

Lecture 8

MS Theory I

Review

§ 2.3 Moments and Moment Generating Functions

Definition 2.3.1 For each integer n , the n th *moment* of X (or $F_X(x)$), μ'_n , is

$$\mu'_n = E X^n.$$

The n th *central moment* of X , μ_n , is

$$\mu_n = E(X - \mu)^n,$$

where $\mu = \mu'_1 = E X$.

	<u>Moments</u>	<u>Central Moment</u>
$X \sim F_X(x)$	$\mu'_1 = E[X] = \mu$	$\mu_1 = E[X - \mu] = E[X - E[X]] = 0$
	$\mu'_2 = E[X^2]$	$\mu_2 = E[(X - \mu)^2] = \text{Var}(X)$
\vdots		\vdots
	$E[X] = \text{mean} = \mu$	$E[(X - \mu)^2] = \text{Var}(X)$

Definition 2.3.2 The *variance* of a random variable X is its second central moment, $\text{Var } X = E(X - E X)^2$. The positive square root of $\text{Var } X$ is the *standard deviation* of X .

Theorem 2.3.4 If X is a random variable with finite variance, then for any constants a and b ,

$$\text{Var}(aX + b) = a^2 \text{Var } X.$$

 Calculation
Easier

$$\text{Var}(X) = E[(X - E[X])^2] = E[X^2] - (E[X])^2$$

$$\text{Since: } \text{Var}(X) = E[(X - E(X))^2]$$

$$= E[X^2 - 2X E[X] + (E[X])^2]$$

$$= E[X^2] - 2(E[X])^2 + (E[X])^2$$

Note $E[X]$
is a constant

If b is constant
 $E[b] = b$

$$\text{Var}(X) = E[X^2] - (E[X])^2$$

Moment Generating Functions

- Generate moments
- Characterize a dist'n (used to show convergence)

Definition 2.3.6 Let X be a random variable with cdf F_X . The *moment generating function (mgf) of X* (or F_X), denoted by $M_X(t)$, is

$$M_X(t) = E e^{tX},$$

provided that the expectation exists for t in some neighborhood of 0. That is, there is an $h > 0$ such that, for all t in $-h < t < h$, $E e^{tX}$ exists. If the expectation does not exist in a neighborhood of 0, we say that the moment generating function does not exist.

More explicitly, we can write the mgf of X as

$$M_X(t) = \int_{-\infty}^{\infty} e^{tx} f_X(x) dx \quad \text{if } X \text{ is continuous,}$$

or

$$M_X(t) = \sum_x e^{tx} P(X = x) \quad \text{if } X \text{ is discrete.}$$

It is very easy to see how the mgf generates moments. We summarize the result in the following theorem.

Theorem 2.3.7 If X has mgf $M_X(t)$, then

$$E X^n = M_X^{(n)}(0),$$

where we define

$$M_X^{(n)}(0) = \left. \frac{d^n}{dt^n} M_X(t) \right|_{t=0}.$$

↙ How to get moments
from mgf.
(derivatives easier than
integrals).

That is, the n th moment is equal to the n th derivative of $M_X(t)$ evaluated at $t = 0$.

ReviewRecall: Gamma distribution (continuous)

Example 2.3.8 (Gamma Mgf).

$$f(x) = \frac{1}{\Gamma(a)B^a} x^{a-1} e^{-x/B} * I_{(0,\infty)}$$

$$I_{(0,\infty)}^{(x)} = \begin{cases} 1 & 0 < x < \infty \\ 0 & \text{else} \end{cases} \quad \begin{matrix} a > 0 \\ B > 0 \end{matrix}$$

Aside: Since $f(x)$ is a pdf, we can assume that for any $a > 0, b > 0$

$$\int_0^\infty \frac{1}{\Gamma(a)b^a} x^{a-1} e^{-x/B} dx = 1 \quad (\text{details later})$$

$$\begin{aligned} M_x(t) &= E[e^{tx}] = \int_0^\infty \frac{1}{\Gamma(a)B^a} e^{tx} x^{a-1} e^{-x/B} dx \\ &= \frac{1}{\Gamma(a)B^a} \int_0^\infty x^{a-1} e^{tx} e^{-x/B} dx \\ &= \frac{1}{\Gamma(a)B^a} \int_0^\infty x^{a-1} e^{-x(\frac{1}{B}-t)} dx \end{aligned}$$

known constants

Integrating over x
 - t assumed fixed
 - $M_x(t)$ will not be
 a ft'n of x .

