

Exercises. Lecture 21 - Solutions

Ex. III.9.1 $G_X(t) = E(t^X) = (1-p)t^0 + pt^1$

When X_1, \dots, X_n iid $\stackrel{=} {=} 1-p+pt$ Bernoulli(p) then
 $Y = X_1 + \dots + X_n \sim \text{binomial}(n, p)$ so

$$G_Y(t) = G_X(t)^n = (1-p+pt)^n.$$

Ex. III.9.2 We use the definition $X \sim \text{geometric}(p)$
 when X is the number of '0's' before the first 1. so $P(X=n) = (1-p)^n p$. Then

$$G_X(t) = E(t^X) = \sum_{x=0}^{\infty} t^x (1-p)^x p$$

$$= p \sum_{x=0}^{\infty} (t(1-p))^x = \frac{p}{1-t(1-p)}$$

$$\mu_X = \frac{d G_X(t)}{dt} \Big|_{t=1} = \frac{(1-p)p}{(1-t(1-p))^2} \Big|_{t=1} = \frac{(1-p)p}{p^2} = \frac{1-p}{p}$$

$$\mu_{X^2} = \frac{d^2 G_X(t)}{dt^2} \Big|_{t=1} = \frac{2(1-p)^2 p}{(1-t(1-p))^3} \Big|_{t=1} = \frac{2(1-p)^2 p}{p^3} = \frac{2(1-p)^2}{p^2}$$

Therefore $\sigma_X^2 = \mu_{X^2} - \mu_X(\mu_X - 1)$

$$= \frac{2(1-p)^2}{p^2} - \frac{1-p}{p} \left(\frac{1-p}{p} - 1 \right) = \frac{(1-p)^2}{p^2} + \frac{1-p}{p} = \frac{1-p}{p} \left(\frac{1-p}{p} + 1 \right)$$

$$= \frac{1-p}{p^2}.$$

Ex. III.9.3 $G_N(t) = e^{\lambda(t-1)}$ and

$$G_X(t) = E(t^X) = (1-p)t^{-1} + pt'$$

$$\text{so } G_Y(t) = G_N(G_X(t)) = \exp\left\{\lambda\left(\frac{1-p}{t} + pt\right) - \lambda\right\}$$

$$\begin{aligned} \text{so } E(Y) &= \left. \frac{dG_Y(t)}{dt} \right|_{t=1} \\ &= \exp\left\{\lambda\left(\frac{1-p}{t} + pt\right) - \lambda\right\} \lambda \left(p - \frac{1-p}{t^2}\right) \Big|_{t=1} \\ &= \exp\left\{\lambda(1-p) + \lambda p - \lambda\right\} \lambda (p - 1 + p) \\ &= \lambda(2p - 1). \end{aligned}$$

Ex. III.9.4 Suppose $E(|X_1|^{i_1} |X_2|^{i_2}) < \infty \forall i_1, i_2$

s.t. $i_1 + i_2 = j$. Then $E(|X_1 + X_2|^j) =$

$$\sum_{i_1+i_2=j} \binom{j}{i_1, i_2} E(|X_1|^{i_1} |X_2|^{i_2}) < \infty$$
 and so by

Prop III.3.4 $E(|X_1 + X_2|^j) < \infty \forall j \in \mathbb{N}$

and this implies $E(|X_1|^{i_1} |X_2|^{i_2}) < \infty \forall i_1, i_2$.

and $i_2 \leq j_2$.

Note The original statement of Prop III.9.4 was not correct

Ex III.9.4 $m_{\underline{y}}(\underline{t}) = E(\exp\{\underline{t}'\underline{y}\})$

$= E(\exp\{\underline{t}'\underline{a} + \sum_{i=1}^n \underline{t}'\underline{c}_i x_i\})$

$= E(\exp\{\underline{t}'\underline{a}\} \prod_{i=1}^n \exp\{\underline{t}'\underline{c}_i x_i\})$

ind. $= \exp\{\underline{t}'\underline{a}\} \prod_{i=1}^n E(\exp\{\underline{t}'\underline{c}_i x_i\})$

$= \exp\{\underline{t}'\underline{a}\} \prod_{i=1}^n m_{x_i}(\underline{c}_i' \underline{t})$

$= \exp\{\underline{t}'\underline{a}\} \prod_{i=1}^n \exp\{\underline{t}'\underline{c}_i \mu_i + \underline{t}'\underline{c}_i \Sigma_i \underline{c}_i' \underline{t} / 2\}$

$= \exp\{\underline{t}'(\underline{a} + \sum_{i=1}^n \underline{c}_i \mu_i) + \underline{t}'(\sum_{i=1}^n \underline{c}_i \Sigma_i \underline{c}_i') \underline{t} / 2\}$

