

Moment Generating Function
of $X: S \rightarrow \mathbb{R}$.

$$\begin{aligned}\psi_X(t) &= E(e^{tX}) \\ &= E\left(\sum_{j=0}^{\infty} (tX)^j / j!\right) \\ &= \sum_{j=0}^{\infty} t^j E(X^j) / j!\end{aligned}$$

$$= \begin{cases} \sum_r f_X(r) e^{tr}, & \text{discrete} \\ \int_{-\infty}^{\infty} f_X(r) e^{tr} dr, & \text{cont. case} \end{cases}$$

Then If $X, Y: S \rightarrow \mathbb{R}$
 and $\varphi_X(t) = \varphi_Y(t)$ for all t
 in an open interval, then $f_X = f_Y$.

Then If $X_1, \dots, X_n: S \rightarrow \mathbb{R}$ are

independent, $\varphi_{X_1 + \dots + X_n}(t) = \prod_i \varphi_{X_i}(t)$

Why? $E(e^{t(X_1 + \dots + X_n)})$ \parallel

$$E(e^{tX_1} \dots e^{tX_n}) = E(e^{tX_1}) \dots E(e^{tX_n})$$

X_1, \dots, X_n
 independent

Example: $X: S \rightarrow \mathbb{R}$ Poisson

$$f_X(j) = e^{-\lambda} \lambda^j / j!$$

for $j=0, 1, \dots$

$$\psi_X(t) = E(e^{tx}) = \sum_{j=0}^{\infty} f_X(j) e^{tj}$$

$$= \sum_{j=0}^{\infty} e^{-\lambda} \frac{\lambda^j}{j!} e^{tj}$$

$$= e^{-\lambda} \sum_{j=0}^{\infty} (\lambda e^t)^j / j!$$

$$= e^{-\lambda} e^{\lambda e^t} = e^{\lambda(e^t - 1)}$$

Cor: If $X_1, \dots, X_n: S \rightarrow \mathbb{R}$ independent Poisson

rates $\lambda_1, \dots, \lambda_n$

Then $X = X_1 + \dots + X_n = \text{Poisson, rate } \lambda = \lambda_1 + \dots + \lambda_n$

Why: $\psi_X(t) = \prod \psi_{X_i}(t)$

$$= \prod_i e^{\lambda_i(e^t - 1)} = e^{(\sum \lambda_i)(e^t - 1)}$$

Example Stifling Outbreaks

Suppose l people in one location
have covid-19

$\lambda_0 = \lambda(x_i)$ = rate at which i^{th} person
creates new cases over 2 weeks

x_i = # cases created by i^{th} person

$X = x_1 + \dots + x_l$ = # cases resulting
from group

Given $0 < \epsilon < 1$ how small

must λ_0 be for $\underline{P}(X=0) \geq \epsilon$?

X Poisson, $\lambda_X = l \lambda_0$

$$e^{-\lambda(x)} \frac{\lambda(x)^0}{0!}$$

$$e^{-l \lambda_0} \geq \log \epsilon, \quad \lambda_0 \leq \frac{-\log \epsilon}{l}$$

Need:

$$l=10, \epsilon=1/2, \quad \lambda_0 \leq \frac{\log 2}{10} = 0.069$$

Covariance $X, Y: S \rightarrow \mathbb{R}$

$$\begin{aligned}\text{Cov}(X, Y) &= E((X - E(X))(Y - E(Y))) \\ &= E(XY) - E(X)E(Y)\end{aligned}$$

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$$

Significance $\text{Cov}(X, Y)$ large if
 $X - E(X)$ and $Y - E(Y)$ have same
sign when large.

Correlation $\rho(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$

Fact: $-1 \leq \rho(X, Y) \leq 1.$

de Wert

Ex: $Y = aX + b$, a, b constant
 $a \neq 0$

$$\rho(X, Y) = \begin{cases} 1 & \text{if } a > 0 \\ -1 & \text{if } a < 0 \end{cases}$$

Proof $\text{cov}(X, Y) = E((X - E(X))(Y - E(Y)))$

$$Y = aX + b \quad E(Y) = aE(X) + b$$

$$Y - E(Y) = a(X - E(X))$$

$$\text{cov}(X, Y) = E(a(X - E(X))^2) = a \text{Var}(X)$$

$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

$$\sigma_X = \sqrt{\text{Var}(X)} \geq 0$$

$$\sigma_Y = \sqrt{\text{Var}(Y)} = \sqrt{E((Y - E(Y))^2)}$$

$$= \sqrt{a^2 E((X - E(X))^2)}$$

$$= \sqrt{a^2 \text{Var}(X)}$$

$$= |a| \cdot \sigma_X$$

$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{a \text{Var}(X)}{|a| \sigma_X^2} = \frac{a}{|a|}$$
$$= \begin{cases} 1 & a > 0 \\ -1 & a < 0 \end{cases}$$

Warning: $\rho(X, Y)$ measures linear relationships between X and Y , not all possible dependencies.

