

## ECE 6010 Lecture 4 – Change of Variables

Reading from G&S: Section 4.7, 4.8, 4.9, 4.10, 4.11

### Changing variables: One dimension

#### A simply invertible function

Let  $Y = g(X)$ , where  $X$  is a continuous r.v. and  $g$  is a one-to-one, onto, measurable function. Then

$$F_Y(y) = P(Y \leq y) = P(g(X) \leq y) = P(X \leq g^{-1}(y)) = F_X(g^{-1}(y))$$

So we can determine the distribution of  $Y$ . Let us now take a different point of view that will allow us to generalize to higher dimensions and develop and understand a commonly used formula.

Consider an interval along the  $X$  axis,

$$P(x \leq X \leq x + dx) \approx f_X(x)dx$$

Suppose the function  $g(x)$  has a positive derivative. The interval along the  $Y$  axis, when  $Y = g(X)$  is  $dy \approx \frac{dy}{dx}dx$  at the point  $x$ . The probability that  $X$  falls in its interval is the probability that  $Y$  falls in its interval:

$$P(x \leq X \leq x + dx) = P(y \leq Y \leq y + dy)$$

where  $y = g(x)$ , or equivalently,  $x = g^{-1}(y)$ . Then

$$f_X(x)dx \approx f_Y(y)dy$$

That is

$$f_Y(y) = f_X(x) \frac{dx}{dy} \Big|_{x=g^{-1}(y)} = f_X(g^{-1}(y)) \frac{dx}{dy}.$$

If we take the other case that  $g(x)$  has a negative derivative, we have to take  $f_X(x)dx = f_Y(y)(-dy)$ . Combining these together we obtain

$$\boxed{f_Y(y) = f_X(g^{-1}(y)) \left| \frac{dx}{dy} \right| = \frac{f_X(g^{-1}(y))}{|dy/dx|} = \frac{f_X(g^{-1}(y))}{|g'(g^{-1}(x))|}.$$

**Example 1** Let  $Y = aX + b$ . Then

$$f_Y(y) = \frac{1}{|a|} f_X((y - b)/a).$$

□

**Example 2** Suppose  $f_X(x) = \frac{a/\pi}{x^2+a^2}$  (Cauchy). Let  $Y = 1/X$ . Then

$$f_Y(y) = \frac{1/a\pi}{y^2 + 1/a^2}$$

(Cauchy)

□

**Example 3** Suppose  $X \sim \mathcal{U}(a, b)$ , with  $0 < a < b$ . Then  $f_X(x) = \frac{1}{b-a}$  for  $x \in [a, b]$ . Let  $Y = 1/X$ . Then

$$f_Y(y) = \frac{1}{(b-a)y^2} \text{ for } \frac{1}{b} < y < \frac{1}{a}.$$

□

**Example 4** Let  $Y = e^X$ . Then

$$f_Y(Y) = \frac{1}{y} f_X(\ln y) \quad y > 0.$$

If  $X \sim \mathcal{N}(\mu, \sigma^2)$  then

$$f_Y(y) = \frac{1}{y\sigma\sqrt{2\pi}} e^{-(\ln y - \mu)^2 / 2\sigma^2}$$

This density is **log-normal**.

□

**Example 5** Suppose  $y = g(x) = \tan x$ , or  $x = \tan^{-1} y$ . This has an infinite number of solutions. However, if we take  $x \in (-\pi/2, \pi/2)$ , then there is a unique inverse. We have

$$g'(x) = \frac{1}{\cos^2 x} = 1 + y^2.$$

Now let  $X \sim \mathcal{U}(-\pi/2, \pi/2)$ . Then

$$f_Y(y) = \frac{1}{\pi(1+y^2)}$$

(Cauchy).

□

**Example 6** Suppose  $X$  has continuous distribution  $F_X(x)$ , and

$$Y = F_X(X).$$

That is, the function we use to transform is actually the c.d.f of  $X$ . Then

$$g'(x) = F'_X(x) = f_X(x)$$

and

$$f_Y(y) = \frac{f_X(x)}{|g'(x)|} = \frac{f_X(x)}{f_X(x)} = 1 \quad 0 < y < 1$$

That is,  $Y$  is uniformly distributed.

