

WLLN



- X_1, X_2, \dots stationary
- $E|X_1|^2 < \infty$
- $C(n) : \text{cov}(X_1, X_{1+n}) \rightarrow 0 \text{ as } n \rightarrow \infty$

$$\Rightarrow \bar{X}_n \xrightarrow{P} EX_1$$

$$C(n) \rightarrow 0$$



"asymptotic independence"

"asymptotic loss of memory"

"mixing"

Newsvendor Model

e.g. a newsvendor at airport

x = order quantity

$$W(x, D) = \underset{\substack{\uparrow \\ \text{demand}}}{r} \min(x, D) + \underset{\substack{\uparrow \\ \max(x-D, 0)}}{s} [x - D]^+ - cx$$

$$\text{Choose } x \xrightarrow{\text{maximize}} \left\{ \begin{array}{l} EW(x, D) \\ \text{median of } W(x, D) \end{array} \right.$$

$$LLN \Rightarrow \frac{1}{n} \sum_{i=1}^n W(x, D_i) \xrightarrow{P} EW(x, D)$$

should maximise $EW(x, D)$

← assume continuous

$$\begin{aligned}
 E W(x, D) &= r \int_0^x y f(y) dy + r x P(D > x) \\
 &\quad + s \int_0^x (x-y) f(y) dy - c x \\
 \frac{d}{dx} &= \cancel{r x f(x)} + r P(D > x) - \cancel{r x f(x)} \\
 &\quad + \frac{d}{dx} \left(s x \int_0^x f(y) dy - s \int_0^x y f(y) dy - c x \right) \\
 &\quad // \\
 &\quad s \int_0^x f(y) dy + \cancel{s x f(x)} - \cancel{s x f(x)} - c \\
 &= r P(D > x) + s \int_0^x f(y) dy - c
 \end{aligned}$$

$$\text{Set } \frac{d}{dx} = 0$$

$$\Rightarrow P(D \leq x^*) = \frac{r-c}{r-s}$$

Investment

reckless investment $1+s$

risky investment w_i

$$V_n = V_0 R_1 R_2 \dots R_n$$

$$\text{e.g. } R_i = f(1+s) + (1-f)w_i \quad \leftarrow \text{i.i.d.}$$

① Maximize Expected Value

$$E V_n = V_0 E R_1 E R_2 \dots E R_n$$

$$= V_0 \underbrace{(E R_1)}_{\text{maximize}}^n$$

$$E w_i > 1+s \quad \Rightarrow \quad f^* = 0$$

$$E V_n = V_0 (E w_i)^n$$

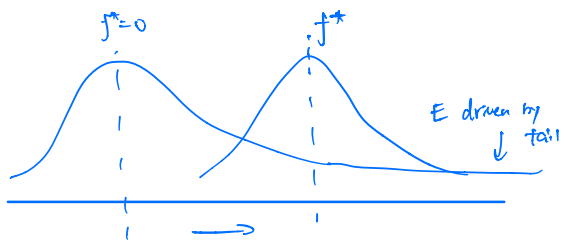
$$\textcircled{2} \quad \frac{1}{n} \log V_n = \frac{1}{n} \log V_0 + \underbrace{\frac{1}{n} \sum_{i=1}^n \log R_i}_{\xrightarrow{P} E \log R_1}$$

$$\frac{1}{n} \log V_n \xrightarrow{P} \frac{1}{n} \log V_0 + E \log (f(1+\delta) + (1-f)W_1)$$

↑
choose f to maximize

$$E \log R_1 < \log E R_1$$

$$V_n \approx V_0 \exp(n E \log (f^*(1+\delta) + (1-f^*)W_1))$$



"diversified"

\Rightarrow maximize expected log-return
rather than expected return

Jensen's inequality

$\log(x)$ concave

$$\left\{ \begin{array}{ll} E \phi(R_1) < \phi(E R_1) & \phi \text{ concave} \\ E \phi(R_1) > \phi(E R_1) & \phi \text{ convex} \end{array} \right.$$

Proof: $\phi(\bar{R}_n) = \phi\left(\frac{1}{n} R_1 + \dots + \frac{1}{n} R_n\right)$
 $\leq \sum_{i=1}^n \frac{1}{n} \phi(R_i)$ (convex)
 $\hookrightarrow E \phi(R_1)$
 $\Rightarrow \phi(E R_1) \leq E \phi(R_1)$

