# PRELIMINARIES: Combinatorial Analysis, Probability Spaces, and Random Variables 

Marianna Bolla, Prof, DSc. Institute of Mathematics, BME

February 13, 2024

## Rules of Counting and Their Use in Combinatorial Probability Spaces

1. Permutations. How many different orders of $n$ objects exist?

- Without repetition (there are $n$ different objects): $n$ !
- With repetition (there are $n$ objects of which $n_{1}, \ldots, n_{r}$ are alike): $\frac{n!}{n_{1}!\ldots n_{r}!}$

2. Variations. How many different orders of $k$ objects selected from a set of $n$ objects exist?

- Without repetition (an object is selected at most once): $n(n-1) \ldots(n-k+1)=\frac{n!}{(n-k)!}$
- With repetition (an object may be selected several times): $n^{k}$

3. Combinations. How many different ways $k$ objects can be selected from a set of $n$ objects?

- Without repetition (an object is selected at most once):

$$
\frac{n!}{k!(n-k)!}=\binom{n}{k}=\binom{n}{n-k}, \quad k \leq n
$$

- With repetition (an object may be selected several times):

$$
\binom{k+n-1}{k}=\binom{k+n-1}{n-1}, \quad k \in \mathbb{N}
$$

Identities containing binomial coefficients:

$$
\begin{array}{cc}
(a+b)^{n}=\sum_{k=0}^{n}\binom{n}{k} a^{k} b^{n-k} & 2^{n}=\sum_{k=0}^{n}\binom{n}{k} \quad 0=\sum_{k=0}^{n}(-1)^{k}\binom{n}{k} \\
\binom{n+1}{k}=\binom{n}{k-1}+\binom{n}{k} & \binom{n+m}{k}=\sum_{i=0}^{k}\binom{n}{i}\binom{m}{k-i} \quad \text { if } k \leq \min \{n, m\}
\end{array}
$$

## Probability Space

$(\mathcal{S}, \mathcal{A}, \mathbb{P})$, where $\mathcal{S}$ is the sample space (set of all possible outcomes=elementary events), $\mathcal{A}=\{A \mid A \subset \mathcal{S}\}$ is the Boole-algebra of the all possible events (including $\emptyset=$ impossible/null event and $\mathcal{S}=$ certain/sure event), and the set function $\mathbb{P}: \mathcal{A} \rightarrow \mathbb{R}$ satisfies the following AXIOMS:

1. For any $A \in \mathcal{A}: \quad 0 \leq \mathbb{P}(A) \leq 1$
2. $\mathbb{P}(\mathcal{S})=1$
3. For any sequence of mutually exclusive events $A_{1}, A_{2}, \ldots: \mathbb{P}\left(\sum_{i} A_{i}\right)=$ $\sum_{i} \mathbb{P}\left(A_{i}\right)$

Propositions implied by the axioms:

- $\mathbb{P}(\bar{A})=1-\mathbb{P}(A)$
- Probability is a monotone set function: if $A \subset B$, then $\mathbb{P}(A) \leq \mathbb{P}(B)$
- $\mathbb{P}\left(\sum_{i=1}^{n} A_{i}\right)=\sum_{k=1}^{n}(-1)^{k-1} S_{k}, \quad S_{k}=\sum_{1 \leq i_{1}<i_{2}<\cdots<i_{k} \leq n} \mathbb{P}\left(A_{i_{1}} A_{i_{2}} \ldots A_{i_{k}}\right)$ (inclusion-exclusion)


## De Morgan identities:

$$
\overline{\sum_{i=1}^{n} A_{i}}=\prod_{i=1}^{n} \bar{A}_{i} \quad \text { and } \quad \overline{\prod_{i=1}^{n} A_{i}}=\sum_{i=1}^{n} \bar{A}_{i}
$$

Examples of probability spaces:

- Combinatorial: the sample space has finite number of equally like outcomes, $\mathbb{P}(A)=|A| /|\mathcal{S}|$.
- Geometric: the sample space is a region with finite measure $\mu$ (length, area, volume), $\mathbb{P}(A)=\mu(A) / \mu(\mathcal{S})$.


## Conditional Probability, Bayes Rule

- Definition. $\mathbb{P}(A \mid B)=\frac{\mathbb{P}(A B)}{\mathbb{P}(B)}, \quad \mathbb{P}(B)>0$. With $B$ fixed, $\mathbb{Q}(A):=\mathbb{P}(A \mid B)$. $(\mathcal{S}, \mathcal{A}, \mathbb{Q})$ is also a probability space with all of its consequences.
- Definition. $B_{1}, B_{2}, \ldots$ is a complete set of mutually exclusive (disjoint) events, if $B_{i} B_{j}=\emptyset(i \neq j)$ and $\sum_{i} \mathbb{P}\left(B_{i}\right)=1$.
- Theorem (of complete probability). Let $B_{1}, B_{2}, \ldots$ be a complete set of mutually exclusive events and $A$ be an arbitrary event. Then

$$
\mathbb{P}(A)=\sum_{i} \mathbb{P}\left(A \mid B_{i}\right) \cdot \mathbb{P}\left(B_{i}\right)
$$

