



7. For binomial (n, p) distribution, prove that

$$\mu_{k+1} = p(1-p) \left(nk\mu_{k-1} + \frac{d\mu_k}{dp} \right)$$

and obtain γ_1 and γ_2 .

(Ans. $\gamma_1 = \frac{1-2p}{\sqrt{np(1-p)}}$, $\gamma_2 = \frac{1-6p(1-p)}{np(1-p)}$)

TBP $\Rightarrow \mu_{r+1} = p(1-p) \left[nr\mu_{r-1} + \frac{d\mu_r}{dp} \right]$

Proof: $\mu_r = E\{(X - m_x)^r\} = E\{(X - np)^r\}$

$$= \sum_{x=0}^n (x - np)^r {}^nC_x p^x (1-p)^{n-x}$$

$$\begin{aligned} \frac{d\mu_r}{dp} &= \sum_{x=0}^n r(x - np)^{r-1} \cdot (-n) {}^nC_x p^x (1-p)^{n-x} + \sum_{x=0}^n (x - np)^r {}^nC_x x p^{x-1} (1-p)^{n-x} \\ &\quad + \sum_{x=0}^n (x - np)^r {}^nC_x p^x \cdot (n-x) \cdot (1-p)^{n-x-1} \cdot (-1) \end{aligned}$$

$$\begin{aligned} \frac{d\mu_r}{dp} &= -nr \sum_{x=0}^n (x - np)^{r-1} {}^nC_x p^x (1-p)^{n-x} \\ &\quad - \sum_{x=0}^n (x - np)^r {}^nC_x p^x (1-p)^{n-x} \left[\frac{x}{p} - \frac{n-x}{1-p} \right] \end{aligned}$$

$$\begin{aligned} \frac{d\mu_r}{dp} &= -nr\mu_{r-1} - \sum_{x=0}^n (x - np)^r {}^nC_x p^x (1-p)^{n-x} \cdot \frac{(x - np)}{p(1-p)} \\ &= -nr\mu_{r-1} - \mu_{r+1} \cdot \frac{1}{p(1-p)} \end{aligned}$$

So, $\mu_{r+1} = p(1-p) \left[nr\mu_{r-1} + \frac{d\mu_r}{dp} \right]$

$$\gamma_1 = \frac{\mu_3}{\sigma^3}$$

$$\mu_3 = p(1-p) \cdot \frac{d\mu_2}{dp} = \frac{p(1-p) \left[(n) (1-2p) \right]}{p(1-p)n \sqrt{np(1-p)}}$$

$$\mu_2 = p(1-p) [nk + 0] = \frac{1-2p}{\sqrt{np(1-p)}}$$

$$\gamma_2 = \beta_2 - 3$$

$$\beta_2 = \frac{\mu_4}{\sigma^4}$$

Compute similarly.

9. Show that the 1st absolute moment about the mean for a normal (m, σ) distribution is $\sqrt{\frac{2}{\pi}} \sigma$.

We need to compute $E(|x - m_x|)$ for $\phi(m, \sigma)$

$$\begin{aligned} E(|x - m_x|) &= \int_{-\infty}^{\infty} |x - m| \cdot \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-m)^2}{2\sigma^2}} dx \\ &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} |x - m| e^{-\frac{(x-m)^2}{2\sigma^2}} dx \end{aligned}$$

Put $y = |x - m_x|$

$$f_y(y) = \begin{cases} \frac{1}{\sqrt{2\pi}\sigma} e^{-y^2/2\sigma^2}, & x - m \geq 0, y \geq 0 \\ \frac{1}{\sqrt{2\pi}\sigma} e^{-(y)^2/2\sigma^2}, & x - m < 0, y > 0 \end{cases}$$

$$\begin{aligned} E(y) &= \int_{-\infty}^0 \frac{1}{\sqrt{2\pi}\sigma} e^{-y^2/2\sigma^2} \cdot y dy + \int_0^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-y^2/2\sigma^2} \cdot y dy \\ &= \frac{2}{\sqrt{2\pi}\sigma} \int_0^{\infty} y e^{-y^2/2\sigma^2} dy \\ &= \underline{\underline{\sqrt{\frac{2}{\pi}} \sigma}} \end{aligned}$$

10. If $X \sim N(m, \sigma)$ variate, then prove that

$$\mu_{2r+2} = \sigma^2 \mu_{2r} + \sigma^3 \frac{d\mu_{2r}}{d\sigma}.$$

Hence find the coefficient of kurtosis β_2 of this distribution. (Ans. $\beta_2 = 3$)

10.) i) $\mu_{2r} = E\{(X - m_x)^{2r}\}$

For $X \sim N(m, \sigma)$
 $m_x = m$

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

$\Rightarrow \mu_{2r} =$

$$\Rightarrow \frac{d\mu_{2r}}{d\sigma} = \frac{1}{\sqrt{2\pi}} \left\{ -\frac{1}{\sigma^2} \times \int_{-\infty}^{\infty} e^{-\frac{(x-m)^2}{2\sigma^2}} (x-m)^{2r} dx \right.$$

$$\left. + \frac{1}{\sigma} \times \int_{-\infty}^{\infty} e^{-\frac{(x-m)^2}{2\sigma^2}} \times \frac{-(x-m)^2}{\sigma^3} (x-m)^{2r} dx \right\}$$

$$\Rightarrow \sigma^3 \frac{d\mu_{2r}}{d\sigma} = \left\{ -\sigma^2 \times \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-m)^2}{2\sigma^2}} (x-m)^{2r} dx \right.$$

$$\left. + \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-m)^2}{2\sigma^2}} (x-m)^{2r+2} dx \right\}$$

$$\Rightarrow \sigma^3 \frac{d\mu_{2r}}{d\sigma} = -\sigma^2 \mu_{2r} + \mu_{2r+2}$$

$$\Rightarrow \mu_{2r+2} = \sigma^2 \mu_{2r} + \sigma^3 \frac{d\mu_{2r}}{d\sigma}$$

So, $\mu_4 = \sigma^2 \mu_2 + \sigma^3 \frac{d\mu_2}{d\sigma}$ (by putting $r=1$) $\mu_2 = \sigma^2$

$$= \sigma^4 + \sigma^3 \times 2\sigma = 3\sigma^4 \Rightarrow \underline{\underline{\beta_2 = 3}}$$