

Math 6261

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Review.

Thm (CLT) Let (X_n) be an i.i.d. sequence of r.v.'s with

$$E(X_n) = 0 \text{ and } \text{Var}(X_n) = \sigma^2.$$

Write $S_n = X_1 + \dots + X_n$. Then for any $x \in \mathbb{R}$,

$$P\left(\frac{S_n}{\sqrt{n}\sigma} \leq x\right) \xrightarrow{\text{as } n \rightarrow \infty} \Phi(x) := \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-y^2/2} dy$$

(standard normal distribution)

Below we present a generalized version of the CLT, which can be proved by using a similar argument.

Thm (The Lindeberg-Feller Thm)

Suppose for each n , the r.v.'s

$$X_{n,1}, X_{n,2}, \dots, X_{n,r_n}$$

are independent, with

$$E(X_{n,k}) = 0, \quad \sigma_{n,k}^2 = E(X_{n,k}^2) \quad \text{and} \quad s_n^2 = \sum_{k=1}^{r_n} \sigma_{n,k}^2.$$

Suppose for each $\varepsilon > 0$

$$\lim_{n \rightarrow \infty} \sum_{k=1}^{r_n} \frac{1}{s_n^2} \int_{|X_{n,k}| > \varepsilon s_n} X_{n,k}^2 dP = 0$$

Then

$$\frac{X_{n,1} + \dots + X_{n,r_n}}{S_n} \xrightarrow{w} Z,$$

where Z has the standard normal distribution.

Corollary. Let X_1, X_2, \dots , be independent r.v.'s. Suppose that

$$E(X_n) = 0 \text{ and } |X_n| \leq C \text{ uniformly.}$$

$$\text{If } S_n^2 = \sum_{k=1}^n \text{Var}(X_k) \rightarrow \infty \text{ as } n \rightarrow \infty, \text{ then}$$

Then

$$\frac{X_1 + \dots + X_n}{S_n} \xrightarrow{w} Z,$$

where Z has the standard normal distribution.

§ 4. Random walks.

§ 4.1 Sums of independent r.v.'s.

Let X_1, X_2, \dots , be independent of r.v.'s. Let

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

We first study whether S_n converges.

$$\text{Define } A = \left\{ \omega : \sum_{n=1}^{\infty} X_n(\omega) \text{ converges} \right\}.$$

Notice that for each m , the values of $X_1(\omega), \dots, X_{m-1}(\omega)$ are not relevant to the question of whether $\omega \in A$. More precisely, for given $m \in \mathbb{N}$,

$$A = \left\{ \omega : \sum_{k=m}^{\infty} X_k(\omega) \text{ converges} \right\}.$$

Notice that

$\omega \in A \Leftrightarrow \forall \ell \in \mathbb{N}, \exists N \geq m$ such that for each $p \geq 0$

$$|X_N(\omega) + \dots + X_{N+p}(\omega)| < \frac{1}{\ell}.$$

Hence

$$A = \bigcap_{\ell=1}^{\infty} \bigcup_{N=m}^{\infty} \bigcap_{p=0}^{\infty} \left\{ \omega : |X_N(\omega) + \dots + X_{N+p}(\omega)| < \frac{1}{\ell} \right\}$$

It follows that

$$A \in \sigma(X_m, X_{m+1}, \dots).$$

$$\text{Hence } A \in \bigcap_{m=1}^{\infty} \sigma(X_m, X_{m+1}, \dots) =: \mathcal{T}.$$

We call \mathcal{T} the tail σ -field associated with X_1, X_2, \dots .

Thm 4.1 (Kolmogorov's Zero-One law).

Suppose that X_1, X_2, \dots are independent and that

$$A \in \mathcal{T} = \bigcap_{n=1}^{\infty} \sigma(X_n, X_{n+1}, \dots).$$

Then either $P(A)=0$ or $P(A)=1$.

pf. We will show that A is independent of itself. Hence

$P(A \cap A) = P(A)P(A)$, i.e. $P(A) = P(A)^2$,
and hence $P(A)=0$ or 1 .

