

Topic 11

Central Limit Theorem

The Classical Central Limit Theorem

Outline

Motivation

Bernoulli Random Variables

Exponential Random Variables

The Classical Central Limit Theorem

Examples

Motivation

For the **law of large numbers**, the **sample means** from a sequence of independent random variables **converge** to their common **distributional mean** as the number n of random variables increases.

$$\frac{1}{n}S_n = \bar{X}_n \rightarrow \mu \text{ as } n \rightarrow \infty.$$

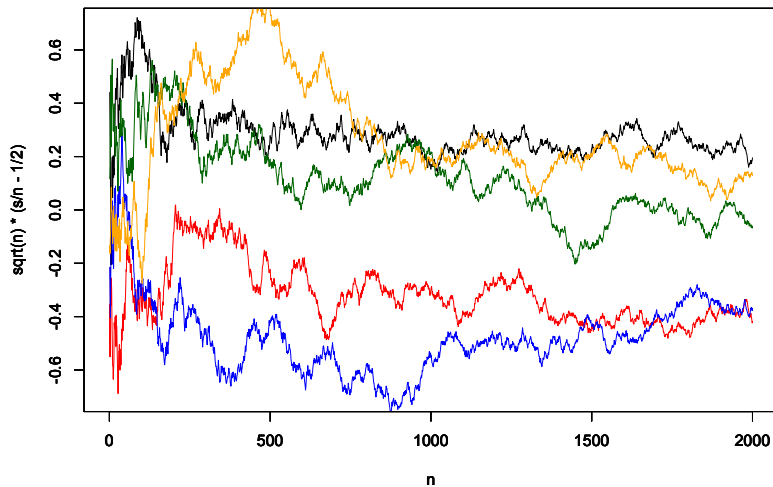
Moreover, the standard deviation of \bar{X}_n is **inversely proportional** to \sqrt{n} . For example, for independent random variables, uniformly distributed on $[0, 1]$, \bar{X}_n converges to

$$\mu = \int_0^1 xf_X(x) \, dx = \int_0^1 x \, dx = \frac{x^2}{2} \Big|_0^1 = \frac{1}{2}$$

Because the standard deviation $\sigma_{\bar{X}_n} \propto 1/\sqrt{n}$, we magnify the difference between the running average and the mean by a factor of \sqrt{n} and investigate the graph of

$$\sqrt{n} \left(\frac{1}{n}S_n - \mu \right) \text{ versus } n$$

Motivation



Motivation

Does the distribution of the size of these fluctuations have any **regular** and **predictable** structure? Let's begin by examining the distribution for the sum of $X_1, X_2 \dots X_n$, **independent** and **identically distributed** random variables

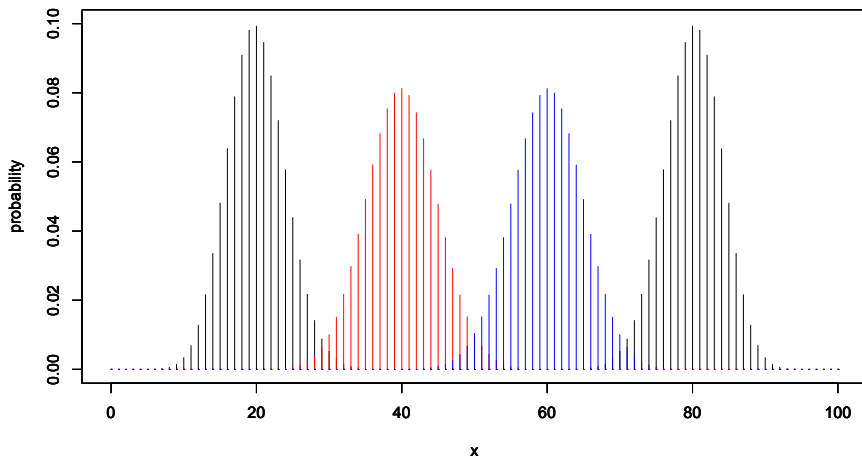
$$S_n = X_1 + X_2 + \dots + X_n.$$

What distribution do we see? We begin with the simplest case, X_i **Bernoulli** random variables. The **sum** S_n is a **binomial** random variable. We examine two cases.

- keep the number of trials the same at $n = 100$ and vary the success probability p .
- keep the success probability the same at $p = 1/2$, but vary the number of trials.

