Limit Theorems

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Probability and Statistics

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Content

- **Probability theory:**
  - Events, probability, conditional probability, Bayes' Theorem, independence of events.
  - Random variables, distribution function, functions of random variables, characteristics of random variables: expected value, variance, moments, generating function, quantiles, critical values, important discrete and continuous distributions.
  - Random vectors, joint and marginal distributions, independence of random variables, conditional distribution, functions of random vectors, covariance and correlation.
  - Markov's and Chebyshev's inequality, weak law of large numbers, strong law of large numbers, Central limit theorem.
- **Mathematical statistics:**
  - Point estimators, sample mean, sample variance, properties of point estimators, Maximum likelihood method.
  - Interval estimators, hypothesis testing, one-sided vs. two-sided alternatives, linear regression, estimators of regression parameters, testing of linear model.

Recap

Discrete random variable X	Continuous random variable X
Probabilities of values / density of X:	
$\mathrm{P}(X = x)$	$f_X(x)$
Independence of X and Y:	
$\mathrm{P}(X = x \cap Y = y) = \mathrm{P}(X = x)\,\mathrm{P}(Y = y)$	$f_{X,Y}(x,y) = f_X(x) f_Y(y)$
Expected value of X:	
$\mathrm{E}\,X = \sum_x x\,\mathrm{P}(X = x)$	$\mathrm{E}\,X = \int_{-\infty}^{\infty} x f_X(x)\,\mathrm{d}x$

Variance of X:

$$\operatorname{var} X = \mathrm{E}(X - \mathrm{E}\,X)^2 = \mathrm{E}(X^2) - (\mathrm{E}\,X)^2$$

Linearity of the expectation (for any X and Y):

$$\mathrm{E}(X + Y) = \mathrm{E}\,X + \mathrm{E}\,Y$$

Variance of a sum of independent or non-correlated X and Y:

$$\operatorname{var}(X + Y) = \operatorname{var} X + \operatorname{var} Y.$$

Limit theorems – motivation

So far we have studied individual random variables and vectors.

Now we concentrate on the behavior of sequences of random variables, which arise from repeated experiments.

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In particular, we are interested in the (arithmetic) **mean**

$$\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} X_i,$$

and the **sum**

$$S_n = \sum_{i=1}^{n} X_i,$$

where $X_1, \ldots, X_n$ are independent random variables with an identical distribution.
Notation: **i.i.d.** – **independent and identically distributed**.

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Limit theorems describe the behavior of $\bar{X}_n$ or S_n in limit for $n \to \infty$.

Markov's inequality

First, we obtain inequalities concerning tail probabilities:

Theorem – Markov's inequality

Let X be a random variable with a finite expectation. Then it holds that

$$\mathrm{P}(|X| \geq a) \leq \frac{\mathrm{E}\,|X|}{a} \qquad \textit{for all } a > 0.$$

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Proof

Denote the event $A = \{|X| \geq a\}$. Then it holds that $|X| \geq a\mathbb{1}_A$, where $\mathbb{1}_A$ is the indicator of the event A.

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Proof

Denote the event $A = \{|X| \geq a\}$. Then it holds that $|X| \geq a\mathbb{1}_A$, where $\mathbb{1}_A$ is the indicator of the event A. By taking expectation on both sides of the inequality we have

$$\mathrm{E}\,|X| \geq a\,\mathrm{E}(\mathbb{1}_A) = a\,\mathrm{P}(A) = a\,\mathrm{P}(|X| \geq a).$$

After dividing by a we obtain the inequality. □

Markov's inequality – example

Example – waiting for a bus

Suppose that the time T which we spend waiting for a bus is exponentialy distributed with the expectation of 3 minutes.

Find an upper bound for the probability that we need to wait for more than 10 minutes.

Compare the estimate with the exact probability.

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Because the waiting time T is non-negative and therefore $T = |T|$, using the Markov's inequality we obtain that

$$\mathrm{P}(T \geq 10) = \mathrm{P}(|T| \geq 10) \leq \frac{\mathrm{E}\,|T|}{10} = \frac{3}{10} = 0.3.$$

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The expectation of the exponentially distributed waiting time is $\mathrm{E}\,T = 1/\lambda = 3$, thus the parameter λ is equal to $1/3$. The exact probability is then

$$\mathrm{P}(T \geq 10) = \int_{10}^{\infty} \lambda e^{-\lambda t}\,\mathrm{d}t = \left[-e^{-\lambda t}\right]_{10}^{\infty} = e^{-\frac{1}{3}\cdot 10} \doteq 0.036.$$

We see that the Markov's inequality provides a fast way to obtain an upper bound of the tail probability.

