

Q: what's the place <sup>(99)</sup>  
 $y_p$  on the positive part  
 of  $\mathbb{R}$  where  $P(0 \leq Z \leq y_p)$   
 $= p$ ?

for ( $y_p > 0$ )

well,  $P(0 \leq Z \leq y_p) = F_Z(y_p) = p$

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

so  $y_p = F_Z^{-1}(p)$

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

$\log(1 - p) = -\lambda y_p$

$y_p = -\frac{\log(1 - p)}{\lambda} = F_Z^{-1}(p)$

Def.

$y_p$  is called the  
 $p^{\text{th}}$  quantile

or the  
 $100 p^{\text{th}}$  percentile

of (the distribution of)  $Z$ .

~~Wrong~~

Some care is required when  $\mathcal{Y}$  is discrete or mixed.

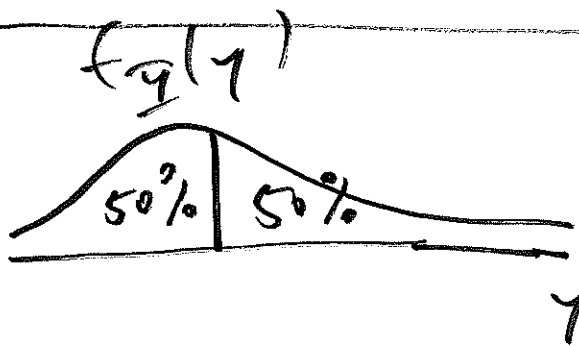
General definition

$\mathcal{Y}$  rv with CDF  $F_{\mathcal{Y}}(y)$ .

For all  $0 < p < 1$  define

$F_{\mathcal{Y}}^{-1}(p) =$  the smallest  $y$  value such that  $F_{\mathcal{Y}}(y) \geq p$

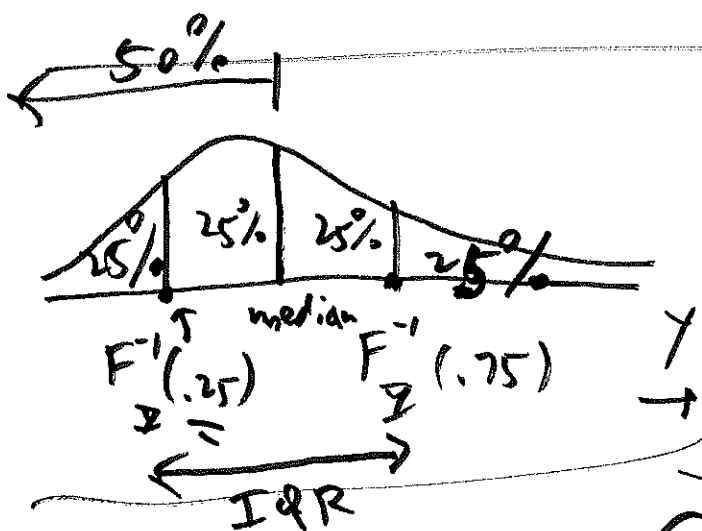
Then  $F_{\mathcal{Y}}^{-1}(p)$  is the  $p^{\text{th}}$  quantile of  $\mathcal{Y}$  and  $F_{\mathcal{Y}}^{-1}$  is the quantile function.



Measures of center for the distribution of a rv  $\mathcal{Y}$

One way to define the center of a distribution is to find the  $50^{\text{th}}$  percentile.

Definition The  $\frac{1}{2}$  quantile  $\stackrel{(0.5)}{=} \equiv$  the 50<sup>th</sup> percentile of a distribution is called the median of the dist. (93)

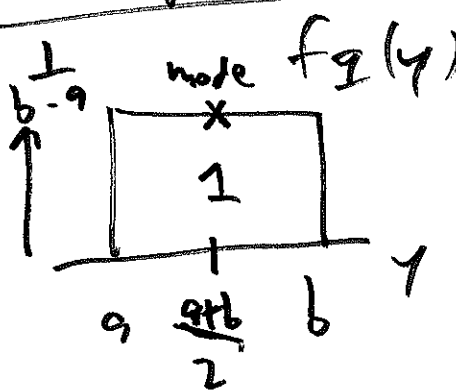


measures of spread for the distribution of a rv  $X$

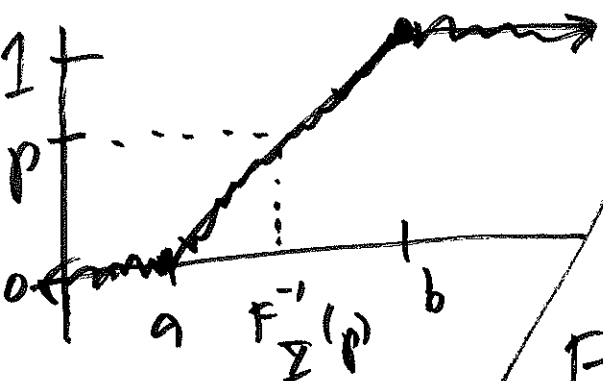
one way to define the spread of a dist. is to see how far apart its 75<sup>th</sup> and 25<sup>th</sup> percentiles are.

