

ASIL SHAAR (PROBABILITY THEORY(STAT3321))

CHAPTER 3

Ch 3 Some special Distributions

3.1 Binomial and Related Distribution

Def A Binomial experiment satisfies

- ① It has n identical trials
- ② Each trial has two outcomes:
success (S) & Failure (F)
- ③ $p(S) = p$
 $p(F) = 1 - p$ } do not change in all trial
- ④ The trials are independent

Def A Binomial random variable X is defined as:

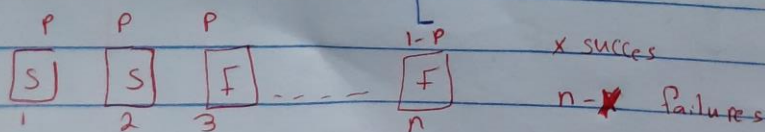
X = number of successes in a binomial experiment

Notation $X \sim b(n, p)$

In words X has a binomial dist. with n trials and prob. of success equal to p

Theorem:

$$X \sim b(n, p) \rightarrow f(x) = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x}, & x=0, 1, 2, \dots, n \\ 0 & \text{else} \end{cases}$$



Idea of proof

Theorem

$$f(x) = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x}, & x=0, 1, \dots, n \\ 0 & \text{else} \end{cases}$$

is a pdf

Proof

$$0 < p < 1$$

□

$$p^x > 0 \\ (1-p)^{n-x} > 0$$

$$\binom{n}{x} > 0 \Rightarrow \binom{n}{x} p^x (1-p)^{n-x} > 0, x=0, 1, \dots, n$$

$$\Rightarrow f(x) > 0 \quad \forall x \in \mathbb{R}$$

$$\square 2) \sum_{x \in \mathbb{R}} f(x) = \sum_{x=0}^n \binom{n}{x} p^x (1-p)^{n-x}$$

$$(a+b)^m = \sum_{k=0}^m \binom{m}{k} a^k b^{m-k}$$

Binomial
Formula

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

Question

$$X \sim b(n, p)$$

Find μ

$$\mu = E(X) = \sum_{x \in \mathbb{R}} x \cdot f(x) = \sum_{x=0}^n x \binom{n}{x} p^x (1-p)^{n-x}$$

$$= \dots$$

\Rightarrow

Question $X \sim b(n, p)$

Find the m.g.f

$$E(e^{tx}) = \sum_{x \in \mathcal{R}} e^{tx} f(x) = \sum_{x=0}^n e^{tx} \binom{n}{x} p^x (1-p)^{n-x}$$

$$= \sum_{x=0}^n \binom{n}{x} (pe^t)^x (1-p)^{n-x} = (1-p + pe^t)^n$$

$$X \sim b(n, p) \rightarrow M(t) = (1-p + pe^t)^n, t \in \mathcal{R}$$

Question $X \sim b(n, p)$

① Find μ

② Find σ

$$\textcircled{1} M(t) = (1-p + pe^t)^n$$

$$\dot{M}(t) = n(1-p + pe^t)^{n-1} (pe^t)$$

$$= \dot{M}(0) = n(1-p + p)^{n-1} (p)$$

$$= np$$

$$E(x) = \mu = np$$

$$\textcircled{2} \ddot{M}(t) = n pe^t (1-p + pe^t)^{n-1}$$

$$\ddot{M}(t) = (npe^t) [(n-1)(1-p + pe^t)^{n-2} (pe^t)] + (1-p + pe^t)^{n-1} (npe^t)$$