Chebyshev's inequality

The Chebyshev's inequality follows from the Markov's inequality:

Theorem – Chebyshev's inequality

Let X be a random variable with a finite expectation and a finite variance. Then it holds that

$$\mathrm{P}(|X - \mathrm{E}\, X| \geq \varepsilon) \leq \frac{\operatorname{var} X}{\varepsilon^2} \qquad \textit{for all } \varepsilon > 0.$$

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Proof

Can be obtained directly, similarly to Markov's inequality (for $(X - \mathrm{E}\,X)^2$), or by inserting $(X - \mathrm{E}\,X)^2$ instead of X and ε^2 instead of a into the Markov's inequality. We obtain

$$\mathrm{P}(|(X - \mathrm{E}\,X)^2| \geq \varepsilon^2) \leq \frac{\mathrm{E}\,|(X - \mathrm{E}\,X)^2|}{\varepsilon^2}.$$

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Since $|(X - \mathrm{E}\,X)^2| = (X - \mathrm{E}\,X)^2 = |X - \mathrm{E}\,X|^2$ and a quadratic function is increasing for positive arguments, it holds that

$$(X - \mathrm{E}\,X)^2 \geq \varepsilon^2 \Leftrightarrow |X - \mathrm{E}\,X| \geq \varepsilon.$$

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Finally we obtain

$$\mathrm{P}(|X - \mathrm{E}\,X| \geq \varepsilon) \leq \frac{\operatorname{var} X}{\varepsilon^2}.$$

□

Chebyshev's inequality – example

Example – waiting for a bus

Suppose that the time T which we spend waiting for a bus is exponentially distributed with the expectation of 3 minutes.

Find an upper bound for the probability that we need to wait for more than 10 minutes using the Chebyshev's inequality. Compare the estimate with the exact probability and with the bound obtained from the Markov's inequality.

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Because $T \sim \mathrm{Exp}(\lambda)$ with $\lambda = 1/3$, we get $\mathrm{E}\,T = 1/\lambda = 3$ and $\operatorname{var} T = 1/\lambda^2 = 9$. Using the Chebyshev's inequality we obtain

$$\mathrm{P}(T \geq 10) = \mathrm{P}(T - \mathrm{E}\,T \geq 10 - 3) \leq \mathrm{P}(|T - \mathrm{E}\,T| \geq 7) \leq \frac{\operatorname{var} T}{7^2} = \frac{9}{49} \doteq 0.184.$$

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The Markov's inequality provided a bound of $\mathrm{P}(T \geq 10) \leq 0.3$, so the Chebyshev's inequality provides a somewhat closer approximation of the exact probability $\mathrm{P}(T \geq 10) = 0.036$.

Tail probabilities – example

Example – waiting for a bus and a tram

Suppose that during our way home, we need to wait for the bus and then for the tram. The time T_1 spent waiting for the bus is exponentially distributed with the expectation of 3 minutes, time T_2 spent waiting for the tram is exponentially distributed with the expectation of 2 minutes. The times are independent.

Tail probabilities – example

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Find an upper bound for the probability that the total time we spend waiting, $T = T_1 + T_2$ will be more than 15 minutes. Use the Markov's and Chebyshev's inequalities and compare the estimate with the exact probability.

Tail probabilities – example

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Find an upper bound for the probability that the total time we spend waiting, $T = T_1 + T_2$ will be more than 15 minutes. Use the Markov's and Chebyshev's inequalities and compare the estimate with the exact probability.

First we find the expectations and variances of T_1, T_2 and T.

$$T_1 \sim \mathsf{Exp}(\lambda), \quad \mathrm{E}\, T_1 = 1/\lambda = 3, \quad \lambda = 1/3, \quad \operatorname{var} T_1 = 1/\lambda^2 = 9.$$
$$T_2 \sim \mathsf{Exp}(\mu), \quad \mathrm{E}\, T_2 = 1/\mu = 2, \quad \mu = 1/2, \quad \operatorname{var} T_2 = 1/\mu^2 = 4.$$

Using the linearity of the expectation and independence of the waiting times we get:

$$\mathrm{E}\, T = \mathrm{E}(T_1 + T_2) \overset{\text{linearity}}{=} \mathrm{E}\, T_1 + \mathrm{E}\, T_2 = 3 + 2 = 5.$$
$$\operatorname{var} T = \operatorname{var}(T_1 + T_2) \overset{\text{independence}}{=} \operatorname{var} T_1 + \operatorname{var} T_2 = 9 + 4 = 13.$$

Tail probabilities – example

Example – waiting for a bus and a tram, continued

Using the Markov's inequality we obtain

$$\mathrm{P}(T \geq 15) = \mathrm{P}(|T| \geq 15) \leq \frac{\mathrm{E}\,|T|}{15} = \frac{5}{15} \doteq 0.333.$$

