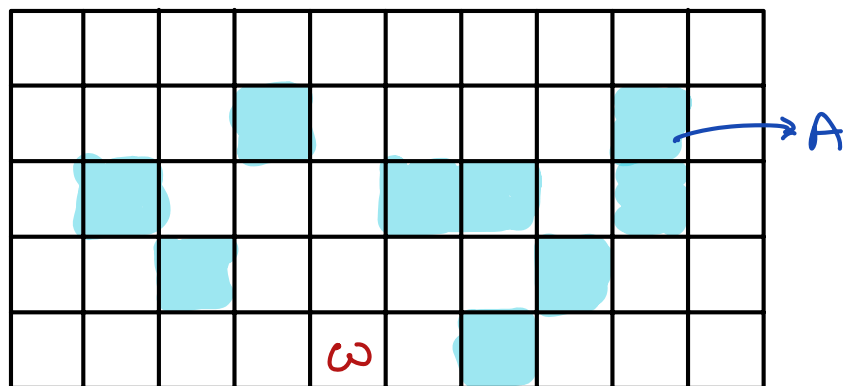


Probability over uncountably infinite spaces

Discrete Case



Ω "outcome space"

$$v: \Omega \rightarrow [0, 1] \quad \sum v(\omega) = 1$$

Event: $A \subseteq \Omega$

$$P[A] = \sum_{\omega \in A} v(\omega)$$

Uncountably infinite case



$$v: \Omega \rightarrow [0, 1] \quad (\text{say})$$

$$S_n = \left\{ x \mid v(x) \geq \frac{1}{n} \right\} \subseteq \Omega$$

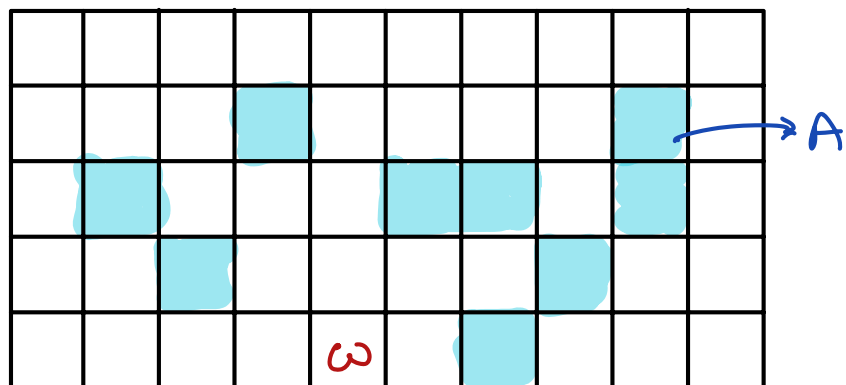
$$v(x) > 0 \Leftrightarrow x \in \bigcup_n S_n$$

$$\frac{1}{n} \cdot |S_n| \leq \sum_{x \in S_n} v(x) \leq 1$$

$$|S_n| \leq n$$

Probability over uncountably infinite spaces

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~~$$v: \Omega \rightarrow [0, 1]$$~~

~~$$P[A] = \sum_{\omega \in A} v(\omega)$$~~

- Cannot define $v: \Omega \rightarrow [0, 1]$

- Only define $P[A]$ for "allowed events" A

Collections of "allowed events": σ -algebras (σ -fields)

► A collection $\mathcal{F}$ of subsets of Ω is a σ -algebra "if

- $\emptyset \in \mathcal{F}$
- $A \in \mathcal{F} \Rightarrow A^c \in \mathcal{F}$
- $A_1, A_2 \in \mathcal{F} \Rightarrow A_1 \cup A_2 \in \mathcal{F}$

(for countable sequence $A_1, A_2, \dots \in \mathcal{F} \Rightarrow A_1 \cup A_2 \cup \dots \in \mathcal{F}$)

