

1 Theorem for WLLN

We need finite second moment.

$$P(|\frac{\sum x_i}{n} - \frac{\sum \mu_i}{n}| > \epsilon) \leq \frac{\sum \sigma_{ij}}{\epsilon^2 n^2}.$$

1.1 Proof:

$$\begin{aligned} P(|\sum x_i - \sum \mu_i| > n\epsilon) &\leq \frac{E(\sum y_i)^2}{n^2 \epsilon^2} \quad (y_i := x_i - \mu_i) \\ &= \frac{\sum \sigma_{ij}}{\epsilon^2 n^2} \end{aligned}$$

because $E(\sum y_i)^2 = E \sum_i \sum_j y_i y_j$.

1.2 Corollary

Suppose $\{x_i\}_{i=1}^\infty$ 1) uncorrelated r.v.s with 2) identical mean μ and 3) bounded variance. Then

$$\frac{\sum x_i}{n} \rightarrow \mu.$$

1.2.1 proof:

$$p(|\frac{\sum x_i}{n}| > \epsilon) \leq \frac{\sum \sigma_{ij}}{\epsilon^2 n^2} = \frac{\sum^n \sigma_i}{\epsilon^2 n^2} \leq \frac{c \cdot n}{\epsilon^2 n^2} \rightarrow 0.$$

1.3 Example

Let n balls drop into n boxes uniformly at random. Let N_n be the number of empty boxes. Then

$$\frac{N_n}{n} \rightarrow_p \frac{1}{e}.$$

1.3.1 Proof:

We label boxes by $1, 2, \dots, n$. Define I_i to be the indicator if box i is empty. Therefore

$$N_n = \sum I_i.$$

Note that

$$EI_i = EI_1 = (1 - 1/n)^n.$$

$$EI_i I_j = P(\text{both } i, j \text{ boxes empty}) = (1 - 2/n)^n.$$

$$\text{cov}(I_1, I_2) = EI_1 I_2 - EI_1 EI_2 = (1 - 2/n)^n - (1 - 1/n)^2 n \rightarrow e^{-2} - e^{-2} \rightarrow 0.$$

So we can relax uncorrelation condition for wlln in this case.

$$\begin{aligned}
P(|\frac{N_n}{n} - \frac{EN_n}{n}| > \epsilon) \\
&= P(|\frac{N_n}{n} - \frac{\sum EI_i}{n}| > \epsilon) \leq \frac{\sum \sigma_{ij}}{\epsilon^2 n^2} \\
&= \frac{\sigma_1 1}{\epsilon^2 n} + \frac{n(n-1)\sigma_1 1}{\epsilon^2 n} \rightarrow 0.
\end{aligned}$$

1.4 Example2

Suppose we have n different coupons. At each time, I get a coupon iid from the n coupons. I define T_n = the first time that all the coupons are collected. Then $\frac{T_n}{n \log n} \rightarrow_p 1$.

1.4.1 Proof:

Define I_i to be the waiting time between the (i-1) and ith coupon.

$$T_n = \sum I_i,$$

each I_i are independent but not identical, $I_i \sim Geo(\frac{n-i+1}{n})$.

$$E(I_i) = \frac{n}{n-i+1}, var(I_i) = \frac{(i-1)n}{(n-i+1)^2}$$

$$E|T_n| = \sum EI_i = n \sum \frac{1}{n-i+1} = n(1 + 1/2 + 1/3 + \dots + 1/n) \approx n \log n$$

for above proof is here <https://math.stackexchange.com/questions/306371/simple-proof-of-showing-the-harmonic-number-h-n-theta-log-n>

$$\begin{aligned}
P(|\frac{T_n}{E|T_n|} - 1| > \epsilon) \\
&= P(|T_n - E|T_n|| > \epsilon E(T_n)) \\
&\leq \frac{var(T_n)}{\epsilon^2 (ET_n)^2} \\
&= \frac{\sum var(I_i)}{\epsilon^2 (ET_n)^2} \\
&\leq \frac{\sum \frac{(i-1)n}{(n-i+1)^2}}{\epsilon^2 (\log n)^2 n^2} \\
&= \frac{n^2 (\sum \frac{1}{(n-i+1)^2})}{\epsilon^2 (\log n)^2 n^2} \rightarrow 0.
\end{aligned}$$

because $(\sum \frac{1}{(n-i+1)^2})$ converges.

