

## 1 Change of Variable for monotone transformations

If  $X$  is continuous with distribution function  $F_X$  and density function  $f_X$ , find the density function of  $Y = 2X$ .  $f_Y(a) = \frac{1}{2}f_X(a)$ . Another way to determine

$$\epsilon f_Y(a) \approx P(a - \epsilon/2 < Y < a + \epsilon/2) = P(a/2 - \epsilon/4 < X < a/2 + \epsilon/4) \approx \epsilon/2 f_X(a/2)$$

The density function of  $X$  is given by

$$f(x) = \begin{cases} 1, & 0 < x < 1 \\ 0, & \text{o.w.} \end{cases}$$

Find  $E(e^X)$ . Alternatively, we can evaluate function of  $Y = e^X$  and then calculate  $EY$ .  $E(e^X) = \int_0^1 e^x dx = e - 1$  Try to find the density of  $Y$ . Take the cdf approach. Clearly

$$F_Y(y) = P(Y \leq y) = \begin{cases} 0, & \text{if } y \leq 1 \\ P(X \leq \log y) = \log y, & \text{if } y \in [1, e] \\ 1 & \text{if } y > e \end{cases}$$

$$f_Y(y) = \begin{cases} 0, & \text{if } y \leq 0 \\ 1/y, & \text{if } y \in [1, e] \\ 0 & \text{if } y > e \end{cases}$$

$$E(Y) = \int_1^e y \cdot 1/y dy = (e - 1).$$

### 1.1 A theorem for monotone transformations

In general, we have the following theorem to obtain the density function of  $Y = g(X)$  given the density of  $X$ .  $X$  is a continuous r.v. with density  $f_X(\cdot)$ . Suppose  $g(\cdot)$  is a strictly monotone and differentiable function. Then  $Y = g(X)$  has a prob density function given by

$$f_Y(y) = \begin{cases} f_X(g^{-1}(y)) \left| \frac{d}{dy} g^{-1}(y) \right| & \text{if } y = g(x) \text{ for some } x \\ 0, & \text{otherwise} \end{cases}$$

Since  $g$  is strictly monotone, we can define the inverse function  $g^{-1}(y)$ . The distribution of  $Y$  is  $F_Y(y) = P(g(X) \leq y) = P(X \leq g^{-1}(y)) = F_X(g^{-1}(y))$  where  $y = g(x)$  for some  $x = g^{-1}(y)$ . Differentiation yields  $f_Y(y) = f_X(g^{-1}(y)) \frac{d}{dy} g^{-1}(y)$ . When  $y \neq g(x)$  for any  $x$ ,  $F_Y(y)$  is either 0 or 1 and thus  $f_Y(y) = 0$ .

If  $Y = X^n$  for any nonnegative random variable  $X$ ,  $g(x) = x^n$ ,  $g(y) = y^{1/n}$ . From the theorem  $f_Y(y) = \frac{1}{n} y^{1/n-1} f(y^{1/n})$  for  $y > 0$  and  $= 0$  if  $y \leq 0$ .

However, this theorem does not apply if  $g$  is not strictly monotone. (show that for  $Y = X^2$ ).

Recommendation for general transformations: Follow the step by step approach:

1. Find the distribution function  $F_X$  of  $X$  from the density  $f_X$  of  $X$ .
2. Using the transformation, find the distribution function  $F_Y$  of  $Y$ .
3. Take derivative of  $F_Y$  to find the density  $f_Y$  of  $Y$ .

## 2 Normal distribution

We say that  $X$  is normally distributed with parameters  $\mu$  and  $\sigma^2$ , denoted by  $X \sim N(\mu, \sigma^2)$  if its density is given by

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

Why call it normal? Many random phenomena obey a normal distribution, e.g., the height of a man, the measurement error (due to the Central Limit Theorem introduced later) See Pages 207-208 of the Sheldon Ross book for some interesting historical notes!!

### 2.1 Some properties

1.  $f(x)$  is a density function, i.e.,

$$\int_{\mathbb{R}} f(x) dx = 1$$

2. If  $X \sim N(\mu, \sigma^2)$ , then  $E(X) = \mu$ ,  $Var(X) = \sigma^2$ .
3. A very important property for normal distribution. If  $X \sim N(\mu, \sigma^2)$ , then any linear function of  $X$  is also normally distributed as a normal distribution is specified by the mean  $\mu$  and the variance  $\sigma^2$  alone. More specifically, if  $aX + b \sim N(a\mu + b, a^2\sigma^2)$ . Hence  $\frac{X-\mu}{\sigma} \sim N(0, 1)$  which is also called the standard normal distribution.

4. If  $X \sim N(0, 1)$ , then the density function is denoted by  $\phi(x)$  and the cdf is denoted by  $\Phi(x) = P(X \leq x)$ .
5. Table of  $\Phi(x)$  or the area under the normal curve to the left of  $x$  is given in Table 5.1 in page 201 for different values of  $x$ . In the table you'll only see values of  $\Phi(x)$  for positive values of  $x$ . This is because you can get  $\Phi$  values for the negative values from the positive values using the simple identity

$$\Phi(-x) = 1 - \Phi(x)$$

which is a result of the symmetry of the standard normal curve.

6. Calculating percentiles of  $Z$  requires a “backwards” look-up in the table. That is, given a probability,  $p$ , find the  $z$  such that  $\Phi(z) = p$ , or equivalently,  $z = z_p = \Phi^{-1}(p)$ .  $z$  is called the  $100 \times p$  th percentile of a standard normal distribution. We probably won't find percentiles exactly using the table and so we need to approximate or interpolate to find the corresponding  $z_p$
7. Percentiles Example: Find the 95th percentile of  $Z$ . (1.65 famous landmark on the standard normal, well worth remembering)

## 2.2 Examples

1. Dominos pizza knows that the average length of time from receiving an order to delivering to the customer is 20 minutes with a standard deviation 7 min 45 seconds. Treat these sample statistics as population parameters for now. Dominoes wants to guarantee a delivery time as part of a marketing campaign, Your pizza in ?? minutes or your money back! Dominoes is willing to refund 10% of their orders, what is the quickest delivery time they should set the guarantee at? ( $\Phi^{-1}(0.9) \times 7.75 + 20 \approx 29.9$ ) So you guarantee delivery in 30 minutes or less and you'll get a refund on 10% of the pizzas. (From another perspective this is a “Buy ten to get one free program”).