

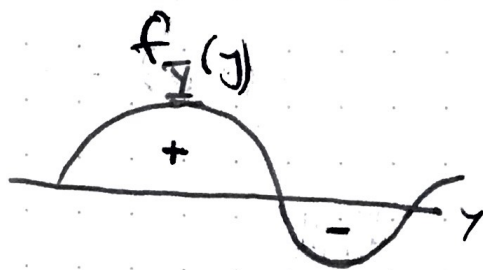
4/30/19

## Lecture 9

Rules for pdf

1)  $f_Y(y) \geq 0$

2)  $\int_{-\infty}^{\infty} f_Y(y) = 1$



Make sure you don't get lost in the calculus portion and use Wolfram Alpha to take care of it.

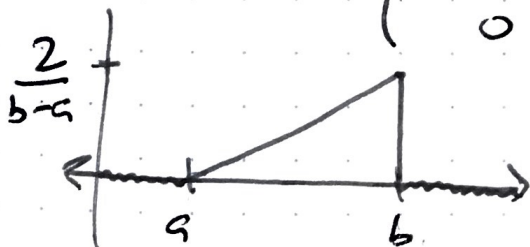
Wolfram Alpha search: integrate  $c(x-a)/(b-a)$  for  $x=a$  to  $b$

Definite integral:

$$\int_a^b \frac{c(x-a)}{b-a} dx = \frac{1}{2} c(b-a)$$

The triangular distribution that starts at 0 for  $y=a$  and rises linearly to  $\frac{2}{b-a}$  at  $y=b$  has density

$$(pdf) f_Y(y) = \begin{cases} \frac{2(y-a)}{(b-a)^2} & \text{for } a \leq y \leq b \\ 0 & \text{else} \end{cases}$$



WA: plot  $2(y-1)/(3-1)^2$  for  $y=1$  to  $3$

Will plot the graph for the special case.

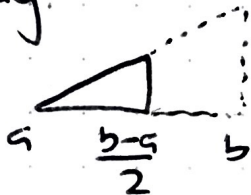
Ex: With the triangular distribution, what's

$$P(a \leq X \leq \frac{b-a}{2})?$$

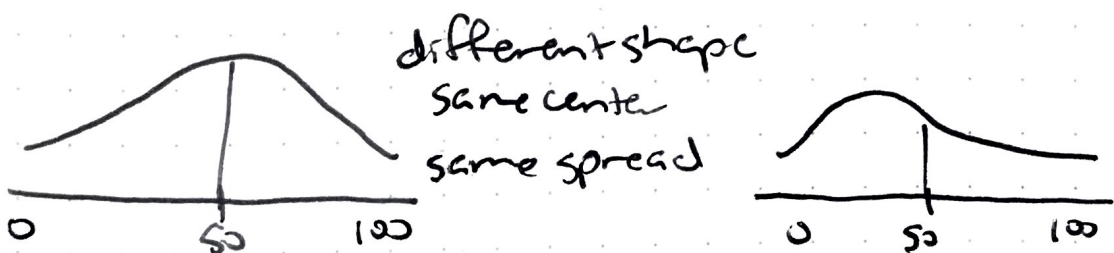
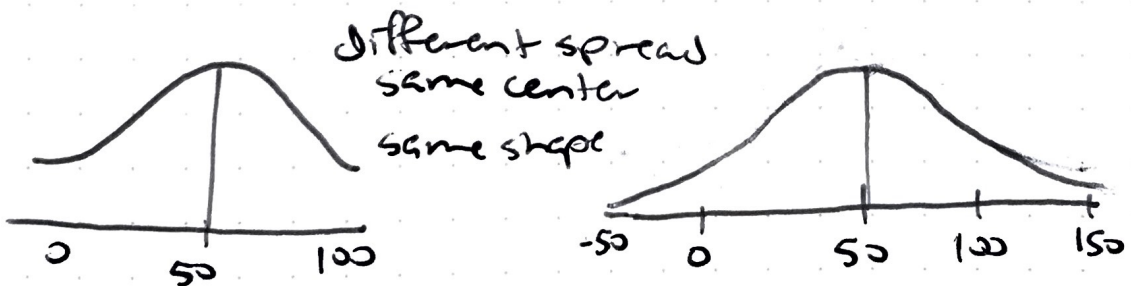
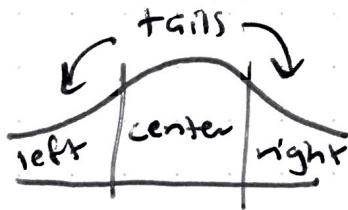
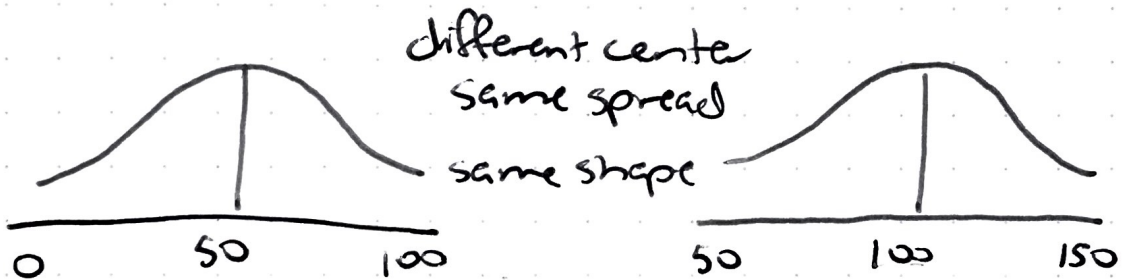
(7)

