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**Abstract:** In this article, we proved central limit theorem for dependent random variables.

**Keywords:** Central limit theorem;  $m$ -dependent random variables

**Theorem.** Let  $\{X_{n,i}\}$  be a triangular array of mean zero random variables. For each  $n=1,2,\dots$  let  $d = d_n$ ,  $m = m_n$  and suppose  $X_{n,1}, \dots, X_{n,d}$  is an  $m$ -dependent sequence of random variables. Define

$$B_{n,k,a}^2 = \text{Var} \left( \sum_{i=a}^{a+k-1} X_{n,i} \right),$$

$$B_n^2 \equiv B_{n,d,1} \equiv \text{Var} \left( \sum_{i=1}^d X_{n,i} \right).$$

Assume the following conditions hold. For some  $\delta > 0$  and some  $-1 \leq \gamma < 1$ :

$$E|X_{n,i}|^{2+\delta} \leq \Delta_n \text{ for all } i, \tag{1}$$

$$B_{n,k,a}^2 / (k^{1+\gamma}) \leq K_n \text{ for all } a \text{ and for all } k \geq m, \tag{2}$$

$$B_n^2 / (dm^{\gamma+1}) \geq L_n, \tag{3}$$

$$K_n / L_n = O(1), \tag{4}$$

$$\Delta_n / L_n^{(2+\delta)/2} = O(1) \tag{5}$$

$$m^{2+(1-\gamma)(1+2/\delta)} / d \rightarrow 0 \tag{6}$$

Then,  $B_n^{-1}(X_{n,1} + \dots + X_{n,d}) \Rightarrow N(0,1)$

**Proof of Theorem .** In the proof we will need a result for bounding moments of  $m$ -dependent sequences. We will state it as a corollary of the following lemma, which implicitly is given in Chow and Teicher (1978) and deals with independent sequences.

**Lemma A.1.** Let  $\{Y_i\}$  be an independent sequence of mean zero random variables.

Assume  $E|Y_i|^q \leq \Delta$  for some  $q \geq 2$  and all  $i$ .

$$\text{Then, } E \left| \sum_{i=1}^n Y_i \right|^q \leq C_q^q \Delta n^{q/2}$$

Where  $C_q$  is a positive constant depending only upon  $q$ .

Proof. See Theorem 2 and Corollary 2 in Section 10:3 of Chow and Teicher (1978).

**Corollary A.1.** Let  $\{X_i\}$  be an  $m$ -dependent sequence of mean zero random variables.

Assume  $E|X_i|^q \leq \Delta$  for some  $q \geq 2$  and all  $i$ .

Then, for all  $n \geq 2m$ ,

$$E \left| \sum_{i=1}^n X_i \right|^q \leq C_q^q \Delta(4mn)^{q/2}$$

where  $C_q$  is a positive constant depending only upon  $q$ .

**Proof.** Define  $t = [n / m]$  where  $[\cdot]$  denotes the integer part. Now split  $X_1 + \dots + X_n$  into  $t$  blocks of size  $m$  and a remainder block:  $X_1 + \dots + X_n \equiv A_1 + \dots + A_t + A_{t+1}$ . Due to  $m$ -dependence, the odd-numbered blocks are independent of each other, as are the even-numbered blocks. This allows us to apply Lemma A.1:

$$\begin{aligned} \left\| \sum_{i=1}^n X_i \right\|_q &\leq \left\| \sum_{i \text{ odd}} A_i \right\|_q + \left\| \sum_{i \text{ even}} A_i \right\|_q \quad (\text{by Minkowski}) \\ &\leq 2C_q m(\Delta)^{1/q} (t / 2 + 1)^{1/2} \quad (\text{by Lemma A.1 and Minkowski}); \end{aligned}$$

But, this is equivalent to

$$\begin{aligned} E \left| \sum_{i=1}^n X_i \right|^q &\leq C_q^q 2^q m^q \Delta (t / 2 + 1)^{q/2} \\ &\leq C_q^q 2^q m^q \Delta (t)^{q/2} \leq C_q^q 2^q \Delta (mn)^{q/2} = C_q^q \Delta (4mn)^{q/2}. \end{aligned}$$

We are now able to prove the theorem. The main idea of the proof follows Berk (1973), but we need some modifications, since our theorem is more general.

For each  $n$ , we choose an integer  $p = p_n > 2m$  so that

$$\lim_{n \rightarrow \infty} m / p = 0, \quad \lim_{n \rightarrow \infty} p^{1+(1-\gamma)(1+2/\delta)} / d = 0. \tag{7}$$

This can be done, for example, by remembering assumption (6) and choosing  $p$  to be the smallest integer greater than  $2m$  and greater than  $m^{1/2} d^{1/2\xi}$ , where  $\xi$  is equal to  $1 + (1 - \gamma)(1 + 2 / \delta)$ . Next, define integers  $t = t_n$  and  $q = q_n$  by  $d = pt + q$ ,  $0 \leq q < p$ . The main idea of the proof is to split the sum  $X_{n,1} + \dots + X_{n,d}$  into alternate blocks of length  $p - m$  (the big blocks) and  $m$  (the little blocks). This is a common approach to proving central limit theorems for dependent random variables, and is attributed to Markov in Bernstein (1927). Let

