

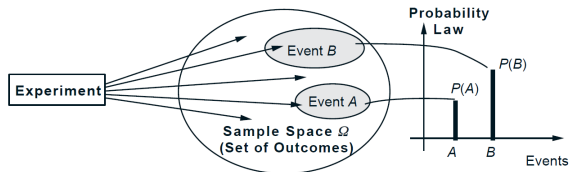
# Statistical Methods for Data Science

## Lesson 03 - Discrete random variables

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# Experiments



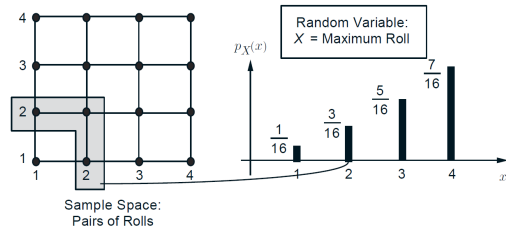
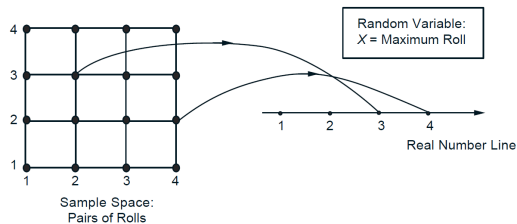
**Experiment:** roll two independent 4 sided die.

We are interested in probability of the *maximum of the two rolls*.

Modeling so far

- |  $\Omega = \{ (1;1); (1;2); (1;3); (1;4); (2;1); \dots; (4;4) \}$
- |  $A = \{ \text{maximum roll is } 2 \}$
- |  $P(A) = P(\{ (1;2); (2;1); (2;2) \}) = 3/16$

# Random variables



Modeling  $X : \Omega \rightarrow \mathbb{R}$

- |  $X((a; b)) = \max(a; b)$
- |  $A = \{ \text{maximum roll is } 2 \} = \{ (a; b) \in \Omega \mid X((a; b)) = 2 \}$
- |  $P(A) = P(X^{-1}(2)) = \frac{3}{16}$
- | We write  $P_X(X = 2) \stackrel{\text{def}}{=} P(X^{-1}(2))$

[Induced probability]

# (Discrete) Random variables

A random variable is a function  $X : \Omega \rightarrow \mathbb{R}$

- | it transforms  $\Omega$  into a more tangible sample space  $\mathbb{R}$   
from  $(a; b)$  to  $\min(a; b)$
- | it decouples the details of a specific  $\Omega$  from the probability of events of interest  
from  $\{H, T\}$  or  $\{\text{good}, \text{bad}\}$  or  $\dots$  to  $[0; 1]$

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DEFINITION. Let  $\Omega$  be a sample space. A *discrete random variable* is a function  $X : \Omega \rightarrow \mathbb{R}$  that takes on a finite number of values  $a_1, a_2, \dots, a_n$  or an infinite number of values  $a_1, a_2, \dots$

# Probability Mass Function (PMF)

DEFINITION. The *probability mass function*  $p$  of a discrete random variable  $X$  is the function  $p : \mathbb{R} \rightarrow [0, 1]$ , defined by

$$p(a) = P(X = a) \quad \text{for } -\infty < a < \infty.$$

Sample space  $\mathbb{R}$  but support is  $\{a_1; \dots; a_n\}$

- |  $p(a_i) > 0$  for  $i = 1; 2; \dots$
- |  $p(a_1) + p(a_2) + \dots = 1$
- |  $p(a) = 0$  if  $a \notin \{a_1; a_2; \dots\}$