Using the Chebyshev's inequality we obtain

$$\mathrm{P}(T \geq 15) = \mathrm{P}(T - \mathrm{E}\,T \geq 15 - 5) \leq \mathrm{P}(|T - \mathrm{E}\,T| \geq 10) \leq \frac{\operatorname{var} T}{10^2} = \frac{13}{100} = 0.13.$$

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The distribution of the sum is considerably more difficult to obtain than when dealing with just one variable. Using convolution we get:

$$\mathrm{P}(T \geq 15) = \int_{15}^{\infty} \int_{0}^{t} \lambda e^{-\lambda u} \mu e^{-\mu \cdot (t-u)} \,\mathrm{d}u\,\mathrm{d}t = \cdots = \frac{\mu e^{-\lambda \cdot 15} - \lambda e^{-\mu \cdot 15}}{\mu - \lambda} \doteq 0.019.$$

Tail probabilities – example

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The upper bounds obtained using the inequalities seem somewhat imprecise, but they are easy to compute, using only expectations and variances.

Characteristics of the mean of random variables

First we compute the expected value and variance of the mean

$$\bar{X}_n = \frac{1}{n} \sum_{i=1}^{n} X_i,$$

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- **Expected value**

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- **Variance**

$$\operatorname{var} \bar{X}_n = \operatorname{var} \frac{1}{n} \sum_{i=1}^{n} X_i = \frac{1}{n^2} \operatorname{var} \sum_{i=1}^{n} X_i = \frac{1}{n^2} \sum_{i=1}^{n} \operatorname{var} X_i = \frac{n\sigma^2}{n^2} = \frac{\sigma^2}{n}.$$

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We used the linearity of the expectation in the first part and the behavior of the variance of a sum of independent random variables in the second part.

Weak law of large numbers

By inserting $\bar{X}_n$ into the Chebyshev's inequality we obtain the **weak law of large numbers**:

Theorem – weak law of large numbers

Let $X_1, X_2, \dots$ be i.i.d. random variables with finite expectation $\mathrm{E}\, X_i = \mu$ and finite variance σ^2. Then $\bar{X}_n$ converges to μ ***in probability***

$$\bar{X}_n \xrightarrow{P} \mu \qquad \text{for} \quad n \to \infty.$$

This means that for all $\varepsilon > 0$ it holds that $\lim\limits_{n\to\infty} \mathrm{P}(|\bar{X}_n - \mu| \geq \varepsilon) = 0.$

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Proof

We use the Chebyshev's inequality for the arithmetic mean $\bar{X}_n$:

$$0 \leq \mathrm{P}(|\bar{X}_n - \mathrm{E}\, \bar{X}_n| \geq \varepsilon) = \mathrm{P}(|\bar{X}_n - \mu| \geq \varepsilon) \leq \frac{\operatorname{var} \bar{X}_n}{\varepsilon^2} = \frac{\sigma^2}{n\varepsilon^2} \to 0 \qquad \text{for } n \to \infty.$$

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The statement follows from the sandwich theorem. □

Strong law of large numbers

Theorem – strong law of large numbers (SLLN)

Let $X_1, X_2, \ldots$ be i.i.d. random variables with expected value $\mathrm{E}\, X_i = \mu$ (not necessarily finite). Then $\bar{X}_n$ converges to μ ***almost surely*** *(with probability 1)*

$$\bar{X}_n \xrightarrow{\text{a.s.}} \mu \qquad \text{for} \quad n \to \infty.$$

It means that the set where $X_n(\omega)$ converges as a numerical sequence has probability 1:

$$\mathrm{P}(\{\omega \in \Omega \colon \bar{X}_n(\omega) \to \mu \text{ for } n \to \infty\}) = 1.$$

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Considerably more difficult, see bibliography. □

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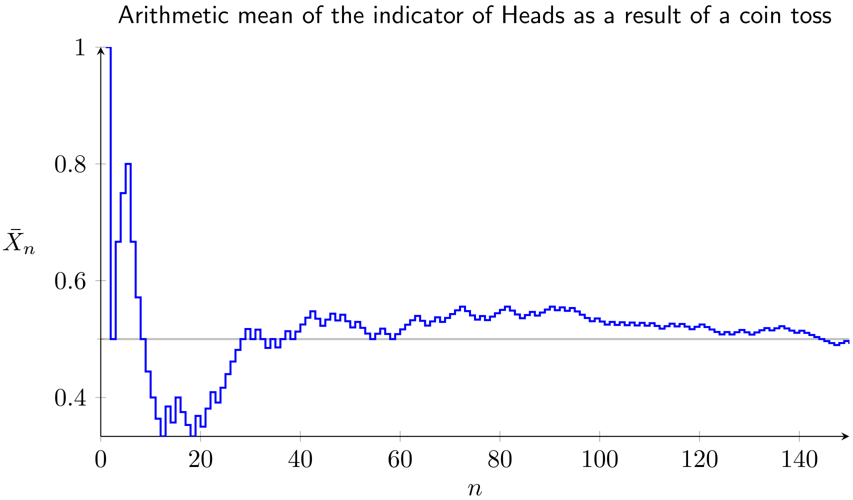
In what sense is this law of large numbers "**stronger**"?

