

The classical one.

### Probability

① The random variable  $X$  has an exponential distribution with parameter 1, so that

$$F_X(x) = P(X \leq x) = 1 - e^{-x}.$$

$$\text{Let } Y = e^{-X}.$$

C. 17. Which option is equivalent to the event

$$Y \leq y.$$

A.  $X \geq -\log y$  B.  $X \leq \log y$  C.  $X \geq -\lambda^{-1} \log y$  D.  $X \geq \log(y/\lambda)$

E.  $X \geq 1 - e^{-y}$

18. Which option is the probability density function of  $Y$  for  $0 \leq y \leq 1$ ?

A.  $\lambda^{-1} y^{\lambda^{-1}}$  B.  $\lambda y^{-\lambda-1}$  C.  $\lambda e^{-\lambda y}$  D.  $\lambda^{-1} y^{-\lambda^{-1}}$  E.  $\lambda y^{\lambda-1}$

some transformation.

① get the cdf

② get the pdf by derivatives.

$$\text{For } 0 \leq y \leq 1, P(Y \leq y) = P(X \geq -\lambda^{-1} \log y) = 1 - F_X(-\lambda^{-1} \log y) = y^{\lambda^{-1}}.$$

$$\text{Thus for } 0 \leq y \leq 1, f_Y(y) = F'_X(y) = \lambda^{-1} y^{\lambda^{-1}-1}.$$

② 这个整体就是一个常数，无需做过多运算。

### Summary

Exponential distribution memoryless.

$$F_X(x) = \begin{cases} 1 - e^{-x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

$$f_X(x) = \frac{d}{dx} F_X(x) = \begin{cases} \lambda e^{-x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

$$E(X) = \int_0^\infty x \lambda e^{-x} dx = \frac{1}{\lambda}$$

$$Var(X) = \frac{2}{\lambda^2} - \frac{1}{\lambda^2} = \frac{1}{\lambda^2}$$

$$E(X^2) = \int_0^\infty x^2 \lambda e^{-x} dx = \frac{2}{\lambda^2}$$

$$\frac{P\{X > s+t, X > t\}}{P\{X > t\}} = P\{X > s\}$$

probability.

Q1 Let  $X$  be an exponential random variable with parameter PDF

$$f_X(x) = \begin{cases} \lambda e^{-\lambda x}, & x \geq 0 \\ 0, & x < 0 \end{cases}$$

(a) If  $t \in \mathbb{R}$ , find  $P(X > t)$

(b) Prove that.

$$P(X > s+t | X > s) = P(X > t) \text{ for all } s \geq 0 \text{ and } t \geq 0.$$

(c) Find the mode and median of  $X$ .

$$F_{X>t} = \int_{-\infty}^t f_X(x) dx \leq x \geq 0 \quad (a) = 1 + \boxed{t \in \mathbb{R}} \text{ classify } t.$$

$$F_{X>t} = \int_0^{\infty} f_X(x) dx \leftarrow t < 0. \quad P(X > t) = 1$$

$$= \int_0^{\infty} \lambda e^{-\lambda x} dx$$

$$= [-e^{-\lambda x}]_0^{\infty}$$

$$= -e^{-\lambda \infty} + 1$$

$$= 1 - e^{-\lambda \infty}$$

$$t \geq 0. \quad P(X \leq t) = 1 - e^{-\lambda t}$$

$$\boxed{P(X > t)} = 1 - P(X \leq t) = \boxed{e^{-\lambda t}}$$

$$(b) P(X > s+t | X > s) = \frac{P(X > s+t)}{P(X > s)} = \frac{e^{-\lambda(s+t)}}{e^{-\lambda s}} = e^{-\lambda t} = P(X > t) \quad \text{qed.}$$

(c). The mode  $y$  if  $f_X(y) \geq f_X(x)$  for all  $x \in \mathbb{R}$ .

since  $f_X(0) = 1$  and  $f_X(x)$  is decreasing on  $(0, \infty)$

so the mode is 0.

$$\text{Median: } \boxed{P(X > m) = 0.5} \quad e^{-\lambda m} = 0.5 \quad m = -\ln 0.5 = \ln 2.$$

这个题最重要内就是要给  $t$  的值分类。

Summary

$$F_{X>t} = \int_{-\infty}^t f_X(x) dx.$$

↓ sometimes need to specify it.

$$\boxed{P(X > m) = 0.5} \Rightarrow \text{MEDIAN}$$

Pabability.

⑨ A random variable  $X$  having a Beta dist.

with parameter  $\alpha > 0$  and  $\beta > 0$  has probability density function.

$$f(x) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1}, & 0 < x < 1 \\ 0 & \text{otherwise.} \end{cases}$$

where for  $t > 0$

$$\Gamma(t) = \int_0^\infty y^{t-1} e^{-y} dy \text{ and } \Gamma(t+1) = t\Gamma(t).$$

(i) Prove that the mean and variance of  $X$  are  $\frac{\alpha}{\alpha+\beta}$  and  $\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$ , respectively.

(Hint). Note that  $\int_0^1 f(x) dx = 1$  for any  $\alpha, \beta > 0$ .

Rearranging this gives you an expression for

$$\int_0^1 x^{\alpha-1} (1-x)^{\beta-1} dx.$$

(ii), If  $\alpha > 1$  and  $\beta > 1$ , find the mode of  $X$ .

$$\Rightarrow (\text{Hint}): \int_0^1 \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} = 1$$

bring out the constant.

$$\int_0^1 x^{\alpha-1} (1-x)^{\beta-1} = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$$

$$\begin{aligned} E(X) &= \int_0^1 x f(x) dx = \int_0^1 x \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} dx. \\ &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \int_0^1 x^{\alpha+1-1} (1-x)^{\beta-1} dx. \end{aligned}$$

$$= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \frac{\Gamma(\alpha+1)\Gamma(\beta)}{\Gamma(\alpha+\beta+1)}$$

$$= \frac{\alpha}{\alpha+\beta}.$$

Since  $\Gamma(t+1) = t\Gamma(t)$   $\Gamma(t) = (t-1)!$

Summary

$$\begin{aligned}
 E(x^{\alpha}) &= \int_0^1 x^{\alpha} f(x) dx \\
 &= \int_0^1 x^{\alpha} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot x^{\alpha-1} (1-x)^{\beta-1} dx \\
 &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \int_0^1 x^{\alpha+2\beta-1} (1-x)^{\beta-1} dx \\
 &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \frac{\Gamma(\alpha+2)\Gamma(\beta)}{\Gamma(\alpha+\beta+2)} \quad \Gamma(t) = (t-1)! \\
 &= \frac{\alpha(\alpha+1)}{(\alpha+\beta+1)\Gamma(\alpha+\beta)}
 \end{aligned}$$

