

Poisson random variable

Let $k > 0$ be a constant

$$f(x) = \begin{cases} \frac{e^{-k} k^x}{x!}; & \text{for } x = 0, 1, 2, \dots \\ 0 & \text{otherwise} \end{cases}$$

Theorem : f is a density function.

Theorem : The m.g.f. of a Poisson random variable X with parameter $k > 0$ is

$$m_X(t) = e^{k(e^t - 1)}$$

$E[X]=k$ and $\text{Var}[X]=k$.

Poisson Process : A process occurring discretely over a continuous interval of time or length or space is called a Poisson Process.

Steps in solving a Poisson problem

- 1 Determine the basic unit of measurement
- 2 Determine the average number of occurrences of the event per unit i.e λ
3. Determine length or size of observation period i.e s
4. Random variable X the number of occurrences of the event in the interval of size s follows a Poisson distribution with parameter $k=\lambda s$

(Continuous Random Variable)

Continuous Densities:

Defn: A random variable is continuous if it can assume any value in some interval(or intervals) of real numbers and the probability that it assume any specific value is 0 (zero).

CONTINUOUS PDF (Density Function)

Definition: Let X be a continuous random variable. A function $f(x):(-\infty, \infty) \rightarrow \mathbb{R}$ is called probability density function of X if

$$i. f(x) \geq 0, \forall x \in (-\infty, \infty)$$

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

$$iii. P(a \leq x \leq c) = \int_a^c f(x) dx$$

Necessary and sufficient condition for $f: (-\infty, \infty) \rightarrow \mathbb{R}$ to be density function of continuous random variable X

$$i. f(x) \geq 0, \forall x \in (-\infty, \infty)$$

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

(Thus $P[a \leq X \leq c]$ is area under graph of $y=f(x)$ between $x=a$ and $x=c$.)

Comment : It is a consequence of the definition that for any specified value of X , say x_0 , we have $P[X=x_0] = 0$, since

$$P[X = x_0] = \int_{x_0}^{x_0} f(x) dx = 0$$

Comment : $f(x_0) \neq P[X=x_0]$. If f is probability density function of continuous random variable X

Comment . X is continuous r.v.
but $f(x)$ need not be continuous
function of x , $f(x)$ is defined on
 $(-\infty, \infty)$.

Comment . If X assumes values in some finite interval $[a,c]$, we simply set $f(x) = 0$ for all $x \notin [a,c]$.

since X is continuous r.v, we have

$$\begin{aligned} P [a \leq x \leq c] \\ &= P [a \leq x < c] \\ &= P [a < x \leq c] \\ &= P [a < x < c] \end{aligned}$$

Example : Find r if $f(x)$ is probability density function of a random variable X

$$f(x) = \begin{cases} r(1-x) & 0 \leq x \leq 1 \\ r(x-1) & 1 < x \leq 3 \\ 0 & \text{otherwise} \end{cases}$$

Conditions to be checked

$$i. f(x) \geq 0, \forall x \in (-\infty, \infty)$$

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

Let X be the continuous r.v. with density $f(x)$. The cumulative distribution function (CDF) for X , denoted by $F(X)$, is defined by

$$F(x) = P(X \leq x) = \int_{-\infty}^x f(w) dw$$

Theorem : If X is continuous random variable then CDF

$F(x) : (-\infty, \infty) \rightarrow [0, 1]$ is a continuous monotonic (nondecreasing) function .

Discrete r.v. X

$$P(a < X \leq c)$$

$$= P(X \leq c) - P(X \leq a)$$

$$= F(c) - F(a)$$

Continuous r.v. X

$$P[a \leq x \leq c]$$

$$= P[a \leq x < c]$$

$$= P[a < x \leq c]$$

$$= P[a < x < c]$$

$$= F(c) - F(a)$$

(Continuous uniform distribution)