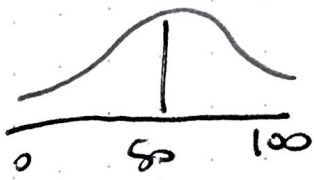
Hard Way: 
$$\int_a^{\frac{b-a}{2}} \frac{2(x-a)}{(b-a)} dx = \frac{(3a-b)^2}{4(b-a)^2}$$

Easier Way:



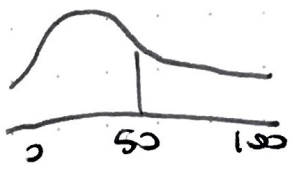
area of a triangle =  $\frac{bh}{2}$



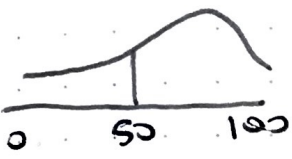


symmetric not skewed (1)

↑ point of symmetry



asymmetric positive skew long right-hand tail (2)

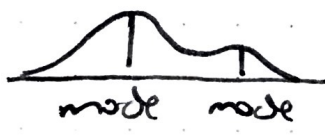


asymmetric negative skew long left-hand tail (3)

What's the difference between these distributions?



unimodal



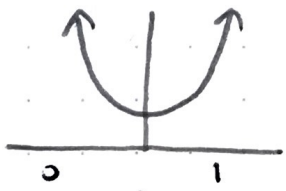
multimodal (bimodal)



: height of all AMS 131 students (mixture distribution)



like the bell curve



↑ point of symmetry

(1) height of adult females → symmetric

(2) family income — positive skew

(3) scores on take home test 1 — negative skew

Sometimes it's mathematically convenient to work w/ an unbounded continuous rv, just as was true in the Poisson case study for discrete rvs

Ex:  $Y$  = voltage in an electrical system

In practice,  $Y$  cannot be infinite, but you may not know ahead of time what its maximum practical value is, so model it as unbounded but with a much probability for extremely large values.

As an example, we're given the pdf  $f_Y(y) = \frac{1}{(1+y)^2} \mathbb{I}(y > 0)$



$$f_Y(y) = \begin{cases} \frac{1}{(1+y)^2} & \text{for } y > 0 \\ 0 & \text{else} \end{cases}$$

You can check that  $\int_{1000}^{\infty} \frac{1}{(1+x)^2} dx = \frac{1}{1001} = 0.001$ , so the right tail beyond  $Y=1000$

has almost no probability, matching the correct qualitative behavior.

Sometimes a rv will be neither discrete nor continuous.

people then say that it has a mixed (discrete/continuous) distribution

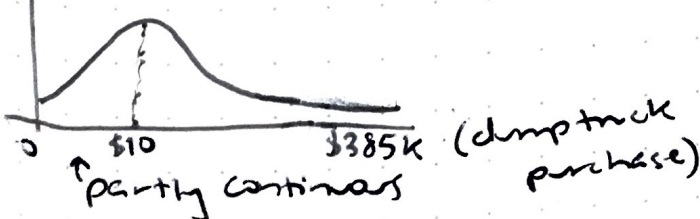
Ebay

eg. 2 weeks



$Y$  = GMV (gross merchandise value) in  $(0, T)$

0.9 is partly discrete





Ex:  
 In medical clinical trials of people with potentially fatal diseases, the outcome variable  $Y_i$  for person  $i$  in the treatment group might be  $Y_i =$  survival time in days from the beginning of the trial

