



國立清華大學
NATIONAL TSING HUA UNIVERSITY

EE 306001 Probability

Lecture 17: further topics on random
variable

李祈均

Outline

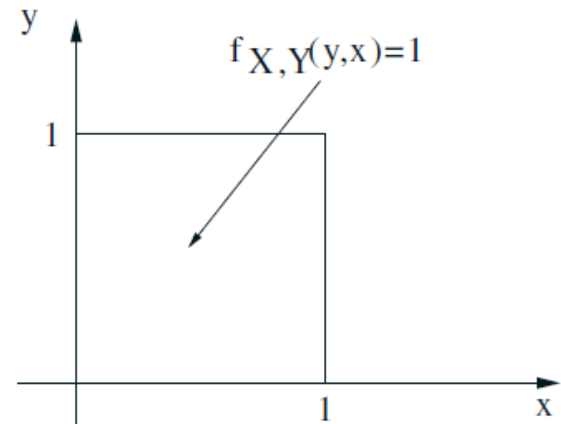
Reading 4.1

- Derived distributions

Derived distribution

Idea:

- Trying to find the distribution of a function of one or more known random variable with known probability law
- These types of distributions are called *derived distribution*
- Say for example:
 - You are told (X,Y) is uniform
 - You are interested in finding X/Y
 - Finding the ratio



Derived distribution

- Essentially, you are trying to obtain the pdf for:

$$g(X, Y) = \frac{Y}{X}$$

- Involves deriving a distribution
 - Note that $g(X, Y)$ is also a random variable
-
- *Important: When not to find them
 - If you don't need to find $g(X, Y)$ if not needed
 - For example:

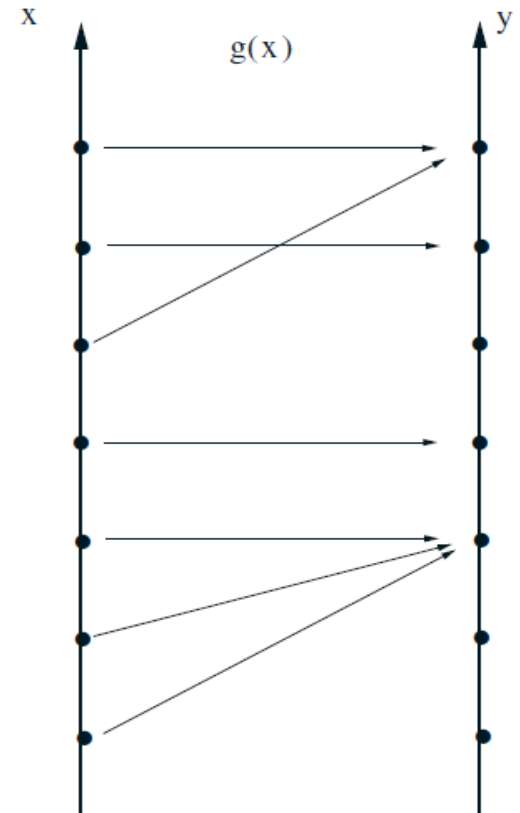
$$E[g(X, Y)] = \iint g(x, y) f_{X,Y}(x, y) dx dy$$

How to find them?

- Discrete case
 - Obtain probability mass for each possible value of $Y = g(X)$

$$p_Y(y) = P(g(X) = y) = \sum_{x:g(x)=y} p_X(x)$$

- Just sum up the probability in the X that leads to $Y = y$ to come up with t new PMF



Continuous case

- Can we do the same thing as in the discrete case?
 - Not really, we don't have probability that operates "points-to-points"
 - Because?
 - Probability in continuous case is zero at every individual point
- So what we want to find is not the probability,
 - We want to find the actual density for Y
 - In essence:
 - Find the probability of falling in a small interval around $Y = y$, and look back at the set of x 's that leads to those y 's
 - Then set those probability equal to each other to find density

Continuous case

- Instead of working with intervals, we work directly with CDF
 - What is CDFs? Cumulative distribution function
 - Essentially, a big intervals!
- Two step procedure
 - Get CDF of Y : $F_Y(y) = P(Y \leq y)$
 - Differentiate the CDF to obtain PDF

$$f_Y(y) = \frac{dF_Y}{dy}(y)$$

Example

- X : uniform on $[0,2]$
- $Y = X^3$
 - Now how to find the PDF for Y ?
- Y can take value from $[0,8]$