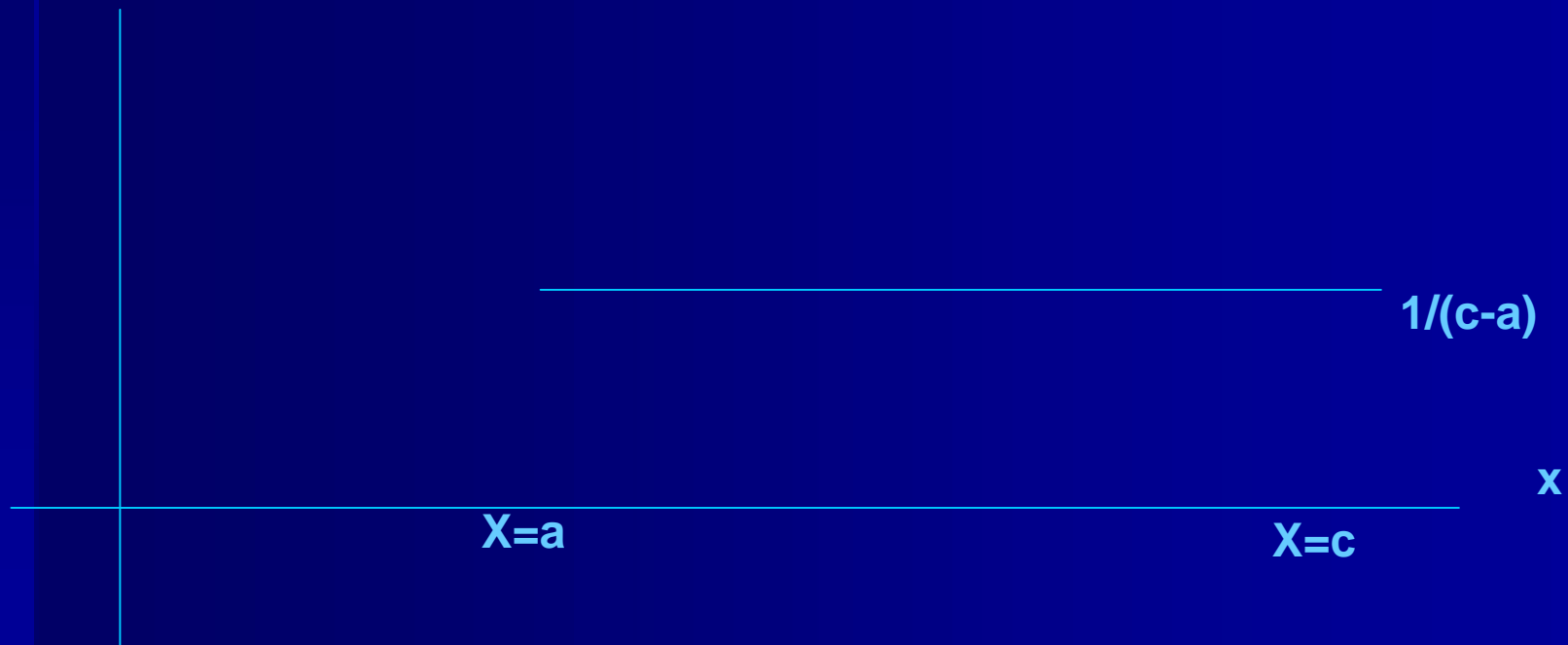
A random variable X is said to be uniformly distributed over an interval (a,c) if its density is given by

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

$f(x)$ is a density for a continuous random variable.

$$\int_a^c \frac{1}{c-a} dx = 1$$

(i) graph of the uniform density.



(iv) Find the CDF $F(x)$ for the uniform r.v. for X defined on (a, c)

$F(x)$ must be found in every interval
 $(-\infty, a], (a, c), \& [c, \infty)$

$$F(x) = \int_{-\infty}^x f(w) dw$$

$$\text{in } -\infty < x \leq a$$

$$F(x) = 0$$

$$F(x) = \int_{-\infty}^x f(w) dw \quad x \in (a, c)$$

$$F(x) = \int_{-\infty}^a f(w) dw + \int_a^x f(w) dw$$

$$= F(a) + \int_a^x \frac{1}{c-a} dw = \frac{x-a}{c-a}$$

$$x \in [c, \infty)$$

$$F(x) = \int_{-\infty}^x f(w) dw \quad x \in [c, \infty)$$

$$F(x) = \int_{-\infty}^c f(w) dw + \int_c^x f(w) dw$$

$$= F(c) + \int_1^x 0 dw = 1, \quad x \in [c, \infty)$$

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

Constructed: Find CDF of random variable X if $f(x)$ is

$$f(x) = \begin{cases} \frac{1}{2} & -1 \leq x \leq 0 \\ x & 0 < x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$F(x)$ must be found in every interval
 $(-\infty, -1), [-1, 0], (0, 1) \text{ \& } [1, \infty)$

$$F(x) = \int_{-\infty}^x f(w) dw$$

$$\text{in } -\infty < x < -1$$

$$F(x) = 0$$

$$F(x) = \int_{-\infty}^x f(w) dw \quad x \in [-1, 0]$$

$$f(x) = \begin{cases} \frac{1}{2} & -1 \leq x \leq 0 \\ x & 0 \leq x < 1 \\ 0 & \text{otherwise} \end{cases}$$

$$F(x) = \int_{-\infty}^{-1} f(w) dw + \int_{-1}^x f(w) dw$$

$$= \int_{-\infty}^{-1} 0 dw + \int_{-1}^x \frac{1}{2} dw = \frac{x+1}{2}$$

$$x \in (0,1)$$

$$F(x) = \int_{-\infty}^x f(w) dw \quad x \in (0,1)$$

$$F(x) = \int_{-\infty}^0 f(w) dw + \int_0^x f(w) dw$$

$$= F(0) + \int_0^x w dw = \frac{1}{2} + \frac{x^2}{2}, \quad x \in (0,1)$$

$$x \in [1, \infty)$$

$$F(x) = \int_{-\infty}^x f(w) dw \quad x \in [1, \infty)$$

$$F(x) = \int_{-\infty}^1 f(w) dw + \int_1^x f(w) dw$$

$$= F(1) + \int_1^x 0 dw = 1, \quad x \in [1, \infty)$$

$$F(x)=0 \quad x < -1$$

$$F(x) = \begin{cases} \frac{x+1}{2} & -1 \leq x \leq 0 \\ \frac{1}{2} + \frac{x^2}{2} & 0 < x < 1 \\ 1 & x \geq 1 \end{cases}$$