- It is enough to consider the existence of the expected value. Moreover, it can be infinite and the variance as well.
- Convergence almost surely **implies** convergence in probability.

Strong law of large numbers – illustration



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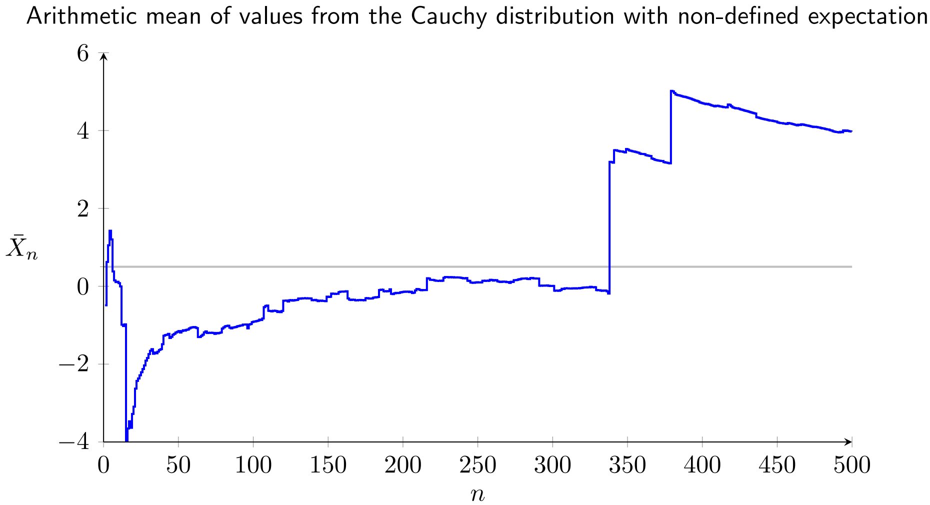

Characteristics of the sum of random variables

Recall that for the arithmetic mean $\bar{X}_n$ of **i.i.d.** random variables with $\mathrm{E}\, X_i = \mu$ and $\operatorname{var} X_i = \sigma^2$ we have

$$\mathrm{E}\, \bar{X}_n = \mu, \qquad \operatorname{var} \bar{X}_n = \frac{\sigma^2}{n}.$$

Let us now find the characteristics of the sum:

$$S_n = \sum_{i=1}^{n} X_i.$$

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- **Variance**

$$\operatorname{var} S_n = \operatorname{var} \sum_{i=1}^{n} X_i \overset{\text{independence}}{=} \sum_{i=1}^{n} \operatorname{var} X_i = \sum_{i=1}^{n} \sigma^2 = n\sigma^2.$$

Characteristics of the sum of random variables

Recall that for the arithmetic mean $\bar{X}_n$ of **i.i.d.** random variables with $\mathrm{E}\, X_i = \mu$ and $\operatorname{var} X_i = \sigma^2$ we have

$$\mathrm{E}\, \bar{X}_n = \mu, \qquad \operatorname{var} \bar{X}_n = \frac{\sigma^2}{n}.$$

Let us now find the characteristics of the sum:

$$S_n = \sum_{i=1}^{n} X_i.$$

- **Expected value**

$$\mathrm{E}\, S_n = \mathrm{E} \sum_{i=1}^{n} X_i \overset{\text{linearity}}{=} \sum_{i=1}^{n} \mathrm{E}\, X_i = \sum_{i=1}^{n} \mu = n\mu.$$

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We can alternatively obtain this properties if we realize that $S_n = n \cdot \bar{X}_n$ and apply the expectation and variance.

Central limit theorem – motivation

Laws of large numbers deal with convergence of the mean to the expected value. For large n, the mean represents a reasonable approximation of the expected value. In other words, the expectation is the ideal average of an infinite number of repeated experiments.

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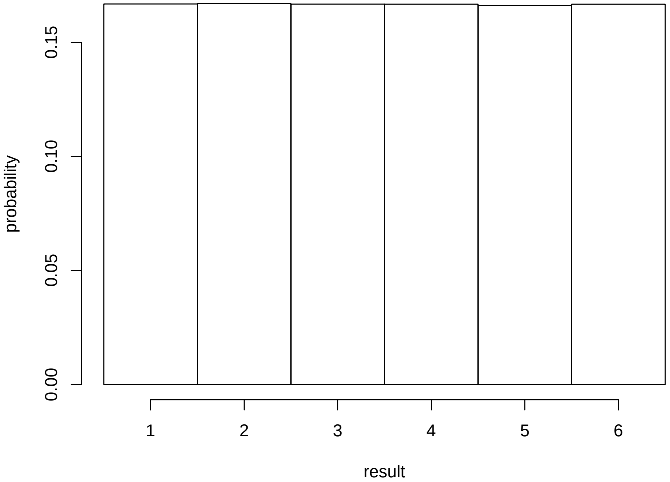
However, what is the distribution of the mean or the sum as a random variable?

