

Lebesgue Decomposition

$(X, \mathcal{A}, \lambda)$ measure space

\mathbb{R} $\mathcal{B}(\mathbb{R})$ (Lebesgue measure) ($\lambda([a,b]) = b-a$)

Another measure $\mu: \mathcal{B}(\mathbb{R}) \rightarrow [0, \infty]$

Def: (a) μ is called absolutely continuous

if $\lambda(A) = 0 \Rightarrow \mu(A) = 0$

for all $A \in \mathcal{B}(\mathbb{R})$. $\mu \ll \lambda$

(b) μ is called singular (w.r.t. λ)

if there is $N \in \mathcal{B}(\mathbb{R})$ with $\lambda(N) = 0$

and $\mu(N^c) = 0$ $\mu \perp \lambda$.

Example: δ_0 Dirac measure ($\delta_0(\{0\}) = 1$)

$N = \{0\}$, $N^c = \mathbb{R} \setminus \{0\}$. $\lambda(N) = 0$.

$\delta_0(\mathbb{R} \setminus \{0\}) = 0$. $\delta_0 \perp \lambda$

Theorem (Decomposition by Lebesgue)

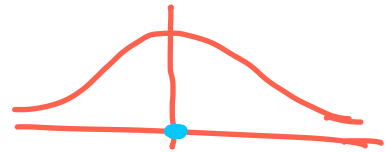
μ, γ prob. measures on (Ω, \mathcal{A}) . Then there exists a unique decomposition

$$\gamma = \gamma_{ac} + \gamma_s \text{ such that}$$

$$\gamma_{ac} \ll \mu \text{ and } \gamma_s \perp \mu.$$

Example: $\gamma = \frac{1}{2} (N(0,1), \delta_0)$

$$\gamma = \gamma_{ac} + \gamma_s$$



where $\gamma_{ac} = \frac{1}{2} N(0,1)$, $\gamma_s = \frac{1}{2} \delta_0$

Cantor distribution: non-trivial distribution that is singular w.r.t. λ .

Construct the Cantor set:

- Start with $C_0 := [0, 1]$

"remove middle part"



- $C_1 := [0, 1/3] \cup [2/3, 1]$

"remove middle part from all intervals"



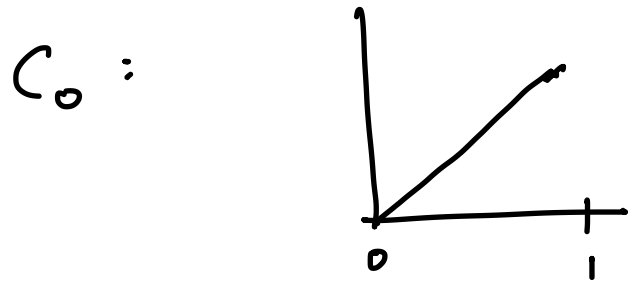
• $C_2 :=$
 \vdots



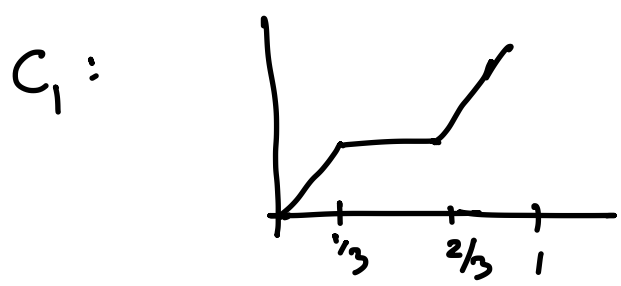
The Cantor set is the limit in this process.

Now construct a prob. distribution:

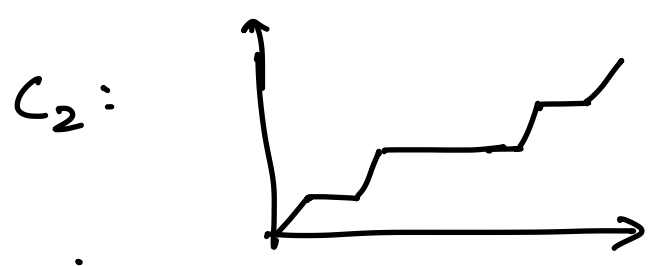
Consider the CDFs of the sets C_0, C_1, C_2, \dots



uniform on $[0, 1]$



uniform on $[0, 1/3] \cup [2/3, 1]$



\vdots

Take limit $\rightarrow T$. Can prove many interesting properties:

- Cantor set is compact, non-empty, empty interior.
 only boundary points.

• The cdf of T is continuous. T is a prob. measure.

