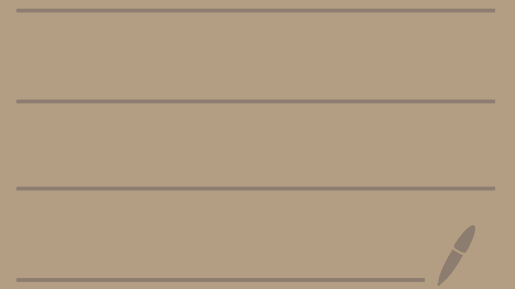


# PTS - Chapter 2

---



## 2 Random Variables

We roll 2 dice: the sum  $X = D_1 + D_2$ ,

$$X: \mathcal{S} \longrightarrow \mathbb{R}$$

is a random variable

Idea: We are not interested in arbitrary events, but only events that can be described by  $X$  having certain values

E.g. - weight  $\geq 100$  kg, height  $< 1.60$  m, - ...



Back to dice

$$P(\lfloor X = 2 \rfloor) = \frac{1}{36}$$

$$P(\lfloor X = 10 \rfloor) = \frac{3}{36}$$

$$P(\lfloor X = 3 \rfloor) = \frac{2}{36}$$

$$P(\lfloor X = 11 \rfloor) = \frac{2}{36}$$

$$P(\lfloor X = 4 \rfloor) = \frac{3}{36}$$

$$P(\lfloor X = 12 \rfloor) = \frac{1}{36}$$

$$P(\lfloor X = 5 \rfloor) = \frac{4}{36}$$

check

$$P(\lfloor X = 6 \rfloor) = \frac{5}{36}$$

$$\sum_{i=2}^{12} P(\lfloor X = i \rfloor) = 1$$

$$P(\lfloor X = 7 \rfloor) = \frac{6}{36}$$

Other poss. events expressible  
by  $X$ :

$$P(\lfloor X = 8 \rfloor) = \frac{5}{36}$$

$$P[5 \leq X \leq 9] = \frac{24}{36} = \frac{2}{3}$$

$$P(\lfloor X = 9 \rfloor) = \frac{4}{36}$$

A random variable  $X: \mathcal{S} \rightarrow \mathbb{R}$

is discrete if it has only finitely (or countably) many values  $x_1, \dots, x_n, \dots$

$X$  is continuous if it takes a continuum of values (e.g. weight, ...)

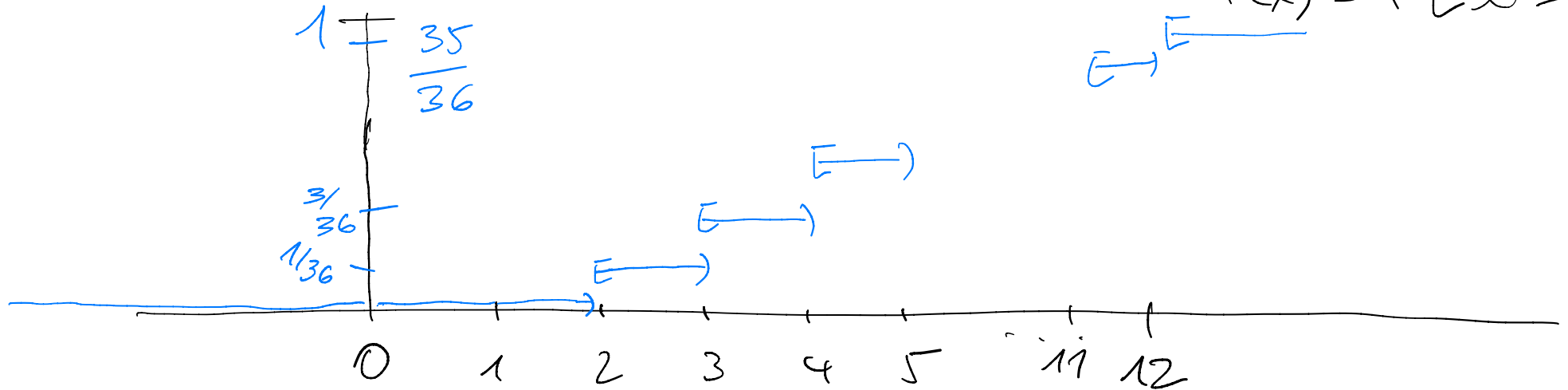
Definition 24: The (cumulative) distribution function of  $X$  is

$$F: \mathbb{R} \rightarrow [0, 1]$$

$$F(x) = P[X \leq x]$$

" $X \sim F$ " means " $F$  is distribution of  $X$ "

Distribution for  $X = D_1 + D_2$



$$F(2) = P[X \leq 2]$$

$$F(3) = P[X \leq 3] = \frac{1}{36} + \frac{2}{36} = \frac{3}{36}$$

$F$  answers all probability questions about  $X$ :

Eg  $P[a < X \leq b] = ?$

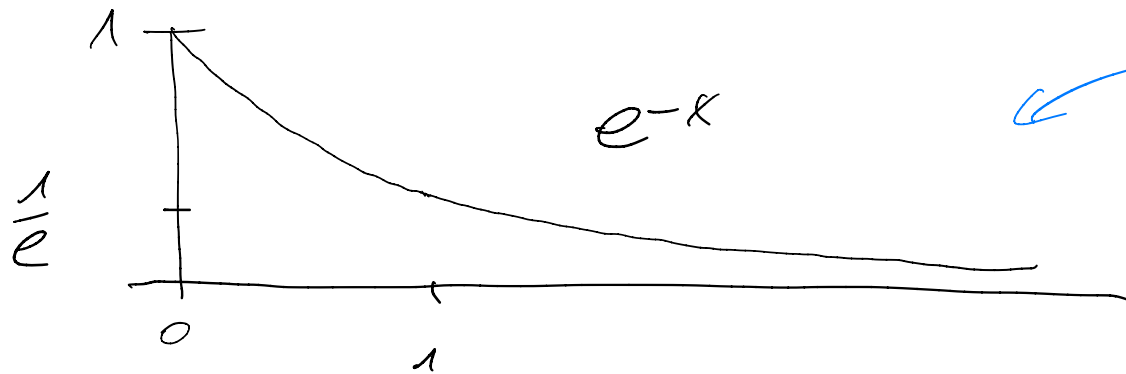
$$\{X \leq b\} = \{X \leq a\} \cup \{a < X \leq b\}$$

$$\begin{aligned} P[a < X \leq b] &= P[\{X \leq b\} - \{X \leq a\}] \\ &= F(b) - F(a) \end{aligned}$$

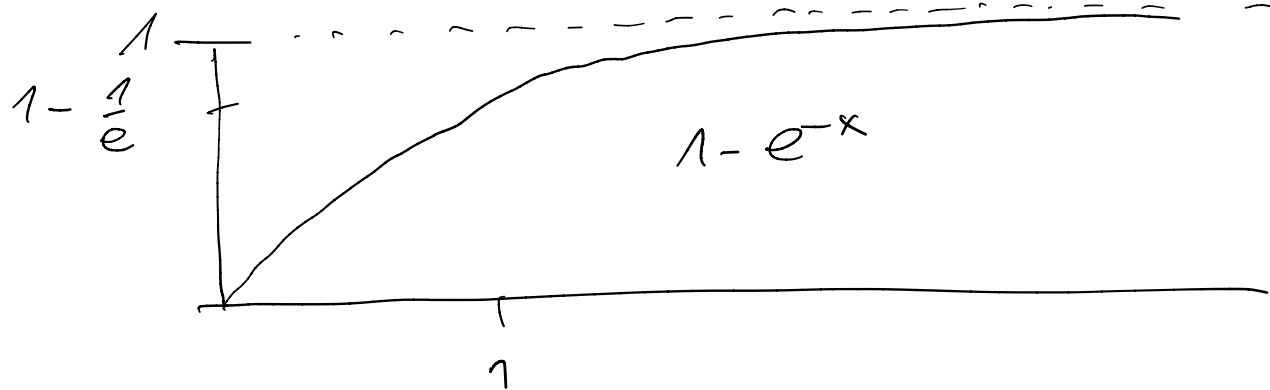
Example 25a) Suppose  $X \sim F$

e.g., time until a device breaks,  
an atom decays

$$F(x) = \begin{cases} 0 & x \leq 0 \\ 1 - e^{-x}, & x > 0 \end{cases}$$



← density of the exponential distribution



$$F(x) = P[X \leq x]$$

All distribution functions satisfy

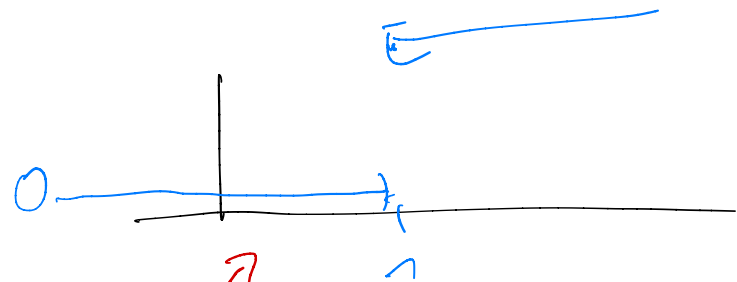
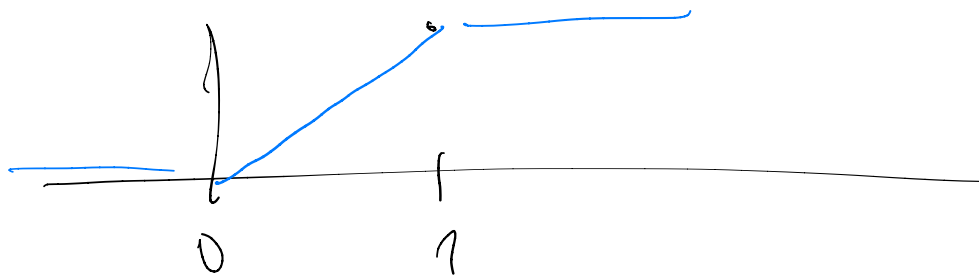
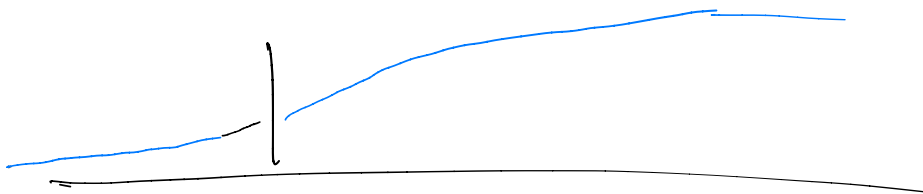
- $0 \leq F(x) \leq 1$  (since  $F(x) = P[X \leq x]$  is a probability)
- $F$  is monotonically increasing

- $\lim_{x \rightarrow -\infty} F(x) = 0$

- $\lim_{x \rightarrow +\infty} F(x) = 1$

- $\lim_{\substack{x \rightarrow +x_0 \\ x > x_0}} F(x) = F(x_0)$

Possible shapes



$H$  is discrete and the only possible value is 1

## 2.1 Types of Random Variables

Let  $X$  be discrete.

$$p: \mathbb{R} \rightarrow [0, 1]$$

$$p(x) = P[X = x]$$

(pmf)

is the probability mass function of  $X$

Let  $x_1, \dots, x_n, \dots$  be the possible values of  $X$

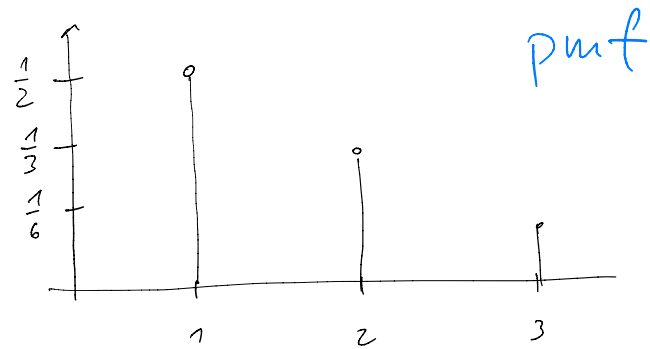
$$\sum_{i=1}^{\infty} p(x_i) = 1$$

Example 26: let  $X$  takes values  $\{1, 2, 3\}$

$$\text{and } p(2) = \frac{1}{3}, \quad p(3) = \frac{1}{6} \Rightarrow p(1) = \frac{3}{6} = \frac{1}{2}$$

Example 26: let  $X$  takes values  $\{1, 2, 3\}$

and  $p(2) = \frac{1}{3}$ ,  $p(3) = \frac{1}{6} \Rightarrow p(1) = \frac{3}{6} = \frac{1}{2}$



Cumulative distribution function

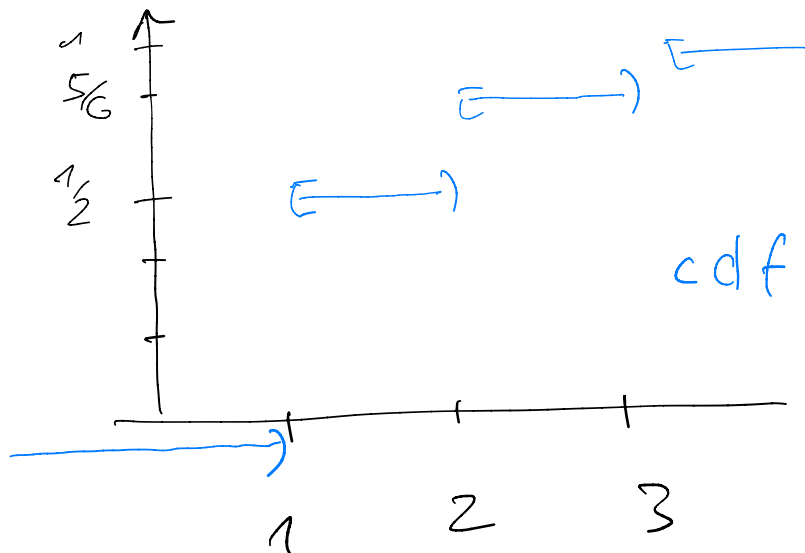
$$F(x) = P[X \leq x] = \sum_{Y \leq x} p(Y)$$

In general:

•  $F$  is constant on each interval

$$[x_i, x_{i+1})$$

•  $F$  is a step function





Definition 27:  $X$  is continuous if there is a fct

$$f: \mathbb{R} \rightarrow \mathbb{R}, \quad f \geq 0, \quad \text{rth (= such that)}$$

$$P[X \in B] = \int_B f(x) dx$$

for all "reasonable"  $B \subseteq \mathbb{R}$ . We call  $f$  the probability density function of  $X$  (pdf)

essentially unions intervals

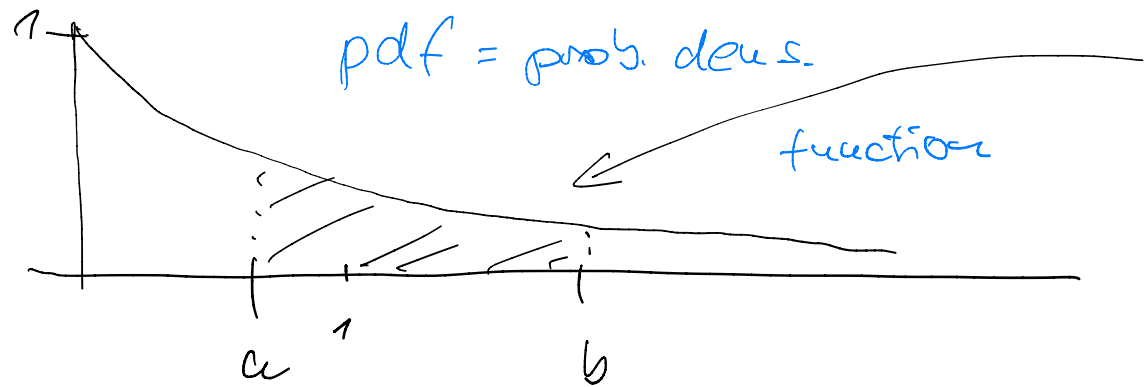
Remark:

$$1 = P[X \in (-\infty, \infty)]$$

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

$$P[a \leq X \leq b] = \int_a^b f(x) dx$$

Example:  $f(x) = \begin{cases} e^{-x} & x \geq 0 \\ 0 & x < 0 \end{cases}$   $F(x) = \begin{cases} 1 - e^{-x} & x \geq 0 \\ 0 & x < 0 \end{cases}$



$P[a < X < b]$   
 = area under the  
 graph of  $f$   
 between  $a$  and  $b$

For a discrete  $X$  we would take

$$\sum_{a < x < b} P(X)$$

Connection between cdf and pdf here:

$$F(x) = P[X \leq x] = \int_{-\infty}^x f(y) dy$$

$$\Leftrightarrow F'(x) = f(x) \quad (\text{and } \lim_{x \rightarrow -\infty} F(x) = 0)$$

Connection between cdf and pdf here:

$$F(x) = P[X \leq x] = \int_{-\infty}^x f(y) dy$$

$$\Leftrightarrow F'(x) = f(x) \quad (\text{and } \lim_{x \rightarrow -\infty} F(x) = 0)$$

What is  $F$ ?

$$f(y) = \begin{cases} e^{-y} & y \geq 0 \\ 0 & y < 0 \end{cases}$$

$$F(x) = \int_{-\infty}^x f(y) dy = \begin{cases} \int_{-\infty}^x 0 dy = 0 & \text{if } x < 0 \\ \int_{-\infty}^x f(y) dy & \text{if } x \geq 0 \end{cases}$$

$$\int_{-\infty}^x f(y) dy = \int_{-\infty}^0 f(y) dy + \int_0^x f(y) dy = 0 + \int_0^x e^{-y} dy$$

$$= [-e^{-y}]_0^x = -e^{-x} - (-e^{-0}) = -e^{-x} + 1 = 1 - e^{-x}$$

This is the cdf of the exp. distribution

Example 30 Assume the following statistical figures for a community of families

$$\text{no children} \quad 15\% \quad = \frac{3}{20}$$

$$1 \text{ child} \quad 20\% \quad = \frac{4}{20}$$

$$2 \text{ children} \quad 35\% \quad = \frac{7}{20}$$

$$3 \text{ children} \quad 30\% \quad = \frac{6}{20}$$

The probability of boys and girls is 50% each.

What is the joint probability mass function for boys and girls?

(i.e.:  $X = \# \text{ boys}$ ,  $Y = \# \text{ girls}$ )

Answer using conditioning on  $\#$  of children!

$$P[X=0, Y=0] = P[\text{no children}] = \frac{3}{20} = \frac{12}{80}$$

$$\begin{aligned} P[X=0, Y=1] &= P[\text{"1 child"} \cap \text{"child is girl"}] \\ &= P[\text{"child is girl"} \mid \text{"1 child"}] \cdot P[\text{"1 child"}] \\ &= \frac{1}{2} \cdot \frac{4}{20} = \frac{8}{80} \end{aligned}$$

$$\begin{aligned} P[X=0, Y=2] &= P[\text{"2 children are girls"} \mid \text{"2 children"}] \\ &\quad \cdot P[\text{"2 children"}] \\ &= \frac{1}{2 \cdot 2} \cdot \frac{7}{20} = \frac{7}{80} \end{aligned}$$

$$\begin{aligned} P[X=0, Y=3] &= P[\text{"3 children are girls"} \mid \text{"3 children"}] \\ &\quad \cdot P[\text{"3 children"}] \\ &= \frac{1}{2^3} \cdot \frac{\cancel{6}^3}{20} = \frac{3}{80} \end{aligned}$$

$$P[X=1, Y=0] = P[X=0, Y=1] = \frac{1}{2} \cdot \frac{4}{20} = \frac{2}{25}$$

$$\begin{aligned} P[X=1, Y=1] &= P[\text{"1 boy, 1 girl"} \mid \text{"2 children"}] \\ &\quad \cdot P[\text{"2 children"}] \\ &= \frac{1}{2} \cdot \frac{7}{20} = \frac{7}{40} \end{aligned}$$

$$\begin{aligned} P[X=1, Y=2] &= P[\text{"1 boy, 2 girls"} \mid \text{"3 children"}] \\ &\quad \cdot P[\text{"3 children"}] \\ &= 3 \cdot \frac{1}{2^3} \cdot \frac{6}{20} = \frac{9}{100} \end{aligned}$$

$$P[X=2, Y=0] = P[X=0, Y=2]$$

$$P[X=2, Y=1] = P[X=1, Y=2]$$

$$P[X=3, Y=0] = P[X=0, Y=3]$$

This is the summary table (multiples of  $\frac{1}{80}$ )

$x \backslash y$	0	1	2	3	Sum	
0	12	8	7	3	30	marginal probabilities of $x$
1	8	14	9	0	31	
2	7	9	0	0	16	
3	3	0	0	0	3	
Sum	30	31	16	3	80	marginal probabilities of $y$

This is the summary table (multiples of  $\frac{1}{80}$ )

$x \backslash y$	0	1	2	3	Sum	
0	$\frac{12}{80}$	$\frac{8}{80}$	$\frac{7}{80}$	3 ...	$\frac{30}{80}$	marginal probabilities of $x$
1	8	14	9	0	$\frac{31}{80}$	
2	7	9	0	0	$\frac{16}{80}$	
3	3	0	0	0	$\frac{3}{80}$	
Sum	30	31	16	3	$\frac{80}{80}$	marginal probabilities of $y$



We want a table of the form

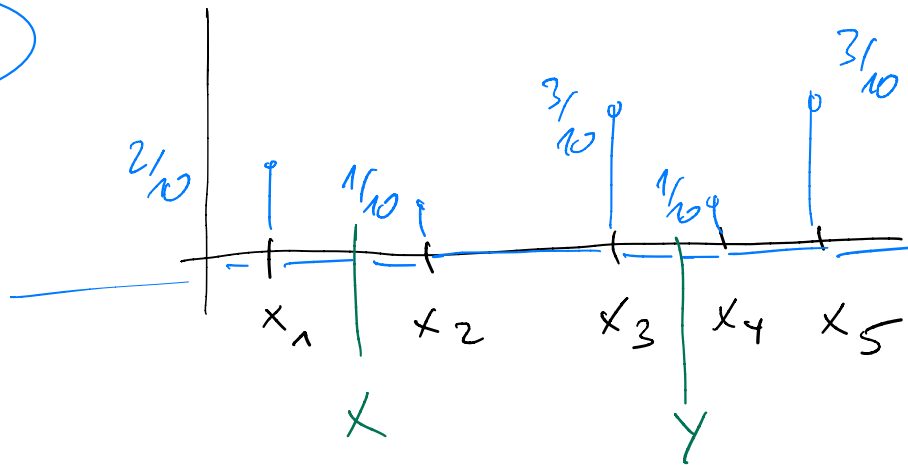
$x \backslash y$	0	1	2	3	Sum
0					
1				0	
2			0	0	
3		0	0	0	
Sum					

# Revision: Random Variables $X: \mathcal{S} \rightarrow \mathbb{R}$

Probabilities  $p(x_i)$   
for each single value  $x_i$   
that  $X$  can take

Distinguish 2 kinds

discrete



$$0 < p(x_i) < 1$$

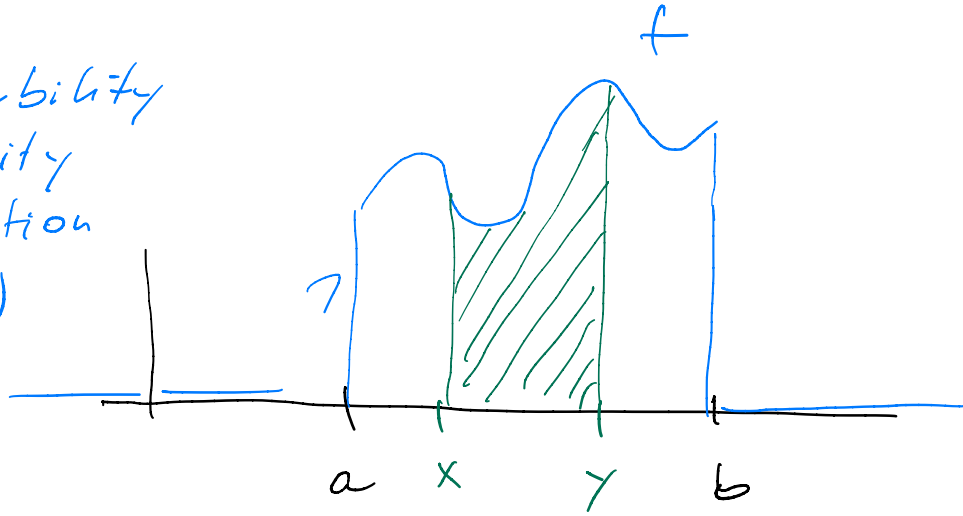
$$\sum_i p(x_i) = 1$$

$p$  is the  
probability mass  
function (pmf)

$$P[x < X \leq y] = \sum_{x < x_i \leq y} p(x_i)$$

continuous

probability  
density  
function  
(pdf)

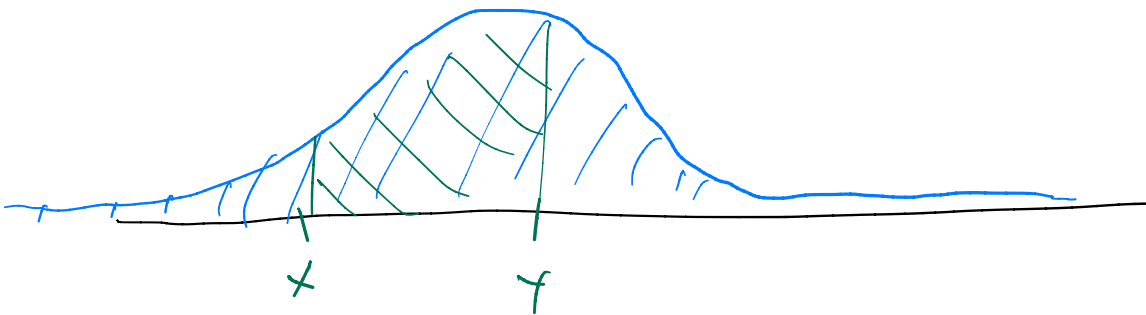


$$P[x < \mathcal{X} \leq y] = P[x \leq \mathcal{X} \leq y] = \int_x^y f(z) dz$$

$$\int_a^b f(z) dz = 1, \quad f(x) \geq 0$$

$$\int_{-\infty}^{\infty} f(z) dz = 1$$

$$\int_{-\infty}^{\infty} f(z) dz = 1$$



In continuous case

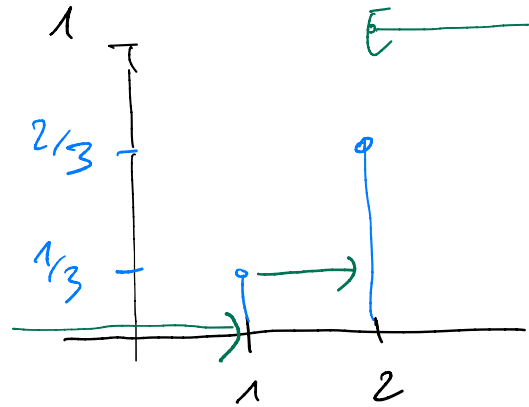
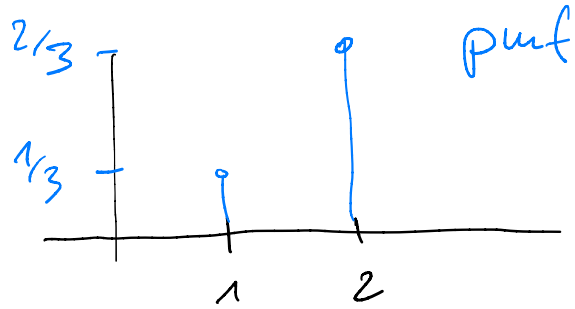
$$P[\mathcal{X} = x] = \int_x^x f(z) dz = 0$$

i.e., a single value has  
probability 0

# Distribution Function

$$F(x) = P[X \leq x]$$

discrete case



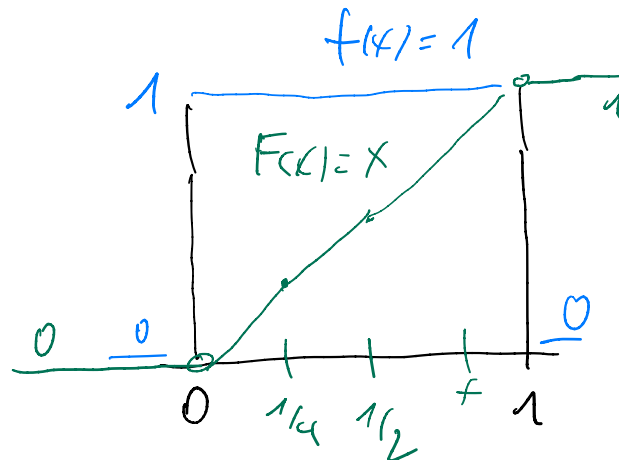
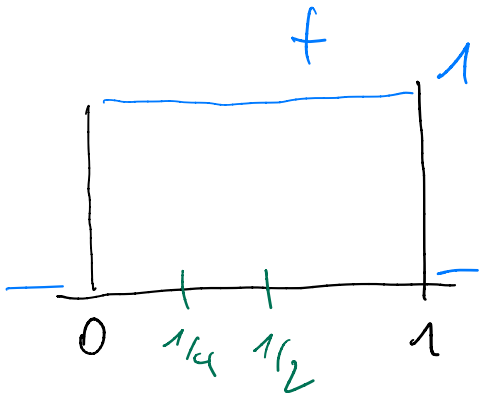
$$F(x) = \sum_{x_i \leq x} P(X=x_i)$$

$$F(x) = \int_{-\infty}^x f(z) dz$$

Uniform distribution  $U[0,1]$   
(special case of  $U[a,b]$ )

$$f(x) = \begin{cases} 1 & \text{if } 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Always:  $F' = f$   
(from Fundamental Theorem of Calculus)

