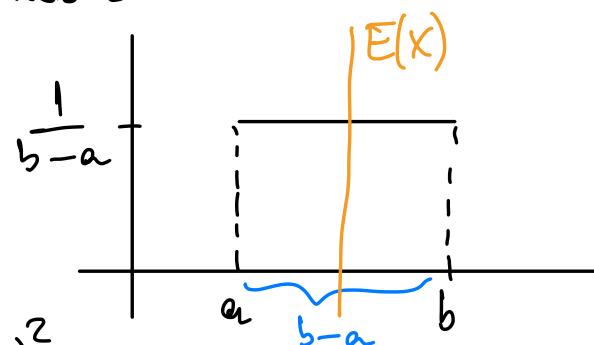


Quick recap: Uniform random variables

$$X \sim \text{Uniform}([a, b])$$

$$E(X) = \frac{a+b}{2}$$

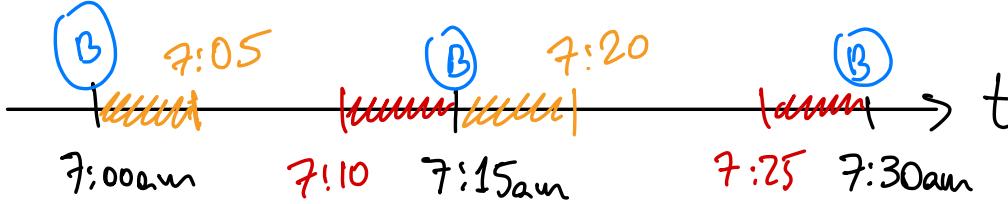
$$\text{Var}(X) = E(X^2) - E(X)^2 = \frac{(b-a)^2}{12}$$



Ex: Buses leave every 15 min starting at 7:00 am from the bus stop near your home, and you typically arrive to the bus stop any time between 7:00 am and 7:30 am, uniformly distributed. What is the prob. that

a) you have to wait < 5 min?

b) > 10 min?



X = minutes past 7:00 when you arrive to bus stop

$$X \sim \text{Uniform}([0, 30]) \quad f(x) = \frac{1}{30-0} = \frac{1}{30}$$

$$P(10 < X < 15) = \int_{10}^{15} \frac{1}{30} dx = \frac{1}{30} \cdot (15-10) = \frac{5}{30} = \frac{1}{6}.$$

$$P(25 < X < 30) = \int_{25}^{30} \frac{1}{30} dx = \frac{1}{6}$$

a) $\frac{1}{3}$

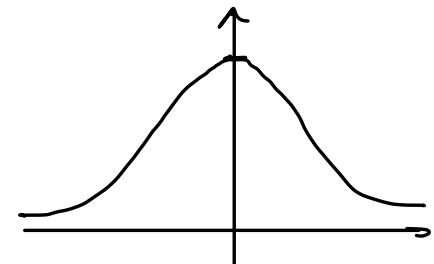
$$a) P(0 < X < 5) + P(15 < X < 20) = \frac{1}{3}$$

two intervals
with the same
combined length as the previous two in a).

Normal random Variables ← Very important
in real life applications

A continuous random variable X is normally distributed if its p.d.f. is of the form

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$



where $\sigma > 0$ and $\mu \in \mathbb{R}$ are parameters.

Fact: $E(X) = \mu$, $\text{Var}(X) = \sigma^2$.

Let us check that $f(x)$ above is a p.d.f.:

$$\begin{aligned} \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx &= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} dz \\ &= \frac{1}{\sqrt{2\pi}} \underbrace{\int_{-\infty}^{+\infty} e^{-\frac{z^2}{2}} dz}_{I = \sqrt{2\pi}} = 1 \end{aligned}$$

$$\text{Let } I = \int_{-\infty}^{+\infty} e^{-\frac{z^2}{2}} dz. (> 0)$$

$$I^2 = \left(\int_{-\infty}^{+\infty} e^{-\frac{x^2}{2}} dx \right) \left(\int_{-\infty}^{+\infty} e^{-\frac{y^2}{2}} dy \right)$$

$$\text{Fubini} \Rightarrow \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-\frac{x^2}{2}} \cdot e^{-\frac{y^2}{2}} dx dy = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} e^{-\frac{x^2+y^2}{2}} dx dy$$

Polar

Replace x, y
w/ r, θ :

$$x^2 + y^2 = r^2$$

$$dx dy = r dr d\theta$$

$$= \int_0^{2\pi} \int_0^{+\infty} e^{-r^2/2} r dr d\theta = 2\pi \int_0^{+\infty} r e^{-r^2/2} dr$$

$$\begin{aligned} u &= -r^2/2 \\ du &= -r dr \end{aligned} \quad = 2\pi \left(-e^{-r^2/2} \right) \Big|_0^{+\infty} = 2\pi(0 - (-1)) = 2\pi$$

$\therefore I = \sqrt{2\pi}$ Thus $f(x)$ is a p.d.f.

