

Let  $A$  and  $B$  be events with  $P(B) \neq 0$ .

$$\text{Then } P(A|B) = \frac{P(AB)}{P(B)}.$$

Remark:  $A$  &  $B$  are independent if  $P(A|B) = P(A)$ .

Propn 1 Let  $A_1, \dots, A_n$  be events with  $P(A_1 \dots A_n) \neq 0$ .

$$\text{Then } P(A_1 \dots A_n) = P(A_1)P(A_2|A_1)P(A_3|A_2A_1) \dots P(A_n|A_1 \dots A_{n-1}).$$

pf "telescoping product."

Propn 2 Suppose  $A_1, \dots, A_n$  are disjoint events,

$$\Omega = \bigcup_{k=1}^n A_k, \text{ and } P(A_k) \neq 0 \text{ for } k=1, \dots, n.$$

Then each event  $B$ ,

$$P(B) = \sum_k \underbrace{P(B|A_k) \cdot P(A_k)}_{P(BA_k)}$$

pf

$$\bigcup_k BA_k$$

Propn 3: Bayes' Theorem (1763). Let  $A_1, \dots, A_n$  be disjoint events with  $\Omega = \bigcup_k A_k$  and  $P(A_k) \neq 0 \forall k$ .

Let  $B$  be an event with  $P(B) \neq 0$ . Then

$$\text{for each } j, P(A_j|B) = \frac{P(A_j)P(B|A_j)}{\sum_k P(A_k)P(B|A_k)}.$$

$$\text{pf } \sum_k P(A_k) P(B|A_k) = P(B).$$

$$P(BA_j) = P(B) P(A_j|B)$$

$$\begin{array}{c} \parallel \qquad \qquad \parallel \\ P(A_j) P(B|A_j) \end{array}$$

□

Eg (False positives).

Suppose a lab test on a blood sample yields two results, positive & negative. It is found that 95% of people with a particular disease produce a positive result. But 2% of people without the disease produce a positive result too.

suppose 1% of people actually have the disease.

What is the probability that a person chosen at random from a population will have the disease, given that the person's blood tests positive?

solution let  $D$  be the event that the person has the disease.

We seek  $P(D|+)$ .  $P(D) = 0.01$ ,  $P(+|D) = 0.95$ ,

and  $P(+|D^c) = 0.02$ .  $P(D^c) = 0.99$

$$\text{So } P(D|+) = \frac{P(D) P(+|D)}{P(+|D) P(D) + P(+|D^c) P(D^c)}$$

$$= \frac{0.01 \cdot 0.95}{0.01 \cdot 0.95 + 0.02 \cdot 0.99}$$

$$= \frac{95}{293}$$

$\approx 32\%$

## Kolmogorov's Strong Law of Large Numbers (1930)

Let  $X_1, X_2, X_3, \dots$  be iid (independent & identically distributed)  
in  $L^1$   $\rightarrow$  integrable real RVs. Then  $\frac{X_1 + \dots + X_n}{n} \rightarrow E(X_1)$  almost  
surely as  $n \rightarrow \infty$

Etemadi ( $\sim 1980$ ) showed that pairwise independence is enough.

The requirement of being identically distributed can also be weakened.

## The iid Central Limit Theorem

Let  $X_1, X_2, X_3, \dots$  be iid square-integrable real RVs.

Let  $\bar{x} = E(X_1)$ ,  $\sigma = \sqrt{\text{Var}(X_1)}$ . Let  $S_n = X_1 + \dots + X_n$ .

$$E(S_n) = n\bar{x} \quad \text{and} \quad \text{Var}(S_n) = n\sigma^2$$

Let  $S_n^* = \frac{S_n - n\bar{x}}{\sigma\sqrt{n}}$ . Then for all real numbers  $a$

and  $b$  with  $a < b$ , we have

$$\lim_{n \rightarrow \infty} P(a < S_n^* \leq b) = \int_a^b \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$$

$$\text{law}(S_n^*) \xrightarrow{w} N(0, 1).$$

$$E(f(S_n^*)) \rightarrow \int f(x) \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \quad \text{for each}$$

$$E(f(S_n^*)) \longrightarrow \int_{\mathbb{R}} f(x) \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx \quad \text{for each}$$

bounded continuous function  $\mathbb{R} \rightarrow \mathbb{R}$ .

### Lévy's Central Limit Theorem

For  $n=1,2,3,\dots$  let  $X_1^n, \dots, X_{k_n}^n$  be independent real RVs.

Suppose for each  $\varepsilon > 0$ ,  $\max_j P(|X_j^n| \geq \varepsilon) \longrightarrow 0$ .

Let  $S_n = \sum_j X_j^n$ . Suppose  $\text{Law}(S_n) \xrightarrow{w} \mu$

for some Borel probability measure  $\mu$  on  $\mathbb{R}$ .

Then  $\mu = N(\bar{x}, \sigma^2)$  for some  $\bar{x} \in \mathbb{R}$  and  $\sigma \in \mathbb{R}_+$ .

iff  $\forall \varepsilon > 0$ ,  $P(\max_j |X_j^n| \geq \varepsilon) \longrightarrow 0$  as  $n \rightarrow \infty$ .