

Week 9

5.2: Continuous Distributions

continuous distributions put prob. mass on cont. spaces

Formally, a continuous RV is one whose cdf is a continuous function

$$\text{Def (Uniform Dist): } X \sim \text{Uniform}(a, b), a < b.$$

$$f(x|a, b) = \begin{cases} \frac{1}{b-a}, & x \in [a, b] \\ 0, & \text{otherwise} \end{cases}$$

Remarks: $E(X) = \frac{a+b}{2}$, $V(X) = \frac{(b-a)^2}{12}$

Recall: $\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$, $x > 0$

change of var: $t = x/\beta$, $\beta > 0$:

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

$$= \beta^{-x} \int_0^\infty x^{x-1} e^{-x/\beta} dx$$

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

$$\text{Def (Gamma Dist): } X \sim \text{Gamma}(x, \beta) \text{ for } x > 0: \text{shape}$$

$$\beta > 0: \text{scale}$$

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

Remarks: sometimes we use $\beta = 1/\theta$ instead as rate parameter

More on Gamma Function

$$\Gamma(x) = \int_0^\infty t^{x-1} e^{-t} dt$$

$$\Rightarrow \Gamma(x+1) = \int_0^\infty t^x e^{-t} dt$$

$$= \int_0^\infty t^x e^{-t} dt \quad \text{w/ IBP}$$

$$= t^x e^{-t} \Big|_0^\infty + \int_0^\infty t^x dt e^{-t}$$

$$= 0 + x \int_0^\infty t^{x-1} e^{-t} dt$$

$$\underbrace{\qquad\qquad\qquad}_{\Gamma(x)}$$

so, $\Gamma(x+1) = x\Gamma(x)$

$$\Gamma(1) = \int_0^\infty e^{-t} dt = e^{-t} \Big|_0^\infty = 1$$

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

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

$$\dots$$

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

Back to the Gamma dist.:

$$E(X) = \int_0^\infty x f(x) dx$$

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

$$= \frac{1}{\Gamma(x)\beta^x} \Gamma(x+1) \beta^{x+1}$$

$$= \frac{1}{\Gamma(x)\beta^x} x \Gamma(x) \beta^{x+1} = x\beta.$$

Similarly,

$$E(X^2) = \frac{1}{\Gamma(x)\beta^x} \Gamma(x+2) \beta^{x+2}$$

$$= \frac{1}{\Gamma(x)\beta^x} (x+1)x \Gamma(x) \beta^{x+2} = (x+1)x\beta^2$$

$$\Rightarrow V(X) = E(X^2) - E^2(X)$$

$$= (x+1)x\beta^2 - x^2\beta^2 = x\beta^2$$

note: $X \sim \text{Gamma}(A, \beta)$, $T(A, \beta)$
 $\frac{X}{\beta} \sim \text{Gamma}(A, 1)$

MGF
 $M_X(t) = E(e^{tX}) = \frac{1}{\Gamma(A)\beta^A} \int_0^\infty e^{tx} x^{A-1} e^{-x/\beta} dx$
 $= \frac{1}{\Gamma(A)\beta^A} \int_0^\infty \exp\left(-\frac{x}{\beta}(1-t\beta)\right) x^{A-1} dx$
 $= \frac{1}{\Gamma(A)\beta^A} \Gamma(A) \left(\frac{\beta}{1-t\beta}\right)^A, \text{ provided } 1-t\beta > 0$
 $= (1-t\beta)^{-A}, t < 1/\beta$

consider cdf for $\text{Gamma}(A, \beta)$, $A \in \mathbb{N}$, $\forall \alpha > 0$

$P(X \leq \alpha) = \frac{1}{\Gamma(A)\beta^A} \int_0^\alpha x^{A-1} e^{-x/\beta} dx$ via IBP
 $= \frac{1}{(A-1)!\beta^A} \int_0^\alpha x^{A-1} (-\beta) d e^{-x/\beta}$
 $= \frac{1}{(A-1)!\beta^A} \left(x^{A-1} \beta e^{-x/\beta} \right)_0^\alpha + \beta \int_0^\alpha e^{-x/\beta} d e^{x-1}$
 $= -\frac{1}{(A-1)!} \left(\frac{x}{\beta} \right)^{A-1} e^{-x/\beta} + \frac{1}{(A-1)!\beta^{A-1}} \int_0^\alpha e^{-x/\beta} d e^{x-1}$
 $= -P(X = A-1) + \text{cdf}_{\text{Gamma}(A-1, \beta)}(\alpha)$
 \uparrow
 $Y \sim \text{Poisson}(X/\beta)$
 $\text{recall: } P(Y) = e^{-\lambda} \frac{\lambda^Y}{Y!}$
 $= -P(Y = A-1) - P(Y = A-2) + \text{cdf}_{\text{Gamma}(A-2, \beta)}(\alpha)$
 \vdots
 $= -P(Y = A-1) - \dots - P(Y = 1) + \text{cdf}_{\text{Gamma}(1, \beta)}(X)$

when $\text{cdf}_{\text{Gamma}(1, \beta)}(X) = \frac{1}{\beta} \int_0^X e^{-t/\beta} dt = -e^{-t/\beta} \Big|_0^X = 1 - e^{-X/\beta}$

so, $LH = -P(Y = A-1) - \dots - P(Y = 1) + 1 - e^{-X/\beta}$
 $= -P(Y = A-1) - \dots - P(Y = 1) - P(Y = 0) + 1$
 $= P(Y \geq A)$

therefore, we have shown

$P(X \leq \alpha) = P(Y \geq A)$ for $\begin{cases} X \sim \text{Gamma}(A, \beta) \\ Y \sim \text{Poisson}(\frac{\alpha}{\beta}) \end{cases}$

so $\int_0^\alpha \text{pdf}_{\text{Gamma}}(x) dx = \sum_{y=A}^\infty \text{pdf}_{\text{Poi}}(y)$

