# Probability Theory 6. The Lemma of Borel-Cantelli

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### Independence

▶ Definition 8.1:  $(A_i)_{i \in I}$  with  $A_i \in \mathcal{F}$  is called *independent*, if

$$\mathsf{P}\Big(\bigcap_{j\in J} A_j\Big) = \prod_{j\in J} \mathsf{P}(A_j) \tag{$\ast$}$$

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for all  $J \subseteq_f I$ .

 $(C_i)_{i \in I}$  with  $C_i \subseteq \mathcal{F}$  is called *independent* if (\*) holds for all  $J \subseteq_f I$  and  $A_j \in C_j, j \in J$ .

 $(X_i)_{i \in I}$  is called independent if  $(\sigma(X_i))_{i \in I}$  is independent.

### Existence of product measures

- ▶ Proposition 8.2:  $(X_i)_{i \in I}$  is independent if and only if for each  $J \subseteq_f I$  $((X_i)_{i \in J})_* P = \bigotimes_{i \in J} (X_i)_* P,$
- Corollary 8.3: Let *E* be Polish, *I* arbitrary. Let  $X_i : \Omega : i \to E$ ZV for probability spaces  $(\Omega_i, \mathcal{F}_i, P_i)$ ,  $i \in I$ . Then there are  $(\Omega, \mathcal{F}, P)$  and  $Y_i : \Omega \to E$  with  $(Y_i)_{i \in I}$  independent and  $Y_i \stackrel{d}{=} X_i$ .
- Lemma 8.4: (Ω'<sub>i</sub>, F'<sub>i</sub>), (Ω''<sub>i</sub>, F''<sub>i</sub>), i ∈ I, measureable spaces. (X<sub>i</sub>)<sub>i∈I</sub> independent rvs, X<sub>i</sub> : Ω → Ω'<sub>i</sub>, and φ<sub>i</sub> : Ω'<sub>i</sub> → Ω''<sub>i</sub> measurable, i ∈ I. Then the family (φ<sub>i</sub>(X<sub>i</sub>))<sub>i∈I</sub> is also independent. Proof: Clear because of σ(φ<sub>i</sub>(X<sub>i</sub>)) ⊆ σ(X<sub>i</sub>).

### Independent and uncorrelated

▶ Proposition 8.5:  $X, Y \in \mathcal{L}^1$  independent,  $\mathbb{R}$ -valued. Then  $XY \in \mathcal{L}^1$  and

$$\mathsf{E}[XY] = \mathsf{E}[X] \cdot \mathsf{E}[Y].$$

Proof: If the statement is true, it is also true for sums:

$$\mathsf{E}\Big[\sum_{i=1}^{n} X_i \cdot \sum_{j=1}^{n} Y_j\Big] = \sum_{i=1}^{n} \sum_{j=1}^{n} \mathsf{E}[X_i Y_j] = \sum_{i=1}^{n} \sum_{j=1}^{n} \mathsf{E}[X_i] \mathsf{E}[Y_j]$$
$$= \mathsf{E}\Big[\sum_{i=1}^{n} X_i\Big] \cdot \mathsf{E}\Big[\sum_{j=1}^{n} Y_j\Big].$$

Clear if  $X = 1_A$ ,  $Y = 1_B$ ;

Clear for simple functions

Clear for non-negative, measurable functions

### Example:

Let X, Y ~ B(1,.5). Then X + Y, X - Y are uncorrelated but not independent.

$$E[(X + Y)(X - Y)] = E[X^2 - Y^2] = E[X^2] - E[Y^2] = 0,$$
  
but

$$P(X + Y = 2, X - Y = 1) = 0$$
  

$$\neq \frac{1}{16} = P(X = Y = 1) \cdot P(X = 1, Y = 0)$$
  

$$= P(X + Y = 2) \cdot P(X - Y = 1).$$

## The Borel-Cantelli lemma

▶ Definition 8.7: For A<sub>1</sub>, A<sub>2</sub>, ... ∈ F,  

$$\limsup_{n \to \infty} A_n := \bigcap_{n \ge 1} \bigcup_{m \ge n} A_m$$
.
▶ Theorem 8.8: Let A<sub>1</sub>, A<sub>2</sub>, ... ∈ F. Then  

$$\sum_{n=1}^{\infty} P(A_n) < \infty \Longrightarrow P(\limsup_{n \to \infty} A_n) = 0.$$
If A<sub>1</sub>, A<sub>2</sub>, ... are independent,  

$$\sum_{n=1}^{\infty} P(A_n) = \infty \Longrightarrow P(\limsup_{n \to \infty} A_n) = 1.$$
Proof:

$$\mathsf{P}(\limsup_{n \to \infty} A_n) = \lim_{n \to \infty} \mathsf{P}\left(\bigcup_{m \ge n} A_m\right) \le \lim_{n \to \infty} \sum_{m = n} \mathsf{P}(A_m) = 0$$
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 $\infty$ 

### The Borel-Cantelli lemma

► Theorem 8.8: Let A<sub>1</sub>, A<sub>2</sub>, ... ∈ F. If A<sub>1</sub>, A<sub>2</sub>, ... are independent,

$$\sum_{n=1}^{\infty} \mathsf{P}(A_n) = \infty \Longrightarrow \mathsf{P}(\limsup_{n \to \infty} A_n) = 1.$$

Proof: We recall  $\log(1-x) \leq -x$  for  $x \in [0,1]$ .

$$P((\limsup_{n \to \infty} A_n)^c) = P\left(\bigcup_{n=1}^{\infty} \bigcap_{m \ge n} A_m^c\right) = \lim_{n \to \infty} P\left(\bigcap_{m=n}^{\infty} A_m^c\right)$$
$$= \lim_{n \to \infty} \prod_{m=n}^{\infty} (1 - P(A_m)) = \lim_{n \to \infty} \exp\left(\sum_{m=n}^{\infty} \log(1 - P(A_m))\right)$$
$$\leq \lim_{n \to \infty} \exp\left(-\sum_{m=n}^{\infty} P(A_m)\right)$$

= 0

### Examples

Let X = (X<sub>1</sub>, X<sub>2</sub>, ...) be an infinite p coin toss with p > 0. Then |{n : X<sub>n</sub> head}| = ∞. head. Indeed: Let A<sub>n</sub> := {X<sub>n</sub> head}. Then, A<sub>1</sub>, A<sub>2</sub>, ... is independent and ∑<sub>n=1</sub><sup>∞</sup> P(A<sub>n</sub>) = ∑<sub>n=1</sub><sup>∞</sup> <sup>1</sup>/<sub>2</sub> = ∞.
The probability that only finitely many of the events

 $B_n := \{X_1 \text{ head}\} \text{ occur is } p.$ 

Let X<sub>n</sub> ~ geo(p) be independent. Then, |{n : X<sub>n</sub> > n}| < ∞ almost surely.

Indeed, let  $A_n := \{X_n > n\}$ . Then,

$$\sum_{n=1}^{\infty} P(A_n) = \sum_{n=1}^{\infty} P(X_n \ge n) = \sum_{n=1}^{\infty} (1-p)^{n-1} = \frac{1}{p} < \infty.$$