$$\ddot{M}(0) = (np)(n-1)(1-p + p)^{n-2} (p) + (1-p + p)^{n-1} (np)$$

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

$$= (np)[(n-1)p + 1]$$

→

$$\sigma^2 = \text{Var}(x)$$

$$= E(x^2) - (E(x))^2$$

$$M''(0) - (M'(0))^2$$

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

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

$$\cancel{n^2p^2} - np^2 + np - \cancel{n^2p^2} = np - np^2 = n(p - p^2)$$

$$\boxed{np(1-p)}$$

$$\boxed{\text{Var}(x) = \sigma^2 = np(1-p)}$$

$$\boxed{\sigma = \sqrt{np(1-p)}}$$

Multinomial Distribution

$$f(x_1, x_2, \dots, x_{k-1})$$

$$= \begin{cases} \frac{n!}{x_1! x_2! \dots x_k!} P_1^{x_1} P_2^{x_2} \dots P_k^{x_k} & \sum_{i=1}^{k-1} x_i = 0, 1, 2, \dots, n \\ 0 & \text{else} \end{cases}$$

We have x_1, \dots, x_{k-1} random variables

$$x_k = n - (x_1 + \dots + x_{k-1})$$

it's better to write

$$x_k = n - (x_1 + x_2 + \dots + x_{k-1})$$

$$P_k = 1 - \sum_{i=1}^{k-1} P_i$$

P_i : prob. of Type i success.

$$\begin{aligned} M(t_1, t_2, \dots, t_{k-1}) &= (P_1 e^{t_1} + P_2 e^{t_2} + \dots + P_{k-1} e^{t_{k-1}} + 1 - P_1 - P_2 - \dots - P_{k-1})^n \\ &= \left(\sum_{i=1}^{k-1} P_i e^{t_i} + P_k \right)^n \quad (t_1, t_2, \dots, t_{k-1}) \in \mathbb{R}^{k-1} \end{aligned}$$

Consider

Trinomial Distribution:

$$f(x, y) = \frac{n!}{x! y! (n-x-y)!} P_1^x P_2^y (1 - P_1 - P_2)^{n-x-y}, \quad x+y = 0, 1, 2, \dots, n$$

0

else

We have 2 random variables X and Y

P_1 : prob of succes of Type I

P_2 : Prob of succes of Type II

you can write:

$$Z = n - x - y$$

$$P_3 = 1 - P_1 - P_2$$

$$M(t_1, t_2) = (P_1 e^{t_1} + P_2 e^{t_2} + 1 - P_1 - P_2)^n, (t_1, t_2) \in \mathbb{R}^2$$

find the marginal and conditional densities, expected value, Variance

check!

3.2 The poisson Distribution

occurrence / event occurrence / event



time or distance between 2 occurrences.

Def

$X \sim \text{Poisson}(\mu)$

In words, X has a poisson distribution with parameter

$$\mu, \text{ if } P(X) = \begin{cases} \frac{\mu^x e^{-\mu}}{x!}, & x = 0, 1, 2, \dots \\ 0 & \text{else} \end{cases}$$

→

Theorem

$$X \sim \text{Poisson}(\mu) \rightarrow M(t) = e^{\mu(e^t - 1)}, \quad t \in \mathbb{R}$$

Q: Find $E(X)$, $E(X^2)$, σ^2 , σ

$X \sim \text{Poisson}(\mu)$

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

$E(e^{tX})$ + Taylor formula for exponential function

$$\dot{M}(t) = M(t) \cdot [\mu e^t]$$

$$\dot{M}(0) = M(0) \cdot [\mu e^0] = \mu$$

$$\ddot{M}(t) = M(t) \cdot [\mu e^t] + [\mu e^t] \dot{M}(t)$$

$$\ddot{M}(0) = M(0) \cdot [\mu e^0] + [\mu e^0] \dot{M}(0)$$

$$\mu + \mu \cdot \mu = \mu + \mu^2$$

$$E(X) = \dot{M}(0) = \mu$$

$$E(X^2) = \ddot{M}(0) = \mu + \mu^2$$

$$\text{Var}(X) = (\mu + \mu^2) - (\mu)^2 = \mu$$

$$\text{Standard deviation of } X = \sigma = \sqrt{\mu}$$

check Ex 1, Ex 2, Ex 3

3.3 The Gamma and the Chi-squared Distributions

Def:

$$\text{Let } \Gamma(\alpha) = \int_0^{\infty} y^{\alpha-1} e^{-y} dy \quad \text{Gamma function}$$