Affine functions of normal random variables are normal:

$$X \sim \text{Normal}(\mu, \sigma^2) \Rightarrow f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

Let $Y = aX + b$, $a, b \in \mathbb{R}$.

$$F'_X(x) = f(x)$$

$$F_X(x) = P(X \leq x), \quad F_Y(y) = P(Y \leq y)$$

Suppose $a > 0$.

$$F_Y(x) = P(Y \leq x) = P(aX + b \leq x) = P\left(X \leq \frac{x-b}{a}\right)$$

$$= F_X\left(\frac{x-b}{a}\right).$$

Taking derivatives on both sides:

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

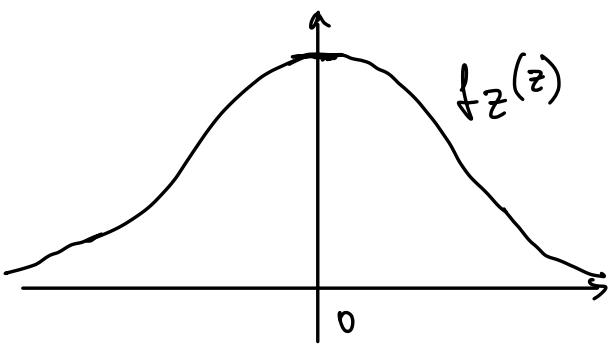
This is exactly the p.d.f.
of a normal random variable:

So $Y \sim \text{Normal}(\underline{a\mu+b}, \underline{a^2\sigma^2})$.

Upshot: If $X \sim \text{Normal}(\mu, \sigma^2)$, and $Y = aX + b$, then:
 $Y \sim \text{Normal}(a\mu + b, a^2\sigma^2)$.

Useful application: "standardization".

Def: A standard normal random variable is a normal random variable with $\mu = 0$ and $\sigma = 1$.



$Z \sim \text{Normal}(0, 1)$.

$$Z = aX + b$$

$$Z \sim \text{Normal} \left(\underbrace{\alpha\mu + b}_{=0}, \underbrace{\alpha^2\sigma^2}_{=1} \right).$$

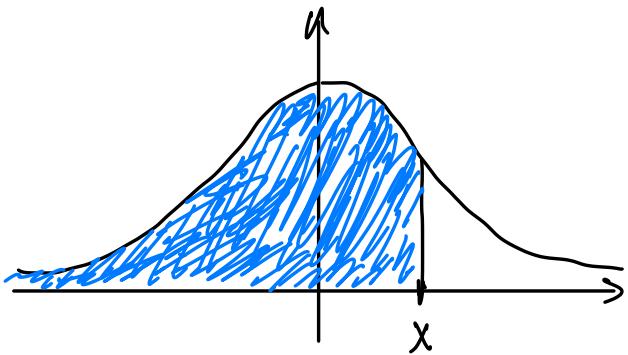
$$= \frac{1}{\sigma} X - \frac{\mu}{\sigma}$$

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

$$\begin{cases} a\mu + b = 0 \Rightarrow b = -a\mu = -\mu/6 \\ a^5 = 1 \Rightarrow a = 1/6 \end{cases}$$

Using "standardization" to compute probabilities $(x > 0)$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-z^2/2} dz$$



$$\mathcal{P}(Z \leq z) = \Phi(z)$$

Table 5.1 Area $\Phi(x)$ Under the Standard Normal Curve to the Left of X .

Ex: The height of maple trees at age 10 is estimated to be normally distributed with $\mu = 200$ cm and $\sigma^2 = 64$ cm. What is the probability that a 10-yr old maple tree has height

- smaller than 204 cm?
- smaller than 180 cm?
- greater than 210 cm?

$$H = \text{height of a 10-yr. old maple tree} \sim \text{Normal}(\underline{\mu}, \underline{\sigma^2})$$

$$\mu = 200, \sigma = 8.$$

$$a) P(H < 204) = P\left(Z < \frac{204 - 200}{8}\right) = P(Z < 0.5) = \Phi(0.5)$$

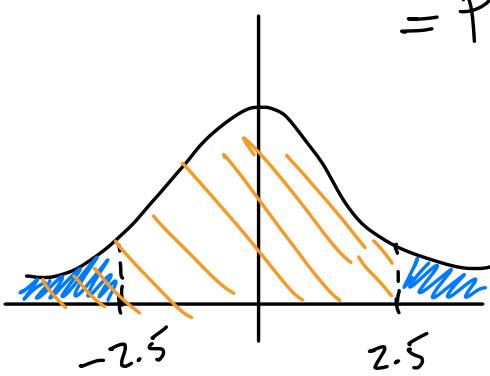
$$Z = \frac{H - 200}{8} \sim \text{Normal}(0, 1)$$

$$\begin{aligned} \text{Table} &\rightarrow = 0.6915 \\ &= \underline{\underline{69.15\%}} \end{aligned}$$

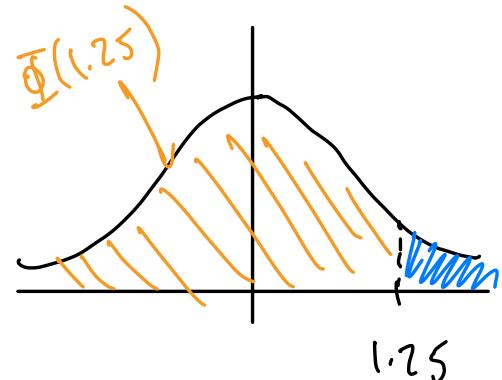
$$b) P(H < 180) = P\left(Z < \frac{180 - 200}{8}\right) = P\left(Z < -\frac{5}{2}\right)$$

$$= P(Z < -2.5) = 1 - P(Z < 2.5)$$

$$\begin{aligned} \text{Table} &\rightarrow = 1 - 0.9938 \\ &= \underline{\underline{0.0062 = 0.62\%}} \end{aligned}$$



$$c) P(H > 210) = P\left(Z > \frac{210 - 200}{8}\right) = P(Z > 1.25)$$



$$= 1 - \Phi(1.25) = 1 - 0.8944 = 0.1056$$

Table →

$$= \underline{\underline{10.56\%}}$$