

CSL003P1M : Probability and Statistics
Lecture 33 (Some More Continuous
Distributions)

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Exercise-1

If X is a normal random variable with parameters $\mu = 3$ and $\sigma^2 = 9$, find (a) $P\{2 < X < 5\}$; (b) $P\{X > 0\}$; $P\{|X - 3| > 6\}$.

Solution: (a)

$$\begin{aligned} P\{2 < X < 5\} &= P\left\{\frac{2-3}{3} < \frac{X-3}{3} < \frac{5-3}{3}\right\} \\ &= P\left\{\frac{-1}{3} < Z < \frac{2}{3}\right\} \\ &= \Phi\left(\frac{2}{3}\right) - \Phi\left(-\frac{1}{3}\right) \\ &= \Phi\left(\frac{2}{3}\right) - \left[1 - \Phi\left(\frac{1}{3}\right)\right] \\ &\approx 0.3779 \end{aligned}$$

Exercise-1

Solution: (b)

$$\begin{aligned}P\{X > 0\} &= P\left\{\frac{X-3}{3} > \frac{0-3}{3}\right\} \\&= P\{Z > -1\} \\&= 1 - \Phi(-1) \\&= \Phi(1) \\&\approx 0.8413\end{aligned}$$

Exercise-1

Solution: (c)

$$\begin{aligned}P\{|X - 3| > 6\} &= P\{X > 9\} + P\{X < -3\} \\&= P\left\{\frac{X - 3}{3} > \frac{9 - 3}{3}\right\} + P\left\{\frac{X - 3}{3} < \frac{-3 - 3}{3}\right\} \\&= P\{Z > 2\} + P\{Z < -2\} \\&= 1 - \Phi(2) + \Phi(-2) \\&= 2[1 - \Phi(2)] \\&\approx 0.0456\end{aligned}$$

Gamma, Cauchy and Beta Distribution

The Gamma Distribution

A random variable is said to have a gamma distribution with parameters (α, λ) , $\lambda > 0$, $\alpha > 0$, if its density function is given by

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

where $\Gamma(\alpha)$, called the **gamma function**, is defined as

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

The Gamma Distribution

Integration of $\Gamma(\alpha)$ by parts yields

$$\begin{aligned}\Gamma(\alpha) &= -e^{-y}y^{\alpha-1}\Big|_0^{\infty} + \int_0^{\infty} e^{-y}(\alpha-1)y^{\alpha-2}dy \\ &= (\alpha-1) \int_0^{\infty} e^{-y}y^{\alpha-2}dy \\ &= (\alpha-1)\Gamma(\alpha-1)\end{aligned}$$

For integral values of α , say $\alpha = n$, we obtain,

$$\Gamma(n) = (n-1)\Gamma(n-1) = (n-1)(n-2)\cdots 3 \cdot 2 \cdot \Gamma(1)$$

and

$$\Gamma(1) = \int_0^{\infty} e^{-x}dx = 1.$$

Thus, for integral values of n ,

$$\Gamma(n) = (n-1)!$$

The Gamma Distribution

- When $\alpha = n$, the gamma distribution with parameters (α, λ) often arises, in practice as the distribution of the amount of time one has to wait until a total of n events has occurred.
- More specifically, if events are occurring randomly, then it turns out that the amount of time one has to wait until a total of n events has occurred will be a gamma random variable with parameters (n, λ) .

We will prove this fact now.

The Gamma Distribution

Let T_n denote the time at which the n th event occurs, and note that T_n is less than or equal to t if and only if the number of events that occurred by time t is at least n . That is, with $N(t)$ equal to the number of events in $[0, t]$.

$$\begin{aligned} P\{T_n \leq t\} &= P\{N(t) \geq n\} \\ &= \sum_{j=n}^{\infty} P\{N(t) = j\} \\ &= \sum_{j=n}^{\infty} \frac{e^{-\lambda t} (\lambda t)^j}{j!} \end{aligned}$$

where the final identity follows because the number of events in $[0, t]$ has a Poisson distribution with parameter λt .

The Gamma Distribution

Differentiation will yield the density function of T_n :

$$\begin{aligned} f(t) &= \sum_{j=n}^{\infty} \frac{e^{-\lambda t} j (\lambda t)^{j-1} \lambda}{j!} - \sum_{j=n}^{\infty} \frac{\lambda e^{-\lambda t} (\lambda t)^j}{j!} \\ &= \sum_{j=n}^{\infty} \frac{\lambda e^{-\lambda t} (\lambda t)^{j-1}}{(j-1)!} - \sum_{j=n}^{\infty} \frac{\lambda e^{-\lambda t} (\lambda t)^j}{j!} \\ &= \frac{\lambda e^{-\lambda t} (\lambda t)^{n-1}}{(n-1)!} \end{aligned}$$

χ^2 (chi-squared) distribution

The gamma distribution with $\lambda = 1/2$ and $\alpha = n/2$, n a positive integer, is called the χ_n^2 distribution with n degrees of freedom.

The Cauchy Distribution

The Cauchy Distribution

A random variable is said to have a Cauchy distribution with parameter θ , $-\infty < \theta < \infty$, if its density is given by

$$f(x) = \frac{1}{\pi} \frac{1}{1 + (x - \theta)^2} \quad -\infty < x < \infty$$

The Beta Distribution

A random variable is said to have a beta distribution if its density is given by

$$f(x) = \begin{cases} \frac{1}{B(a, b)} x^{a-1} (1-x)^{b-1} & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

where

$$B(a, b) = \int_0^1 x^{a-1} (1-x)^{b-1} dx$$

The Beta Distribution

- The beta distribution can be used to model a random phenomenon whose set of possible values is some finite interval $[c, d]$ - which, by letting c denote the origin and taking $d - c$ as a unit measurement, can be transformed into the interval $[0, 1]$.
- When $a = b$, the beta density is symmetric about $1/2$, giving more and more weight to regions about $1/2$ as the common value a increases.
- When $b > a$, the density is skewed to the left and it is skewed to the right when $a > b$.

The Beta Distribution

The relationship

$$B(a, b) = \frac{\Gamma(a)\Gamma(b)}{\Gamma(a+b)}$$

can be shown to exist between

$$B(a, b) = \int_0^1 x^{a-1}(1-x)^{b-1} dx$$

and the gamma function.

Thank You