

CSE 107 S-6-25

Recall: if X is Geometric(p)

$$P_X(k) = p(1-p)^{k-1} \quad (k=1, 2, 3, \dots)$$

Thus

$$\begin{aligned} F_{\text{geo}}(n) &= \sum_{k=1}^n p(1-p)^{k-1} \\ &= p \cdot \sum_{k=0}^{n-1} (1-p)^k \\ &= \cancel{p} \cdot \frac{1 - (1-p)^n}{\cancel{1 - (1-p)}} \\ &= 1 - (1-p)^n \end{aligned}$$

→ If Y is Exponential(λ) then

$$f_Y(x) = \lambda e^{-\lambda x} \quad (x \geq 0)$$

Thus for $x > 0$:

$$\begin{aligned} F_{\text{exp}}(x) &= \int_0^x \lambda e^{-\lambda t} dt \\ &= -e^{-\lambda t} \Big|_0^x = -(e^{-\lambda x} - 1) \\ &= 1 - e^{-\lambda x} \end{aligned}$$

To compare F_{geo} , F_{exp} Pick

$\delta > 0$ so that

$$\boxed{e^{-\lambda \delta} = 1 - p}$$

$$\therefore p = 1 - e^{-\lambda f}$$

$$\therefore -\lambda f = \ln(1-p)$$

$$\therefore f = \frac{-\ln(1-p)}{\lambda}$$

