

Central Limit theorem

Suppose X_1, X_2, \dots are identical, independent random variables
w/ mean $\mu = E[X_i]$ variance $\sigma^2 = \text{Var}(X_i)$

Then

$$\lim_{n \rightarrow \infty} P\left(\frac{\left(\sum_{i=1}^n X_i\right) - n\mu}{\sigma\sqrt{n}} \leq a\right)$$

$$\stackrel{''}{=} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^a e^{-x^2/2} dx = P(Z \leq a)$$

Z is "unit" normal random variable
p.d.f. $\frac{1}{\sqrt{2\pi}} e^{-x^2/2}$

$$E[X+Y] = E[X] + E[Y] \quad \mu_{X+Y} = \mu_X + \mu_Y$$

$$E[X - \mu_X] = E[X] - E[\mu_X] = \mu_X - \mu_X = 0$$

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y)$$

(if X, Y independent)

$$\begin{aligned}\text{Var}(\lambda X) &= \text{Cov}(\lambda X, \lambda X) = \lambda^2 \text{Cov}(X, X) \\ &= \lambda^2 \text{Var}(X).\end{aligned}$$

$$\text{So } \frac{\sum_{i=1}^n X_i - n\mu}{\sigma\sqrt{n}}$$

is a random var w/
mean 0
variance 1

Basic Tool: Moment generating function

Recall: $M_X(t) = E[e^{tX}]$

$$t=2 \quad E[e^{2X}] = \text{same \#} \quad M_X(2)$$

$$t=3 \quad E[e^{3X}] \dots \quad M_X(3)$$

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f(x) dx$$

cont. case

Compare $\hat{f}(t) = \int_{-\infty}^{\infty} e^{-2\pi ixt} f(x) dx$

$$\text{i.e. } M_X(-2\pi i t) = \hat{f}(t)$$

$$\text{Important property: } f(x) = \int_{-\infty}^{\infty} e^{2\pi i x t} \hat{f}(t) dt$$

$$f(x) = \int_{-\infty}^{\infty} e^{2\pi i x t} M_X\left(\frac{t}{-2\pi i}\right) dt$$

$$\left(e^{i\theta} = \cos\theta + i\sin\theta \right)$$

Properties of $M_X(t)$

• Determines X i.e. $M_X(t) = M_Y(t) \Leftrightarrow X = Y$

• X & Y indep $M_{X+Y}(t) = M_X(t) M_Y(t)$

• $M'(0) = E[X]$ $M''(0) = E[X^2]$, ...
 $M(0) = E[e^0] = 1$

Power series expansion:

$$M(t) = M(0) + M'(0)t + \frac{1}{2}M''(0)t^2 + \dots$$

$$= \sum \frac{M^{(n)}(0)}{n!} t^n = \sum_{i=0}^{\infty} \frac{E[X^n]}{n!} t^n$$

Step 1 of CLT proof

$$M_z(t) \quad z \text{ p.d.f.} \quad \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

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

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-x^2/2 + tx} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-(x^2 - 2xt)/2} dx$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{\frac{-(x-t)^2 + t^2}{2}} dx$$

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

p.d.f for normal var w/
mean t
var 1

$$M_z(t) = e^{t^2/2}$$

Suppose X_1, X_2, \dots are random vars
 identical, independent w/
 mean 0 & Var 1

$$Y_n = \frac{\sum_{i=1}^n X_i}{\sqrt{n}}$$

let $M_n(t) = \text{MGF of } Y_n.$

if $M(t) = M_{X_i}(t)$

$$M_n(t) = M(t/\sqrt{n})^n$$

$$\begin{aligned} M_{\lambda X}(t) &= E[e^{t\lambda X}] \\ &= M_X(\lambda t) \end{aligned}$$

$\lim_{n \rightarrow \infty} M_n(t)$ (will show $= e^{t^2/2}$)
 then will be done.

$$\lim_{n \rightarrow \infty} M(t/\sqrt{n})^n$$

$$L(t) = \log M(t)$$

$$L(0) = \log M(0) = \log 1 = 0$$

$$L'(t) = \frac{M'(t)}{M(t)}$$

$$L'(0) = \frac{M'(0)}{M(0)} = \frac{0 e^{\mu}}{1} = 0$$

$$L''(t) = \frac{M(t)M''(t) - M'(t)^2}{M(t)^2}$$

$$L''(0) = \frac{M(0) \cdot 1 - 0}{1^2} = 1$$

$$\begin{aligned} \log \left(\lim_{n \rightarrow \infty} M\left(\frac{t}{\sqrt{n}}\right)^n \right) &= \lim_{n \rightarrow \infty} n \log M\left(\frac{t}{\sqrt{n}}\right) \\ &= \lim_{n \rightarrow \infty} \frac{L\left(t n^{-1/2}\right)}{n^{-1}} \end{aligned} \quad \begin{array}{l} \text{"0"} \\ 0 \end{array}$$

L'Hopital

$$= \lim_{n \rightarrow \infty} \frac{L'(t n^{-1/2}) t (-\frac{1}{2}) n^{-3/2}}{-n^{-2}}$$

$$= \lim_{n \rightarrow \infty} \frac{L'(t n^{-1/2}) t}{2 n^{-1/2}} \quad \begin{array}{l} \text{"0"} \\ 0 \end{array}$$

L'Hop

$$= \lim_{n \rightarrow \infty} \frac{L''(t n^{-1/2}) t (-\frac{1}{2}) n^{-3/2} t}{2 (-\frac{1}{2}) n^{-3/2}}$$

$$= \lim_{n \rightarrow \infty} \frac{L''(t n^{-1/2}) t^2}{2} = L''(0) \frac{t^2}{2} = \frac{t^2}{2}$$

$$\log \lim_{n \rightarrow \infty} M\left(\frac{t}{\sqrt{n}}\right)^n = \frac{t^2}{2}$$

$$\lim_{n \rightarrow \infty} M_n(t) = e^{t^2/2}$$

$$\lim_{n \rightarrow \infty} \frac{\sum X_i}{\sqrt{n}} = Z$$

"Convergence" $\Rightarrow \lim_{n \rightarrow \infty} P\left(\frac{X_1 + \dots + X_n}{\sqrt{n}} \leq a\right) = P(Z \leq a)$

Consequently, if X_1, X_2, \dots are general iid, indep. ...
 mean μ var σ^2

$$P\left(\frac{X_1 + \dots + X_n - n\mu}{\sigma\sqrt{n}} \leq a\right)$$

$$P\left(\frac{\frac{(X_1 - \mu)}{\sigma} + \frac{(X_2 - \mu)}{\sigma} + \dots + \frac{(X_n - \mu)}{\sigma}}{\sqrt{n}} \leq a\right)$$

$$= P(Z \leq a) \quad \square$$