

02.03.2016

If  $\Omega$  is at most countable,  $\mathcal{A} = \mathcal{P}(\Omega)$ .  $\mathbb{P}(A) = \sum_{\omega \in A} \underbrace{\mathbb{P}(\{\omega\})}_{p(\omega)}$ .

If we have  $\infty$  many coin tosses,  $\Omega = \{0, 1\}^{\mathbb{N}}$  is uncountable.

**Definition** (Conditional probability).  $A, B \in \mathcal{A}$

$$\mathbb{P}(A|B) = \begin{cases} \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(B)} & \mathbb{P}(B) > 0 \\ 0 & \mathbb{P}(B) = 0 \end{cases}$$

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**Lemma** (Rule of total probability).  $\Omega = \bigsqcup_{i \in I} B_i$  for  $B_i \in \mathcal{A}$ ,  $I$  finite or countable. Then

$$\mathbb{P}(A) = \sum_{i \in I} \mathbb{P}(A|B_i) \mathbb{P}(B_i)$$

*Proof.* Let  $A \in \mathcal{A}$ .

$$A = \bigsqcup_{i \in I} A \cap B_i$$

$$\begin{aligned} \mathbb{P}(A) &= \sum_{i \in I} \mathbb{P}(A \cap B_i) \\ &= \end{aligned}$$

□

**Example** (very simple example on this kind of proof). There are 2 urns. Experiment:

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1. Transfer a random ball from urn I to urn II
2. extract a ball from urn II

We want to compute  $\mathbb{P}[\text{ball extracted from II is red}]$ . Now consider:

$$\begin{aligned} A &= [\text{ball extracted from II is red}] \\ B_1 &= [\text{transferred ball is red}] \\ B_2 &= [\text{transferred ball is yellow}] \end{aligned}$$

So we can write

$$\begin{aligned} \mathbb{P}(A) &= \underbrace{\mathbb{P}(A|B_1)}_{\frac{3}{10}} \underbrace{\mathbb{P}(B_1)}_{\frac{6}{10}} + \underbrace{\mathbb{P}(A|B_2)}_{\frac{2}{10}} \underbrace{\mathbb{P}(B_2)}_{\frac{4}{10}} \\ &= \frac{26}{100} \end{aligned}$$

Another question:

Suppose the ball from I is red. What is the probability that the transferred ball was red?

$$\mathbb{P}[\text{transferred ball was red}] = ?$$

Use the formula of Bayes:

$$\begin{aligned}\mathbb{P}(B|A) &= \frac{\mathbb{P}(A \cap B)}{\mathbb{P}(A)} \frac{\mathbb{P}(B)}{\mathbb{P}(A \cap B)} \\ &= \mathbb{P}(A|B) \frac{\mathbb{P}(B)}{\mathbb{P}(A)}\end{aligned}$$

Combination of total probability and Bayes (sometimes also called formula of Bayes):

$$\mathbb{P}(B_j|A) = \frac{\mathbb{P}(A|B_j)\mathbb{P}(B_j)}{\sum_i \mathbb{P}(A|B_i)\mathbb{P}(B_i)}$$

Now we can use this formula:

$$\begin{aligned}\mathbb{P}(B_1|A) &= \frac{\mathbb{P}(A|B_1)\mathbb{P}(B_1)}{\mathbb{P}(A)} \\ &= \frac{\frac{3}{10} \cdot \frac{6}{10}}{\frac{26}{100}} = \frac{18}{26}\end{aligned}$$

**Definition.**  $A, B \in \mathcal{A}$  are independent if

$$\mathbb{P}(A \cap B) = \mathbb{P}(A) \cdot \mathbb{P}(B)$$

**Definition.** Let  $k \geq 2$ .  $A_1, A_2, \dots, A_n \in \mathcal{A}$  are independent, if for all  $\{i_1, \dots, i_k\} \subset \{1, \dots, n\}$

$$\mathbb{P}\left(\bigcap_{j=1}^{\infty} A_{i_j}\right) = \prod_{j=1}^k \mathbb{P}(A_{i_j})$$

**Example.** Experiment: Extract a random ball. For  $i = 1, 2, 3$ :

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$$A_i = [\text{extracted ball carries digit } i]$$