For this f , we have

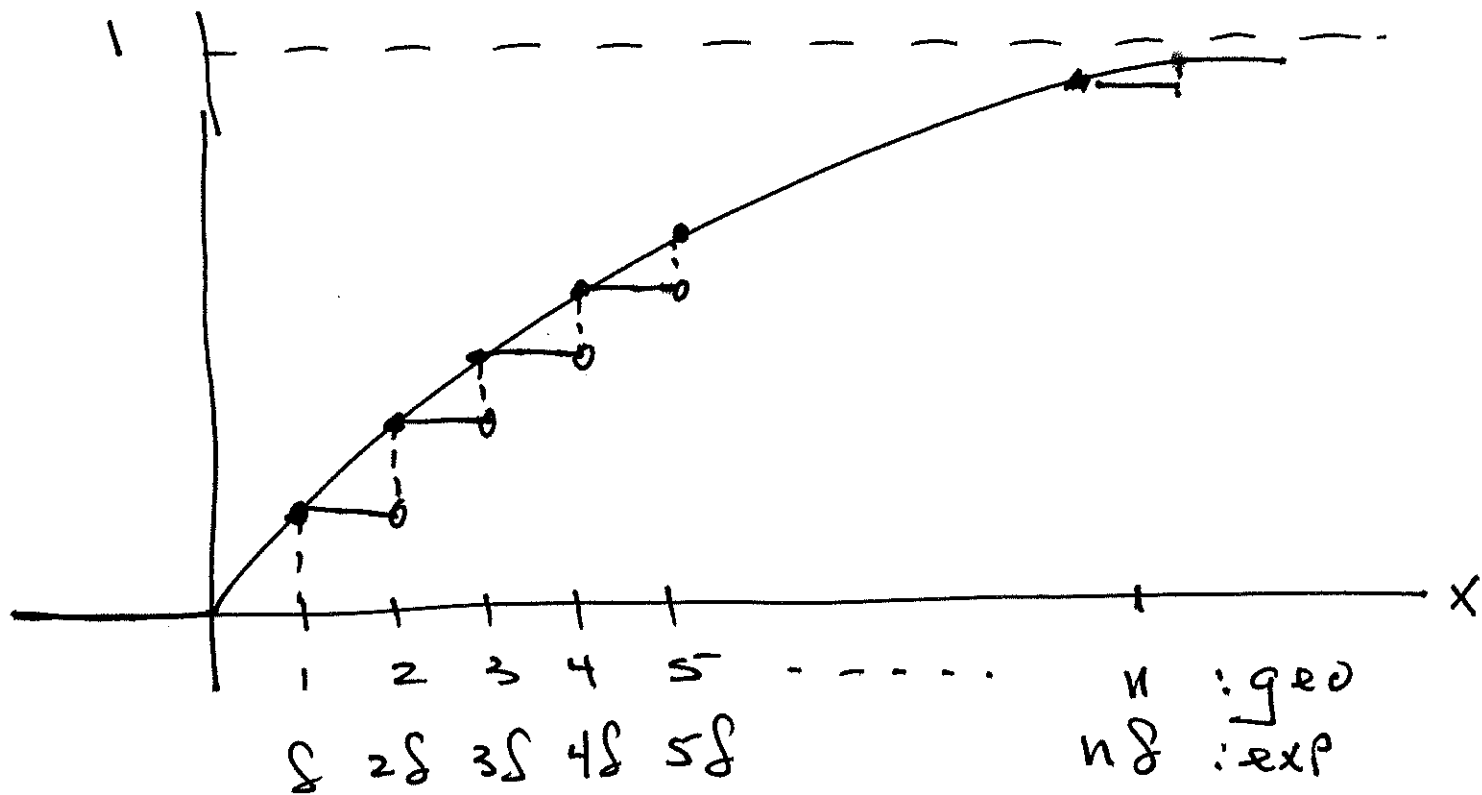
$$(e^{-\lambda f})^n = (1-p)^n$$

$$\therefore 1 - e^{-\lambda f n} = 1 - (1-p)^n$$

$$\therefore F_{\text{exp}}(fn) = F_{\text{geo}}(n)$$

Graph

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If we toss a coin quickly
with

$$p = 1 - e^{-\lambda \delta}$$

we get $\bar{F}_{geo} \rightarrow \bar{F}_{exp}$

3.3 Normal Random Variable

Let X be a continuous r.v. with

PDF

$$f_X(x) = \frac{1}{\sqrt{2\pi} \cdot \sigma} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (x \in \mathbb{R})$$

X is called Normal or Gaussian.

Fact:

$$\int_{-\infty}^{\infty} f_X(x) dx = 1$$

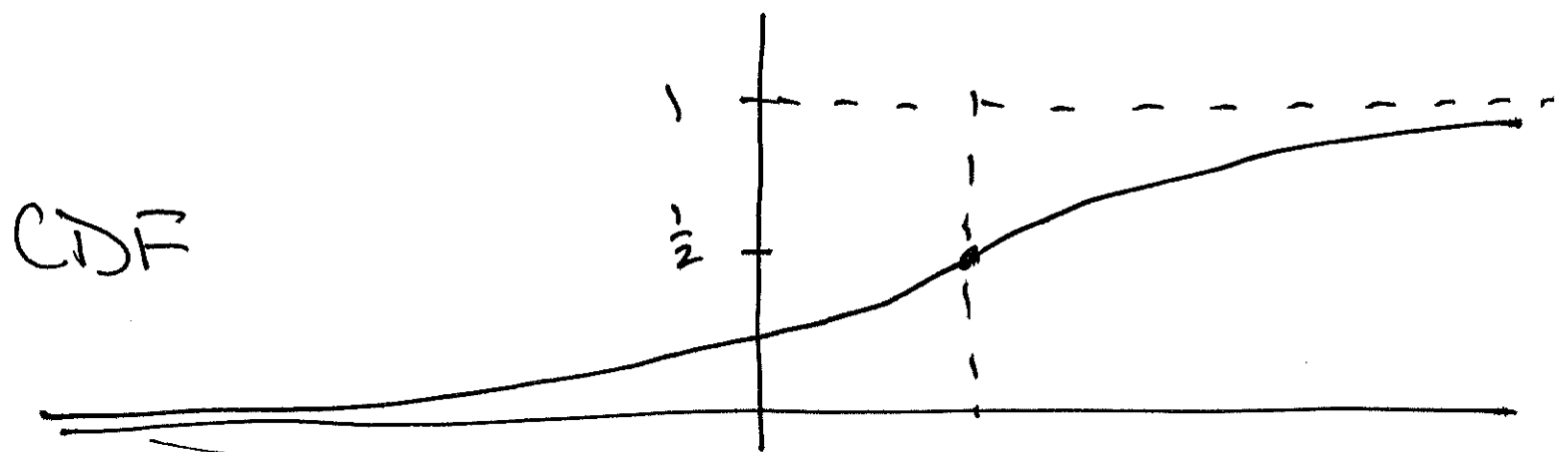
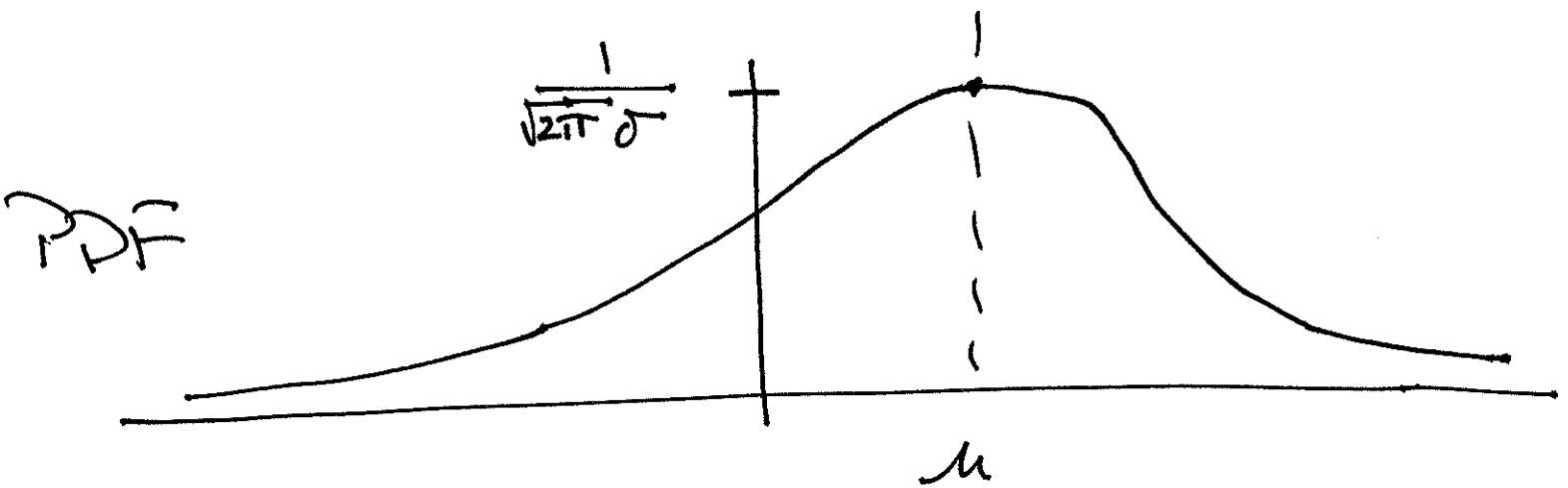
See Handout: Gaussian Integral.

