

# Classical limit theorems

Recall our question:

$$\frac{1}{N} \sum_{i=1}^N m_i \xrightarrow[N \rightarrow \infty]{??} \int m \pi(m) dm$$

## Central limit theorem (CLT)

- Assume  $m_i$  are i.i.d. draws from  $\pi(m)$

$$m_i \sim \pi(m)$$

denote  $\bar{m} := \mathbb{E}_{\pi(m)}[m] = \int m \pi(m) dm < \infty$

$$\sigma^2 := \mathbb{E}_{\pi}[(m - \bar{m})^2] < \infty$$

Then:

$$Z_N(w) := \frac{1}{\sigma \sqrt{N}} (m_1 + \dots + m_N) - \frac{\bar{m}}{\sigma} \sqrt{N}$$

Converges, in distribution, to a standard normal random variable. In particular:

$$\lim_{N \rightarrow \infty} \mathbb{P} [Z_N \leq a] = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^a \exp\left(-\frac{t^2}{2}\right) dt$$

il def

$$\mu_{Z_N} [Z_N \leq a] = \int_{\{Z_N \leq a\}} \pi_{Z_N}(m) dm$$


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## Law of large numbers (LLN)

Assume  $m_i$  are i.i.d. draws from  $\pi(m)$

$$m_i \sim \pi(m)$$

define

$$\left\{ \begin{array}{l} \bar{m} = \mathbb{E}_{\pi}(m) < \infty \\ \sigma^2 = \mathbb{E}_{\pi}[(m - \bar{m})^2] < \infty \end{array} \right.$$

first two moments of  $\pi(m)$

Then:

$$\lim_{N \rightarrow \infty} S_N := \frac{1}{N} (m_1 + \dots + m_N) = \bar{m}$$

ALMOST SURELY = ALMOST EVERY WHERE

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Convergence with probability 1

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HOW ABOUT THE CONVERGENCE RATE

OF  $S_N$  ?

(This allows us to estimate  $N$  for a given error  $S_N - \bar{m}$ )

\* 1st Answer: CLT:

$$z_N \underset{N \rightarrow \infty}{\sim} N(0, 1)$$

$\Downarrow$

$$V[z_N] \approx 1$$

$\Downarrow$  def

$$\int (z_N - 0)^2 \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z_N^2}{2}\right) dz_N \approx 1$$

def  $\parallel$  back to  $m_i$

$$\int \left[ \frac{1}{\sigma \sqrt{N}} \sum m_i - \frac{\bar{m}}{\sigma} \sqrt{N} \right]^2 \pi(m) dm$$

LAST TIME:

1) assume  $\{m_i\}$  are i.i.d. draws from

$$\pi(m), \quad + \quad \mathbb{E}_{\pi}[m] = \bar{m} < \infty$$

$$+ \quad \mathbb{E}_{\pi}[(m - \bar{m})^2] = V(m) < \infty$$

2) CLT:

$$z_N(w) := \frac{1}{\sigma \sqrt{N}} \sum m_i(w) - \frac{\bar{m}}{\sigma} \sqrt{N} \xrightarrow[N \rightarrow \infty]{\text{in distribution}}$$

a standard normal random variable

2) LLN:

$$S_N = \frac{1}{N} \sum m_i \xrightarrow[N \rightarrow \infty]{a.s.} \bar{m}$$


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TOPAT: Convergence rate of  $S_N$ :

I/ Using CLT:

$$Z_N \xrightarrow{N \rightarrow \infty} N(0, 1)$$

$\Downarrow$

$$\frac{1}{\sqrt{N}}$$

$\Downarrow$

$$V[Z_N]$$

$\parallel$  def

$$E[(Z_N - \bar{Z}_N)^2]$$

$$\parallel \bar{Z}_N \approx 0 \text{ since } Z_N \xrightarrow{N \rightarrow \infty} N(0, 1)$$

$$E[(Z_N(\omega))^2]$$

$\parallel$  def  $Z_N$

$$E\left[\left(\frac{1}{\sigma\sqrt{N}} \sum m_i - \frac{\bar{m}}{\sigma} \sqrt{N}\right)^2\right]$$