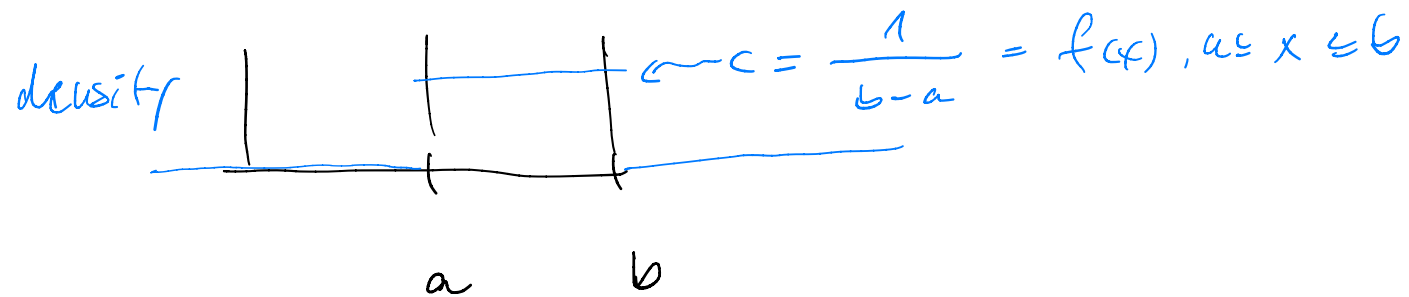


Here,  $F(x) = \int_0^x f(z) dz$   
 $= \int_0^x 1 dz = x$   
since  $f$  is 0 on  $[-\infty, 0]$

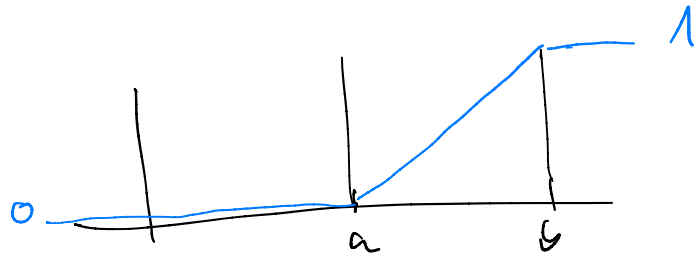
# Examples of Continuous Distributions

1) Uniform Distribution: "waiting for bus"

$U[a, b]$ : uniform on  $[a, b]$



distribution



## 2 Exponential Distribution

Waiting for: a customer, an email, an atom to decay

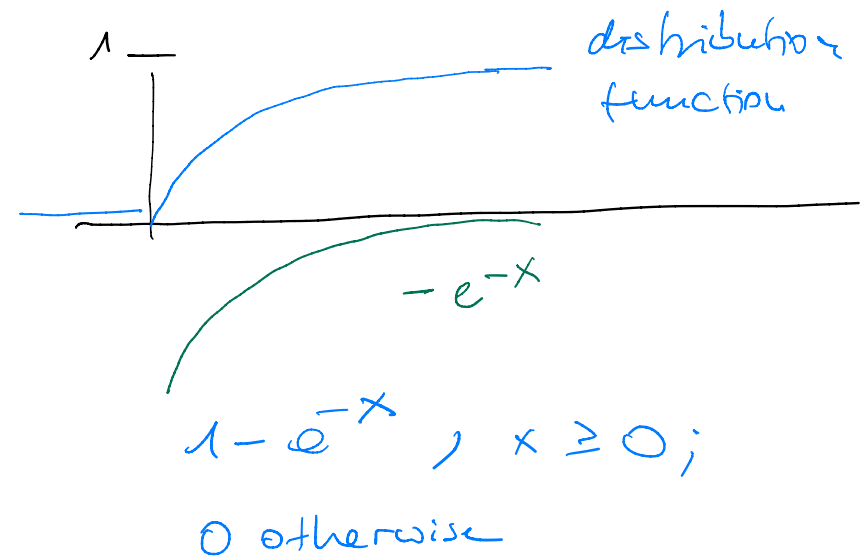
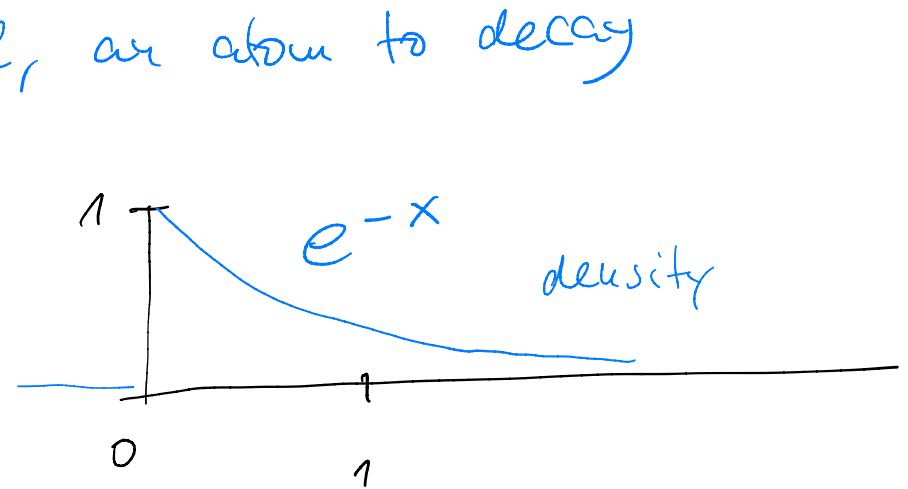
Process w/o memory:

The probability to wait at least  $a$  minutes does not depend on having waited already  $b$  minutes

$$P[X > a] = P[X > a + b | X > b]$$

This leads to the exponential distribution,

Check: the derivative of the distribution is the density



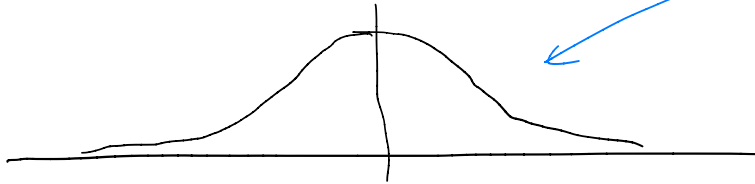
$$\frac{d}{dx} 1 - e^{-x} = 0 - e^{-x}(-1) = e^{-x}$$

3. Normal Distribution  $N(0, \frac{1}{2})$

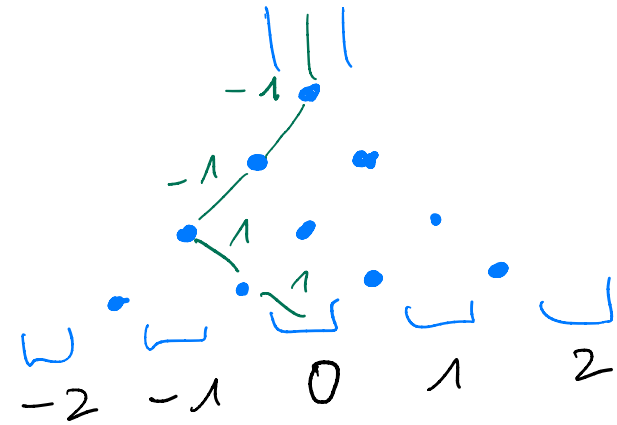
$\nearrow$  mean  
 $\nwarrow$  variance

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

density of  $N(0, \frac{1}{2})$



Sum of independent RVs,  
with same distribution,  
 e.g. Galton Board

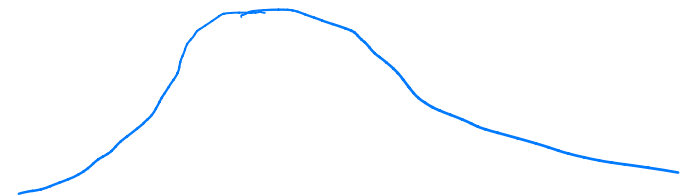


$N(0, \frac{1}{2})$  distribution



Distribution function  
 of the normal distribution  
 is written

$$\Phi \text{ for } N(0, 1)$$



# Density vs. Distribution (Student Question)

$F(x) = P[\mathcal{X} \leq x]$  is the definition of the distribution function of  $\mathcal{X}$

Suppose  $f$  is the density of  $\mathcal{X}$  ( $\mathcal{X}$  continuous)



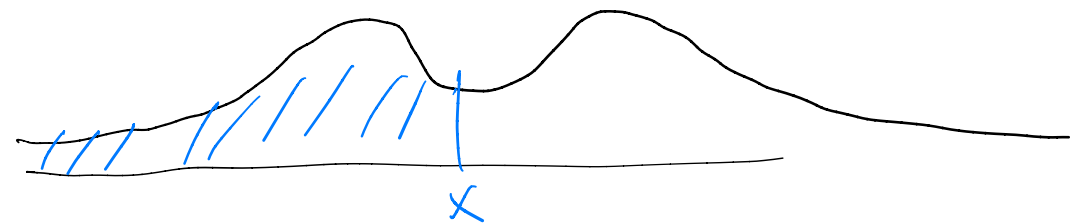
Then  $f \geq 0$ ,

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

" $f$  is density of" means  $P[a \leq \mathcal{X} \leq b] = \int_a^b f(x) dx$

What is  $F$  in this case?

$$F(x) = P[\mathcal{X} \leq x] = \int_{-\infty}^x f(y) dy$$



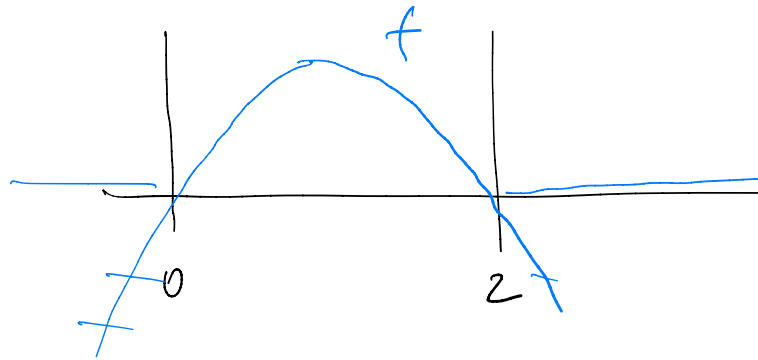


## Exercise (Quiz)

$$f(x) = \begin{cases} c(2x - x^2), & 0 \leq x \leq 2 \\ 0 & \text{otherwise} \end{cases}$$

$$f(x) = c \cdot x(2-x) \\ = -c(x-0)(x-2)$$

Which  $c$  turns  $f$   
into a density?



We want

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

$$\text{Here, } \int_{-\infty}^{\infty} f(x) dx = \int_0^2 f(x) dx = \int_0^2 c(2x - x^2) dx$$

$$= c \int_0^2 2x - x^2 dx = c \left( \int_0^2 2x dx - \int_0^2 x^2 dx \right)$$

$$= c \left( \left[ x^2 \right]_0^2 - \left[ \frac{x^3}{3} \right]_0^2 \right) = c \left( (2^2 - 0^2) - \left( \frac{2^3}{3} - \frac{0^3}{3} \right) \right)$$

$$= c \left( 4 - \frac{8}{3} \right) = c \left( \frac{12}{3} - \frac{8}{3} \right) = c \frac{4}{3} = 1 \Rightarrow c = \frac{3}{4}$$

## 2.4 Expectation

Throwing a die: let  $X$  be the value of the die. On "average," we see

$$1 \cdot \frac{1}{6} + 2 \cdot \frac{1}{6} + 3 \cdot \frac{1}{6} + 4 \cdot \frac{1}{6} + 5 \cdot \frac{1}{6} + 6 \cdot \frac{1}{6} = \frac{7}{2}$$

Tossing a coin  $n$  times: Expected # of heads:

$$1 \cdot \frac{1}{2} + 0 \cdot \frac{1}{2} = \frac{1}{2} \quad \text{if we toss once}$$

$$n = 2$$

$$0 \cdot \frac{1}{4} + 1 \cdot \frac{1}{2} + 2 \cdot \frac{1}{4} = 0 + \frac{1}{2} + \frac{1}{2} = 1$$

$$\text{In general:} \quad \frac{n}{2} = n \cdot \frac{1}{2}$$

Tossing the coin until first head:

$$1 \cdot \frac{1}{2} + 2 \cdot \left(\frac{1}{2}\right)^2 + 3 \cdot \left(\frac{1}{2}\right)^3 + \dots$$

↑  
head  
1st time

↑  
T, H

↑  
T, T, H

$$= \sum_{k=1}^{\infty} k \cdot \left(\frac{1}{2}\right)^k =$$

Geometric series

$$\sum_{k=0}^{\infty} x^k = \frac{1}{1-x} \quad (|x| < 1)$$

$$\sum_{k=0}^n x^k = \frac{1-x^{n+1}}{1-x}$$

$\sum \frac{1}{n}$   
not converging...

We want to calculate:

$$\sum_{k=1}^{\infty} k \cdot \left(\frac{1}{2}\right)^k$$

It turns out that a more general sum is easier to calculate:

$$\sum_{k=1}^{\infty} k \cdot x^k, \quad |x| < 1$$

Note that

$$k \cdot x^{k-1} = \frac{d}{dx} x^k$$

consequently,

$$k x^k = x \cdot k \cdot x^{k-1} = x \cdot \frac{d}{dx} x^k$$

Reminders: Geometric series

$$\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}, \quad |x| < 1$$

Therefore, we can rewrite our sum as follows:

$$\begin{aligned}\sum_{k=1}^{\infty} k \cdot x^k &= \sum_{k=1}^{\infty} x \cdot k \cdot x^{k-1} = x \cdot \sum_{k=1}^{\infty} k \cdot x^{k-1} \\ &= x \cdot \sum_{k=1}^{\infty} \frac{d}{dx} x^k \stackrel{f+g'=(f+g)'}{=} x \cdot \frac{d}{dx} \sum_{k=1}^{\infty} x^k \stackrel{\sum_{k=0}^{\infty} x^k = \frac{1}{1-x}}{=} x \cdot \frac{d}{dx} \frac{1}{1-x} \\ &= x \cdot \frac{d}{dx} (1-x)^{-1} \stackrel{\frac{d}{dx} x^a = a x^{a-1}}{=} x \cdot (-1) (1-x)^{-2} = \frac{x}{(1-x)^2}\end{aligned}$$

Now, we can plug in  $\frac{1}{2}$  for  $x$ :

$$\sum_{k=1}^{\infty} k \left(\frac{1}{2}\right)^k = \frac{\frac{1}{2}}{\left(1-\frac{1}{2}\right)^2} = \frac{\frac{1}{2}}{\left(\frac{1}{2}\right)^2} = \frac{1}{\frac{1}{2}} = 2$$

So, the expected number of coin tosses until the first head is 2.

