

Important Distributions/Functions of Random Variables

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Functions of a Random Variable

- Knowledge of some characteristic of the system, with knowledge of the input, allows some estimate of the behavior at the output.
- E. g., the input random variable X and its density $f(x)$ are known and the input-output behavior is characterized by:

$$Y = \Phi(X)$$

- To compute the density of the random variable Y .
- We assume that Φ is continuous or piecewise continuous, so $Y = \Phi(X)$ will be a random variable.

Functions of a Random Variable

Example ($Y=X^2$)

- Let $Y = \Phi(X) = X^2$ X could denote the measurement error in a certain physical experiment, and Y would then be the square of the error.
- Note that $F_Y(y) = 0$ for $y \leq 0$. For $y > 0$:

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(X^2 \leq y) \\ &= P(-\sqrt{y} \leq X \leq \sqrt{y}) \\ &= F_X(\sqrt{y}) - F_X(-\sqrt{y}) \end{aligned}$$

- And by differentiation the density of Y is:

$$f_Y(y) = \begin{cases} \frac{1}{2\sqrt{y}} [f_X(\sqrt{y}) + f_X(-\sqrt{y})], & y > 0, \\ 0, & \text{otherwise.} \end{cases}$$

Functions of a Random Variable

$X=\text{Std. Normal}$

- As a special case of Example 1, let X have the standard normal distribution $[N(0,1)]$ so that:

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}}, \quad -\infty < x < \infty$$

- Then:

$$\begin{aligned} f_Y(y) &= \begin{cases} \frac{1}{2\sqrt{y}} \left(\frac{1}{\sqrt{2\pi}} e^{-y/2} + \frac{1}{\sqrt{2\pi}} e^{-y/2} \right), & y > 0, \\ 0, & y \leq 0, \end{cases} \\ f_Y(y) &= \begin{cases} \frac{1}{\sqrt{2\pi y}} e^{-\frac{y}{2}}, & y > 0, \\ 0, & y \leq 0. \end{cases} \end{aligned}$$

Functions of a Random Variable

X=Std. Normal (cont.)

- We conclude that Y has a gamma distribution with $\alpha = 1/2$ and $\lambda = 1/2$.
- Since $GAM(\frac{1}{2}, n/2) = X_n^2$, it follows that if X is standard normal then $Y = X^2$ is a chi-square distributed with one degree of freedom.

Example, Simulation Application

X=Uniform

- Let X be uniformly distributed on $(0, 1)$.
- Show $Y = -\lambda^{-1} \ln(1-X)$ has an exponential distribution with parameter $\lambda > 0$.
- Y is a nonnegative random variable implying $F_Y(y) = 0$ for $y \leq 0$.
- For $y > 0$:

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P[-\lambda^{-1} \ln(1-X) \leq y] \\ &= P[\ln(1-X) \geq -\lambda y] \\ &= P[1-X \geq e^{-\lambda y}] \end{aligned}$$

since e^x is an increasing function of x ,

$$\begin{aligned} &= P(X \leq 1 - e^{-\lambda y}) \\ &= F_X(1 - e^{-\lambda y}) \end{aligned}$$

Example (cont.), Use in Simulation

- Since X is uniform over $(0, 1)$, $F_X(x) = x$, $0 \leq x \leq 1$.
- Thus, $F_Y(y) = 1 - e^{-\lambda y}$
- Y is exponentially distributed with parameter λ .
- This fact can be used in Monte Carlo simulation. In such simulation programs, it is important to be able to generate values of variables with known distribution functions (random deviates).
- Most computer systems provide built-in functions to generate random deviates from the uniform distribution over $(0, 1)$, say u .
- To generate a random deviate, y , of an exponentially distributed random variable Y with the parameter λ , then from this example it follows that $y = -\lambda^{-1} \ln(1 - u)$.

Theorem (generalize Ex. 2, 3)

- Let X be a continuous random variable with density f_X that is nonzero on a subset I of real numbers (i. e., $f_X(x) > 0, x \in I$ and $f_X(x) = 0, x \notin I$)
- Let Φ be a differentiable monotone function whose domain is I and whose range is the set of real numbers.
- Then $Y = \Phi(X)$ is a continuous random variable with the density, $f_Y(y)$ given by:

$$f_Y(y) = \begin{cases} f_X[\Phi^{-1}(y)]|(\Phi^{-1})'(y)|, & y \in \Phi(I) \\ 0, & \text{otherwise,} \end{cases}$$

- Where Φ^{-1} is the uniquely defined inverse of Φ and $(\Phi^{-1})'$ is the derivative of the inverse function.

Theorem (cont.)

- **Proof:**
 - We prove the theorem assuming that $\Phi(x)$ is an increasing function of x . The proof for the other case follows in a similar way.

$$\begin{aligned}F_Y(y) &= P(Y \leq y) = P[\Phi(X) \leq y] \\&= P[X \leq \Phi^{-1}(y)], \quad \text{since } \Phi \text{ is monotone increasing} \\&= F_X[\Phi^{-1}(y)]\end{aligned}$$

- Taking derivatives and using the chain rule, we get the required result.