Theorem: Let F be the continuous CDF of a continuous r.v with pdf f , then

$$f(x) = \frac{d}{dx} F(x),$$

for all x at which F is
differentiable

Def: Let X be a continuous random variable with pdf f . The expected value of X is defined as

$$E [X] = \int_{-\infty}^{\infty} x f (x) \, d x .$$

Again $E(x)$ exists if and only if

$$\int_{-\infty}^{\infty} | x | f (x) \, d x \text{ is finite}$$

For a random variable X which is a function, say $H(x)$, the definition takes the form:

$$E[H(x)] = \int_{-\infty}^{\infty} H(x) f(x) dx.$$

provided

$$\int_{-\infty}^{\infty} |H(x)| f(x) dx \text{ is finite}$$

Moment generating function :

$$m_X(t) = E[e^{tX}]$$

$$= \int_{-\infty}^{\infty} e^{tx} f(x) dx$$

where f is density of X .

X is Continuous r.v.

Thm : Prove for real numbers a & c ,
 $E[aX+c] = aE[X] + c$.

Def : If a Continuous random variable X has mean μ , its variance $\text{Var}(X)$ or σ^2 is defined by

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

Properties of variance

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

Thm : $\text{Var}[aX+c] = a^2 \text{Var}(X)$

Proof : Let $W=aX+c$

$$\sim_w = a\sim_x + c$$

$$\text{Var}(W) = E[(W - \sim_w)^2] = E(aX + c - a\sim_x - c)^2$$

$$= E(aX - a\sim_x)^2 = E[a^2(X - \sim_x)^2]$$

$$= a^2 E[(X - \sim_x)^2] \text{ (Why?)}$$

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

mean and variance of uniform
random variable on interval (a,c)

$$E(X) = \frac{a + c}{2}$$

$$Var(X) = \frac{(c - a)^2}{12}$$

$$Var(X) = \frac{1}{c-a} \int_a^c \left(x - \frac{a+c}{2}\right)^2 dx = \frac{1}{c-a} \left[\frac{\left(x - \frac{a+c}{2}\right)^3}{3} \right]_a^c$$

$$= \frac{1}{3(c-a)} \left[\left(\frac{c-a}{2}\right)^3 - \left(\frac{a-c}{2}\right)^3 \right]$$

$$= \frac{1}{3(c-a)} \left[\left(\frac{c-a}{2}\right)^3 + \left(\frac{c-a}{2}\right)^3 \right]$$

$$= \frac{2}{3(c-a)} \left[\left(\frac{c-a}{2}\right)^3 \right] = \frac{(c-a)^2}{12}$$

Moment generating function :

$$m_X(t) = E[e^{tX}]$$

$$= \int_{-\infty}^{\infty} e^{tx} f(x) dx$$

where f is density of X .

MGF of uniform distribution
random variable on (a, c) :

$$E(e^{tx}) = \int_a^c e^{tx} \frac{dx}{c-a}$$
$$= \frac{1}{t} \left(\frac{e^{tc} - e^{ta}}{c-a} \right), \quad t \neq 0$$

Section 4.3:

Definition : The **Gamma function** is the function Γ defined by

$$\Gamma(r) = \int_0^{\infty} z^{r-1} e^{-z} dz, \quad r > 0$$

4.3: Gamma Random variable

Gamma Function: which is an improper integral allows us to define exponential and chi-square random variables.

Gamma function:

$$\Gamma(r) = \int_0^{\infty} z^{r-1} e^{-z} dz, r > 0$$

Theorem: (Properties of Gamma function)

1. $\Gamma(1) = 1$

2. $\Gamma(r) = (r-1)\Gamma(r-1)$, *for all* $r > 1$

Proof:

by definition of Gamma function, we have

$$\Gamma(1) = \int_0^{\infty} z^0 e^{-z} dz = \int_0^{\infty} e^{-z} dz = 1$$

by integration by parts, we have

$$\Gamma(r) = \int_0^{\infty} z^{r-1} e^{-z} dz, r > 0$$

$$= - \left. e^{-z} z^{r-1} \right|_0^{\infty} + (r-1) \int_0^{\infty} e^{-z} z^{(r-1)-1} dz$$

$$\lim_{z \rightarrow \infty} \frac{z^{r-1}}{e^z} = 0 \& \left[\lim_{z \rightarrow 0} \frac{z^{r-1}}{e^z} = 0 \text{ if } r > 1 \right]$$

$$= (r-1) \Gamma(r-1), r > 1$$

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

$$\text{Since, } \Gamma(n) = (n-1) \Gamma(n-1)$$

$$= (n-1)(n-2)\Gamma(n-2)$$

$$= (n-1)(n-2)\cdots\Gamma(1) = (n-1)!$$

Thus, Gamma function is generalization of the Factorial notation

$$\Gamma\left(\frac{1}{2}\right) = \int_0^{\infty} z^{-1/2} e^{-z} dz = \sqrt{f}$$

