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# EE 306001 Probability

Lecture 15: continuous random variable

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# Summary of joint PDF

Let  $X$  and  $Y$  be jointly continuous random variables with joint PDF  $f_{X,Y}(x, y)$

- The joint PDF can be used to calculate probabilities

$$P((X, Y) \in B) = \iint_{(x,y) \in B} f_{X,Y}(x, y) dx dy$$

- The marginal PDFs of  $X$  and  $Y$  can be obtained from the joint PDF, using the following:

$$f_X(x) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dy, \quad f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x, y) dx$$

- The joint CDF is defined by  $F_{X,Y}(x, y) = P(X \leq x, Y \leq y)$ , and determines the joint PDF through the following formula:

$$f_{X,Y}(x, y) = \frac{d^2 F_{X,Y}}{dxdy}(x, y)$$

- A function  $g(X, Y)$  of  $X$  and  $Y$  defines a new random variable, and:

$$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{X,Y}(x, y) dx dy$$

- If  $g$  is linear, of the form  $aX + bY + c$ , then we have:

$$E[aX + bY + c] = aE[X] + bE[Y] + c$$

# Conditional PDF given an event

- The conditional PDF,  $f_{X|A}$  of a continuous random variable  $X$ , given an event  $A$  with  $P(A) > 0$ , satisfies

$$P(X \in B|A) = \int_B f_{X|A}(x) dx$$

- If  $A$  is a subset of the real line with  $P(X \in A) > 0$ , then

$$f_{X|\{X \in A\}}(x) = \begin{cases} \frac{f_X(x)}{P(X \in A)}, & \text{if } x \in A \\ 0, & \end{cases}$$

- Let  $A_1, A_2, \dots, A_n$  be disjoint events that form a partition of the sample space, and assume that  $P(A_i) > 0$  for all  $i$ , then

$$f_X(x) = \sum_{i=1}^n P(A_i) f_{X|A_i}(x)$$

- A version of total probability theorem

# Conditional PDF given a random variable

Let  $X, Y$  be jointly continuous random variable with joint PDF  $f_{X,Y}$

- The joint, marginal, and conditional PDF are related to one another via the following formula:

$$f_{X,Y}(x, y) = f_Y(y)f_{X|Y}(x|y)$$

The conditional PDF is defined only for those  $y$ 's for which  $f_Y(y) > 0$

# Conditional Expectations

Let  $X$  and  $Y$  be jointly continuous random variables, and let  $A$  be an event with  $P(A) > 0$

- Definition: the conditional expectation of  $X$  given the event  $A$  is defined by

$$E[X|A] = \int_{-\infty}^{\infty} x f_{X|A}(x) dx$$

- The conditional expectation of  $X$  given that  $Y=y$  is defined by

$$E[X|Y = y] = \int_{-\infty}^{\infty} x f_{X|Y}(x|Y = y) dx$$

- The expected value rule: for a function  $g(X)$ , we have:

$$E[g(X)|A] = \int_{-\infty}^{\infty} g(x)f_{X|A}(x) dx$$

And

$$E[g(X)|Y = y] = \int_{-\infty}^{\infty} g(x)f_{X|Y}(x|y)dx$$

- Total expectation theorem: let  $A_1, A_2, \dots, A_n$  be disjoint events that form a partition of the sample space, and assume that  $P(A_i) > 0$  for all  $i$ , then