Some patients may still be alive at the time  $T_{end}$  at which the trial finishes

Your probability model for  $Y_i$  would then have a continuous part for  $0 \leq Y_i \leq T_{end}$  and a discrete lump of probability  $p$  at  $Y_i = T_{end}$  signifying  $(Y_i > T_{end})$  but we don't know what  $Y_i$  would have been if we could have observed it:

$$\int_0^{T_{end}} f_{Y_i}(y) dy = (1-p) \text{ and } P(Y_i > T_{end}) = p$$

$(Y_i > T_{end})$  : the person was still alive at the end of the trial so we don't know what their survival time was

All we know is they lived at least that long

This is an example of not getting full data on the subjects of interest to you, called censoring

This one is right-censoring

Unifying idea connecting discrete & continuous rvs

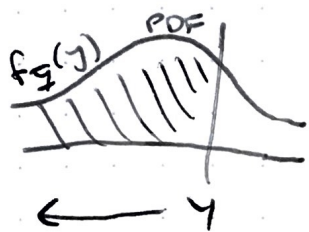
Discrete  $\leftrightarrow$  pmf (pmf)  
 Continuous  $\leftrightarrow$  pdf  
 Mixed  $\leftrightarrow$  (pmf + pdf)

Q: Is there something that uniquely characterizes the distribution of  $\bar{Y}$ , both when  $\bar{Y}$  is discrete & when it's continuous & when it's mixed?

A: Yes, the cumulative distribution function (cdf)

$$F_{\bar{Y}}(y)$$

Def: The cumulative distribution function (CDF) of a rv  $\bar{Y}$  is defined to be  $F_{\bar{Y}}(y) = P(\bar{Y} \leq y)$  for all  $-\infty < y < \infty$



CDF cont.

$$F_{\bar{Y}}(y) = P(\bar{Y} \leq y) = \int_{-\infty}^y f_{\bar{Y}}(t) dt$$

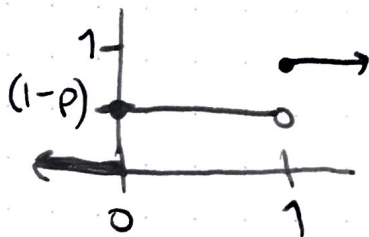
↑  
dummy variable of integration



$$0 \leq F_{\bar{Y}}(y) \leq 1$$

Ex:  $\bar{Y} \sim \text{Bernoulli}(p)$   $P(\bar{Y} = y) = \begin{cases} p & \text{for } y=1 \\ 1-p & 0 \\ 0 & \text{else} \end{cases}$  PMF

Clear way to write this:  $P(\bar{Y} = y) = p^y (1-p)^{1-y} I_{\{0,1\}}(y)$



$$F_{\bar{Y}}(y) = P(\bar{Y} \leq y)$$

The cdf of  $\bar{Y}$  is 0 for  $y < 0$ ; at  $\bar{Y} = 0$  it jumps up to  $(1-p)$  and stays there for  $0 \leq y < 1$ ; and at  $\bar{Y} = 1$  it jumps up to 1 & stays there for  $y \geq 1$

CDF can never dip down  $\swarrow$   $F_Y(y)$  has to be non-decreasing

If  $\gamma_1 < \gamma_2$  then  $F_{\mathcal{Y}}(\gamma_1) \leq F_{\mathcal{Y}}(\gamma_2)$

$\lim_{\gamma \rightarrow -\infty} F_{\mathcal{Y}}(\gamma) = 0$  and  $\lim_{\gamma \rightarrow \infty} F_{\mathcal{Y}}(\gamma) = 1$

CDFs  $F_{\mathcal{Y}}$  can be all of  $\mathbb{R}$  (When  $\mathcal{Y}$  is continuous)  
but certainly don't have to be (see the CDF of the  
Bernoulli ( $p$ ) distribution)

Technical fact:

Def:  $F_{\mathcal{Y}}(\gamma^-) = \lim_{\gamma^* \rightarrow \gamma} F_{\mathcal{Y}}(\gamma^*) = \lim_{\gamma^* \uparrow \gamma} F_{\mathcal{Y}}(\gamma^*)$

limit from  
the left

$\gamma^* < \gamma$

$\gamma^* \uparrow \gamma$

( $\gamma$  goes to  $\gamma$  from below)