$\text{Var}(x) = E(x^2) - [E(x)]^2 = \frac{\alpha(\alpha+1)}{(\alpha+\beta+1)\Gamma(\alpha+\beta)} - \left(\frac{\alpha}{\alpha+\beta}\right)^2 = \frac{\alpha\beta}{(\alpha+\beta+1)\Gamma(\alpha+\beta)}$   
(iii): The mode must satisfy  $\frac{\alpha\beta}{\alpha+x} = 0$ .  
 $\frac{df}{dx} = 0$ . (product rule.)  
 $\left[ (\alpha-1)x^{\alpha-2} (1-x)^{\beta-1} + x^{\alpha-1} (1-x)^{\beta-2} \right] \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} = 0$ .

don't forget the "-"  
 it's actually a composition function.

$$\begin{aligned}
 (\alpha-1) x^{\alpha-2} (1-x)^{\beta-1} - x^{\alpha-1} (1-x)^{\beta-2} &= 0 \\
 (\alpha-1) (1-x)^{\beta-1} - x (1-x)^{\beta-2} &= 0 \\
 (\alpha-1) (1-x) - x (\beta-1) &= 0
 \end{aligned}$$

$$x = \frac{\alpha-1}{\alpha+\beta-2} = (\alpha-1)/\alpha+\beta-2$$

Summary

## Probability generating function (Bramp<sup>6</sup>)

滾筒或剛剛倒的時候好像

指勝了 - 一个新方法。

$$P_X(s) = E[s^X] = \sum_{k=0}^{\infty} s^k (1-p)^{k-1} p \\ = sp \sum_{k=1}^{\infty} [s(1-p)]^{k-1} \\ = sp \frac{\sum_{k=1}^{\infty} [s(1-p)]^{k-1}}{1-s(1-p)} \\ = \frac{sp}{1-s(1-p)}$$

我直接把底面補齊了

口/80/8---

$$P_X(s) = E[s^X] = \sum_{k=1}^{\infty} s^k \cdot (1-p)^{k-1} p \\ = p \sum_{k=1}^{\infty} s^k (1-p)^{k-1} \\ = \frac{p}{1-p} \sum_{k=1}^{\infty} s^k (1-p)^k \\ = \frac{p}{1-p} \sum_{k=1}^{\infty} [s(1-p)]^k$$

$$\sum_{k=1}^{\infty} g^k = \frac{s}{1-s} \quad (-1 < s < 1 \rightarrow \text{converge})$$

$$\sum_{k=1}^{\infty} g^k = g + g^2 + \dots + g^n = \frac{g}{1-g}$$

$$\lim_{n \rightarrow \infty} \sum_{k=1}^n g^k = \frac{s}{1-s}$$

$$= \frac{p}{1-p} \cdot \frac{s(1-p)}{1-s(1-p)}$$

$$= \frac{sp}{1-s(1-p)} \quad (-1 < s(1-p) < 1)$$

let  $y \sim NB(n, p)$ . (Negative Binomial)

trials until  $n^{\text{th}}$  success.

for every trial in NB, it is

$y = x_1 + \dots + x_n$ .  $x_i \sim \text{Geo}(p)$ .

a Geometric dist.

~~$$\sum_{k=n}^{\infty} \binom{k-1}{n-1} (1-p)^{k-n} p^n \quad (-1 < s < 1)$$~~

~~$$P_{Y \leq s} = E[s^Y] = \sum_{k=n}^{\infty} s^k \binom{k-1}{n-1} (1-p)^{k-n} p^n \quad (-1 < s < 1)$$~~

$$= (sp)^n \sum_{k=n}^{\infty} \binom{k-1}{n-1} (1-p)^{k-n}$$

## Summary

### Negative Binomial distribution

$$P_X(k) = \binom{k-1}{r-1} (1-p)^{k-r} p^r. \quad k=r, r+1, \dots$$

$$E(X) = \frac{r}{p}$$

$$\text{Var}(X) = \frac{rp(1-p)}{p^2}$$

This method only  
shows  $0 < s < 1$ , but  
can never show  
 $-1 < s < 0$ .

$$P_Y(s) = E[s^Y] = \sum_{k=0}^{\infty} s^k \binom{k}{n-1} (1-p)^{k-n} p^n \quad (-1 < s < 1)$$

①  $\sum_{k=0}^{\infty} s^k \binom{k-1}{n-1} [s(1-p)]^{k-n} (sp)^n \rightarrow \text{sum is not 1}$   
 $= \frac{(sp)^n}{[1-s(1-p)]^n} \sum_{k=0}^{\infty} \binom{k-1}{n-1} [s(1-p)]^{k-n} [1-s(1-p)]^n.$   
 $= \frac{(sp)^n}{[1-s(1-p)]^n} \quad 0 < s(1-p) < 1$   
 $0 < s < \frac{1}{1-p}$

②  $Y = x_1 + \dots + x_n \quad x_i \sim \text{Geo}(p)$

$$P_Z = \frac{ps}{1-s+ps}$$

$$P_Y(s) = \prod_{i=1}^n P_{x_i}(s) = \frac{(ps)^n}{(1-s+ps)^n} \quad (-1 < s < 1)$$

$\downarrow$  生成函数中一个有用的运用：

我发现两个推导过程  
都只用  $s$  去乘  $(1-p)$

$(1-p)$  这个变量，相当于  
依照原函数的样子  
把  $s$  当一个新变量算在  
一起，最后再找一个  
和新变量相加为 1  
的变量凑成新的pmf.

### Summary

Lemma:

$$Z = x_1 + x_2 + \dots + x_n.$$

$$P_Z(s) = \prod_{i=1}^n P_{x_i}(s)$$

## Probability.

continuous.

How to integrate.

(93) Let  $X$  and  $Y$  be continuous random variables with joint distribution function.

$$F(x, y) = Kxye^{-(x+y)}, \quad 0 < x < 1, \quad 0 < y < 1$$

(a) Evaluate the constant  $K$ , and find the joint pdf of  $X$  and  $Y$ .

(b) Find the marginal and conditional pdfs of  $X$ .