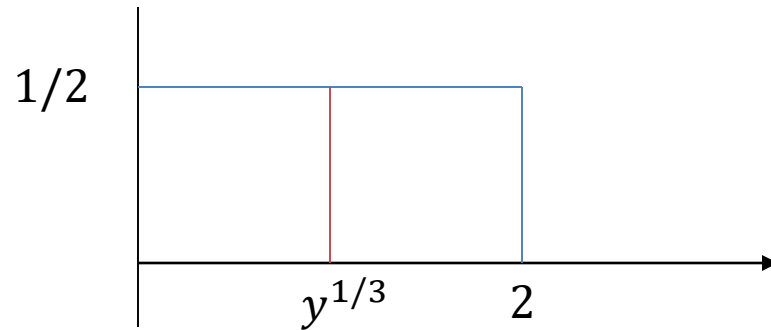
Example

- Lets try to apply the two-step procedure

$$\begin{aligned}F_Y(y) &= P(Y \leq y) = P(X^3 \leq y) \\ &= P(X \leq y^{1/3})\end{aligned}$$

What is this, X is uniform, and this is cumulative distribution in the interval of $[0, y^{1/3}]$

- $P(X \leq y^{1/3})$
 - What is the probability (essentially the area)



- Area: $\frac{1}{2}y^{1/3}$

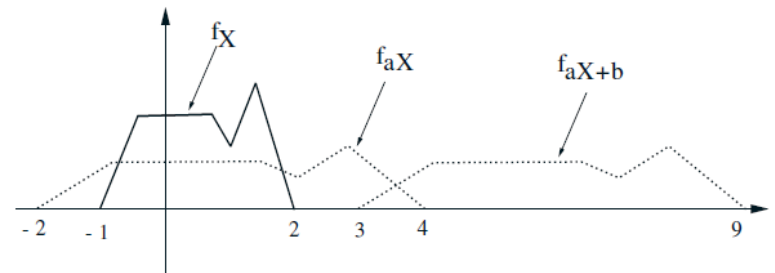
$$F_Y(y) = P(X \leq y^{1/3}) = \frac{1}{2}y^{1/3}$$

$$f_Y(y) = \frac{dF_Y}{dy}(y) = \frac{1}{6y^{2/3}}, 0 \leq y \leq 8$$

This is not a uniform distribution!

Linear case

- Lets say Y is linear function of X
$$Y = 2X + 5$$
- Imagine simple intuition to reason:
 - Stretch and rescale



From figure above,

Let's write the formula first (in the case of Y is linear function of X : $Y = aX + b$)

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

- Multiplying means stretching
- Shifting just moving the pdfs

Let's derive this using two step approach

Assume $a > 0$

$$F_Y(y) = P(Y \leq y) = P(aX + b \leq y)$$

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

Now, let's differentiate this,

Using chain rule:

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

- With $a < 0$

$$\begin{aligned} F_Y(y) &= P(Y \leq y) = P(aX + b \leq y) \\ &= P\left(X \geq \frac{y - b}{a}\right) = 1 - F_X\left(\frac{y - b}{a}\right) \end{aligned}$$

Now, let's differentiate this,

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

Example on normal random variable

Suppose that X is normal random variable with mean μ , and variance σ^2

Now we say, $Y = aX + b$, a b are scalars, $a \neq 0$

Let's apply the formula

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

What is X?

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2}$$

Now what is Y?

$$f_Y(y) = \frac{1}{|a|} \frac{1}{\sqrt{2\pi}\sigma} \exp\left\{-\left(\frac{y-b}{a} - \mu\right)^2 / 2\sigma^2\right\}$$

$$f_Y(y) = \frac{1}{|a|} \frac{1}{\sqrt{2\pi}\sigma} \exp \left\{ - \left(\frac{y-b}{a} - \mu \right)^2 / 2\sigma^2 \right\}$$
$$= \frac{1}{\sqrt{2\pi}\sigma|a|} \exp \left\{ - \frac{(y-b-a\mu)^2}{2a^2\sigma^2} \right\}$$

