

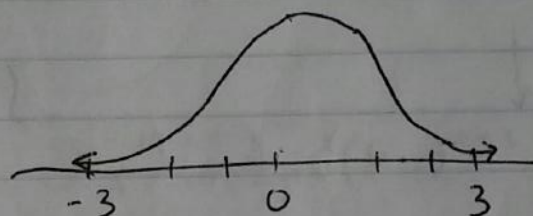
Lecture 19: November 22, 2016

• $Z \sim N(0, 1) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$ (Answer to 3a)

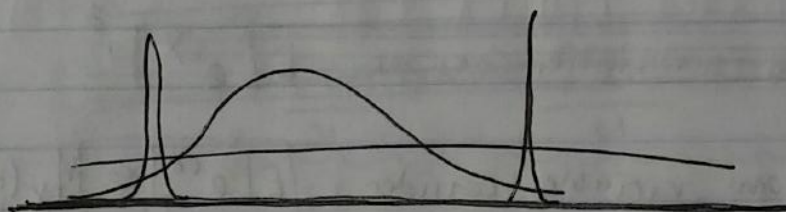
$\text{Supp}[Z] = \mathbb{R}$

$E[Z] = 0$

$\text{SE}[Z] = 1$



• $X \sim N(\mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2}$ → Allows us to center curve wherever we want



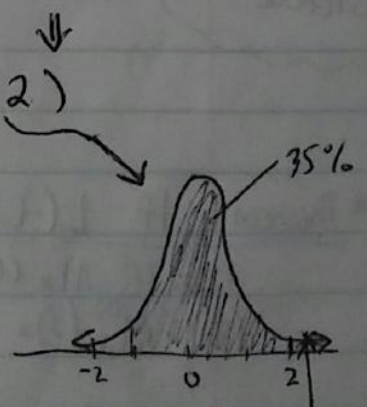
- X is random variable model for male height. X is normally distributed with mean 70 inches & SE 4 inches. What is probability that a male is more than 78 inches tall?

$Z = \frac{x-\mu}{\sigma} \sim N(0, 1)$

$X \sim N(70, 4^2) := P(X \geq 78) := P\left(\frac{x-70}{4} \geq \frac{78-70}{4}\right)$

$\boxed{2.5\%} \leftarrow P(Z > 2)$

*Why should height be normally distributed?



~~Why should height be normally distributed?~~

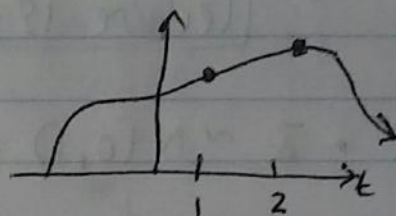
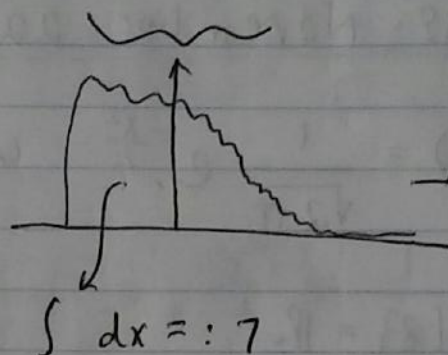
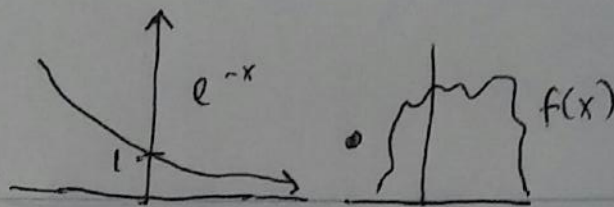
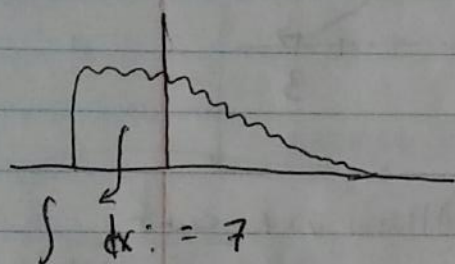
• fn. $f(x)$, let $L(t) := \int_{-\infty}^{+\infty} e^{+tx} f(x) dx$