GAMMA RANDOM VARIABLE

A random variable X with density function is said to have a Gamma Distribution with parameters α and β , for $x > 0$, $\alpha > 0$, $\beta > 0$.

$$f(x) = \begin{cases} \frac{1}{(\Gamma(r)) s^r} x^{r-1} e^{-x/s}, & x > 0, r > 0, s > 0 \\ 0, & x \leq 0 \end{cases}$$

To check the necessary and sufficient condition of pdf:

$$f(x) \geq 0 \text{ for all } x \in (-\infty, \infty)$$

$$\int_{-\infty}^{\infty} f(x) dx = \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{r-1} e^{-x/s} dx$$

Let $\frac{x}{s} = z \Rightarrow dx = s dz$, and $x = sz$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} s^{r-1} z^{r-1} e^{-z} s dz$$

$$= \frac{s^r}{\Gamma(r) s^r} \int_0^{\infty} z^{r-1} e^{-z} dz = 1$$

Hence $f(x)$ is a pdf

Theorem: Let X be a gamma random variable with parameters α and β .

Then m.g.f for X is given by:

$$i. m_x(t) = (1 - st)^{-r}, t < \frac{1}{s}$$

$$ii. E[X] = rs$$

$$iii. Var(x) = rs^2$$

$$m_x(t) = E[e^{tx}] = \frac{1}{\Gamma(r) s^r} \int_0^{\infty} e^{tx} x^{r-1} e^{-x/s} dx$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{r-1} e^{-\left(\frac{1}{s} - t\right)x} dx$$

$$z = (1 - st) \frac{x}{s} \Rightarrow x = \frac{zs}{(1 - st)}, \quad dx = \frac{s dz}{(1 - st)}$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} \left(\frac{zs}{1 - st} \right)^{r-1} e^{-z} \frac{s dz}{(1 - st)}$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} \left(\frac{s z}{1 - s t} \right)^{r-1} e^{-z} \frac{s dz}{(1 - s t)}$$

$$= \frac{1}{\Gamma(r) s^r} \frac{s^r}{(1 - s t)^r} \int_0^{\infty} z^{r-1} e^{-z} dz$$

$$= \frac{1}{\Gamma(r) s^r} \frac{s^r}{(1 - s t)^r} \Gamma(r)$$

$$m_x(t) = (1 - st)^{-r}, \quad t < \frac{1}{s}$$

$$m_x(t) = (1 - st)^{-r}, \quad t < \frac{1}{s}$$

$$\frac{dm_x(t)}{dt} = -r(1 - st)^{-r-1}(-s)$$

$$\begin{aligned} \left. \frac{dm_x(t)}{dt} \right|_{t=0} &= -r(1 - st)^{-r-1}(-s) \Big|_{t=0} \\ &= rs \end{aligned}$$

$$\frac{dm_X(t)}{dt} = -r(1-st)^{-r-1}(-s)$$

$$m_X''(t) = \frac{d}{dt} \left[-r(1-st)^{-r-1}(-s) \right]$$

$$= -r s s (-r-1)(1-st)^{-r-2}$$

$$m_X''(t) \Big|_{t=0} = r(r+1)s^2$$

Exponential distribution : exponential random variable is Gamma random variable with $\alpha=1$. The density is

$$f(x) = \begin{cases} \frac{1}{s} e^{-\frac{x}{s}} & x > 0, s > 0 \\ 0 & x \leq 0 \end{cases}$$

$\beta > 0$ is the parameter of this exponential distribution.

$$E[X] = \beta, \text{Var}[X] = \beta^2.$$

The c.d.f. of exponential distribution with parameter s is given by

$$F(x) = \int_{-\infty}^x f(x)dx = 0 \quad \text{if } x \leq 0$$

$$\text{if } x > 0 \Rightarrow F(x) = \int_{-\infty}^x f(x)dx = \int_0^x \frac{1}{s} e^{-\frac{s}{s}} ds$$

$$F(x) = \int_0^x \frac{1}{s} e^{-\frac{s}{s}} ds = \frac{1}{s} \frac{e^{-\frac{s}{s}}}{-\frac{1}{s}} \bigg|_0^x$$

$$= -e^{-\frac{s}{s}} \bigg|_0^x = 1 - e^{-\frac{x}{s}} \quad x > 0$$

$$F(x) = \begin{cases} 0 & x \leq 0 \\ 1 - e^{-x/s}, & x > 0, \end{cases}.$$

Moment generating function, Mean and Variance of exponential distribution

Comment: Put $r=1$ in the gamma distribution we get the required results.

$$m_X(t) = (1 - St)^{-1}$$

$$E[X] = \text{mean} = S$$

$$Var(X) = S^2$$

Poisson Process and Exponential

dist : For a Poisson process with parameter λ , the *waiting time* W is the time in the given interval before the 1st success.

Theorem : W has an exponential distribution with parameter $\lambda = 1/\mu$.

