

Propn Let (X, \mathcal{A}, μ) be a measure space.

Let $f: X \rightarrow [0, \infty]$ be mble.

$$\text{Then } \int_X f d\mu = \int_0^\infty \mu(f > y) dy.$$

One "proof":

$$\begin{aligned} \int_X f d\mu &= \int_X \int_0^\infty 1_{[0, f(x))}(y) dy d\mu(x) \\ &= \int_0^\infty \int_X 1_{[0, f(x))}(y) d\mu(x) dy && (\text{provided } \mu \text{ is } \sigma\text{-finite}) \\ &= \int_0^\infty \int_X 1_{\{f(x) > y\}} d\mu(x) dy \\ &= \int_0^\infty \mu(f > y) dy. \end{aligned}$$

Another proof: ① Suppose f is simple. Let y_1, \dots, y_n be the distinct elements of $f[X]$. Let $A_k = \{f = y_k\}$ for $k = 1, \dots, n$.

Then $X = \bigcup_{k=1}^n A_k$. So

$$\begin{aligned} \int_0^\infty \mu(f > y) dy &= \int_0^\infty \mu(\{f > y\} \cap \bigcup_{k=1}^n A_k) dy \\ &= \int_0^\infty \mu\left(\bigcup_{k=1}^n (\{f > y\} \cap A_k)\right) dy \\ &= \int_0^\infty \sum_{k=1}^n \mu(\{f > y\} \cap A_k) dy \\ &\stackrel{(*)}{\leq} \int_0^\infty \mu(\{f > y\}) dy. \end{aligned}$$

$$= \sum_{k=1}^n \int_0^{\infty} \mu(\{f > y\} \cap A_k) dy$$

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On A_k , $f = y_k$.

So $\{f > y\} \cap A_k = A_k$ if $y < y_k$
and $\{f > y\} \cap A_k = \emptyset$ if $y \geq y_k$

$$= \sum_{k=1}^n \int_0^{y_k} \mu(A_k) dy$$

$$= \sum_{k=1}^n y_k \mu(A_k)$$

$$= \int f d\mu$$

② now consider any mble $f: X \rightarrow [0, \infty]$.

Then there is an increasing sequence (f_n) of simple functions $f_n: X \rightarrow [0, \infty)$ s.t. $f_n \uparrow f$ pointwise.

Then $\forall y \in [0, \infty)$, $\{f_n > y\} \uparrow \{f > y\}$, so
 $\mu(f_n > y) \uparrow \mu(f > y)$. Hence

$$\begin{aligned} \int f d\mu &= \lim_{n \rightarrow \infty} \int f_n d\mu \stackrel{①}{=} \lim_{n \rightarrow \infty} \int_0^{\infty} \mu(f_n > y) dy \\ &\stackrel{\text{MCT}}{=} \int_0^{\infty} \mu(f > y) dy. \end{aligned}$$

□

Corollary Let (Ω, \mathcal{F}, P) be a probability space, and let

$Z: \Omega \rightarrow [0, \infty]$ be a RV.

$$\text{Then } E(Z) = \int_0^{\infty} P(Z > z) dz.$$

Sums of independent Normal RVs

Let X and Y be standard normal RVs. This means that

$$\text{for each borel set } A \subseteq \mathbb{R}, \quad P(X \in A) = \int_A c e^{-x^2/2} dx$$

$$\text{and } P(Y \in A) = \int_A c e^{-y^2/2} dy,$$

where c is chosen so that $P(X \in \mathbb{R}) = 1$.

$$\left(\begin{array}{l} \text{We say } X \text{ has density } \varphi \text{ where } \varphi(x) = c e^{-x^2/2}. \\ \text{likewise } Y \text{ has density } \varphi. \end{array} \right)$$

Suppose in addition that X and Y are independent.

$$\text{Then } (X, Y) \text{ has density } \varphi(x, y) = \varphi(x) \varphi(y) = c^2 e^{-(x^2+y^2)/2} \quad (*)$$

More detail about (*): $\forall A, B \in \text{Borel}(\mathbb{R}),$

$$P((X, Y) \in (A, B)) = P(X \in A, Y \in B) = P(X \in A) P(Y \in B) \text{ because } X \text{ \& } Y \text{ are indep.}$$

define μ and ν on $\text{Borel}(\mathbb{R}^2)$ by

$$\mu(C) = P((X, Y) \in C) \quad \text{and} \quad \nu(C) = \iint_C \varphi(x, y) dx dy.$$

$$\text{Then } \mu(A \times B) = P(X \in A) P(Y \in B) = \left(\int_A \varphi(x) dx \right) \left(\int_B \varphi(y) dy \right)$$

$\uparrow \uparrow$
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$$\begin{aligned} \mu(A \times B) &= \mu(\{(x,y) \in \mathbb{R}^2 : x \in A, y \in B\}) = \left(\int_A \varphi(x) dx \right) \left(\int_B \varphi(y) dy \right) \\ &= \iint_{B \times A} \varphi(x) \varphi(y) dx dy = \iint_C \varphi(x,y) dx dy = \nu(A \times B). \end{aligned}$$

In particular, $\mu(\mathbb{R}^2) = \nu(\mathbb{R}^2) = 1 < \infty$.

