

## Two 0–1 laws

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Beyond various limit theorems, convergence theorems, and concentration inequalities, another class of useful results in probability are **0–1 laws**, which provide sufficient conditions for an event to be *trivial*,  $\mathbb{P}(\cdot) = 0$  or  $1$ . In applications, *any* lower bound or upper bound is enough to show that such an event is almost sure or almost never.

One of the most common arguments for showing that a  $\sigma$ -algebra  $\mathcal{F}$  is trivial is to show that  $\mathcal{F}$  is independent of itself:  $\mathbb{P}(A) = \mathbb{P}(A \cap A) = \mathbb{P}(A) \cdot \mathbb{P}(A) = \mathbb{P}(A)^2$  iff  $\mathbb{P}(A) \in \{0, 1\}$ .

**Theorem 1** (Kolmogorov's 0–1 law).

Let  $X_1, X_2, \dots$  be a sequence of independent random variables, and let

$$\mathcal{T} = \bigcap_{n=1}^{\infty} \sigma(X_n, X_{n+1}, \dots)$$

be the tail  $\sigma$ -algebra, analogous to the limit superior of the information in  $(X_n)_{n \geq 1}$ . Then  $\mathcal{T}$  is trivial: every  $A \in \mathcal{T}$  has  $\mathbb{P}(A) = 0$  or  $1$ .

*Proof.* It suffices to show that  $\mathcal{T}$  is independent of  $\sigma(X_1, X_2, \dots) \supseteq \mathcal{T}$ . And, as  $\bigcup_{n=1}^{\infty} \sigma(X_1, \dots, X_n)$  is a  $\pi$ -system generating  $\sigma(X_1, X_2, \dots)$ , it suffices to show that  $\mathcal{T} \perp\!\!\!\perp \bigcup_{n=1}^{\infty} \sigma(X_1, \dots, X_n)$ . For any  $B \in \sigma(X_1, \dots, X_n)$ ,

$$A \in \mathcal{T} \subseteq \sigma(X_{n+1}, X_{n+2}, \dots) \implies A \perp\!\!\!\perp B.$$

□

The following 0–1 law is a stronger result showing the triviality of a larger  $\sigma$ -algebra.

**Theorem 2** (Hewitt–Savage 0–1 law).

Let  $X_1, X_2, \dots$  be a sequence of i.i.d. random variables, and let

$$\mathcal{E} = \{A \in \sigma(X_1, X_2, \dots) : A \text{ invariant under any finite permutation of the indices}\}$$

be the exchangeable  $\sigma$ -algebra. Then  $\mathcal{E}$  is trivial.

*Proof.* To show that  $\mathcal{E}$  is independent of itself, it suffices to show that  $\mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E}) = \mathbb{E}(f(X_1, \dots, X_k))$  for every  $k \geq 1$  and bounded measurable function  $f$ , in which case  $\mathcal{E} \perp\!\!\!\perp \bigcup_{k=1}^{\infty} \sigma(X_1, \dots, X_k)$ . Let

$$\mathcal{E}_n = \{A \in \sigma(X_1, X_2, \dots) : A \text{ invariant under every permutation } \pi \in S_n\},$$

such that  $\mathcal{E} = \bigcap_{n=1}^{\infty} \mathcal{E}_n$ .

- i. We observe that  $\mathbb{E}(f(X_1) | \mathcal{E}_n) = \mathbb{E}(f(X_i) | \mathcal{E}_n)$  for all  $i = 1, \dots, n$  by a simple change of measure, along with the i.i.d.ness of the  $X_i$  and the invariance of events in  $\mathcal{E}_n$ . Then

$$\mathbb{E}(f(X_1) | \mathcal{E}_n) = \frac{1}{n} \sum_{i=1}^n f(X_i),$$

where the right-hand side is  $\mathcal{E}_n$ -measurable and equal to the left-hand side by linearity of conditional expectation. Using the same argument,

$$\mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E}_n) = \frac{1}{\binom{n}{k}} \sum_{1 \leq i_1 < \dots < i_k \leq n} f(X_{i_1}, \dots, X_{i_k}).$$

- ii. Let  $M_n := \mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E}_n)$ . We observe that  $(M_n)_{n \rightarrow \infty}$  is a bounded *backwards martingale*, which makes it automatically uniformly integrable, with limit

$$\mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E}_n) \rightarrow M := \mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E}) \quad \text{a.s. and in } L^1.$$

- iii. But, by step i, the right-hand side  $M$  is also equal to the  $\mathcal{T}$ -measurable

$$\lim_{n \rightarrow \infty} \frac{1}{\binom{n}{k}} \sum_{1 \leq i_1 < \dots < i_k \leq n} f(X_{i_1}, \dots, X_{i_k}).$$

Tail-measurable random variables are trivial, so  $M$  is in fact constant almost surely. Because

$$\mathbb{E}(M_n) = \mathbb{E}(\mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E}_n)) \equiv \mathbb{E}(f(X_1, \dots, X_k))$$

for every  $n$  by the law of iterated expectation,  $\mathbb{E}(M_n) \rightarrow \mathbb{E}(M)$  must equal  $\mathbb{E}(f(X_1, \dots, X_k))$ , by which we are done: we have shown that  $M = \mathbb{E}(f(X_1, \dots, X_k) | \mathcal{E})$  equals  $\mathbb{E}(f(X_1, \dots, X_k))$  almost surely. □

We have already seen the Borel–Cantelli lemmas, but Blumenthal’s and Lévy’s 0–1 laws are yet to be covered. We will leave them to another day. ■