## 550.420 Probability - SPRING 2016

- **1.** Suppose that X is a continuous random variable having pdf  $f(x) = \begin{cases} \frac{3x^2}{2} & \text{if } -1 < x < 1 \\ 0 & \text{otherwise} \end{cases}$
- (a) Compute the cdf  $F_X(x)$  of X. Recall that (just as a pdf) a cdf should be defined on the entire real line. For x < -1, f(x) = 0 which implies  $F_X(x) = 0$ .

For 
$$-1 \le x \le 1$$
,  $f(x) = \frac{3}{2}x^2$  which implies  $F_X(x) = \int_{-1}^x \frac{3}{2}u^2 du = \frac{u^3}{2}\Big|_{u=-1}^{u=x} = \frac{1}{2} + \frac{x^3}{2}$ .

For x > 1,  $F_X(x) = 1$  since all the probability mass under this pdf would have been accumulated already.

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$$x > 1$$
,  $F_X(x) = 1$  since all the probability in Therefore,  $F_X(x) = \begin{cases} 0 & \text{if } x < -1 \\ \frac{1+x^3}{2} & \text{if } -1 \le x \le 1 \\ 1 & \text{if } x > 1 \end{cases}$ 

- (b) Compute  $P(0 < X \le \frac{1}{2})$ .  $P(0 < X \le \frac{1}{2}) = F_X(\frac{1}{2}) F_X(0) = (\frac{1 + (\frac{1}{2})^3}{2}) (\frac{1 + (0)^3}{2}) = \frac{1}{16}$ .
- 2. Suppose that X has a Gamma( $\alpha, \beta$ ) distribution where  $\alpha > 0$  is the shape parameter and  $\beta > 0$  is the scale parameter.
- (a) By performing an appropriate integration, clearly show why  $E(X) = \alpha \beta$ .  $E(X) = \int_0^\infty x \cdot \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)} dx = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} \int_0^\infty x^{(\alpha+1)-1}e^{-x/\beta} dx = \frac{\beta^{\alpha+1}\Gamma(\alpha+1)}{\beta^{\alpha}\Gamma(\alpha)} \int_0^\infty \frac{x^{(\alpha+1)-1}e^{-x/\beta}}{\beta^{\alpha+1}\Gamma(\alpha+1)} dx = \frac{\beta^{\alpha+1}\Gamma(\alpha+1)}{\beta^{\alpha}\Gamma(\alpha)}$ since the last integral is 1 because  $\frac{x^{(\alpha+1)-1}e^{-x/\beta}}{\beta^{\alpha+1}\Gamma(\alpha+1)}$  is a pdf on  $0 < x < \infty$ . But then by the reduction property of the Euler Gamma function:  $E(X) = \frac{\beta^{\alpha+1}\Gamma(\alpha+1)}{\beta^{\alpha}\Gamma(\alpha)} = \frac{\beta\alpha\Gamma(\alpha)}{\Gamma(\alpha)} = \alpha\beta$ .
- (b) If we further assume  $\alpha > 1$ , compute  $E(\frac{1}{X})$ . For an extra bonus point, why assume  $\alpha > 1$ ? In a very similar way  $E(\frac{1}{X}) = \int_0^\infty \frac{1}{x} \cdot \frac{x^{\alpha 1} e^{-x/\beta}}{\beta^\alpha \Gamma(\alpha)} \, dx = \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty x^{(\alpha 1) 1} e^{-x/\beta} \, dx = \frac{\beta^{\alpha 1} \Gamma(\alpha 1)}{\beta^\alpha \Gamma(\alpha)} \int_0^\infty \frac{x^{(\alpha 1) 1} e^{-x/\beta}}{\beta^{\alpha 1} \Gamma(\alpha 1)} \, dx = \frac{\beta^{\alpha 1} \Gamma(\alpha 1)}{\beta^\alpha \Gamma(\alpha)} = \frac{\Gamma(\alpha 1)}{\beta(\alpha 1)\Gamma(\alpha 1)} = \frac{1}{(\alpha 1)\beta}.$  Since  $\Gamma(\alpha 1)$  is only defined when  $\alpha 1 > 0$ , we see this is equivalent to  $\alpha > 1$ .
  - Since I  $(\alpha 1)$  is only defined when  $\alpha 1 > 0$ , we see this is equivalent to  $\alpha > 1$ .
- 3. Suppose that X and Y are jointly discrete random variables having the following joint pmf:

$p_{X,Y}(x,y)$	y = 1	y = 2	y = 3	
x = 1	.30	.18	.12	$p_X(1) = .6$ $p_X(2) = .4$
x = 2	.20	.12	.08	$p_X(2) = .4$
	$p_Y(1) = .5$	$p_Y(2) = .3$	$p_Y(3) = .2$	

- (a) Clearly verify whether or not X and Y are independent. Be sure to state your conclusion. X and Y are independent since  $p_{X,Y}(x,y) = p_X(x)p_Y(y)$  for every x = 1, 2 and y = 1, 2, 3. Check:  $.3 = .5 \times .6$ ,  $.18 = .3 \times .6$ ,  $.12 = .2 \times .6$ ,  $.2 = .5 \times .4$ ,  $.12 = .3 \times .4$ ,  $.08 = .2 \times .4$ .
- (b) Compute
  - (i)  $P(Y > X) = p_{X,Y}(1,2) + p_{X,Y}(1,3) + p_{X,Y}(2,3) = .18 + .12 + .08 = .38.$
  - (ii)  $P(Y = 1) = p_Y(1) = .5$ .
  - (iii)  $P(X = 1|Y \le 2) = P(X = 1) = .6$  since X and Y are independent.
- (c) Compute
  - (i)  $E(X) = 1 \times .6 + 2 \times .4 = 1.4$ .
  - (ii)  $E(Y|X=1) = E(Y) = 1 \times .5 + 2 \times .3 + 3 \times .2 = 1.7$ .

- 4. (a) If Z is a standard normal random variable, compute P(-2.1 < Z < 2.1). From the standard normal table:  $P(-2.1 < Z < 2.1) = \Phi(2.1) = \Phi(-2.1) = \Phi(2.1) - (1 - \Phi(2.1)) = 2\Phi(2.1) - 1 = 2(.9821) - 1 = .9642$ .
- (b) Suppose W represents the score on a certain exam. Assume that W is normally distributed having a mean  $\mu = 50$  points and variance  $\sigma^2 = 400$  points<sup>2</sup> (i.e.,  $\sigma = 20$  points). Compute the probability that W will be between 8 and 92 inclusive.

will be between 8 and 92 inclusive.  $P(8 \le W \le 92) = P(\frac{8-50}{20} \le \frac{W-\mu}{\sigma} \le \frac{92-50}{20}) = P(-2.1 \le Z \le 2.1) = .9642 \text{ (from part (a) since } Z \text{ is a continuous random variable the two probabilities are the same.}$ 

**5.** Suppose  $U \sim \text{uniform}(0, \frac{1}{2})$ , i.e., U is a continuous random variable with pdf f(x) = 2 for  $0 < x < \frac{1}{2}$ . Compute the n-th moment of U, i.e.,  $E(U^n)$ , where  $n \geq 0$  is an integer.

For any 
$$n \ge 0$$
,  $E(U^n) = \int_0^{1/2} u^n \cdot 2 \, du = \frac{2u^{n+1}}{n+1} \Big|_{u=0}^{u=1/2} = \frac{1}{2^n(n+1)}$ .

(bonus question) Show that  $\sum_{n=0}^{\infty} \frac{1}{2^n(n+1)} = 2\ln(2)$  by computing  $E(\frac{1}{1-U})$  two different ways.