Special cases of Gamma Dist (X, β)

1) Let $\begin{cases} A = p/2, p \text{ integer} \\ \beta = 2 \end{cases}$

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

$\sim \chi_p^2$
 $\sim \sum_{i=1}^p z_i^2$ where $z_i \sim N(0, 1)$
see later

2) Let $A=1, \beta > 0$, noting that $\Gamma(1)=1$

$f(x/\beta) = \frac{1}{\beta} \exp\left(-\frac{x}{\beta}\right), x > 0$

$\sim \text{Exponential}(\beta)$

\vdots

Memoryless Property (line geom. dist)

\vdots

3) Let $X \sim \text{Exp}(\beta), \beta > 0$

Let $Y = X^{1/\beta}, \beta > 0$

then $P(Y \leq y) = P(X \leq y^\beta)$
 $= 1 - e^{-y^\beta/\beta}$

$\Rightarrow Y$ has pdf

$f_Y(y) = \frac{d}{dy} P(Y \leq y) = \frac{1}{\beta} y^{\beta-1} e^{-y^\beta/\beta}, 0 < y < \infty$

$\sim \text{Weibull}(\beta, \beta)$

and useful for modelling extreme rare events:



3.2.6: Continuous Dist. (cont.)

DEF (Normal Dist.): $X \sim \text{Normal}(\mu, \sigma^2)$, $\mu \in \mathbb{R}$, $\sigma^2 > 0$

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

Remarks: Parameters: μ : mean, σ^2 : variance

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

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

$\int_{-\infty}^{\infty} x^2 e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx = \mu^2 + \sigma^2 = \mathbb{E}(X^2) = \text{Var}(X) + \mu^2$ (3)

$\forall \mu \in \mathbb{R}, \sigma^2 > 0$.

Fact: If $X \sim \text{Normal}(\mu, \sigma^2)$, then $\frac{X-\mu}{\sigma} \sim \text{N}(0, 1)$.

We say $Z = \frac{X-\mu}{\sigma}$ is a standard normal RV

Proof: $\mathbb{E}(Z) = \frac{1}{\sigma} (\mathbb{E}(X) - \mu) = \frac{1}{\sigma} (\mu - \mu) = 0$

$\text{Var}(Z) = \frac{1}{\sigma^2} \left(\frac{1}{\sigma^2} \text{Var}(X) \right) = \frac{1}{\sigma^2} (\sigma^2) = 1$

$$\begin{aligned} P(Z \leq z) &= P\left(\frac{X-\mu}{\sigma} \leq z\right) = P(X \leq \mu + \sigma z) \\ &= \int_{-\infty}^{\mu + \sigma z} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx \\ &\quad \text{letting } y = \frac{x-\mu}{\sigma} \\ &= \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}y^2\right) dy \\ &= \int_{-\infty}^z \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}y^2\right) dy \end{aligned}$$

the pdf of z is defined as

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2}, z \sim \text{N}(0, 1)$$

Proof (2): Need to show $\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} dx = 1$

By change-of-var, letting $z = \frac{1}{\sigma}(x-\mu)$,

it suffices to prove (1) via

$$\int_{-\infty}^{\infty} e^{-\frac{1}{2}y^2} dy = \sqrt{2\pi}$$

The integrand is symmetric, so we obtain

$$\int_0^{\infty} e^{-\frac{1}{2}y^2} dy = \frac{\sqrt{2\pi}}{2}$$

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

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

$$\Leftrightarrow \int_0^{\infty} \int_0^{\infty} e^{-\frac{1}{2}(y^2 + t^2)} dy dt = \frac{\pi}{2}$$

Another change-of-variables, using polar coords:

$$\begin{cases} x = r \cos \theta \\ y = r \sin \theta \end{cases} \text{ for } r \geq 0, \theta \in [0, 2\pi)$$

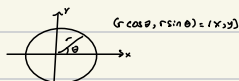
$$dx = dr \cos \theta - r \sin \theta d\theta$$

$$dy = dr \sin \theta + r \cos \theta d\theta$$

$$\frac{dx dy}{dr d\theta} = \begin{vmatrix} \cos \theta & -r \sin \theta \\ \sin \theta & r \cos \theta \end{vmatrix} = r \text{ (determinant)} = r$$

hence $dx dy = r dr d\theta$

$$\begin{aligned} \text{So,} \\ \int_0^{\infty} \int_0^{\infty} e^{-\frac{1}{2}r^2} r dr d\theta \\ = \int_0^{2\pi} \left[-e^{-\frac{1}{2}r^2} \right]_0^{\infty} d\theta \end{aligned}$$



$$= \int_0^{2\pi} d\theta = 2\pi.$$

⋮

finish