We prove this in two steps.

Step 1: If $B \in \sigma(X_1, X_2, \dots, X_k)$ and $C \in \sigma(X_{k+1}, X_{k+2}, \dots)$,
then B and C are independent.

Clearly, $\sigma(X_1, X_2, \dots, X_k)$ and $\bigcup_{j=1}^{\infty} \sigma(X_{k+1}, \dots, X_{k+j})$
are independent. Since the second one is a π -system, so

$\sigma(X_1, X_2, \dots, X_k)$ and $\sigma\left(\bigcup_{j=1}^{\infty} \sigma(X_{k+1}, \dots, X_{k+j})\right) = \sigma(X_{k+1}, \dots)$
are independent.

Step 2: If $B \in \sigma(X_1, X_2, \dots)$ and $C \in \mathcal{G}$, then B and C are
independent.

For any k , since $\mathcal{G} \subset \sigma(X_{k+1}, X_{k+2}, \dots)$ so
 \mathcal{G} and $\sigma(X_1, \dots, X_k)$ are independent. It follows that

\mathcal{G} and $\bigcup_{k=1}^{\infty} \sigma(X_1, \dots, X_k)$ are independent.

Therefore \mathcal{G} and $\sigma\left(\bigcup_{k=1}^{\infty} \sigma(X_1, \dots, X_k)\right) = \sigma(X_1, X_2, \dots)$ are
independent.

Let $A \in \mathcal{G}$. Since $\mathcal{G} \subset \sigma(X_1, \dots, X_k, \dots)$, by Step 2, A is independent of itself. \square

By the Kolmogorov's zero-one law, if X_1, X_2, \dots are independent, then the set where $\sum_{n=1}^{\infty} X_n(\omega)$ converges has probability either 0 or 1.

Below we discuss how to determine which of 0 and 1 is the prob. of the set. First we prove two maximal inequalities.

Prop 4.2. Suppose X_1, X_2, \dots, X_n are independent r.v.'s with mean 0 and finite variance. For $d > 0$,

$$P\left(\max_{1 \leq k \leq n} |S_k| \geq d\right) \leq \frac{1}{d^2} \text{Var}(S_n).$$

Remark: By Chebyshev inequality, $P(|S_n| \geq d) \leq \frac{1}{d^2} \text{Var}(S_n)$.

Pf of Prop 4.2.

$$\text{Let } A_k = \{\omega : |S_k(\omega)| \geq d \text{ and } |S_j(\omega)| < d \text{ for } j < k\}, k=1, 2, \dots$$

Then A_k are disjoint.

Hence

$$\begin{aligned}
E(S_n^2) &\geq \sum_{k=1}^n \int_{A_k} S_n^2 dP \\
&= \sum_{k=1}^n \int_{A_k} S_k^2 + 2S_k(S_n - S_k) + (S_n - S_k)^2 dP \\
&\geq \sum_{k=1}^n \int_{A_k} S_k^2 + 2S_k(S_n - S_k) dP
\end{aligned}$$

Since A_k and S_k are in $\sigma(X_1, \dots, X_k)$ and $S_n - S_k$ in $\sigma(X_{k+1}, \dots, X_n)$,

$$\begin{aligned}
\int_{A_k} 2S_k(S_n - S_k) dP &= 2 \int \mathbb{1}_{A_k} S_k (S_n - S_k) dP \\
&= 2 \left(\int \mathbb{1}_{A_k} S_k dP \right) \underbrace{\left(\int S_n - S_k dP \right)}_{=0} \\
&= 0.
\end{aligned}$$

Hence

$$\begin{aligned}
E(S_n^2) &\geq \sum_{k=1}^n \int_{A_k} S_k^2 dP \\
&\geq d^2 \sum_{k=1}^n P(A_k) \\
&= d^2 \cdot P\left(\max_{1 \leq k \leq n} |S_k| \geq d\right).
\end{aligned}$$