2 Theorem SLLN

Let $\{X_n\}$ be a sequence of pairwise independent and identically distribution r.v.s with $E|X_1| < \infty$ then

$$\frac{\sum x_i}{n} \rightarrow Ex_1 = \mu \text{ a.s.}$$

1. It suffices to show SLLN for $x_i \geq 0$
2. Let $Y_i = x_i 1_{x_i \leq i}$, we claim it truncated version.

2.1 proof 1:

Note that

$$\begin{aligned} & \sum_{i=1}^{\infty} P(x_i \neq y_i) \\ &= \sum_{i=1}^{\infty} P(x_i > i) \\ &= \sum_{i=1}^{\infty} P(x_1 > i) < \infty. \end{aligned}$$

Then By B-C,

$$P(X_i \neq Y_i \text{ i.o.}) = 0.$$

Therefore, the event

$$\{w | x_i(w) = y_i(w) \text{ for all but finitely many } i's.\}$$

has prob 1. hence for every $w \in A$,

$$\frac{\sum_{i=1}^{\infty} x_i(w)}{n} \rightarrow \mu \iff \frac{\sum_{i=1}^{\infty} y_i(w)}{n} \rightarrow \mu.$$

Thus, it is suffices to show

$$\sum y_i/n \rightarrow \mu \text{ a.s.}$$

Next

$$\begin{aligned} E(y_i) - \mu &= E(y_i) - E(x_i) \\ &= -E(x_i 1_{x_i > i}) \\ &= -E(X_1 1_{x_1 > i}) \xrightarrow{MCT} 0. \end{aligned}$$

In the last equation, we use the fact that $EX_1 < \infty$ implies $X_1 < \infty$ a.s. and define $z_i := x_1 1_{x_1 > i}$, then $z_1 \geq z_2 \geq \dots$

Therefore it suffices to show

$$Z_n := \frac{\sum (y_i - Ey_i)}{n} \xrightarrow{\text{a.s.}} 0.$$

Now we will show there is $\{k_n\}$ such that $z_{k_n} \rightarrow 0$ a.s. since

$$P(|Z_{k_n}| > \epsilon) \leq \frac{\sum \text{var}(Y_i)}{\epsilon^2 k_n^2},$$

$$\begin{aligned} \sum_{n=1}^{\infty} P(|Z_{k_n}| > \epsilon) &\leq \sum_{n=1}^{\infty} \frac{\sum_{i=1}^{k_n} \text{var}(Y_i)}{\epsilon^2 k_n^2} \\ &= \frac{1}{\epsilon^2} \sum_{i=1}^{\infty} \sum_{n: k_n \geq i} \frac{\text{var}(Y_i)}{k_n^2} \quad (\text{이해 잘 안감}) \\ &= \frac{1}{\epsilon^2} \sum_{i=1}^{\infty} \text{var}(y_i) \left(\sum_{n: k_n \geq i} \frac{1}{k_n^2} \right) \end{aligned} \quad (1)$$

We know that, and (take any $\alpha > 1, k_n = \lfloor \alpha^n \rfloor$ 나중예 $k_n/(k_{n-1}) \rightarrow \alpha$.)

$$\sum_{n: k_n \geq i} \frac{1}{k_n^2} \leq \sum_{n: k_n \geq i} \frac{1}{i^2} \leq \frac{1}{i^2} c \quad (2)$$

By applying (2) into (1),

$$\sum_{n=1}^{\infty} P(|Z_{k_n}| > \epsilon) \leq \frac{c}{\epsilon^2} \left(\sum_{i=1}^{\infty} \frac{\text{var}(y_i)}{i^2} \right)$$

Also,

$$\sum_{i=1}^{\infty} \frac{\text{var}(y_i)}{i^2} \leq \sum_{i=1}^{\infty} \frac{E(X_1^2 1_{x_1 \leq i})}{i^2} = E(x_1^2 \sum_{x_1 \leq i} \frac{1}{i^2}) \leq c' E(X_1^2 \frac{1}{X_1}) \leq c' EX_1 < \infty$$

Then by B-C again, and $P(Z_{k_n} > \epsilon) \leq P(|Z_{k_n}| > \epsilon)$,

$$P(Z_{k_n} > \epsilon \text{ i.o.}) = 0$$

therefore, $Z_{k_n} \rightarrow 0$ a.s.