“ $X = a$ ” shorthand for the event  $\{a\} \cap \mathbb{R}$

# Cumulative Distribution Function (CDF) and CCDF

$$F(a) = P(f a_i \leq a) = \sum_{a_i \leq a} p(a_i)$$

if  $a < b$  then  $F(a) < F(b)$

$$P(a < X < b) = F(b) - F(a) = \sum_{a < a_i < b} p(a_i)$$

*[Non-decreasing]*

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*[Non-decreasing]*

## Complementary cumulative distribution function (CCDF)

$$\bar{F}(a) = P(X > a) = 1 - P(X \leq a) = 1 - F(a)$$

$$\bar{F}(a) = P(\{a_i \mid a_i > a\}) = \sum_{a_i > a} p(a_i)$$

**See R script**



### Uniform discrete distribution

A discrete random variable  $X$  has the *uniform distribution* with parameters  $m; M \in \mathbb{Z}$  such that  $m < M$ , if its pmf is given by

$$p(a) = \frac{1}{M - m + 1} \quad \text{for } a = m; m + 1; \dots; M$$

We denote this distribution by  $U(m; M)$ .

**Intuition:** all integers in  $[m; M]$  have equal chances of being observed.

$$F(a) = \frac{a - m + 1}{M - m + 1} \quad \text{for } m \leq a \leq M$$

**See R script**

## Benford's law

A discrete random variable  $X$  has the *Benford's distribution*, if its pmf is given by

$$p(a) = \log_{10} \left( 1 + \frac{1}{a} \right) \quad \text{for } a = 1; 2; \dots; 9$$

We denote this distribution by *Ben*.

Related to the frequency distribution of leading digits in many real-life numerical datasets. See [Wikipedia](#) for its interesting history!

**See R script**

# $X$ $Ber(p)$

DEFINITION. A discrete random variable  $X$  has a **Bernoulli distribution** with parameter  $p$ , where  $0 \leq p \leq 1$ , if its probability mass function is given by

$$p_X(1) = P(X = 1) = p \quad \text{and} \quad p_X(0) = P(X = 0) = 1 - p.$$

We denote this distribution by  $Ber(p)$ .

$X$  models success/failure in tossing a coin (H, T), testing for a disease (infected, not infected), membership in a set (member, non-member), etc.

$p_X$  is the *pmf* (to distinguish from parameter  $p$ )

Also,  $p_X(a) = p^a (1 - p)^{1 - a}$  for  $a \in \{0, 1\}$

**See R script**

# $X$ $Bin(n; p)$

DEFINITION. A discrete random variable  $X$  has a **binomial distribution** with parameters  $n$  and  $p$ , where  $n = 1, 2, \dots$  and  $0 \leq p \leq 1$ , if its probability mass function is given by

$$p_X(k) = P(X = k) = \binom{n}{k} p^k (1-p)^{n-k} \quad \text{for } k = 0, 1, \dots, n.$$

We denote this distribution by  **$Bin(n, p)$** .

$X$  models the number of successes in  $n$  trials (How many H's when tossing  $n$  coins?)

**Intuition:** for  $X_1; X_2; \dots; X_n$  such that  $X_i \sim Ber(p)$  (**and independent**):

$$X = \sum_{i=1}^n X_i \sim Bin(n; p)$$

$p^k (1-p)^{n-k}$  is the probability of observing first  $k$  H's and then  $n-k$  T's

$\binom{n}{k} = \frac{n!}{k!(n-k)!}$  number of ways to choose the first  $k$  variables

$p_X(k)$  computationally expensive to calculate (no closed formula, but approximation/bounds)

**See R script**

### Identically distributed random variables

Two random variables  $X$  and  $Y$  are said *identically distributed* (in symbols,  $X \stackrel{d}{=} Y$ ), if  $F_X = F_Y$ , i.e.,

$$F_X(a) = F_Y(a) \quad \text{for } a \in \mathbb{R}$$

Identically distributed does **not** mean equal

Toss a fair coin  $n$  times, where  $n$  is odd

- | let  $X$  be the number of heads
- | let  $Y$  be the number of tails

$X \sim \text{Bin}(n; 0.5)$  and  $Y \sim \text{Bin}(n; 1 - 0.5) = \text{Bin}(n; 0.5)$

Thus,  $X \stackrel{d}{=} Y$  but are clearly always unequal.

# $X$ $Geo(p)$

DEFINITION. A discrete random variable  $X$  has a *geometric distribution* with parameter  $p$ , where  $0 < p \leq 1$ , if its probability mass function is given by

$$p_X(k) = P(X = k) = (1 - p)^{k-1} p \quad \text{for } k = 1, 2, \dots$$

We denote this distribution by  $Geo(p)$ .