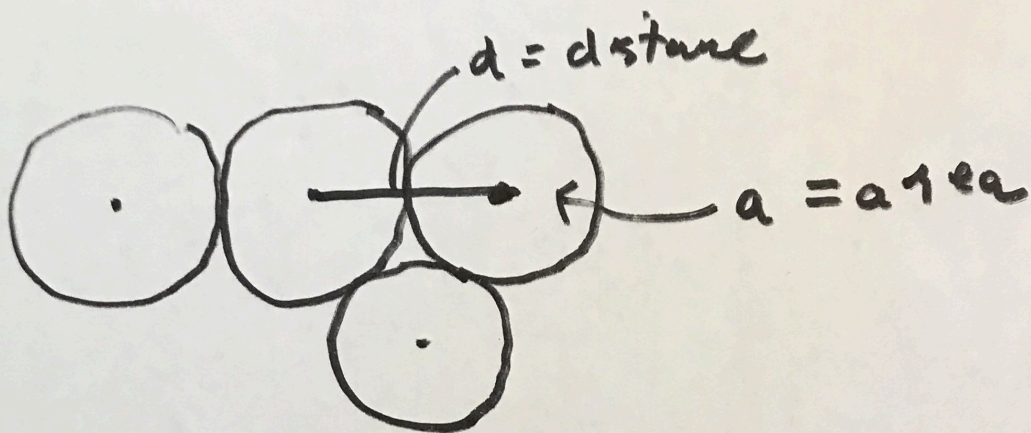
Ex: X takes values $\{-1, 0, 1\}$ with probability $1/3$ each
 $Y = X^2$ not independent!

$$f_{X,Y} \neq f_X \cdot f_Y$$

$$\begin{aligned} \text{Cov}(X, Y) &= E(XY) - E(X)E(Y) \\ &= E(X^3) - E(X)E(Y) \\ &= E(X) - E(X)E(Y) = 0 \end{aligned}$$

$$\rho(X, Y) = 0$$

Ex: $S =$ set of US cities
 $X: S \rightarrow \mathbb{R}$ prop. of pop. with covid-19
 $Z: S \rightarrow \mathbb{R}$ (pop. density, avg. square feet per person.)



Ask: Does prop. of pop. with covid-19 vary linearly with ~~the~~ average distance or average area per person?

Distance: $\rho(x, \sqrt{z})$

Area: $\rho(x, z)$

Log normal Distributions + Log Central Limit Theorem

Y_1, \dots, Y_n independent, same density function

$$Y = Y_1 \cdot Y_2 \cdots Y_n$$

$$\log Y = \log Y_1 + \dots + \log Y_n$$

Central Limit Theorem: As $n \rightarrow \infty$

$\log Y$ has density function tending to a normal distribution X with

$$E(X) = n E(\log Y_i) \text{ any } i$$

$$\sigma_x^2 = \text{Var}(X) = n \text{Var}(\log Y_i)$$

Def. Y tends to log normal random variable $Z = e^X$, $\log f_Z = f_X = \text{normal}$

Fact.

$$E(Y) = e^{E(X) + \sigma_X^2/2}$$

$$\text{Var}(Y) = e^{2E(X) + \sigma_X^2} (e^{\sigma_X^2} - 1)$$

Scenario: At some starting time,

Say we have an amount A

in a bank. Flip a fair ~~coin~~

coin n times. If get a

head on a flip, multiply what

you have by $r > 1$,

if get a tail mult. by $r^{-1} < 1$.

After n days what is the
 expect amount in the account?

$$S = \left\{ \omega = (\omega_1, \dots, \omega_n) ; \omega_i \in \{-1, 1\} \right\}$$

$$Y_i : S \rightarrow \mathbb{R}, \quad Y_i(\omega) = r^{\omega_i}$$

$Y = Y_1 \cdots Y_n$, find amount YA

$$E(YA) = A E(Y) \approx$$

$$\approx A e^{E(X) + \sigma_X^2/2}$$

$$X = \log Y_1 + \cdots + \log Y_n$$

$$E(X) = n E(\log Y_i) = n \left(\frac{1}{2} \log r + \frac{1}{2} \log r^{-1} \right)$$

$$\sigma_X^2 = \text{Var}(X) = n \text{Var}(\log Y_i)$$

$$= n \left(E((\log Y_i)^2) \right)$$

$$= n \cdot \left(\frac{1}{2} (\log r)^2 + \frac{1}{2} (-\log r)^2 \right) = n (\log r)^2$$

$$E(Y) = e^{E(X) + \sigma_X^2/2} = e^{n(\log r)^2/2} > 1$$

Note: If $1 < r < e$, $0 < \log r < 1$,

$$(\log r)^2 < \log r$$

$$e^{n(\log r)^2/2} < e^{n \log r/2} = r^{n/2}$$

Conclusion: If we use coin flips
with a fair coin to go up or down
by a factor of r or r^{-1} , we'll
end up increasing the account
after n days!

A coin flip $\Delta = (\Delta_{11}, \dots, \Delta_n)$

would have same # of heads + tails.

Outcome in this case $r^{\# \text{ heads} - (\# \text{ tails})} = 1$

But if Δ has a more heads than tails
there's a twin Δ' coming from
switching heads + tails.

Δ gives factor r^a

Δ' gives factor r^{-a}

$$r^a + r^{-a} > 2 \text{ if } r > 1, a > 0$$