Central limit theorem (CLT) says that under particular circumstances the distribution of the mean or a sum can be approximated by the **normal** distribution.

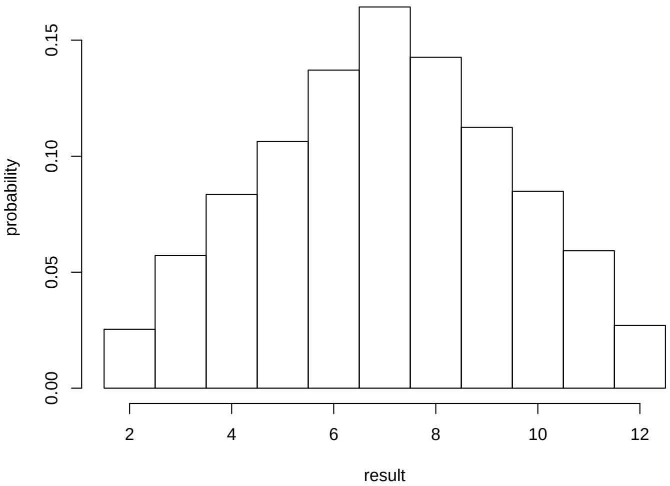
Distribution of sums of dice rolls

Distribution of one die roll (simulation).



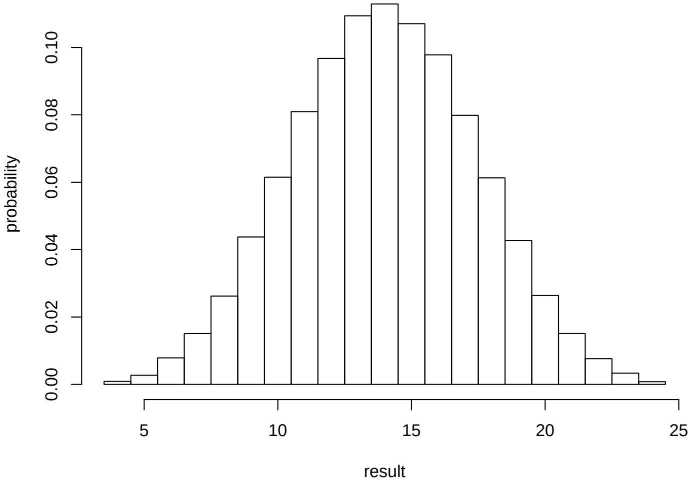
Distribution of sums of dice rolls

Distribution of the sum of two dice rolls (simulation).



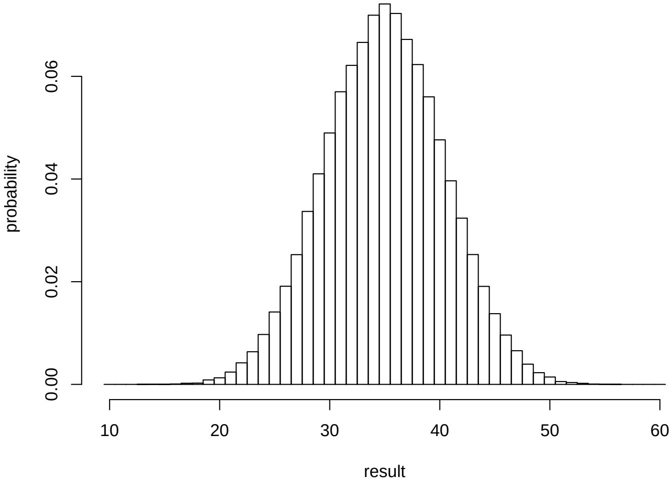
Distribution of sums of dice rolls

Distribution of the sum of four dice rolls (simulation).



Distribution of sums of dice rolls

Distribution of the sum of ten dice rolls (simulation).



Convergence in distribution

For understanding the statement of central limit theorem we need to define the convergence in distribution.

Definition

Let $X_1, X_2, \ldots$ be a sequence of random variables with distribution functions $F_{X_1}, F_{X_2}, \ldots$ and X be a random variable with a distribution function F_X.
We say that variables X_i converge to X **in distribution**,

$$X_n \xrightarrow{\mathcal{D}} X \quad \text{or} \quad X_n \xrightarrow{\mathcal{L}} X \quad \text{for } n \to \infty,$$

if

$$\lim_{n\to\infty} F_{X_n}(x) = F_X(x)$$

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- $\mathrm{P}(a < X_n \leq b) = F_{X_n}(b) - F_{X_n}(a) \approx F_X(b) - F_X(a) = \mathrm{P}(a < X \leq b)$.