In the image processing literature, this is called *histogram equalization*.

□

**Example 7** Let  $X \sim \mathcal{U}(0, 1)$ , and let  $Y$  have a specified c.d.f  $F_Y(y)$ , which we take to be continuous. Let

$$g(x) = F_Y^{-1}(x), \quad 0 < x < 1,$$

so

$$x = F_Y(y).$$

Then

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

Since  $f_X$  is 1 for all values of  $y$ , and since

$$\left| \frac{dx}{dy} \right| = |f_Y(y)| = f_Y(y),$$

putting all the pieces together we find

$$f_Y(y) = f_Y(y).$$

That is,  $Y$  has the desired distribution!

The point of this is that if we can generate  $\mathcal{U}(0, 1)$ , we can (in principle!) transform it to produce any other continuous distribution.  $\square$

## Multiple inverses

It may happen that  $g$  is not a uniquely invertible function. That is, for a given  $y$  there may be more than one value of  $x$  such that  $y = g(x)$ . For example,  $y = g(x) = x^2$ : then  $x = \sqrt{y}$  and  $x = -\sqrt{y}$  are both inverses.

We will prove the concept for two solutions, Let  $y = g(x_1) = g(x_2)$ , assuming to be specific that the slope is positive at  $x_1$  and negative at  $x_2$ .

$$P(y < Y < y + dy) = P(x_1 < X < x_1 + dx_1) + P(x_2 + dx_2 < X < x_2)$$

That is

$$f_Y(y)dy = f_X(x_1)dx_1 + f_X(x_2)|dx_2|$$

From this,

$$f_Y(y) = f_X(x_1) \left| \frac{dx_1}{dy} \right| + f_X(x_2) \left| \frac{dx_2}{dy} \right|$$

This is sometimes written

$$f_Y(y) = \frac{f_X(x_1)}{|g'(x_1)|} + \frac{f_X(x_2)}{|g'(x_2)|}$$

In general, with  $n$  solutions  $x_1, x_2, \dots, x_n$  we have

$$f_Y(y) = \frac{f_X(x_1)}{|g'(x_1)|} + \frac{f_X(x_2)}{|g'(x_2)|} + \dots + \frac{f_X(x_n)}{|g'(x_n)|}$$

**Example 8** Suppose  $X \sim \mathcal{U}(-\pi, \pi)$  and  $Y = a \sin(X + \theta)$ . Generally the sin function has an infinite number of inverses, but there are only inverses in the stated range of  $X$ . We have

$$g'(x) = a \cos(x + \theta) = \sqrt{a^2 - y^2}.$$

The density of  $X$  is  $f_X(x) = \frac{1}{2\pi}$ , for  $x \in [-\pi, \pi]$ . Then

$$f_Y(y) = \frac{1}{2\pi} \frac{1}{\sqrt{a^2 - y^2}} + \frac{1}{2\pi} \frac{1}{\sqrt{a^2 - y^2}} = \frac{1}{\pi \sqrt{a^2 - y^2}}, \quad |y| < a.$$

$\square$

## $g(X)$ constant in an interval

If the function  $g(X)$  is constant over any interval, then there is no inverse, nor even multiple inverses. However, we can still compute the distribution. Let  $g(x) = y_1$  for  $x_0 < x \leq x_1$  (i.e., constant). Then

$$P(Y = y_1) = P(x_0 < X \leq x_1) = F_X(x_1) - F_X(x_0).$$

Hence, there is probability mass at the point  $y_1$ . This results in a c.d.f which is not continuous at that point.

**Example 9** Suppose  $g(x)$  is the limiter:

$$g(x) = \begin{cases} -b & x < -b \\ x & -b \leq x \leq b \\ b & x > b. \end{cases}$$

