

Models 7/10/25 :

If we are given 2 r.v. x_1, x_2 and their joint prob. $p(x_1, x_2)$, then we say that x_1 and x_2 are indep if.

$$p(x_1, x_2) = p(x_1)q(x_2)$$

where $x_1 \sim p(x_1)$ and $x_2 \sim q(x_2)$. In general $p \neq q$. Also, if $p = q$. then we say that x_1 and x_2 are independent and identically distributed.

If we are given x_1, x_2 that are i.i.d. what is the distribution of

$$x = x_1 + x_2 \quad x \sim p(x)$$

$$\begin{aligned} (15) \quad p(x) &= \int \delta(x - (x_1 + x_2)) p(x_1, x_2) dx_1 dx_2 \equiv \langle \delta(x - x_1 - x_2) \rangle \\ &\quad \text{we select all possible } x_1, x_2 \text{ s.t. their sum is } x. \\ \text{i.i.d.} \quad &= \int \delta(x - x_1 - x_2) q(x_1) q(x_2) dx_1 dx_2 \\ &= \int q(x-y) q(y) dy \quad \text{it's a convolution.} \end{aligned}$$

We can calculate the c.f. of $p(x)$:

$$\begin{aligned} \underline{p(k)} &\equiv \langle e^{ikx} \rangle = \int e^{ikx} p(x) dx = \int dx e^{ikx} \delta(x - x_1 - x_2) q(x_1) q(x_2) dx_1 dx_2 \\ &= \int e^{ik(x+x_2)} q(x_1) q(x_2) dx_1 dx_2 = \underline{[\varphi(k)]^2} \quad (16) \end{aligned}$$

Exerc.: • What is the distribution of the sum if they are indep but not ident. distrib.?

• What is the c.f. of distrib. of the sum of n iid?

- Calculate the distrib. of $x = x_1 + x_2$ where x_1, x_2 are iid drawn from a) $U([0, 1])$, b) $N(\mu, \sigma)$, c) $\lambda e^{-\lambda x}$.
- Calculate the distribution of the product $x = x_1 x_2$ where x_1, x_2 are positive iid.

The (weak) law of large numbers

If we are given n iid rand. var. whose pdf is $q(x)$ with a c.f. $\varphi_1(k)$, what happens to $x = \frac{1}{n} \sum_{i=1}^n x_i$ as $n \rightarrow \infty$?

We assume that the mean of x_i is μ ($\mu = \int dx q(x)x < \infty$).
(See Grimmett & Stirzaker, p. 193, Prob. and Random Processes).

proof:

Let $\varphi(n)$ be the c.f. of the average of the rand. variables

$$\varphi(n) \equiv \langle e^{ikx} \rangle = \langle e^{ik \frac{1}{n} \sum_{i=1}^n x_i} \rangle = \int e^{i \frac{k}{n} \sum_{i=1}^n x_i} q(x_1) \dots q(x_n) dx_1 \dots dx_n$$

\downarrow
 $x = \frac{1}{n} \sum_{i=1}^n x_i$

(17)

$$= \left(\int e^{i \frac{k}{n} x_1} q(x_1) dx_1 \right) \dots \left(\int e^{i \frac{k}{n} x_n} q(x_n) dx_n \right) = \left(\varphi_1\left(\frac{k}{n}\right) \right)^n$$

$$\varphi_1\left(\frac{k}{n}\right) = \int e^{i \frac{k}{n} x} q(x) dx = 1 + \frac{ik}{n} \langle x \rangle + O\left(\frac{1}{n}\right) \text{ as } n \rightarrow \infty$$

\uparrow Taylor convergence in distribution
 \downarrow

from (17) $\left(1 + \frac{ik}{n} \langle x \rangle + \dots \right)^n \xrightarrow{n \rightarrow \infty} e^{i\mu k} = \int \underbrace{\delta(x - \mu)}_{p(x) = \delta(x - \mu)} e^{ikx} dx$

The strong law of large numbers

Let x_1, \dots, x_n be a sequence of i.i.d. r.v. each with finite mean μ . Then the empirical average $\frac{1}{n} \sum_{i=1}^n x_i$ approaches μ as $n \rightarrow \infty$ (Grimmett, p. 329).

