

ERASMUS, B4 Course

Winter 2020/2021

FPM&IT, December 10, part I

Subject: Limit theorems in P.T.

Introduction

We begin with the formulation of the following problem:

Problem 1

Assume that \mathcal{R} ~~denote~~ is a set of all distributions (discrete and continuous).

Then each $r \in \mathcal{R}$ represents the ^{rigid} distribution,
($(r_n)_{n \geq 1}$ - the sequence of distributions).

More specifically, taking r or $(r_n)_{n \geq 1}$ we mean that:

a) there exists a RE

b) RE has its KPM (Ω, \mathcal{E}, P)

c) for r we have the R.V. $X: \Omega \rightarrow \mathcal{R}$;

for $(r_n)_{n \geq 1}$ we have the sequence of R.V.'s

$(X_n)_{n \geq 1}$, where $X_n: \Omega \rightarrow \mathcal{R}$

Let $(X_n)_{n \geq 1}$ be given as above then to define
the convergence of such a sequence?

What is to be its LIMIT?

Before we answer the above questions, let us return to the classical problem of convergence, namely to the theory of real sequences.

Let $(a_n)_{n \in \mathbb{N}}$, $a_n \in \mathbb{R}$ be given.

By definition we say that $(a_n)_{n \in \mathbb{N}}$ is convergent if there exists a number $g \in \mathbb{R}$, such that

$$\forall \varepsilon > 0 \quad \exists n_0 \quad \forall n > n_0 \quad |a_n - g| < \varepsilon,$$

so $a_n \in (g - \varepsilon, g + \varepsilon)$ for every $n > n_0$.

Then we write $(a_n) \rightarrow g$, or simply $a_n \rightarrow g$.

Now our situation is more complicated, because X_n is not a number! On the other hand,

if we have $(X_n)_{n \in \mathbb{N}}$, then for every fixed $\omega \in \Omega$, $(X_n(\omega))_{n \in \mathbb{N}}$ is a sequence of numbers!

In probability theory we consider at least two
types of convergence :

(1) "Almost sure convergence" (a.s.), where

by the def. we say that $(X_n)_{n \geq 1}$ is convergent a.s.

iff \exists such that
r.v. X_0

$$P(\{\omega \in \Omega : X_n(\omega) \rightarrow X_0(\omega)\}) = 1,$$

and we write $X_n \xrightarrow{\text{a.s.}} X_0$.

(2) "Convergence by distribution" (d), where

by the def. we say that $(X_n)_{n \geq 1}$ is convergent d

iff \forall $F_{X_n}(t) \rightarrow F_{X_0}(t)$, and
t.e.r

we write $X_n \xrightarrow{d} X_0$.

Our first theorem explains, that in fact we have two different types of convergence, namely

Th. For every sequence r.v.'s (X_n) ,

$$X_n \xrightarrow{d} X_0 \implies X_n \xrightarrow{q.s.} X_0$$

but not vice-versa.

Limit Theorems.

(I) The strong LAW of the LARGE NUMBERS of BERNULLI (SLLNB)

Problem 2.

Let us take X with $\begin{array}{c|c} 0 & 1 \\ \hline q & p \end{array}$.

How to find a value p ?

Problem 3.

We know, that for given RE and its p.d. represented by random variable X , the

result of the observation of RE is $EX = m$

- its mean value of X .

It is not problem to find $E X$ if we know that distribution. But we cannot to assume that we know the distribution during the observation process. So, how else to determine this number $-E X$.

Remarks

We note, that in P2, $\rho = E X$.

As we will see in a moment, SLLNB gives the solution of the Problem 2 & Problem 3.

Formulation of SLLNB THEOREM

Assume we observe some r.v. about which we only know, that X has its second moment, so X has $E X$ and $\text{var } X$ (but we do not know the value of $E X$ and $\text{var } X$!).

We make the observation in the form of an infinite series of repetitions of X , so we have the sequence $(X_n)_{n \geq 1}$, when

$$\forall_{n \geq 1} d(X_n) = d(X).$$

Assume that in addition the members of (X_n) are
stochastically independent.

Let us take the event

$A = \{ \omega \in \Omega : \text{the sequence}$

$$\underbrace{\frac{1}{n} (X_1(\omega) + X_2(\omega) + \dots + X_n(\omega))}_{\text{the average}} \longrightarrow m = EX \}$$

Then (SLLNB says that)

$$\underline{\underline{P(A) = 1}}$$

REMARKS

- 1) The above theorem is the first different ^{weaker} version
was proven first by J. Bernoulli.
- 2) The proof of the above theorem is too hard, and
we ~~are~~ will skip it.

3) Instead of, we will show below the proof of a weaker version, namely

Let $(X_n)_{n \geq 1}$ be as above, so

- $d(X_n) = d(X), n \geq 1$

- (X_n) are s. ind.

- EX^2 exists.

Then $\forall \epsilon > 0$

$$(*) \quad P\left(\exists n \in \mathbb{N} : \left| \frac{X_1 + \dots + X_n}{n} - m \right| \geq \epsilon\right) \rightarrow 0$$

Proof

Let $Y_n = \frac{1}{n} (X_1 + \dots + X_n)$.