$$E[X] = \sum_{i=1}^n P(A_i)E[X|A_i]$$

Similarly,

$$E[X] = \int_{-\infty}^{\infty} E[X|Y = y]f_Y(y)dy$$



# Independence

Let  $X$  and  $Y$  be jointly continuous random variables

- $X$  and  $Y$  are independent if

$$f_{X,Y}(x, y) = f_X(x)f_Y(y), \text{ for all } x, y$$

- If  $X$  and  $Y$  are independent, then

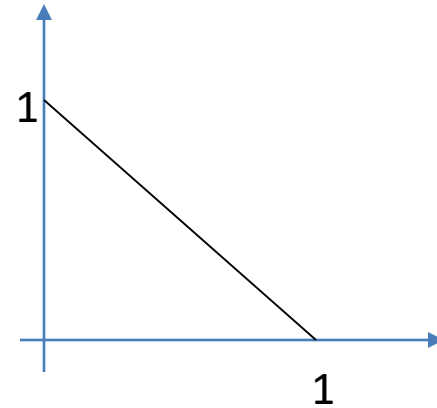
$$E[XY] = E[X]E[Y]$$

- If  $X$  and  $Y$  are independent, then

$$\text{var}(X + Y) = \text{var}(X) + \text{var}(Y)$$

# Example 1

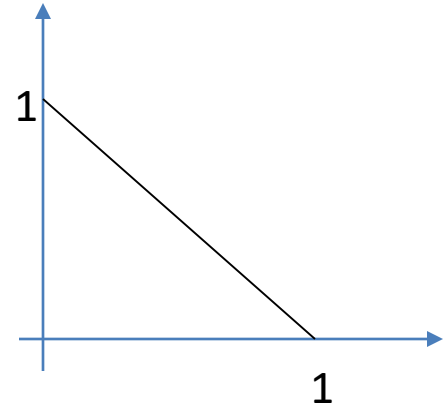
Let the random variables  $X$  and  $Y$  have a joint PDF which is uniform over the triangle with vertices  $(0,0)$ ,  $(0,1)$  and  $(1,0)$



a) Find the joint PDF of X and Y

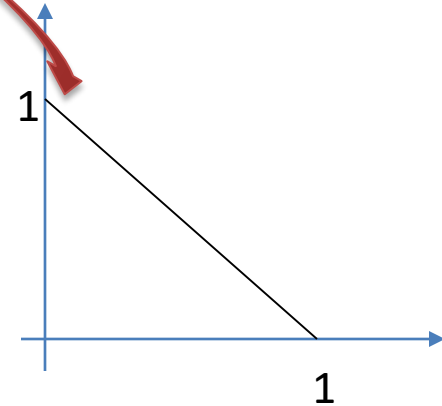
The area of the triangle is  $\frac{1}{2}$

$$f_{X,Y}(x, y) = 2, (x, y) \text{ in the triangle shown} \\ = 0, \text{ elsewhere}$$



b) Find the marginal PDF of Y

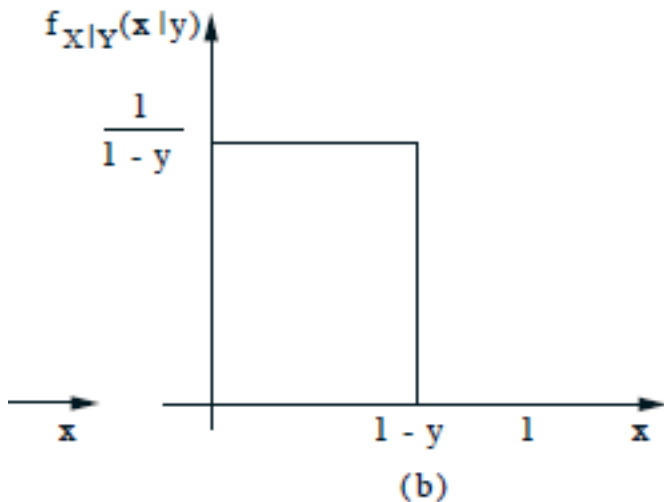
$$f_Y(y) = \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx$$
$$= \int_0^{1-y} 2 dx = 2(1-y), 0 \leq y \leq 1$$



## c) Find the conditional PDF of X given Y

- We have:

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{2}{2(1-y)} = \frac{1}{1-y}, 0 \leq x \leq 1-y$$



Intuitively, since the joint PDF is constant, the conditional PDF (a slice of joint PDF) is also constant.

