if } 2 \leq x+y \leq 7 \\ \frac{\int_{e=x+y-6}^6 e^2}{13-(x+y)}, & \text{if } 7 \leq x+y \leq 12 \end{cases}$$
$$= \begin{cases} \frac{(x+y-1)(x+y)(2(x+y)-1)}{6(x+y-1)}, & \text{if } 2 \leq x+y \leq 7 \\ \frac{91 - (x+y-8)(x+y-6) \frac{(2(x+y)-13)}{(x+y-13)}}{6(13-(x+y))}, & \text{if } 7 \leq x+y \leq 12 \end{cases}$$

[7] U and V have joint density $f(x,y) = 3x^2$ on $[0,1] \times [0,1]$

\Rightarrow U has density $f_1(x) = 3x^2$ on $[0,1]$

V has density $f_2(y) = 1$ on $[0,1]$: $Y \sim \text{Unif}([0,1])$

and they are independent

$$\Rightarrow E(V^2|U) = E(V^2) = \int_0^1 y^2 dy = \underline{\underline{\frac{1}{3}}}$$

[8] Let $U = Y + Z$, so

$$\text{Cov}(X, U) = \text{Cov}(X, Y + Z) = \text{Cov}(X, Y) + \text{Cov}(X, Z) = \frac{1}{3} + 0 = \frac{1}{3}.$$

~~Then $\text{Cov}(U, X - \lambda U) = \text{Cov}(U, X) - \lambda$~~

$$\text{and } \text{Cov}(U, U) = \text{Cov}(Y + Z, Y + Z) = \text{Var } Y + 2\text{Cov}(Y, Z) + \text{Var } Z = 1 + 0 + 1 = 2.$$

Then for any $\lambda \in \mathbb{R}$

$$\text{Cov}(U, X - \lambda U) = \text{Cov}(U, X) - \lambda \text{Cov}(U, U) = \frac{1}{3} - \lambda \cdot 2.$$

So if we choose $\lambda = \frac{1}{6}$, then $\text{Cov}(U, X - \lambda U) = \text{Cov}(U, X - \frac{U}{6}) = 0$

and they are jointly Gaussian \Rightarrow INDEPENDENT

$$\Rightarrow \boxed{\mathbb{E}(X | U) = \mathbb{E}\left(X - \frac{U}{6} + \frac{U}{6} \mid U\right) = \underbrace{\mathbb{E}\left(X - \frac{U}{6} \mid U\right)}_{\parallel \text{independence}} + \mathbb{E}\left(\frac{U}{6} \mid U\right) = \mathbb{E}\left(X - \frac{U}{6}\right) + \frac{U}{6} \parallel \frac{U}{6} \in \sigma(U)$$

$$= \underbrace{\mathbb{E}\left(X - \frac{U}{6}\right)}_0 + \frac{U}{6} = \underbrace{\mathbb{E}X}_0 - \frac{1}{6} \underbrace{\mathbb{E}U}_0 + \frac{U}{6} = \frac{U}{6}$$