Bilateral Laplace Transform

2.5%
want to find
 ≥ 2

$$* L(t) = \int_{\mathbb{R}} e^{tx} f(x) dx$$

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* Theorem: If $L(t)$ exists, $L(t)$ & $f(x)$ are one-to-one.

~~* X is a random variable. Consider $E[e^{tX}]$.~~

* X is a random variable. Consider

$$E[e^{tX}] \leftarrow M_X(t)$$

$$E(X) = \int_{\mathbb{R}} x f(x) dx$$

(cts)

if continuous

$$\int_{\mathbb{R}} e^{tx} f(x) dx$$

if discrete

$$\sum_{x \in \text{supp}(X)} e^{tx} p(x)$$

Moment
Generating
Function (MGF)
of X

$$E[X] = \sum_{x \in \text{supp}(X)} x p(x)$$

discrete

* Theorem: If $L(-t)$ exists, $L(-t)$ & $f(x)$ are one-to-one.

(I) If $M_X(t) = M_Y(t) \Rightarrow X' = Y$

(II) $M_X^{(k)}(0) = E[X^k]$

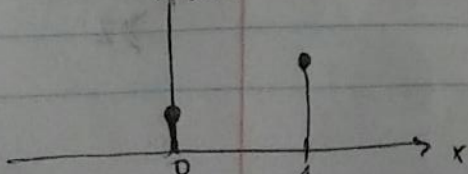
* $X \sim \text{Bern}(p)$

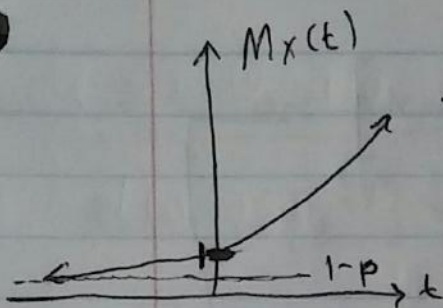
* This

$$M_X(t) = E[e^{tX}] = \sum_{x \in \text{supp}(X)} e^{tx} p(x)$$

$$= e^{t(0)} p(0) + e^{t(1)} p(1)$$

$$= (1-p) + pe^t = 1-p+pe^t$$





* & this are equal & are one-to-one.

* Consider $X \sim \text{Binomial}(n, p)$

~~Find~~ Find $E[X^k] = \sum_{x=0}^n x^k \binom{n}{x} p^x (1-p)^{n-x}$

impossible, really hard to solve

Recall the Taylor Series of $f(x)$ near $x=c$.

$$f(x) = f(c) + \frac{f'(c)}{1!} (x-c) + \frac{f''(c)}{2!} (x-c)^2 + \frac{f'''(c)}{3!} (x-c)^3 + \dots$$

can say

$$f(x) \approx f(c) + \frac{f'(c)}{1!} (x-c) + \frac{f''(c)}{2!} (x-c)^2 + \dots$$

called a 2nd order approximation

Let $f(x) = e^x$ near $x=0 \Rightarrow c=0$

$$e^x = e^0 + \frac{e^0}{1!} x + \frac{e^0}{2!} x^2 + \frac{e^0}{3!} x^3 + \dots$$

$$= 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots \quad e = \sum_{i=0}^{\infty} \frac{1}{i!}$$

$$* e^{tX} = 1 + tX + \frac{t^2 X^2}{2!} + \frac{t^3 X^3}{3!} + \frac{t^4 X^4}{4!} + \dots *$$