Definition The  $\frac{1}{4}$  quantile  $\stackrel{(0.25)}{=} =$  the 25<sup>th</sup> percentile  $F_X^{-1}(.25)$  is the lower quartile; the  $\frac{3}{4}$  quantile  $\stackrel{(0.75)}{=} =$  the 75<sup>th</sup> percentile is the upper quartile; and  $(F_X^{-1}(.75) - F_X^{-1}(.25)) =$  interquartile range (IQR)

Example  $I \sim \text{Uniform}(a, b)$ ; then (44)



$$F_I(y) = \begin{cases} 0 & \text{for } y \leq a \\ \frac{y-a}{b-a} & a \leq y \leq b \\ 1 & y \geq b \end{cases}$$



Easy to invert  $F_I$ :

$$F_I^{-1}(p) = (1-p)a + pb \text{ for } 0 < p < 1$$

And (no surprise) the median is  $\frac{a+b}{2}$ .

Studying  
Two random  
variables  
at a time

Def.  $X, Y$  rvs: the  
joint (or bivariate)  
distribution of  $(X, Y)$   
is the collection  $P[(X, Y) \in C]$  of all  
probabilities for all sets  $C \in \mathbb{R}^2$  such that  $(X, Y) \in C$   
isn't weird.

Case 1) ( $X$  and  $Y$  both discrete) (95)

Def.  $X, Y$  r.v.  $\rightarrow$  If there are only finitely or countably infinitely many possible values  $(x, y)$  for  $(X, Y)$ ,  $X$  and  $Y$  have a discrete joint dist.

Def. The joint probability <sup>(mass)</sup> function

(joint pmf) of  $(X, Y)$  discrete is the function  $f_{X, Y}(x, y) = P(X=x, Y=y)$  (and)

the set  $\{(x, y) : f_{X, Y}(x, y) > 0\}$  is the support of  $f_{X, Y}$

Consequences

①  $\sum_{\text{all } (x, y)} f_{X, Y}(x, y) = 1$   
(omit some)

② For any set  $C$  of ordered pairs

$(x, y)$ ,  $P[(X, Y) \in C] = \sum_{(x, y) \in C} f_{X, Y}(x, y)$

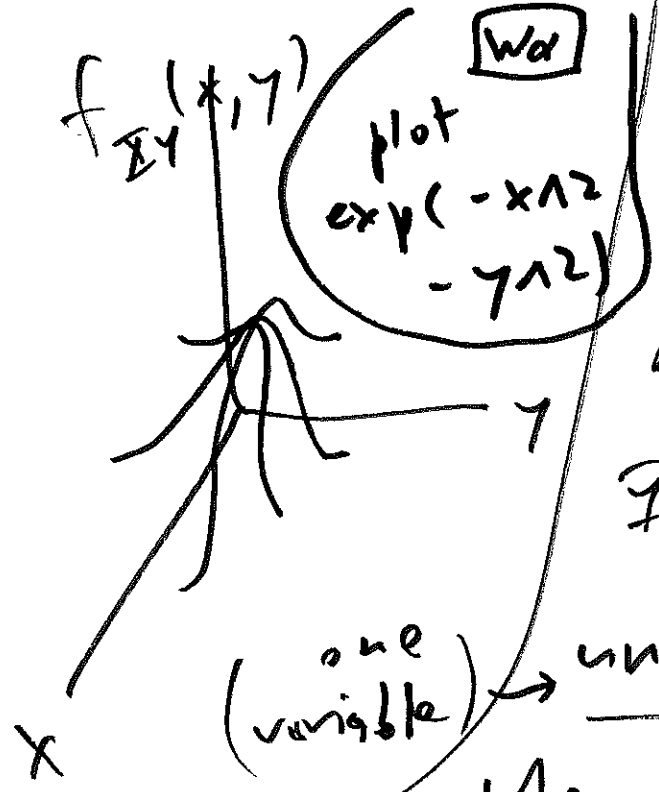
Def. Two rv  $X$  and  $Y$  have a (20)  
96

Case 2: continuous joint distribution  
 $X, Y$  both continuous  
if you can find a nonnegative function  $f_{X,Y}(x,y)$  defined for all  $(x,y) \in \mathbb{R}^2$  (the real plane)

such that for every (non-weird) subset  $C$  of the plane  $P[(X,Y) \in C] = \iint_C f_{X,Y}(x,y) dx dy$   
 $f_{X,Y}(x,y)$  is the joint pdf of  $(X,Y)$ .

the set  $\{(x,y) : f_{X,Y}(x,y) > 0\}$  is the support of  $f$  (the dist. of)  $(X,Y)$ .

