

# Lecture 4

## Independence.

Fix a probability space  $(\Omega, \mathcal{F}, P)$ .

Def<sup>n</sup>: Let  $E_1, E_2, \dots$  be events (finite or countable).

We say that they are independent

if  $P(E_{i_1} \cap E_{i_2} \cap \dots \cap E_{i_k}) = P(E_{i_1}) \cdot P(E_{i_2}) \cdot \dots \cdot P(E_{i_k})$   
for all choices of  $i_1 < i_2 < \dots < i_k$ .

Example: Consider throw of a die:

$E_1$  = number is  $\leq 2 = \{1, 2\}$ ,  $P(E_1) = \frac{1}{3}$

$E_2$  = number is even =  $\{2, 4, 6\}$ ,  $P(E_2) = \frac{1}{2}$

Since  $P(E_1 \cap E_2) = P(\{2\}) = \frac{1}{6} = \frac{1}{2} \cdot \frac{1}{3} = P(E_1)P(E_2)$

the events  $E_1, E_2$  are independent.

Let  $E_3$  = number is  $\leq 3 = \{1, 2, 3\}$ .

Then  $P(E_2 \cap E_3) = P(\{2\}) = \frac{1}{6} \neq \frac{1}{2} \cdot \frac{1}{2} = P(E_2)P(E_3)$

So  $E_2$  and  $E_3$  are not independent.

Def<sup>n</sup> Random variables  $X_1, X_2, \dots$  are said to be independent if for any choice of  $i_1 < i_2 < \dots < i_k$  and Borel sets  $A_1, \dots, A_k$ , the events  $\{X_{i_j} \in A_j\}$  ( $j=1, 2, \dots, k$ ) are independent.

$$\text{That is, } P(\{X_{i_1} \in A_1\} \cap \{X_{i_2} \in A_2\} \cap \dots \cap \{X_{i_k} \in A_k\}) \\ = \prod_{j=1}^k P(\{X_{i_j} \in A_j\})$$

Def<sup>n</sup> Sub  $\sigma$ -algebras  $\mathcal{G}_1, \mathcal{G}_2, \dots$  are said to be independent if  $P(G_{i_1} \cap G_{i_2} \cap \dots \cap G_{i_k}) = \prod_{j=1}^k P(G_{i_j})$  for all choices of indices  $i_1 < i_2 < \dots < i_k$  and events  $G_{i_j} \in \mathcal{G}_{i_j}$ .

Remark: Independence of events and random variables are special cases of independence of  $\sigma$ -algebras.

1) Let  $E_1, E_2, \dots$  be events.

Set  $\mathcal{G}_j = \{\emptyset, E_j, E_j^c, \Omega\} = \sigma(E_j)$ . Then,

$E_1, E_2, \dots$  independent  $\Leftrightarrow \mathcal{G}_1, \mathcal{G}_2, \dots$  independent.

2) Let  $X_1, X_2, \dots$  be random variables.

Let  $\mathcal{G}_j = \sigma(X_j)$ . Then,

$X_1, X_2, \dots$  independent  $\Leftrightarrow \mathcal{G}_1, \mathcal{G}_2, \dots$  independent.

Lemma Let  $\mathcal{G}, \mathcal{H}$  be sub  $\sigma$ -algebras of  $\mathcal{F}$ .

and let  $\mathcal{I}, \mathcal{J}$  be  $\pi$ -systems that generate  $\mathcal{G}$  and  $\mathcal{H}$ :

$\sigma(\mathcal{I}) = \mathcal{G}$  and  $\sigma(\mathcal{J}) = \mathcal{H}$ .

Then  $\mathcal{G}, \mathcal{H}$  are independent if and only if

$P(I \cap J) = P(I)P(J)$  for all  $I \in \mathcal{I}, J \in \mathcal{J}$ . (\*)

Proof: " $\Rightarrow$ " is clear as  $\mathcal{I} \subseteq \mathcal{G}, \mathcal{J} \subseteq \mathcal{H}$ .

" $\Leftarrow$ ": Assume (\*) holds. Define

$P_I(H) = P(I \cap H)$  for all  $H \in \mathcal{H}$ .

This is a measure on  $(\Omega, \mathcal{H})$ :

$$\bullet P_I(\emptyset) = P(I \cap \emptyset) = P(\emptyset) = 0$$

$$\begin{aligned} \bullet P_I\left(\bigcup_{i=1}^{\infty} A_i\right) &= P\left(I \cap \bigcup_{i=1}^{\infty} A_i\right) \\ &= P\left(\bigcup_{i=1}^{\infty} I \cap A_i\right) = \sum_{i=1}^{\infty} P(I \cap A_i) \\ &= \sum_{i=1}^{\infty} P_I(A_i) \text{ for disjoint } A_i. \end{aligned}$$

Moreover,  $P'_I(H) = P(I) \cdot P(H)$  is a measure on  $(\Omega, \mathcal{H})$ .