Imagine the previous figure, if you take a slice of joint PDF at  $Y=y$ ,  $X$  ranges from 0 to  $1-y$

In order for the condition PDF to integrate to 1, it's height must be  $1/(1-y)$

d) Find  $E[X|Y=y]$ , and use the total expectation theorem to find  $E[X]$  in terms of  $E[Y]$

For  $y > 1$  or  $y < 0$ , the conditional PDF is undefined

For  $0 \leq y \leq 1$ , the conditional mean:

$$\begin{aligned} E[X|Y = y] &= \int_0^{1-y} x \frac{1}{1-y} dx = \frac{1}{1-y} \frac{1}{2} x^2 \Big|_0^{1-y} \\ &= \frac{1-y}{2} \end{aligned}$$

- The total expectation theorem yields:

$$\begin{aligned} E[X] &= \int E[X|Y = y]f_Y(y)dy = \int_0^1 \frac{1-y}{2} f_Y(y)dy \\ &= \frac{1}{2} - \frac{1}{2} \int_0^1 y f_Y(y)dy = \frac{1 - E[Y]}{2} \end{aligned}$$

e) Use the symmetry of the problem to find the value of  $E[X]$

- Because of symmetry:

We have  $E[X] = E[Y]$

Therefore,  $E[X] = \frac{(1-E[X])}{2}$

$$E[X] = \frac{1}{3}$$



## Example 2

Random variables  $X$  and  $Y$  are distributed according to joint PDF:

$$f_{X,Y}(x, y) = \begin{cases} ax, & \text{if } 1 \leq x \leq y \leq 2 \\ 0, & \text{otherwise} \end{cases}$$

## a) Evaluate the constant a

- Because of the required normalization property of any joint PDF,

$$\begin{aligned} 1 &= \int_{x=1}^2 \int_{y=x}^2 ax dy dx = \int_{x=1}^2 ax(2-x) dx \\ &= a \left( 2^2 - 1^2 - \frac{2^3}{3} + \frac{1^3}{3} \right) = \frac{2}{3} a \end{aligned}$$

$$a = 3/2$$

b) Determine the marginal PDF  $f_Y(y)$

- For  $1 \leq y \leq 2$

$$\begin{aligned} f_Y(y) &= \int_1^y ax dx = \frac{a}{2}(y^2 - 1) \\ &= \frac{3}{4}(y^2 - 1) \end{aligned}$$

And,  $f_Y(y) = 0$ , otherwise

$$f_{X,Y}(x,y) = \begin{cases} ax, & \text{if } 1 \leq x \leq y \leq 2 \\ 0, & \text{otherwise} \end{cases}$$

c) Determine the expected value of  $1/x$ , given that  $Y=3/2$

- Since we know  $Y = 3/2$ , then, for  $1 \leq x \leq 3/2$

$$\begin{aligned} f_{X|Y} \left( x | Y = \frac{3}{2} \right) &= \frac{f_{X,Y} \left( x, \frac{3}{2} \right)}{f_Y \left( \frac{3}{2} \right)} \\ &= \frac{(3/2)x}{\frac{3}{4} \left( \left( \frac{3}{2} \right)^2 - 1^2 \right)} = \frac{8x}{5} \end{aligned}$$

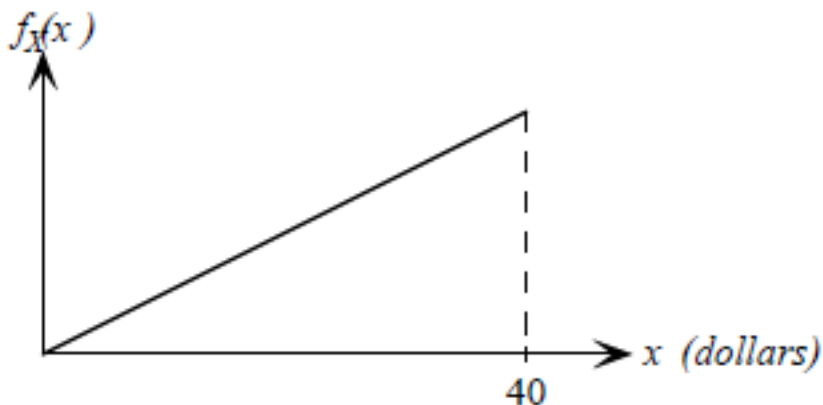
- Knowing this:

$$E \left[ \frac{1}{X} \mid Y = \frac{3}{2} \right] = \int_1^{\frac{3}{2}} \frac{1}{x} \frac{8x}{5} dx = \frac{4}{5}$$

## Example 3

Paul is vacationing. The amount  $X$  (in dollars) he takes to casino each evening is a random variable with the PDF shown in the figure.