(c) Evaluate  $P(X < 0.5, Y < 0.5)$ ,  $P(X < 0.5)$ ,  $P(Y < 0.5)$ .

$$\because F(-\infty, \infty) = 1 \quad F(\infty, \infty) = F(1, 1) = 1$$

$$\therefore 2K = 1 \quad K = \frac{1}{2}.$$

get the pdf. alternative.

$$f_{xy} = \frac{\partial^2}{\partial x \partial y} F(x, y) = \frac{\partial^2}{\partial x \partial y} \left\{ \frac{x^2}{2} + \frac{xy^2}{2} \right\}$$

$$= \begin{cases} x+y & 0 < x, y < 1 \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{pdf of } X. \Rightarrow \text{integrate pdf.} \quad \therefore f_x(x) = \int_{-\infty}^{\infty} f_{xy} dy = \int_0^1 x+y dy$$

$$= \begin{cases} x+\frac{1}{2} & \text{if } 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$f_y(y) = \int_{-\infty}^{\infty} f_{xy} dx = \int_0^1 x+y dx = \begin{cases} y+\frac{1}{2} & 0 < y < 1 \\ 0 & \text{otherwise.} \end{cases}$$

$$f_{x|y}(x|y) = \frac{f_{xy}}{f_y(y)} = \begin{cases} \frac{x+y}{\frac{1}{2}+y} & \text{if } 0 < x < 1 \\ 0 & \text{otherwise.} \end{cases}$$

$$\therefore P(X < 0.5, Y < 0.5) = F(\frac{1}{2}, \frac{1}{2}) = \frac{1}{8}$$

$$P(X < 0.5) = \int_0^{\frac{1}{2}} f_x(x) dx = \int_0^{\frac{1}{2}} \frac{1}{2} + x dx = \frac{3}{8}$$

$$P(Y < 0.5) = \int_0^{\frac{1}{2}} f_y(y) dy = \frac{3}{8}.$$

Summary

Probability.

(P4) The joint probability density function of  $X$  and  $Y$  is given by.

$$f(x, y) = \frac{6}{7} (x^2 + \frac{xy}{2}), 0 < x < 1, 0 < y < 2$$

$$\text{Find } P(Y > \frac{1}{2} | X < \frac{1}{2})$$

$$P(Y > \frac{1}{2} | X < \frac{1}{2}) = \int_{x=0}^{\frac{1}{2}} \int_{y=\frac{1}{2}}^{+\infty} \frac{6}{7} (x^2 + \frac{xy}{2}) dy dx$$

$$= \frac{69}{448}$$

$$P(X < \frac{1}{2}) = \int_{x=0}^{\frac{1}{2}} \int_{y=0}^2 \frac{6}{7} (x^2 + \frac{xy}{2}) dy dx$$

$$= \frac{5}{28}$$

$$P(Y > \frac{1}{2} | X < \frac{1}{2}) = \frac{P(Y > \frac{1}{2}, X < \frac{1}{2})}{P(X < \frac{1}{2})} = \frac{69}{80}$$

Probability

$$(85) F(y) = \begin{cases} 0 & y \leq 1 \\ (y-1)^4 & 1 \leq y \leq 2 \\ 1 & y > 2 \end{cases}$$

$$\text{Find } P(\frac{3}{4} < Y < \frac{7}{4})$$

it's not in the range!!!!!!

$$\text{incorrect: } F(\frac{7}{4}) - P(\frac{3}{4}) = \frac{5}{16}$$

$$\text{correct: } F(\frac{7}{4}) - 0 = (\frac{7}{4} - 1)^4 - 0 = \frac{81}{256}$$

it's easy to just use the function directly.

We MUST CHECK WHETHER IT IS IN THIS RANGE

这个题太容易粗心了。  
保险的保费就要求  
出了  $F(y)$ . 然后  
找值过程一个个验  
验

Summary

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## Probability

$$(1) f_{x,y}(x,y) = \begin{cases} \frac{1}{4}x^2y^2(4y+x) & 0 \leq x \leq 2, 0 \leq y \leq 1 \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{Find } P(X \geq 1 \mid Y = \frac{1}{2})$$

$$f_{x|Y}(x \mid Y) = \frac{f_{x,y}(x,Y)}{f_Y(Y)}$$

$$f_{x|Y}(x \mid \frac{1}{2}) = \frac{f_{x,y}(x, \frac{1}{2})}{f_Y(\frac{1}{2})}$$

$$f_{x,y}(x, \frac{1}{2}) = \frac{1}{8}x^2 + \frac{1}{16}x^3 \quad | \text{直接代入.}$$

$$f_Y(y) = \int_0^2 f_{x,y}(x,y) dx = \frac{1}{12}$$

$$f_{x|Y}(x \mid \frac{1}{2}) = \frac{f_{x,y}(x, \frac{1}{2})}{f_Y(\frac{1}{2})} = \frac{\frac{1}{8}x^2 + \frac{1}{16}x^3}{\frac{1}{12}} = \begin{cases} \frac{3}{28}(2x^2 + x^3) & 0 \leq x \leq 2 \\ 0 & \text{otherwise.} \end{cases}$$

$$P(X \geq 1 \mid Y = \frac{1}{2}) = \int_1^\infty f_{x|Y}(x \mid \frac{1}{2}) dx = \int_1^2 \frac{3}{28}(2x^2 + x^3) dx = \frac{101}{112}$$

(2) Three card: One is red on both sides / One is black on both sides / One is red, one is black. Card is shuffled and one is chosen at random. If the upper side is red.  
What is the probability that the other side is red?

key step. Let the event

card be event

现在还是想简点写吧.

不要用 PR RB BB 了.

Summary  
用脚标代替吧 E1, E2, E3.

Let F = 'Upper is red' E1 = RR E2 = BB E3 = RB card.

We want  $P(E \mid F)$   $P(E_1) = P(E_2) = P(E_3) = 1/3$

$$P(F \mid E_1) = 1 \quad P(F \mid E_2) = 0 \quad P(F \mid E_3) = \frac{1}{2}$$

$$P(E_1 \mid F) = \frac{P(F \mid E_1) P(E_1)}{P(F \mid E_1) P(E_1) + P(F \mid E_2) P(E_2) + P(F \mid E_3) P(E_3)} = \frac{2}{3}$$

概率论易错知识 → A probability measure is a real-valued set

Three axioms. function  $P$  defined on the events of a sample space  $\Omega$  which

A1:  $P(E) \geq 0$  for any event  $E$  [ satisfies the following three axioms .

$$\text{Az: } p(s_2) = 1$$

$\text{Ans:}$  If  $E_1, E_2, \dots, E_n$  are s.t.  $E_i \cap E_j = \emptyset$  for  $i \neq j$ , then

$$P(E_1 \cup E_2 \cup \dots) = P(E_1) + P(E_2) + \dots$$

Common trick: use to prove  $P(E \cup F) = P(E) + P(F) - P(E \cap F)$

$$E_{\text{EF}} = E_{\text{U}}(F \cap E^c) \quad F = (F \cap E) \cup (F \cap E^c)$$

我可以先写一下之后的甘的

不过是试图消灭  
减去( $\vdash \wedge E^C$ )。

- Permutation of length  $r$  of  $n$  objects

$${}^n P_r = n(n-1)(n-2)\cdots(n-r+1) = \frac{n!}{(n-r)!} \quad {}^n P_n = n!$$

- Combination of  $r$  objects from a collection of  $n$  objects.

$${}^n C_r = {}^n P_r / r! = \frac{n!}{(n-r)!r!} \quad ({}^n C_r) = ({}^n C_{n-r})$$

像这种如此奇怪的书  
用一个相方办法把他消除

$$\binom{n}{m} = \binom{n-1}{m-1} + \binom{n-1}{m} \quad \binom{n}{m} = \frac{n}{m} \binom{n-1}{m-1} \quad \binom{n}{n} + \binom{n}{1} + \dots + \binom{n}{m} = 2^n$$

$$P(\Sigma_1 | F) = 1 \quad P(\emptyset | F) = 0$$

$$P(CA^c|F) = 1 - P(CA|F) \quad \text{proof by common trick.}$$

$$P(C \cap A | B \cap F) = \frac{P(C \cap A \cap B \cap F)}{P(B \cap F)}$$

$$P(A \cap B \cap C) = P(C|A \cap B) P(B|A) P(A). \quad \text{注意着順序先后}$$

$$P(AB) \quad P(AB)$$

partition can be  $\leq$

finite or infinite.