$$M_X(t) = E(e^{tX}) = E\left[1 + tX + \frac{t^2 X^2}{2!} + \frac{t^3 X^3}{3!} + \frac{t^4 X^4}{4!} + \dots\right]$$

going to mark this as ♡

$$\frac{d}{dt} [M_X(t)] = \frac{d}{dt} E \left[1 + tX + \frac{t^2 X^2}{2!} + \frac{t^3 X^3}{3!} + \dots \right]$$

$$\frac{d}{dt} \int e^{tX} f(x) dx$$

$$E \left[X + \frac{tX^2}{1!} + \frac{t^2 X^3}{2!} + \frac{t^3 X^4}{3!} + \dots \right] \Leftarrow E \left[\frac{d}{dt} [\heartsuit] \right]$$

$$M'_X(0) = E[X]$$

$$M''_X(t) = E \left[0 + X^2 + tX^3 + \frac{t^2 X^4}{2!} + \dots \right]$$

$$M''_X(0) = E[X^2]$$

$$M'''_X(t) = E \left[0 + X^3 + tX^4 + \dots \right]$$

$$M'''_X(0) = E[X^3]$$

leads us to rule # II

$$M_X^{(k)}(0) = E[X^k]$$

• Let $Y = aX + c$ [move it over by c , expand or contract by a]

$$M_Y(t) = E[e^{tY}] = E[e^{t(ax+c)}] = E[e^{tax} e^{tc}]$$

$$e^{tc} M_X(t') = e^{tc} E[e^{t'X}]$$

$$\Downarrow$$

$$M_Y(t)$$

$$\Leftarrow e^{tc} E[e^{taX}]$$

let $t' = at$

leads us to Rule # III

$$M_Y(t) = e^{tc} M_X(t')$$

• X_1 & X_2 are independent random variables. let $Y = X_1 + X_2$

$$M_Y(t) = E[e^{tY}] = E[e^{t(X_1 + X_2)}] = E[e^{tX_1} + e^{tX_2}]$$

$$\boxed{M_{X_1}(t) M_{X_2}(t)} \quad \Downarrow \quad E[e^{tX_1}] E[e^{tX_2}]$$

leads us to rule # IV

$$M_Y(t) = M_{X_1}(t) M_{X_2}(t)$$

if $X_1, X_2 \stackrel{iid}{\sim}$
 $Y = X_1 + X_2$
 $M_Y(t) = M_{X_1}(t) M_{X_2}(t)$
 $= (M_X(t))^2$

• $X_1, \dots, X_n \stackrel{iid}{\sim} \text{Bern}(p)$
 $T = X_1 + \dots + X_n \sim \text{Binomial}(n, p)$

what is $M_T(t) = ?$

By rule #4, b/c iid & summing then:

$$M_T(t) = (M_Y(t))^n = \boxed{(1-p + p e^t)^n}$$

• $X \sim \text{geom}(p)$ — $\sum_{i=0}^{\infty} a^i = \frac{1}{1-a}$ if $a \in (0, 1)$

$$M_X(t) = E[e^{tX}] = \sum_{x=0}^{\infty} e^{tx} (1-p)^{x-1} p \Rightarrow p \sum_{x=0}^{\infty} e^{tx} (1-p)^{x-1} \frac{1-p}{1-p}$$

$$\frac{p}{1-p} \left(\sum_{x=0}^{\infty} (e^t(1-p))^x - 1 \right) \Leftarrow \frac{p}{1-p} \sum_{x=1}^{\infty} (e^t(1-p))^x \Leftarrow \frac{p}{1-p} \sum_{x=0}^{\infty} \underbrace{e^{tx} (1-p)^x}_{(e^t)^x}$$

$$\hookrightarrow \text{if } e^t(1-p) < 1 \Rightarrow e^t < \frac{1}{1-p} \Leftrightarrow t < \ln\left(\frac{1}{1-p}\right)$$

$$\Downarrow$$

$$\frac{p}{1-p} \left(\frac{1}{1-e^t(1-p)} - 1 \right) \Rightarrow \frac{p}{1-p} \frac{e^t(1-p)}{1-e^t(1-p)} = \boxed{\frac{p}{1-e^t(1-p)} \text{ if } t < \ln\left(\frac{1}{1-p}\right)}$$

