Printed Name:	
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STAT610 Exam II Thursday, 31 October 2024

Instructions.

- You have 75 minutes.
- You may use a stand-alone calculator, but no other resources.
- Please write your solutions on separate sheets of paper, and return them in order with this sheet on top.
- You may use any results from class or homework as long as you explain clearly the result you are using (by name or description).
- To ensure credit, explain or show all of your steps.
- There are 60 points total.
- Attempt all parts of a question; some may not rely on successful completion of earlier parts.
- 1. (10 points) Suppose T has pdf $f_T(t) = \frac{1}{t \log(2)}$ for $1 \le t \le 2$ and the conditional distribution of X, given T, is exponential with scale parameter T. That is, $f_{X|T}(x|t) = \frac{1}{t}e^{-x/t}$ for x > 0.
 - (a) (10 points) Express the marginal pdf for X as a simple integral and then attempt the integration. It will help to note that the anti-derivative of $\frac{a}{t^2}e^{-a/t}$ is $e^{-a/t}$.
 - (b) (10 points) Find $\mathsf{E}(X)$ by using iterated expectation.
- 2. Let $T \sim \text{gamma}(\alpha, 1)$ and $R \sim \text{uniform}(0, 1)$, independent. Let (X, Y) = (RT, (1 R)T).
 - (a) (10 points) Compute $\mathsf{E}(XY)$. Hint: it may help to think about this in terms of expectations for (R,T).
 - (b) (10 points) Find the joint pdf for (X,Y). (Note that T=X+Y and $R=\frac{X}{X+Y}$.)
- 3. (10 points) Recall that $Cov(X,Y) = E((X \mu_X)(Y \mu_Y))$. Prove, for any real-valued a, that

$$\mathsf{E}((X - \mu_X)(Y - \mu_Y)) = \mathsf{E}((X - a)(Y - \mu_Y)).$$

Do not assume or use properties about covariances; just use expectations.

4. (10 points) Suppose $\beta > 0$ and W has probability mass function

$$f_W(w) = c(\beta)w^2 e^{-(w/\beta)^2}$$
 for $w = 1, 2, 3...$,

and $c(\beta)$ is defined to be the constant so that $f_W(w)$ sums to 1. Does this model define an exponential family with parameter β ? Why or why not?

(distribution formulas on next page)

Some common probability density functions and probability mass functions are provided below.

$$\begin{split} \mathbf{beta}(\alpha,\beta) \ f(x) &= \tfrac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1}, \ \text{for} \ 0 < x < 1, \ \alpha > 0, \ \beta > 0. \\ \mathsf{E}(X) &= \tfrac{\alpha}{\alpha+\beta}, \mathsf{Var}(X) = \tfrac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}. \end{split}$$

binomial
$$(n,p)$$
 $f(x) = \binom{n}{x} p^x (1-p)^{n-x}$, for $x = 0, 1, ..., n$; $0 .
 $\mathsf{E}(X) = np$, $\mathsf{Var}(X) = np(1-p)$.$

exponential(
$$\beta$$
) $f(x) = \frac{1}{\beta} e^{-x/\beta}$, for $x > 0$; $\beta > 0$.
 $E(X) = \beta$, $Var(X) = \beta^2$.

$$\mathbf{gamma}(\alpha,\beta) \ f(x) = \frac{1}{\beta^{\alpha}\Gamma(\alpha)} x^{\alpha-1} e^{-x/\beta}, \text{ for } x > 0; \ \alpha > 0, \ \beta > 0.$$

$$\mathsf{E}(X) = \alpha\beta, \mathsf{Var}(X) = \alpha\beta^2.$$

geometric(p)
$$f(x) = p(1-p)^{x-1}$$
, for $x = 1, 2, ...; 0 . $E(X) = \frac{1}{p}$, $Var(X) = \frac{1-p}{p^2}$.$

hypergeometric
$$(N, M, n)$$
 $f(x) = \binom{M}{x} \binom{N-M}{n-x} / \binom{N}{n}$, for $x = 0, 1, ..., n; n > 0, M > 0, N > 0$. $E(X) = \frac{nM}{N}$, $Var(X) = \frac{N-n}{N-1} \frac{nM}{N} (1 - \frac{M}{N})$.

negative binomial
$$(k,p)$$
 $f(x) = \binom{k+x-1}{k-1} p^k (1-p)^x$, for $x = 0, 1, 2, ...; 0 0$. $\mathsf{E}(X) = \frac{k(1-p)}{p}$, $\mathsf{Var}(X) = \frac{k(1-p)}{p^2}$.

$$\mathbf{normal}(\mu, \sigma^2) \ f(x) = \frac{1}{\sqrt{2\pi}\sigma} \mathrm{e}^{-(x-\mu)^2/2\sigma^2}, \ \text{for } -\infty < x < \infty; \ -\infty < \mu < \infty, \ \sigma^2 > 0.$$

$$\mathsf{E}(X) = \mu, \ \mathsf{Var}(X) = \sigma^2.$$

Poisson(
$$\lambda$$
) $f(x) = \frac{\lambda^x}{x!} e^{-\lambda}$, for $x = 0, 1, 2, ...; \lambda > 0$. $E(X) = \lambda$, $Var(X) = \lambda$.

uniform
$$(a,b)$$
 $f(x) = \frac{1}{b-a}$, for $a < x < b$; $a < b$.
 $\mathsf{E}(X) = \frac{a+b}{2}$, $\mathsf{Var}(X) = \frac{(b-a)^2}{12}$.

$$\begin{aligned} \mathbf{Weibull}(\gamma,\beta) \ f(x) &= \tfrac{\gamma}{\beta} x^{\gamma-1} \mathrm{e}^{-x^{\gamma}/\beta}, \ \mathrm{for} \ x > 0; \ \gamma > 0, \ \beta > 0. \\ \mathbf{E}(X) &= \beta^{1/\gamma} \Gamma(1+\tfrac{1}{\gamma}), \ \mathsf{Var}(X) = \beta^{2/\gamma} (\Gamma(1+\tfrac{2}{\gamma}) - \Gamma(1+\tfrac{1}{\gamma})^2). \end{aligned}$$