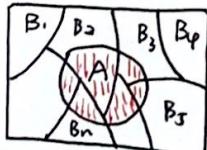
Theorem of Total Probability → 是一通事件，说明制3：假以  
对凡而言。

Definition: A partition of a sample space  $S_2$  is a collection of events  $E_1, E_2, \dots$  in  $S_2$  s.t.

(ii)  $E_i \cap E_j = \emptyset$  for all  $i \neq j$  (disjoint sets)

$$\text{or, } \bigcup_{i=1}^n E_i = E_1 \cup E_2 \cup \dots = S$$

$$P(F) = \sum_i P(F|E_i) P(E_i)$$



Baye's Theorem.

Simple form:  $P(E|F) = \frac{P(F|E)P(E)}{P(F)}$   $P(E) > 0$  and  $P(F) > 0$

General form: if  $E_1, E_2, \dots$  form a partition of  $\Omega$

$$P(E_i|F) = \frac{P(F|E_i)P(E_i)}{\sum_j P(F|E_j)P(E_j)}$$

Mutually independent:  $P(\bigcap_j E_j) = \prod_j P(E_j)$

Probability mass function of a random variable  $X$  (pmf)

$$P_X(x) = P(X=x) = P\{\omega : X(\omega) = x\}.$$

$E_i = \{\omega : X(\omega) = x_i\}$ . Then  $\{E_i\}$  is a partition of  $\Omega$ . So

$$\sum_i P_X(x_i) = \sum_i P(E_i) = P(\bigcup_i E_i) = P(\Omega) = 1$$

Cumulative distribution function (c.c.d.f.)

$$F_X(x) = F(x) = P(X \leq x) = \sum_{y \leq x} P_X(y) \quad x \in \mathbb{R}$$

(i)  $F_X$  is non-decreasing, i.e. if  $x \leq y$ ,  $F_X(x) \leq F_X(y)$

(ii)  $P_X(x_i) = F_X(x_i) - F_X(x_{i-1})$ ;

(iii) if  $a < b$ ,  $P(a < X \leq b) = P(X \leq b) - P(X \leq a)$

本身是不會被減掉的。  
$$= F_X(b) - F_X(a)$$

(iv)  $P(a < X < b) = P(X < b) - P(X \leq a) = \sum_{y \in (a, b)} P_X(y)$

(v)  $P(a \leq X < b) = P(X=a) + \sum_{y \in (a, b)} P_X(y)$

(vi)  $F_X(\infty) = P(X \leq \infty) = 1 \quad F_X(-\infty) = P(X \leq -\infty) = 0$

**Mode:** the mode of a discrete random variable is the outcome with the highest probability.

Summary

Expectation =  $E(x) = \sum x \cdot p(x)$  (also called the mean.)

Lemma:  $g(x)$  is a function of  $x$ .  $E[g(x)] = \sum g(x) p(x)$

Properties: ① if  $g(x) = b$  a constant.  $E[g(x)] = b$

② For all  $a, b \in \mathbb{R}$ .  $E[ag(x) + bh(x)] = aE[g(x)] + bE[h(x)]$

③  $E[ax+b] = aE(x) + b$

The variance gives a measure of how spread out the mass function of  $X$  is.

Variance:  $\text{Var}(x) = E[(x - E(x))^2] = \sum [x - E(x)]^2 p(x)$ .

Standard deviation of  $X$  is  $\sqrt{\text{Var}(x)}$

Properties: ①  $\text{Var}(x) = E(x^2) - [E(x)]^2$

②  $\text{Var}(x) \geq 0$   $\text{Var}(x) = 0 \Leftrightarrow P(x = E(x)) = 1$

③ For all  $a, b \in \mathbb{R}$   $\text{Var}(ax+b) = a^2 \text{Var}(x)$

further properties

①  $E(x+y) = E(x) + E(y)$

②  $E(x_1 + x_2 + \dots + x_n) = E(x_1) + E(x_2) + \dots + E(x_n)$

③ if  $x, y$  are independent then  $\text{Var}(x+y) = \text{Var}(x) + \text{Var}(y)$ .

④ if  $x_1, x_2, \dots, x_n$  are mutually independent, then

$\text{Var}(x_1 + x_2 + \dots + x_n) = \text{Var}(x_1) + \text{Var}(x_2) + \dots + \text{Var}(x_n)$ .

Summary

## STANDARD DISCRETE DISTRIBUTION

Bernoulli distribution: A Bernoulli trial is a simple random experiment with two outcomes: success or failure.

$$X = \begin{cases} 1 & \text{success } p \\ 0 & \text{failure } 1-p \end{cases}$$

Proof of  $E(X)$ :

$$\begin{aligned} E(X) &= \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k} \\ &= \sum_{k=0}^n k \cdot \frac{n!}{k!(n-k)!} p^k (1-p)^{n-k} \\ &= \sum_{k=0}^n \frac{n!}{(k-1)!(n-k)!} p^k (1-p)^{n-k} \\ &= \sum_{k=0}^n \frac{(n-1)!}{(k-1)!(n-k-1)!} p^{k-1} (1-p)^{n-k} \end{aligned}$$

$$= \sum_{k=0}^n \frac{(n-1)!}{(k-1)!(n-k-1)!} p^{k-1} (1-p)^{n-k}$$

$$= np \sum_{k=0}^{\infty} \dots$$

$$= np.$$

$$E(X) = p \cdot 1 + 0 \cdot (1-p) = p$$

$$\text{Var}(X) = p(1-p)$$

Binomial distribution:  $n$  independent Bernoulli trials

$X \sim \text{Bin}(n, p)$

$$P(X=k) = P(X=k) = \binom{n}{k} p^k (1-p)^{n-k} \quad k=0, 1, \dots, n$$

$$E(X) = \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k} = np$$

$$\text{Var}(X) = np(1-p)$$

$$F_X(x) = P(X \leq x) = \sum_{k=0}^{\lfloor x \rfloor} \binom{n}{k} p^k (1-p)^{n-k} \quad (\text{use table})$$