At the end of each night, the amount  $Y$  that he has on leaving the casino is uniformly distributed between zero and twice the amount he took in



a) Determine the joint PDF  $f_{X,Y}(x, y)$

Multiplication rule:

$$f_{X,Y}(x, y) = f_X(x)f_{Y|X}(y|x)$$

What is  $f_X(x)$ ?

$$f_X(x) = ax$$
$$1 = \int_0^{40} ax dx = 800a$$

So,  $f_X(x) = x/800$

From the problem statement,

$$f_{Y|X}(y|x) = \frac{1}{2x}, \text{ for } y \in [0, 2x]$$

- Therefore,

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{1600}, & \text{if } 0 \leq x \leq 40, 0 < y < 2x \\ 0, & \text{otherwise} \end{cases}$$



b) What is the probability that on any given night Paul makes a positive profit at the casino?

- Paul makes a positive profit if  $Y > X$ , the probability associated with that is:

$$f_{X,Y}(x, y) = \begin{cases} \frac{1}{1600}, & \text{if } 0 \leq x \leq 40, 0 < y < 2x \\ 0, & \text{otherwise} \end{cases}$$

$$\begin{aligned} P(Y > X) &= \iint_{y>x} f_{X,Y}(x, y) dy dx = \int_0^{40} \int_x^{2x} \frac{1}{1600} dy dx \\ &= \frac{1}{2} \end{aligned}$$

c) Find the probability density function of Paul's profit on any particular night,  $Z = Y - X$ . What is  $E[Z]$ ?

Let's compute the joint density first (easier to get)

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

Since Z is conditionally uniformly distributed given X,

$$f_{Z|X}(z|x) = \frac{1}{2x}, \text{ for } -x \leq z \leq x$$

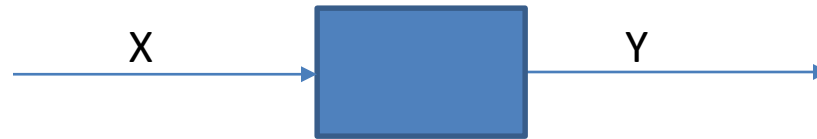
Therefore,

$$f_{X,Z}(x, z) = \frac{1}{1600}, \text{ for } 0 \leq x \leq 40, -x \leq z \leq x \text{ (} z \leq |x| \text{)}$$

Now, we can compute marginal density  $f_Z(z)$

$$\begin{aligned} f_Z(z) &= \int_x f_{X,Z}(x, z) dx = \int_{|z|}^{40} \frac{1}{1600} dx \\ &= \begin{cases} \frac{40 - |z|}{1600}, & \text{if } |z| < 40 \\ 0, & \text{otherwise} \end{cases} \end{aligned}$$

# Bayes rule



- X is unknown, but we have some prior belief in how X is distributed
- We observe random variable Y
- Need a model of the box:
  - If the true state of the world is X, how do we expect Y to be distributed
  - Inference problem, knowing Y, what can we say about X?
  - Inference problem is about finding probability distribution
    - $P(X|Y)$

$$P_{X|Y}(x|y) = \frac{P_{X,Y}(x, y)}{P_Y(y)} = \frac{P_{Y|X}(y|x)P_X(x)}{P_Y(y)}$$

$$P_Y(y) = \sum_x p_X(x)p_{Y|X}(y|x)$$

- Say, this is the discrete case
- Typical example:
  - $X = 1,0$  : airplane present/no present
  - $Y = 1,0$  : something did/did not register on radar
- Inference problem:
  - $P(X|Y)$  : given the radar measurement, calculate the probability that the plane is up there