Since measures are uniquely determined by  $\pi$ -systems,  $P'_I(H) = P_I(H)$  for all  $H \in \mathcal{H}$  by using (\*) over all  $H \in \mathcal{J}$ .

So  $P(I \cap H) = P(I)P(H)$  for all  $I \in \mathcal{I}$ ,  $H \in \mathcal{H}$

Repeating the argument on the left gives

$P(G \cap H) = P(G)P(H)$  for all  $G \in \mathcal{G}$ ,  $H \in \mathcal{H}$ .  $\square$

Remark •  $\{E_i\}$  is a  $\pi$  system.

• Events of the form  $\{X_i \leq x\}$  form a  $\pi$ -system generating  $\sigma(X_i)$ . So, to verify that

$X_1, X_2, \dots$  are independent it suffices to check

$P(X_{i_1} \leq x_1 \& X_{i_2} \leq x_2 \& \dots) = P(X_{i_1} \leq x_1)P(X_{i_2} \leq x_2) \dots$

for all  $i_1, i_2, \dots$ , and  $x_1, x_2, \dots$

## Second Borel-Cantelli lemma:

Assume that  $E_1, E_2, \dots$  are independent events and  $\sum_{i=1}^{\infty} P(E_i) = \infty$ . Then,

$$P(\limsup_{n \rightarrow \infty} E_n) = P(E_n \text{ occurs infinitely often}) = 1$$

Proof: Recall that  $\limsup_{n \rightarrow \infty} E_n = \bigcap_{n \in \mathbb{N}} \bigcup_{m \geq n} E_m$ .

Its complement is  $\bigcup_{n \in \mathbb{N}} \bigcap_{m \geq n} E_m^c$ .

$$\text{Now } P\left(\bigcap_{m \geq n} E_m^c\right) \leq P\left(\bigcap_{m=n}^M E_m^c\right) = \prod_{m=n}^M P(E_m^c)$$

$$= \prod_{m=n}^M (1 - P(E_m))$$

$$\leq \prod_{m=n}^M e^{-P(E_m)}$$

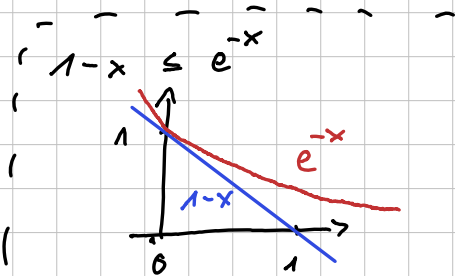
$$= \exp\left(-\sum_{m=n}^M P(E_m)\right)$$

$$\rightarrow " \exp(-\infty) " = 0.$$

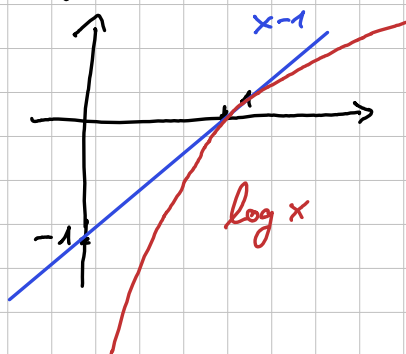
$$\text{Hence } P\left(\bigcap_{m \geq n} E_m^c\right) = 0 \quad \forall n$$

and by countable unions,

$$P\left(\bigcup_n \bigcap_{m \geq n} E_m^c\right) = 0. \quad \square$$



$$\log x \leq x-1$$



Remark: Independence is crucial!

If e.g.  $E_1 = E_2 = \dots$ , then  $P(\limsup E_n) = P(E_n)$  which can take any value in  $[0, 1]$ .

Example: Take a random card from a deck of  $n$  cards on the  $n$ -th draw. Assume the cards are labelled  $\{1, 2, \dots, n\}$ . Let  $E_n = \{\text{card 1 is drawn on } n\text{-th draw}\}$ .

Assuming all draws are independent and uniform in probability,  $P(E_n) = \frac{1}{n}$ . Hence, by the second BC-lemma,  $P(\text{"1 is drawn infinitely often"}) = P(\limsup E_n) = 1$ , since  $\sum P(E_n) = \sum \frac{1}{n} = \infty$ .