$X \sim \text{geom}(p)$

• $X \sim \text{Exp}(\lambda)$ ~~XXXXXXXXXX~~

$$M_X(t) = E[e^{tx}] = \int_0^\infty e^{tx} \lambda e^{-\lambda x} dx \Rightarrow \lambda \int_0^\infty e^{(t-\lambda)x} dx$$

$$\frac{\lambda}{t-\lambda} (0-1) = \boxed{\frac{\lambda}{\lambda-t} \text{ if } t < \lambda} \Leftarrow \frac{\lambda}{t-\lambda} \left(\lim_{x \rightarrow \infty} e^{(t-\lambda)x} = 1 \right) \Leftarrow \frac{\lambda}{t-\lambda} \left[e^{(t-\lambda)x} \right]_0^\infty$$

(if $t - \lambda \leq 0 \Rightarrow t < \lambda$)

$$\lim_{x \rightarrow \infty} e^{-x} = 0$$

$$\lim_{x \rightarrow \infty} e^{-32x} = 0$$

$$\lim_{x \rightarrow \infty} e^x = \infty$$

$$\lim_{x \rightarrow \infty} e^{ax} \begin{cases} 0 & \text{if } a \text{ is } - \\ \infty & \text{if } a \text{ is } + \end{cases}$$

• $X \sim \text{Exp}(\lambda)$ $Y = aX \sim ?$

$$M_Y(t) = e^{tc} M_X(at) = \frac{\lambda}{\lambda - at} \cdot \frac{1/a}{1/a} = \frac{\frac{\lambda}{a}}{\frac{\lambda}{a} - t} = \frac{\lambda'}{\lambda' - t}$$

$$\text{let } \lambda' = \frac{\lambda}{a}$$

$$Y \sim \text{Exp}(\lambda')$$

$$Y \sim \text{Exp}\left(\frac{\lambda}{a}\right)$$

• $Z \sim N(0,1)$, $M_Z(t) = E(e^{tz}) = \int_{\mathbb{R}} e^{tx} \frac{1}{\sqrt{2\pi}} e^{-x^2/2} dx$

~~$$\frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{tx} e^{-x^2/2} dx$$~~

$$\Leftarrow \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-\frac{1}{2}x^2 + tx} dx$$

$$\frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-\frac{1}{2}(x-t)^2 + \frac{t^2}{2}} dx \Rightarrow \frac{1}{\sqrt{2\pi}} \int_{\mathbb{R}} e^{-\frac{1}{2}(x-t)^2} dt$$

$f(x)$ - density - for $N(t, 1)$

this integral is 1

So...

$$= \boxed{e^{\frac{t^2}{2}}}$$

$$\left(\frac{1}{2}x^2 + tx \right) = -\frac{1}{2}(x^2 - 2tx)$$

Note:

$$(x-t)^2 =$$

$$x^2 - 2xt + t^2$$

$$(x-t)^2 - t^2 =$$

$$x^2 - 2tx$$

$$\frac{1}{2}((x-t)^2 - t^2) \Leftarrow$$

$$-\frac{1}{2}(x-t)^2 + \frac{t^2}{2}$$

• $X \sim N(\mu, \sigma^2)$

we know $X = \underbrace{\mu}_{\text{mean}} + \underbrace{\sigma Z}_{\text{std}}$

$$M_X(t) = e^{t\mu} M_Z(\sigma t) = e^{t\mu} e^{\frac{\sigma^2 t^2}{2}} = e^{t\mu + \frac{\sigma^2 t^2}{2}}$$

Next class go over LLN $\bar{X} \rightarrow \mu$