Facts:

• $E[X] = \mu$

• $\text{Var}(X) = \sigma^2$

• $\sqrt{\text{Var}(X)} = \sigma$



Thm

for any PDF f_X , if

$$f_X(x) = f_X(-x) \quad \forall x \in \mathbb{R}$$

then

$$E[X] = 0$$

Proof

$$E[X] = \int_{-\infty}^{\infty} x f_X(x) dx$$

$$= \underbrace{\int_{-\infty}^0 x f_X(x) dx}_{\substack{t = -x \quad dt = -dx \\ x = -t \quad dx = -dt \\ x \leq 0 \leftrightarrow t \geq 0}} + \int_0^{\infty} x f_X(x) dx$$

$$\begin{aligned} t &= -x & dt &= -dx \\ x &= -t & dx &= -dt \\ x \leq 0 &\leftrightarrow t \geq 0 \end{aligned}$$

$$= \int_{-\infty}^0 \cancel{t} \cancel{f_X(t)} \overset{\text{Symm}}{\downarrow} \cancel{(-1)} dt + \int_0^{\infty} x f_X(x) dx$$

$$= - \int_0^{\infty} t f_X(t) dt + \int_0^{\infty} x f_X(x) dx$$

$$= 0$$



Theorem

If X is normal (μ, σ^2) , and
if $a \neq 0$, then

$$Y = aX + b$$

is also normal with

$$E[Y] = a\mu + b$$

$$\text{Var}(Y) = a^2 \sigma^2$$

Proof

let $Y = aX + b$ with $a > 0$.

$$\begin{aligned} F_Y(y) &= P(Y \leq y) \\ &= P(aX + b \leq y) \\ &= P(X \leq \frac{y-b}{a}) \end{aligned}$$

$$F_Y(y) = F_X\left(\frac{y-b}{a}\right)$$

$\frac{d}{dy} \downarrow$

$$\begin{aligned} f_Y(y) &= \frac{1}{a} f_X\left(\frac{y-b}{a}\right) \\ &= \frac{1}{a} \cdot \frac{1}{\sqrt{2\pi} \cdot \sigma} \cdot e^{-\frac{\left(\frac{y-b}{a} - \mu\right)^2}{2\sigma^2}} \\ &= \frac{1}{\sqrt{2\pi} \cdot (a\sigma)} \cdot e^{-\frac{\left(\frac{y-b-a\mu}{a}\right)^2}{2\sigma^2}} \end{aligned}$$

$$= \frac{1}{\sqrt{2\pi} \cdot (a\sigma)} \cdot e^{-\frac{(y - (a\mu + b))^2}{2(a\sigma)^2}}$$

normal with mean $a\mu + b$
and s.d. $a\sigma$, so var $a^2\sigma^2$



Exercise do case $a < 0$.