Central limit theorem

Theorem – Central limit theorem (CLT)

Let $X_1, X_2, \dots$ be a sequence of i.i.d. random variables with finite expectations $\mathrm{E}\, X_i = \mu$ and finite variances $\operatorname{var} X_i = \sigma^2 > 0$. Then

$$\frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} \xrightarrow{\mathcal{D}} \mathsf{N}(0,1) \qquad \text{for } n \to \infty.$$

Similarly

$$\frac{S_n - n\mu}{\sigma\sqrt{n}} \xrightarrow{\mathcal{D}} \mathsf{N}(0,1) \qquad \text{for } n \to \infty.$$

Proof

See bibliography. □

The symbol $\mathsf{N}(0,1)$ stands for a variable with the **standard normal distribution**.

Central limit theorem

Recall that

$$\operatorname{E}\bar{X}_n = \mu, \qquad \operatorname{E}S_n = n\cdot\mu,$$
$$\operatorname{var}\bar{X}_n = \sigma^2/n. \qquad \operatorname{var}S_n = n\cdot\sigma^2,$$

The central limit theorem states that if we take either the **standardised mean** or the **standardised sum**

$$Z_n = \frac{\bar{X}_n - \operatorname{E}\bar{X}_n}{\sqrt{\operatorname{var}\bar{X}_n}} = \frac{S_n - \operatorname{E}S_n}{\sqrt{\operatorname{var}S_n}} = \frac{\bar{X}_n - \mu}{\sqrt{\sigma^2/n}}, = \frac{S_n - n\mu}{\sqrt{n\sigma^2}}$$

the resulting variable **converges to the standard normal distribution**. For any $z \in \mathbb{R}$:

$$\operatorname{P}(Z_n \leq z) \overset{n\to\infty}{\longrightarrow} \operatorname{P}(Z \leq z) = \Phi(z).$$

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This allows us to effectively approximate the behavior of sums or means for large n.

The theorem can be used regardless of the original distribution, even if it is unknown. However, the closer to the normal distribution, the more precise is the approximation.

Central limit theorem

CLT allows us to express probabilities of types $\mathrm{P}(\bar{X}_n < x)$, $\mathrm{P}(\bar{X}_n > x)$, etc. by means of the distribution function Φ of the standard normal distribution

$$\Phi(z) = \mathrm{P}(Z \leq z) \quad \text{for} \quad Z \sim \mathsf{N}(0, 1).$$

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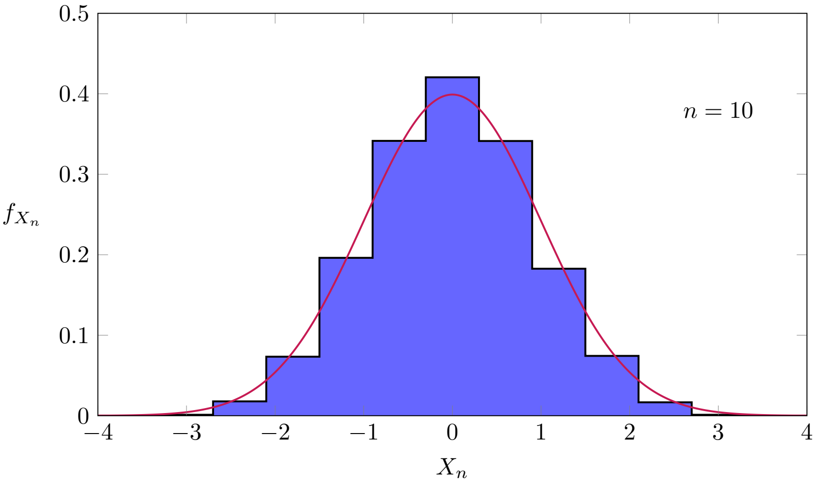
Another variants of the statement:

- $\dfrac{\sqrt{n}(\bar{X}_n - \mu)}{\sigma} \xrightarrow{\mathcal{D}} \mathsf{N}(0,1)$,
- $\bar{X}_n \overset{\text{approx.}}{\sim} \mathsf{N}\left(\mu, \dfrac{\sigma^2}{n}\right)$ for large n,
- $S_n \overset{\text{approx.}}{\sim} \mathsf{N}(n\mu, n\sigma^2)$ for large n..

