

Lec 19 Mon 24/ 11/22/16

1

$$Z \sim N(0,1) := \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}}$$

$$\text{Supp}(Z) = \mathbb{R}$$

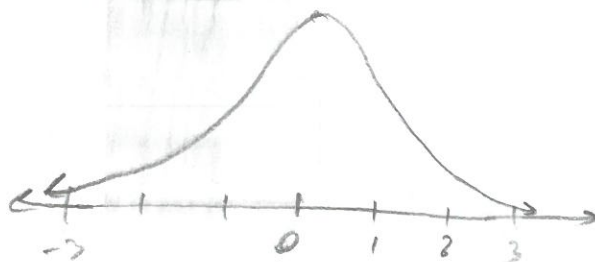
$$E(Z) = 0, \text{sd}(Z) = 1$$

Standard

Z-scores

-2? +1? +3?

peaking?



Why draw this way?

$$P(Z \in [-3,3]) \approx 99.7\%$$

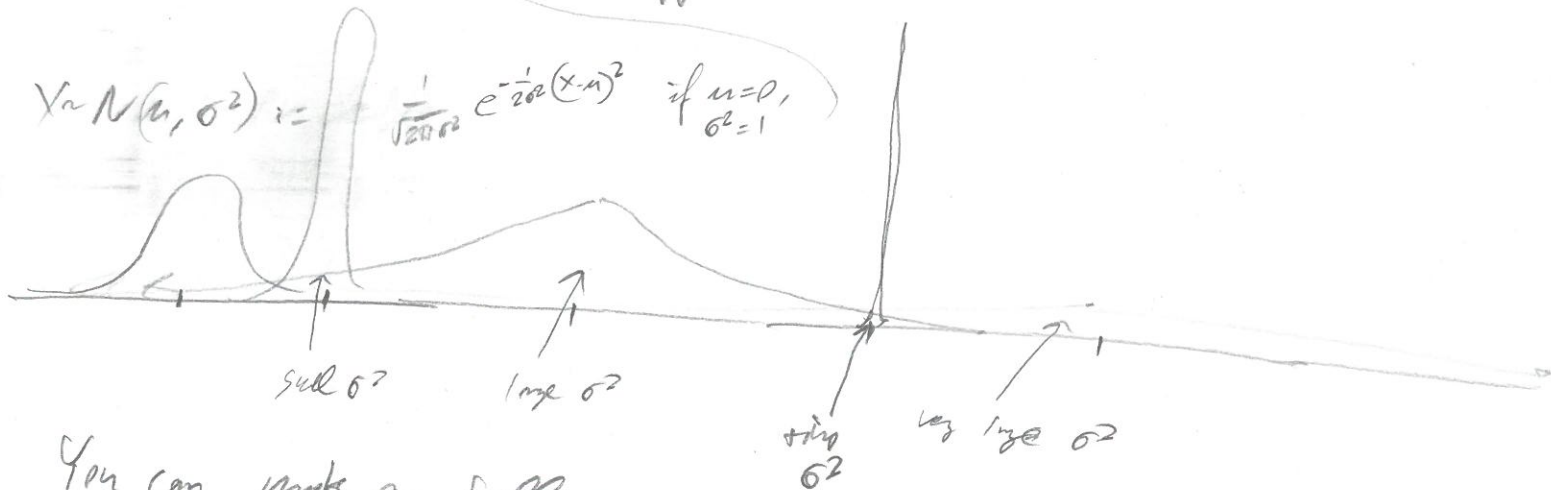
$$P(Z \in [-2,2]) \approx 95\%$$

$$P(Z \in [-1,1]) \approx 68\%$$

Empirical Rule

why approx? Exact answers unknown...

$$X \sim N(\mu, \sigma^2) := \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{1}{2\sigma^2}(x-\mu)^2} \text{ if } \mu=0, \sigma^2=1$$



You can make any bell curve you want all $\text{Supp}(X) = \mathbb{R}, \mu \in \mathbb{R}, \sigma^2 \in (0, \infty)$

$\sigma^2 = 0$? Not possible, $\sigma^2 < 0 \dots V_n(X) \geq 0$ so not possible

$$\text{Remark: } X = \mu + \sigma Z \Rightarrow Z = \frac{X - \mu}{\sigma}$$

I can take any normal ^{rule} and do this linear transform and get std normal

Eg. X is Height. Height is normally distributed, $\mu = 70"$, $\sigma = 4"$

What is the prob someone is more than 78" tall?