Let $T_n := \sum_{i=1}^n Y_i$, then for each m, we can find k_n, k_{n-1} such that $k_{n-1} \leq m \leq k_{n+1}$. Then

$$\frac{T_{k_n}}{k_{n+1}} \leq \frac{T_m}{m} \leq \frac{T_{k_{n+1}}}{k_n}$$

Note that

$$\begin{aligned} \frac{T_{k_{n+1}}}{k_n} &= \frac{T_{k_{n+1}}}{k_{n+1}} \frac{k_{n+1}}{k_n} \\ \frac{T_{k_n}}{k_{n+1}} &= \frac{T_{k_n}}{k_n} \frac{k_n}{k_{n+1}} \end{aligned}$$

We know $\frac{T_{k_{n+1}}}{k_{n+1}}$ converges. When $m \rightarrow \infty, n(m) \rightarrow \infty, \frac{T_{k_n}}{k_n} \rightarrow \mu$ and

$$\frac{k_n}{k_{n+1}} \rightarrow \alpha$$

Therefore

$$\frac{\mu}{\alpha} \leq \liminf \frac{T_m}{m} \leq \limsup \frac{T_m}{m} \leq \alpha \mu$$

take $\alpha \rightarrow 1$ then we have the result a.s.

3 The law of iterated logarithm

Let X_1, X_2, \dots be independent with mean 0 and variance 1. Then

$$P(\limsup \frac{S_n}{\sqrt{2n \log \log n}} = 1) = 1$$

In other words, for each $\epsilon > 0$,

$$P(S_n \geq (1 + \epsilon)\sqrt{2n \log \log n} \text{ i.o.}) = 0,$$

$$P(S_n > (1 - \epsilon)\sqrt{2n \log \log n} \text{ i.o.}) = 1.$$

Let X_1, \dots, X_n iid r.v.s with $EX_1 = 0, \text{var}(X_1) = 1$,

$$LLN \quad \frac{\sum X_i}{n} \rightarrow EX_1 = 0, S_n = \sum X_i = o_p(n)$$

$$CLT \quad \frac{\sum X_i}{\sqrt{n}} \rightarrow N(0, 1), S_n = \sum X_i = O_p(\sqrt{n})$$

3.1 Theorem

Convergence in distribution implies bounded in probability.

$$X_n \rightarrow_D X, \text{ then } X_n = o_p(1).$$

3.2 Lemma 1.

If $a_n \rightarrow \infty$, and $\frac{a_n}{\sqrt{\log n}} \rightarrow 0$, then

$$\begin{aligned} P\left(\frac{\sum^n X_i}{\sqrt{n}} \geq a_n\right) &= \exp(-1/2a_n^2(1 + \xi_n)) \\ &= \exp(-1/2a_n^2(1 + o(1))), \text{ where } \xi_n \rightarrow 0. \end{aligned}$$

3.3 Lemma 2. Maximal inequality

Define $M_n = \max_{i \leq n} S_n$ be the maximum process.

For $\alpha \geq \sqrt{2}$, we have

$$P\left(\frac{M_n}{\sqrt{n}} \geq \alpha\right) \leq \alpha P\left(\frac{S_n}{\sqrt{n}} \geq \alpha - \sqrt{2}\right).$$

3.4 Proof for lemma2 maximal inequality

Using the previous result,

$$-S_{n_{k-1}} \leq 2\sqrt{2n_{k-1} \log \log n_{k-1}}$$

with prob. 1 for a large enough k .