Example: "Monkey & typewriter"

A monkey types a sequence of random characters on a keyboard. Assume each character has pos. prob. of occurring (at least  $\varepsilon > 0$ ). Let  $S$  be a fixed string of length  $s$ . Then,

$$\left\{ \begin{array}{l} P(\text{First } s \text{ characters are exactly } S) \geq \varepsilon^s \\ P(\text{Characters } s+1, \dots, 2s \text{ are exactly } S) \geq \varepsilon^s \\ \vdots \end{array} \right.$$

independent!

$$\sum_{k=1}^{\infty} P(k\text{-th set of } s \text{ characters is exactly } S) \geq \sum_{k=1}^{\infty} \varepsilon^s = \infty.$$

By the second BC lemma:

$$P(\text{monkey types } S \text{ infinitely often}) = 1.$$

Note: If  $E_1, E_2, \dots$  is a sequence of independent events, and since

$$\sum P(E_j) = \infty \quad \text{or} \quad \sum P(E_j) < \infty$$

must hold, the BC lemmas give

$$P\left(\limsup_n E_n\right) = \begin{cases} 0 & \sum P(E_n) < \infty \\ 1 & \sum P(E_n) = \infty \end{cases}.$$

This is a special case of Kolmogorov's 0-1 law!

Def<sup>n</sup> Let  $X_1, X_2, \dots$  be a sequence of random variables. Set  $\mathcal{T}_n = \sigma(X_{n+1}, X_{n+2}, \dots)$  and  $\mathcal{T} = \bigcap_{n \in \mathbb{N}} \mathcal{T}_n$ . We say  $\mathcal{T}$  is a tail  $\sigma$ -algebra.

Some "typical" events in the tail  $\sigma$ -algebra (tail events) are

$$\{ \lim X_n \text{ exists} \}, \{ \sum_{n=1}^{\infty} X_n \text{ converges} \}$$

Theorem (Kolmogorov 0-1 law)

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

Then, for every  $T \in \mathcal{T}$ , either  $P(T) = 0$  or  $1$ .

In particular, if  $\mathcal{E}$  is a  $\mathcal{T}$  measurable random variable, then  $P(\mathcal{E} = c) = 1$  for some  $c \in [-\infty, \infty]$ .

Proof: 1) Define  $\mathcal{X}_n = \sigma(X_1, \dots, X_n)$ .

Note that  $\mathcal{X}_n$  and  $\mathcal{T}_n = \sigma(X_{n+1}, \dots)$  are independent for all  $n \in \mathbb{N}$ .

2) Since  $\mathcal{T} \subseteq \mathcal{T}_n$  for all  $n$ ,  $\mathcal{T}$  and  $\mathcal{X}_n$  are independent.



3)  $\mathcal{X}_\infty = \sigma(X_1, X_2, \dots)$  and  $\mathcal{T}$  are independent because  $\bigcup_{n \geq 1} \mathcal{X}_n$  is a  $\pi$  system that generates  $\mathcal{X}_\infty$

4)  $\mathcal{T} \subseteq \mathcal{X}_\infty$  and  $\mathcal{T}$  is independent of itself !!!

So for any  $F \in \mathcal{T}$ ,  $P(F \cap F) = P(F)P(F)$ .

Hence  $P(F) = x$  is a solution to  $x = x^2$   
 $\Rightarrow x \in \{0, 1\}$ .

Now if  $\xi$  is  $\mathcal{T}$  measurable we set

$$c = \sup \{x : P(\xi \leq x) = 0\} \in [-\infty, \infty].$$

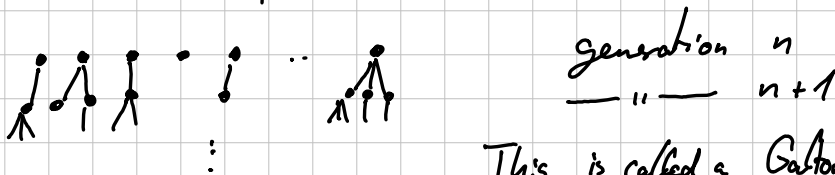
Then,  $\{\xi < c\} = \bigcup_n \underbrace{\{\xi \leq c - \frac{1}{n}\}}_{\text{null set by def}} \Rightarrow P(\{\xi < c\}) = 0$   
 and

$$\{\xi \leq c\} = \bigcap_n \underbrace{\{\xi \leq c + \frac{1}{n}\}}_{\substack{\text{not null by def} \\ \text{so by 0-1 law almost sure}}} \Rightarrow P(\{\xi \leq c\}) = 1$$

Hence  $P(\{\xi = c\}) = 1$ .

## "Application" (Extra / non-examinable)

We consider a population (e.g. of humans) for which every member has offspring independent of other members & exactly one ancestor (e.g. matrilineal or patrilineal descent):



This is called a Galton-Watson process.

The following is a tail event: let  $v_n$  be an arbitrary member of the population at generation  $n$ . Then  $\{ \text{a randomly picked individual in a population will eventually be descended from } v_n \} \in \mathcal{T}$ .

Hence by the Kolmogorov 0-1 law, eventually everyone or no one will be descended from  $v_n$ .

NB: Recent studies into Y chromosomes & mitochondrial DNA seem to suggest such male/female ancestors already exist and lived  $\sim 280,000$  and  $155,000$  years ago.