□

Prop 4.3. Let X_1, \dots, X_n be independent. Then for $d > 0$,

$$P\left(\max_{1 \leq k \leq n} |S_k| > 3d\right) \leq 3 \max_{1 \leq k \leq n} P(|S_k| \geq d).$$

Pf. Let $B_k = \{\omega : |S_k(\omega)| > 3d \text{ and } |S_j(\omega)| < 3d \text{ for } j < k\}$

Then B_1, \dots, B_n are disjoint with $\bigcup_{k=1}^n B_k = \left\{ \max_{1 \leq k \leq n} |S_k| > 3d \right\}$

$$P\left(\max_{1 \leq k \leq n} |S_k| > 3d\right)$$

$$\leq P(|S_n| \geq d) + \sum_{k=1}^{n-1} P(B_k \cap \{|S_n| < d\})$$

$$\leq P(|S_n| \geq d) + \sum_{k=1}^{n-1} P(B_k \cap \{|S_n - S_k| > 2d\})$$

$$= P(|S_n| \geq d) + \sum_{k=1}^{n-1} P(B_k) P(|S_n - S_k| > 2d)$$

(since $B_k, S_n - S_k$ are independent)

$$\leq P(|S_n| \geq d) + \max_{1 \leq k \leq n-1} P(|S_n - S_k| \geq 2d)$$

$$\leq P(|S_n| \geq d) + \max_{1 \leq k \leq n-1} (P(|S_n| \geq d) + P(|S_k| \geq d))$$

$$\leq 3 \max_{1 \leq k \leq n} P(|S_k| \geq d).$$

□

Now we are ready to prove

Thm 4.4. Suppose that X_1, X_2, \dots are independent with mean 0.

If $\sum_{n=1}^{\infty} \text{Var}(X_n) < \infty$, then $\sum_{n=1}^{\infty} X_n$ converges with prob. 1.

Pf. By Prop 4.2.

$$\begin{aligned} P\left(\max_{1 \leq k \leq r} |S_{n+k} - S_n| > \varepsilon\right) &\leq \frac{1}{\varepsilon^2} \text{Var}(S_{n+r} - S_n) \\ &= \frac{1}{\varepsilon^2} \sum_{k=1}^r \text{Var}(X_{n+k}). \\ &\leq \frac{1}{\varepsilon^2} \sum_{k=1}^{\infty} \text{Var}(X_{n+k}). \end{aligned}$$

Letting $r \rightarrow \infty$ gives

$$P\left(\sup_{k \geq 1} |S_{n+k} - S_n| > \varepsilon\right) \leq \frac{1}{\varepsilon^2} \sum_{k=1}^{\infty} \text{Var}(X_{n+k})$$

Hence

$$\lim_{n \rightarrow \infty} P\left(\sup_{k \geq 1} |S_{n+k} - S_n| > \varepsilon\right) = 0. \quad (*)$$

Let $E(n, \varepsilon)$ denote the set where $\sup_{k, j \geq n} |S_k - S_j| > 2\varepsilon$

$$\text{and } E(\varepsilon) = \bigcap_{n=1}^{\infty} E(n, \varepsilon).$$

Then $E(n, \varepsilon) \downarrow E(\varepsilon)$.

$$\text{Since } \left(\sup_{k \geq 1} |S_{n+k} - S_n| > \varepsilon\right) \supset E(n, \varepsilon) \supset E(\varepsilon),$$

$$\text{by } (*), P(E(\varepsilon)) = 0.$$

Notice that $(S_n \text{ diverges}) \subset \bigcup_{\varepsilon \in \mathbb{Q}_+} E(\varepsilon)$,

$$\text{So } P(S_n \text{ diverges}) = 0. \quad \square$$

Example 4.5. Consider the random series $\sum_{n=1}^{\infty} \pm \frac{1}{n}$, where the signs are chosen on the toss of a coin. Then the series converges with prob. 1.