Thus by the Uniqueness Theorem

$\underline{y} \sim N_n(\underline{a} + \sum_{i=1}^n \underline{c}_i \mu_i, \sum_{i=1}^n \underline{c}_i \Sigma_i \underline{c}_i')$

Ex III.9.5 ETR 3, 4, 13

For geometric (θ) $m_x(t) = \sum_{i=0}^{\infty} e^{t i} (1-\theta)^i \theta$

$= \theta \sum_{i=0}^{\infty} (e^t (1-\theta))^i = \theta (1 - e^t (1-\theta))^{-1}$

when $e^t (1-\theta) \leq 1$ or $t \leq -\log(1-\theta)$

If x_1, \dots, x_r iid geometric(θ), then $x = \sum_{i=1}^r x_i$
 \sim negative binomial (r, θ). Therefore

$$m_x(t) = \prod_{i=1}^r m_{x_i}(t) = m_x^r(t)$$

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

$$\frac{d m_x(t)}{dt} \Big|_{t=0} = e^r \left(r e^t (1-\theta) (1 - e^t(1-\theta))^{-r-1} \right) \Big|_{t=0}$$

$$= r e^r (1-\theta) e^{-(r+1)} = r \frac{1-\theta}{e}$$

$$\frac{d^2 m_x(t)}{dt^2} \Big|_{t=0} = e^r \left[r e^t (1-\theta) (1 - e^t(1-\theta))^{-r-1} + r(r+1) e^{2t} (1-\theta)^2 (1 - e^t(1-\theta))^{-r-2} \right] \Big|_{t=0}$$

$$= e^r \left[r \frac{1-\theta}{e^{r+1}} + r(r+1) \frac{(1-\theta)^2}{e^{r+2}} \right]$$

$$= r \frac{(1-\theta)}{e} \left[1 + (r+1) \frac{(1-\theta)}{e} \right]$$

Therefore $Var(X) = \frac{r(1-\theta)}{e} \left[1 + (r+1) \frac{(1-\theta)}{e} - \frac{r(1-\theta)}{e} \right]$

$$= \frac{r(1-\theta)}{e} \left[1 + \frac{1-\theta}{e} \right]$$

$$= \frac{r(1-\theta)}{e^2}$$

Ex. 9.6 ExR 3.4.16

$$\begin{aligned}
m_Y(t) &= E(e^{tx}) = \int_{-\infty}^{\infty} e^{tx} \frac{e^{-|x|}}{2} dx \\
&= \frac{1}{2} \left[\int_{-\infty}^0 e^{x(1+t)} dx + \int_0^{\infty} e^{x(1-t)} dx \right] \\
&= \frac{1}{2} \left[(1+t)^{-1} e^{x(1+t)} \Big|_{x=-\infty}^0 + (1-t)^{-1} e^{x(1-t)} \Big|_{x=0}^{\infty} \right] \\
&= \frac{1}{2} \left[\frac{1}{1+t} + \frac{1}{1-t} \right] = \frac{1}{2} \frac{2}{(1+t)(1-t)} = \frac{1}{1-t^2}
\end{aligned}$$

for $|t| < 1$.

$$\frac{dm_Y(t)}{dt} \Big|_{t=0} = 2t(1-t^2)^{-2} \Big|_{t=0} = 0$$

$$\begin{aligned}
\frac{d^2 m_Y(t)}{dt^2} &= \left[2(1-t^2)^{-2} + 8t^2(1-t^2)^{-3} \right] \Big|_{t=0} \\
&= 2
\end{aligned}$$

Therefore $Var(Y) = 2$.

Ex III. 9.7 EYR 3.4.20

Suppose $X \sim \text{gamma}(\alpha, \lambda)$. Then

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

$$= \frac{\lambda^\alpha}{\Gamma(\alpha)} \int_0^\infty x^{\alpha-1} e^{-(\lambda-t)x} dx$$

$$= \lambda^\alpha (\lambda-t)^{-\alpha} \int_0^\infty \frac{(\lambda-t)^\alpha}{\Gamma(\alpha)} x^{\alpha-1} e^{-(\lambda-t)x} dx$$

since this is the integral of a gamma($\alpha, \lambda-t$) density provided $t < \lambda$

$$= (1-t/\lambda)^{-\alpha} \text{ when } |t| < \lambda,$$

Ex. III. 9.8 EYR 3.4.29

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

$$f_X(t) = \exp\{i\mu t - \sigma^2 t^2/2\} \text{ so}$$

$$\ln f_X(t) = i\mu t - \sigma^2 t^2/2 \text{ and both cumulant is}$$

$$\frac{d^k \ln f_X(t)}{dt^k} \Big|_{t=0} = \begin{cases} \mu & k=1 \\ \sigma^2 & k=2 \\ 0 & k \geq 2 \end{cases}$$