We can now recognize this PDF is also just a normal distribution:

$$Y \sim N(a\mu + b, a^2\sigma^2)$$

It's also a normal distribution

Linear scaling of normal distribution is still a normal distribution

Monotonic cases

- Generalizing the linear case to monotonic function
- Say let X be a random variable
 - Suppose that its range is contained in an interval I
- Now, consider Y is a function of X
 - $Y = g(X)$
 - Assume g is strictly monotonic over that interval I

- Monotonically increasing:
 - $g(x) < g(x')$ for all $x, x' \in I$, satisfying $x < x'$
- Monotonically decreasing:
 - $g(x) > g(x')$ for all $x, x' \in I$, satisfying $x < x'$
- Assume g is differentiable
- Also derivative will necessarily be non-negative in the increasing case, and non-positive in the decreasing case
- A strict monotonic function can be “inverted”
$$y = g(x), x = h(y)$$
- h is the inverted function

- Example

$$g(x) = ax + b, h(y) = \frac{y - b}{a}$$

$$g(x) = e^{ax}, h(y) = \frac{\ln y}{a}$$

- If strictly monotonic function is used, we can use the following formula directly

$$f_Y(y) = f_X(h(y)) \left| \frac{dh}{dy}(y) \right|$$

Redo the example

- You are driving from Boston to New York. You are on cruise control, hence your speed is uniformly distributed between 30 and 60 mph.
- You are going to drive a distance of 200 miles, and the time to take for the trip is $200/V$
 - $T(V) = \frac{200}{V}$
 - $h(T)=V=200/T$
 - $V \sim UNIFORM(30,60)$
 - Now we have distribution of V , can we find the distribution of T ?

$$f_T(t) = f_V(h(t)) \left| \frac{dh}{dt}(t) \right|$$

$$f_V(v = h(t)) = \frac{1}{30}$$

$$h(t) = 200/t$$

$$\left| \frac{dh}{dt}(t) \right| = 200/t^2$$

$$f_T(t) = \frac{1}{30} \frac{200}{t^2}$$

Another example

Let $Y = g(X) = X^2$, where X is a continuous uniform random variable on the interval $(0,1]$.

Within this interval, g is strictly monotonic,

First, find the inverse:

$$h(y) = \sqrt{y}$$

- Thus,
for any $y \in (0,1]$, we have

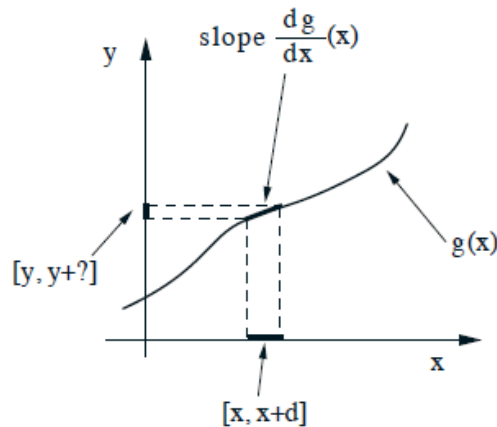
$$f_X(x = \sqrt{y}) = 1, \quad \left| \frac{dh}{dy}(y) \right| = \frac{1}{2\sqrt{y}}$$

So finally,

$$f_Y(y) = \begin{cases} \frac{1}{2\sqrt{y}} & , \text{if } y \in (0,1] \\ 0, & \text{otherwise} \end{cases}$$

Quick summarization

- Let $Y = g(X)$, g strictly monotonic



- What is happening?
 - Event $x \leq X \leq x + \delta$ is the same as $g(x) \leq Y \leq g(x + \delta)$
 - Or approximately, $g(x) \leq Y \leq g(x) + \delta \left| \left(\frac{dg}{dx} \right) (x) \right|$

- Hence, it explains the formula (it actually is a mass to mass transfer)

$$\delta f_X(x) = \delta f_Y(y) \left| \frac{dg}{dx}(x) \right|$$

where $y = g(x)$

Example

Let X be a random variable with PDF f_X

Find the PDF of the random variable $Y = |X|$

a) When $f_X(x) = \begin{cases} \frac{1}{3}, & \text{if } -2 < x \leq 1 \\ 0, & \text{otherwise} \end{cases}$

- Since $Y = |X|$, you can visualize the PDF for any given y as the following:

$$f_Y(y) = \begin{cases} f_X(y) + f_X(-y), & \text{if } y \geq 0 \\ 0, & \text{if } y < 0 \end{cases}$$