• But: $\lambda(C) = 0$

$\Rightarrow \lambda \perp T$

Cumulative Distribution Function

Let P be a probability measure on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$. Define the function

$$F: \mathbb{R} \rightarrow \mathbb{R}, \quad x \mapsto P((-\infty, x])$$

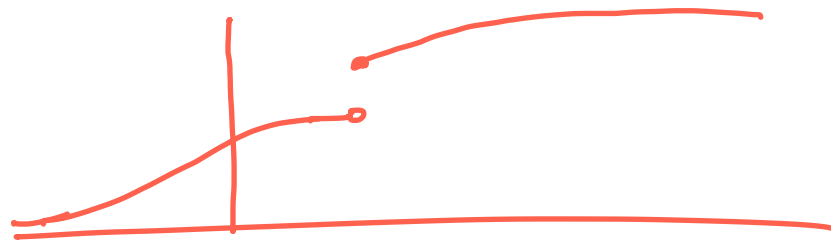
We say that F is a cumulative distribution function (cdf), that satisfies the following properties:

(i) F is monotonically increasing,

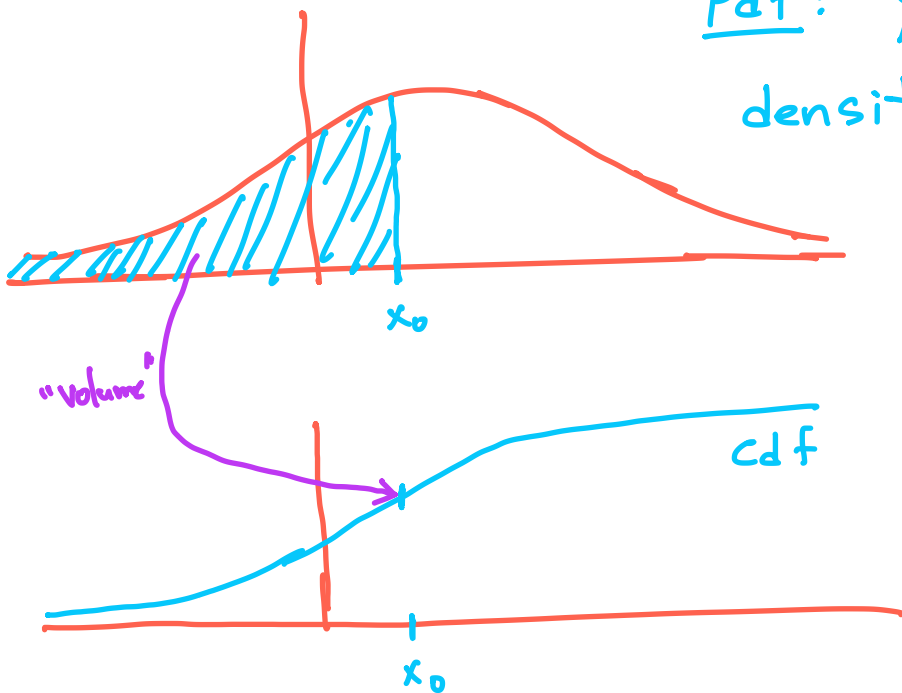
$$\lim_{x \rightarrow -\infty} F(x) = 0, \quad \lim_{x \rightarrow \infty} F(x) = 1$$

(ii) F is continuous from the right:

$(x_n)_{n \in \mathbb{N}}$ sequence with $x_n \searrow x$
(i.e. $x_n \geq x_{n+1}$ and $x_n \rightarrow x$) then also
 $F(x_n) \rightarrow F(x)$



Pdf: prob. density func.
density of normal dist.



Let $F: \mathbb{R} \rightarrow \mathbb{R}$ be a function with properties (i) and (ii). Then there exists a unique probability measure P on $(\mathbb{R}, \mathcal{B}(\mathbb{R}))$ such that $P((-\infty, x]) := F(x)$.

Remark: We can go both ways. Given a PDF construct CDF & given a CDF we can construct a unique PDF.

Random Variable

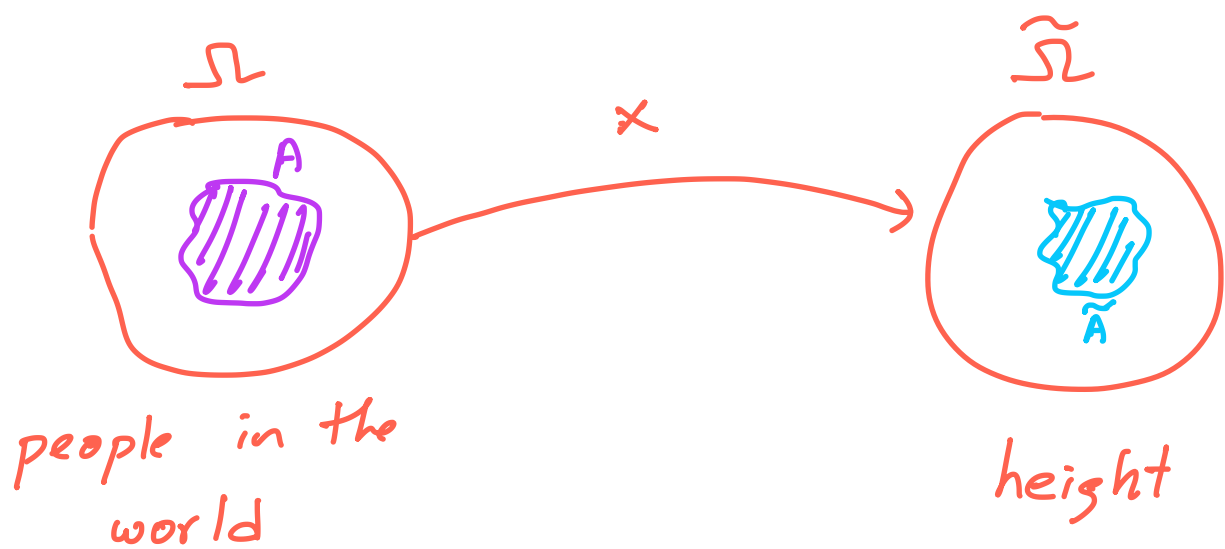
Def: Let (Ω, \mathcal{A}, P) be a probability space,