Then: $EY_n = \frac{1}{n} \cdot n EX = m$

$$\text{Var}(Y_n) = \frac{1}{n^2} n \text{Var} X = \frac{\sigma^2}{n} \quad (\sigma^2 = \text{var} X).$$

It means, let for $\{Y_n\}$ ($n \geq 2$) we can apply the Tshelysheff inequality

$$P(\omega \in \Omega: |\bar{Y}_n(\omega) - m| \geq \varepsilon) \leq \frac{1}{t^2} = \frac{\sigma_{\bar{Y}_n}^2}{\varepsilon^2}$$

where $\varepsilon = t \sigma_{\bar{Y}_n} > 0$

$$t = \frac{\varepsilon}{\sigma_{\bar{Y}_n}}$$

But $\sigma_{\bar{Y}_n}^2 = \frac{\sigma^2}{n}$, ($\sigma^2 = \text{var}(X)$), so

finally

$$P(\omega \in \Omega: |\bar{Y}_n(\omega) - m| \geq \varepsilon) \leq \frac{\sigma^2}{n \varepsilon^2} = \frac{\sigma^2}{\varepsilon^2} \frac{1}{n}$$

But $\frac{1}{n} \rightarrow 0$ and $\frac{\sigma^2}{\varepsilon^2}$ is fixed,
so (*) is true!

h) From SLLNB follows that

$\exists \Omega_0 \subset \Omega$, $P(\Omega_0) = 1$, let

for every $\omega \in \Omega_0$

the (real sequence) (a_n/m_n) , where

$$a_n = \frac{1}{n} (X_1(u_0) + X_2(u_0) + \dots + X_n(u_0)), \quad n \geq 1$$

is convergent, and the limit of it is equal to $m = EX$, so

$$a_n \longrightarrow m.$$

It means, that for given (small) $\varepsilon > 0$
the condition

$$|a_n - m| < \varepsilon \text{ is satisfied for}$$

all $n > n_0$, for some n_0 .

So, if n is sufficient large, then

a_n is very close to m , so

we can write (estimation rule!)

$$a_n \approx m.$$

5). Let us return to the Problem 2.

$$X : \begin{array}{c|c} 0 & 1 \\ \hline q & p \end{array}$$

Let $(X_n)_{n \geq 1}$ be such that:

$$d(X_n) = d(X), \quad n \geq 1 \quad \text{and} \quad \underline{\text{S.L.}}$$

We note, that for every $\omega \in \Omega$,

$$\frac{1}{n} (X_1(\omega) + X_2(\omega) + \dots + X_n(\omega)) = \frac{\# \text{ of the } j \text{ } X_j(\omega) = 1}{\# \text{ of repetitions}}$$

For this reason, the above number is denoted by $f_n(\omega)$ and is called the FREQUENCY.

So from SLLNB, for X as above we have:

with probability 1,

$$f_n(\omega) \longrightarrow p \quad (p = EX)$$

Therefore we can approximate p by $f_n(\omega)$!

$$f_n(\omega) \approx p \quad \text{with probability 1,}$$

therefore: p is called the theoretical probability,

$f_n(\omega)$ - the empirical probability.

6) Let us take an example.

Suppose that for every $n \geq 2$ and fixed $p \in (0, 1)$

$B_n \in B(n, p)$ (Bernoulli distribution)

From factorization property of $P(n, p)$ we know that

we have

$$B_n(\omega) = X_{n,1}(\omega) + X_{n,2}(\omega) + \dots + X_{n,n}(\omega),$$

$$\text{where } \forall_{1 \leq k \leq n} X_{n,k} = \begin{array}{c|c} 0 & 1 \\ \hline q & p \end{array} \text{ and}$$

on S.L.

For $n \geq 2$ and fixed $\varepsilon > 0$ we consider

the event

$$A_{\varepsilon, n} = \left\{ \omega \in \Omega : \left| \frac{1}{n} B_n(\omega) - p \right| \geq \varepsilon \right\}$$

$$\frac{1}{n} (X_{n,n}(\omega) - t \cdot X_{n,n}(\omega))$$

We are going to approximate $P(A_{\varepsilon, n})$.

Since: $E\left(\frac{1}{n} B_n\right) = \frac{1}{n} \cdot np = p$

$$\text{Var}\left(\frac{1}{n} B_n\right) = \frac{1}{n^2} \cdot npq = \frac{pq}{n}$$

if we put $\varepsilon = t\sigma_n = t\sqrt{\text{Var}\frac{1}{n}B_n} = t\sqrt{\frac{pq}{n}}$,

by Chebyshev's inequality we obtain

$$P\left(\left\{ \omega \in \Omega : \left| \frac{1}{n} B_n(\omega) - p \right| \geq \varepsilon \right\}\right) \leq \left(\frac{\varepsilon^2}{\sigma_n^2}\right)^{-1} = \frac{pq}{n\varepsilon^2}$$

or equivalently

$$(*) P(A_{\varepsilon, n}^c) > 1 - \frac{pq}{n\varepsilon^2}$$

Let us do a numeric simulation:

$$p=q=0,5, \quad \varepsilon = 10^{-k}, \quad k \geq 2.$$

Then

$$\frac{pq}{n\varepsilon^2} = \frac{1/4}{n \cdot 10^{-2k}} = \frac{1}{4 \cdot n \cdot 10^{-2k}}.$$

Assume that for $k \geq 2$ we have

$$1 - \frac{1}{4 \cdot n \cdot 10^{-2k}} \geq 1 - 10^{-3} \quad (\Rightarrow)$$

$$\frac{1}{4 \cdot n \cdot 10^{-2k}} \leq 10^{-3} \quad (\Rightarrow)$$

$$n > \frac{1}{4} \cdot 10^{3+2k}.$$

We note, that only for $k=2$ we have

(xx) is satisfied for

$$n > \frac{1}{4} \cdot 10^7 = \underline{\underline{2.500.000}}, \text{ so}$$

$$P\left(\sum_{i=1}^n X_i: \left|\frac{1}{n} \sum_{i=1}^n X_i - \mu\right| < 0,005\right) \geq 0,99,$$

if $n \geq 2.500.000$.

I think you understood why in the name of Bernoulli th. we have the words LARGE NUMBERS!