Definition Let  $X$  be a discrete R.V., with values  $x_1, \dots, x_n, \dots$

Then  $E[X] := \sum_{i=1}^n x_i P[X = x_i]$ , if  $X$  has  $n$  values

$E[X] := \sum_{i=1}^{\infty} x_i P[X = x_i]$ , if  $X$  has  $\infty$  many values,

$E[X]$  is the expected value of  $X$ .

Definition Let  $X$  be a continuous R.V. with density  $f$ .

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

is the expected value of  $X$

(if the integral exists)



$f(x) \cdot \Delta$   
prob. of  
 $P[X \leq x \leq x + \Delta]$

Waiting time for alarm :

$X$  waiting time  $RU$ , takes value  $[0, 2]$

$$\text{Density } f(x) = \begin{cases} 1/2 & x \in [0, 2] \\ 0 & \text{otherwise} \end{cases}$$

$$E[X] = \int_{-\infty}^{\infty} x f(x) dx = \int_0^2 x \frac{1}{2} dx$$

$$= \left[ \frac{1}{2} \frac{x^2}{2} \right]_0^2 = \left[ \frac{x^2}{4} \right]_0^2 = \frac{2^2}{4} - \frac{0^2}{4} = 1 \quad \text{Ans}$$

Uniform probability



$$c \cdot 2 = 1$$

## 2.2 Joint Distributions

Consider two RVs  $X, Y$  together. Study probabilities

$$P[X = x, Y = y]$$

or

$$P[a < X \leq b, c < Y \leq d]$$



Example 29: 9 batteries, 2 new, 3 part. charged, 4 empty.

Randomly select 3 out of 9 batteries.

$x$  # new batteries  $x \in \{0, 1, 2\}$   
 $y$  # partially charged  $y \in \{0, 1, 2, 3\}$

let  $p(x, y) = P[X=x, Y=y]$  joint pmf of  $x$  and  $y$

$$p(0,0) = \frac{\binom{4}{3}}{\binom{9}{3}} = \frac{4}{84}$$

$$p(0,1) = \frac{\binom{3}{1} \binom{4}{2}}{\binom{9}{3}} = \frac{18}{84}$$

$$p(0,2) = \frac{\binom{3}{2} \binom{4}{1}}{\binom{9}{3}} = \frac{12}{84}$$

$$p(0,3) = \frac{\binom{3}{3}}{\binom{9}{3}} = \frac{1}{84}$$

$$p(1,0) = \frac{\binom{2}{1} \binom{4}{2}}{\binom{9}{3}} = \frac{12}{84}$$

$$\binom{9}{3} = \frac{9 \cdot 8 \cdot 7}{3 \cdot 2 \cdot 1} = 12 \cdot 7 = 84$$

$$p(1,1) = \frac{\binom{2}{1} \binom{3}{1} \binom{4}{1}}{\binom{9}{3}} = \frac{24}{84}$$

$$p(1,2) = \frac{\binom{2}{1} \binom{3}{2}}{\binom{9}{3}} = \frac{6}{84}$$

$$p(2,0) = \frac{\binom{2}{2} \binom{4}{1}}{\binom{9}{3}} = \frac{4}{84}$$

$$p(2,1) = \frac{\binom{2}{2} \binom{3}{1}}{\binom{9}{3}} = \frac{3}{84}$$

We have computed the joint pmf of  $X$  and  $Y$ .  
 Summarize in table (by multiples of  $\frac{1}{84}$ )

$X \backslash Y$	0	1	2	3	Sum
0	4	18	12	1	35
1	12	24	6	0	42
2	4	3	0	0	7
Sum	20	45	18	1	84

joint pmf

probability  
 of  $X=i$ , i.e.  
 $P[X=i]$

prob. of  $Y=j$ , i.e.  
 $P[Y=j]$

marginal  
 probabilities

Joint cumulative probability distrib.

$$F(x, y) = P[X \leq x, Y \leq y]$$

Distribution of  $X$

$$\begin{aligned} F_X(x) &= P[X \leq x] = P[X \leq x, Y < \infty] \\ &= F(x, \infty) \end{aligned}$$

How we get the marginal pdf of  $X$  out of the joint pdf  $p(x, y) = P[X=x, Y=y]$  ?

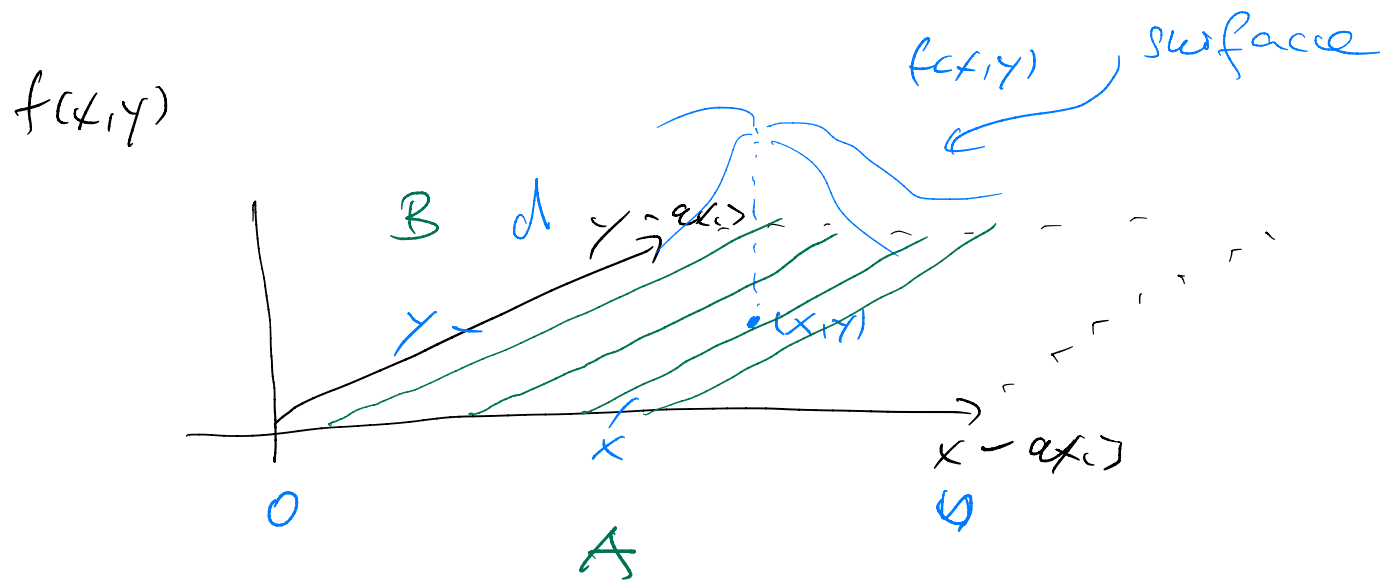
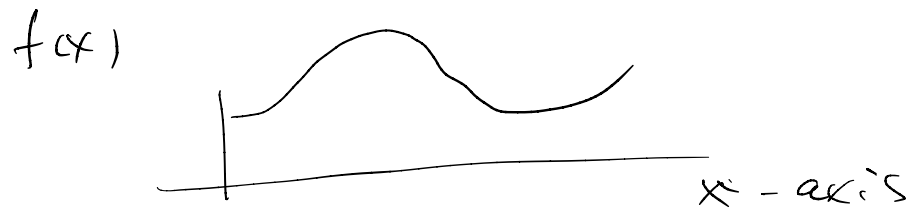
$$P_X(x) = P[X=x] = \sum_{j=1}^n P[X=x, Y=y_j]$$
$$= \sum_{j=1}^n p(x, y_j)$$

$$P_Y(y) = P[Y=y] = \sum_{i=1}^m p(x_i, y)$$

How can we model joint probabilities in cont. case?

discrete case: joint pmf  $P(X, Y)$

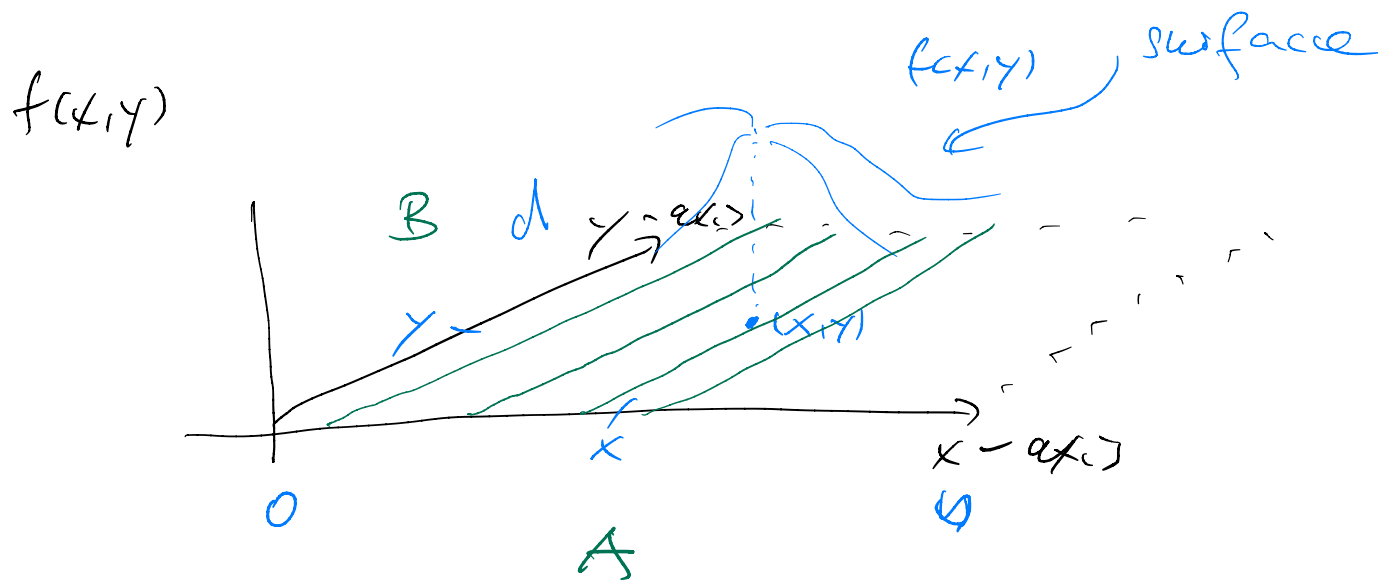
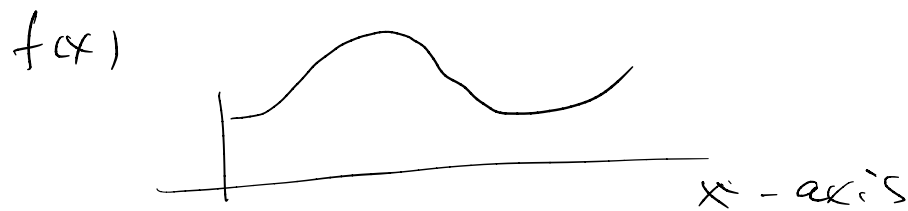
continuous case: joint pdf  
(p. density f.)  $f(x, y)$



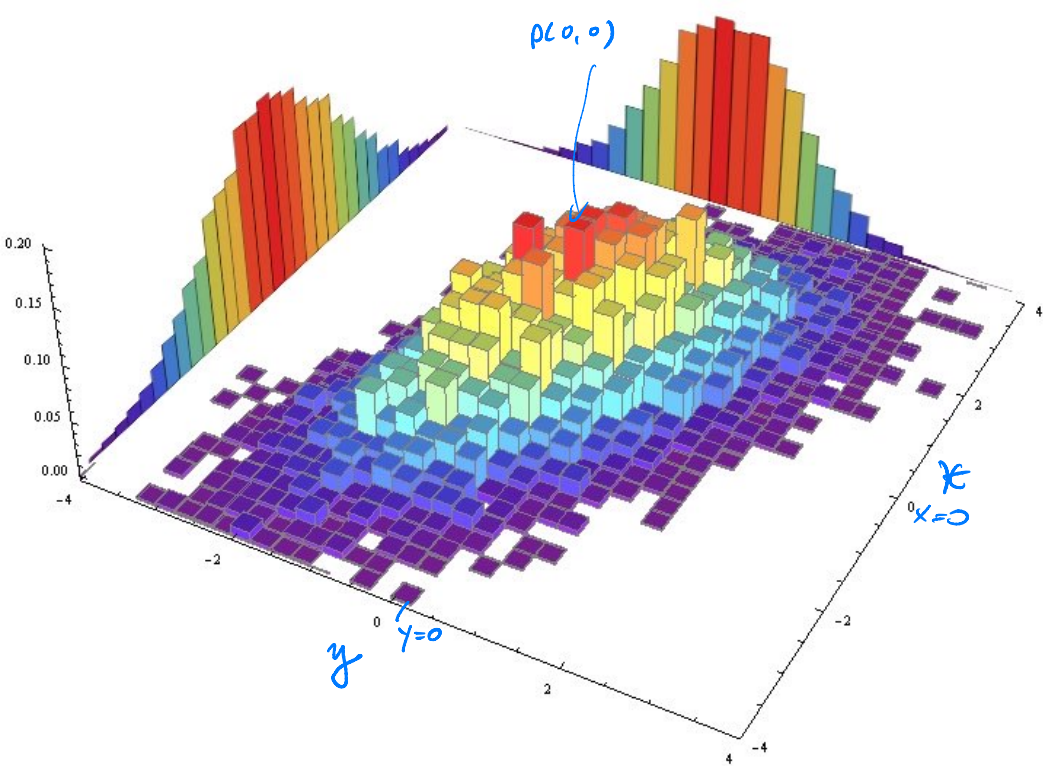
Integrals  
= areas under  
surface

How can we model joint probabilities in the continuous case?