Immediate Consequences | ① For all  $(x,y)$  in  $\mathbb{R}^2$ ,  
 $f_{X,Y}(x,y) \geq 0$ , and  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx dy = 1$ .



(2) If  $(X, Y)$  have a continuous joint distribution, then  $X$  and  $Y$  each have a continuous (marginal) univariate distribution when considered separately. (97)

(3) For all continuous pdfs  $f_{XY}(x, y)$ ,

(a) Every individual point, and every countably infinite sequence (or set) of points in  $\mathbb{R}^2$  (0-dimensional) has probability 0 under  $f_{XY}$ .

(b) If  $g$  is a continuous function of one real variable defined on  $(a, b)$ , then the sets  $\{(x, y) : y = g(x), a < x < b\}$  and  $\{(x, y) : x = g(y), a < y < b\}$  also have probability 0. (1-dimensional)

④ This means that the converse of ② is (unfortunately) not true: If  $X$  has a continuous distribution on  $\mathbb{R} = \mathbb{R}^1$  and  $Y \triangleq X$ , then both  $X$  and  $Y$  have continuous distributions but  $P\left(\begin{matrix} (X, Y) \text{ lies on the} \\ \text{line } y=x \end{matrix}\right) = \frac{1}{0}?$

So  $(X, Y)$  can't have a continuous joint distribution on  $\mathbb{R}^2$ .

Example

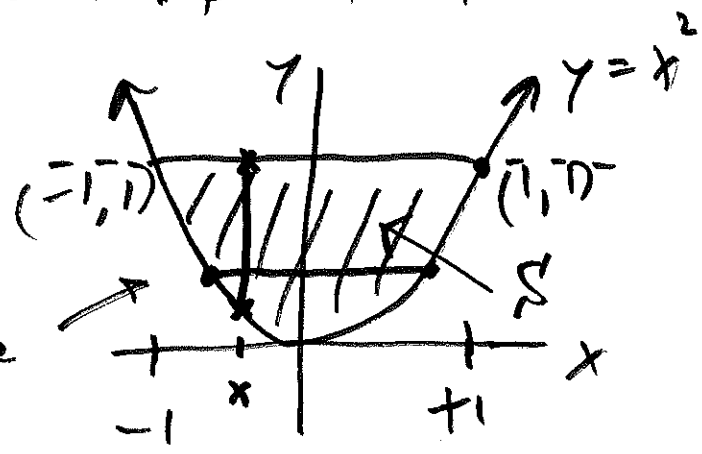
Joint distributions can lead to tricky integrals

Suppose that  $(X, Y)$  have joint pdf  $f_{XY}(x, y) = \begin{cases} cx^2y & \text{for } 0 \leq x \leq y \leq 1 \\ 0 & \text{else} \end{cases}$

let's work out the

normalizing constant.

The support of  $f_{XY}$  is the shaded region here





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

$$= \iint_{\Sigma} f_{\Sigma \Gamma}(x, y) dy dx$$

$$= \int_{-1}^{+1} \int_{x^2}^1 c x^2 y dy dx$$

$$= \int_{-1}^1 c x^2 \left( \int_{x^2}^1 y dy \right) dx$$

$$= \int_{-1}^1 c x^2 \left( \frac{y^2}{2} \Big|_{x^2}^1 \right) dx$$

$$= \int_{-1}^1 c x^2 \left( \frac{1}{2} - \frac{x^4}{2} \right) dx$$

$$= \frac{1}{2} c \int_{-1}^1 x^2 dx - \frac{1}{2} c \int_{-1}^1 x^6 dx$$

$$= \frac{1}{2} c \left( \frac{x^3}{3} \Big|_{-1}^1 \right) - \frac{c}{2} \left( \frac{x^7}{7} \Big|_{-1}^1 \right) = \frac{4}{21} c = 1$$

