

Math 502AB - Lecture 10

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1 Lecture - Part 1

1.1 Identities

Examples

1. Consider $X \sim \text{Poisson}(\lambda)$. Then, we have:

$$P(X = x + 1) = \frac{\lambda}{x + 1} P(X = x)$$

To prove something like this, it isn't very difficult:

$$\begin{aligned} P(X = x + 1) &= \frac{e^{-\lambda} \lambda^{x+1}}{(x + 1)!} \\ &= \frac{\lambda}{x + 1} \cdot \frac{e^{-\lambda} \lambda^x}{x!} \\ &= \frac{\lambda}{x + 1} \cdot P(X = x) \end{aligned}$$

2. Consider $X \sim \text{gamma}(\alpha, \beta)$ with $\alpha > 1$. Then for any a and b :

$$P(a < X < b) = \beta (f(a|\alpha, \beta) - f(b|\alpha, \beta)) + P(a < Y < b)$$

Where $Y \sim \text{gamma}(\alpha - 1, \beta)$.

Proof:

$$\begin{aligned} P(a < X < b) &= \frac{1}{\beta^\alpha \Gamma(\alpha)} \int_a^b e^{-x/\beta} x^{\alpha-1} dx \\ \text{Let } u &= x^{\alpha-1} \quad dv = e^{-x/\beta} dx \\ \Rightarrow du &= (\alpha - 1)x^{\alpha-2} dx \quad v = -\beta e^{-x/\beta} \end{aligned}$$

Then we have:

$$\begin{aligned}
& \frac{1}{\beta^\alpha \Gamma(\alpha)} \left\{ -\beta x^{-\alpha-1} e^{-x/\beta} \Big|_a^b + \int_a^b (\alpha-1) x^{\alpha-2} \beta e^{-x/\beta} dx \right\} \\
&= \beta \{f(a|\alpha, \beta) - f(b|\alpha, \beta)\} + \int_a^b \frac{1}{\beta^{\alpha-1} \Gamma(\alpha-1)} x^{\alpha-2} e^{-x/\beta} dx \\
&= \beta (f(a|\alpha, \beta) - f(b|\alpha, \beta)) + P(a < Y < b)
\end{aligned}$$

1.2 Stein's Lemma

Let $Z \sim N(0, 1)$ and $g(x)$ be a differentiable function that satisfies $E|g'(z)| < \infty$.

Then:

$$E[z \cdot g(z)] = E[g'(z)]$$

Proof:

We have:

$$f(z) = \frac{1}{\sqrt{2\pi}} e^{-z^2/2} \Rightarrow f'(z) = \frac{1}{\sqrt{2\pi}} - z e^{-z^2/2} = -z f(z)$$

$$\begin{aligned}
E[g'(z)] &= \int_{-\infty}^{\infty} g'(z) f_Z(z) dz \\
&= \int_{-\infty}^0 g'(z) f_Z(z) dz \quad (1^*) + \int_0^{\infty} g'(z) f_Z(z) dz \quad (2^*)
\end{aligned}$$

(2*):

$$\begin{aligned}
\int_0^{\infty} g'(z) \left[\int_{-\infty}^z f'_Z(t) dt \right] dz &= \int_0^{\infty} \int_{-\infty}^z g'(z) f'_Z(t) dt dz \\
&= \int_0^{\infty} \int_{-\infty}^z -t f_Z(t) g'(z) dt dz \\
&= \int_{-\infty}^0 \int_0^{\infty} -g'(z) t f_Z(t) dz dt + \int_0^{\infty} \int_t^{\infty} -g'(z) t f_Z(t) dz dt \\
&= \int_0^{\infty} t f_Z(t) \left[\int_0^{\infty} g'(z) dz \right] dt - \int_0^{\infty} t f_Z(t) g'(z) dt dz \\
&= \int_0^{\infty} t f_Z(t) \left[\int_0^{\infty} g'(z) dz - \int_t^{\infty} g'(t) dz \right] dt \\
&= \int_0^{\infty} t f_Z(t) \left[\int_0^t g'(z) dz \right] dt \\
&= \int_0^{\infty} t f_Z(t) [g(t) - g(0)] dt
\end{aligned}$$

(2*): Similarly, it can be shown that

$$\int_{-\infty}^0 g'(z) f_Z(z) dz = \int_{-\infty}^0 t f_Z(t) [g(t) - g(0)] dt$$

Combining **(1*)** and **(2*)** we get:

$$\begin{aligned} \int_{-\infty}^{\infty} t[g(t) - g(0)] f_Z(t) dt &= E[Zg(Z) - Zg(0)] \\ &= E[Zg(Z)] - g(0)E[Z] \\ &= E[zg(z)] \end{aligned}$$

1.3 Stein's Lemma (Case: $N(\mu, \sigma^2)$)

Let $X \sim N(\mu, \sigma^2)$, then $Z = \frac{X-\mu}{\sigma} \sim N(0, 1)$. By the lemma that we just proved, we have:

$$E \left[\frac{X-\mu}{\sigma} g \left(\frac{X-\mu}{\sigma} \right) \right] = E \left[g' \left(\frac{X-\mu}{\sigma} \right) \right]$$

Let $h(x) = g \left(\frac{x-\mu}{\sigma} \right)$ and $h'(x) = \frac{1}{\sigma} g' \left(\frac{x-\mu}{\sigma} \right)$. This implies that:

$$E \left[\left(\frac{X-\mu}{\sigma} \right) h(X) \right] = E [\sigma h'(x)]$$

And, equivalently:

$$E [(X - \mu)h(X)] = E [\sigma^2 h'(x)]$$

Example:

Consider obtaining higher order moments of $X \sim N(\mu, \sigma^2)$. We know that $E(X) = \mu$, $E(X^2) = \mu^2 + \sigma^2$. But what if we wanted to find $E(X^3)$?