Discrete case:	joint pmf	$p(x, y)$	"discrete"
Continuous case:	joint pdf	$f(x, y)$	



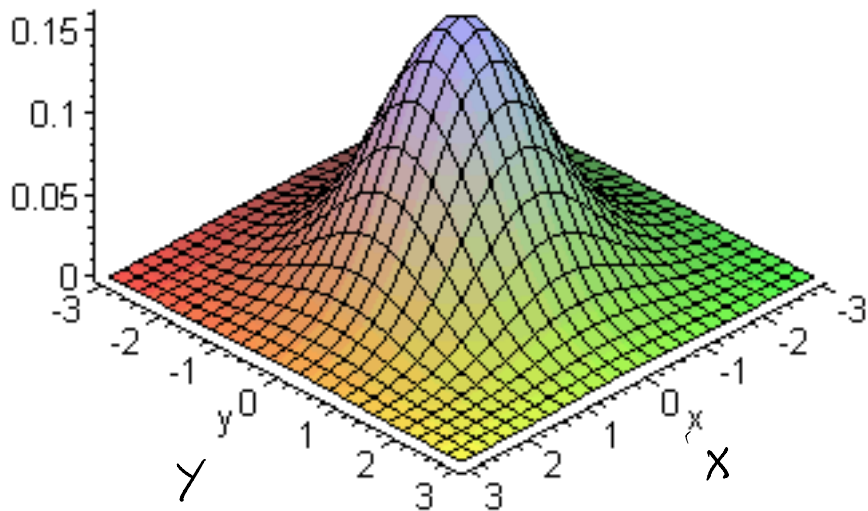
Integrals =  
volume  
under  
surface

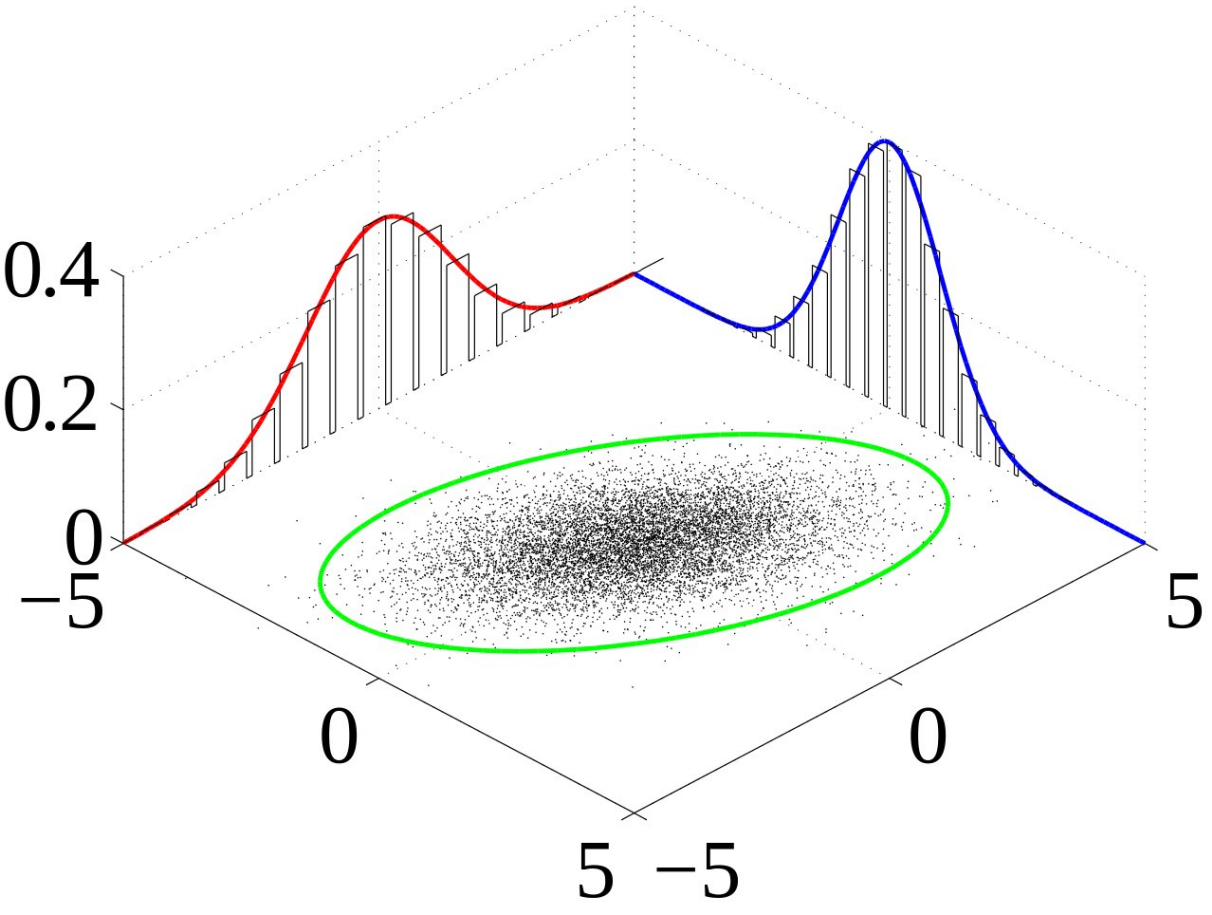




# Bivariate Normal

*Cavalieri's Principle*





Let  $X, Y$  continuous, joint pdf is a fct

$$f: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R},$$

For  $C \subseteq \mathbb{R} \times \mathbb{R}$ , a reasonable subset, we have

$$P[(X, Y) \in C] = \iint_{(x, y) \in C} f(x, y) dx dy$$

Requirements of  $f$ :

$$f(x, y) \geq 0, \quad \iint_{\mathbb{R} \times \mathbb{R}} f(x, y) dx dy = 1$$

If  $A, B \subseteq \mathbb{R}$ , then

$$\begin{aligned} P[X \in A, Y \in B] &= \int_A \left( \int_B f(x, y) dy \right) dx \\ &= \int_B \left( \int_A f(x, y) dx \right) dy \end{aligned}$$

Change of integration order is similar to change of summation order:

Consider

$$\begin{array}{cc} a_{11} & a_{12} \\ a_{21} & a_{22} \end{array}$$

Then

$$\sum_{i=1}^2 \sum_{j=1}^2 a_{ij} = (a_{11} + a_{12}) + (a_{21} + a_{22})$$

$$\sum_{j=1}^2 \sum_{i=1}^2 a_{ij} = (a_{11} + a_{21}) + (a_{12} + a_{22})$$

The two sums are identical due to associativity and commutativity of addition.

Similarly, we have  $\int_A \int_B f(x,y) dx dy = \int_B \int_A f(x,y) dy dx$

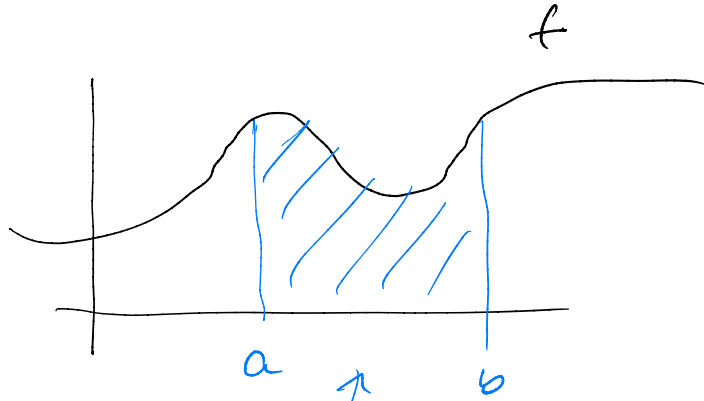
Example 32: let the joint pdf of  $x, y$  be

$$f(x, y) = \begin{cases} 2e^{-x}e^{-2y} & x, y > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy &= \int_0^{\infty} \int_0^{\infty} 2e^{-x}e^{-2y} dx dy \\ &= \int_0^{\infty} 2e^{-2y} \left( \int_0^{\infty} e^{-x} dx \right) dy = \int_0^{\infty} 2e^{-2y} \left[ -e^{-x} \right]_0^{\infty} dy \end{aligned}$$

$$\begin{aligned} \int_0^{\infty} 2e^{-2y} (0 - (-1)) dy &= \int_0^{\infty} 2e^{-2y} dy = \left[ -e^{-2y} \right]_0^{\infty} \\ &= 0 - (-e^{-2 \cdot 0}) = 0 - (-1) = 1 \end{aligned}$$

Student Question: "When evaluating an integral of  $f$  with an antiderivative  $F$ , why do we plug the upper bound first into  $F$ ?"



$F$  is an antiderivative of  $f$   
if  
 $F' = f$

$$\int_a^b f(x) dx = F(b) - F(a) = [F(x)]_a^b$$

$$\int_a^{\infty} f(x) dx = \lim_{b \rightarrow \infty} \int_a^b f(x) dx =$$

$$\lim_{b \rightarrow \infty} (F(b) - F(a)) = \left( \lim_{b \rightarrow \infty} F(b) \right) - F(a)$$

$$P[X > 1, Y < 1]$$

$$= \int_1^{\infty} \int_0^1 f(x, y) dy dx$$

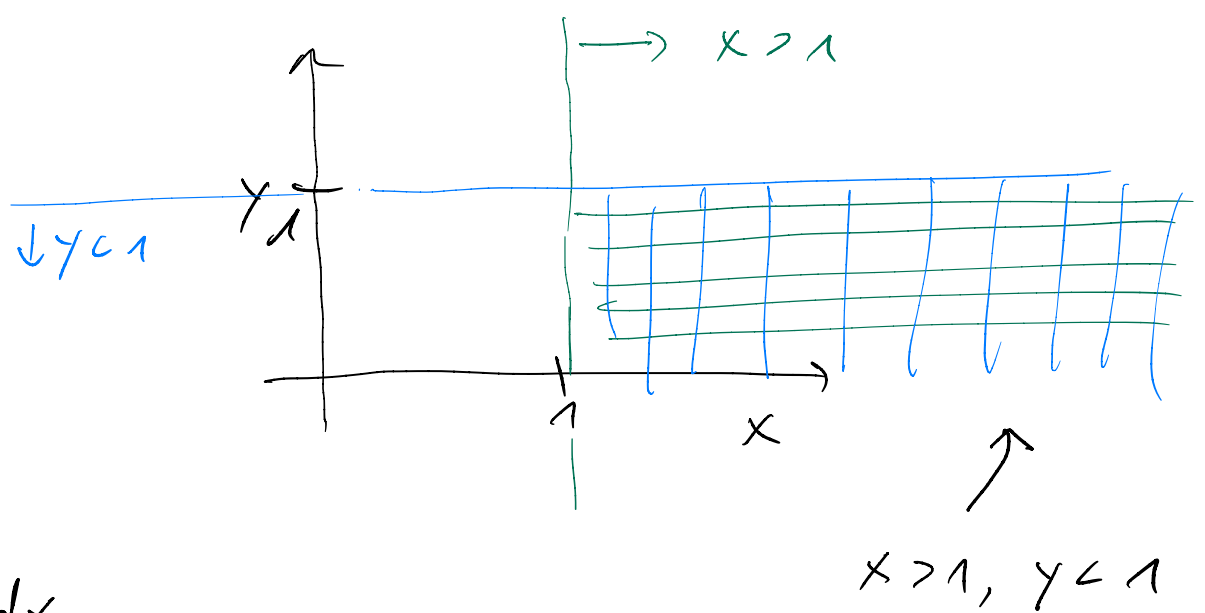
$$= \int_1^{\infty} \int_0^1 e^{-x} 2e^{-2y} dy dx$$

$$= \int_1^{\infty} e^{-x} \int_0^1 2e^{-2y} dy dx = \int_1^{\infty} e^{-x} [-e^{-2y}]_0^1 dx$$

$$= \int_1^{\infty} e^{-x} (-e^{-2} - (-e^0)) dx = \int_1^{\infty} e^{-x} (1 - e^{-2}) dx$$

$$= (1 - e^{-2}) \int_1^{\infty} e^{-x} dx = (1 - e^{-2}) [-e^{-x}]_1^{\infty}$$

$$= (1 - e^{-2}) e^{-1} = e^{-1} - e^{-3}$$



$$\int_1^{\infty} \int_0^1 e^{-x} 2e^{-2y} dy dx$$

This is a constant that can be pulled out of the integral.



Special case of:

$$\int_A \int_B g(x) \cdot h(y) dy dx = \int_A g(x) \int_B h(y) dy dx$$

$$= \int_B h(y) dy \cdot \int_A g(x) dx = \int_A g(x) dx \cdot \int_B h(y) dy$$

If

1)  $f(x) = g(x)h(x)$

2) Integration area has

form  $A \times B$

Then

$$\iint_{A \times B} f \cdot g = \int_A f - \int_B g$$



$$\int_1^{\infty} \int_0^1 e^{-x} 2e^{-2y} dy dx$$

$$= \int_1^{\infty} e^{-x} dx \cdot \int_0^1 2e^{-2y} dy = \left[ -e^{-x} \right]_1^{\infty} \cdot \left[ -e^{-2y} \right]_0^1$$

$$= e^{-1} (1 - e^{-2})$$

$$P[X < a]$$

$$a > 0$$

$$= \int_0^a \int_0^{\infty} e^{-x} \cdot 2e^{-2y} dy dx$$

$$= \int_0^a e^{-x} dx \cdot \int_0^{\infty} 2e^{-2y} dy$$

Density of  $\text{Exp}(2)$

$$= [-e^{-x}]_0^a \cdot [-e^{-2y}]_0^{\infty}$$

$$= (e^0 - e^{-a}) \cdot (e^0 - 0)$$

$$= (1 - e^{-a}) \cdot 1$$

$$P[X < Y]$$

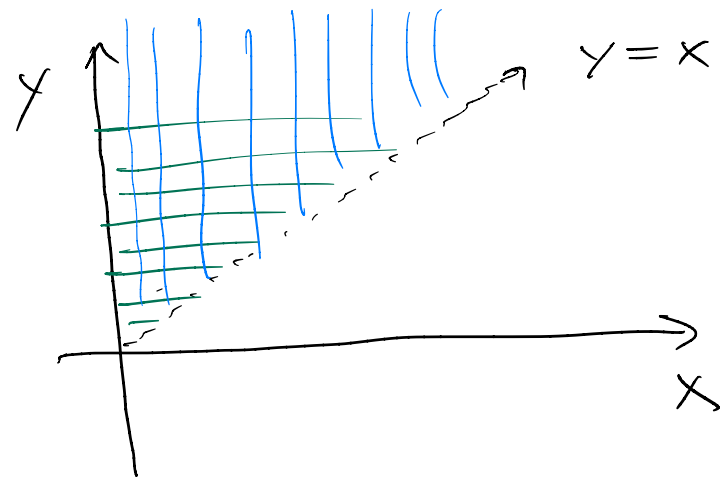
$$= \int_0^{\infty} \int_x^{\infty} f(x, y) dy dx \quad (*)$$

$$= \int_0^{\infty} \int_0^y f(x, y) dx dy$$

$$(*) \int_0^{\infty} \int_x^{\infty} e^{-x} 2e^{-2y} dy dx = \int_0^{\infty} e^{-x} \left[ -e^{-2y} \right]_x^{\infty} dx$$

$$= \int_0^{\infty} e^{-x} e^{-2x} dx = \int_0^{\infty} e^{-3x} dx = \left[ -\frac{1}{3} e^{-3x} \right]_0^{\infty}$$

$$= \frac{1}{3} e^{-3 \cdot 0} = \frac{1}{3}$$



## 2.3 Independent Random Variables

$$\mathcal{E}, \mathcal{F} \text{ ind.} \Leftrightarrow P[\mathcal{E} \cap \mathcal{F}] = P(\mathcal{E}) \cdot P(\mathcal{F})$$

$$\Leftrightarrow P(\mathcal{E} | \mathcal{F}) = P(\mathcal{E})$$

$$\left( \begin{array}{l} \mathcal{E} = "x \in A" \\ \mathcal{F} = "y \in B" \end{array} \right)$$

$X, Y$  are independent iff

$$P[X \in A, Y \in B] = P[X \in A] \cdot P[Y \in B]$$

for all  $A, B \subseteq \mathbb{R}$

$$\text{Equivalent: } P[X \leq a, Y \leq b] = P[X \leq a] \cdot P[Y \leq b],$$

f.o.  $a, b \in \mathbb{R}$

that is

$$F(a, b) = F_X(a) \cdot F_Y(b)$$

Equivalent for discrete RVs:

$$P(x, y) = P_x(x) \cdot P_y(y) \quad \text{f.o. } x, y \in \mathbb{R}$$

For cont. RVs

$$f(x, y) = f_x(x) \cdot f_y(y) .$$

Example 33: let  $X, Y$  be independent, each with

density

$$f(x) = \begin{cases} e^{-x}, & x > 0 \\ 0 & \text{otherwise} \end{cases}$$

What can we say  
about the quotient  
of two independent

and exponentially  
distributed RVs?