If  $X \sim \text{Bin}(n, p)$ ,  $Y = n - X \sim \text{Bin}(n, 1-p)$ .

$$\begin{aligned} P(Y=k) &= P(X=n-k) = \binom{n}{n-k} p^{n-k} (1-p)^{n-(n-k)} \\ &= \binom{n}{k} (1-p)^k p^{n-k}. \end{aligned}$$

$$E[X(X-1)]$$

$$= \sum_{k=0}^n k(k-1) \binom{n}{k} p^k (1-p)^{n-k}$$

$$= \sum_{k=0}^n k(k-1) \frac{n!}{(n-k)! k!} p^k (1-p)^{n-k}$$

$$= \sum_{k=0}^n p^n \frac{(n-2)!}{(k-2)!(n-2-k)!} p^{k-2} (1-p)^{n-k}$$

$$= n(n-1)p^2.$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2$$

$$= [E(X(X-1))] + E(X) - [E(X)]^2$$

$$= n(n-1)p^2 + np - n^2 p^2$$

$$= np(1-p).$$

这种做的好处就是自动把它和阶乘联系在一起。

但是这种有  $\binom{n}{k}$  的，用  $E(X(X-1))$  可以直接消掉阶乘。



$$n \uparrow \cdot pV = E[X]$$

Poisson approximation

large  $n$ , small  $p$ .

$$\text{Bin}(n, p) \approx \text{Pois}(np)$$

Negative Binomial distribution: the number of trials until  $r$  success.

$$P(X=k) = \binom{k-1}{r-1} p^r (1-p)^{k-r}, \quad k=r, r+1, r+2, \dots$$

(must have  $k$ <sup>th</sup> trial successful, and  $r-1$  successes in first  $k-1$  trials)

$$X \sim \text{NB}(r, p) \rightarrow X_i \sim \text{Geom}(p)$$

$$E(X) = E[X_1 + X_2 + \dots + X_r] = \frac{r}{p}$$

$$\text{Var}(X) = \text{Var}[X_1 + \dots + X_r] = \frac{r(1-p)}{p^2}$$

Discrete Uniform distribution

$$P(X=x) = \frac{1}{n} \quad x=1, 2, \dots, n$$

$$E(X) = \sum_{x=1}^n x \cdot p = (1+2+3+\dots+n) \cdot \frac{1}{n} = \frac{n(n+1)}{2} \cdot \frac{1}{n} = \frac{n+1}{2}$$

$$E(X^2) = \sum_{x=1}^n x^2 \cdot p = (1^2+2^2+3^2+\dots+n^2) \cdot \frac{1}{n} = \frac{n(n+1)(2n+1)}{6} \cdot \frac{1}{n} = \frac{(n+1)(2n+1)}{6}$$

$$\text{Var}(X) = E(X^2) - [E(X)]^2$$

$$= \frac{(n+1)(2n+1)}{6} - \left(\frac{n+1}{2}\right)^2 = \frac{n^2-1}{12}$$

Hypergeometric distribution.  $n \leq A+B$ .

$$P(X=k) = \frac{\binom{A}{k} \binom{B}{n-k}}{\binom{A+B}{n}} \quad k=0, 1, \dots, n$$

$$E(X) = \frac{An}{A+B} \quad \text{Var}(X) = \frac{ABn(A+B-n)}{(A+B)^2(A+B-1)}$$

Summary

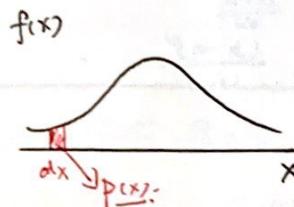
## CONTINUOUS DISTRIBUTIONS

Cumulative distribution function (cdf)

$$F_X(x) = P(X \leq x) = \begin{cases} 0 & x < 0 \\ x & 0 \leq x < 1 \\ 1 & x \geq 1 \end{cases}$$

Probability density function (pdf) of continuous r.v.

$$f_X(x) = \int_{-\infty}^x f_X(y) dy \quad \text{for all } x \in \mathbb{R}$$



①  $f_X(x) \geq 0$

②  $\int_{-\infty}^{\infty} f_X(y) dy = F_X(\infty) = 1$

③  $f_X(x) = \frac{dF_X(x)}{dx}$

④  $f_X(x) = \frac{dF_X(x)}{dx} \approx \frac{F_X(x+h) - F_X(x)}{h}$

$$\Rightarrow h f_X(x) \approx F_X(x+h) - F_X(x) = P(X \leq x+h) - P(X \leq x) \\ = P(x < X \leq x+h)$$

Expectation for continuous r.v / Variance

$$E(X) = \int_{-\infty}^{\infty} x f_X(x) dx \quad E[g(x)] = \int_{-\infty}^{\infty} g(x) f_X(x) dx$$

$$\text{var}(X) = E(X^2) - [E(X)]^2$$

Check by

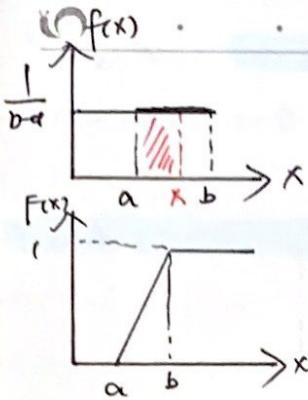
$$\frac{d}{dx} f_X(x) = 0$$

Median : is defined as  $x_0$  s.t.  $F_X(x_0) = 0.5$

Mode : of  $X$  is point at which  $f_X$  is maximised i.e.

mode is  $x_0$  if and only if  $f_X(x_0) \geq f_X(x)$  for all  $x$

Summary



## STANDARD CONTINUOUS DISTRIBUTIONS

Uniform distribution  $x \sim U(a, b)$

$$f_x(x) = \begin{cases} \frac{1}{b-a} & a \leq x \leq b \\ 0 & \text{otherwise} \end{cases}$$

$$F_x(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{b-a} & a \leq x < b \\ 1 & x \geq b \end{cases}$$

$$E(x) = \frac{a+b}{2}$$

$$\text{var}(x) = \frac{(b-a)^2}{12}$$

$$\begin{aligned} E(x^2) &= \int_0^\infty x^2 \cdot \frac{1}{b-a} e^{-\lambda x} dx \quad \text{by parts.} \\ &= [-x^2 e^{-\lambda x}]_0^\infty - \frac{1}{\lambda} \int_0^\infty 2x e^{-\lambda x} dx \\ &= -\frac{1}{\lambda} [0-1] \\ &= \frac{1}{\lambda}. \end{aligned}$$

$$\begin{aligned} E(x^3) &= \int_0^\infty x^3 \cdot \frac{1}{b-a} e^{-\lambda x} dx \\ &= [\frac{x^3}{\lambda} \cdot e^{-\lambda x}]_0^\infty + \int_0^\infty \frac{3x^2}{\lambda} e^{-\lambda x} dx \\ &= \frac{3}{\lambda} \int_0^\infty x^2 \cdot \frac{1}{b-a} e^{-\lambda x} dx \\ &= 2 \left[ E(x^2) \cdot \frac{1}{\lambda} e^{-\lambda x} \right]_0^\infty + \int_0^\infty \frac{1}{\lambda} e^{-\lambda x} dx \\ &= \frac{3}{\lambda} \int_0^\infty e^{-\lambda x} dx \\ &= \frac{3}{\lambda} \cdot [-\frac{1}{\lambda} e^{-\lambda x}]_0^\infty \\ &= \frac{3}{\lambda} \cdot [0 + \frac{1}{\lambda}] \\ &= \frac{3}{\lambda^2} \end{aligned}$$