Proof: **W is the time in the given interval before the 1st success.**

The distribution function F for W is given by

$$F(w) = P[W \leq w] = 1 - P[W > w]$$

i.e., we have that the first occurrence of the event will take place after time w only if number of occurrences in the time interval [0,w] is zero

$$F(w) = 0 \quad \text{if } w < 0$$

Let X be the number of occurrences of the event in this time interval [0,w]. $w > 0$

X is a poisson random variable with parameter λw .

$$\Rightarrow P[W > w] = P[X = 0]$$

$$= \frac{e^{-\lambda w} (\lambda w)^0}{0!} = e^{-\lambda w}$$

$$\Rightarrow F(w) = 1 - P[W > w] = 1 - e^{-\lambda w} \quad w > 0$$

$$= 0 \quad \text{if} \quad w \leq 0$$

$$\Rightarrow F(w) = 1 - P[W > w] = 1 - e^{-\frac{1}{\lambda}w} \quad w > 0$$

$$= 0 \quad \text{if } w \leq 0$$

$$f(w) = \frac{dF}{dw} = \frac{1}{\lambda} e^{-\frac{1}{\lambda}w} \quad \text{if } w > 0$$

$$= 0 \quad w \leq 0$$

W has an exponential distribution with parameter $\lambda = 1/\lambda$.

GAMMA RANDOM VARIABLE

A random variable X with density function $f(x)$ is said to have a Gamma Distribution with parameters α and β , for $x > 0$, $\alpha > 0$, $\beta > 0$.

$$f(x) = \begin{cases} \frac{1}{(\Gamma(r))s^r} x^{r-1} e^{-x/s}, & x > 0, r > 0, s > 0 \\ 0, & \text{other wise} \end{cases}$$

$$E[X]$$

$$= \int_0^{\infty} x \frac{1}{\Gamma(r) s^r} x^{r-1} e^{-x/s} dx$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{(r+1)-1} e^{-(\frac{1}{s})x} dx$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{(r+1)-1} e^{-\left(\frac{1}{s}\right)x} dx$$

$$\text{let } z = \frac{x}{s} \Rightarrow x = zS$$

$$\text{and } dx = S dz$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{(r+1)-1} e^{-\left(\frac{1}{s}\right)x} dx$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} (s z)^{r+1-1} e^{-z} s dz$$

$$= \frac{s^{r+1}}{\Gamma(r) s^r} \int_0^{\infty} z^{r+1-1} e^{-z} dz$$

$$= \frac{s^{r+1}}{\Gamma(r) s^r} \int_0^{\infty} z^{r+1-1} e^{-z} dz$$

$$= \frac{s^{r+1}}{\Gamma(r) s^r} \Gamma(r+1) = rs$$

$$E[X^2]$$

$$= \int_0^{\infty} x^2 \frac{1}{\Gamma(r) s^r} x^{r-1} e^{-x/s} dx$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{(r+2)-1} e^{-(\frac{1}{s})x} dx$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} x^{(r+2)-1} e^{-\left(\frac{1}{s}\right)x} dx$$

let $z = \frac{x}{s} \Rightarrow x = zS$

and $dx = S dz$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} (S z)^{r+2-1} e^{-z} S dz$$

$$= \frac{1}{\Gamma(r) s^r} \int_0^{\infty} (s z)^{r+2-1} e^{-z} s dz$$

$$= \frac{s^{r+2}}{\Gamma(r) s^r} \int_0^{\infty} z^{r+2-1} e^{-z} dz$$

$$= \frac{s^{r+2}}{\Gamma(r) s^r} \Gamma(r+2)$$

$$= \frac{s^{r+2}}{\Gamma(r) s^r} \Gamma(r+2)$$

$$= \frac{(r+1)\Gamma(r+1)s^2}{\Gamma(r)}$$

$$= \frac{(r+1)r \Gamma(r)s^2}{\Gamma(r)} = r(r+1)s^2$$

GAMMA RANDOM VARIABLE

A random variable X with density function is said to have a Gamma Distribution with parameters α and β , for $x > 0$, $\alpha > 0$, $\beta > 0$

$$f(x) = \begin{cases} \frac{1}{(\Gamma(r))s^r} x^{r-1} e^{-x/s}, & x > 0, r > 0, s > 0 \\ 0, & \text{other wise} \end{cases}$$

Chi-square distribution : If a random variable X has a gamma distribution with parameters $\beta=2$ and $\alpha=\gamma/2$, then X is said to have a chi-square (χ^2) distribution with γ degrees of Freedom and denoted by X^2_γ , γ is a positive Integer.

$$f(x) = \frac{1}{\Gamma\left(\frac{\gamma}{2}\right) 2^{\gamma/2}} x^{\frac{\gamma}{2}-1} e^{-x/2}, x > 0$$