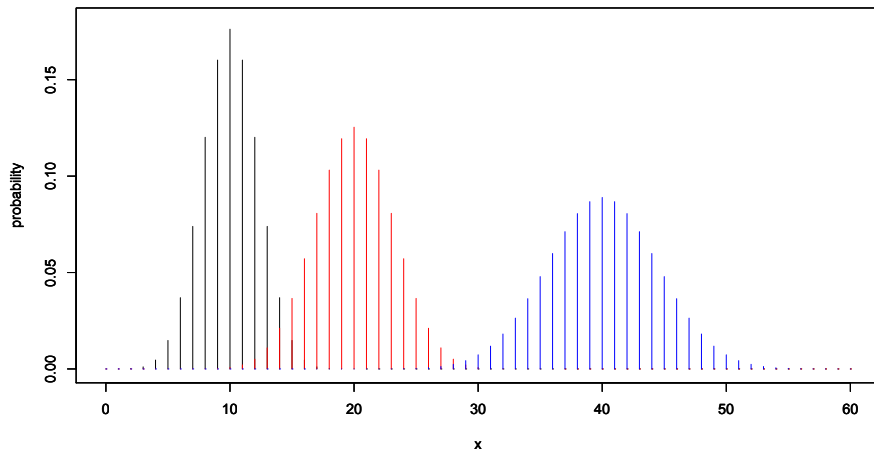


Bernoulli Random Variables



Successes in 100 Bernoulli trials with $p = 0.2, 0.4, 0.6$ and 0.8 .

Bernoulli Random Variables



Successes in 20, 40, and 80 Bernoulli trials with $p = 0.5$.

Bernoulli Random Variables

The **binomial** random variable S_n has

mean np and **standard deviation** $\sqrt{np(1-p)}$.

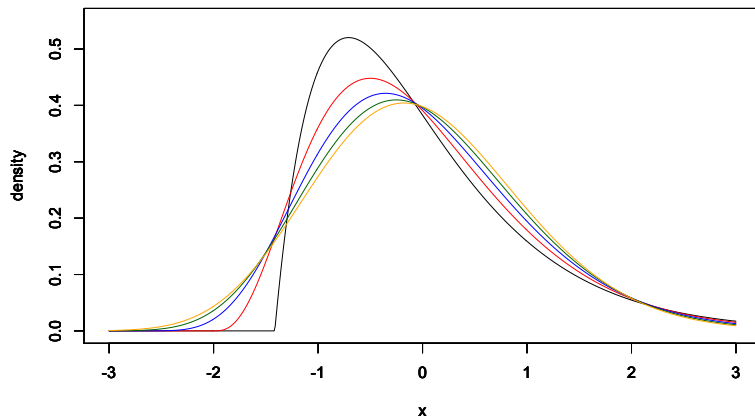
Thus, if we take the standadized version of these sums of Bernoulli random variables

$$Z_n = \frac{S_n - np}{\sqrt{np(1-p)}},$$

then these **bell curve** graphs would lie on top of each other.

Now, let's consider **exponential** random variables

Exponential Random Variables



The **density** of the standardized random variables that result from the sum of 2, 4, 8, 16, and 32 **exponential** random variables

The Classical Central Limit Theorem

To obtain the standardized random variables,

- we can either standardize using the **sum** S_n having **mean** $n\mu$ and **standard deviation** $\sigma\sqrt{n}$, , or
- we can standardize using the **sample mean** \bar{X}_n having **mean** μ and **standard deviation** σ/\sqrt{n} .

This yields two equivalent versions of the **standardized score** or **z-score**.

$$Z_n = \frac{S_n - n\mu}{\sigma\sqrt{n}} = \frac{\bar{X}_n - \mu}{\sigma/\sqrt{n}} = \frac{\sqrt{n}}{\sigma}(\bar{X}_n - \mu).$$

The theoretical result behind these numerical explorations is called the **classical central limit theorem**.

The Classical Central Limit Theorem

Theorem. Let $\{X_i; i \geq 1\}$ be independent random variables having a common distribution. Let μ be their **mean** and σ^2 be their **variance**. Then Z_n , the standardized scores, converges **in distribution** to Z a **standard normal** random variable, i.e., the **distribution function** F_{Z_n} converges to Φ , the **distribution function** of the standard normal for every value z .

$$\lim_{n \rightarrow \infty} F_{Z_n}(z) = \lim_{n \rightarrow \infty} P\{Z_n \leq z\} = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^z e^{-x^2/2} dx = \Phi(z).$$

In practical terms the central limit theorem states that

$$P\{a < Z_n \leq b\} \approx P\{a < Z \leq b\} = \Phi(b) - \Phi(a).$$

The number value is obtained in R using the command `pnorm(b)-pnorm(a)`.

