Probability Theory & Random Processes EE5817

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Outline

- 1 Transformation of a Random Variable
- 2 Examples
- 3 Generalizations

Affine Transformations

$$Y = aX + b$$

$$\to F_Y(y) = P(Y \le y)$$

$$= P(aX + b \le y)$$

$$= P\left(X \le \frac{y - b}{a}\right) \text{ if } a > 0$$

$$= F_X\left(\frac{y - b}{a}\right) \text{ if } a > 0$$

$$\to f_Y(y) = \frac{1}{a}f_X\left(\frac{y - b}{a}\right) \text{ if } a > 0$$

Affine Transformations

$$Y = aX + b \text{ if } a < 0$$

$$\to F_Y(y) = P(Y \le y)$$

$$= P(aX + b \le y)$$

$$= P\left(X \ge \frac{y - b}{a}\right)$$

$$= 1 - F_X\left(\frac{y - b}{a}\right)$$

$$\to f_Y(y) = \frac{-1}{a}f_X\left(\frac{y - b}{a}\right)$$

Affine Transformations

$$Y = aX + b$$

$$\rightarrow f_Y(y) = \frac{1}{|a|} f_X \left(\frac{y - b}{a}\right)$$

$$E[Y] = E[aX + b]$$

$$= a\mu_X + b$$

$$E[(Y - \mu_Y)^2] = E[(aX + b)^2 - (a\mu_X + b)^2]$$

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

$$= a^2 \sigma_X^2$$

Example for Affine Transformation

 $X \sim N(0,1)$, then $Y = \sigma X + \mu$ is Gaussian with mean μ and variance σ^2 $Y \sim N(\mu,\sigma^2)$, then $X = \frac{1}{\sigma}(Y-\mu)$ is Gaussian with mean 0 and variance 1

Square

$$Y = X^{2}$$

$$\to F_{Y}(y) = P(Y \le y)$$

$$= P(X^{2} \le y)$$

$$= P(-\sqrt{y} \le X \le \sqrt{y})$$

$$= F_{X}(\sqrt{y}) - F_{X}(-\sqrt{y})$$

$$\to f_{Y}(y) = \frac{1}{2\sqrt{y}}f_{X}(\sqrt{y}) + \frac{1}{2\sqrt{y}}f_{X}(-\sqrt{y})$$

Chi-square

 $Y \sim N(0,1)$, then $Z = Y^2$ is Chi-square distributed with one degree of freedom

$$\begin{array}{rcl} f_Z(z) & = & \displaystyle \frac{1}{\sqrt{2\pi z}} \exp\left(\frac{-z}{2}\right) \\ \mu_Z & = & 1 \\ \sigma_Z^2 & = & 2 \\ \text{Skewness} & = & \sqrt{8} \\ \text{Excess kurtosis} & = & 12 \\ \text{MGF} & = & (1-2s)^{-0.5} \text{ for } s < 0.5 \\ \text{Characteristic function} & = & (1-2j\omega)^{-0.5} \end{array}$$

Self Reading: Start with the distribution of Z as Chi-square and derive the distribution of $Y = \sqrt{Z}$

Log-normal distribution

 $X \sim N(\mu, \sigma^2)$ and $X = \log(Y)$, then Y is Log-Normal distributed

$$\begin{split} f_Y(y) &= \frac{1}{y\sqrt{2\pi\sigma^2}} \exp\left(-\frac{(\log(y)-\mu)^2}{2\sigma^2}\right) \\ \mu_Y &= \exp(\mu+0.5\sigma^2) \\ \sigma_Y^2 &= [\exp(\sigma^2)-1] \exp(2\mu+\sigma^2) \\ \mathrm{Skewness} &= [\exp(\sigma^2)+2] \sqrt{\exp(\sigma^2)-1} \\ \mathrm{Excess \ kurtosis} &= \exp(4\sigma^2)+2\exp(3\sigma^2)+3\exp(2\sigma^2)-6 \end{split}$$

Self Reading: Median, Mode, MGF, CF



Self reading

Self Reading:

 $X \sim \textit{Uniform}(0,1)$, then $Y = \left(\frac{x}{\alpha}\right)^{\frac{1}{\beta}}$ will have Pareto distribution $X \sim \textit{Exponential}(\lambda)$, then $Y = \sqrt{X}$ will have Rayleigh distribution

Discrete Random Variable

Y = g(X), and both are discrete then

$$P(Y = y_i) = \sum_{x_i \in g^{-1}(y_i)} P(X = x_i)$$

Continous RV

Let Y = g(X), with g(.) being a one-one and increasing function over the range of X. Then,

$$F_Y(y) = P(Y \le y)$$

$$= P(g(X) \le y)$$

$$= P(X \le g^{-1}(y))$$

$$= F_X(g^{-1}(y)) \text{ using chain rule,}$$

$$\to f_Y(y) = \frac{d}{dy} F_X(g^{-1}(y)) = f_X(g^{-1}(y)) \frac{d}{dy} (g^{-1}(y))$$

Continous RV

Let Y = g(X), with g(.) being a one-one and decreasing function over the range of X. Then,

$$F_{Y}(y) = P(Y \le y)$$

$$= P(g(X) \le y)$$

$$= P(X \ge g^{-1}(y))$$

$$= 1 - F_{X}(g^{-1}(y)) \text{ using chain rule,}$$

$$\to f_{Y}(y) = -\frac{d}{dy} F_{X}(g^{-1}(y)) = -f_{X}(g^{-1}(y)) \frac{d}{dy}(g^{-1}(y))$$

Continous RV

For Y = g(X), with g(.) being a one-one and monotonic function over the range of X.

$$f_Y(y) = f_X(g^{-1}(y)) \left| \frac{d}{dy} \left(g^{-1}(y) \right) \right|$$

Self Reading: What if g(.) is many-to-one

Let X a continuous RV with $F_X(x)$ strictly increasing. Then, $F_X^{-1}()$ exists.

Let
$$U = F_X(X)$$
, then for $u \in [0, 1]$
 $F_U(u) = P(U \le u)$
 $= P(F_X(X) \le u)$
 $= P(X \le F_X^{-1}(u))$
 $= F_X(F_X^{-1}(u))$
 $= u$

Alternatively, for $U \sim \textit{Uniform}(0,1)$ Let, $X = F_X^{-1}(U)$, then,

$$P(X \le x) = P(F_X^{-1}(U) \le x)$$

$$= P(U \le F_X(x))$$

$$= F_U(F_X(x))$$

$$= F_X(x)$$

Some examples:

$$F_X(x) = \begin{cases} 0 \text{ if } x < a, \\ \frac{(x-a)}{(b-a)} \text{ if } a \le x \le b, \\ 1 \text{ if } x > b. \end{cases}$$
Then, $u = \frac{(x-a)}{(b-a)}, \quad (b-a)u + a = x = F_X^{-1}(u)$

Some examples:

$$F_X(x) = \begin{cases} 0 \text{ if } x < 0, \\ 1 - \exp\left(\frac{-x}{\beta}\right) \text{ if } x \ge 0. \end{cases}$$
 Then, $U = 1 - \exp\left(\frac{-X}{\beta}\right), \quad x = -\beta \log(1 - u)$

Questions