$\beta=2$ and $\alpha=\gamma/2$,

i. $E[X] = \gamma$

ii. $Var(x) = \gamma$

$$E[X^2] = \gamma^2 + \gamma, Var[X^2] = 2\gamma$$

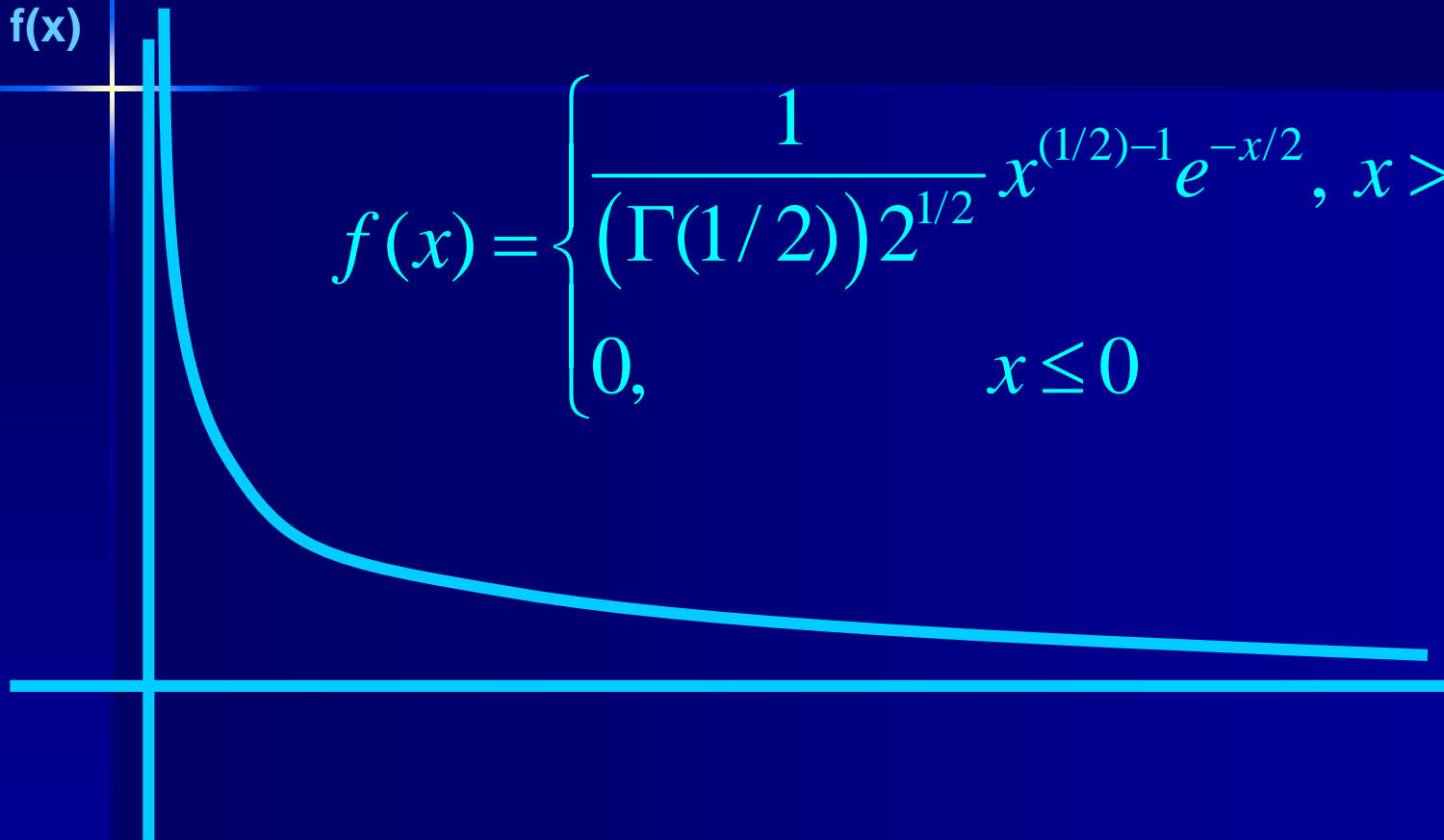
Chi square distribution

for $\chi = 1$

$f(x)$

$$f(x) = \begin{cases} \frac{1}{(\Gamma(1/2))2^{1/2}} x^{(1/2)-1} e^{-x/2}, & x > 0, \\ 0, & x \leq 0 \end{cases}$$

x



Chi square distribution *for* $\chi = 2$

$f(x)$

$$f(x) = \frac{1}{\Gamma\left(\frac{\chi}{2}\right) 2^{\chi/2}} x^{\frac{\chi}{2}-1} e^{-x/2}, x > 0$$

$$f(x) = \frac{1}{2} e^{-x/2}, x > 0$$

for $x > 2$

$$f(x) = \frac{1}{\Gamma\left(\frac{x}{2}\right) 2^{x/2}} x^{\frac{x}{2}-1} e^{-x/2}, x > 0$$

