

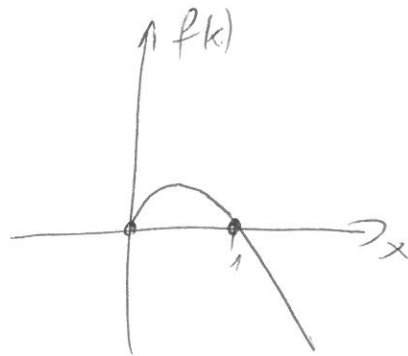
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$$A_n = \int_0^1 x^{-nx} dx = \int_0^1 e^{-nx \ln x} dx = \int_0^1 e^{n f(x)} dx$$

where $f(x) = -x \ln x$

$$f'(x) = -\ln x - 1$$

$$f''(x) = -\frac{1}{x}$$



The maximum of f is at $0 = f'(x) = -\ln x - 1$

so $x = e^{-1}$

the 2nd derivative at the maximum is

$$-B := f''(e^{-1}) = -\frac{1}{e^{-1}} = -e < 0, \text{ so it is indeed a maximum}$$

The value at the maximum is

$$A := f(e^{-1}) = -e^{-1} \ln(e^{-1}) = e^{-1}$$

f is twice differentiable* on $[0, 1]$ with a unique global maximum at $x_0 = e^{-1}$, so by the almost Gaussian approximation theorem

$$\underline{\underline{I_n = \int_0^1 e^{n f(x)} dx \sim e^{nA} \sqrt{\frac{2\pi}{nB}} = e^{n/e} \sqrt{\frac{2\pi}{ne}}}}$$

[* Remark: Actually f is not differentiable at 0, only on $(0, 1]$, but this is not a problem - see the remarks to the theorem.]

[2] Let $Y = X_1 X_2 \dots X_{10}$. Since μ is the distribution of Y ,

$$\int x^3 d\mu(x) = \mathbb{E}(Y^3) = \mathbb{E}(X_1^3 X_2^3 \dots X_{10}^3) \quad \begin{array}{l} X_1, \dots, X_{10} \text{ are} \\ \text{independent} \end{array}$$

$$= \mathbb{E}(X_1^3) \mathbb{E}(X_2^3) \dots \mathbb{E}(X_{10}^3) \quad \underline{\underline{X_i \sim \text{Uni}[0,1]}}$$

$$= \left[\int_0^1 x^3 dx \right]^{10} = \left(\left[\frac{x^4}{4} \right]_0^1 \right)^{10} = \left(\frac{1}{4} \right)^{10} = \underline{\underline{\frac{1}{2^{20}}}}$$

[3] $dV = g d\mu$, so

$$V(\Sigma_{0,1}) = \int_0^1 1 dV = \int_0^1 1 \cdot g(\eta) d\mu(\eta) \quad \begin{array}{l} \mu = \frac{1}{2} \lambda \\ \uparrow \\ \text{integral substitution} \\ \text{theorem} \end{array} \int_{f^{-1}(\Sigma_{0,1})} g \circ f d\lambda =$$

use the density

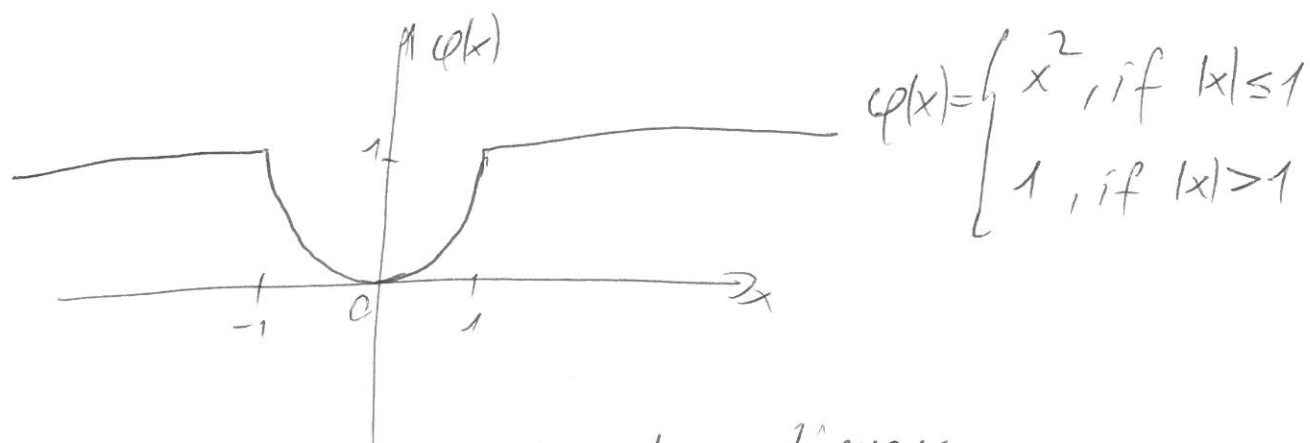
but $f^{-1}(\Sigma_{0,1}) = \Sigma_{0,1}$

$$= \int_0^1 (\sqrt{x})^2 dx = \int_0^1 x dx = \underline{\underline{\frac{1}{2}}}$$

[4] Proof:

Since X_n and X are all bounded by 1,

we have $X_n^2 = \varphi(X_n)$ and $X^2 = \varphi(X)$ where



So φ is bounded and continuous

\Rightarrow the definition of weak convergence implies

$$\begin{array}{ccc} E\varphi(X_n) & \xrightarrow{n \rightarrow \infty} & E\varphi(X) \\ \parallel & & \parallel \\ E(X_n^2) & & E(X^2) \quad \square \end{array}$$