Note: $\Gamma(\alpha)$ exists and positive for all $\alpha > 0$

Note 1.

$$\Gamma(1) = \int_0^{\infty} y^{1-1} e^{-y} dy = \int_0^{\infty} e^{-y} dy = \left. \frac{e^{-y}}{-1} \right|_0^{\infty} = e^{-y} \Big|_0^{\infty}$$
$$= 1 - 0 = 1$$

$$\boxed{\Gamma(1) = 1}$$

Note:

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

$$f = y^{\alpha-1} \quad x \, dg = e^{-y} dy$$
$$df = (\alpha-1)y^{\alpha-2} dy \quad y, -e^{-y}$$

$$\Gamma(\alpha) = f \cdot g \Big|_0^{\infty} - \int_0^{\infty} g \, df$$

$$\Gamma(\alpha) = \left[(y^{\alpha-1})(-e^{-y}) \right]_0^{\infty} - \int_0^{\infty} (-e^{-y})(\alpha-1)y^{\alpha-2} dy$$

$$= [0 - 0(-1)] + \int_0^{\infty} (\alpha-1)y^{\alpha-2} e^{-y} dy$$

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

Note 3

$\alpha = 2, 3, 4, \dots$

$$\Gamma(2) = (1) \Gamma(1) = 1 = 1!$$

$$\Gamma(3) = (2) \Gamma(2) = (2)(1) = 2!$$

$$\Gamma(4) = (3) \Gamma(3) = (3)(2)(1) = 3!$$

$$\Gamma(\alpha) = (\alpha - 1)! \quad \alpha = 2, 3, 4, \dots$$

Def $0! = 1$

Def $X \sim \text{Gamma}(\alpha, \beta)$

In words, X has a gamma distribution with parameters α & β , i.f.:

$$f(x) = \begin{cases} \frac{1}{\Gamma(\alpha) \beta^\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}}, & x > 0 \\ 0 & \text{else} \end{cases}$$

for $\alpha > 0, \beta > 0$

Note: $f(x) \geq 0 \quad \forall x \in \mathbb{R}$

$$\int_{-\infty}^{\infty} f(x) dx = \int_{-\infty}^0 0 dx + \int_0^{\infty} \frac{1}{\Gamma(\alpha) \beta^\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}} dx$$

$$y = \frac{x}{\beta} \quad dy = \frac{1}{\beta} dx$$

$$x=0 \Rightarrow y=0$$

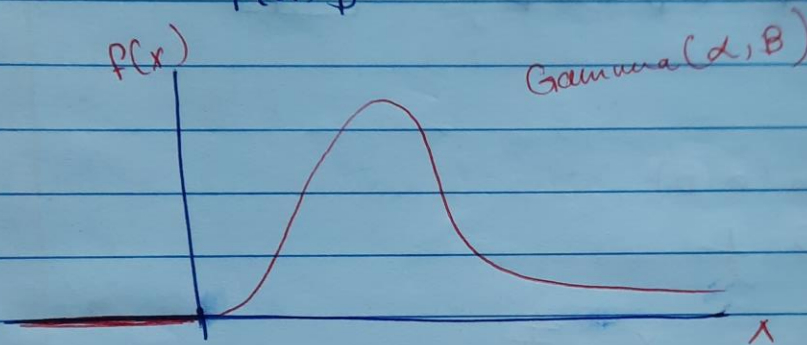
$$x \rightarrow \infty \Rightarrow y \rightarrow \infty$$