$$= \frac{1}{\Gamma(a)B^a} \int_0^\infty x^{a-1} e^{-x[\frac{1}{B}-\frac{t}{B}]} dx$$

$$\text{Define } b = \frac{B}{1-Bt}$$

$$= \frac{1}{\Gamma(a)B^a} * \frac{b^a}{b^a} * \int_0^\infty x^{a-1} e^{-x/b} dx$$

$$= \underbrace{\left(\frac{b}{B}\right)^a \int_0^\infty \frac{1}{\Gamma(a)b^a} x^{a-1} e^{-x/b} dx}_{1 \text{ (since pdf)}}$$

assumes $b > 0$
 $\Rightarrow (1-Bt) > 0$
 $0 < Bt < 1$
 $\Rightarrow t < \frac{1}{B}$

$$= \left(\frac{b}{B}\right)^a = \left(\frac{B}{1-Bt} + \frac{1}{B}\right)^a = \boxed{\left(\frac{1}{1-Bt}\right)^a} \quad \left\{ \text{for } t < \frac{1}{B} \right.$$

$$M_x(t) = \left(\frac{1}{1-Bt}\right)^a$$

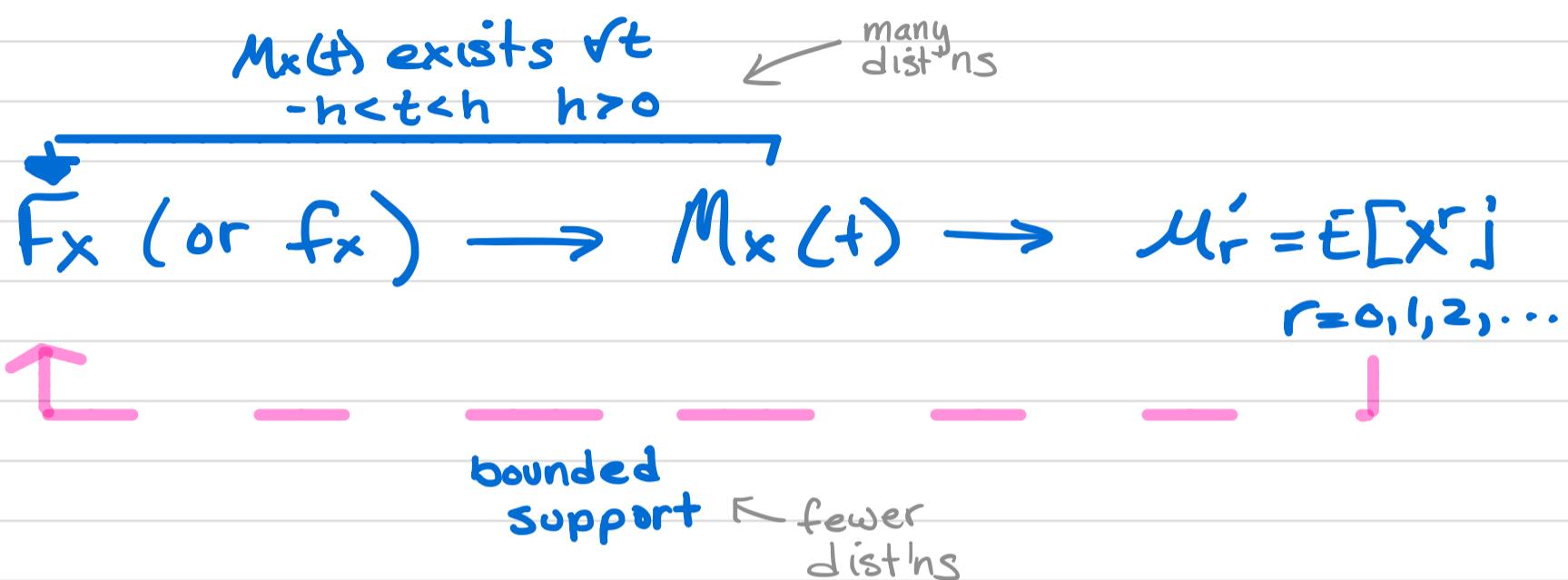
$$E[X] = \left. \frac{d}{dt} \left(\frac{1}{1-Bt}\right)^a \right|_{t=0} = \frac{d}{dt} (1-Bt)^{-a} = -a(1-Bt)^{-a-1}(-B)$$