[5] $f_k \geq 0$, so the sequence S_n is monotone increasing

and non-negative and $S_n \rightarrow S$ by the definition of the infinite sum, so the monotone convergence

theorem implies $\int_{\mathbb{R}} S_n d\mu \xrightarrow{n \rightarrow \infty} \int_{\mathbb{R}} S d\mu \quad \square$

[6]

a.) Y is a function of X , so it is $\sigma(X)$ -measurable

$$\Rightarrow \mathbb{E}(Y|X) = \mathbb{E}(Y|\sigma(X)) = \underline{\underline{Y}}$$

b.) Y only takes 2 values, so $\sigma(Y)$ consists of only 2 atoms:

$$\mathcal{G} := \sigma(Y) = \{ \emptyset, \{Y=0\}, \{Y=1\}, \Omega \} = \{ \emptyset, \underbrace{[0,1]}_A, \underbrace{(1,\infty)}_B, \Omega \}$$

A and B have positive probability, so the conditional expectation w.r.t. \mathcal{G} takes the values of the ordinary conditional expectation w.r.t. an event:

$$\mathbb{E}(X|\mathcal{G})|_A = \mathbb{E}(X|A) = \frac{\int_A X dP}{P(A)} = \frac{\int_0^1 w e^{-w} dw}{\int_0^1 1 \cdot e^{-w} dw} =$$

$$= \frac{[-(w+1)e^{-w}]_0^1}{[-e^{-w}]_0^1} = \frac{1-2e^{-1}}{1-e^{-1}} = \frac{e-2}{e-1}$$

$$\mathbb{E}(X|\mathcal{G})|_B = \mathbb{E}(X|B) = \frac{\int_B X dP}{P(B)} = \frac{\int_1^{\infty} w e^{-w} dw}{\int_1^{\infty} 1 \cdot e^{-w} dw} = \frac{[-(w+1)e^{-w}]_1^{\infty}}{[-e^{-w}]_1^{\infty}} = \frac{2e^{-1}}{e^{-1}} = 2$$

$$\Rightarrow \boxed{\mathbb{E}(X|Y)(w) = \begin{cases} \frac{e-2}{e-1} & \text{if } w \leq 1 \\ 2 & \text{if } w > 1 \end{cases}} \quad \boxed{\mathbb{E}(X|Y) = \begin{cases} \frac{e-2}{e-1} & \text{if } Y=0 \\ 2 & \text{if } Y=1 \end{cases}}$$

[7]

$\mathcal{F}_0 = \sigma(\emptyset) = \{\emptyset, \Omega\}$ is the indiscrete σ -algebra,

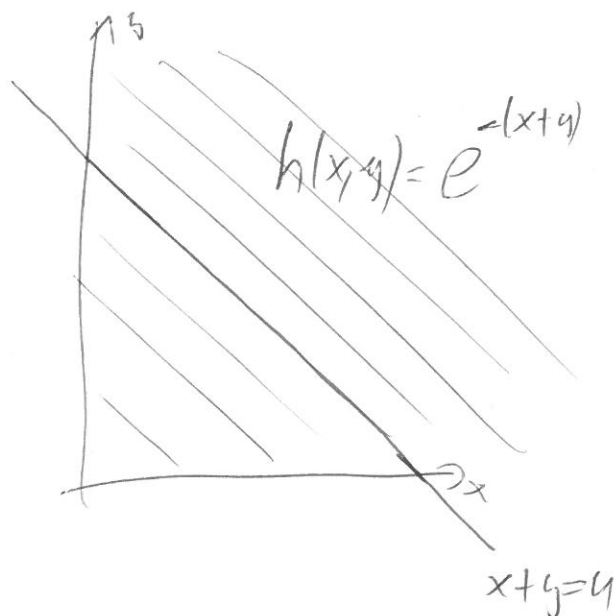
$$\text{so } E(Y | \mathcal{F}_0) = EY = EX_1 + \dots + EX_4 = 4 \cdot \frac{7}{2} = 14$$

is a number, so of course all further conditional expectations leave it unchanged:

$$\text{Answer} = E(E(E(E(14 | \mathcal{F}_1) | \mathcal{F}_2) | \mathcal{F}_3) | \mathcal{F}_4)) = \underline{\underline{14}}$$

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Solution 1: The joint density $h(x,y) := e^{-x} \cdot e^{-y}$ is constant on level lines of $x+y$:



So under the condition $\{x+y=u\}$, X is uniform on $[0, u]$:

$$E(X^2 | x+y) \Big|_{x+y=u} = \int_0^u \frac{1}{u} t^2 dt = \frac{1}{u} \left[\frac{t^3}{3} \right]_0^u = \frac{u^2}{3}$$

$$\Rightarrow E(X^2 | x+y) = \frac{(x+y)^2}{3}$$

Solution 2: We have seen in class that $U := X+Y$

and $V := \frac{X}{X+Y}$ are independent and V has a Beta distribution, which happens to be $\text{Uni}[0,1]$ in this case. So

$$\boxed{E(X^2 | U) = E((VU)^2 | U) = E(U^2 V^2 | U) \stackrel{U^2 \in \sigma(U)}{=} U^2 E(V^2 | U) = U^2 E(V^2) = U^2 \int_0^1 t^2 dt = \frac{U^2}{3}}$$

independence