

1 Continuous Random Variable

Cumulative Distribution Function $F_Y(y)$: The probability that Y will take on a value less than y .

Properties: • $\lim_{y \rightarrow -\infty} F_Y(Y) = 0$ • $\lim_{y \rightarrow \infty} F_Y(Y) = 1$ • $F_Y(b) - F_Y(a) = P(a \leq Y \leq b)$

Probability Density Function $f_Y(y)$: The probability per unit length.

Quantile ϕ_p : $F_Y(y) = P(y \leq \phi_p) = p$

1.1 Multivariate Probability Distributions

Joint CDF: $F(y_1, y_2) = P(Y_1 \leq y_1, Y_2 \leq y_2) =$

$$\int_{-\infty}^{y_2} \int_{-\infty}^{y_1} f(t_1, t_2) dt_1 dt_2$$

Joint PDF: $f(y_1, y_2)$

Marginal PDF:

$$(1) f_{y_1}(y_1) = \int f(y_1, y_2) dy_2 \quad (2) f_{y_2}(y_2) = \int f(y_1, y_2) dy_1$$

Conditional Density:

$$f(y_1 | y_2) = \frac{f(y_1, y_2)}{f_{y_2}(y_2)} = \frac{f(y_1, y_2)}{\int f(y_1, y_2) dy_1}$$

1.2 Independence

Y_1, Y_2 are independent

- $\iff F(y_1, y_2) = F_{y_1}(y_1)F_{y_2}(y_2)$
- $\iff f(y_1, y_2) = f_{y_1}(y_1)f_{y_2}(y_2)$
- $\iff f(y_1 | y_2) = f_{y_1}(y_1)$
- $\iff E[Y_1, Y_2] = E[Y_1] E[Y_2]$
- $\implies f(y_1, y_2) = g(y_1)h(y_2)$

1.3 Expectation

Expectation and Joint Expectation:

$$(1) E[Y] = \int y f_Y(y) dy \quad (2) E[Y_1 Y_2] = \int \int y_1 y_2 f(y_1, y_2) dy_1 dy_2$$

Variance and Joint Variance:

$$(1) \text{Var}[Y_1] = E[Y^2] - E[Y]^2 \quad (2) \text{Var}[aY_1 \pm bY_2] = a^2 \text{Var}[Y_1] + b^2 \text{Var}[Y_2] \pm 2ab \text{Cov}[Y_1, Y_2]$$

Covariance:

$$\text{Cov}[Y_1, Y_2] = E[Y_1 Y_2] - E[Y_1] E[Y_2]$$

Properties:

- $E[a \cdot f(y) + b \cdot g(y) + \dots] = a E[f(y)] + b E[g(y)] + \dots$
- $\text{Var}[af(y) + bg(y) + c] = a^2 \text{Var}[f(y)] + b^2 \text{Var}[g(y)]$
- If Y_1, Y_2 independent $\implies \text{Cov}[Y_1, Y_2] = 0$

1.3.1 Conditional Expectation

$$E[Y_1 | Y_2 = y_2] = \int y_1 f(y_1 | y_2) dy_1 = \int y_1 \frac{f(y_1, y_2)}{\int f(y_1, y_2) dy_1} dy_1$$

2 Continuous Distributions Dictionary

- $Y \sim \text{Uniform}(a, b)$:

$$f(y) = \frac{1}{b-a}; \quad y \in [a, b] \implies \mu = \frac{a+b}{2} \text{ and } \sigma^2 = \frac{(b-a)^2}{12}$$

$$M_Y(t) = \frac{e^{tb} - e^{ta}}{t(b-a)}$$

- $Y \sim \text{Normal}(\mu, \sigma^2)$ ¹:

$$f(y) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(y-\mu)^2}{2\sigma^2}\right]; \quad y \in (\pm\infty) \implies \mu = \mu \text{ and } \sigma^2 = \sigma^2$$

$$M_Y(t) = \exp\left[\mu t + \frac{t^2\sigma^2}{2}\right]$$

- $Y \sim \text{Gamma}(\alpha, \beta)$:

$$f(y) = \frac{y^{\alpha-1} \exp[-y\beta^{-1}]}{\Gamma(\alpha)\beta^\alpha}; \quad y \in (0, \infty) \implies \mu = \alpha\beta \text{ and } \sigma^2 = \alpha\beta^2$$

$$M_Y(t) = (1 - \beta t)^{-\alpha}$$

- $Y \sim \text{Exponential}(\beta) = Y \sim \text{Gamma}(1, \beta)$:

$$f(y) = \beta^{-1} \exp[-y\beta^{-1}]; \quad y \in (0, \infty) \implies \mu = \beta \text{ and } \sigma^2 = \beta^2$$

$$M_Y(t) = (1 - \beta t)^{-1}$$

- $Y \sim \chi^2(\nu) = Y \sim \text{Gamma}(\nu/2, 2)$:

$$f(y) = \frac{y^{\nu/2-1} \exp[-y/2]}{\Gamma(\nu/2)2^{\nu/2}}; \quad y^2 > 0 \implies \mu = \nu \text{ and } \sigma^2 = 2\nu$$