Then

$$P(Y = -b) = P(X \leq -b) = F_X(-b).$$

$$P(Y = b) = P(X > b) = 1 - F_X(b).$$

For  $-b \leq Y < b$ ,  $F_Y(y) = F_X(y)$ . □

**Example 10** Suppose

$$g(x) = \begin{cases} 1 & x > 0 \\ -1 & x < 0. \end{cases}$$

Then

$$P(Y = -1) = P(X \leq 0) = F_X(0)$$

$$P(Y = 1) = P(X > 0) = 1 - F_X(0).$$

We have a two-valued discrete random variable. □

## Changing Variables: Multiple dimensions

Consider now multiple variables. Let  $\mathbf{g} : \mathbb{R}^n \rightarrow \mathbb{R}^n$  where

$$\mathbf{Y} = \mathbf{g}(\mathbf{X})$$

We go with the equal probability idea. The probability of falling in a region in  $\mathbf{X}$  space should be the same as the probability of falling in the corresponding region in  $\mathbf{Y}$  space. We'll draw pictures in two dimensions, but the concepts apply to higher dimensions.

$$P(x_1 < X_1 < x_1 + dx_1, x_2 < X_2 < x_2 + dx_2) \approx f_X(x_1, x_2) dx_1 dx_2$$

Suppose the region  $dx_1 dx_2$  maps to the region  $dA$  in the  $y$  coordinates. Equating probabilities We have

$$f_Y(y_1, y_2) dA = f_X(x_1, x_2) dx_1 dx_2$$

We need to evaluate  $dA$ .

The region  $dA$  is a parallelepiped described by the vectors

$$\left( \frac{dy_1}{dx_1} dx_1, \frac{dy_2}{dx_1} dx_1 \right) \quad \text{and} \quad \left( \frac{dy_1}{dx_2} dx_2, \frac{dy_2}{dx_2} dx_2 \right)$$

Fact: Recall from calculus that that (signed) area of the parallelepiped described by the vectors  $\mathbf{v} = (v_1, v_2)$  and  $\mathbf{w} = (w_1, w_2)$  is obtained from the cross product. Let us express this in matrix form

$$\mathbf{v} \otimes \mathbf{w} = \det \begin{bmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ v_1 & v_2 & 0 \\ w_1 & w_2 & 0 \end{bmatrix}$$

In our case, we have

$$\det \begin{bmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ \frac{dy_1}{dx_1} dx_1 & \frac{dy_2}{dx_1} dx_1 & 0 \\ \frac{dy_1}{dx_2} dx_2 & \frac{dy_2}{dx_2} dx_2 & 0 \end{bmatrix} = \mathbf{k} \left( \frac{dy_1}{dx_1} dx_1 \frac{dy_2}{dx_2} dx_2 - \frac{dy_2}{dx_1} dx_1 \frac{dy_1}{dx_2} dx_2 \right)$$

The (signed) area is then

$$\frac{dy_1}{dx_1} dx_1 \frac{dy_2}{dx_2} dx_2 - \frac{dy_2}{dx_1} dx_1 \frac{dy_1}{dx_2} dx_2 = \left( \frac{dy_1}{dx_1} \frac{dy_2}{dx_2} - \frac{dy_2}{dx_1} \frac{dy_1}{dx_2} \right) dx_1 dx_2$$

Let

$$J = \det \begin{bmatrix} \frac{dy_1}{dx_1} & \frac{dy_1}{dx_2} \\ \frac{dy_2}{dx_1} & \frac{dy_2}{dx_2} \end{bmatrix}$$

This matrix of partial derivatives is called the **Jacobian** of the function  $\mathbf{g}$ .

Back to probabilities. We have

$$f_Y(y_1, y_2) dA = f_X(x_1, x_2) dx_1 dx_2$$

or

$$f_Y(y_1, y_2) |J| dx_1 dx_2 = f_X(x_1, x_2) dx_1 dx_2$$

or

$$f_Y(y_1, y_2) = |J|^{-1} f_X(x_1, x_2)$$

or, in general for an invertible function  $\mathbf{g}$ ,

$$\boxed{f_Y(\mathbf{y}) = |J|^{-1} f_X(\mathbf{g}^{-1}(\mathbf{y}))}$$

**Example 11** Box-Muller transformation. Let  $X_1 \sim \mathcal{U}(0, 1)$  and  $X_2 \sim \mathcal{U}(0, 1)$  (independent). Let

$$Y_1 = \sqrt{-2 \ln X_1} \cos 2\pi X_2 \quad Y_2 = \sqrt{-2 \ln X_1} \sin 2\pi X_2$$