Exponential distribution

$$f_x(x) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

密度是递减的.

$$F_x(x) = \begin{cases} 1 - e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$

$$E(x) = \int_0^\infty x \lambda e^{-\lambda x} dx = \frac{1}{\lambda} \quad E(x^2) = \int_0^\infty x^2 \lambda e^{-\lambda x} dx = \frac{2}{\lambda^2} \quad (\text{true}).$$

$$\text{var}(x) = E(x^2) - [E(x)]^2 = \frac{2}{\lambda^2} - (\frac{1}{\lambda})^2 = \frac{1}{\lambda^2}$$

Normal distribution  $x \sim N(\mu, \sigma^2)$

$$f_x(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}, x \in \mathbb{R}$$

$$E(x) = \int_{-\infty}^{\infty} x f_x(x) dx = \mu \quad \text{用换元法把 } x-\mu \text{ 代进去.}$$

$$E(x^2) = \int_{-\infty}^{\infty} x^2 f_x(x) dx = \sigma^2 + \mu^2 \quad y = x-\mu.$$

$$\text{var}(x) = \sigma^2 + \mu^2 - \mu^2 = \sigma^2$$

我记得当时找了一个很好的例子

当 Normal Dis. 的波动很小时

讲的我也没听太懂. 只知道  $f(x) = K e^{-\frac{1}{2}c x^2}$

Summary  
 $c$  为负, 才收敛  $c = -\frac{1}{2\sigma^2}$   $K = \frac{1}{\sqrt{2\pi}\sigma}$

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} \cdot e^{-\frac{x^2}{2\sigma^2}} \quad x = x - \bar{x} = x - \mu.$$

不知道现在是否记得了.

Proof:  $X \sim N(\mu, \sigma^2)$

$$E(X) = \int_{-\infty}^{\infty} x \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

Let  $y = x - \mu$ ,  $dy = dx$

$$E(X) = \int_{-\infty}^{\infty} (y + \mu) \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy$$

$$= \int_{-\infty}^{\infty} y \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy + \underbrace{\int_{-\infty}^{\infty} \mu \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy}_{\text{constant.}} = 0 + \mu = \mu \quad \text{pof.} = 1.$$

$$\text{Let } y = \frac{x-\mu}{\sigma}, \frac{dy}{dx} = \frac{1}{\sigma}$$

轉換成 SN.  $\leftarrow$

$$E(X^2) = \int_{-\infty}^{\infty} (y + \mu)^2 \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy$$

$$= \int_{-\infty}^{\infty} (\sigma^2 y^2 + 2\mu y + \mu^2) \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy$$

$$= \int_{-\infty}^{\infty} \sigma^2 y^2 \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy + \int 2\mu y \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy + \int \mu^2 \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{y^2}{2\sigma^2}} dy$$

$$= \sigma^2 + 2\mu\mu + \mu^2 = \sigma^2 + \mu^2$$

$$\text{var}(X) = E(X^2) - [E(X)]^2 = \sigma^2 + \mu^2 - \mu^2 = \sigma^2$$

### Standard normal distribution

$$f_{X(x)} = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, x \in \mathbb{R}, \mu = 0, \sigma = 1$$

$$F_{X(x)} = \Phi(x) = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}} dy. \quad (\text{table})$$

$$\cdot P(a \leq Z \leq b) = \Phi(b) - \Phi(a)$$

$$\cdot P(Z > a) = P(Z \geq a) = 1 - \Phi(a)$$

Further transformation  $X \sim N(\mu, \sigma^2) \Rightarrow Y = aX + b$

Proof: Note  $X = \sigma Z + \mu$

$Z$  is standard normal

$$Y = a(\sigma Z + \mu) = (a\sigma)Z + (a\mu + b)$$

$$Y \sim N(a\mu + b, a^2\sigma^2)$$

↓  
若要如何用  $Z$  將  $X$  表示出來， $Z$  是一個隨量

Summary 量

More generally.  $X_1, \dots, X_n$  be indep. r.v's

$$Y = a_1 X_1 + a_2 X_2 + \dots + a_n X_n \quad Y \sim N(\mu, \sigma^2)$$

$$\mu = a_1 \mu_1 + \dots + a_n \mu_n$$

$$\sigma^2 = a_1^2 \sigma_1^2 + \dots + a_n^2 \sigma_n^2$$

$$\begin{aligned} E(x) &= \int_0^\infty \frac{1}{\Gamma(\alpha)} \beta^{\alpha-1} x^{\alpha-1} e^{-\beta x} \alpha dx \\ &= \frac{1}{\Gamma(\alpha)} \int_0^\infty \beta^\alpha x^{\alpha-1} e^{-\beta x} \alpha dx \\ &= \frac{\Gamma(\alpha+1)}{\Gamma(\alpha)\beta} \int_0^\infty \beta^{\alpha+1} x^{\alpha+1-1} e^{-\beta x} \alpha dx \\ &= \frac{\Gamma(\alpha+1)}{\Gamma(\alpha)\beta} \times \text{1st part} = \frac{1}{\beta} \alpha! \\ &= \frac{\alpha}{\beta} \\ E(x^2) &= \frac{1}{\Gamma(\alpha)} \int_0^\infty \beta^\alpha x^{\alpha+1} e^{-\beta x} \alpha dx \\ &= \frac{\Gamma(\alpha+2)}{\Gamma(\alpha)\beta^2} \int_0^\infty \beta^{\alpha+2} x^{\alpha+2-1} e^{-\beta x} \alpha dx \\ &= \frac{\alpha(\alpha+1)}{\beta^2} \end{aligned}$$

$$\text{Var}(x) = E(x^2) - [E(x)]^2$$

$$= \frac{\alpha}{\beta^2}$$

$$\begin{aligned} \int_0^1 f_{\alpha, \beta}(x) dx &= 1 \\ \int_0^1 x^{\alpha-1} (1-x)^{\beta-1} dx &= \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)} \\ E(x) &= \int_0^1 \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot x^{\alpha-1} (1-x)^{\beta-1} dx \\ &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \frac{\Gamma(\alpha+1)\Gamma(\beta)}{\Gamma(\alpha+\beta+1)} \\ &= \frac{(\alpha+\beta-1)! \alpha!}{(\alpha+\beta)! (\alpha-1)!} \\ &= \frac{\alpha}{\alpha+\beta} \\ E(x^2) &= \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \cdot \frac{\Gamma(\alpha+2)\Gamma(\beta)}{\Gamma(\alpha+\beta+2)} \\ &= \frac{(\alpha+\beta-1) \cdot (\alpha+1)!}{(\alpha+1)! (\alpha+\beta-1)!} \\ &= \frac{\alpha(\alpha+1)}{(\alpha+\beta+1)\alpha(\alpha+1)} \end{aligned}$$

$$\text{Summary } \text{Var}(x) = E(x^2) - [E(x)]^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