$$U_{n,i} = X_{n,(i-1)p+1} + \dots + X_{n,ip-m}, \quad 1 \leq i \leq t,$$

$$V_{n,i} = X_{n,ip-m+1} + \dots + X_{n,ip}, \quad 1 \leq i \leq t$$

$$U_{n,t+i} = X_{n,tp+1} + \dots + X_{n,d}.$$

By definition,  $X_{n,1} + \dots + X_{n,d} = \sum_{i=1}^{t+1} U_{n,i} + \sum_{i=1}^t V_{n,i}$ . Since the  $X_{n,i}$  are  $m$ -dependent and  $p > 2m$ ,  $\{U_{n,i}\}$  and  $\{V_{n,i}\}$  are each independent sequences. It is easily seen that the difference between  $B_n^{-1}(X_{n,1} + \dots + X_{n,d})$  and has variance approaching zero. Indeed,

$$\begin{aligned} \text{Var}\left(B_n^{-1} \sum_{i=1}^{t+1} V_{n,i}\right) &= B_n^{-2} \sum_{i=1}^l \text{Var}(V_{n,i}) \\ &\leq B_n^{-2} t \left[ \sup_i \text{Var}(V_{n,i}) \right] \leq B_n^{-2} t K_n m^{1+\gamma} \quad (\text{by assumption (2)}) \\ &\leq B_n^{-2} (d / p) K_n m^{1+\gamma} \\ &\leq \frac{K_n m}{L_n n} \rightarrow 0 \quad (\text{by assumption (3) and (4)}). \end{aligned}$$

Hence, provided they exist, the asymptotic distributions of the two quantities  $B_n^{-1} \sum_{i=1}^{t+1} U_{n,i}$  and  $B_n^{-1} \sum_{i=1}^d X_{n,i}$  are the same, and the goal now is to show that

$$B_n^{-1} \sum_{i=1}^{t+1} U_{n,i} \Rightarrow N(0,1).$$

In order to apply assumption (3) again, we will first establish that  $B_n^{-2} \text{Var}\left(\sum_{i=1}^{t+1} U_{n,i}\right)$

tends to one, or, equivalently,  $B_n^{-2} \text{Cov}\left(\sum_{i=1}^{t+1} U_{n,i}, \sum_{i=1}^t V_{n,i}\right)$  tends to zero. Note first that  $\text{Cov}(U_{n,i}, V_{n,i}) = 0$  unless  $j = i$  or  $i - 1$ . Furthermore,

$$\begin{aligned} \left| \text{Cov}(U_{n,i}, V_{n,i}) \right| &= \left| E(U_{n,i}, V_{n,i}) \right| \leq \left[ \text{Var}(U_{n,i}) \text{Var}(V_{n,i}) \right]^{1/2} \\ &\leq K_n (mp)^{(1+\gamma)/2} \quad (\text{by assumption (2)}). \end{aligned}$$

Combining these two facts, we obtain  $\left| \text{Cov}\left(\sum_{i=1}^{t+1} U_{n,i}, \sum_{i=1}^t V_{n,i}\right) \right| \leq 2K_n (mp)^{(1+\gamma)/2}$

and finally,

$$\begin{aligned} B_n^{-2} \text{Cov}\left(\sum_{i=1}^{t+1} U_{n,i}, \sum_{i=1}^t V_{n,i}\right) &\leq 2 \frac{K_n}{L_n} \frac{t}{dm^\gamma} (mp)^{(1+\gamma)/2} \\ &\leq 2 \frac{K_n}{L_n} \frac{1}{pm^\gamma} (mp)^{(1+\gamma)/2} \\ &= 2 \frac{K_n}{L_n} \left(\frac{m}{p}\right)^{(1-\gamma)/2} \rightarrow 0 \quad (\text{by assumption (4) and since } \gamma < 1). \end{aligned}$$

By Lyapounov's theorem, it will now suffice to verify that  $\sum_{i=1}^{t+1} E|U_{n,i}|^{2+\delta} / B_n^{2+\delta}$  tends to zero. By Corollary A.1,

$$E|U_{n,i}|^{2+\delta} \leq C_{2+\delta}^{2+\delta} \Delta_n (4pm)^{(2+\delta)/2}, \quad 1 \leq i \leq t+1,$$

And therefore

$$\sum_{i=1}^{t+1} E|U_{n,i}|^{2+\delta} / B_n^{2+\delta} \leq \text{Const.} \Delta_n (d / p + 1) (pm)^{(2+\delta)/2} / B_n^{2+\delta}$$

By assumption (3), finally,

$$\Delta_n (d / p) (pm)^{(2+\delta)/2} / B_n^{2+\delta} \leq \Delta_n L_n^{-(2+\delta)/2} \frac{d}{p} \left(\frac{pm}{dm^\gamma}\right)^{(2+\delta)/2}$$

$$\leq \Delta_n L_n^{-(2+\delta)/2} \left(\frac{p}{d}\right)^{\delta/2} m^{(1-\gamma)(2+\delta)/2}$$

$= O(1)AB$  (by assumption (5));

where  $A = p^{\delta/2+(1-\gamma)(2+\delta)/2} d^{-\delta/2}$  and  $B = \left(\frac{m}{p}\right)^{(1-\gamma)(2+\delta)/2}$ . The second condition on  $p$  in

(7) implies that  $A$  tends to zero. The first condition on  $p$  in (7), together with the fact that  $\gamma \leq 1$ , imply that  $B$  tends to zero as well.

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