Then

$$Y_1 \sim \mathcal{N}(0, 1) \quad Y_2 \sim \mathcal{N}(0, 1).$$

□

## Many-to-one mappings

Let  $Y = g(X_1, X_2)$  where  $X_1$  and  $X_2$  are jointly distributed random variables. For a given value of  $y$ , the inverse may form a curve in  $(x_1, x_2)$  space. Let  $A_y$  denote the region in the  $X_1 X_2$  plane such that  $g(X_1, X_2) \leq y$ . (This may not be a connected region.) Then

$$\{Y \leq y\} = \{g(X_1, X_2) \leq y\} = \{(X_1, X_2) \in A_y\}$$

so

$$F_Y(y) = \int \int_{A_y} f_{X_1 X_2}(x_1, x_2) dx_1 dx_2$$

Let  $\Delta A_y$  denote the region of the  $X_1 X_2$  plane such that  $y < g(x_1, x_2) \leq y + dy$ . then

$$f_Y(y) dy = \int \int_{\Delta A_y} f_{X_1 X_2}(x_1, x_2) dx_1 dx_2$$

**Example 12** Let  $Z = X + Y$ . The region in the  $xy$  plane such that  $x + y \leq z$  is the part of plane below the line  $x + y = z$ . We have

$$F_Z(z) = \int_{-\infty}^{\infty} \int_{-\infty}^{z-y} f_{XY}(x, y) dx dy$$

Differentiating this with respect to  $z$  we have

$$f_Z(z) = \int_{-\infty}^{\infty} f_{XY}(z-y, y) dy.$$

Independence... □

**Example 13** Let  $Z = X/Y$ . The region of the plane such that  $x/y \leq z$  can be determined as follows. Fix  $z$ . For  $y > 0$  we want the region where  $x \leq yz$ , and for  $y < 0$  we want the region where  $x \geq yz$ . We obtain

$$F_Z(z) = \int_0^{\infty} \int_{-\infty}^{yz} f_{XY}(x, y) dx dy + \int_{-\infty}^0 \int_{zy}^{\infty} f_{XY}(x, y) dx dy.$$

To get the density: The region  $\Delta_{A_z}$  is the triangular sector bounded by the lines  $x = yz$  and  $x = y(z + dz)$ . The coordinates of a point are  $x = yz$  and  $y$ . The area of a differential is  $|y| dy dz$ . We obtain

$$f_Z(z) dz = \int_{-\infty}^{\infty} f_{XY}(zy, y) |y| dy dz$$

Then cancel  $dz$ :

$$f_Z(z) = \int_{-\infty}^{\infty} f_{XY}(zy, y) |y| dy.$$

□

**Example 14** Let  $Z = \sqrt{X^2 + Y^2}$ . The region  $A_z$  is the circle  $x^2 + y^2 \leq z^2$ . If  $f_{XY}(x, y) = \frac{1}{2\pi\sigma^2} e^{-(x^2+y^2)/2\sigma^2}$  we have

$$F_Z(z) = \frac{1}{2\pi\sigma^2} \int_0^z r e^{-r^2/2\sigma^2} dr = 1 - e^{-z^2/2\sigma^2} \quad z > 0.$$

so

$$f_Z(z) = \frac{z}{\sigma^2} e^{-z^2/2\sigma^2},$$

$z > 0$ . This is a *Rayleigh* distribution. □

Sometimes it is helpful to introduce an auxiliary variable, then integrate it out.

Suppose  $Z = XY$ . Introduce the auxiliary variable  $W = X$ . Then the inverse functions are straightforward to compute,

$$X = W \text{ and } Y = Z/W.$$

The Jacobian is

$$J = \begin{bmatrix} \frac{\partial z}{\partial x} & \frac{\partial z}{\partial y} \\ \frac{\partial w}{\partial x} & \frac{\partial w}{\partial y} \end{bmatrix} = -x = -w.$$

The joint density is

$$f_{ZW}(z, w) = \frac{1}{|w|} f_{XY}(w, z/w).$$

Then the density of  $Z$  can be obtained by integration:

$$f_Z(z) = \int_{-\infty}^{\infty} \frac{1}{|w|} f_{XY}(w, z/w) dw.$$