\Rightarrow

$$\int_{-\infty}^{\infty} f(x) dx = \int_0^{\infty} \frac{1}{\Gamma(\alpha) \beta^{\alpha}} (y\beta)^{\alpha-1} e^{-y} \beta dy$$

$$= \frac{1}{\Gamma(\alpha) \beta^{\alpha}} \left(\int_0^{\infty} y^{\alpha-1} e^{-y} dy \right)$$

$$= \frac{\Gamma(\alpha) \beta^{\alpha}}{\Gamma(\alpha) \beta^{\alpha}}$$



Theorem $X \sim \text{Gamma}(\alpha, \beta)$

$$M(t) = E(e^{tx}) = \int_0^{\infty} e^{tx} \frac{1}{\Gamma(\alpha) \beta^{\alpha}} x^{\alpha-1} e^{-x/\beta} dx$$

$$M(t) = \frac{1}{(1-\beta t)^{\alpha}}, \quad t < \frac{1}{\beta}$$

Note:

$$M(t) = (1-\beta t)^{-\alpha}, \quad t < \frac{1}{\beta}$$

$$\begin{aligned} \mu'(t) &= -\alpha (1-\beta t)^{-\alpha-1} (-\beta) \\ &= \alpha \beta (1-\beta t)^{-\alpha-1} \end{aligned}$$

$$\begin{aligned} \mu''(t) &= \alpha \beta (-\alpha-1) (1-\beta t)^{-\alpha-2} (-\beta) \\ &= \alpha \beta (\alpha+1) \beta (1-\beta t)^{-\alpha-2} \end{aligned}$$

→

$$E(x) = M = \dot{M}(0) = \alpha B(1-0)^{-\alpha-1} = \alpha B$$

$$E(x^2) = \dot{M}'(0) = \alpha B(\alpha+1) B(1-0)^{-\alpha-2} \\ = \alpha B(\alpha+1) B = \alpha(\alpha+1) B^2$$

$$\text{Var}(x) = \sigma^2 = E(x^2) - (E(x))^2 \\ = \alpha(\alpha+1) B^2 - (\alpha B)^2 \\ = \alpha^2 B^2 + \alpha B^2 - \alpha^2 B^2 = \boxed{\alpha B^2}$$

Special Case

$$X \sim \text{Gamma}(\alpha, \beta)$$

$$\alpha = 1 \quad \beta = \frac{1}{\lambda}$$

$$f(x) = \begin{cases} \frac{1}{\Gamma(1) \left(\frac{1}{\lambda}\right)^1} \cdot x^{1-1} e^{-\frac{x}{\lambda}} & , x > 0 \\ 0 & , \text{else} \end{cases}$$

$$f(x) = \begin{cases} \lambda e^{-\lambda x} & , x > 0 \\ 0 & , \text{else} \end{cases}$$

$$X \sim \text{Exponential}(\lambda)$$

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

$$M(t) = \frac{1}{\left(1 - \frac{t}{\lambda}\right)} \quad , t < \lambda$$

⇒

Def $X \sim \chi^2(r)$

In words, X has chi-squared distribution with degrees of freedom $df=r$ if:

$$X \sim \text{Gamma}(\alpha, \beta)$$

$$\alpha = \frac{r}{2}, \quad \beta = 2$$

Note:-

$$M(t) = \frac{1}{(1-2t)^{\frac{r}{2}}}, \quad t < \frac{1}{2}$$

$$E(X) = r, \quad \text{var}(X) = 2r$$

check Q3.36

χ^2 table

Example 6

$$X \sim \text{Gamma}(\alpha, \beta)$$

$$\text{pr}(a < X < b) = ?$$

$$Y = \frac{2X}{\beta} \sim \chi^2(r)$$

$$r = 2\alpha$$

$$X \sim \text{Gamma}(\alpha, \beta)$$

$$f(x) = \begin{cases} \frac{1}{\Gamma(\alpha)\beta^\alpha} x^{\alpha-1} e^{-\frac{x}{\beta}}, & x > 0 \\ 0, & \text{else} \end{cases}$$

$$G(y) = \text{pr}(X \leq y) = \text{pr}\left(\frac{2X}{\beta} \leq \frac{2y}{\beta}\right)$$

$$= \text{pr}\left(X \leq \frac{\beta y}{2}\right) = \int_0^{\frac{\beta y}{2}} f(x) dx, \quad y > 0$$