Ex: $A_1, A_2 \in \mathcal{F} \Rightarrow A_1 \cap A_2 \in \mathcal{F}$

Collections of "allowed events": σ -algebras (σ -fields)

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Prob. Space: $(\Omega, \mathcal{F}, \mu)$

(for countable sequence $A_1, A_2, \dots \in \mathcal{F} \Rightarrow A_1 \cup A_2 \dots \in \mathcal{F}$)

Ex: $A_1, A_2 \in \mathcal{F} \Rightarrow A_1 \cap A_2 \in \mathcal{F}$

► Given σ -algebra $\mathcal{F}$, $\nu: \mathcal{F} \rightarrow [0,1]$ is a probability measure if

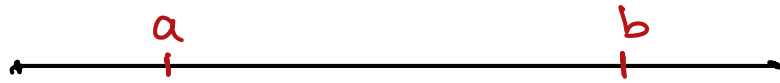
- $\nu(\emptyset) = 0 = 1 - \nu(\Omega)$

- $\nu(A^c) = 1 - \nu(A)$

- For disjoint $A_1, A_2, \dots \in \mathcal{F}$, $\nu[A_1 \cup A_2 \dots] = \sum_i \nu(A_i)$

Defining the "uniform distribution" over $[0,1]$

$[a,b] \subseteq \Omega$. Would like



$$\Omega = [0,1]$$

$$\nu([a,b]) = b - a$$

- σ -algebra must include all intervals $[a,b]$

(Borel σ -algebra, also over $\mathbb{R}$)

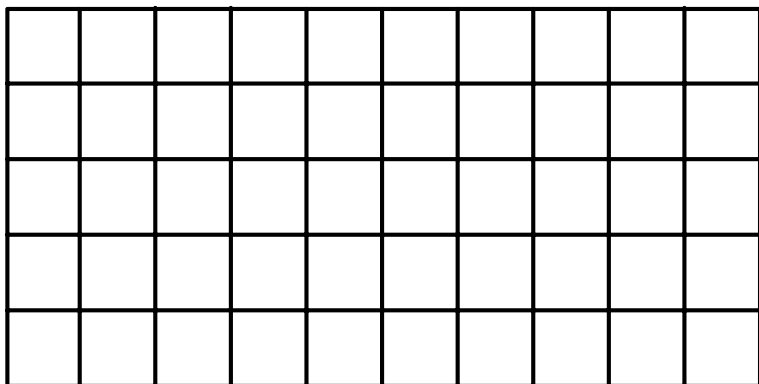
- $\nu: \mathcal{F} \rightarrow [0,1]$ must satisfy $\nu([a,b]) = b - a$

(Lebesgue measure)

- Also extends to $[0,1]^d$ ($\mathbb{R}^d$)