Gamma Distribution,  $G(\alpha, \beta)$  or  $\Gamma(\alpha, \beta)$ ,  $\alpha, \beta > 0$

$$f_{\alpha, \beta}(x) = \begin{cases} \frac{\beta^\alpha x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)} & x > 0 \\ 0 & x \leq 0. \end{cases}$$

$$\Gamma(\alpha) = \int_0^\infty y^{\alpha-1} e^{-y} dy.$$

$$\Gamma(\alpha) = (\alpha-1)\Gamma(\alpha-1) \quad \Gamma(1) = 1!$$

$$E(x) = \frac{\alpha}{\beta} \quad \text{Var}(x) = \frac{\alpha}{\beta^2}$$

if  $\alpha, \dots, x_n$  are indep. Exponential distribution each with mean  $\beta^{-1}$ , then  $\sum_{i=1}^n x_i \sim G(n, \beta)$

Beta distribution,  $\alpha, \beta > 0$ .

$$f_{\alpha, \beta}(x) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

Special case. If  $\alpha=\beta=1$  then  $f_{\alpha, \beta}(x)=1$  i.e.  $X \sim U(0, 1)$

$$E(x) = \frac{\alpha}{\alpha+\beta} \quad \text{Var}(x) = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

## DISCRETE BIVARIATE DISTRIBUTIONS

$X, Y$ : two discrete random variables. taking values  $\{x_i\}$  and  $\{y_j\}$  respectively. Their joint pmf.  $P_{X,Y}(x,y)$ .

$$P_{X,Y}(x,y) = P\{X=x \cap Y=y\} \\ = P(X=x, Y=y)$$

cdf.

$$F_{X,Y}(x,y) = P\{X \leq x \cap Y \leq y\} \\ = P(X \leq x, Y \leq y)$$

Properties

$$\textcircled{1} \quad 0 \leq P_{X,Y}(x,y) \leq 1$$

$$\textcircled{2} \quad \sum_i \sum_j P_{X,Y}(x_i, y_j) = 1.$$

$$\textcircled{3} \quad P_X(x_i) = P(X=x_i) = \sum_j P_{X,Y}(x_i, y_j) \quad \left. \begin{array}{l} \text{marginal pmf.} \\ P_Y(y_j) = P(Y=y_j) = \sum_i P_{X,Y}(x_i, y_j) \end{array} \right.$$

$$\textcircled{4} \quad \text{If } g(x,y) \text{ is a function of } (X, Y) \text{ then}$$

$$E[g(x,y)] = \sum_i \sum_j g(x_i, y_j) P_{X,Y}(x_i, y_j)$$

$$\text{eq. } E[X] = \sum_i \sum_j x_i P_{X,Y}(x_i, y_j).$$

### Covariance of $X, Y$ .

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

$$\text{cor}(X, Y) = E[XY] - E[X]E[Y]$$

### The correlation coefficient

$$\rho(X, Y) = \frac{\text{cov}(X, Y)}{\sqrt{\text{var}(X)\text{var}(Y)}} \quad -1 \leq \rho(X, Y) \leq 1$$

$$\rho(X, Y) = 0 \iff \text{cov}(X, Y) = 0.$$

Summary

如果单凭  $\text{cov}(x, y) = 0$ , 无法判断  $x, y$  是否 independent.

### Independent.

Proof:

$$\begin{aligned} E[XY] &= \sum_i \sum_j x_i y_i P_{X,Y}(x_i, y_i) \\ &= \sum_i \sum_j x_i y_i P_X(x_i) P_Y(y_i) \\ &= \left( \sum_i x_i P_X(x_i) \right) \left( \sum_j y_j P_Y(y_j) \right) \\ &= E[X] E[Y] \end{aligned}$$

$$\therefore \text{cov}(x, y) = E[XY] - E[X]E[Y]$$

= 0

Proof:

$$\begin{aligned} E(X) &= \sum_x \sum_y x P_{X,Y}(x,y) \\ &= \sum_y P_{Y|y} \cdot \sum_x x P_{X|y}(x|y) \\ &= \sum_y P_{Y|y} \sum_x x \cdot P_{X|y}(x|y) \\ &= \sum_y P_{Y|y} E[X|Y=y]. \end{aligned}$$

Proof:  $P_Z(n) = \sum_{k=0}^n P_{X,Y}(k, n-k)$

by the theorem of total

probability.

$$\begin{aligned} P_Z(n) &= P(Z=n) = \sum_{k=0}^n P(Z=n|x=k) \cdot P(x=k) \\ &= \sum_{k=0}^n P(Z=n \text{ and } X=k) \\ &= \sum_{k=0}^n P(X=k, Y=n-k) \\ &= \sum_{k=0}^n P_{X,Y}(k, n-k) \end{aligned}$$

### Conditional distribution.

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

$$P_{X|Y}(x|y) = P(X=x | Y=y) = \frac{P(X=x, Y=y)}{P(Y=y)} = \frac{P_{X,Y}(x,y)}{P_Y(y)}$$

### Conditional Expectation.

$$E[X|Y=y] = \sum_x x \cdot P_{X|Y}(x|y)$$

Theorem  $E(X) = \sum_y P_{Y|y} \cdot E[X|Y=y]$

因为我求它的時候會先求  $P_{X|Y}(x|y)$ .

Summary

$$Z = X + Y, \quad n=0, 1, \dots$$

$$P_Z(n) = \sum_{k=0}^n P_{X,Y}(k, n-k)$$

Prove. Assum.  $X, Y$   
discrete.