For $\alpha = v/2 > 1$ maximum
Value of density is at
 $x = (\alpha - 1)\beta$

x

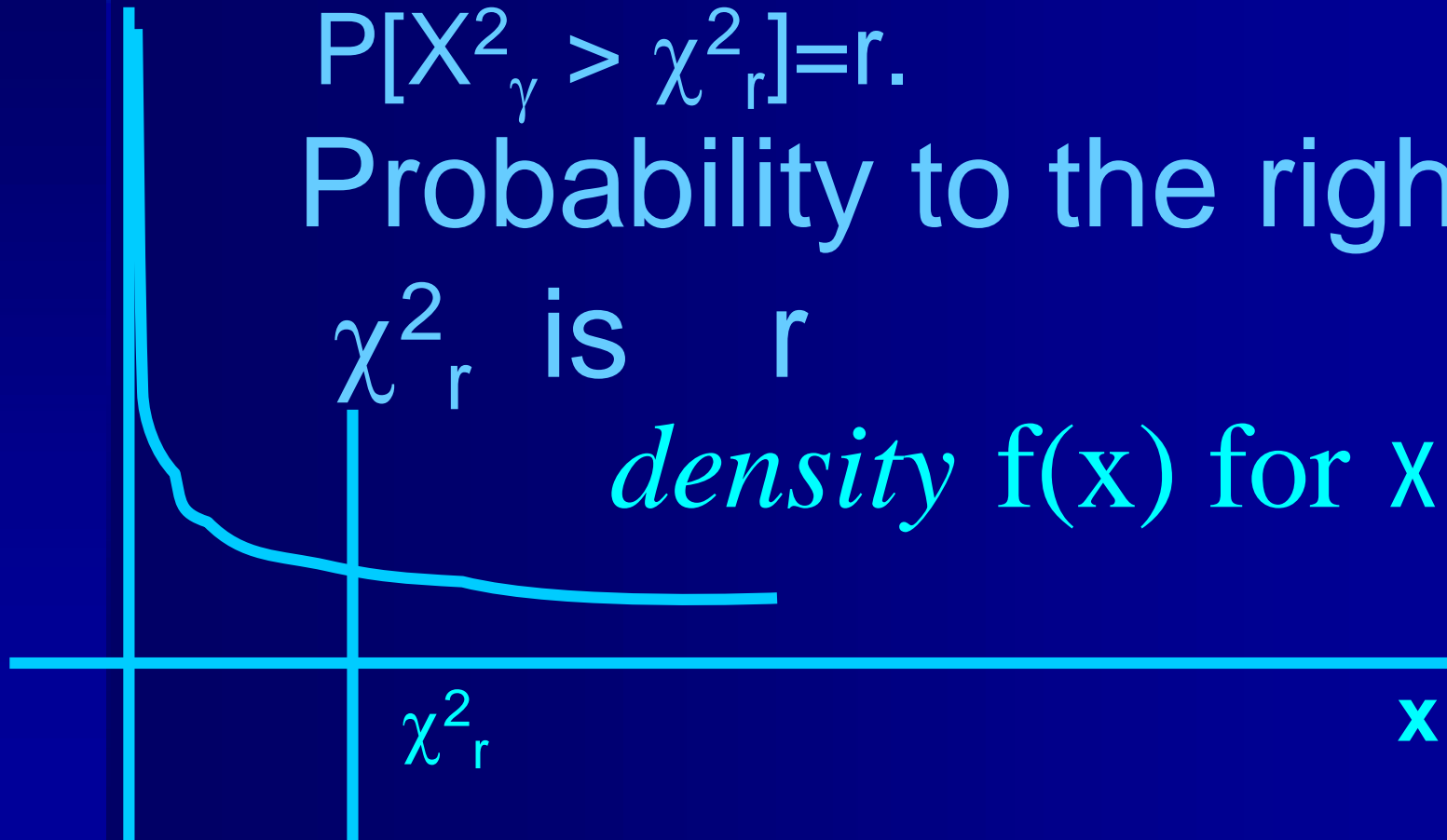
tabulation : For $0 < r < 1$, we denote by χ^2_r , for a chi-square r.v. with γ degrees of freedom, a unique number such that

$$P[X^2_\gamma > \chi^2_r] = r.$$

Probability to the right of

χ^2_r is r

density $f(x)$ for $x = 2$



We do not have explicit formula for CDF F of X^2_γ . In stead values are tabulated on p. 695-696 as below (F occurs in margin here, and related value of r.v. inside the table):

		$P[X^2_{\gamma} < t]$		
$\gamma \backslash F$		0.10	0.250	0.500
5		1.61	2.67	4.35
6		2.20	3.45	5.35
7		2.83	4.25	6.35

If F is CDF for Chi square random Variable Having 5 degrees of freedom

$$F(1.61) = .1$$

$$F(4.35) = .5$$

4.4 The Normal Distribution

A random variable X with density $f(x)$ is said to have normal distribution with parameters μ and $\sigma > 0$, where $f(x)$ is given by:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}, \quad x, \mu \in (-\infty, \infty); \sigma > 0.$$

$$(i) f(x) \geq 0 \quad \forall x \in (-\infty, \infty) \quad (ii) \int_{-\infty}^{\infty} f(x) dx = 1$$

to prove

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

$$\text{let } \left(\frac{x - \tilde{x}}{\dagger} \right) = z \Rightarrow dx = \dagger dz$$

$$\Rightarrow \frac{1}{\sqrt{2f\dagger^2}} \int_{-\infty}^{\infty} e^{-\frac{1}{2} \left(\frac{x - \tilde{x}}{\dagger} \right)^2} dx$$