$$= \left. \frac{aB}{(1-Bt)^{a+1}} \right|_{t=0} = aB$$

Review

Theorem 2.3.11 Let $F_X(x)$ and $F_Y(y)$ be two cdfs all of whose moments exist.

- a. If X and Y have bounded support, then $F_X(u) = F_Y(u)$ for all u if and only if $E X^r = E Y^r$ for all integers $r = 0, 1, 2, \dots$.
- b. If the moment generating functions exist and $M_X(t) = M_Y(t)$ for all t in some neighborhood of 0, then $F_X(u) = F_Y(u)$ for all u .



a) If X and Y bounded Support :

$$F_X(u) = F_Y(u) \forall u \iff E[X^r] = E[Y^r] \text{ for all } r = 0, 1, 2, 3, \dots$$

b) If mgfs exist $\forall t \quad -h < t < h \quad h > 0$

$$M_X(t) = M_Y(t) \Rightarrow F_X(u) = F_Y(u) \forall u.$$

Finally

Theorem 2.3.12 (Convergence of mgfs) Suppose $\{X_i, i = 1, 2, \dots\}$ is a sequence of random variables, each with mgf $M_{X_i}(t)$. Furthermore, suppose that

$$\lim_{i \rightarrow \infty} M_{X_i}(t) = M_X(t), \quad \text{for all } t \text{ in a neighborhood of 0,}$$

and $M_X(t)$ is an mgf. Then there is a unique cdf F_X whose moments are determined by $M_X(t)$ and, for all x where $F_X(x)$ is continuous, we have

$$\lim_{i \rightarrow \infty} F_{X_i}(x) = F_X(x).$$

That is, convergence, for $|t| < h$, of mgfs to an mgf implies convergence of cdfs.

example sequence
of R.V.s

$$\begin{aligned} \bar{X}_1 &= X_1/1 \\ \bar{X}_2 &= (X_1 + X_2)/2 \\ \bar{X}_3 &= (X_1 + X_2 + X_3)/3 \\ &\vdots \\ \bar{X}_n &= \sum_{i=1}^n X_i/n \end{aligned}$$

each \bar{X}_i has
own mgf
 $M_{\bar{X}_i}(t)$
and cdf $F_{\bar{X}_i}(t)$

Summary of Thm 2.3.12

$$\lim_{i \rightarrow \infty} M_{X_i}(t) = M_X(t) \quad \sqrt{|t| < h} \quad \text{implies} \quad \lim_{i \rightarrow \infty} F_{X_i}(x) = F_X(x)$$

mgfs \Rightarrow cdfs
Converge Converge

Example: For n large and np small show

Binomial \rightarrow Poisson
mgf mgf

Aside: Some Tools needed for this problem

Lemma 2.3.14 Let a_1, a_2, \dots be a sequence of numbers converging to a , that is,
 $\lim_{n \rightarrow \infty} a_n = a$. Then

$$\lim_{n \rightarrow \infty} \left(1 + \frac{a_n}{n}\right)^n = e^a.$$

We'll use this lemma a few times this year.
I will remind you when we need it

[Proof of CLT]

Poisson(λ)

pmf $P(X = x | \lambda) = \frac{e^{-\lambda} \lambda^x}{x!}; \quad x = 0, 1, \dots; \quad 0 \leq \lambda < \infty$

← Easier to calculate than binomial(n, p).