What is the density of  $\frac{X}{Y}$ ?

Two steps:

1) cdf of  $\frac{X}{Y}$

2) pdf is derivative of cdf

$$\begin{aligned}
1) \quad F(a) &= P[X/Y \leq a] = P[X \leq aY] \\
&= \int_0^{\infty} \int_0^{ay} e^{-x} e^{-y} dx dy \\
&= \int_0^{\infty} e^{-y} \left[ -e^{-x} \right]_0^{ay} dy = \int_0^{\infty} e^{-y} (1 - e^{-ay}) dy \\
&= \int_0^{\infty} e^{-y} dy - \int_0^{\infty} e^{-(1+a)y} dy \\
&= 1 - \left[ -\frac{1}{1+a} e^{-(1+a)y} \right]_0^{\infty} = 1 + \left[ \dots \right]_0^{\infty} \\
&= 1 + \left( -\frac{1}{1+a} \right) = 1 - \frac{1}{1+a} \quad \text{cdf}
\end{aligned}$$

$$\begin{aligned}
2) \quad f(a) &= \frac{d}{da} F(a) = -\frac{d}{da} (1+a)^{-1} = -(-1) (1+a)^{-2} \\
&= \frac{1}{(1+a)^2} \quad \text{pdf}
\end{aligned}$$

Remark: Generalization to  $n$  RVs  $X_1, \dots, X_n$

is possible:

- joint pmf

$$p(x_1, \dots, x_n)$$

- joint pdf

$$f(x_1, \dots, x_n)$$

- independence

$$p(x_1, \dots, x_n) = p_{X_1}(x_1) \cdot \dots \cdot p_{X_n}(x_n)$$

$$f(x_1, \dots, x_n) = f_{X_1}(x_1) \cdot \dots \cdot f_{X_n}(x_n)$$



# Joint distribution of RVs $X, Y$ : Revision

Individual RVs can be described by

pmfs (discrete)  
pdfs (continuous)

Joint pmfs:  $P(X_i, Y_j)$  if  $x_i, y_j$  are the possible values of  $X, Y$

Joint pdfs:  $f(x, y)$

$$\sum_{i,j} P(X_i, Y_j) = 1$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dy dx = 1$$

$$\sum_i \sum_j P(X_i, Y_j)$$
$$\sum_j \sum_i P(X_i, Y_j)$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(x, y) dx dy$$

## Marginal pmfs, pdfs

$$P_X(x_i) = \sum_j P(x_i, y_j)$$

$$P_Y(y_j) = \sum_i P(x_i, y_j)$$

$$f_X(x) = \int_{-\infty}^{\infty} f(x, y) dy$$

$$f_Y(y) = \int_{-\infty}^{\infty} f(x, y) dx$$

## Independence of events

$\mathcal{E}, \mathcal{F}$  indep. if

• "inf about  $\mathcal{E}$  does not provide information about  $\mathcal{F}$ "

•  $P(\mathcal{F}|\mathcal{E}) = P(\mathcal{F}) \quad (\Leftrightarrow P(\mathcal{F}|\mathcal{E}) = P(\mathcal{E}))$

$\Leftrightarrow P(\mathcal{E}\mathcal{F}) = P(\mathcal{E})P(\mathcal{F})$

## Independence of RVs

$X, Y$  are indep. if

all events that can be described in terms of  $X$

" $5 < X < 9$ ", " $X > 2$ ", " $X < 0$  or  $X > 2$ "

are independent of events that can be described

in terms of  $Y$ .

" $Y \geq 4$ "

Proposition  $X, Y$  are independent iff

- $P(X_i, Y_j) = P_X(X_i) \cdot P_Y(Y_j)$  , f.a.  $X_i, Y_j$

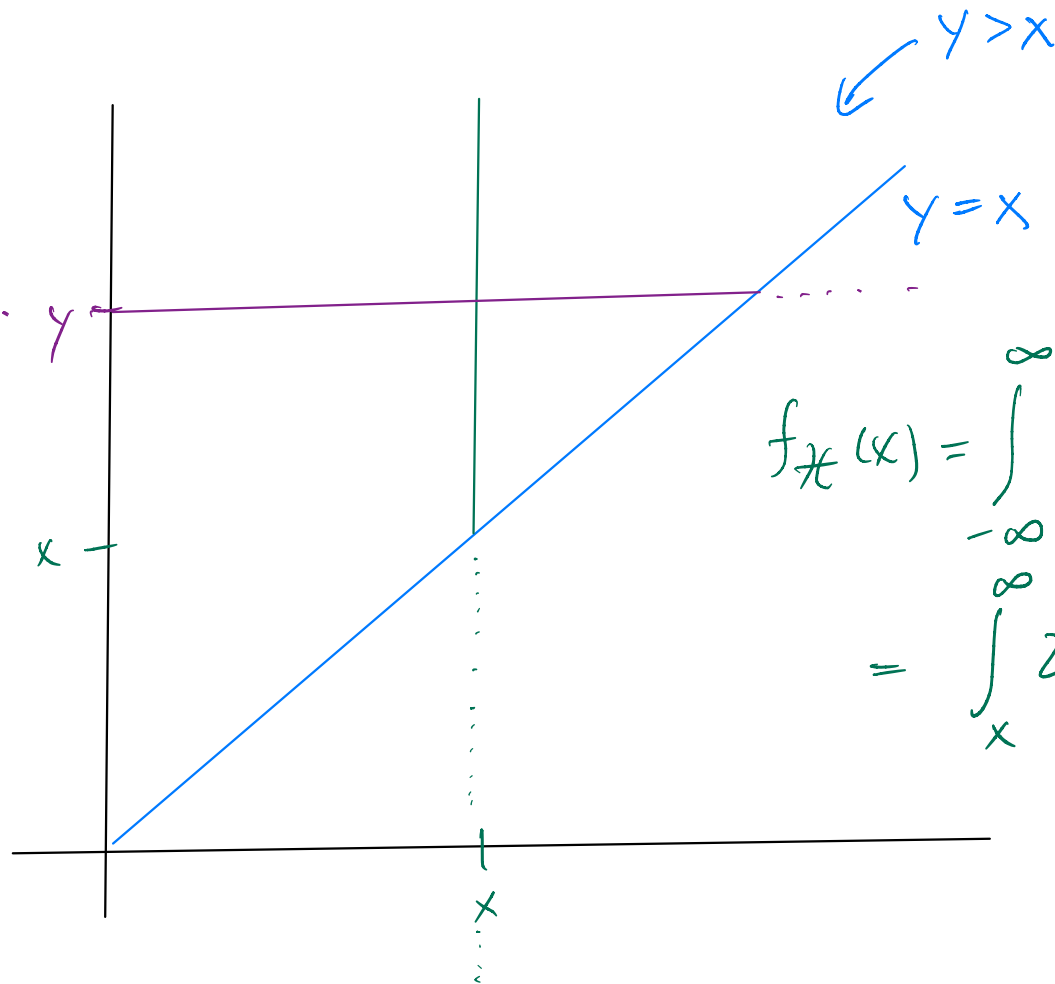
- $f(x, y) = f_X(x) \cdot f_Y(y)$  , f.a.  $x, y$

## Marginal Densities and Independence

Suppose  $X, Y$  have the joint distribution

$$f(x, y) = \begin{cases} 2e^{-x}e^{-y} & 0 < x < y \\ 0 & \text{otherwise} \end{cases}$$

$$\begin{aligned} f_Y(y) &= \int_{-\infty}^{\infty} f(x, y) dx \\ &= \int_0^y 2e^{-x}e^{-y} dx \end{aligned}$$



$$\begin{aligned} f_X(x) &= \int_{-\infty}^{\infty} f(x, y) dy \\ &= \int_x^{\infty} 2e^{-x}e^{-y} dy \end{aligned}$$

$$f_X(x) = \int_{-\infty}^{\infty} f(x,y) dy = \int_x^{\infty} 2e^{-x}e^{-y} dy$$

$$= 2e^{-x} \int_x^{\infty} e^{-y} dy = 2e^{-x} [-e^{-y}]_x^{\infty}$$

$$= 2e^{-x} e^{-x} = 2e^{-2x}$$

$$f_Y(y) = \int_{-\infty}^{\infty} f(x,y) dx = \int_0^y 2e^{-x}e^{-y} dx$$

$$= 2e^{-y} \int_0^y e^{-x} dx = 2e^{-y} [-e^{-x}]_0^y$$

$$= 2e^{-y} (1 - e^{-y})$$

## Expected Values of RVs

Die:  $X$  has values  $1, \dots, 6$ , all with  $p(X_i) = \frac{1}{6}$

$$\begin{aligned} E[X] &= 1 \cdot p(1) + 2 \cdot p(2) + \dots + 6 \cdot p(6) \\ &= (1 + 2 + \dots + 6) \frac{1}{6} = \frac{35}{6} \end{aligned}$$

Discrete RV  $X$

$$E[X] = \sum_i x_i \cdot p(x_i)$$

Continuous RV

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

## 2.5 Properties of Expectation

$X$  RV,  $g(x)$  function  $\Rightarrow g(X)$  is a RV

$X$  points of die,  $g(x) = x^2 \Rightarrow g(X) = X^2$ , squares of points

$X^2$  is a new RV

values	probabilities
1	$1/6$
4	$1/6$
9	$1/6$
16	$1/6$
25	$1/6$
36	$1/6$

$$\begin{aligned} E[X^2] &= 1 \cdot \frac{1}{6} + 4 \cdot \frac{1}{6} + \dots \\ &\quad \dots 36 \cdot \frac{1}{6} \\ &= \frac{1 + 4 + 9 + 16 + 25 + 36}{6} \\ &= \frac{91}{6} \end{aligned}$$



Imagine: a die with numbers  $-3, -2, -1, 1, 2, 3$

$X$  is the number on top of the die:  $E[X] = 0$

Let  $Z := X^2$

1) Find the pmf of  $Z$  and compute  $E[Z]$

$$E[Z] = 1 \cdot \frac{1}{3} + 4 \cdot \frac{1}{3} + 9 \cdot \frac{1}{3}$$

pmf of  $Z$

values	probabilities
9	$\frac{1}{6} + \frac{1}{6} = \frac{1}{3}$
4	— " —
1	— " —

2) Take a weighted average of the  $g(x_i)$

$$\begin{aligned} E[X^2] &= (-3)^2 \cdot \frac{1}{6} + (-2)^2 \cdot \frac{1}{6} + (-1)^2 \cdot \frac{1}{6} \\ &= 3^2 \cdot \frac{1}{6} + 2^2 \cdot \frac{1}{6} + 1^2 \cdot \frac{1}{6} \\ &= \sum_i x_i^2 \cdot p(x_i) \end{aligned}$$

We found:

$$E[g(X)] = \sum_i g(x_i) \cdot p(x_i)$$

Proposition 39 ("Law of the Unconscious Statistician",  
LOTUS)

$X \in \mathbb{R}^n$ ,  $g: \mathbb{R} \rightarrow \mathbb{R}$

$$\bullet E[g(X)] = \sum_i g(x_i) p(x_i)$$

$$\bullet E[g(X)] = \int_{-\infty}^{\infty} g(x) \cdot f(x) dx$$

## Applications of LOTUS

$$X \text{ RV, } a, b \in \mathbb{R}, \quad g(x) = ax + b$$

$$E[ax + b] \stackrel{?}{=} a E[X] + b,$$

$$E[g(X)] = \int_{-\infty}^{\infty} (ax + b) f(x) dx = \int_{-\infty}^{\infty} ax f(x) + b f(x) dx$$

$$= a \int_{-\infty}^{\infty} x f(x) dx + \int_{-\infty}^{\infty} b \cdot 1 f(x) dx$$

$$= a E[X] + b \cdot \int_{-\infty}^{\infty} 1 f(x) dx$$

$$= a E[X] + b \cdot 1$$

let  $X, y$  be RVs. What about  $E[X + y]$ ?

$$E[X + y] = E[X] + E[y] \quad (\text{Do we need independence?})$$

Lotus also holds for 2-dim. densities:

let  $X, y$  be RVs with joint pdf  $f(x, y)$ , let  $g: \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$

Then

$$E[g(X, y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f(x, y) dx dy$$

The summation law follows with  $g(x, y) = x + y$

$E[g(x, y)]$  $g(x, y)$  $E[x + y]$ 

by

$$\int_{\mathbb{R}} \int_{\mathbb{R}} (x + y) f(x, y) dx dy$$

$$= \int_{\mathbb{R}} \int_{\mathbb{R}} x \cdot f(x, y) dx dy + \int_{\mathbb{R}} \int_{\mathbb{R}} y \cdot f(x, y) dx dy$$

$$= \int_{\mathbb{R}} x \left( \int_{\mathbb{R}} f(x, y) dy \right) dx + \int_{\mathbb{R}} y \left( \int_{\mathbb{R}} f(x, y) dx \right) dy$$

$f_X(x)$   $f_Y(y)$

$$= \int_{\mathbb{R}} x \cdot f_X(x) dx + \int_{\mathbb{R}} y \cdot f_Y(y) dy$$

$$= E[x] + E[y]$$

Generalization

$$E\left[\sum_{i=1}^n X_i\right] = \sum_{i=1}^n E[X_i]$$

Throwing 2 dice, adding result  $X_1 + X_2$

$$E[X_1 + X_2] = E[X_1] + E[X_2] = \frac{7}{2} + \frac{7}{2} = 7$$

Example 42: Tossing coin  $n$  times,  $E[\# \text{ heads}] = ?$

$$p(\#) = p, \quad p(\bar{c}) = 1-p$$

Let  $X_i = 1$  iff head with  $i$ -th toss  $\Rightarrow E[X_i] = p$

$$n \text{ times: } E\left[\sum_{i=1}^n X_i\right] = n E[X_1] = np$$

Note:  $E[X] = 1 \cdot p + 0 \cdot (1-p) = p$  !!

