LECTURE 12

• Readings: Section 4.1

Lecture outline

- Definition of Transforms
- Why transforms?
- Moment Generating Property
- Examples
- Application to Sums of Indep. R.V.s

Definition of Transforms

$$M_X(s) = \mathbf{E}[e^{sX}]$$

- Discrete, PMF: $M_X(s) = \mathbf{E}[e^{sX}] = \sum_{x} e^{sx} p_X(x)$
- Continuous, PDF: $M_X(s) = \mathbf{E}[e^{sX}] = \int_{-\infty}^{\infty} e^{sx} f_X(x) dx$
- Inversion theorem:





Why Transforms?

• A new kind of representation.

- Sometimes convenient for:
 - Calculations
 - Analytic Derivations
 - Theorem Proving

Moment Generating Property

- Moments: $E[X^n]$, we need to integrate.
- Can instead differentiate the transform:

$$M_X(s) = \mathbf{E}[e^{sX}] = \begin{cases} \sum_{x} e^{sx} p_X(x) \\ \int_{-\infty}^{\infty} e^{sx} f_X(x) dx \end{cases}$$
$$M_X(s)|_{s=0} = \mathbf{E}[e^{0X}] = 1$$
$$\frac{d}{ds} M_X(s)\Big|_{s=0} = \mathbf{E}[X]$$
$$\frac{d^n}{ds^n} M_X(s)\Big|_{s=0} = \mathbf{E}[X^n]$$

Example: Exponential PDF

$$f_X(x) = \lambda e^{-\lambda x}$$
 over $x \ge 0$ $(\lambda > 0)$



$$M_X(s) = \lambda \int_0^\infty e^{sx} e^{-\lambda x} dx = \lambda \int_0^\infty e^{(s-\lambda)x} dx = \frac{\lambda}{\lambda-s}$$
$$\mathbf{E}[X] = \left. \frac{d}{ds} M_X(s) \right|_{s=0} = \frac{\lambda}{(\lambda-s)^2} \right|_{s=0} = \frac{1}{\lambda}$$

• We can get all higher order moments, (E[X²], etc.) in a similar fashion.

Example: Geometric PMF

• If we know X takes nonnegative integer values:

$$M_X(s) = \mathbf{E}[e^{sX}] = \sum_x e^{sx} p_X(x)$$

= $p_X(0) + p_X(1)e^s + p_X(2)e^{2s} + \cdots$

- Now, say we have: $M_X(s) = \frac{pe^s}{1 (1 p)e^s}$ Recall: $\frac{1}{1 \alpha} = 1 + \alpha + \alpha^2 + \cdots$ for $|\alpha| < 1$

So:
$$M_X(s) = pe^s \left(1 + (1-p)e^s + (1-p)^2 e^{2s} + \cdots \right)$$

• We recognize: $p_X(x) = p(1-p)^{x-1}$ for $x = 1, 2, \cdots$

This is the geometric PMF.

The Transform of X + Y .

- Let X, Y be two **independent** r.v.s.
- Let W = X + Y.



• We get: $M_W(s) = M_X(x)M_Y(s)$

Transform of the Normal PDF

- General normal X: $f_X(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$
- Transform: $M_X(s) = e^{(s^2\sigma^2/2) + s\mu}$
- Sum of independent normals:

 $X \sim N(\mu_x, \sigma_x^2) \qquad Y \sim N(\mu_y, \sigma_y^2) \qquad W = X + Y$ $M_W(s) = M_X(x)M_Y(s)$ $= e^{(s^2\sigma_x^2/2) + s\mu_x} \cdot e^{(s^2\sigma_y^2/2) + s\mu_y}$ $= e^{[s^2(\sigma_x^2 + \sigma_y^2)/2 + s(\mu_x + \mu_y)]}$

• Conclude: $W \sim N(\mu_x + \mu_y, \sigma_x^2 + \sigma_y^2)$