\Rightarrow

$$g(y) = \frac{d}{dy} \int_0^{\frac{\beta y}{2}} f(x) dx = f\left(\frac{\beta y}{2}\right) \cdot \frac{\beta}{2} - f(0) \cdot 0, y > 0$$

$$g(y) = \frac{\beta}{2} f\left(\frac{\beta}{2} y\right), y > 0$$

$$= \frac{\beta}{2} \frac{1}{\Gamma(\alpha) \beta^\alpha} \left(\frac{\beta y}{2}\right)^{\alpha-1} e^{-\frac{\beta y}{2}}, y > 0$$

$$= \left(\frac{\beta}{2}\right)^\alpha \cdot \frac{1}{\Gamma(\alpha)} \cdot \frac{1}{\beta^\alpha} y^{\alpha-1} e^{-\frac{y}{2}}, y > 0$$

$$= \frac{1}{\Gamma(\alpha) 2^\alpha} y^{\alpha-1} e^{-\frac{y}{2}}, y > 0$$

$$Y \sim \text{Gamma}(\alpha, 2)$$

$$Y \sim X^2(r), r = 2\alpha$$

$$X \sim \text{Gamma}(\alpha, \beta)$$

$$Y = \frac{2X}{\beta} \quad Y \sim X^2(r) \quad r = 2\alpha$$

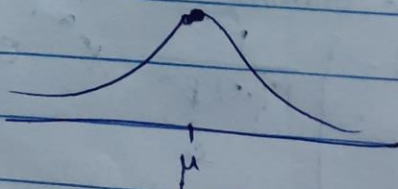
3.4 The normal distribution

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

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

$$E(X) = \mu$$

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



$$Z = \frac{X - \mu}{\sigma}$$

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

$$E(Z) = 0$$

$$\text{Var}(Z) = 1$$

Question

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

MGR, 670

why $f(x)$ is a p.d.f?

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

$$\frac{x-\mu}{\sigma} = z$$

$$= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}z^2} \sigma dz = \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz = I$$

$$I^2 = \left(\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \right)^2$$

$$= \left(\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{w^2}{2}} dw \right) \left(\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} du \right)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{2\pi} e^{-\frac{1}{2}(w^2+u^2)} dw du$$

$$r^2 = w^2 + u^2$$

$$r dr d\theta = dw du$$

$$I^2 = \int_0^{2\pi} \int_0^{\infty} \frac{1}{2\pi} e^{-\frac{1}{2}r^2} r dr d\theta = \left(\int_0^{2\pi} \frac{1}{2\pi} d\theta \right) \left(\int_0^{\infty} r e^{-\frac{r^2}{2}} dr \right)$$

$$= (1) \int_0^{\infty} \frac{1}{2} e^{-\frac{y}{2}} dy$$

$$= \frac{1}{2} \left. e^{-\frac{y}{2}} \right|_0^{\infty} = \frac{1}{2} (0 - 1) = -\frac{1}{2}$$

$$\boxed{\begin{matrix} r^2 = y \\ 2r dr = dy \end{matrix}}$$

$$= \boxed{1}$$

$$\left(\int_{-\infty}^{\infty} f(x) dx \right)^2 = 1$$

But $f(x) > 0 \quad \forall x \in \mathbb{R}$

$$\Rightarrow \int_{-\infty}^{\infty} f(x) dx = 1$$

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

Theorem

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

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

$$\Rightarrow M(t) = e^{\mu t + \frac{1}{2} \sigma^2 t^2}, \quad t \in \mathbb{R}$$