(2)

$$X \sim N(70'', 4''^2)$$

$$\Rightarrow Z = \frac{X - 70''}{4''} \sim N(0, 1)$$

$$78'' = 2 \cdot 4'' = 8''$$

$$P(X \geq 78'') = P\left(\frac{X - 70''}{4''} \geq \frac{78'' - 70''}{4''}\right) = P(Z \geq 2) \approx 2.5\%$$

Lots of ships are normally late... why? ... Perhaps...

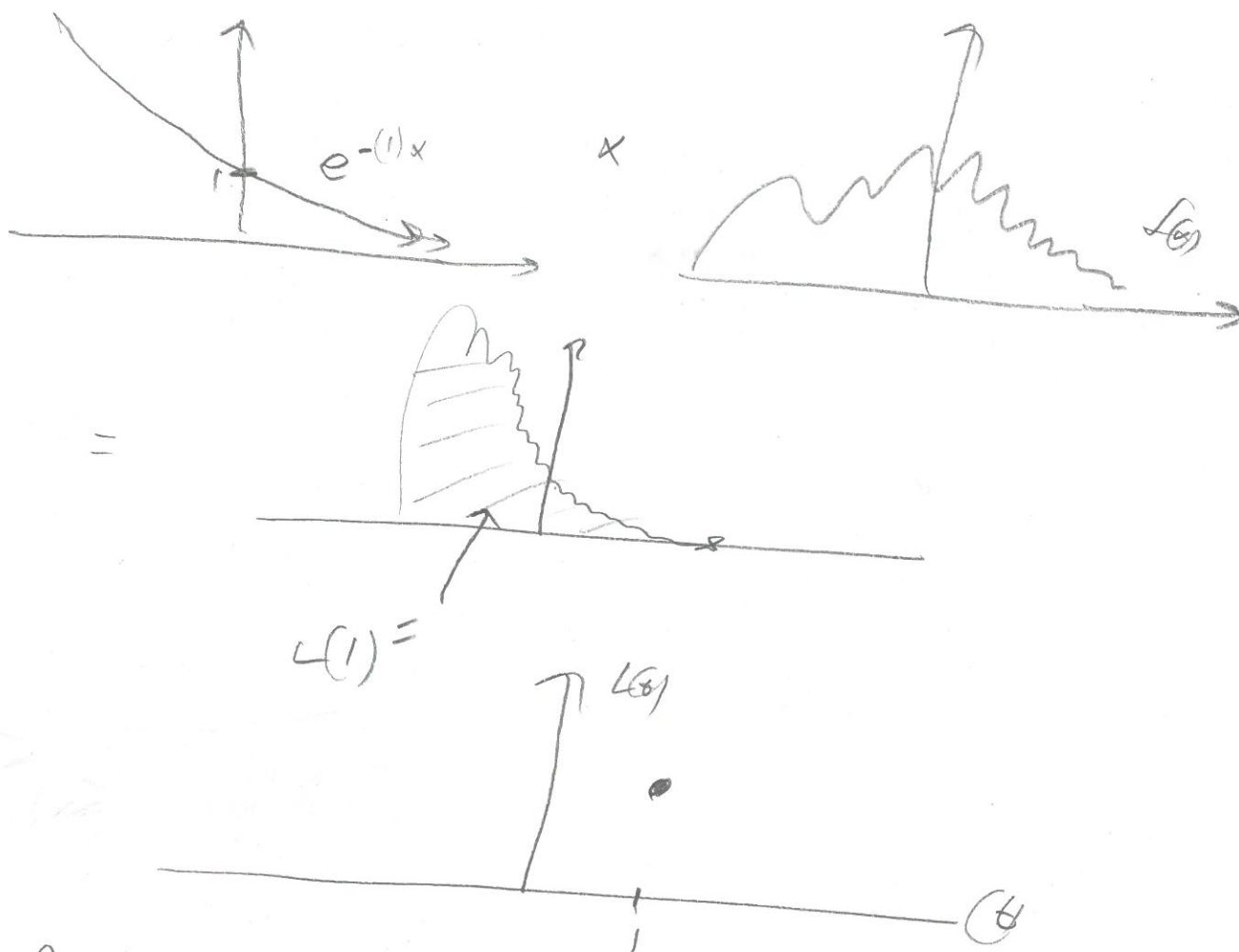
$$\text{let } L(\xi) = \int_{\mathbb{R}} e^{-\xi x} f(x) dx$$

L is called the "Bilateral Laplace Transform" of f

What does this look like?

