PROBABILITY THEORY LECTURE 3

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OVERVIEW LECTURE 3

- ► Transforms
- ► Probability generating function
- Moment generating function
- Characteristic function
- Transforms and distributions with random parameters

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- $X \stackrel{d}{=} Y \iff g_X(t) = g_Y(t)$
- ► **Summation** of independent variables corresponds to **multiplication** of transforms. Nice!

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TH Let $X_1, X_2, ..., X_n$ be independent. Then

$$g_{X_1+X_2+...+X_n}(t) = \prod_{k=1}^n g_{X_k}(t)$$

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► Moments can be computed

$$EX = g_X'(1)$$

$$ext{Var} X = g_X''(1) + g_X'(1) - \left(g_X'(1)
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$$g_X(t) = \prod_{i=1}^n g_{X_i(t)} = \prod_{i=1}^n (q + pt) = (q + pt)^n$$

so $X \sim Bin(n, p)$.

- ✓ Poisson prob func: $p(X = k) = e^{-m} m^k / k!$
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$$g_{X_1+X_2}(t) = e^{m_1(t-1)}e^{m_2(t-1)} = e^{(m_1+m_2)(t-1)}$$

so
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- ▶ Taylor expansion around t = 0 [note $\frac{\partial^k e^{tX}}{\partial t^k} = X^k e^{tX}$]

$$e^{tX} = 1 + \sum_{n=1}^{\infty} \frac{t^n X^n}{n!}$$

so

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MOMENT GENERATING FUNCTION - EXAMPLES



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$$\psi_X(t) = Ee^{tX} = qe^{t\cdot 0} + pe^{t\cdot 1} = q + pe^t$$

- $\psi'_X(t) = pe^t \text{ so } E(X) = \psi'_X(0) = p.$
- $\psi_X'''(t) = pe^t \text{ so } E(X^2) = \psi_X''(0) = p.$
- $Var(X) = E(X^2) [E(X)]^2 = p p^2 = pq$
- \longrightarrow $X \sim \Gamma(p, a)$

Moment Generating Function - examples

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$$\psi_X(t) = \frac{1}{(1 - at)^p}$$

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If $X \sim \Gamma(d, p)$, what is the distribution of $Y = \sigma \cdot X$?

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$$\psi_X(t) = \frac{1}{(1 - dt)^p}$$

$$\psi_Y(t) = \frac{1}{(1 - d\sigma t)^p},$$

which is the mgf of $\Gamma(d\sigma,p)$. Gamma family is closed under scaling.

Per Sidén (Statistics, Liu) Probability Theory - L3

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$$\varphi_X(t) = Ee^{itX} = E(\cos tX + i\sin tX)$$

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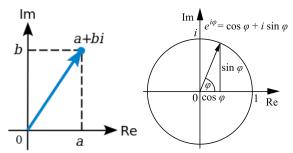
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 \longrightarrow $X \sim U(a, b)$, then

$$\varphi_X(t) = \frac{e^{itb} - e^{ita}}{it(b-a)}$$

COMPLEX NUMBERS

- ▶ Complex number $z = a + b \cdot i$
- ightharpoonup Re(z) = a is the real part of z
- ▶ Im(z) = b is the imaginary part of z
- ▶ Complex conjugate $\bar{z} = a b \cdot i$
- ► Addition: $z_1 + z_2 = a_1 + a_2 + (b_1 + b_2) \cdot i$
- ► Multiplication: $z_1z_2 = a_1a_2 b_1b_2 + (a_1b_2 + a_2b_1)i$
- ► Modulus: $|z| = \sqrt{a^2 + b^2}$. Length of vector.
- ► Complex exponentials: $e^{ix} = \cos x + i \cdot \sin x$



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TH Let F be the distribution function of X. If F is continuous at a and b, and $\int_{-\infty}^{\infty} |\varphi(t)| dt < \infty$ then

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$$\varphi_{aX+b}(t) = e^{ibt} \varphi_X(at)$$

TRANSFORMS - DISTRIBUTIONS WITH RANDOM PARAMETERS

- ▶ Transforms are expected values (or t^X , e^{tX} or e^{itX}), so the law of iterated expectation is useful.
- Let $X|(N=n) \sim Bin(n,p)$ and $N \sim Po(\lambda)$. What is the marginal distribution of X?

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- Let $X|(N=n) \sim Bin(n,p)$ and $N \sim Po(\lambda)$. What is the marginal distribution of X? X is non-negative and integer-valued, so $g_X(t)$ is defined.

$$g_X(t) = E\left(E(t^X|N)\right) = Eh(N)$$

where

PARAMETERS

$$h(n) = E(t^X | N = n) = (q + pt)^n.$$

We then have

$$g_X(t) = E\left((q + pt)^N\right) = g_N(q + pt) = e^{\lambda[(q+pt)-1]} = e^{\lambda p(t-1)}.$$

 $X|y \sim N(0,y)$ and $y \sim \text{Exp}(1)$, then $X \sim L(1/\sqrt{2})$. Prove using characteristic functions.

TRANSFORMS - SUMS OF RANDOM NUMBER OF RANDOM VARIABLES

TH Let $S_n = X_1 + X_2 + ... + X_n$ be a sum of i.i.d variables and N be a non-negative integer valued random variable. Then

$$g_{S_N}(t) = g_N(g_X(t))$$

$$\psi_{S_N}(t) = g_N(\psi_X(t)).$$

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$$\longrightarrow$$
 $X_1, X_2, \ldots \sim Exp(1)$ (i.i.d) and $N \sim Fs(p)$. S_N ?

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 (i.i.d) and $N \sim Fs(p)$. S_N ?

$$\psi_{S_N}(t) = g_N(\psi_X(t)) = \frac{1}{1 - \frac{t}{\rho}}$$

 $\Rightarrow S_N \sim Exp(1/\rho)$