Here the convergence is almost sure.

$$P\left(\left\{ \frac{1}{n} \sum_{i=1}^n x_i \rightarrow \mu \text{ as } n \rightarrow \infty \right\}\right) = 1$$

This theorem tells us that for large n the sum $\sum_{i=1}^n x_i$ is well approximated by μn . Of course there will be fluctuations around μn . A natural question is: what can we say about $\sum_{i=1}^n x_i - \mu n$? How fast do we approach the limit? What about the fluctuations around μn ? Whenever x_i have finite variance σ^2 :

- 1) $\sum_{i=1}^n x_i - \mu n$ is about as big as \sqrt{n}
- 2) The distribution of $\frac{\sum_{i=1}^n x_i - \mu n}{\sqrt{n}}$ approaches a Gaussian distribution as $n \rightarrow \infty$ IRRESPECTIVE of the distribution of x_i .

The claims in 2) and 5) are the core meaning of the Central Limit Theorem

Let x_1, \dots, x_n be a sequence of i.i.d. r.v. with finite mean μ and finite (nonzero) variance σ^2 . Then the PDF of

$$(19) \quad Y_n = \frac{\sum_{i=1}^n x_i - \mu n}{\sqrt{n} \sigma} \xrightarrow[n \rightarrow \infty]{\text{convergence in distrib.}} N(0, 1) \quad \text{Gaussian distr. with mean 0 and variance 1.}$$

Obs:

$$\langle Y_n \rangle = \frac{1}{\sqrt{n}\sigma} \left(\sum_i \langle x_i \rangle - \mu n \right) = 0$$

Ex:

$$- \text{Var}(Y_n) = \dots = 1$$

- Let x_1, x_2 be two i.i.d. Gaussian r.v. such that
 $\langle x_i \rangle = 0$, $\langle x_i^2 \rangle = 1$, $\langle x_1 x_2 \rangle = 0$ $i=1,2$.

Calculate $\langle y_i \rangle$, $\langle y_i^2 \rangle$, $\langle y_1 y_2 \rangle$ $i=1,2$ where

$$\begin{cases} y_1 = \rho + \sqrt{1-\rho^2} x_1 \\ y_2 = \rho + \sqrt{1-\rho^2} (\gamma x_1 + \sqrt{1-\gamma^2} x_2) \end{cases}$$

where $|\rho| \leq 1$, $|\gamma| \leq 1$.

Obs: the definition of Y_n means that it is centered at 0 with a variance that does not depend on n .

Proof:

Let's assume that each r.v. has a p.d.f. $g(x)$ with c.f. $\varphi_1(k)$. $\varphi(k)$ is the c.f. of Y_n :

$$\varphi(k) = \langle e^{ikY_n} \rangle = \int e^{ik \frac{\sum_i x_i - \mu n}{\sqrt{n}\sigma}} g(x_1) \dots g(x_n) dx_1 \dots dx_n =$$

$$= e^{-\frac{ik\mu\sqrt{n}}{\sigma}} \left(\underbrace{\int e^{\frac{ikx}{\sqrt{n}\sigma}} g(x) dx}_{\varphi_1\left(\frac{k}{\sqrt{n}\sigma}\right)} \right)^n$$

(20)

As in the previous theorem we can expand φ_1 as $n \rightarrow \infty$

Taylor and ⑤

$$\varphi_1\left(\frac{k}{\sqrt{n}\sigma}\right) \stackrel{\downarrow}{=} 1 + \frac{ik}{\sqrt{n}\sigma} \langle x \rangle - \frac{k^2}{2n\sigma^2} \langle x^2 \rangle + \underbrace{O(n^{-3/2})}_{\leftarrow \text{show this!}}$$

$$= e^{\frac{ik}{\sqrt{n}\sigma} \mu - \frac{k^2}{2n}}$$

from ②

$$\varphi(k) = e^{-\frac{ik\mu}{\sigma} \sqrt{n}} \underbrace{e^{\frac{ik\mu}{\sigma} \sqrt{n} - \frac{k^2}{2}}}_{= e^{-\frac{k^2}{2}}}$$

this is the c.f. of $p(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \equiv N(0, 1)$

□

EX: 1) Show that $\sum_i x_i \underset{\substack{\uparrow \\ \text{drawn from}}}{\sim} N(n\mu, n\sigma^2)$

2) Show that $\frac{1}{n} \sum_i x_i \underset{\uparrow}{\sim} N\left(\mu, \frac{\sigma^2}{n}\right)$