$$\mathbb{E} \left[ \frac{1}{\sigma^2} \left( \frac{\sum_{i=1}^N m_i}{N} - \bar{m} \right)^2 \right]$$

$$\frac{1}{\sigma^2} \mathbb{E} \left[ (S_N - \bar{m})^2 \right]$$

$$\text{ii } L^2(\mathbb{P}) := \left\{ f(\omega) : \int_{\Omega} (f(\omega))^2 d\mathbb{P} < \infty \right\}$$

$$\frac{1}{\sigma^2} \|S_N - \bar{m}\|_{L^2(\mathbb{P})}^2 : \text{mean-squared error}$$

Thus we have "shown":

$$\frac{1}{\sigma^2} \|S_N - \bar{m}\|_{L^2(\mathbb{P})}^2 \approx 1$$

$$\Rightarrow \|S_N - \bar{m}\|_{L^2(\mathbb{P})} \approx \frac{\sigma}{\sqrt{N}}$$

$$S_N - \bar{m} \sim \frac{1}{\sqrt{N}}$$

$$\boxed{\|S_N - \bar{m}\| = c \frac{\sigma}{\sqrt{N}}}$$

$$\Downarrow$$

$$\|S_N - \bar{m}\| = c \frac{\sigma}{\sqrt{N}}$$

II / Direct approach:

$$\|S_N - \bar{m}\|_{L^2(\mathbb{P})}^2$$

$$\| \text{def } S_N$$

$$\mathbb{E} \left[ \left( \frac{1}{N} \sum m_i - \bar{m} \right) \left( \frac{1}{N} \sum m_j - \bar{m} \right) \right]$$

$$\mathbb{E} \left[ \frac{1}{N^2} \left\{ \sum (m_i - \bar{m}) \right\} \left\{ \sum (m_j - \bar{m}) \right\} \right]$$

$$\frac{1}{N^2} \mathbb{E} \left[ \sum_i (m_i - \bar{m})(m_i - \bar{m}) + \sum_{i \neq j} (m_i - \bar{m})(m_j - \bar{m}) \right]$$

$$\frac{1}{N^2} \mathbb{E} \left[ \sum_i (m_i - \bar{m})(m_i - \bar{m}) \right] +$$

$$\frac{1}{N^2} \mathbb{E} \left[ \sum_{i \neq j} (m_i - \bar{m})(m_j - \bar{m}) \right]$$

$$\begin{aligned} &= \mathbb{E} \left[ \sum_{i \neq j} (m_i - \bar{m})(m_j - \bar{m}) \right] \\ &= \sum_{i \neq j} \mathbb{E} [(m_i - \bar{m})(m_j - \bar{m})] \\ &\stackrel{\text{i.i.d.}}{=} \sum_{i \neq j} \underbrace{\mathbb{E}[m_i - \bar{m}]}_0 \underbrace{\mathbb{E}[m_j - \bar{m}]}_0 \end{aligned}$$

$$\frac{1}{N^2} \sum_i \mathbb{E} [(m_i - \bar{m})(m_i - \bar{m})]$$

$$\parallel \text{ def: } \mathbb{E} [(m_i - \bar{m})^2] = \sigma^2$$

$$\frac{\sigma^2}{N}$$

Thus :

$$\| S_N - \bar{m} \|_{L^2(\mathbb{P})}^2 = \frac{\sigma^2}{N}$$

- So the mean-square error of i.i.d draws (Monte Carlo method) converges to

zero with the rate  $\frac{1}{\sqrt{N}}$  Independent

of the dimension of  $m$  (only true if  $\sigma$   
DOES NOT depend on the  
dimension)

- In general:

$$S_N := \frac{1}{N} \sum_i f(m_i) \xrightarrow[N \rightarrow \infty]{a.s.} \mathbb{E}_{\pi}[f(m)]$$

and the convergence rate is

$$\|S_N - \overline{f(m)}\|_{L^2(\mathbb{P})} = \frac{\sqrt{\mathbb{V}[f(m)]}}{\sqrt{N}}$$