3

$$L(1) = \int e^{-1/x} f(x) dx$$



Do this for all values of t .

Then: if $L(t)$ exists... $L(t)$ & $f(x)$ are 1:1.

$$L(t) \Rightarrow f(x), f(x) \Rightarrow L(t)$$

Note: if $f(x)$ is PDF then

$$\text{Since } E[g(x)] = \int g(x) f(x) dx$$

$$\int_{\mathbb{R}} e^{-tx} f(x) dx = E[e^{-tx}]$$

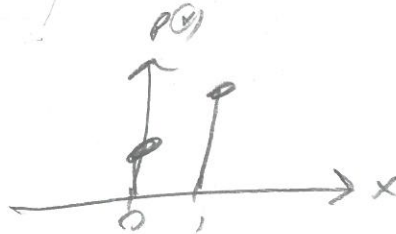
Defn $M_X(t) := E[e^{tX}] = \int e^{tx} f(x) dx$ cont.
 $= \sum_{x \in \mathcal{X}} e^{tx} p(x)$ discrete.
 moment generating function (MGF) of r.v. X

(4)

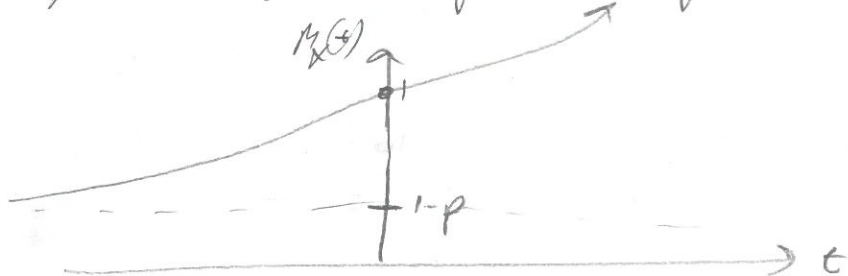
(I) $M_X(t)$ is 1:1 with $f(x)$ or $p(x)$

ideally discr. r.v.'s are safer!

e.g. $X \sim \text{bin}(p) := p^x (1-p)^{1-x}$



$$M_X(t) = E[e^{tX}] = e^{t(0)} p(0) + e^{t(1)} p(1) = (1-p) + pe^t$$



are the same!!
 why infy each order...
 genotype vs phenotype

M_X is $M_X(t)$ useful...

Consider $X \sim \text{binomial}(n, p)$ $E[X^{17}] = \sum_{x=0}^n x^{17} \binom{n}{x} p^x (1-p)^{n-x}$
 not possible to figure out...

Recall $f(x)$ when $x \approx c$ can be approximated by...

$$f(x) \approx f(c) + \frac{f'(c)}{1!} (x-c) + \frac{f''(c)}{2!} (x-c)^2 + \frac{f'''(c)}{3!} (x-c)^3 \quad \text{3rd degree approx.}$$

$$\hookrightarrow = \sum_{i=0}^{\infty} \frac{f^{(i)}(c)}{i!} (x-c)^i$$

Let $f(x) = e^x$ to see the Taylor expansion $x \approx 0 \Rightarrow c=0$

$$e^x \approx e^0 + \frac{e^0}{1!} x + \frac{e^0}{2!} x^2 + \frac{e^0}{3!} x^3 = 1 + x + \frac{x^2}{2} + \frac{x^3}{6} \dots$$

$$\Rightarrow e^x = \sum_{i=0}^{\infty} \frac{1}{i!} x^i$$

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

$$M_X(t) = E[e^{tX}] = E\left[\right]$$

$$\frac{d}{dt} M_X(t) = 1 + t E(X) + \frac{t^2}{2!} E(X^2) + \frac{t^3}{3!} E(X^3) + \frac{t^4}{4!} E(X^4) + \dots$$