Central limit theorem – illustration

Estimate of the density of the arithmetic mean of n coin tosses (1000 realizations)



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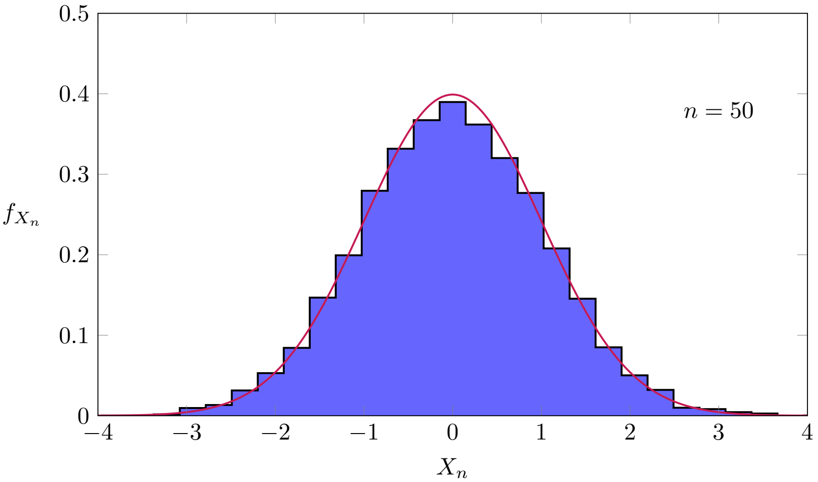

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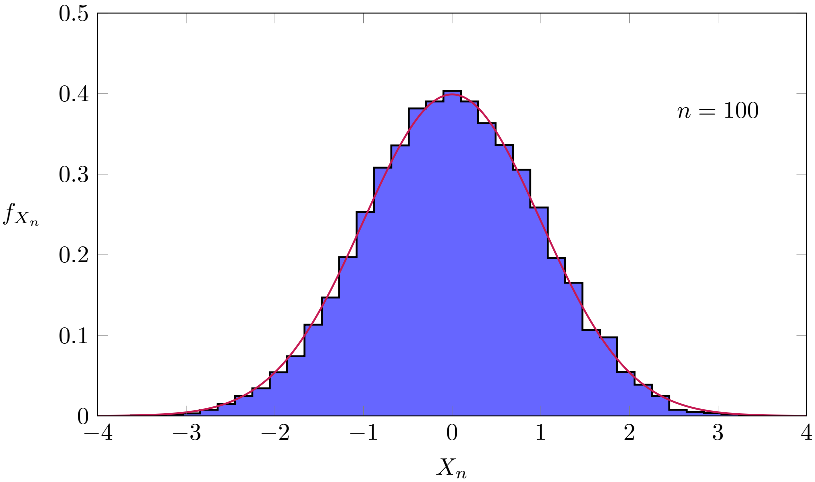

Central limit theorem – example

Example

What is the probability that in 1000 independent tosses with a coin we get more than 525 times Heads?

Central limit theorem – example

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Let X_i be an indicator variable denoting, whether in the i-th toss Heads appears ($X_i = 1$) or not ($X_i = 0$). We want to calculate $\mathrm{P}(S_{1000} > 525)$. The number of successes (Heads) among n attempts (rolls) follows the binomial distribution Binom(n, p) with $n = 1000$ and $p = 1/2$. Computing the probability directly would be very demanding.

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Instead of using the binomial distribution we use CLT. For tossing a coin it holds that $\mathrm{E}\, X_i = p = 1/2$ and $\operatorname{var} X_i = p(1-p) = 1/4$. For the sum it holds that $\mathrm{E}\, S_{1000} = np = 500$, and $\operatorname{var} S_{1000} = np(1-p) = 250$.

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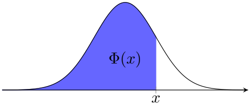
$$\mathrm{P}\left(\sum_{i=1}^{1000} X_i > 525\right) = \mathrm{P}(S_{1000} - 500 > 525 - 500) = \mathrm{P}\left(\frac{S_{1000} - 500}{\sqrt{250}} > \frac{25}{\sqrt{250}}\right) =$$

$$= 1 - \mathrm{P}\left(\frac{S_{1000} - 500}{\sqrt{250}} \leq \frac{5}{\sqrt{10}}\right) \approx 1 - \Phi\left(\frac{5}{\sqrt{10}}\right) = 1 - \Phi(1.58) = 0.0571.$$

Tables of the values of the distribution function Φ of the standard normal distribution $\mathrm{N}(0, 1)$