mean and variance $EX = \lambda, \quad \text{Var } X = \lambda$

mgf $M_X(t) = e^{\lambda(e^t - 1)}$

The approximation: $P(X=x) \approx P(Y=x)$

for $X \sim \text{bin}(n, p)$ $Y \sim \text{Pois}(\lambda)$ $\lambda = np$

$\lambda = np$

n 'large'
 np small

One rule:
 $n \geq 20$
 $p \leq .05$
 $np < 10$

$$\text{Poisson}(\lambda) \text{ pmf: } P(Y=y) = \frac{e^{-\lambda} \lambda^y}{y!} * I_{[0,1,2,\dots]}$$

$$\text{Recall } M_X(t) = [\text{Binomial}]^n \quad \text{and } M_Y(t) = e^{\lambda(e^t - 1)}$$

If $\lambda = np$ then $p = \lambda/n$

$$M_X(t) = [pe^t + (1-p)]^n = \left[1 + \frac{1}{n}(e^t - 1)(np)\right]^n$$

$$\text{if } p = \frac{\lambda}{n} \quad = \left[1 + \frac{1}{n}(e^t - 1)\lambda\right]^n \quad \begin{bmatrix} \text{Now use} \\ \text{Lemma 2.3.14} \end{bmatrix}$$

define:

$$a = an = (e^t - 1)\lambda$$

$$\text{Then } \lim_{n \rightarrow \infty} M_X(t) = \boxed{e^{\lambda(e^t - 1)}} = M_Y(t)$$

$$\therefore \lim_{n \rightarrow \infty} F_X(u) = F_Y(u) \quad u = \{0, 1, 2, \dots\}$$

Note: we must recognize $e^{\lambda(e^t - 1)}$ is Mgf of Poisson for this to be useful Thm.

Finally:

Theorem 2.3.15 For any constants a and b , the mgf of the random variable $aX + b$ is given by

$$M_{aX+b}(t) = e^{bt} M_X(at).$$

Proof:

$$\begin{aligned} M_{(aX+b)}(t) &= E[e^{(ax+b)t}] \\ &= E[e^{(ax)t} e^{bt}] \\ &= e^{bt} E[e^{(ax)t}] \\ &= e^{bt} M_X(at). \end{aligned}$$

$$= e^{bt} \int_{-\infty}^{\infty} e^{(at)x} f_x(x) dx$$

or

$$e^{bt} \sum_x e^{(at)x} P(X=x)$$

a, b constants

properties of exponents

assuming t fixed:

e^{bt} constant

continuous dist'n

discrete dist'n

§2.4 Differentiating under integral sign

- We will frequently need to interchange integration & differentiation.
- Need to know when legitimate to interchange $\int + \frac{d}{d\theta}$
- Assume interested in calculating:

$$\frac{d}{d\theta} \int_{a(\theta)}^{b(\theta)} f(x, \theta) dx \quad -\infty < a(\theta), b(\theta) < \infty$$

- Use application of Fundamental Thm of Calculus and chain rule.

Theorem 2.4.1 (Leibnitz's Rule) If $f(x, \theta)$, $a(\theta)$, and $b(\theta)$ are differentiable with respect to θ , then

$$\frac{d}{d\theta} \int_{a(\theta)}^{b(\theta)} f(x, \theta) dx = f(b(\theta), \theta) \frac{d}{d\theta} b(\theta) - f(a(\theta), \theta) \frac{d}{d\theta} a(\theta) + \int_{a(\theta)}^{b(\theta)} \frac{\partial}{\partial \theta} f(x, \theta) dx.$$

Notice that if $a(\theta)$ and $b(\theta)$ are constant, we have a special case of Leibnitz's Rule:

$$\frac{d}{d\theta} \underbrace{\int_a^b f(x, \theta) dx}_{\text{ft'n of } \theta} = \int_a^b \underbrace{\frac{\partial}{\partial \theta} f(x, \theta)}_{\text{ft'n } x, \theta} dx. \quad \text{partial derivative}$$

Example Beta (α, β)