Then

$$\mathbb{P}(A_i) = \frac{2}{4} = \frac{1}{2}$$

$$\mathbb{P}(A_i \cap A_j) = \frac{1}{4} = \mathbb{P}(A_i) \cdot \mathbb{P}(A_j) \text{ for } i \neq j$$

$$\mathbb{P}(A_1 \cap A_2 \cap A_3) = \frac{1}{4} + \mathbb{P}(A_1) \cdot \mathbb{P}(A_2) \cdot \mathbb{P}(A_3)$$

**Observations.** 1. If  $A$  and  $B$  are independent, then

- (a)  $A^C$  and  $B$
- (b)  $A$  and  $B^C$
- (c)  $A^C$  and  $B^C$

are independent.

2. Let  $A_i^1 := A_i$  and  $A_i^{-1} := A_i^C$ . Then  $A_1, \dots, A_n$  are independent if and only if for all  $\varepsilon_1, \dots, \varepsilon_n \in \{-1, 1\}$

$$\mathbb{P}(A_1^{\varepsilon_1} \cap \dots \cap A_n^{\varepsilon_n}) = \prod_{i=1}^n \mathbb{P}(A_i^{\varepsilon_i})$$

**Definition.** Let  $A_i$  where  $(i \in I)$  be a collection of events (in  $\mathcal{A}$ ) are independent, if any finite subcollection is independent:

$$\forall J \subset I, J \text{ finite}$$

$$\mathbb{P}\left(\bigcap_{j \in J} A_j\right) = \prod_{j \in J} \mathbb{P}(A_j)$$

## 0.1 Random variables

**Definition.** A random variable is a function

$$X : (\Omega, \mathcal{A}) \rightarrow \mathbb{R}$$

which is measurable

$$X^{-1}(I) \in \mathcal{A}$$

for all interval  $I \subset \mathbb{R}$ . Equivalent:

$$X^{-1}(B) \in \mathcal{A}$$

for all  $B \in \mathcal{B}_{\mathbb{R}}$ .

**Example.** Coin toss:  $\Omega = \{0, 1\} \times \mathbb{R}^2 \times \mathbb{N}_0$   $X_1$ : 0 or 1 and  $\omega = (\varepsilon, x, y, n)$   
 $\varepsilon \in \{0, 1\}$ ,  $x, y \in \mathbb{R}$ ,  $n \in \mathbb{N}_0$ .

$$X_1(\omega) = \varepsilon$$

$$X_2(\omega) = \sqrt{x^2 + y^2}$$

The distribution of  $X$  is the probability measure on  $(\mathbb{R}, \mathcal{B}_{\mathbb{R}})$  given by

$$\begin{aligned} P_X(B) &= \mathbb{P}(X^{-1}(B)) \\ &= \mathbb{P}[X \in B] \end{aligned}$$

for  $B \in \mathcal{B}_{\mathbb{R}}$ .

Typical classes of Random variables and distributions

1. value set of  $X$  is at most countable (finite or countable).

$$X(\Omega) = \{x_i : i \in I\}$$

where  $I$  is finite or countable.

$$\begin{aligned} P_X(B) &= \sum_{i: x_i \in B} P_X(\{x_i\}) \\ &= \sum_{i: x_i \in B} \underbrace{\mathbb{P}[X = x_i]}_{p(x_i) = p_X(x_i)} \\ \sum_i p_X(x_i) &= 1 \end{aligned}$$

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only in discrete case, you write

$$p_X(x) = \mathbb{P}[X = x] = \begin{cases} 0 & x \notin \{x_i : i \in I\} \\ p_X(x_i) & \end{cases}$$

$$\sum_{x \in \mathbb{R}} p_X(x) = 1$$

2. *continuous*

There is a density function  $f_X : \mathbb{R} \rightarrow [0, \infty)$  such that

$$\mathbb{P}_X(B) = \int_B f_X(x) dx$$

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$$\int_{\mathbb{R}} f_X(x) dx = 1$$

$$\mathbb{P}[X = x] = 0$$

Note: for us, two random variables  $X, X'$  are the same, if

$$\mathbb{P}[X \neq X'] = 0$$

which is the same as

$$\mathbb{P}(\{\omega \in \Omega : X(\omega) \neq X'(\omega)\}) = 0$$

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