- Continuous case:

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)} = \frac{f_X(x)f_{Y|X}(y|x)}{f_Y(y)}$$

$$f_Y(y) = \int_x f_X(x) f_{Y|X}(y|x) dx$$

- Typical example
  - X: some signal, e.g., current through resistor, with  $f_X(x)$
  - Y: signal with some noise, e.g., Gaussian noise
- Inference problem is the same
  - Compute  $f_{X|Y}$
  - $f_{Y|X}$  is the model of signal with noise

# Discrete X, Continuous Y

- Typical example (communication)
  - X: discrete signal (say a bit, 0,1),
  - Y: measured signal (X + Gaussian noise)
- prior:  $P_X(x)$ 
  - Could be equally-likely to send 0,1 (PMF)
- Continuous noise model:  $f_{Y|X}(y|x)$ 
  - Conditional densities of y in a universe that's specified by a particular value of x



$$P(X = x|Y = y) \approx P(X = x|y \leq Y \leq y + \delta)$$

$$= \frac{P(X = x)P(y \leq Y \leq y + \delta|X = x)}{P(y \leq Y \leq y + \delta)}$$

$$\approx \frac{P(X = x)f_{Y|X}(y|x)\delta}{f_Y(y)\delta}$$

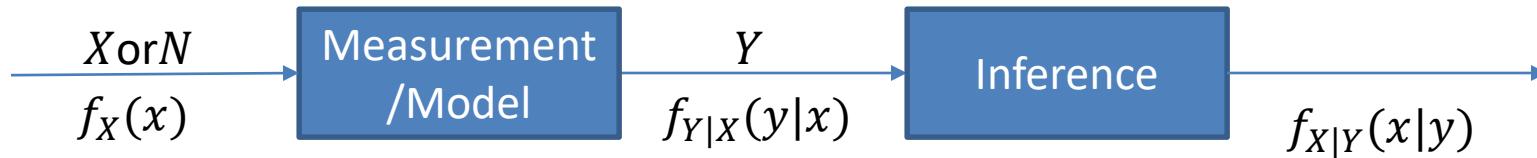
$$= \frac{P_X(x)f_{Y|X}(y|x)}{f_Y(y)}$$

$$f_Y(y) = \sum_i P_X(i)f_{Y|X}(y|i)$$

Put it together:

$$P_{X|Y}(x|y) = \frac{p_X(x)f_{Y|X}(y|x)}{f_Y(y)}$$

# Look at it again: Bayes rule



- If Y is a continuous random variable, we have:

- If X is continuous random variable

$$f_{X,Y}(x,y) = f_Y(y)f_{X|Y}(x|y) = f_X(x)f_{Y|X}(y|x)$$

So,

$$f_{X|Y}(x|y) = \frac{f_X(x)f_{Y|X}(y|x)}{f_Y(y)} = \frac{f_X(x)f_{Y|X}(y|x)}{\int_{-\infty}^{\infty} f_X(t)f_{Y|X}(y|t)dt}$$

- If N is discrete random variable, we have

$$f_Y(y)P(N = n|Y = y) = p_N(n)f_{Y|N}(y|n)$$

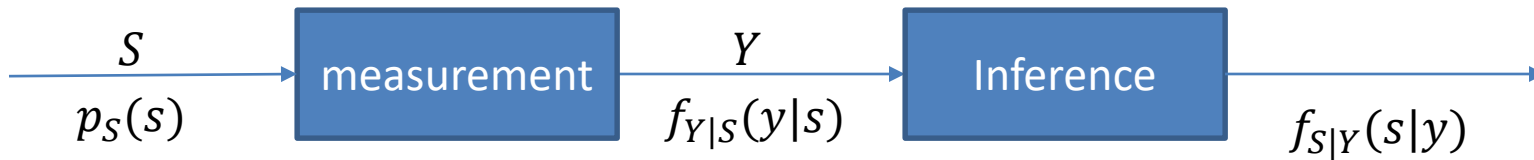
Resulting in the formula:

$$P(N = n|Y = y) = \frac{p_N(n)f_{Y|N}(y|n)}{f_Y(y)} = \frac{p_N(n)f_{Y|N}(y|n)}{\sum_i p_N(i)f_{Y|N}(y|i)}$$