So by the π - λ theorem, $\mu = \nu$.

$$\text{So } P((X,Y) \in C) = \iint_C \varphi(x,y) dx dy \quad \forall C \in \text{Borel}(\mathbb{R}^2).$$

Let's determine C . We know φ is a probability measure on \mathbb{R}^2 . Thus

$$\begin{aligned} 1 &= \iint_{\mathbb{R}^2} c^2 e^{-(x^2+y^2)/2} dx dy = \int_0^{2\pi} \int_0^\infty c^2 e^{-r^2/2} r dr d\theta \\ &= 2\pi c^2 \int_0^\infty e^{-u} du = 2\pi c^2 \end{aligned}$$

$$\text{So } c = \frac{1}{\sqrt{2\pi}} \text{ and thus } \varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}.$$

Clearly $E(X) = 0 = E(Y)$.

Let's find $\text{var}(X)$ and $\text{var}(Y)$.

$$\text{Let } R = (X^2 + Y^2)^{1/2} \quad \forall t \geq 0,$$

$$P(R^2 > t) = P(R > \sqrt{t})$$

$$= P((X, Y) \text{ lies outside the circle of radius } \sqrt{t} \text{ centered at the origin}).$$

$$= \iint_{|(x,y)| > \sqrt{t}} \psi(x,y) dx dy$$

$$= \int_0^{2\pi} \int_{\sqrt{t}}^{\infty} \frac{1}{2\pi} e^{-r^2/2} r dr d\theta$$

$$= \int_{t/2}^{\infty} e^{-u} du$$

$$= e^{-t/2}.$$

So R^2 has an exponential distribution

with parameter $1/2$.

$$E(R^2) = \int_0^{\infty} P(R^2 > t) dt = \int_0^{\infty} e^{-t/2} dt = 2.$$

So, since $R^2 = X^2 + Y^2$ and X & Y have same distribution,

$$E(X^2) = \frac{1}{2} E(R^2) = 1.$$

$$\text{So } \text{Var}(X^2) = E(X^2) - (E(X))^2 = 1.$$

$$\text{Similarly, } \text{Var}(Y^2) = 1.$$

Now since Ψ , the density of (X, Y) , is constant on each circle centered at the origin, and since rotations preserve area, if (X_θ, Y_θ) is the random point obtained by rotating (X, Y) about the origin through an angle θ , then (X_θ, Y_θ) has the same law (prob. distribution) as (X, Y) :

$$P((X_\theta, Y_\theta) \in C) = P((X, Y) \in C) \quad \text{for each } C \in \mathcal{B}(\mathbb{R}^2).$$

$$(X, Y) = X e_1 + Y e_2, \quad \text{where } e_1 = (1, 0) \text{ and } e_2 = (0, 1).$$

A rotation through an angle θ about the origin maps

$$e_1 \quad \text{to} \quad u_1 = (\cos \theta, \sin \theta)$$

$$e_2 \quad \text{to} \quad u_2 = (-\sin \theta, \cos \theta).$$

$$(X_\theta, Y_\theta) = X u_1 + Y u_2.$$

$$\text{Hence } X_\theta = X \cos \theta - Y \sin \theta$$

Thus for each $\theta \in \mathbb{R}$, $X \cos \theta - Y \sin \theta$ is also standard normal.

Now for any $\alpha, \beta \in \mathbb{R}$ with $\alpha^2 + \beta^2 = 1$, $\exists \theta \in \mathbb{R}$

$$\text{s.t. } (\alpha, \beta) = (\cos \theta, -\sin \theta).$$

So $\alpha X + \beta Y$ is standard normal.

Now suppose X is normal w/ mean μ and variance σ^2 ,

Now suppose X is normal w/ mean μ and variance a ,
and Y is normal with mean ν and variance b .

$$\text{Let } U = \frac{X - \mu}{\sqrt{a}}. \quad \text{Let } V = \frac{Y - \nu}{\sqrt{b}}.$$

Suppose X and Y are independent.

Then U and V are independent standard normal RVs.

$$\text{Let } \alpha = \sqrt{\frac{a}{a+b}} \quad \text{and} \quad \beta = \sqrt{\frac{b}{a+b}}. \quad \alpha^2 + \beta^2 = 1.$$

So $\alpha U + \beta V$ is standard normal. In other words,

$$\frac{(X - \mu) + (Y - \nu)}{\sqrt{a+b}} = \frac{(X + Y) - (\mu + \nu)}{\sqrt{a+b}} \quad \text{is standard normal.}$$

So $X + Y$ is normal with mean $\mu + \nu$
and variance $a + b$.

Lemma $\log(1+t) = t - \frac{t^2}{2} + R(t)$

$$\text{where } |R(t)| \leq |t|^3 \quad \text{for } -\frac{2}{3} \leq t < \infty.$$

pf: $\frac{1-u^2}{1+u} = 1-u \quad \text{for } u \neq -1.$

$$\text{Hence } \frac{1}{1+u} = 1-u + \frac{u^2}{1+u} \quad \text{for } u \neq -1.$$

$$\text{hence for } t > -1, \quad \log(1+t) = t - \frac{t^2}{2} + R(t)$$

hence for $t > -1$, $\log(1+t) = t - \frac{t^2}{2} + R(t)$

$$\text{where } R(t) = \int_0^t \frac{u^2}{1+u} du.$$

For $0 \leq t < \infty$, we have $0 \leq R(t) \leq \int_0^t u^2 du = \frac{t^3}{3}$.

For $-\frac{2}{3} \leq t \leq u \leq 0$, we have $\frac{1}{3} = 1 - \frac{2}{3} \leq 1+u$,

$$\text{so } 0 \leq \frac{u^2}{1+u} \leq 3u^2, \text{ so } 0 \leq \int_t^0 \frac{u^2}{1+u} du \leq \int_t^0 3u^2 du = -t^3 = |t|^3.$$

$$\text{So } |R(t)| \leq |t|^3.$$

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