Since $Y = |X|, Y \geq 0$

So when $f_X(x) = \begin{cases} \frac{1}{3}, & \text{if } -2 < x \leq 1 \\ 0, & \text{otherwise} \end{cases}$

- Essentially $f_X(x)$ for $-1 \leq x \leq 0$ get added to $f_Y(y)$ for $0 \leq y \leq 1$

Therefore,

$$f_Y(y) = \begin{cases} \frac{2}{3}, & \text{if } 0 \leq y \leq 1 \\ \frac{1}{3}, & \text{if } 1 < y \leq 2 \\ 0, & \text{otherwise} \end{cases}$$

b)

- What if

$$f_X(x) = \begin{cases} 2e^{-2x}, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

- So we are told that $X > 0$; hence there is no negative values of X that need to be considered, thus:

$$f_Y(y) = f_X(y) = \begin{cases} 2e^{-2x}, & \text{if } x > 0 \\ 0, & \text{otherwise} \end{cases}$$

Example

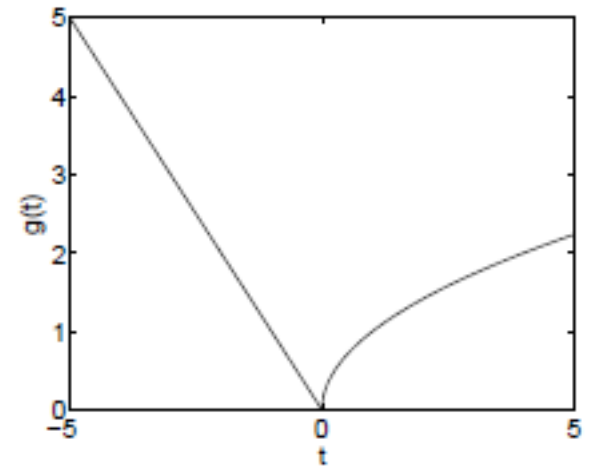
- Let X be a normal random variable with mean 0, variance 1

$$f_X(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2}$$

Let $Y = g(X)$

$$g(t) = \begin{cases} -t, & \text{for } t \leq 0 \\ \sqrt{t}, & \text{for } t > 0 \end{cases}$$

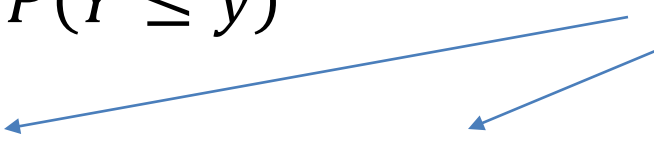
Find PDF of Y



- Because of the definition on g , Y can only take non-negative values

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(X \in [-y, 0]) + P(X \in (0, y^2)) \\ &= (F_X(0) - F_X(-y)) + (F_X(y^2) - F_X(0)) \\ &= F_X(y^2) - F_X(-y) \end{aligned}$$

Think back in the original X space, in what region has mass been moved

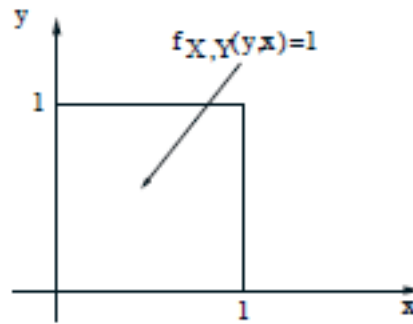


- Taking the derivative:

$$f_Y(y) = 2yf_X(y^2) + f_X(-y)$$

$$= \frac{1}{\sqrt{2\pi}} \left(2ye^{-y^4/2} + e^{-y^2/2} \right)$$

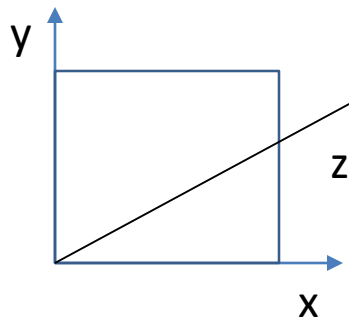
Example



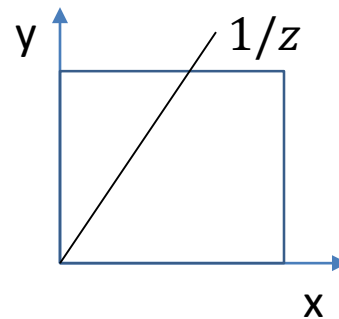
Back to the beginning, Find the PDF of $Z = g(X, Y) = \frac{Y}{X}$