# Last topic: Expected value of a RV

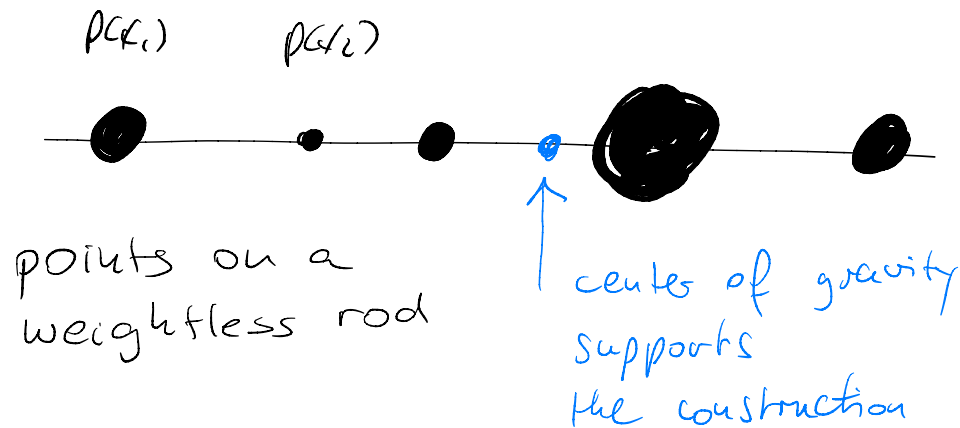
Idea: long term average

$X$  discr.  $\sum_i x_i p(x_i)$ ,  $x_i$  poss. values of  $X$

$X$  cont.  $\int_{\mathbb{R}} x \cdot f(x) dx$ ,  $f$  pdf

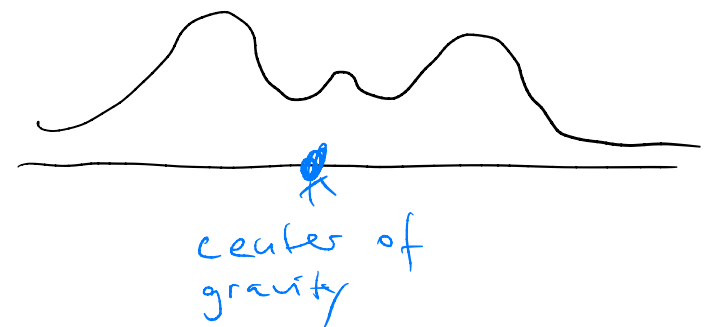
Another interpretation: center of gravity

$X$  discr.: a number of points  $x_1, x_2, \dots$ ,  
with weight  $p(x_i)$



$X$  cont

weight proportional to height of curve



Properties of Exp. V.:

$$E[aX] = a E[X]$$

$$E[b] = b$$

$$E[X + Y] = E[X] + E[Y]$$

$$E[X_1 + \dots + X_n] = \sum_{i=1}^n E[X_i]$$

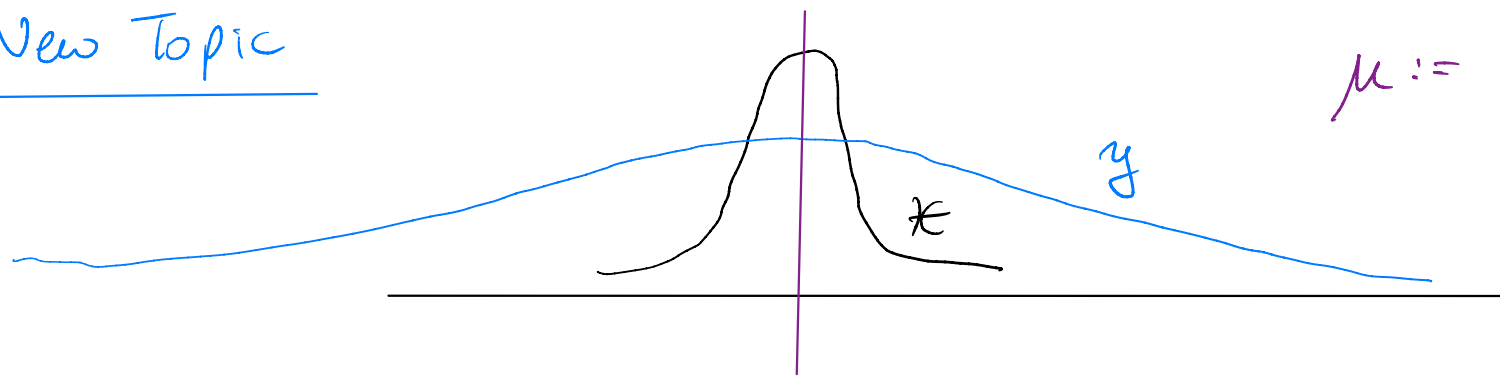
! holds also if  $X, Y$  are not independent

lots

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



## New Topic



$$\mu := E[X] = E[Y]$$

$\mu$  mean of  $x, y$

Values of  $y$  are spread much farther around  $\mu$  than the values of  $x$ .

### 2.6 Variance

$$\text{Var}(X) := E[(X - \mu)^2]$$

$$g(x) = (x - \mu)^2$$

is the variance of  $X$ .

Why not  $E[|X - \mu|]$  ?

The definition with the square has better mathematical properties.

How can we calculate  $\text{Var}(X)$ ?

Suppose  $X \sim f$ .

1.) Apply LOTUS:

$$\text{Var}(X) = \int_{\mathbb{R}} (x - \mu)^2 f(x) dx$$

$$= \int_{\mathbb{R}} (x^2 - 2x\mu + \mu^2) f(x) dx$$

$$= \int_{\mathbb{R}} x^2 f(x) dx - 2\mu \int_{\mathbb{R}} x f(x) dx + \mu^2 \int_{\mathbb{R}} f(x) dx$$

$$= E[X^2] - 2\mu E[X] + \mu^2 \cdot 1$$

$$= E[X^2] - 2\mu^2 + \mu^2$$

$$= E[X^2] - E[X]^2$$

↑  
2nd moment of  $X$

↑  
square of mean

Shortcut

$$\text{Var}(X) = E[(X - \mu)^2]$$

$$= E[X^2 - 2\mu X + \mu^2]$$

$$= E[X^2] - 2\mu E[X] + \mu^2$$

$$= E[X^2] - 2\mu^2 + \mu^2 = E[X^2] - \mu^2$$

Example 44

$X$  = number on die

$$E[X] = \frac{7}{2}$$

Also  $E[X^2] = \frac{91}{6}$  (Ex. 37)

$$\text{Var}(X) = E[X^2] - E[X]^2 = \frac{91}{6} - \left(\frac{7}{2}\right)^2 = \frac{182 - 3 \cdot 49}{12}$$

$$= \frac{182 - 147}{12} = \frac{35}{12}$$

Units: unit of measurement of  $X$  is metre, sec

$\Rightarrow$  unit of measurement of  $X^2$  is  $\text{metre}^2, \text{sec}^2$

Get back to original unit: take  $\sqrt{\cdot}$ :

$$\sigma := \sqrt{\text{Var}(X)}$$

is the standard deviation.

One often writes the variance as the square of the standard deviation;

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

$$x = (x_1, x_2, x_3)$$

$$y = (y_1, y_2, y_3)$$

---

$$\text{dist}(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2 + (x_3 - y_3)^2}$$

## Properties of $\text{Var}(\cdot)$

Suppose  $X$  has  $E[X] = \mu$ .

$$\bullet \text{Var}(X + b) = \text{Var}(X)$$

$$\bullet \text{Var}(aX) = a^2 \text{Var}(X)$$

$$\bullet \text{Var}(X + Y) \stackrel{?}{=} \text{Var}(X) + \text{Var}(Y) \quad \text{only if } X, Y \text{ independent}$$

$$\begin{aligned} \text{Var}(aX + b) &= E[\overbrace{y}^2} - E[y]^2] \\ &= E[(aX + b)^2] - E[aX + b]^2 \\ &= E[a^2X^2 + 2abX + b^2] - (aE[X] + b)^2 \\ &= a^2 E[X^2] + 2abE[X] + E[b^2] \\ &\quad - a^2\mu^2 - 2ab\mu - b^2 \end{aligned}$$

$$= a^2 E[X^2] + 2abE[X] + E[b^2] \\ - a^2\mu^2 - 2ab\mu - b^2$$

$$= a^2 E[X^2] + 2ab\mu + b^2 \\ - a^2\mu^2 - 2ab\mu - b^2$$

$$= a^2 (E[X^2] - \mu^2) = a^2 \text{Var}(X)$$

Note:  $\sigma_{aX} = a\sigma_X$

## 2.7 Covariance

We note

$$\begin{aligned}\text{Var}(X + X) &= \text{Var}(2X) = 4 \text{Var}(X) \\ &\neq \text{Var}(X) + \text{Var}(X)\end{aligned}$$

Definition 45:  $X, Y \in \mathcal{R}^U$ ,  $\mu_X = E[X]$ ,  $\mu_Y = E[Y]$

Then

$$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

This assumes a joint distribution of  $X$  and  $Y$ .



## Property of Cov

$$\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$$

$$\begin{aligned}\text{Cov}(X, Y) &= E[X Y - \mu_X Y - \mu_Y X + \mu_X \mu_Y] \\ &= E[XY] - \mu_X E[Y] - \mu_Y E[X] + \mu_X \mu_Y \\ &= E[XY] - \mu_X \mu_Y - \mu_Y \mu_X + \mu_X \mu_Y \\ &= E[XY] - E[X]E[Y]\end{aligned}$$

Observation:  $X, Y$  independent  $\Rightarrow E[XY] = E[X] \cdot E[Y]$   
 $\Rightarrow \text{Cov}(X, Y) = 0$

Observation:  $X, Y$  ind.  $\Rightarrow E[XY] = E[X] \cdot E[Y]$

Suppose  $X \sim f, Y \sim g$ .

$$E[XY] \stackrel{\text{LoTus}}{=} \int_{\mathbb{R}} \left( \int_{\mathbb{R}} x \cdot y \cdot f(x) g(y) dx \right) dy$$

$$= \int_{\mathbb{R}} y \cdot g(y) \left( \int_{\mathbb{R}} x \cdot f(x) dx \right) dy$$

$$= \int_{\mathbb{R}} x \cdot f(x) dx \cdot \int_{\mathbb{R}} y \cdot g(y) dy$$

$$= E[X] \cdot E[Y]$$

Proposition 46

$$\text{Cov}(X_1 + X_2, Y) = \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)$$

$$\begin{aligned}\text{Cov}(X_1 + X_2, Y) &= E[(X_1 + X_2) \cdot Y] - E[X_1 + X_2] \cdot E[Y] \\ &= E[X_1 Y] + E[X_2 Y] - E[X_1] \cdot E[Y] - E[X_2] \cdot E[Y] \\ &= E[X_1 Y] - E[X_1] \cdot E[Y] \\ &\quad + E[X_2 Y] - E[X_2] \cdot E[Y] \\ &= \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)\end{aligned}$$

Theorem 47

$$\text{Cov}\left(\sum_i X_i, \sum_j Y_j\right) = \sum_i \sum_j \text{Cov}(X_i, Y_j)$$

Consequence:

$$\text{Var}\left(\sum_i X_i\right) = \text{Cov}\left(\sum_i X_i, \sum_i X_i\right)$$

$$= \sum_i \sum_j \text{Cov}(X_i, X_j)$$

$$= \sum_i \left( \sum_{j \neq i} \text{Cov}(X_i, X_j) + \text{Cov}(X_i, X_i) \right)$$

$$= \left( \sum_i \sum_{j \neq i} \text{Cov}(X_i, X_j) \right) + \sum_i \text{Cov}(X_i, X_i)$$

$$= \sum_i \text{Var}(X_i) + \sum_i \sum_{j \neq i} \text{Cov}(X_i, X_j)$$

For  $n=2$ :

$$\text{Var}(X+Y) = \text{Var}(X) + \text{Var}(Y) + 2 \text{Cov}(X, Y)$$

## Meaning of covariance $\text{Cov}(X, Y)$

$> 0$ :  $X, Y$  grow together in the same direction

$< 0$ :  $X, Y$  grow in sync in opposite directions

$\approx 0$ :  $X, Y$  vary independently

Normalize RVs  $X, Y$  by taking  $\frac{X}{\sigma_X}$ ,  $\frac{Y}{\sigma_Y}$ ,

i.e.,  $\frac{X}{\sqrt{\text{Var}(X)}}$ ,  $\frac{Y}{\sqrt{\text{Var}(Y)}}$

$$\text{Corr}(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

$$= \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \cdot \text{Var}(Y)}}$$