	.00	.01	.02	.03	.04	.05	.06	.07	.08	.09
0.0	.5000	.5040	.5080	.5120	.5160	.5199	.5239	.5279	.5319	.5359
0.1	.5398	.5438	.5478	.5517	.5557	.5596	.5636	.5675	.5714	.5753
0.2	.5793	.5832	.5871	.5910	.5948	.5987	.6026	.6064	.6103	.6141
0.3	.6179	.6217	.6255	.6293	.6331	.6368	.6406	.6443	.6480	.6517
0.4	.6554	.6591	.6628	.6664	.6700	.6736	.6772	.6808	.6844	.6879
0.5	.6915	.6950	.6985	.7019	.7054	.7088	.7123	.7157	.7190	.7224
0.6	.7257	.7291	.7324	.7357	.7389	.7422	.7454	.7486	.7517	.7549
0.7	.7580	.7611	.7642	.7673	.7704	.7734	.7764	.7794	.7823	.7852
0.8	.7881	.7910	.7939	.7967	.7995	.8023	.8051	.8078	.8106	.8133
0.9	.8159	.8186	.8212	.8238	.8264	.8289	.8315	.8340	.8365	.8389
1.0	.8413	.8438	.8461	.8485	.8508	.8531	.8554	.8577	.8599	.8621
1.1	.8643	.8665	.8686	.8708	.8729	.8749	.8770	.8790	.8810	.8830
1.2	.8849	.8869	.8888	.8907	.8925	.8944	.8962	.8980	.8997	.9015
1.3	.9032	.9049	.9066	.9082	.9099	.9115	.9131	.9147	.9162	.9177
1.4	.9192	.9207	.9222	.9236	.9251	.9265	.9279	.9292	.9306	.9319
1.5	.9332	.9345	.9357	.9370	.9382	.9394	.9406	.9418	.9429	.9441

Central limit theorem – example

Example – CLT vs. Markov's and Chebyshev's inequalities

Suppose that we operate a cargo lift with a maximum load of 600 kg. We need to lift 25 packages, each having an expected weight of 20 kilograms and a standard deviation of 8 kilograms.

What is the probability that the lift will be overloaded? Use the Markov's and Chebyshev's inequalities and CLT.

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Let X_i be the weight of the i-th package. We have

$$\mathrm{E}\, X_i = \mu = 20 \qquad \text{and} \qquad \operatorname{var} X_i = \sigma^2 = 8^2 = 64.$$

The total weight of all $n = 25$ packages is $S_n = \sum_{i=1}^{n} X_i$, with

$$\mathrm{E}\, S_n = n\mu = 25 \cdot 20 = 500 \qquad \text{and} \qquad \operatorname{var} S_n = n\sigma^2 = 25 \cdot 64 = 1600.$$

Central limit theorem – example

Example – CLT vs. Markov's and Chebyshev's inequalities, continued

The weights are surely non-negative, thus the Markov's inequality gives us:

$$\mathrm{P}(S_n \geq 600) = \mathrm{P}(|S_n| \geq 600) \leq \frac{E|S_n|}{600} = \frac{500}{600} \doteq 0.83.$$

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Using the Chebyshev's inequality we get

$$\mathrm{P}(S_n \geq 600) \leq \mathrm{P}(|S_n - \mathrm{E}\,Sn| \geq 600 - 500) \leq \frac{\operatorname{var} S_n}{100^2} = \frac{1600}{10000} = 0.16.$$

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CLT gives us

$$\mathrm{P}(S_n > 600) = 1 - \mathrm{P}(S_n \leq 600) = 1 - \mathrm{P}\left(\frac{S_n - \mathrm{E}\, S_n}{\sqrt{\operatorname{var} S_n}} \leq \frac{600 - 500}{\sqrt{1600}}\right)$$
$$= 1 - \mathrm{P}\left(Z_n \leq \frac{100}{40}\right) \approx 1 - \Phi(2.5) = 0.0062.$$

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We were able to use the inequalities and the central limit theorem to approximate the probability, even if we didn't know the distribution of the weights.

Recap

Suppose we observe a **sequence of independent and identically distributed** (`i.i.d.`) random variables $X_1, X_2, \ldots$, with expectation $\mathrm{E}\, X_i = \mu$ and variance $\operatorname{var} X_i = \sigma^2$.

- If we denote the arithmetic **mean** and the **sum** of the variables as

$$\bar{X}_n = \frac{1}{n}\sum_{i=1}^{n} X_i \qquad \text{and} \qquad S_n = \sum_{i=1}^{n} X_i,$$

  we get that

$$\begin{aligned} \mathrm{E}\, \bar{X}_n &= \mu, & \mathrm{E}\, S_n &= n \cdot \mu, \\ \operatorname{var} \bar{X}_n &= \sigma^2/n, & \operatorname{var} S_n &= n \cdot \sigma^2. \end{aligned}$$

- According to the **law of large numbers**, the arithmetic mean converges to the expectation, provided that it is finite:

$$\bar{X}_n \xrightarrow{n\to\infty} \mu.$$

- According to the **central limit theorem**, the distribution of the standardised mean or sum converges to standard normal:

$$Z_n = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{S_n - n\mu}{\sqrt{n}\sigma} \xrightarrow{n\to\infty} \mathsf{N}(0,1).$$