$X$  models the number of trials before a success (how many tosses to have a H?)

**Intuition:** for  $X_1; X_2; \dots$  such that  $X_i \sim Ber(p)$  (**and independent**):

$$X = \min_i (X_i = 1) \sim Geo(p)$$

$$\bar{F}(a) = P(X > a) = (1 - p)^{a-1}$$

$$F(a) = P(X \leq a) = 1 - \bar{F}(a) = 1 - (1 - p)^{a-1}$$

**See R script**

# You cannot always loose

H is 1, T is 0,  $0 < p < 1$

$B_n = \text{first } n\text{-th coin tosses}$

$P(\bigcap_{i=1}^n B_i) = ?$

# You cannot always loose

H is 1, T is 0,  $0 < p < 1$

$B_n = \text{first } n \text{ coin tosses are T}$

$P(\bigcap_{i=1}^n B_i) = ?$

$X \sim \text{Geom}(p)$

$P(B_n) = P(X > n) = (1 - p)^n$

$P(\bigcap_{i=1}^n B_i) = \lim_{n \rightarrow \infty} P(B_n) = \lim_{n \rightarrow \infty} (1 - p)^n = 0$



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$P(\bigcap_{i=1}^n B_i) = \lim_{n \rightarrow \infty} P(B_n)$  for  $B_n$  non-increasing

[Borel-Cantelli Lemma]

# But if you lost so far, you can lose again

## Memoryless property

For  $X \sim \text{Geo}(p)$ , and  $n, k = 0; 1; 2; \dots$ :

$$P(X > n + k | X > k) = P(X > n)$$

### Proof

$$\begin{aligned} P(X > n + k | X > k) &= \frac{P(fX > n + kg \mid fX > kg)}{P(fX > kg)} \\ &= \frac{P(fX > n + kg)}{P(fX > kg)} \\ &= \frac{(1 - p)^{n+k}}{(1 - p)^k} \\ &= (1 - p)^n = P(X > n) \end{aligned}$$

# $X$ $NBin(n; p)$

## Negative binomial

A discrete random variable  $X$  has a negative binomial with parameters  $n$  and  $p$ , where  $n = 0; 1; 2; \dots$  and  $0 < p < 1$ , if its probability mass function is given by

$$p_X(k) = P(X = k) = \binom{k+n-1}{k} (1-p)^k p^n \quad \text{for } k = 0; 1; 2; \dots$$

$X$  models the number of failures before the  $n$ -th success (how many T's to have  $n$  H's?)

**Intuition:** for  $X_1; X_2; \dots; X_n$  such that  $X_i \sim \text{Geo}(p)$  (**and independent**):

$$X = \sum_{i=1}^n X_i \sim n \text{ } NBin(n; p)$$

$(1-p)^k p^n$  is the probability of observing first  $k$  T's and then  $n$  H's

$\binom{k+n-1}{k} = \frac{(k+n-1)!}{k!(n-1)!}$  number of ways to choose the first  $k$  variables among  $k+n-1$  (the last one must be a success!)

**See R script**

# $X$ $Poi(\mu)$

DEFINITION. A discrete random variable  $X$  has a *Poisson distribution* with parameter  $\mu$ , where  $\mu > 0$  if its probability mass function  $p$  is given by

$$p(k) = P(X = k) = \frac{\mu^k}{k!} e^{-\mu} \quad \text{for } k = 0, 1, 2, \dots$$

We denote this distribution by  $Pois(\mu)$ .

$X$  models the number of events in a fixed interval if these events occur with a known constant mean rate and independently of the last event

- | telephone calls arriving in a system
- | number of patients arriving at an hospital
- | customers arriving at a counter

$\mu$  denotes the mean number of events

$Bin(n; \mu=n)$  is the number of successes in  $n$  trials, assuming  $p = \mu/n$ , i.e.,  $p \ll n$

When  $n \rightarrow \infty$  :  $Bin(n; \mu=n) \rightarrow Poi(\mu)$  [Law of rare events]

See R script

