

# Intro Prob Lecture Notes

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## Last Time: Gamma PDF

- $X \sim \text{Gamma}(\alpha, \beta)$  where  $\alpha > 0, \beta > 0$  has pdf

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$$f(x) = \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\beta^{\alpha} \Gamma(\alpha)}$$

- For  $x > 0$
- The denominator is the normalizing constant.
- We usually aren't interested in finding the area under the curve, but we may later come back to compute tail probabilities.

- Remark: By recognizing this pdf in one form another and using the fact

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$$\int_0^{\infty} x^{\alpha-1} e^{-\frac{x}{\beta}} dx = \beta^{\alpha} \Gamma(\alpha)$$

- Will allow us to compute  $\mathbb{E}(X^n) \forall n$ .

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$$\begin{aligned}\mathbb{E}(X) &= \int_0^{\infty} x \cdot \frac{x^{\alpha-1} e^{-\frac{x}{\beta}}}{\beta^{\alpha} \Gamma(\alpha)} dx \\ &= \frac{1}{\beta^{\alpha} \Gamma(\alpha)} \int_0^{\infty} x^{\alpha} e^{-\frac{x}{\beta}} dx \\ &= \frac{1}{\beta^{\alpha} \Gamma(\alpha)} \beta^{\alpha+1} \Gamma(\alpha+1)\end{aligned}$$

This substitution is the "Normalization trick" - you don't always have to integrate it out

$$\begin{aligned}&= \frac{\beta^{\alpha+1} \Gamma(\alpha+1)}{\beta^{\alpha} \Gamma(\alpha)} \\ &= \frac{\beta^{\alpha+1} \alpha \Gamma(\alpha)}{\beta^{\alpha} \Gamma(\alpha)} \\ &= \alpha \beta\end{aligned}$$

- Exercise: Show  $\mathbb{E}(X^2) = \alpha(\alpha+1)\beta^2$  by using the normalization trick

## Beta-family of pdf's

- Important for ordered statistics, Bayesian statistics
- We say  $X \sim \text{Beta}(\alpha, \beta)$  if  $X$  has the pdf with  $\alpha > 0, \beta > 0$
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$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{\int_0^1 x^{\alpha-1}(1-x)^{\beta-1} dx}$$

– for  $0 < x < 1$ .

- Where, in fact,  $\int_0^1 x^{\alpha-1}(1-x)^{\beta-1} dx = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$  (show this for extra credit)
- Therefore the pdf is
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$$f(x) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1}(1-x)^{\beta-1}$$

– for  $0 < x < 1$ .

- Exercise: Show  $\mathbb{E}(x) = \frac{\alpha}{\alpha+\beta}$

## CDF technique

- Suppose  $X \sim f_X(x)$ 
  - “ $X$  is a random variable that has  $f_X(x)$  as its pdf”
- And  $Y = g(X)$ . What is the pdf of  $Y$ ?
- Example 1: Suppose  $Z \sim \text{Normal}(0, 1)$

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$$\phi = \frac{e^{-\frac{x^2}{2}}}{\sqrt{2\pi}} \text{ for } -\infty < x < \infty$$

- Find the pdf of  $Y = Z^2$
- Step 1: Compute the cdf of  $Y$  in terms of the cdf of  $X$
- Step 2: Take a derivative and use the chain rule
- Step 1
  - \* Assume  $y \geq 0$
  - \*

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(Z^2 \leq y) \\ &= P(|Z| \leq \sqrt{y}) \\ &= P(-\sqrt{y} \leq Z \leq \sqrt{y}) \\ &= P(-\sqrt{y} < Z \leq \sqrt{y}) \\ &= \Phi(\sqrt{y}) - \Phi(-\sqrt{y}) \end{aligned}$$

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## Step 2

$$\begin{aligned}
\frac{d}{dy}F_Y(y) &= f_Y(y) \\
&= \frac{d}{dy}(\Phi(\sqrt{y}) - \Phi(-\sqrt{y})) \\
&= \phi(\sqrt{y})\frac{d}{dy}(\sqrt{y}) - \phi(-\sqrt{y})\frac{d}{dy}(-\sqrt{y}) \\
&= \phi(\sqrt{y})\frac{d}{dy}(\sqrt{y}) + \phi(\sqrt{y})\frac{d}{dy}(\sqrt{y}) \\
&= \dots \\
&= 2 \cdot \phi(\sqrt{y})\frac{1}{2\sqrt{y}} \\
&= \frac{1}{\sqrt{y}}\phi(\sqrt{y}) \\
&= \frac{1}{y^{\frac{1}{2}}} \cdot \frac{e^{-\frac{y}{2}}}{\sqrt{2\pi}} \\
&= \frac{y^{-\frac{1}{2}}e^{-\frac{y}{2}}}{\sqrt{2\pi}} \text{ for } y > 0 \\
&= \text{Gamma}(\frac{1}{2}, 2) \sim \chi_1^2
\end{aligned}$$

- Example 2: Suppose  $Y = g(X)$  and  $g$  is strictly monotone

– Claim

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

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### Case 1: $g$ strictly increasing

$$\begin{aligned}
F_Y(y) &= P(g(X) \leq y) \\
&= P(X \leq g^{-1}(y)) \\
&= F_X(g^{-1}(y))
\end{aligned}$$

$$* \quad f_Y(y) = f_X(g^{-1}(y)) \cdot \frac{d}{dy}(g^{-1}(y))$$

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### Case 2: $G$ decreasing

$$\begin{aligned}F_Y(y) &= P(g(X) \leq y) \\&= P(X \leq g^{-1}(y)) \\&= F_X(g^{-1}(y)) \\&= 1 - F_X(g^{-1}(y))\end{aligned}$$

$$* \quad f_Y(y) = -f_X(g^{-1}(y)) \cdot \frac{d}{dy}(-g^{-1}(y)) = f_X(g^{-1}(y)) \cdot \left| \frac{d}{dy}(-g^{-1}(y)) \right|$$

### Weibull distribution

- $X \sim \exp(1)$   $f_X(x) = e^{-x}$  for  $x > 0$
- Find pdf of  $Y = \nu + \alpha X^{\frac{1}{\beta}}$  ( $\nu \in \mathbb{R}, \alpha > 0, \beta > 0$ )