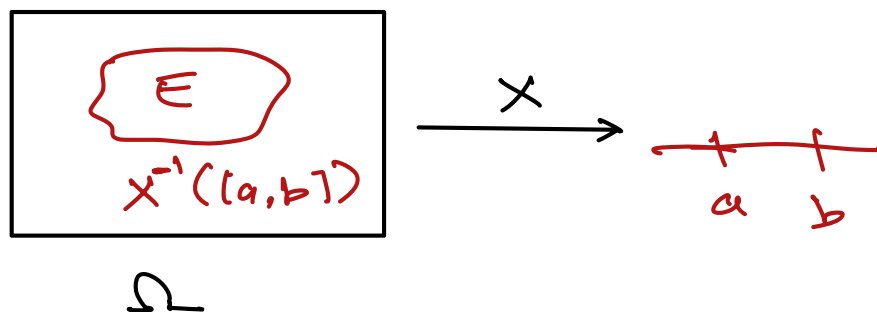
Random Variables

Discrete Case



$$X : \Omega \rightarrow \mathbb{R}$$

Uncountably infinite case

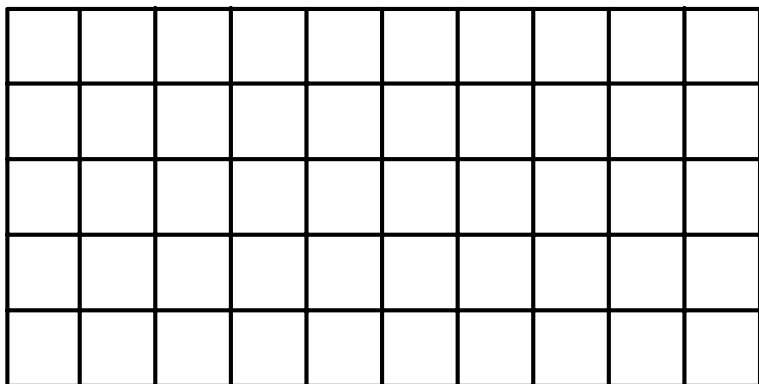


$$P[X \in [a, b]] = ?$$

$$= P[X^{-1}([a, b])]$$

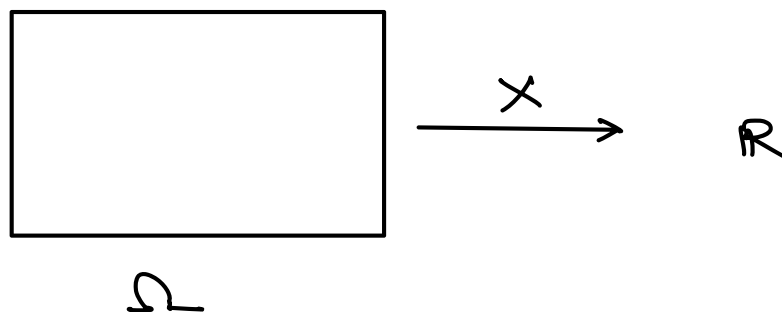
Random Variables

Discrete Case



$$X : \Omega \rightarrow \mathbb{R}$$

Uncountably infinite case



$$X : (\Omega, \mathcal{F}) \longrightarrow (\mathbb{R}, \mathcal{B})$$

measurable

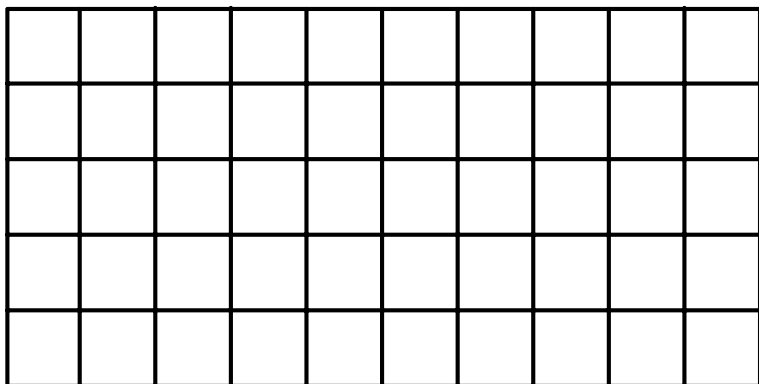
$$\text{if } \forall A \in \mathcal{B}, X^{-1}(A) \in \mathcal{F}$$

$\mathbb{P}[X \in A]$ is well-defined

Ex: $X_1, X_2 : (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B})$ measurable
 $\Rightarrow c_1 X_1 + c_2 X_2$ measurable
(also $X_1 \cdot X_2$ measurable)