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

$$\int_0^{\infty} e^{-\frac{1}{2}z^2} dz = I$$

$$I \times I = \left(\int_0^{\infty} e^{-\frac{1}{2}x^2} dx \right) \left(\int_0^{\infty} e^{-\frac{1}{2}y^2} dy \right)$$

$$\begin{aligned} I \times I &= \left(\int_0^{\infty} e^{-\frac{1}{2}x^2} dx \right) \left(\int_0^{\infty} e^{-\frac{1}{2}y^2} dy \right) \\ &= \left(\int_0^{\infty} \int_0^{\infty} e^{-\frac{1}{2}(x^2+y^2)} dx dy \right) \end{aligned}$$

$$\left(\int_0^{\infty} \int_0^{\infty} e^{-\frac{1}{2}(x^2+y^2)} dx dy \right)$$

$$= \lim_{R \rightarrow \infty} \left(\int_0^{f/2} \int_0^R e^{-\frac{1}{2}(r^2)} r dr d\theta \right)$$

$$= \lim_{R \rightarrow \infty} \left(\int_0^{f/2} \int_0^R e^{-\frac{1}{2}(r^2)} r dr d_{\parallel} \right)$$

$$= \lim_{R \rightarrow \infty} \left(\int_0^{f/2} \int_0^{R^2/2} e^{-w} dw d_{\parallel} \right)$$

$$= \frac{f}{2}$$

$$i.e. \quad I = \sqrt{\frac{f}{2}}$$

$$\frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{-\frac{1}{2}z^2} dz = 2 \frac{1}{\sqrt{2f}} \int_0^{\infty} e^{-\frac{1}{2}z^2} dz$$

$$= \frac{\sqrt{2}}{\sqrt{f}} \times \frac{\sqrt{f}}{\sqrt{2}} = 1$$

Standard Normal distribution

A random variable Z with density $f(z)$ is said to be standard normal random variable if $f(z)$ is

$$f(z) = \frac{1}{\left(\sqrt{2\pi}\right)} e^{-\frac{z^2}{2}}, -\infty < z < \infty$$

Moment Generating Function

Let Z be normally distributed with parameters $\mu=0$ and $\sigma=1$, then the moment generating function for Z is given by

$$m_Z(t) = e^{t^2/2}$$

$$m_Z(t) = E(e^{tz}) = \frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{tz} e^{-\frac{1}{2}(z)^2} dz$$

$$= \frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{tz - \frac{1}{2}(z)^2} dx$$

$$tz - \frac{1}{2}(z)^2 = -\left(\frac{z^2 - 2tz + t^2}{2}\right) + \frac{t^2}{2}$$

$$= \frac{t^2}{2} - \left(\frac{(z-t)^2}{2}\right)$$

$$m_Z(t) = \left(e^{t^2/2} \right) \frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{-\frac{(z-t)^2}{2}} dz$$

$$\text{let } (z-t) = w \Rightarrow dz = dw$$

$$m_Z(t) = \left(e^{t^2/2} \right) \frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{-\frac{w^2}{2}} dw$$

$$= \left(e^{t^2/2} \right) \left(\text{as } \frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{-\frac{w^2}{2}} dw = 1 \right)$$

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$$= \left(e^{t^2/2} \right) \quad \left(\text{as } \frac{1}{\sqrt{2f}} \int_{-\infty}^{\infty} e^{-\frac{w^2}{2}} dw = 1 \right)$$

Theorem: Let X be normal with parameters μ & σ . Then variable

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

is standard normal.

$$F_W(a) = P(W \leq a) = P\left(\frac{X - \tilde{\mu}}{\tau} \leq a\right)$$

$$= P(X \leq \tau a + \tilde{\mu}) = \frac{1}{\sqrt{2f\tau}} \int_{-\infty}^{\tau a + \tilde{\mu}} e^{-\frac{(s - \tilde{\mu})^2}{2\tau^2}} ds,$$

$$\frac{s - \tilde{\mu}}{\tau} = z, \quad \Rightarrow s = \tilde{\mu} + \tau z, \quad ds = \tau dz$$

$$F_W(a) = P(X \leq \dagger a + \sim) = \frac{1}{\sqrt{2f \dagger}} \int_{-\infty}^{\dagger a + \sim} e^{-\frac{(s - \sim)^2}{2 \dagger^2}} ds,$$

$$\frac{s - \sim}{\dagger} = z, \Rightarrow s = \sim + \dagger z, ds = \dagger dz$$

$$F_W(a) = P(X \leq \dagger a + \sim) = \frac{1}{\sqrt{2f}} \int_{-\infty}^a e^{-z^2/2} dz, \\ = F_Z(a)$$

Mean and Standard deviation for Normal distribution

Theorem : Let X be a normal random variable with parameters μ and σ . Then μ is the mean of X and σ is its standard deviation.

Moment Generating Function

Let X be normally distributed with parameters μ and σ , then the moment generating function for X is

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

$$m_X(t) = E(e^{tx}) = E(e^{t(\dagger z + \sim)})$$

$$= E(e^{t\sim} e^{t\dagger z})$$

$$= e^{t\sim} E(e^{(t\dagger)z})$$

$$= e^{t\sim} e^{t^2 \dagger^2 / 2}$$

Mean and Standard deviation for Normal random variable

Theorem : Let X be a normal random variable with parameters μ and σ . Then μ is the mean of X and σ is its standard deviation.