- $Y \sim \text{Beta}(\alpha, \beta)$:

$$f(y) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} y^{\alpha-1} (1-y)^{\beta-1}; \quad y \in (0, 1) \implies \mu = \frac{\alpha}{\alpha+\beta} \text{ and } \sigma^2 = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

2.1 Special Cases

- $Y \sim \chi^2(1) = [Y \sim \text{Normal}(0, 1)]^2$
- $Y \sim \text{Beta}(1, 1) = Y \sim \text{Uniform}(0, 1)$

2.2 Gamma Function

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

$$\Gamma(k \in \mathbb{N}) = (k-1)!$$

2.3 Standardizing the Normal Distribution

If $Y \sim \text{Normal}(\mu, \sigma^2) \implies$

$$Z = \frac{Y - \mu}{\sigma} \sim \text{Normal}(0, 1)$$

¹CDF is not in closed form.

3 Discrete Distribution Dictionary

- $Y \sim \text{Binomial}(n, p)$: Observing $y \in [0, n]$ successes in fixed n trials.

$$P(Y = y) = \binom{n}{y} p^y (1-p)^{n-y} \implies \mu = n \cdot p \text{ and } \sigma^2 = np(1-p)$$

$$M_Y(t) = [pe^t + (1-p)]^n$$

- $Y \sim \text{NB}(r, p)$: Observing the fixed r^{th} success in $y \in [r, \infty)$ trials.

$$P(Y = y) = \binom{y-1}{r-1} p^r (1-p)^{y-r} \implies \mu = \frac{r}{p} \text{ and } \sigma^2 = \frac{r(1-p)}{p^2}$$

$$M_Y(t) = \left[\frac{pe^t}{1 - (1-p)e^t} \right]^r$$

- $Y \sim \text{Geometric}(p) = \text{NB}(1, p)$: Observing 1 success in $y \in [1, \infty)$ trials.

$$P(Y = y) = (1-p)^{y-1} p \implies \mu = \frac{1}{p} \text{ and } \sigma^2 = \frac{1-p}{p^2}$$

$$M_Y(t) = \frac{pe^t}{1 - (1-p)e^t}$$

- $Y \sim \text{Hypergeometric}(N, r, n)$: Observing $y \in \begin{cases} [0, n] & \text{if } n \leq r, \\ [0, r] & \text{if } n > r \end{cases}$ successes in n draws, without replacement, from a population of N that contains r success states.

$$P(Y = y) = \frac{\binom{r}{y} \binom{N-r}{n-y}}{\binom{N}{n}} \implies \mu = \frac{r \cdot n}{N} \text{ and } \sigma^2 = n \left(\frac{r}{N} \right) \left(\frac{N-r}{N} \right) \left(\frac{N-n}{N-1} \right)$$

- $Y \sim \text{Poisson}(\lambda)$: Observing $y \in [0, \infty)$ independent events that occur with a constant mean rate of λ in a fixed interval of time or area. Note: $Y \sim \text{Poisson}(n \cdot p) = Y \sim \text{Binomial}(n, p)$ if n is very large, or p is small. That is to say, it may be used to approximate the binomial distribution.

$$P(Y = y) = \frac{\lambda^y e^{-\lambda}}{y!} \implies \mu = \lambda \text{ and } \sigma^2 = \lambda$$

$$M_Y(t) = e^{\lambda(e^t - 1)}$$

3.1 Moment Generating Functions

MGF of Y :

$$M_Y(t) = \mathbb{E}[e^{tY}] = \int e^{ty} f(y) \, dy$$

k^{th} Moment of Y : $\mathbb{E}[Y^k]$

$$\left. \frac{d^k}{dt^k} M_Y(t) \right|_{t=0} = \begin{cases} k=1 & \implies \mathbb{E}[Y] \\ k=2 & \implies \mathbb{E}[Y^2] \\ \vdots & \\ k=n & \implies \mathbb{E}[Y^n] \end{cases}$$

4 Calculus

Chain Rule:

$$(f \circ g)' = (f \circ g)' g'$$

Product Rule:

$$(f \cdot g)' = f'g + fg'$$

Quotient Rule:

$$\left(\frac{f}{g} \right)' = \frac{f'g - fg'}{g^2}$$

Integration by parts:

$$\int u \, dv = uv - \int v \, du$$

Power Rule:

$$\int x^n \, dx = \frac{1}{n+1} x^{n+1}$$