A study memo on weak law of large numbers and crude Monte Carlo Simulation

1 Law of large numbers

Proposition 1.1 (Weak law of large numbers). Let

- (S1) (Ω, \mathscr{F}, P) is a probability space.
- (A1) $\{X_i\}_{i=1}^{\infty}$ is a sequence of independent random variables on (Ω, \mathscr{F}, P) .
- (A2) There is a $\mu \in \mathscr{P}(\mathbb{R})$ such that $X_i \sim \mu(\forall i)$.
- (A3) $E[\mu] = \nu$ and $V[\mu] = \sigma^2$ exist.

then the followings hold.

(i) $\{X_i\}_{i=1}^{\infty}$ stochastic converges to μ , i.e., for any $\epsilon > 0$

$$\lim_{n \to \infty} \mu(|\bar{X} - \mu| \ge \epsilon) = 0 \tag{1}$$

Hereafter we denote stochastic convergence by $\xrightarrow{p}{N \to \infty}$ or plim.

(ii) For any $\epsilon > 0$,

$$\mu(|\bar{X} - \mu| \ge \epsilon) \le \frac{\sigma^2}{n\epsilon^2} \tag{2}$$

A proof using Chebyshev's inequality. For any $n \in \mathbb{N}$,

$$\mu(|\bar{X} - \mu| \ge \epsilon) = \frac{\epsilon^2 \mu(|\bar{X} - \mu|^2 \ge \epsilon^2)}{\epsilon^2}$$

$$\leq \frac{1}{\epsilon^2} \int_{\{|\bar{X} - \mu|^2 \ge \epsilon^2\}} \epsilon^2 dP$$

$$\leq \frac{1}{\epsilon^2} V[\bar{X}] = \frac{\sigma^2}{n\epsilon^2}$$
(3)

This implies the above equation.

A proof using Central limit theorem. By resetting $X_i \to \frac{X_i - \mu}{\sigma}$, we can assume $\mu = 0$ and $\sigma = 1$. Let us fix arbitrary $\epsilon > 0$ and $\delta > 0$. There is a > 0 such that

$$N(0,1)((-\infty,-a)\cup(a,\infty))<\delta\tag{4}$$

By Central limit theorem, there is $n_0 \in \mathbb{N}$ such that

$$\frac{a}{\sqrt{n_0}} < \delta \tag{5}$$

and for any $n \ge n_0$

$$|\mu(|\sqrt{n}\bar{X}| \ge a) - N(0,1)((-\infty, -a) \cup (a,\infty))| < \delta$$
(6)

So for any $n \ge n_0$

$$\mu(|\bar{X}| \ge \epsilon) \le \mu(|\bar{X}| \ge \frac{a}{\sqrt{n}}) = \mu(\sqrt{n}|\bar{X}| \ge a)$$
$$\le 2\delta \tag{7}$$

So $\overline{\lim_{n \to \infty}} \mu(|\bar{X}| \ge \epsilon) \le 2\delta$. Consequently, $\lim_{n \to \infty} \mu(|\bar{X}| \ge \epsilon) = 0$.

2 Crude Monte Carlo method

Proposition 2.1. Let

- (S1) $(S := \{1, 2, ..., M\}, 2^{\Omega}, H)$ is a probability space.
- (S2) (Ω, \mathscr{F}, P) is a probability space.
- (S3) $\{X_n\}_{n=1}^{\infty}$ is a sequence of independet random variables on Ω such that $X_n(\Omega) \subset S$ for any $n \in \mathbb{N}$.
- (A1) $X_n \sim H$ for any $n \in \mathbb{N}$. $X_n \sim H$) means that $P(\{X_n = i\}) = H(i)$
- (S4) g is a function on S.
- (S5) $\{Y_n\}_{n=1}^{\infty}$ is a sequence of independet random variables on Ω such that $Y_n(\Omega) \subset S$ for any $n \in \mathbb{N}$.
- (A2) $Y_n \sim C$ for any $n \in \mathbb{N}$. Here, C is the counting measure of S.

then

$$\lim_{N \to \infty} \frac{\sum_{i=1}^{N} g(X_i)}{N} = \sum_{s \in S} g(s) H(\{s\}) = \#S \lim_{N \to \infty} \frac{\sum_{i=1}^{N} g(Y_i) H(\{Y_i\})}{N}$$
(8)

STEP1. Showing (the left side)=(the middle side). Clearly $\{g(X_n)\}_{n=1}^{\infty}$ is a sequence of independet random variables on Ω . By (A1),

$$\int_{\Omega} g(X_n) dP = \sum_{s \in S} g(s) H(\{s\})$$
(9)

and

$$\int_{\Omega} g(X_n)^2 dP = \sum_{s \in S} g^2(s) H(\{s\})$$
(10)

So by weak law of large numbers (8) holds.

STEP2. Showing (the right side) = (the middle side) . We set

$$G: S \ni s \mapsto g(s)H(\{s\}) \# S \in \mathbb{R}$$

$$\tag{11}$$

By applying the method of STEP1 to G and C,

$$\lim_{N \to \infty} \frac{\sum_{i=1}^{N} g(Y_i) H(\{Y_i\}) \# S}{N} = \sum_{s \in S} g(s) H(\{s\}) \# SC(\{s\})$$
$$= \sum_{s \in S} g(s) H(\{s\})$$
(12)

References

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