- Bayes' Theorem. Let $B_{1}, B_{2}, \ldots$ be a complete set of mutually exclusive events and $A$ be an arbitrary event. Then

$$
\mathbb{P}\left(B_{k} \mid A\right)=\frac{\mathbb{P}\left(A \mid B_{k}\right) \cdot \mathbb{P}\left(B_{k}\right)}{\sum_{i} \mathbb{P}\left(A \mid B_{i}\right) \cdot \mathbb{P}\left(B_{i}\right)}, \quad k=1,2, \ldots
$$

- Theorem (factorization). Let $A_{1}, A_{2}, \ldots, A_{n}$ be arbitrary events. Then

$$
\mathbb{P}\left(A_{1} A_{2} \ldots A_{n}\right)=\mathbb{P}\left(A_{1}\right) \cdot \mathbb{P}\left(A_{2} \mid A_{1}\right) \ldots \mathbb{P}\left(A_{n} \mid A_{1} \ldots A_{n-1}\right)
$$

## Independence

- Definition. $A$ and $B$ are independent if

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

Remark: If $\mathbb{P}(A) \neq 0$ and $\mathbb{P}(B) \neq 0$, then the independence of $A$ and $B$ means that $\mathbb{P}(A \mid B)=\mathbb{P}(A)$ and $\mathbb{P}(B \mid A)=\mathbb{P}(B)$; also, then $A$ and $B$ cannot be exclusive and independent at the same time. $\mathcal{S}$ and $\emptyset$ are independent of any other event.

- Definition. The events $A_{1}, \ldots, A_{n}$ are (completely) independent if

$$
\mathbb{P}\left(A_{1} \ldots A_{n}\right)=\mathbb{P}\left(A_{1}\right) \ldots \mathbb{P}\left(A_{n}\right)
$$

(If $\mathbb{P}\left(A_{i} A_{j}\right)=\mathbb{P}\left(A_{i}\right) \mathbb{P}\left(A_{j}\right)$ for $i \neq j$, then $A_{1} \ldots A_{n}$ are pairwise independent; this is weaker than independence.)

## Random variables

- Random Variable (r.v.): an $X: \mathcal{S} \rightarrow \mathbb{R}$ stochastic function that is measurable with respect to $\mathcal{A}$. It means that

$$
A=\{s \mid X(s) \in B\} \in \mathcal{A} \quad \forall B \in \mathcal{B}
$$

where $\mathcal{B}$ denotes the set of Borel-sets of $\mathbb{R}$. Distribution of $X$ : the collection of the probabilities $\mathbb{P}(A)$ 's of the above $A$ 's. Of course, we need not give all of them.

- Special types of random variables:

1. Discrete probability distributions: $X$ takes on values $x_{1}, x_{2}, \ldots$. $\mathbb{P}\left(X=x_{i}\right)=p_{i}, i=1,2, \ldots \quad\left(\sum_{i} p_{i}=1\right)$. The collection of $p_{i}$ 's is called probability mass function (p.m.f.) of $X$. The mode of $X$ : the value(s) taken on with the largest probability.
2. (Absolutely) continuous probability distributions: The range of $X$ is not countable and for any $x \in \mathbb{R}: \mathbb{P}(X=x)=0$. However, there is an $f: \mathbb{R} \rightarrow \mathbb{R}$ nonnegative, integrable function such that

$$
\int_{-\infty}^{\infty} f(x) d x=1 \quad \text { and } \quad \int_{B} f(x) d x=\mathbb{P}(X \in B), \quad \forall B \in \mathcal{B} .
$$

$f$ is called probability density function (p.d.f.) of $X$.
Cumulative distribution function (c.d.f.) of $X: F: \mathbb{R} \rightarrow \mathbb{R}$ such that

$$
F(x)=\mathbb{P}(X<x)=\int_{-\infty}^{x} f(t) \mathrm{d} t, \quad x \in \mathbb{R}
$$

$F$ is continuous, increasing, $\lim _{x \rightarrow-\infty} F(x)=0, \lim _{x \rightarrow \infty} F(x)=1$. $F$ is almost everywhere differentiable (at the points of continuity of $f$ ) and for such $x$ 's: $F^{\prime}(x)=f(x)$.

$$
\mathbb{P}(a<X<b)=F(b)-F(a)=\int_{a}^{b} f(x) d x \quad(a<b)
$$

(For discrete distributions the above $F$ is a stepwise constant, increasing, left-continuous function.)

- Expectation of $X$ (center of gravity of the mass distribution):

1. $\mathbb{E}(X)=\sum_{i} x_{i} p_{i} \quad$ (if it is absolutely convergent).
2. $\mathbb{E}(X)=\int_{-\infty}^{\infty} x f(x) d x \quad$ (if it is absolutely convergent).

For $X \geq 0: 1 . \mathbb{E}(X)=\sum_{i=0}^{\infty} \mathbb{P}(X>i)$ if $X \in \mathbb{N}, \quad$ 2. $\mathbb{E}(X)=\int_{0}^{\infty}(1-$ $F(x)) d x$.