$$M_X'(t) = E(X) + \frac{t}{1!} E(X^2) + \frac{t^2}{2!} E(X^3) + \frac{t^3}{3!} E(X^4) + \dots$$

let $t=0$

$$M_X'(0) = E(X)$$

$$M_X''(t) = E(X^2) + \frac{t}{1!} E(X^3) + \frac{t^2}{2!} E(X^4) + \dots$$

$$M_X''(0) = E(X^2)$$

$$M_X'''(t) = E(X^3) + \frac{t}{1!} E(X^4) + \dots$$

$$M_X'''(0) = E(X^3)$$

this is only it gets more !!! General moments...

$$\textcircled{\text{II}} \quad M_X^{(k)}(0) = E[X^k]$$

Other cool properties

6

$$Y = aX + c$$

III

$$M_Y(t) = M_{aX+c}(t) = E[e^{t(aX+c)}] = E[e^{atX} e^{tc}] = e^{tc} E[e^{atX}] = e^{tc} M_X(at)$$

$$Y = X_1 + X_2 \quad \text{and } X_1, X_2 \text{ indep.}$$

IV

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

The mgf of a sum of indep. r.v.'s is the product of the mgfs of the constituent r.v.'s

$$X_1, \dots, X_n \stackrel{\text{iid}}{\sim} \text{Bern}(p)$$

$$T = X_1 + \dots + X_n \sim \text{Binom}(n, p) \quad \text{what is mgf of binomial?}$$

$$M_T(t) = M_{X_1+\dots+X_n}(t) = M_{X_1}(t) \dots M_{X_n}(t) \stackrel{\text{why? I}}{=} (M_X(t))^n = (1-p+pe^t)^n$$

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

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

$$\text{if } e^t(1-p) < 1 \Rightarrow$$

$$\Rightarrow e^t < \frac{1}{1-p}$$

$$\Rightarrow t < \ln\left(\frac{1}{1-p}\right)$$

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

$$X \sim \text{Exp}(\lambda)$$

$$m_X(t) = E(e^{tx}) = \int_0^{\infty} e^{tx} \lambda e^{-\lambda x} dx = \lambda \int_0^{\infty} e^{(t-\lambda)x} dx = \frac{\lambda}{t-\lambda} \left[e^{(t-\lambda)x} \right]_0^{\infty} = \frac{\lambda}{t-\lambda} (0-1) = \frac{\lambda}{\lambda-t} \quad \frac{1}{t-\lambda}$$

$$\text{if } t-\lambda < 0 \Rightarrow t < \lambda$$

$$Y = aX$$

$$m_Y(t) = m_{aX}(t) = m_X(at) = \frac{\lambda}{\lambda - at} = \frac{\lambda' a}{\lambda' a - t} = \frac{\lambda'}{\lambda' - t} \Rightarrow Y \sim \text{Exp}\left(\frac{\lambda'}{a}\right)$$

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

$$X \sim \text{Exp}(\lambda) \Rightarrow m_X(t) = E(e^{tx}) = e^{-\lambda t}$$

$$Z \sim N(0,1)$$

LLN

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

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

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

complex to square

$$X \sim N(\mu, \sigma^2) \Rightarrow X = \mu + \sigma Z$$

$$\Rightarrow m_X(t) = e^{t\mu} e^{\frac{\sigma^2 t^2}{2}} = e^{t\mu + \frac{\sigma^2 t^2}{2}}$$

$$X \sim N(t, 1) \Rightarrow f(x) =$$

Proof:

$$SE(Z) = 1 \Rightarrow SE(Z) = \sqrt{Var(Z)} = \sqrt{E(Z^2) - (m'_2(0))^2} = \sqrt{E(Z^2)} = \sqrt{m''_2(0)} = 1$$

$$m'_2(t) = -te^{\frac{t^2}{2}} \quad m'_2(0) = 0$$

$$m''_2(t) = e^{\frac{t^2}{2}} + t^2 e^{\frac{t^2}{2}} \quad m''_2(0) = 1$$