Question

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

$$M(t) = e^{\mu t + \frac{1}{2} \sigma^2 t^2}, \quad t \in \mathbb{R}$$

$$\dot{M}(t) = M(t) [\mu + \sigma^2 t]$$

$$\ddot{M}(t) = M(t) [\sigma^2] + [\mu + \sigma^2 t] \dot{M}(t)$$

$$E(x) = \dot{M}(0) = M(0) \cdot [\mu + 0]$$

$$1 \cdot [\mu] = \mu$$

$$E(x^2) = \ddot{M}(0) = M(0) [\sigma^2] + [\mu + 0] \dot{M}(0)$$

$$\sigma^2 + \mu \cdot \mu$$

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

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

Theorem 1

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

$$Z = \frac{X - \mu}{\sigma}$$

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

Proof

$$G(Z) = \Pr(Z \leq z) = \int_{-\infty}^z g(t) dt$$

$$= \Pr\left(\frac{X - \mu}{\sigma} \leq z\right)$$

$$= \Pr(X - \mu \leq \sigma z) = \Pr(X \leq \mu + \sigma z)$$

$$= \int_{-\infty}^{\mu + \sigma z} f(x) dx$$

$$g(z) = f(\mu + \sigma z) \cdot \sigma = \lim_{c \rightarrow \infty} f(c) \cdot c$$

$$= \sigma \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\mu + \sigma z - \mu)^2}{2\sigma^2}}$$

$$= \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}, \quad z \in \mathbb{R}$$

Theorem 2

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

$$W = \left(\frac{X - \mu}{\sigma}\right)^2$$

$$\Rightarrow W \sim \chi^2(1)$$

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

$$W \sim \text{Gamma}\left(\frac{1}{2}, 2\right)$$

$$W \sim \chi^2(1)$$

Note: $X \sim N(\mu, \sigma^2)$, $Z = \frac{X - \mu}{\sigma}$, $Z \sim N(0, 1)$

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

$$\Phi(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{w^2}{2}} dw$$

Page 548 Table III \rightarrow section 3.4

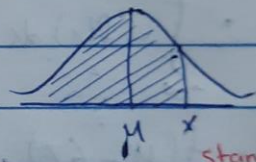
Note: $X \sim \text{Gamma}(\alpha, \beta)$, $Y = \frac{2X}{\beta}$, $Y \sim \chi^2(2\alpha)$

$$P(a \leq X \leq b) = P(c \leq Y \leq d)$$

Page 547 Table II \rightarrow section 3.3

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

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



$$F(x) = \int_{-\infty}^x f(t) dt$$

$$M(t) = e^{\mu t + \frac{1}{2} \sigma^2 t^2}$$

$$E(x) = \mu \quad \text{Var}(x) = \sigma^2$$

$\mu = 0, \sigma = 1, Z \sim N(0, 1)$

$$g(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}, \quad z \in \mathbb{R}$$

$$\Phi(z) = G(z) = \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} e^{-\frac{w^2}{2}} dw$$

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

$$Z = \frac{X - \mu}{\sigma}$$

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

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

$$W = \left(\frac{X - \mu}{\sigma}\right)^2$$

$\Rightarrow W \sim \chi^2(1)$

3.5 Bivariate Normal Distribution

Def:

X and Y are called bivariate normal random variables with parameters $\mu_x, \mu_y, \sigma_x > 0, \sigma_y > 0, \rho_{xy}$ if we have the following density:

$$f(x, y) = \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho_{xy}^2}} e^{-\frac{q}{2}}, \quad (x, y) \in \mathbb{R}^2$$
$$q = \frac{1}{1-\rho_{xy}^2} \left[\left(\frac{x-\mu_x}{\sigma_x} \right)^2 - 2\rho_{xy} \left(\frac{x-\mu_x}{\sigma_x} \right) \left(\frac{y-\mu_y}{\sigma_y} \right) + \left(\frac{y-\mu_y}{\sigma_y} \right)^2 \right]$$

assuming: $\mu_x \in \mathbb{R}, \mu_y \in \mathbb{R}, \sigma_x > 0, \sigma_y > 0$ فقد داعی نظماً
 $-1 < \rho_{xy} < 1$

