

# Independence

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Let  $(\Omega, \mathcal{F}, \mathbf{P})$  be a probability triple.

## Definitions of independence

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### Independent $\sigma$ -algebras

Sub- $\sigma$ -algebras  $\mathcal{G}_1, \mathcal{G}_2, \dots$  of  $\mathcal{F}$  are called *independent* if, whenever  $G_i \in \mathcal{G}_i (i \in \mathbf{N})$  and  $i_1, \dots, i_n$  are distinct, then

$$P(G_{i_1} \cap \dots \cap G_{i_n}) = \prod_{k=1}^n P(G_{i_k})$$

### Independent random variables

Random variables  $X_1, X_2, \dots$  are called *independent* if the  $\sigma$ -algebras

$$\sigma(X_1), \sigma(X_2), \dots$$

are independent.

### Independent events

Events  $E_1, E_2, \dots$  are called *independent* if the  $\sigma$ -algebras  $\mathcal{E}_1, \mathcal{E}_2, \dots$  are independent, where

$$\mathcal{E}_n \text{ is the } \sigma\text{-algebra } \{\emptyset, E_n, \Omega \setminus E_n, \Omega\}$$

Since  $\mathcal{E}_n = \sigma(I_{E_n})$ , it follows that

event  $E_1, E_2, \dots$  are independent if and only if the random variables  $I_{E_1}, I_{E_2}, \dots$  are independent.

## The $\pi$ -system Lemma; and the more familiar definitions

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We study independence via  $\pi$ -systems rather than  $\sigma$ -algebras.

(a) **LEMMA.** Suppose that  $\mathcal{G}$  and  $\mathcal{H}$  are sub- $\sigma$ -algebras of  $\mathcal{F}$ , and that  $\mathcal{I}$  and  $\mathcal{J}$  are  $\pi$ -systems with

$$\sigma(\mathcal{I}) = \mathcal{G}, \quad \sigma(\mathcal{J}) = \mathcal{H}$$

Then  $\mathcal{G}$  and  $\mathcal{H}$  are *independent* if and only if  $\mathcal{I}$  and  $\mathcal{J}$  are independent in that

$$P(I \cap J) = P(I)P(J), \quad I \in \mathcal{I}, \quad J \in \mathcal{J}$$

(b)

Suppose that  $X$  and  $Y$  are two random variables on  $(\Omega, \mathcal{F}, \mathbf{P})$  such that, whenever  $x, y \in \mathbf{R}$ ,

$$P(X \leq x; Y \leq y) = P(X \leq x)P(Y \leq y)$$

The  $\pi$ -systems  $\pi(X)$  and  $\pi(Y)$  are independent. Hence  $\sigma(X)$  and  $\sigma(Y)$  are independent.

## Second Borel-Cantelli Lemma (BC2)

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If  $E_n : n \in \mathbf{N}$  is a sequence of **independent** events, then

$$\sum P(E_n) = \infty \Rightarrow P(E_n, \text{ i.o.}) = P(\limsup E_n) = 1$$

## Definitions. Tail $\sigma$ -algebras

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Let  $X_1, X_2, \dots$  be random variables. Define

$$\mathcal{T}_n := \sigma(X_{n+1}, X_{n+2}, \dots), \quad \mathcal{T} := \bigcap_n \mathcal{T}_n$$

The  $\sigma$ -algebra  $\mathcal{T}$  is called the *tail  $\sigma$ -algebra* of the sequence  $(X_n : n \in \mathbf{N})$ .

## Theorem. Kolmogorov's 0-1 Law

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Let  $(X_n : n \in \mathbf{N})$  be a sequence of **independent** random variables, and let  $\mathcal{T}$  be the tail  $\sigma$ -algebra of  $(X_n : n \in \mathbf{N})$ . Then  $\mathcal{T}$  is  $P$ -trivial, that is

(i)  $F \in \mathcal{T} \Rightarrow P(F) = 0$  or  $P(F) = 1$

(ii) if  $\xi$  is a  $\mathcal{T}$ -measurable random variable, then,  $\xi$  is almost deterministic in that for some constant  $c$  in  $[-\infty, +\infty]$ ,

$$P(\xi = c) = 1$$

We allow  $\xi = \pm\infty$  at (ii) for obvious reasons.