Uniform Random Variables

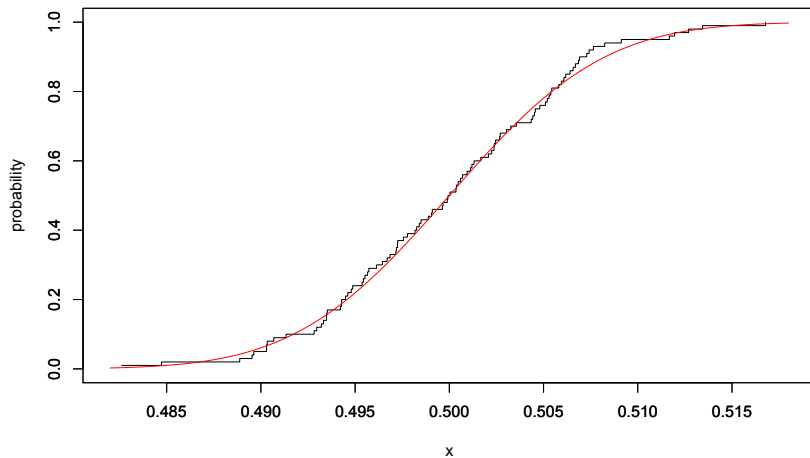
Example.

- For a single $U(0, 1)$ random variables,
 - mean $\mu = 1/2$ and standard deviation $\sigma = 1/\sqrt{12}$.
- For \bar{X} the sample mean of 2000 independent of $U(0, 1)$ random variables, then \bar{X}
 - has mean $\mu = 1/2$ and standard deviation $\sigma = 1/\sqrt{24000}$.

We show the empirical cumulative distribution function for 100 simulations and compare it to the **distribution function** of a normal with mean $\mu = 1/2$ and standard deviation $\sigma = 1/\sqrt{24000}$.

Exercise. Show that the standard deviation of a $U(0, 1)$ random variable is $1/\sqrt{12}$.

Uniform Random Variables



Bernoulli Trials

For a 100 question multiple choice exam with 4 options per question, a student randomly guesses. Each guess is a Bernoulli trial with success probability $p = 1/4$. Thus, the number of correct answers S_{100} has a binomial distribution with

$$\text{mean } np = 100 \cdot \frac{1}{4} = 25 \text{ and standard deviation } \sqrt{np(1-p)} = \sqrt{100 \cdot \frac{1}{4} \cdot \frac{3}{4}} = \frac{5}{2}\sqrt{3} \approx \frac{13}{3}$$

A student has 7 correct answers. This has a z -score

$$z \approx \frac{7 - 25}{13/3} = \frac{54}{13} < -4$$

Did this student *try* to give incorrect answers?

Exercise. Find the exact z -score and use `pnorm` to estimate the probability of 7 or fewer correct answers. Compare this value to the value obtained using `pbinom`.

Exponential Random Variables

Times between of customer arrivals at a bank are modeled as independent $\text{Exp}(1)$ random variables. These random variables have mean and standard deviation 1. We approximate the probability that the 50-th customer arrives within the first hour of business. S_n , the time of arrival of the n -th customer, is the sum of the times between arrivals and thus is the sum of n $\text{Exp}(1)$ random variables. S_{50} has mean 50 and standard deviation $\sqrt{50}$. We are asking

$$P\{S_{50} \leq 60\} = P\{S_{50} - 50 \leq 10\} = P\left\{Z_n = \frac{S_{50} - 50}{\sqrt{50}} \leq \frac{10}{\sqrt{50}}\right\}.$$

By the **central limit theorem**, we have the approximation

```
> pnorm((60-50)/sqrt(50))  
[1] 0.9213504
```

We can obtain the same answer using `pnorm(60,50,sqrt(50))`.

Example

You want to store 400 pictures on your smart phone. Pictures have a mean size of 450 kilobytes (KB) and a standard deviation of 50 KB. Assume that the size of the pictures are independent. S_{400} , the total storage space needed for the 400 pictures, has

mean $400 \times 450 = 180,000$ KB and standard deviation $50\sqrt{400} = 1000$ KB.

To estimate the space required to be 99% certain that the pictures will have storage space on the phone, note that

```
> qnorm(0.99, 400*450, 50*sqrt(400))  
[1] 182326.3
```

So we need about 182.3 megabytes (MB).

Exercise. Give the storage space to be 95% certain to have the space for 300 pictures.