On the one hand, 
$$E(\frac{1}{1-U}) = \int_0^{1/2} \frac{1}{1-u} \cdot 2 \, du = -2 \ln(1-u)|_{u=0}^{u=1/2} = 2 \ln(2)$$
.  
On the other hand, since  $|U| \leq \frac{1}{2} < 1$ , we have  $\sum_{n=0}^{\infty} U^n = \frac{1}{1-U}$  so  $E(\frac{1}{1-U}) = E(\sum_{n=1}^{\infty} U^n) = \sum_{n=0}^{\infty} E(U^n) = \sum_{n=0}^{\infty} \frac{1}{2^n(n+1)}$ .  
Therefore,  $\sum_{n=0}^{\infty} \frac{1}{2^n(n+1)} = 2 \ln(2)$ .

**6.** Suppose  $X|Y=y\sim \mathrm{uniform}(0,y)$  and  $Y\sim \mathrm{Gamma}(2,1)$ . That is,

$$f_{X|Y}(x|y) = \begin{cases} \frac{1}{y} & \text{if } 0 < x < y \\ 0 & \text{otherwise} \end{cases}$$
 and  $f_Y(y) = \begin{cases} ye^{-y} & \text{if } y > 0 \\ 0 & \text{otherwise} \end{cases}$ .

- (a) Find the marginal pdf of X. Be careful with your ranges of integration! First we find the joint pdf of X and Y:  $f_{X,Y}(x,y) = f_{X|Y}(x|y)f_Y(y) = \frac{1}{y} \cdot ye^{-y} = e^{-y}$  for 0 < x < y, y > 0. Therefore, the marginal of X is  $f_X(x) = \int_x^\infty e^{-y} dy = e^{-x}$  for x > 0; and,  $f_X(x) = 0$  for  $x \le 0$ .
- (b) Compute only one of the following (you choose): P(3 < X < 7|Y = 10) or  $P(3 < X < 7|Y \le 10)$ . Do not compute both!

The easiest one to compute is the first one:  $P(3 < X < 7|Y = 10) = \int_3^7 f_{X|Y}(x|10) dx = \int_3^7 \frac{1}{10} dx = .4$ .

7. Suppose  $X_1$  and  $X_2$  are independent random variables with  $X_i \sim \text{Poisson}(\lambda_i)$  for i = 1, 2. Suppose we observe  $X_1 + X_2 = n$ . Find the probability that  $X_1 = x$ , that is, compute  $P(X_1 = x | X_1 + X_2 = n)$  for appropriate x.

Feel free to use any results you may recall from homework about sums of independent Poisson random variables.

I will use the fact that a sum of independent Poisson random variables is again a Poisson with the parameters adding; i.e.,  $X_1 + X_2$  has a Poisson $(\lambda_1 + \lambda_2)$  distribution. In this case, for any  $x = 0, 1, \ldots, n$  (x cannot be bigger than n)

$$P(X_{1} = x | X_{1} + X_{2} = n) = \frac{P(X_{1} = x, X_{1} + X_{2} = n)}{P(X_{1} + X_{2} = n)} = \frac{P(X_{1} = x, X_{2} = n - x)}{\frac{e^{-(\lambda_{1} + \lambda_{2})(\lambda_{1} + \lambda_{2})^{n}}}{n!}}$$

$$= \frac{P(X_{1} = x)P(X_{2} = n - x)}{\frac{e^{-(\lambda_{1} + \lambda_{2})(\lambda_{1} + \lambda_{2})^{n}}}{n!}} = \frac{\frac{e^{-\lambda_{1} \lambda_{1}^{x}} e^{-\lambda_{2} \lambda_{2}^{n - x}}}{x!}}{\frac{e^{-(\lambda_{1} + \lambda_{2})(\lambda_{1} + \lambda_{2})^{n}}}{n!}}$$

$$= \frac{n!}{x!(n - x)!} \cdot (\frac{\lambda_{1}}{\lambda_{1} + \lambda_{2}})^{x} (\frac{\lambda_{2}}{\lambda_{1} + \lambda_{2}})^{n - x}$$

i.e., the conditional distribution is binomial with parameters n and  $p = \lambda_1/(\lambda_1 + \lambda_2)$ .