$$\begin{aligned} S_{n_k} &\geq X_k + S_{n_{k-1}} \geq X_k - 2\sqrt{2n_{k-1} \log \log n_{k-1}} \\ &\geq (1 - \theta^{-1})\sqrt{2n_{k-1} \log \log n_{k-1}} - \frac{2}{\sqrt{\theta}} \frac{1}{\sqrt{2n_k \log \log n_k}} \\ &\quad \text{(definition of } X_k) \\ &= (1 - \theta^{-1} - \frac{2}{\sqrt{\theta}}) \frac{1}{\sqrt{2n_k \log \log n_k}} \\ &\geq (1 - \frac{3}{\sqrt{\theta}}) \frac{1}{\sqrt{2n_k \log \log n_k}} \\ &> \frac{1 - \epsilon}{\sqrt{2n_k \log \log n_k}}. \end{aligned}$$

Now

$$\left\{\frac{M_n}{\sqrt{n}} \geq \alpha\right\} \subset \left\{\frac{S_n}{\sqrt{n}} \geq \alpha\right\} \cup \left\{\frac{S_n}{\sqrt{n}} < \alpha - \sqrt{2}, \text{ but } \frac{S_i}{\sqrt{n}} > \alpha \text{ for some } i\right\},$$

hence

$$P\left(\frac{M_n}{\sqrt{n}} \geq \alpha\right) \leq P\left(\frac{S_n}{\sqrt{n}} \geq \alpha\right) + p\left(\frac{S_n}{\sqrt{n}} < \alpha - \sqrt{2}, \text{ but } \frac{S_i}{\sqrt{n}} > \alpha \text{ for some } i\right) \quad (1)$$

Let A_i be the event that

$$\frac{M_i}{\sqrt{n}} \geq \alpha \text{ but } \frac{M_j}{\sqrt{n}} < \alpha \text{ for every } j \leq i.$$

A_i are disjoint. Note that under A_i and $\frac{S_n}{\sqrt{n}} < \alpha - \sqrt{2}$. We know $\frac{S_i}{\sqrt{n}} > \alpha$ and $\frac{S_n}{\sqrt{n}} > \alpha - \sqrt{2}$

$$\Rightarrow S_i - S_n > \sqrt{2n}.$$

Now,

$$\begin{aligned}
P((1)) &= p\left(\frac{S_n}{\sqrt{n}} < \alpha - \sqrt{2}, \bigcup_{i=1}^n A_i\right) \\
&\leq \sum_{i=1}^n P\left(\frac{S_n}{\sqrt{n}} < \alpha - \sqrt{2} \mid A_i\right) && \text{(union bound)} \\
&\vdots \\
&\leq \sum_{i=1}^n P\left(\frac{S_i - S_n}{\sqrt{n}} > \sqrt{2} \mid A_i\right) && \text{(tricky)} \\
&= \sum_{i=1}^n P\left(\frac{S_i - S_n}{\sqrt{n}} > \sqrt{2}\right) P(A_i) \\
&\leq \sum_{i=1}^n \frac{n-1}{2n} P(A_i) \\
&\leq \frac{1}{2} \sum_{i=1}^{n-1} P(A_i) \\
&= \frac{1}{2} P\left(\bigcup_{i=1}^{n-1} A_i\right) \\
&\leq \frac{1}{2} P(M_n \geq \alpha).
\end{aligned}$$

$$P(M_n \geq \alpha) \leq P(S_n \geq \alpha - \sqrt{2}) + \frac{1}{2} P(M_n \geq \alpha)$$

Therefore

$$P(M_n \geq \alpha) \leq P(S_n \geq \alpha - \sqrt{2}).$$

□

3.5 Proof of LIL

. Fix $\epsilon > 0$ and choose θ such that $1 \leq \theta^2 < 1 + \epsilon$ and let $n_k = \theta^k$.