## A quick example

- A Binary signal  $S$  is transmitted, and we are given that
$$P(S = 1) = p, P(S = -1) = 1 - p$$

The received signal is  $Y = N + S$ , where  $N$  is Gaussian noise ( $\mu=0, \sigma^2=1$ ), independent of  $S$ . What is the probability that  $S=1$ , as a function of the observed value  $y$  of  $Y$ ?



$$P(S = 1|Y = y) = \frac{p_S(1)f_{Y|S}(y|1)}{f_Y(y)}$$

$$f_Y(y) = \sum_i p_N(i)f_{Y|N}(y|i)$$

What is  $f_{Y|S}$ ?

If the measurement is additive Gaussian noise ( $N(0,1)$ ) to the original signal  $S$ , that is  $Y = S + \text{Noise}$

$$f_{Y|S}(y|S = 1) \sim N(\mu = 1, \sigma^2 = 1)$$

$$f_{Y|S}(y|S = -1) \sim N(\mu = -1, \sigma^2 = 1)$$

$$f_{Y|S}(y|S = 1) \sim N(\mu = 1, \sigma^2 = 1) = \frac{1}{\sqrt{2\pi}} e^{-(y-1)^2/2}$$

$$\begin{aligned} f_{S|Y}(S = 1|Y = y) &= \frac{p_S(1)f_{Y|S}(y|1)}{f_Y(y)} \\ &= \frac{p * \frac{1}{\sqrt{2\pi}} e^{-(y-1)^2/2}}{\frac{p}{\sqrt{2\pi}} e^{-(y-1)^2/2} + \frac{1-p}{\sqrt{2\pi}} e^{-(y+1)^2/2}} \\ &= \frac{pe^y}{pe^y + (1-p)e^{-y}} \end{aligned}$$

With this probability density function, we can do ‘informed’ probabilistic inference, e.g., finding the probability that your received signal  $y$  is within a particular range

## Continuous X, Discrete Y

$$f_{X|Y}(x|y) = \frac{f_X(x)p_{Y|X}(y|x)}{p_Y(y)}$$

$$p_Y(y) = \int_x f_X(x)p_{Y|X}(y|x)dx$$

- Typical example:
  - X: a continuous signal (intensity of light beam)
  - Y: discrete variable (count the number of photons)

# Example 1

- A light bulb produced by the company is known to have an exponentially distributed lifetime  $Y$ . However, the company has been experiencing quality control problems. On any given day, the parameter  $\lambda$  of the PDF of  $Y$  is actually a random variable, uniformly distributed in the interval  $[1, 3/2]$ .
- We test a light bulb and record its lifetime. What can we say about the underlying parameter  $\lambda$

- Let's model the parameter,  $\lambda$ , as a uniform random variable  $\Lambda$  with PDF:

$$f_{\Lambda}(\lambda) = 2, \text{ for } 1 \leq \lambda \leq \frac{3}{2}$$

So if we test the light bulb and record its lifetime ( $Y = y$ ), then how can we use that ( $Y = y$ ) to modify our original belief of  $f_{\Lambda}(\lambda)$

Therefore, the available information about  $\Lambda$  is captured by the conditional PDF  $f_{\Lambda|Y}(\lambda|Y = y)$ , we can compute it using continuous Bayes rule

$$f_{\Lambda|Y}(y) = \frac{f_{\Lambda}(\lambda)f_{Y|\Lambda}(y|\lambda)}{\int_{-\infty}^{\infty} f_{\Lambda}(t)f_{Y|\Lambda}(y|t)dt} = \frac{2\lambda e^{-\lambda y}}{\int_1^{3/2} 2te^{-ty}dt}, \text{ for } 1 \leq \lambda \leq \frac{3}{2}$$

This is statistics – somewhat, we will come back to this

Think about it, after you measure it, what's the most likely parameter for this exponential distribution