Let $h(x) = x^2$. Then:

$$\begin{aligned} E[(X - \mu)X^2] &= E[\sigma^2(2X)] \\ E[X^3] - \mu E[X^2] &= 2\sigma^2 E(X) \\ \Rightarrow E[X^3] &= \mu(\mu^2 + \sigma^2) + 2\sigma^2 \mu \end{aligned}$$

Theorem:

Let $X_p \sim \chi_{(p)}^2$. Then:

$$E[h(X_p)] = p E \left[\frac{h(X_{p+2})}{X_{p+2}} \right]$$

Proof:

$$\begin{aligned}
E[h(X_p)] &= \int_0^\infty \frac{h(x)}{\Gamma\left(\frac{p}{2}\right) 2^{p/2}} x^{\frac{p}{2}-1} e^{-x/2} dx \\
&= \frac{1}{\Gamma\left(\frac{p}{2}\right) 2^{p/2}} \int_0^\infty x^{\frac{p}{2}-1} e^{-x/2} h(x) \cdot \frac{x}{x} dx \\
&= \frac{1}{\Gamma\left(\frac{p}{2}\right) 2^{p/2}} \int_0^\infty \frac{h(x)}{x} x^{p/2} e^{-x/2} dx
\end{aligned}$$

We recognize that The right side is the *kernel* of a $\chi^2_{(p+2)}$ distribution, since $\frac{p}{2} = \frac{p+2}{2} - 1$. So we then have:

$$\begin{aligned}
\Gamma\left(\frac{p}{2}\right) &= \frac{\frac{p}{2} \Gamma\left(\frac{p}{2}\right) 2^{p/2}}{p/2} \\
&= \frac{\Gamma\left(\frac{p}{2} + 1\right) 2^{\frac{p}{2}+1}}{p} = \frac{\Gamma\left(\frac{p+2}{2}\right) 2^{\frac{p+2}{2}}}{p}
\end{aligned}$$

Example:

Consider $X_p \sim \chi^2_{(p)}$. Let $h(x) = x$. Now, using the above theorem, we have:

$$E[X_p] = pE\left[\frac{X_{p+2}}{X_{p+2}}\right] = p$$

Let's calculate the variance. We will let $h(x) = x^2$, and, by the theorem we have:

$$\begin{aligned}
E[X_p^2] &= pE\left[\frac{X_{p+2}^2}{X_{p+2}}\right] = pE[x_{p+2}] = p(p+2) \\
\Rightarrow \text{Var}(X_p) &= E[X_p^2] - E[X_p]^2 = p(p+2) - p^2 = 2p
\end{aligned}$$

1.4 Discrete Case Identities

Poisson (Hwang Theorem)

Suppose that $X \sim \text{poisson}(\lambda)$ and $g(x)$ is a function such that $-\infty < E[g(X)] < \infty$ and $-\infty < g(-1) < \infty$. Then we have:

$$E[\lambda g(X)] = E[Xg(X-1)]$$

Proof:

We first note that:

$$E[\lambda g(X)] = \sum_{x=0}^{\infty} \lambda g(x) \frac{e^{-\lambda} \lambda^x}{x!}$$

Letting $y = x + 1$, we get $x = y - 1$:

$$\sum_{y=1}^{\infty} \lambda g(y-1) \frac{e^{-\lambda} \lambda^{y-1}}{(y-1)!}$$

Using the same trick as the other theorem, we multiply by $\frac{y}{y}$ to get:

$$\begin{aligned} \sum_{y=1}^{\infty} \lambda y g(y-1) \frac{e^{-\lambda} \lambda^{y-1}}{y(y-1)!} \\ &= \sum_{y=1}^{\infty} y g(y-1) \frac{e^{-\lambda} \lambda^y}{y!} \\ &= \sum_{y=0}^{\infty} y g(y-1) \frac{e^{-\lambda} \lambda^y}{y!} = E[Y g(Y-1)] \end{aligned}$$

Example:

Consider $X \sim \text{poisson}(\lambda)$. Then we know that $E[X] = \lambda$ and $E[X^2] = \lambda + \lambda^2$. Now, suppose that we let $g(x) = x^2$. Then we have:

$$\begin{aligned} E[\lambda X^2] &= E[X(X-1)^2] \\ \lambda E[X^2] &= E[X(X^2 - 2X + 1)] \\ E[X^3] &= \lambda E[X^2] + 2E[X^2] - E[X] \\ &= (\lambda + 2)(\lambda + \lambda^2) - \lambda \end{aligned}$$