- What is X?
 - Uniform distribution over $[0,1]$
- What is Y?
 - Uniform distribution over $[0,1]$
- X,Y independent of one another

- So we need to find the CDF of Z , and Z is a ratio between X and Y
 - Can imagine z is essentially a slope term
 - So we need to find $P(Y/X < z)$
 - Split into two cases, and find the area under the curve



Case 1: $0 < z < 1$



Case 2: $z > 1$

$$F_Z(z) = P\left(\frac{Y}{X} < z\right)$$

Area for case 1: $\frac{z}{2}$

Area for case 2: $1 - \left(\frac{1}{(2z)}\right)$

Put it together:

$$= \begin{cases} \frac{z}{2}, & \text{if } 0 \leq z \leq 1 \\ 1 - \frac{1}{2z}, & \text{if } z > 1 \\ 0, & \text{otherwise} \end{cases}$$

- In order to find the PDF, we then differentiate with respect to CDF:

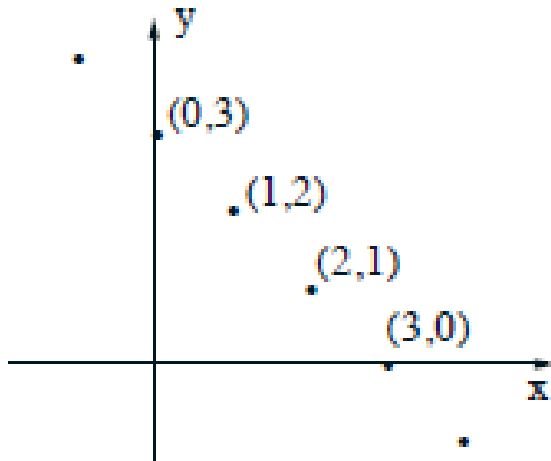
$$f_Z(z) = \begin{cases} \frac{1}{2}, & \text{if } 0 \leq z \leq 1 \\ \frac{1}{(2z^2)}, & \text{if } z > 1 \\ 0, & \text{otherwise} \end{cases}$$

Okay,

So this is the general way of finding a derived distribution, and the steps involved when dealing with multiple random variables are exactly the same as single random variable

The distribution of $X+Y$

- Before jumping into continuous case, let's take a look at discrete case:
 - $W = X + Y$; X, Y , are independent



Say we want to compute $W = 3$

We look at each possible values of (X, Y) that would make the sum into 3

And add up the probabilities for each of these associations

$$\begin{aligned} p_W(w) &= P(X + Y = w) \\ &= \sum_x P(X = x)P(Y = w - x) \\ &= \sum_x p_X(x)p_Y(w - x) \end{aligned}$$

What is the mechanics of these?

- Put the two pmf's on top of each other
- Flip the pmf of Y
- Shift the flipped pmf by w (to right if $w > 0$)
- Cross-multiply and add

Continuous case?

- Extremely similar to discrete case, as always..

Say $Z = X + Y$

First note the following:

$$P(Z \leq z | X = x) = P(X + Y \leq z | X = x)$$

$$= P(x + Y \leq z | X = x) = P(x + Y \leq z)$$

$$= P(Y \leq z - x)$$

If we take differentiation on both sides:

$$f_{Z|X}(z|x) = f_Y(z - x)$$

- Knowing that, then invoke multiplication rule for joint PDF:

$$f_{X,Z}(x, z) = f_X(x)f_{Z|X}(z|x) = f_X(x)f_Y(z - x)$$

Now to find the $f_Z(z)$ -> marginal PDF, integrate out x

$$f_Z(z) = \int_{-\infty}^{\infty} f_{X,Z}(x, z)dx = \int_{-\infty}^{\infty} f_X(x)f_Y(z - x)dx$$

$$p_W(w) = \sum_x p_X(x)p_Y(w - x)$$

Both cases are similar, and intuitions are exactly the same:
This operation is called **convolution!**