Def:  $F_{\mathcal{Y}}(\gamma) = F_{\mathcal{Y}}(\gamma^+)$  for all  $-\infty < \gamma < \infty$

People call this continuity from the right or  
continuity from above

If  $F_{\mathcal{Y}}(\gamma^-) = F_{\mathcal{Y}}(\gamma^+) = F_{\mathcal{Y}}(\gamma)$  then  $F_{\mathcal{Y}}$  is continuous at  $\gamma$

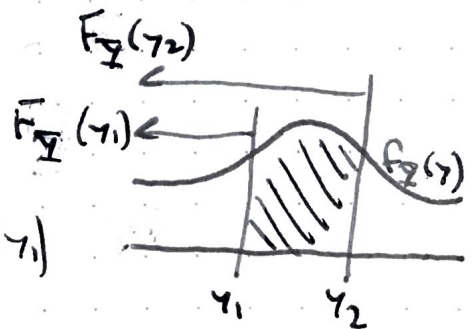
Consequences of the CDF definition

1)  $P(\mathcal{Y} > \gamma) = 1 - F_{\mathcal{Y}}(\gamma)$

2) For all  $\gamma_1, \gamma_2$  with  $\gamma_1 < \gamma_2$

$$P(\gamma_1 \leq \mathcal{Y} \leq \gamma_2) = F_{\mathcal{Y}}(\gamma_2) - F_{\mathcal{Y}}(\gamma_1)$$

↓  
Cont.



If  $\mathcal{Y}$  is continuous, there's an infinite connection between  
 $F_{\mathcal{Y}}(\gamma)$  and  $f_{\mathcal{Y}}(\gamma)$   
(CDF) (PDF)

$\mathcal{Y}$  continuous:  $\gamma_1 < \gamma_2$

$$P(\gamma_1 < \mathcal{Y} < \gamma_2) = F_{\mathcal{Y}}(\gamma_2) - F_{\mathcal{Y}}(\gamma_1) \\ = \int_{\gamma_1}^{\gamma_2} f_{\mathcal{Y}}(\gamma) d\gamma$$

Theorem: If  $\mathcal{Y}$  is a continuous rv, with pdf  $f_{\mathcal{Y}}(\gamma)$  and CDF  $F_{\mathcal{Y}}(\gamma)$  then

$$F_{\mathcal{Y}}(\gamma) = \int_{-\infty}^{\gamma} f_{\mathcal{Y}}(t) dt \quad \text{and at all continuity points}$$

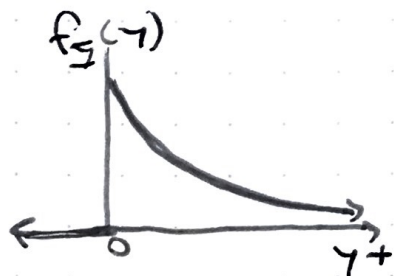
$$\text{of } f \quad \frac{d}{d\gamma} F_{\mathcal{Y}}(\gamma) = f_{\mathcal{Y}}(\gamma)$$

$\mathcal{Y}$  continuous  $\leftrightarrow$  the derivative of  $F_{\mathcal{Y}}(\gamma)$  is  $f_{\mathcal{Y}}(\gamma)$  <sup>PDF</sup> and  $F_{\mathcal{Y}}(\gamma)$  is an anti-derivative (integral) of  $f_{\mathcal{Y}}(\gamma)$

Def:  $\mathcal{Y}$  follows an exponential distribution  $E(\lambda)$  with (rate) parameter  $\lambda > 0$

$$f_{\mathcal{Y}}(\gamma) = \begin{cases} \lambda e^{-\lambda\gamma} & \gamma > 0 \\ 0 & \gamma \leq 0 \end{cases}$$

pdf



$$f_{\mathcal{Y}}(\gamma) = \begin{cases} ce^{-\lambda\gamma} & \text{for } \gamma \geq 0 \\ 0 & \text{else} \end{cases}$$

( $\lambda > 0$ )

The exponential dist. has a fundamental connection to the Poisson distribution in Poisson processes that we'll explore later



$$\text{CDF of } \underline{Y} : F_{\underline{Y}}(y) = \begin{cases} 0 & \text{for } y < 0 \\ 1 - e^{-\lambda y} & \text{for } y \geq 0 \\ 1 & \text{as } y \rightarrow \infty \end{cases}$$

for  $y \geq 0$

$$F_{\underline{Y}}(y) = \int_0^y \lambda e^{-\lambda t} dt$$
$$= 1 - e^{-\lambda y}$$