A normal r.v. Y is called
standard normal iff its

mean is $\boxed{0}$, and its variance
is $\boxed{1}$

$$PDF: f_Y(y) = \frac{1}{\sqrt{2\pi}} e^{-\frac{y^2}{2}}$$

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The CDF of the std. normal
r.v. is denoted

$$\Phi(y) = P(Y \leq y)$$

$$= P(Y < y)$$

$$= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^y e^{-t^2/2} dt$$

Handout: Standard Normal Table

gives values of $\Phi(y)$ for

$$0 \leq y \leq 3.49$$

If $y > 3.49$, $\Phi(y) \approx 1$. The identity

$$\Phi(-y) = 1 - \Phi(y) \quad (y \in \mathbb{R})$$

gives us $\Phi(y)$ for $y < 0$.

Ex.

$$\bullet \Phi(1.84) = \boxed{.9671}$$

$$\begin{aligned} \bullet \Phi(-1.84) &= 1 - \Phi(1.84) \\ &= 1 - (.9671) = \boxed{.0329} \end{aligned}$$

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If X is normal with mean μ , s.d. σ , Let

$$Y = \frac{X - \mu}{\sigma} = \frac{1}{\sigma} X - \frac{\mu}{\sigma}$$

Then Y is normal with

$$E[Y] = \frac{1}{\sigma} E[X] - \frac{\mu}{\sigma} = \frac{\mu}{\sigma} - \frac{\mu}{\sigma} = 0$$

and

$$\text{Var}(Y) = \frac{1}{\sigma^2} \text{Var}(X) = \frac{\sigma^2}{\sigma^2} = 1$$

$\therefore Y$ is standard normal.

Thus

$$F_X(x) = P(X \leq x)$$

$$= P\left(\frac{X-\mu}{\sigma} \leq \frac{x-\mu}{\sigma}\right)$$

$$= P\left(Z \leq \frac{x-\mu}{\sigma}\right)$$

$$= \Phi\left(\frac{x-\mu}{\sigma}\right)$$

Ex. The mean high temp. in Santa Cruz on Nov. 1 is $66^\circ F$ with S.d of 4.4° what is the probability that the high temp. will be $\leq 57^\circ$. (assume normal.)

Solu

Let X be the high temp
on Nov. 1. Then

$$\begin{aligned} P(X \leq 57) &= P\left(\frac{X-66}{4.4} \leq \frac{57-66}{4.4}\right) \\ &= P(Y \leq -2.04) \\ &= \Phi(-2.04) \\ &= 1 - \Phi(2.04) \\ &= 1 - (.9793) \\ &= \boxed{.0207} \end{aligned}$$

Ex.

what is the prob. that
a normal r.v. is within
1 s.d. of its mean?

Soln

$$P(\mu - \sigma \leq X \leq \mu + \sigma)$$

$$= P\left(\frac{(\mu - \sigma) - \mu}{\sigma} \leq \frac{X - \mu}{\sigma} \leq \frac{(\mu + \sigma) - \mu}{\sigma}\right)$$

$$= P(-1 \leq Y \leq 1)$$

$$= P(Y \leq 1) - P(Y < -1)$$

$$= \Phi(1) - \Phi(-1)$$

$$= \Phi(1) - (1 - \Phi(1))$$

$$= \boxed{2\Phi(1) - 1}$$

$$= 2(.8413) - 1 = \boxed{.6826}$$

Same Problem, but $z=3$ s.d.s!

• $\rightarrow (X \text{ is within } 2\sigma \text{ of } \mu)$

$$= 2\Phi(2) - 1 = 2(.9772) - 1 = \boxed{.9544}$$

• $\rightarrow (X \text{ is within } 3\sigma \text{ of } \mu)$

$$= 2\Phi(3) - 1 = 2(.9987) - 1 = \boxed{.9974}$$