Example 1, Simulation Issues

- Now let ϕ be the distribution function, F , of a random variable, X , with density f .
- Applying the theorem:

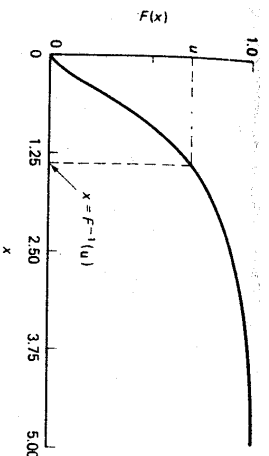
$$F_Y(y) = F_X(\phi^{-1}(y))$$

$$Y = F(X) \text{ and } F_Y(y) = F_X(F_X^{-1}(y)) = y.$$

- Therefore, the random variable $Y=F(X)$ has the density given by:
$$f_Y(y) = \begin{cases} 1, & 0 < y < 1, \\ 0, & \text{otherwise.} \end{cases}$$
- In other words, if X is a continuous random variable with CDF of F , then the new random variable $Y=F(X)$ is uniformly distributed over the interval $(0,1)$.

Example 1, Simulation Issues (cont.)

- This idea can be used to generate a random deviate x of X by:
 1. Generating a random number u from a uniform distribution of $(0, 1)$ and then
 2. Using the relation $x=F^{-1}(u)$ as illustrated in the figure below.
- The generation of the $(0, 1)$ random number can be done easily.
- Question is whether $x=F^{-1}(u)$ can be expressed in a closed mathematical form. This is possible for distributions such as the exponential; for distributions such as the normal, we must use other techniques.



Example 2: Log Normal Distribution

- Let X be normally distributed and consider $Y = e^X$

- Since:

$$f_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right]$$

and

$$\Phi^{-1}(y) = \ln(y) \text{ implies that } [\Phi^{-1}]'(y) = \frac{1}{y}$$

Example 2: Log Normal Distribution (cont.)

- Then, using the theorem, the density of Y is:

$$f_Y(y) = \frac{f(\ln y)}{y} \\ = \frac{1}{\sigma y \sqrt{2\pi}} \exp \left[-\frac{(\ln y - \mu)^2}{2\sigma^2} \right], \quad y > 0$$

- The random variable Y is said to have log-normal distribution.
- Another form of the central limit theorem, which states that the product of n mutually independent random variables has a log-normal distribution in the limit $n \rightarrow \infty$.

Example 3

- Consider a SCSI disk drive. Assume that the number of tracks N to be traversed between two disk requests is a normally distributed random variable with mean $\mu = n/3$ and $\sigma^2 = n^2/18$ where n is the total number of tracks. The seek time T is a random variable related to the seek distance N by:

$$T = a + bN$$

- Assume that experimental data show $a = 45$, $b = 0.43$, and $n = 200$. Determine the pdf of T . Recalling that T is a nonnegative random variable whereas the normal model allows negative values, make appropriate assumptions.

Example 3 (cont.)

- We use the theorem:
- If Φ be a differentiable monotone function whose domain is I and whose range is the set of real numbers.
- Then $Y = \Phi(X)$ is a continuous random variable with the density, $f_Y(y)$ given by:

$$f_Y(y) = \begin{cases} f_X[\Phi^{-1}(y)]|(\Phi^{-1})'(y)|, & y \in \Phi(I) \\ 0, & \text{otherwise,} \end{cases}$$

Example 3 (cont)

- If $\Phi(y)$ is linear, i.e., $Y = cX+d$.
- Then, use of the theorem yields:

$$f_Y(y) = \begin{cases} \frac{1}{|c|} f_X\left\{\frac{y-d}{c}\right\}, & y \in cI + d, \\ 0, & \text{otherwise,} \end{cases}$$

where I is the interval over which $f(x) \neq 0$.

Example 3 (cont.)

- Since T must be positive, we use *truncated normal density*;

$$f(x) = \begin{cases} 0 & x < 0 \\ \frac{1}{\alpha\sigma\sqrt{2\pi}} \exp\left[\frac{-(x-\mu)^2}{2\sigma^2}\right] & x \geq 0 \end{cases}$$

- Where:

$$\alpha = \int_0^{\infty} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[\frac{-(t-\mu)^2}{2\sigma^2}\right] dt$$

Example 3 (cont.)

- In our case T will be normally distributed with

$$\mu_T = a + b\frac{n}{3} = 45 + 0.43\frac{200}{3} = 73.67$$

$$\sigma_T^2 = b^2\sigma^2 = (0.43)^2\frac{n^2}{18} = 410.89$$

Example 3 (cont.)

- We show that α is close to 1:

$$\begin{aligned}\alpha &= \int_0^\infty \frac{1}{\sigma_T \sqrt{2\pi}} \exp\left[-\frac{(t - \mu_T)^2}{2\sigma_T^2}\right] dt = \\ 1 - F_Z\left(\frac{0 - \mu_T}{\sigma_T}\right) &= 1 - F_Z\left(\frac{-73.67}{20.27}\right) = \\ 1 - (1 - F_Z(3.63)) &= F_Z(3.63) = 0.99986\end{aligned}$$