Beta(α, β)

pdf $f(x|\alpha, \beta) = \frac{1}{B(\alpha, \beta)} x^{\alpha-1} (1-x)^{\beta-1}, \quad 0 \leq x \leq 1, \quad \alpha > 0, \quad \beta > 0$

mean and variance $EX = \frac{\alpha}{\alpha+\beta}, \quad \text{Var } X = \frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$

mgf $M_X(t) = 1 + \sum_{k=1}^{\infty} \left(\prod_{r=0}^{k-1} \frac{\alpha+r}{\alpha+\beta+r} \right) \frac{t^k}{k!}$

notes The constant in the beta pdf can be defined in terms of gamma functions, $B(\alpha, \beta) = \frac{\Gamma(\alpha)\Gamma(\beta)}{\Gamma(\alpha+\beta)}$. Equation (3.2.18) gives a general expression for the moments.

$$f(x|\alpha, \beta) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} x^{\alpha-1} (1-x)^{\beta-1} * I_{[0,1]}(x)$$

$$= \frac{\alpha \Gamma(\alpha)}{\Gamma(\alpha) \alpha!} x^{\alpha-1} * I_{[0,1]}(x) = \alpha x^{\alpha-1} I_{[0,1]}(x)$$

$$f(x|a, B=1) = \alpha x^{\alpha-1} I_{[0,1]}^{(x)}$$

want $\frac{d}{da} \int_0^1 g(x,a) dx^{a-1} dx$ $g(x,a)$ often something like $\ln f(x|a) \dots$ (more later).

here $a(\theta)=1$ and $b(\theta)=0$ (both constant)!

$$\text{so } \frac{d}{da} \int_0^1 g(x,a) dx^{a-1} dx = \int_0^1 \frac{\partial}{\partial a} [g(x,a) dx^{a-1}] dx$$



Example $U(0,\theta)$

Uniform(a, b)

pdf $f(x|a, b) = \frac{1}{b-a}, \quad a \leq x \leq b$

mean and variance $EX = \frac{b+a}{2}, \quad \text{Var } X = \frac{(b-a)^2}{12}$

mgf $M_X(t) = \frac{e^{bt}-e^{at}}{(b-a)t}$

notes If $a = 0$ and $b = 1$, this is a special case of the beta ($\alpha = \beta = 1$).

Caution:

Sample space is ft'n of parameters that define dist'n!

$$f(x) = \frac{1}{\theta} I_{[0,\theta]}^{(x)}$$

$$a(\theta)=0, \quad b(\theta)=\theta$$

$$\frac{d}{d\theta} \int_0^\theta g(x,\theta) \frac{1}{\theta} dx \neq \int_0^\theta \left[\frac{\partial}{\partial \theta} g(x,\theta) \frac{1}{\theta} \right] dx$$



$$\begin{aligned} \frac{d}{d\theta} \int_0^\theta g(x,\theta) \frac{1}{\theta} dx &= g\left(\frac{\theta, \theta}{\theta}\right) \frac{d}{d\theta} \theta \\ &- g\left(\frac{0, \theta}{\theta}\right) \frac{d}{d\theta}(0) \\ &+ \int_0^\theta \frac{\partial}{\partial \theta} g(x,\theta) \frac{1}{\theta} dx \end{aligned}$$

More theorems in C+B to cover when $0 < x < \infty$ or $-\infty < x < \infty$
 $a(\theta) = -\infty$ or $b(\theta) = \infty$

Can we assume:

$$\frac{d}{d\theta} \int_{-\infty}^{\infty} f(x, \theta) dx = \int_{-\infty}^{\infty} \frac{\partial}{\partial \theta} f(x, \theta) dx ?$$



The property illustrated for the exponential distribution holds for a large class of densities, which will be dealt with in Section 3.4.

→ 'exponential families'

"obviously" the sample space / support
 won't be a ft'n of Θ .

Similarly for 'exponential families' we can assume that we can interchange differentiation and summation.

$$\frac{d}{d\theta} \quad \text{and} \quad \sum_{i=1}^{\infty} \text{ or } \sum_{i=1}^n .$$

More in chapter-3

3 Common Families of Distributions

- 3.1 Introduction
- 3.2 Discrete Distributions
- 3.3 Continuous Distributions
- 3.4 Exponential Families ←
- 3.5 Location and Scale Families
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