Expectations

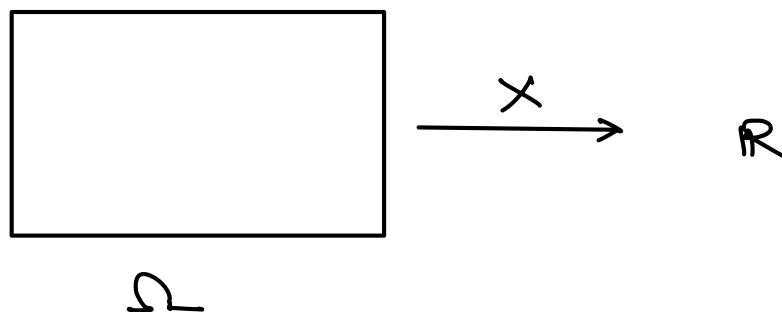
Discrete Case



$$X : \Omega \rightarrow \mathbb{R}$$

$$E[X] = \sum p(\omega) \cdot X(\omega)$$

Uncountably infinite case



$$X : (\Omega, \mathcal{F}) \longrightarrow (\mathbb{R}, \mathcal{B})$$

measurable

$$E[X] =$$

Continuous Random Variables

(say) $X: (\Omega, \mathcal{F}) \rightarrow (\mathbb{R}, \mathcal{B})$

Let $F(x) = P[X \leq x]$

if $\exists$ function $f(x)$ s.t. $F(x) = \int_{-\infty}^x f(y) dy$

$$\begin{aligned} & \text{For } a < b \\ & P[X \in (a, b)] \\ &= P[X \leq b] \\ & \quad - P[X \leq a] \\ &= \int_a^b f(x) dx \end{aligned}$$

then X is called a continuous random variable

with density function $f(x)$

$$E[X] = \int_{-\infty}^{\infty} y \cdot f(y) \cdot dy$$

What about all the other stuff

Continuous random variable X with density f

$$\mu = \mathbb{E}[X] = \int_{-\infty}^{\infty} y \cdot f(y) \cdot dy \quad \mathbb{E}[X^2] = \int_{-\infty}^{\infty} y^2 \cdot f(y) \cdot dy$$

$$\text{Var}[X] = \mathbb{E}[X^2] - (\mathbb{E}[X])^2 = \mathbb{E}[(X - \mu)^2]$$

Markov: For non-negative r.v. Z

$$\mathbb{E}[Z] = \mathbb{E}[Z \cdot (\underbrace{\mathbb{1}_{\{Z \geq t\}} + \mathbb{1}_{\{Z < t\}}}_{\text{measurable}})]$$

$$\geq \mathbb{E}[Z \cdot \mathbb{1}_{\{Z \geq t\}}] \quad \text{using } Z \geq 0$$

$$\geq \mathbb{E}[t \cdot \mathbb{1}_{\{Z \geq t\}}] \quad \text{using } Z \cdot \mathbb{1}_{\{Z \geq t\}} \geq t \cdot \mathbb{1}_{\{Z \geq t\}}$$

Chebyshev: Markov on $Y = (X - \mu)^2$

Multiple Independent Variables

$$\underline{X : \Omega \rightarrow \mathbb{R}}$$

density $f(x)$

$$\underline{Y : \Omega \rightarrow \mathbb{R}}$$

density $g(y)$

$$\begin{aligned} P[(X, Y) \in [a, b] \times [c, d]] &= P[X \in [a, b]] \cdot P[Y \in [c, d]] \\ &= \int_a^b f(x) \cdot dx \int_c^d g(y) \cdot dy \\ &= \int_a^b \int_c^d f(x) g(y) \cdot dx \cdot dy \end{aligned}$$

$$\text{Density for } (X, Y) : \Omega \rightarrow \mathbb{R}^2 = f(x) g(y)$$

Gaussian Random Variables

A specific (very useful!) continuous random variable

$$X \sim \underline{N(\mu, \sigma^2)}$$

density $f(x) = \frac{e^{-(x-\mu)^2/2\sigma^2}}{\sqrt{2\pi}\sigma}$

Normal distribution
with mean μ , variance σ^2

$$X \sim N(0, 1)$$

$$f(x) = \frac{e^{-x^2/2}}{\sqrt{2\pi}}$$

(Standard Normal Distribution)

$$P[X \in [a, b]] = \int_a^b f(x) dx = \int_a^b \frac{e^{-x^2/2}}{\sqrt{2\pi}} dx$$