Special case: if  $X$  and  $Y$  are independent  $Z = X + Y$

$$P_Z(n) = \sum_{k=0}^n P_X(k) P_Y(n-k)$$

$$E[X+Y] = \sum_i \sum_j (x_i + y_j) P_{X,Y}(x_i, y_j)$$

$$= \sum_i \sum_j x_i P_{X,Y}(x_i, y_j) + \sum_i \sum_j y_j P_{X,Y}(x_i, y_j) \quad E[X+Y] = E[X] + E[Y]$$

$$= E[X] + E[Y]$$

⊕  $X, Y$  independent

$$E[XY] = \sum_i \sum_j x_i y_j P_{X,Y}(x_i, y_j) \quad E[XY] = E[X]E[Y]$$

$$= \sum_i \sum_j x_i y_j P_X(x_i) P_Y(y_j) \quad \text{var}(X+Y) = \text{var}(X) + \text{var}(Y)$$

$$= \sum_i x_i P_X(x_i) \sum_j y_j P_Y(y_j) \quad \text{var}(aX+bY) = \text{Var}(aX) + \text{Var}(bY) = a^2 \text{Var}(X) + b^2 \text{Var}(Y)$$

$$= E[X] \cdot E[Y].$$

↓ generalize

$$E[(X+Y)^2] = E(X^2 + 2XY + Y^2)$$

$$= E(X^2) + 2E(X)E(Y) + E(Y^2)$$

$$\text{var}(X+Y) = E[(X+Y)^2] - E^2(X+Y) \quad \text{if } x_1, x_2, \dots, x_n \text{ are random variables}$$

$$= E(X^2) + 2E(X)E(Y) + E(Y^2) - (E[X] + E[Y])^2$$

$$= [E(X^2) - E^2(X)] + [E(Y^2) - E^2(Y)]$$

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

$$\text{if } x_1, x_2, \dots, x_n \text{ are random variables}$$

$$E\left[\sum_{i=1}^n x_i\right] = \sum_{i=1}^n E[x_i]$$

if  $x_1, x_2, \dots, x_n$  are independent then

$$E\left[\prod_{i=1}^n x_i\right] = \prod_{i=1}^n E[x_i] \quad \text{var}\left[\sum_{i=1}^n x_i\right] = \sum_{i=1}^n \text{var}[x_i]$$

In particular, if  $x_1, x_2, \dots, x_n$  are indept. and identically distributed with  $E[X] = \mu$  and  $\text{var}(X) = \sigma^2$ , then.

$$E\left[\sum_{i=1}^n x_i\right] = n\mu \quad \text{and} \quad \text{var}\left(\sum_{i=1}^n x_i\right) = n\sigma^2$$

Summary

## Probability Generating Functions.

Pgf:

$$P_x(s) = E[s^X]$$

$$= \sum_{k=0}^{\infty} P_x(k) s^k.$$

Note:  $P_x(s)$  is defined for all  $s \in [-1, 1]$

Proof:

$$\begin{aligned} P_x^{(n)}(s) &= \frac{d^n}{dx^n} \left( \sum_{k=0}^{\infty} P_x(k) s^k \right) \\ &= \sum_{k=n}^{\infty} P_x(k) k(k-1)\dots(k-n+1)s^{k-n} \end{aligned}$$

$$\therefore P_x^{(n)}(1) = \sum_{k=n}^{\infty} P_x(k) k(k-1)\dots(k-n+1) = E[X(X-1)\dots(X-n+1)]$$

Let  $P_x^{(n)}(s)$  denote the  $n$ th derivative of  $P_x(s)$

$$P_x^{(n)}(1) = E[X(X-1)\dots(X-n+1)] \quad (n=1, 2, \dots)$$

Special Case

Proof:

$$\begin{aligned} \text{Var}(x) &= E[X^2] - [E(X)]^2 \\ &= E[X(X-1)] + E(X) - [E(X)]^2 \\ &= P_x''(1) + P_x'(1) - [P_x'(1)]^2 \end{aligned}$$

$$\textcircled{1} \quad E(X) = P_x'(1)$$

$$\textcircled{2} \quad \text{Var}(x) = P_x''(1) + P_x'(1) - [P_x'(1)]^2 \quad \begin{matrix} \text{第}-n\text{項. } N \\ \text{第 } n\text{項. } N \end{matrix}$$

$$\begin{aligned} P_x^{(n)}(s) &= \sum_{k=n}^{\infty} P_x(k) k(k-1)\dots(k-n+1) s^{k-n} \\ \Rightarrow P_x^{(n)}(1) &= P_x(n) n! \end{aligned}$$

Proof:

$$\begin{aligned} P_{Z,Y}(s) &= E[s^Z s^Y] = E[s^{X+Y}] \\ &= E[s^X s^Y] \\ &= E[s^X] E[s^Y] \\ &= P_x(s) \cdot P_y(s) \end{aligned}$$

$$Z = X+Y \quad P_{Z,Y}(s) = P_x(s) P_y(s)$$

$$Z = X_1 + X_2 + \dots + X_n \quad P_Z(s) = \prod_{i=1}^n P_{X_i}(s)$$

Summary

In other words, the CDF of  $\frac{S_n - n\mu}{\sigma\sqrt{n}}$  tends to that of a standard normal random variables as  $n \rightarrow \infty$ . This implies  $S_n \approx N(n\mu, n\sigma^2)$

**Central Limit Theorem.** Let  $x_1, x_2, \dots, x_n$  be independent and identically distributed (i.i.d.) random variables, each with mean  $\mu$  and variance  $\sigma^2$ . Let  $S_n = x_1 + x_2 + \dots + x_n$ .

Then for all  $x \in \mathbb{R}$

$$P\left[\frac{S_n - n\mu}{\sigma\sqrt{n}} \leq x\right] \rightarrow P[Z \leq x] \text{ as } n \rightarrow \infty$$

where  $Z \sim N(0, 1)$

**The Sample mean  $\bar{x}$**

$$\bar{x} = \frac{S_n}{n} = \frac{x_1 + x_2 + \dots + x_n}{n}$$

$$E[\bar{x}] = E\left[\frac{S_n}{n}\right] = \frac{1}{n} E[x_1 + x_2 + \dots + x_n] = \mu$$

$$\text{Var}[\bar{x}] = \text{var}\left[\frac{S_n}{n}\right] = \frac{1}{n^2} \text{Var}(S_n) = \frac{\sigma^2}{n}$$

So,  $S_n \approx N(n\mu, n\sigma^2)$

$$\bar{x} \approx NC(\mu, \sigma^2/n)$$

**Normal Approximation to Binomial Distribution**

$$X = x_1 + x_2 + \dots + x_n \quad E[x_i] = p \quad \text{var}(x_i) = p(1-p)$$

Restrictions:  $n \geq 20, np \geq 5, n(1-p) \geq 5$

Then  $X \approx NC(np, np(1-p))$

**Continuity correction:**

$$P(X=x) \approx P(x-0.5 < Y < x+0.5)$$

where  $Y \sim N(np, np(1-p))$

Summary

$$\lim_{n \rightarrow \infty} F_n(x) = \lim_{n \rightarrow \infty} \left\{ \frac{\sum_{i=1}^n x_i - n\mu}{\sigma\sqrt{n}} \leq x \right\} = \frac{1}{\sigma\sqrt{n}} \int_{-\infty}^x e^{-\frac{(x-\mu)^2}{2}} dx$$