- Variance of $X$ (inertia with resp. to the center of gravity of the mass distribution):

$$
\operatorname{Var}(X)=\mathbb{E}(X-\mathbb{E} X)^{2}=\mathbb{E}\left(X^{2}\right)-\mathbb{E}^{2}(X), \quad \text { provided } \mathbb{E}\left(X^{2}\right)<\infty
$$

Standard deviation of $X: \mathbb{D}(X)=\sqrt{\operatorname{Var}(X)} \geq 0$ and $=0$ if and only if $\mathbb{P}(X=$ cst. $)=1$.

- $k$-th Moment of $X: M_{k}(X)=\mathbb{E}\left(X^{k}\right), k$-th Central Moment of $X: M_{k}^{c}(X)=$ $\mathbb{E}(X-\mathbb{E} X)^{k}$ (if exists, then also exists for $\left.1 \leq s<k\right) . \mathbb{E}(X)=M_{1}(X)$, $\operatorname{Var}(X)=M_{2}^{c}(X)=M_{2}(X)-\left[M_{1}(X)\right]^{2}$.
- Steiner's Theorem: $\mathbb{E}(X-c)^{2}=\mathbb{E}(X-\mathbb{E} X)^{2}+(\mathbb{E} X-c)^{2} \geq \operatorname{Var}(X)$, min. if $c=\mathbb{E} X$.
- $p$-quantile value or $100 p$-percentile of $X$ is $x_{p}$ if $F\left(x_{p}\right)=p$. Median: 0.5 -quantile value.


## Examples to Notable Distributions, Prob. Models (see TABLES)

1. We have $N$ balls, $M$ red and $N-M$ white, mixed in an urn. $n$ balls are selected randomly without replacement (or at the same time). Suppose that $n \leq \min \{M, N-M\}$. What is the probability that among the selected $n$ balls there are $k$ red ones $(k=0,1, \ldots, n)$.
2. We have $N$ balls, $M$ red and $N-M$ white, mixed in an urn. $n$ balls are selected randomly with replacement. What is the probability that among the selected (visited) $n$ balls there are $k$ red ones $(k=0,1, \ldots, n)$.
3. What is the probability that by a 5 -lottery ticket one wins a prize (one has at least a 2 -hit)? ( 5 numbers are selected from $\{1,2, \ldots, 90\}$ )
4. In a class of 20 students 8 are not prepared for the class. The teacher selects 5 students at random and asks them. Give the distribution of the number of students who are not able to answer the teacher's question among the selected 5 .
5. What is the probability that we have a $k$-hit by filling in a TOTO ticket at random $(k=0,1, \ldots, 13)$ ? (bet 1,2 , or x on the outcome of each of 13 soccer matches)
6. Give the distribution of the number of girls in a family having $n$ children. Give the mode of this random variable! (The gender of the children is independent of each other with probability $1 / 2-1 / 2$.) Equivalent problem: $n$ fair coins are tossed, or a fair coin is tossed $n$ times; give the distribution of the number of heads.
7. Waiting for the first boy. Consider the following population model: each family waits for a boy, and once they have him, they do not want more children. Give the boys/girls proportion in this population. (The gender of children is independent of each other with probability $1 / 2-1 / 2$.)
8. Cookies are made in a big bakery: the blueberries are mixed into the mass and then the cookies are formed randomly. About how many blueberries have to be planned for a cookie, if they want to make the probability of possible complaints (of not having any blueberry in the cookie) as small as 0.01 . Give the mode of the actual number of blueberries in a cookie!
9. Let $X$ denote the lifetime of a radioactive isotope. Assuming, it has exponential distribution, prove the Markovian (ever-lasting) property of it:

$$
\mathbb{P}(X>t+s \mid X>s)=\mathbb{P}(X>t), \quad t, s>0
$$

If the halving time (median) is 100 years, find the parameter $\lambda$ and the expected lifetime.
10. Let $X \sim \mathcal{N}\left(\mu, \sigma^{2}\right)$ be Gaussian random variable. Calculate $\mathbb{P}(\mu-\sigma<$ $X<\mu+\sigma)$ and $\mathbb{P}(\mu-2 \sigma<X<\mu+2 \sigma)$.

The following theorem states that the Gaussian distribution has a distinguished importance. Let $X_{1}, X_{2}, \ldots$ be i.i.d. r.v.'s (they are independent and identically distributed) with (existing) expectation $\mu$ and standard deviation $\sigma$. Let

$$
\bar{X}:=\frac{X_{1}+\cdots+X_{n}}{n}, \quad n=1,2, \ldots
$$

Obviously, $\mathbb{E}(\bar{X})=\mu$ and $\mathbb{D}(\bar{X})=\frac{\sigma}{\sqrt{n}}$.
Central Limit Theorem (CLT): In the above setup, the standardized $\bar{X}$ is approximately Gaussian:

$$
Z=\frac{\bar{X}-\mu}{\sigma / \sqrt{n}}=\frac{\bar{X}-\mu}{\sigma} \sqrt{n} \rightarrow \mathcal{N}(0,1), \quad n \rightarrow \infty
$$

in terms of the convergence in distribution (convergence of distribution functions).