Correlation  
between  
 $X$  and  $Y$

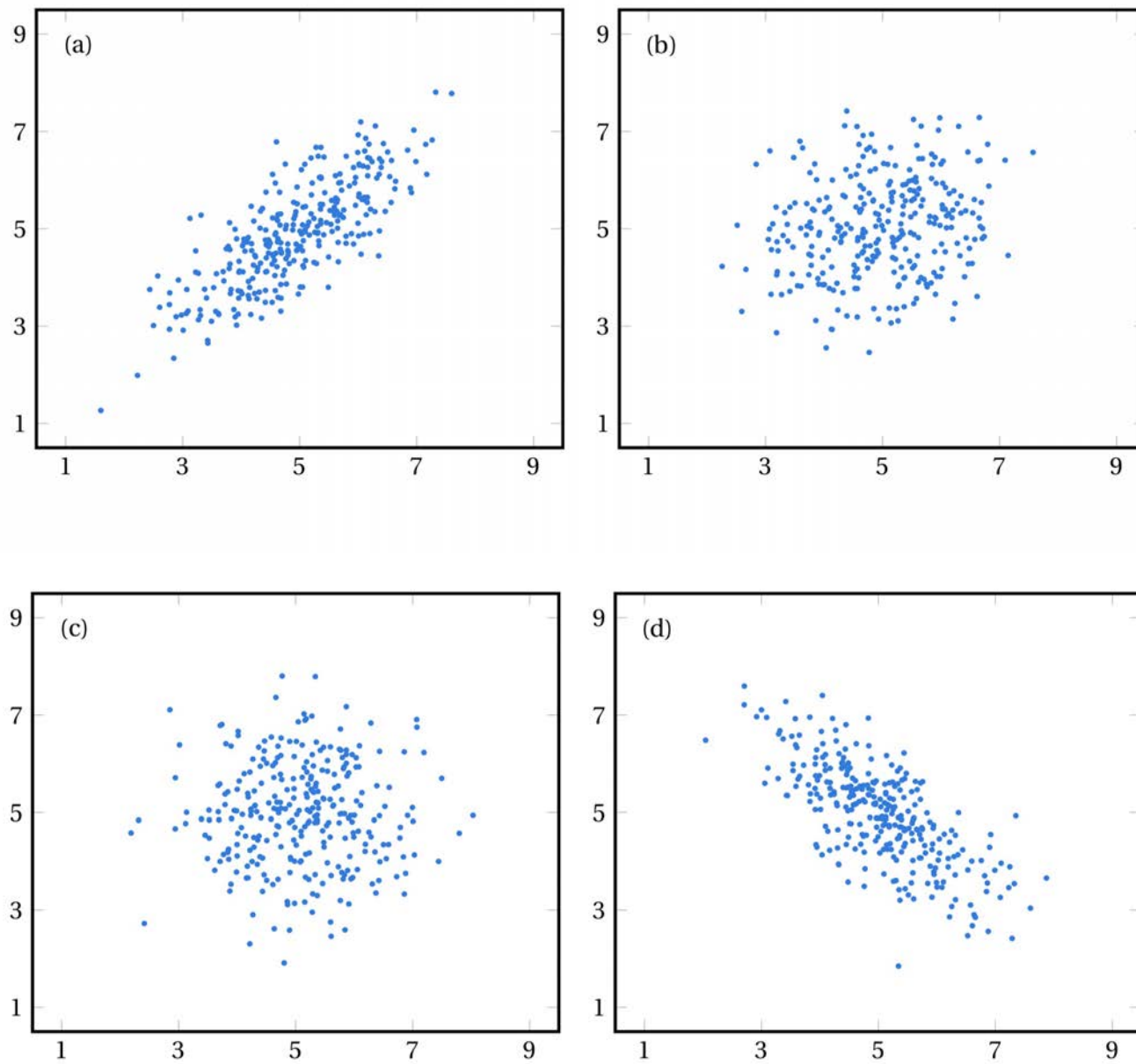


Figure 9: Random variables  $\mathcal{X}$  and  $\mathcal{Y}$  with correlations (a) 0.75; (b) 0.2; (c) 0; and (d) -0.75.

Example: 10 independent dice rolls:  $X_i$  is  $i$ -th roll

$$\begin{aligned}\text{Var} \left( \sum_{i=1}^n X_i \right) &= \sum_{i=1}^n \text{Var} (X_i) \\ &\stackrel{\text{ind}}{=} \sum_{i=1}^n \frac{35}{12} = 10 \cdot \frac{35}{12}\end{aligned}$$

What about the standard deviation?

Var has grown by factor 10,

$\sigma$  grows by factor  $\sqrt{10}$ !

## 2.8 The Weak Law of Large Numbers

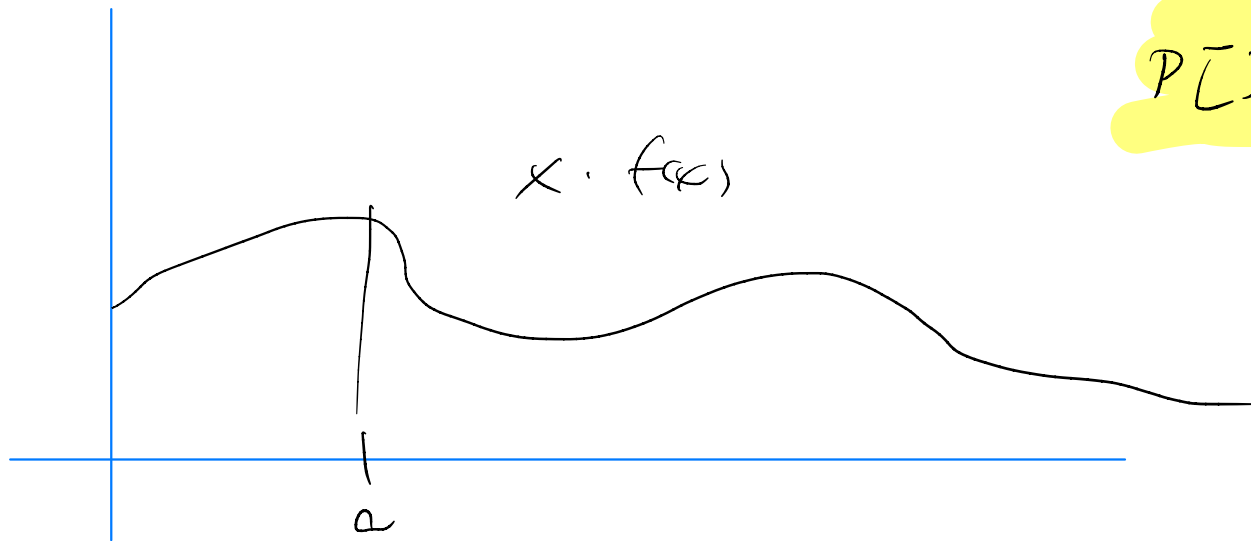
---

Markov's inequality

let  $X \geq 0$  sth  $E[X]$  exists. let also  $a > 0$ . Then

$$\begin{aligned} E[X] &= \int_0^{\infty} x f(x) dx \geq \int_a^{\infty} x f(x) dx \\ &\geq \int_a^{\infty} a f(x) dx = a \int_a^{\infty} f(x) dx = a P[X \geq a] \end{aligned}$$

$$P[X \geq a] \leq \frac{E[X]}{a}$$





Apply Markov's inequality:

$$y := (X - \mu)^2, \quad a = k^2$$

Assume:  $\text{Var}(X) = \sigma^2 \Rightarrow E[y] = \text{Var}(X) = \sigma^2$

$$P[|X - \mu| \geq k]$$

$$= P[(X - \mu)^2 \geq k^2] = P[y \geq k^2]$$

$$\leq \frac{E[y]}{k^2} = \frac{\sigma^2}{k^2}$$

Tchebychev's inequality:

$$P[|X - \mu| \geq k] \leq \frac{\sigma^2}{k^2} \quad \text{if } \text{Var}(X) = \sigma^2$$

Example 52 Suppose the working time of a person is a RV  $X$  with  $\mu = 40$  hrs.

1) How probable is it that the person will work more than 60 hrs?

Apply:  $P[X \geq a] \leq \frac{E[X]}{a}$

$$P[X \geq 60] \leq \frac{\mu}{60} = \frac{40}{60} = \frac{2}{3}$$

Example 52 Suppose the working time of a person is a RV  $X$  with  $\mu = 40$  hrs.

2) If  $\text{Var}(X) = 16$ , how probable is it the person will work between 32 and 48 hrs?

Apply:  $P[|X - \mu| \geq k] \leq \frac{\sigma^2}{k^2}$

$$P[|X - 40| \geq 8] \leq \frac{\sigma^2}{8^2} = \frac{16}{8^2} = \frac{1}{4}$$

$$\Rightarrow P[|X - 40| \leq 8] \geq 1 - \frac{1}{4} = \frac{3}{4}$$

## Example: Small Schools

Educational scientists found that among the schools that fare best in evaluations of teaching success, there are many more small schools than there are small schools among all schools.

(See statistics from North Carolina)

The Gates Foundation decided in the early 2000s to invest heavily in the establishment of small schools (e.g., by splitting larger schools into smaller ones)

Was that a good idea?

The story is from Daniel Kahneman, "Thinking, Fast and Slow"

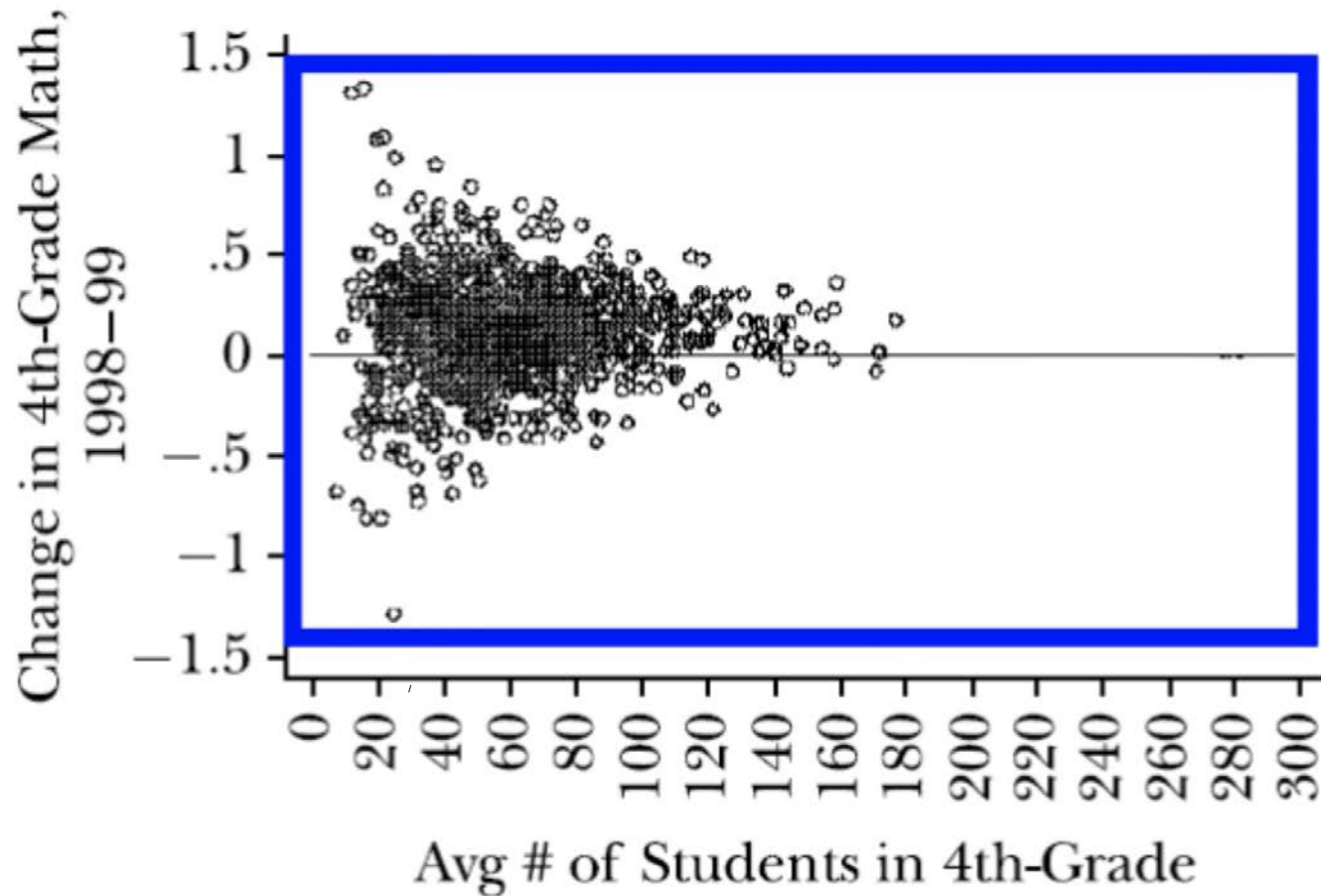
<i>School Size</i>	<i>Percentage Ever "Top 25" 1997-2000</i>
Smallest decile	27.7%
2nd	11.8
3rd	8.2
4th	3.6
5th	2.4
6th	3.6
7th	4.8
8th	7.1
9th	0
Largest decile	1.2
Total	7.0

Performance of  
small schools in  
North Carolina

From  
Alex Tabarrok  
"The Small Schools Myth",  
September 2, 2010  
<https://marginalrevolution.com>

# Distribution of Performance wrt Student Numbers

---



From  
Alex Tabarrok  
"The Small Schools Myth",  
September 2, 2010  
<https://marginalrevolution.com>

What happens if we execute an experiment many times  
and take averages of the outcomes?

let  $X$  be a RV, let  $X_1, \dots, X_n$  be RVs that

1) have the same distribution as  $X$

2) are independent

(i.i.d. RVs, i.e., independent identically distributed RVs)

let  $\sigma^2 = \text{Var}(X) = \text{Var}(X_i)$ ,  $\mu = E[X] = E[X_i]$ ,

$$\bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}$$

We have  $\bar{X}_n = \frac{\sum_{i=1}^n X_i}{n}$ . Then

$$E[\bar{X}_n] = \frac{1}{n} \sum_{i=1}^n E[X_i] = \frac{1}{n} \cdot (n \cdot \mu) = \mu$$

$$\text{Var}(\bar{X}_n) = \text{Var}\left(\frac{1}{n} \sum_{i=1}^n X_i\right) = \frac{1}{n^2} \text{Var}\left(\sum_{i=1}^n X_i\right)$$

independence  
of the  $X_i$

$$= \frac{1}{n^2} \sum_{i=1}^n \text{Var}(X_i) = \frac{1}{n^2} \sum_{i=1}^n \sigma^2 = \frac{1}{n^2} \cdot (n \cdot \sigma^2) = \frac{\sigma^2}{n}$$

Chebyshev with  $\bar{X}_n$  and  $k = \varepsilon$

Probability of  $\varepsilon$ -outliers

$$P\left[\left|\frac{\sum_{i=1}^n X_i}{n} - \mu\right| > \varepsilon\right] = P\left[|\bar{X}_n - \mu| > \varepsilon\right]$$

$$\leq \frac{\frac{\sigma^2}{n}}{\varepsilon^2} = \frac{1}{n} \cdot \frac{\sigma^2}{\varepsilon^2} \longrightarrow 0 \quad (n \rightarrow \infty)$$



## Theorem (Weak Law of Large Numbers)

Let  $X_1, \dots, X_n, \dots$  be i.i.d. RVs with mean  $\mu$  and  $\text{Var}(X) < \infty$ .

Then for every  $\varepsilon > 0$

$$\lim_{n \rightarrow \infty} P \left[ \left| \frac{1}{n} \sum_{i=1}^n X_i - \mu \right| > \varepsilon \right] = 0$$

i.e., the probability of  $\varepsilon$ -outliers goes toward 0.

There is also a Strong Law of Large Numbers, which says

$$P \left[ \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i = \mu \right] = 1$$

for i.i.d. RVs  $X_i$  provided  $E[X_i] < \infty$ .