$(\tilde{\Omega}, \tilde{\mathcal{A}})$ be another measurable space.

A mapping $X: \Omega \rightarrow \tilde{\Omega}$ is called a

random variable if X is measurable, i.e.

$$\forall \tilde{A} \in \tilde{\mathcal{A}}: X^{-1}(\tilde{A}) := \{\omega \in \Omega \mid X(\omega) \in \tilde{A}\} \in \mathcal{A}.$$



$A =$ "people that are at least 6ft"

$$P(A) = 0.1$$

$\tilde{A} =$ "at least 6ft"

Example: sum of two dice.

$$\Omega = \{ (i, j) \mid i, j \in \{1, 2, \dots, 6\} \}$$

$$\mathcal{A} = \mathcal{P}(\Omega)$$

$$\tilde{\Omega} = \{2, 3, \dots, 12\}$$

$$P(\{(i, i)\}) = \frac{1}{36}$$

$$\tilde{\mathcal{A}} = \mathcal{P}(\tilde{\Omega})$$

X "sum of the two dice"

$$X: \Omega \rightarrow \{2, 3, \dots, 12\}, \quad (i, j) \rightarrow i+j$$

Is measurable.

Def: A random variable $X: \Omega \rightarrow \tilde{\Omega}$ induces a measure on the target space:

For $\tilde{A} \in \tilde{\mathcal{A}}$ we define

$$P_X(\tilde{A}) := P(X^{-1}\{\tilde{A}\})$$

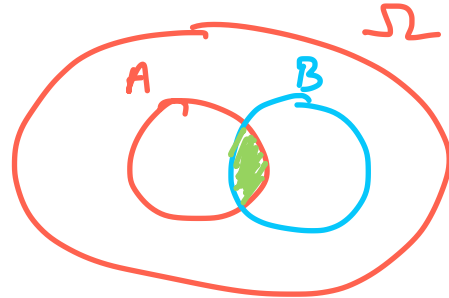
This is a probability measure on $(\tilde{\Omega}, \tilde{\mathcal{A}})$ and it is called the distribution of X.

Def: $X: (\Omega, \mathcal{A}, P) \rightarrow (\tilde{\Omega}, \tilde{\mathcal{A}})$. Then the family $\sigma(X) := \{ X^{-1}(\tilde{A}) \mid \tilde{A} \in \tilde{\mathcal{A}} \}$ is a σ -algebra on Ω and it is called the σ -algebra induced by X .

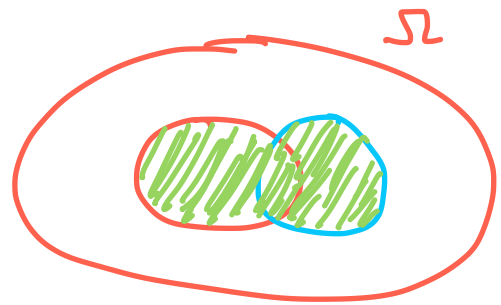
(it is the smallest σ -algebra on Ω that makes X measurable)

Conditional Probabilities

Notation: $P(A \cap B) = P(\text{"A and B"})$



$P(A \cup B) = P(\text{"A or B"})$



Def: Let (Ω, \mathcal{A}, P) be a probability space.

$A, B \in \mathcal{A}$, $P(B) > 0$. Then

$P(A|B) := \frac{P(A \cap B)}{P(B)}$ is called

the conditional probability of

A given B.

Theorem: The mapping $P_B : \mathcal{A} \rightarrow [0,1]$,

$A \mapsto P(A|B)$ is a probability measure on (Ω, \mathcal{A}) , it is called the conditional distribution of P with respect to B .

Examples: ① two dice

$$P(\text{"sum is 9"} \mid \text{"first die was 3"})$$

② $\Omega =$ all persons on earth

$$\mathcal{A} = \mathcal{P}(\Omega)$$

$$P = \text{"uniform"}$$

Event A : "person has been vaccinated"

B : "person has disease"

$$\left\{ \begin{array}{l} P(\text{disease} \mid \text{vaccinated}) \rightarrow \text{all person} \\ P(\text{vaccinated} \mid \text{disease}) \end{array} \right.$$

Diagram illustrating the relationship between events A and B:

- A red oval labeled "all person" contains two sub-ovals: "not vacc." and "vacc."
- A purple oval labeled "dis" contains two sub-ovals: "no dis" and "dis".