Define

$$\begin{aligned}
X_k &= \theta \sqrt{2 \log \log n_k} \\
&= \theta \sqrt{2 \log \log \theta^k} \\
&= \theta \sqrt{2(\log k + \log(\log \theta))} \\
&= \theta \sqrt{2 \log k} \frac{\sqrt{2 \log k + 2 \log \log \theta}}{\sqrt{2 \log k}} \\
&= \theta \sqrt{2 \log k} (1 + o(1)).
\end{aligned}$$

$$p\left(\frac{M_{n_k}}{\sqrt{n_k}} \geq X_k\right) \leq 2P\left(\frac{S_{n_k}}{\sqrt{n_k}} \geq X_k - \sqrt{2}\right) \quad (\text{lemma2})$$

$$= 2\exp\left(-\frac{1}{2}(X_k - \sqrt{2})^2(1 + 0(1))\right) \quad (\text{lemma1})$$

$$= 2\exp\left(-\frac{1}{2}(X_k - \sqrt{2})^2(1 + 0(1))\right)$$

$$= 2\exp\left(-\frac{1}{2}(\theta\sqrt{2\log k})^2(1 + 0(1))\right)$$

$$= 2\exp\left(-\frac{1}{2}\theta^2 2\log k(1 + 0(1))\right)$$

$$= 2\frac{1}{k^{\theta^2(1+0(1))}}$$

By Borel Cantelli-I, sum of the series is finite, hence we have that

$$p\left(\frac{M_{n_k}}{\sqrt{n_k}} \geq \theta\sqrt{2\log\log n_k} \text{ i.o.}\right) = 0$$

Suppose $S_n \geq (1 + \epsilon)\sqrt{2n\log\log n}$ i.o. i.e.,

$$P(S_n \geq (1 + \epsilon)\sqrt{2n\log\log n} \text{ i.o.}) = 1.$$

then choose

$$n_{k-1} < n \leq n_k,$$

then

$$\begin{aligned} \frac{M_{n_k}}{X_k \sqrt{n_k}} &= \frac{M_{n_k}}{\theta \sqrt{2n_k \log\log n_k}} \\ &\geq \frac{S_n \theta \sqrt{2n \log\log n}}{\theta \sqrt{2n \log\log n} \theta \sqrt{2n_k \log\log n_k}} \\ &\geq \frac{S_n}{\theta \sqrt{2n \log\log n}} \frac{\theta \sqrt{2n_{k-1} \log\log n_{k-1}}}{\theta \sqrt{2n_k \log\log n_k}} \\ &\geq \frac{S_n}{\theta \sqrt{2n \log\log n}} \frac{1}{\theta^{1/2}} (1 + 0(1)) \\ &= \frac{S_n}{\theta^{1.5} \sqrt{2n \log\log n}} (1 + 0(1)) \\ &\geq \frac{1 + \epsilon}{\theta^{1.5}} (1 + 0(1)) \quad (\text{by assumption}) \\ &> 1 \quad (\text{contradiction}) \end{aligned}$$

Above implies that

$$\Rightarrow P(S_n \geq (1 + \epsilon)\sqrt{2n\log\log n} \text{ i.o.}) = 0$$

For the other direction, fix any ϵ and $\theta \in N^*$ such that $\frac{3}{\sqrt{\theta}} < \epsilon$ and $n_k = \theta^k$. Define

$$X_k = (1 - \theta^{-1})\sqrt{2n_k \log \log n_k}$$

$$\begin{aligned} P(S_{n_k} - S_{n_{k-1}} \geq X_k) &= \exp\left(-\frac{X_k^2}{2(n_k - n_{k-1})}(1 + o(1))\right) \quad (\text{lemma 1}) \\ &= \exp\left(-\frac{(1 - \theta^{-1})^2 2n_k \log \log n_k}{2n_k(1 - \theta^{-1})}(1 + o(1))\right) \\ &= \exp(-(1 - \theta^{-1})\log \log n_k(1 + o(1))) \\ &= \exp(-(1 - \theta^{-1})\log k(1 + o(1))) \\ &= \frac{1}{k^{(1-\theta^{-1})(1+o(1))}} \end{aligned} \quad (1)$$

Where in (1),

$$\log \log n_k = \log k \left(1 + \frac{\log \log \theta}{\log k}\right) = \log k(1 + o(1)).$$

Therefore

$$\sum P(S_{n_k} - S_{n_{k-1}} \geq X_k) = \infty,$$

by the Borel-Cantelli 2, we have that

$$P(S_{n_k} - S_{n_{k-1}} \geq X_k \text{ i.o.}) = 1$$

□