"Kelly investing"

Central Limit Theorem (CLT)

- $S_n = X_1 + \dots + X_n$
- X_1, X_2, \dots i.i.d.
- $\text{var } X_1 < \infty$

$$\bar{X}_n \xrightarrow{P} E X_1$$

$$\Rightarrow \sqrt{n} (\bar{X}_n - E X_1) \Rightarrow \mathcal{N}(0, 1)$$

↑ ↑
rate of convergence $\text{sd}(X_1)$

$$\bar{X}_n - EX_1 \Rightarrow \frac{1}{\sqrt{n}} N(0,1)$$

\uparrow
 weak convergence
 convergence in distribution

$\phi(x)$: pdf of $N(0,1)$

$$\frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

$$\Phi(x) = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-t^2/2} dt$$



Convergence in Distribution

$$Z_n \Rightarrow Z_\infty$$

iff

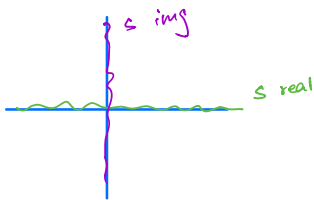
$$P(Z_n \leq z) \rightarrow P(Z_\infty \leq z)$$

as $n \rightarrow \infty$ at every z which is a continuous point of $P(Z_n \leq z)$

$$P\left(\frac{1}{n}(\bar{X}_n - EX_1) \leq z\right) \rightarrow \Phi(z) \quad \text{as } n \rightarrow \infty$$

Laplace transform

Fourier transform



$$E e^{sx} = C_x(s) \quad \leftarrow \text{complex-valued function}$$

$$E e^{\lambda x} = M(\lambda) \quad \leftarrow \begin{matrix} \lambda \text{ real} \\ \downarrow \end{matrix}$$

moment-generating function

$$E e^{i\theta x} = C(\theta) \quad \leftarrow \begin{matrix} e^{i\theta x} \text{ imaginary} \\ \uparrow \end{matrix}$$

characteristic function

$$\int_{-\infty}^{\infty} e^{i\theta x} f_X(x) dx$$

\hookrightarrow always well-defined for $\theta \in \mathbb{R}$

$$\int_{-\infty}^{\infty} |e^{i\lambda x} f_X(x)| dx \leq \int_{-\infty}^{\infty} f_X(x) dx = 1$$

For m.f.f. through $\int_{-\infty}^{\infty} e^{\lambda x} (1+x)^{-p} dx = \infty \quad \forall \lambda \neq 0$

Extension of CLT:

$$\bar{X}_n \xrightarrow{P} EX_1$$

$$n^{\frac{1}{2}} (\bar{X}_n - EX_1) \Rightarrow \sigma N(0,1)$$

confidence interval for EX_1

$$S_n \xrightarrow{P} \sigma = \sqrt{\text{Var} X_1}$$

$$S_n = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2} \quad \text{"sample standard deviation"}$$

\downarrow EX_1
 \downarrow
 $\sqrt{\text{Var} X_1}$

CLT for S_n ?

\Rightarrow "Delta Method"

$$S_n = \sqrt{\frac{1}{n-1} \sum_{i=1}^n (X_i - \bar{X}_n)^2}$$

$$\approx \sqrt{\left(\frac{1}{n} \sum_{i=1}^n X_i^2, \frac{1}{n} \sum_{i=1}^n X_i \right)}$$

$\downarrow P$ $\downarrow P$
 EX_1^2 EX_1

$$g(x, y) = \sqrt{x - y^2}$$

$$Z_i = (X_i^2, X_i)^T$$

$$Z_1, \dots, Z_n$$

$$S_n \approx f(\bar{z}_n)$$

$$0 = f(Ez)$$

$$S_n - 0 = f(\bar{z}_n) - f(Ez)$$

$$\approx Df(Ez) \cdot (\bar{z}_n - Ez)$$

$$= \bar{y}_n$$

$$y_i = Df(Ez) \begin{pmatrix} x_i^2 - Ex_i^2 \\ x_i - Ex_i \end{pmatrix}$$

↑
i.i.d. scalar mean 0 r.v.'s

$$n^{1/2} \bar{y}_n \Rightarrow \beta N(0,1)$$

$$\beta = sd(y_i) = \sqrt{E y_i^2}$$