Theorem:

Let X, Y be bivariate normal random variables with parameters $\mu_x, \mu_y, \sigma_x, \sigma_y, \rho_{xy}$

(1) $f(x, y)$ is a p.d.f ✓

(2) $X \sim N(\mu_x, \sigma_x^2)$ ✓

$Y \sim N(\mu_y, \sigma_y^2)$

(3) $\rho_{xy} = \frac{\text{Cov}(X, Y)}{\sigma_x \sigma_y} = \frac{E(XY) - \mu_x \mu_y}{\sigma_x \sigma_y}$ ✓

(4) $Y|X=x \sim N\left(\mu_y + \rho_{xy} \frac{\sigma_y}{\sigma_x} (x - \mu_x), \sigma_y^2 (1 - \rho_{xy}^2)\right)$ ✓

$X|Y=y \sim N\left(\mu_x + \rho_{xy} \frac{\sigma_x}{\sigma_y} (y - \mu_y), \sigma_x^2 (1 - \rho_{xy}^2)\right)$

→

$$⑤ N(t_1, t_2) = e^{-\mu_x t_1 - \mu_y t_2 + \frac{1}{2} \sigma_x^2 t_1^2 + \frac{1}{2} \sigma_y^2 t_2^2 + \rho_{xy} \sigma_x \sigma_y t_1 t_2}$$

$(t_1, t_2) \in \mathbb{R}^2$

فرضه ای نیست

Proof: Not required

Theorem:

X, Y bivariate normal random variables

X, Y independent $\iff X, Y$ uncorrelated

proof: Not required.

Ex 1 page 149

X_1 : height of husband.

X_2 : " " wife.

$$\left[\begin{array}{l} X_1, X_2 \text{ bivariate normal.} \\ \mu_1 = 5.8 \quad \sigma_1 = 0.2 \\ \mu_2 = 5.3 \quad \sigma_2 = 0.2 \quad \rho = 0.6 \end{array} \right]$$

① $\text{pr}(5.28 < X_2 < 5.92)$

$$= \text{pr}\left(\frac{5.28 - 5.3}{0.2} < \frac{X_2 - \mu_2}{\sigma_2} < \frac{5.92 - 5.3}{0.2}\right) \quad (X_2 \sim N(\mu_2, \sigma_2^2))$$

$$= \text{pr}(-0.1 < Z < 3.1) \quad \left(\frac{X_2 - \mu_2}{\sigma_2} \sim N(0, 1)\right)$$

$$= \Phi(3.1) - \Phi(-0.1)$$

$$= \Phi(3.1) - (1 - \Phi(0.1))$$

$$0.999 - (1 - 0.54) = 0.539$$

\Rightarrow

$$\textcircled{2} \text{ pr } (5.28 < X_2 < 5.92 / X_1 = 6.3)$$

$$X_2 / X_1 = X \sim N \left(\mu_2 + \rho \frac{\sigma_2}{\sigma_1} (X - \mu_1), \sigma_2^2 (1 - \rho^2) \right)$$

$$X_2 / X_1 = 6.3 \sim N \left(5.3 + 0.6 \frac{0.2}{0.2} (6.3 - 5.2), (0.2)^2 (1 - 0.6^2) \right)$$

$$X_2 / X_1 = 6.3 \sim N (5.6, (0.16)^2)$$

$$\rightarrow = \text{pr} \left(\frac{5.28 - 5.6}{0.16} < Z < \frac{5.92 - 5.6}{0.16} \right)$$

$$= \text{pr} (-2 < Z < 2)$$

$$= \Phi(2) - \Phi(-2) = \Phi(2) - (1 - \Phi(2)) = 0.954$$