Search on "iterated integrals in wolfram alpha"

$$\text{So } c = \frac{21}{4}$$

The other way to parameterize the support (100)

is to let  $y$  go from 0 to 1

while  $x$  goes from  $-\sqrt{y}$  to  $\sqrt{y}$ :

$$1 = \iint_{\mathcal{R}} f_{\mathcal{R}}(x, y) dx dy$$

$$= \int_0^1 \int_{-\sqrt{y}}^{\sqrt{y}} c x^2 y dx dy$$

$$= \int_0^1 c y \left( \int_{-\sqrt{y}}^{\sqrt{y}} x^2 dx \right) dy$$

$$= \int_0^1 c y \left( \frac{x^3}{3} \Big|_{-\sqrt{y}}^{\sqrt{y}} \right) dy$$

$$= c \int_0^1 y \cdot \frac{1}{3} (y^{3/2} - -y^{3/2}) dy$$

$$= \frac{c}{3} \int_0^1 2y^{5/2} dy = \frac{2c}{3} \left( \frac{y^{7/2}}{7/2} \Big|_0^1 \right) \textcircled{10}$$

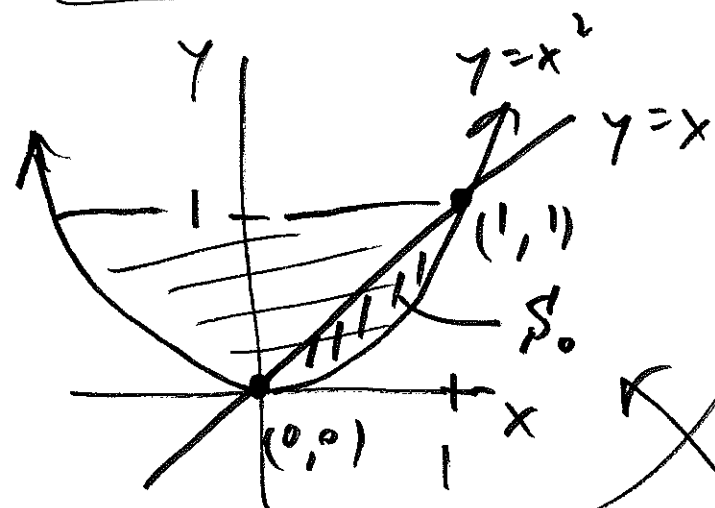
$$= \frac{4}{21} c \text{ as before ( } \iint dx dy \text{ and } \iint dy dx$$

always have to agree, of course).

Example, continued

let's compute

$$P(\bar{X} \geq \bar{Y})$$



The relevant part  $S_0$  of  $S$  where  $x \geq y$  is sketched

here, so

$$P(\bar{X} \geq \bar{Y}) = \iint_{S_0} f_{\bar{X}\bar{Y}}(x, y) dy dx$$

$$= \int_0^1 \int_{x^2}^x \frac{21}{4} x^2 y dy dx = \frac{3}{20} \dots$$

integrate  $\frac{21}{4} x^2 y$   $dy, y = x^2$  to  $x$

then integrate result from  $x=0$  to  $x=1$

You can have bivariate distributions (102) in which one of  $(X, Y)$  is discrete and the other is continuous.

Case 3

Mixed bivariate distribution

Definition

$(X, Y)$  rv such that  $X$  is discrete and  $Y$  is continuous  $\rightarrow$  suppose you can find a function  $f_{XY}(x, y)$  defined on  $\mathbb{R}^2$  such that for every pair of (non-void) subsets  $A$  and  $B$  of  $\mathbb{R}$  (assume interval exists)

$$P(X \in A \text{ and } Y \in B) = \int_B \sum_{x \in A} f_{XY}(x, y) dy.$$

Then  $f_{XY}$  is the joint pmf/pdf of  $(X, Y)$

Immediate consequence: If  $X$  takes on values  $x_1, x_2, \dots$ , then  $\int_{-\infty}^{\infty} \sum_{i=1}^{\infty} f(x_i, y) dy = 1.$

Example | Randomized controlled (clinical) <sup>123</sup>  
trial; patients in  $\textcircled{T}$  get a treatment,

patients in  $\textcircled{C}$  get a placebo. Outcome

is success (e.g., cancer goes into remission)

or failure; let  $X_i = \begin{cases} 1 & \text{if patient } i \\ & \text{in } \textcircled{T} \text{ is a success} \\ 0 & \text{else} \end{cases}$

and let  $\theta$   $\leftarrow$  (unknown) be the proportion of patients

in the population of all patients who

would get the treatment who would have

no relapse if they had been in the

study. Then our uncertainty about

$\theta$  is continuous on  $(0, 1)$  and

$(X_i, \theta)$  has a mixed bivariate distribution.

If you model  $(X | \theta)$  as Bernoulli( $\theta$ )  
and  $\theta \sim \text{Uniform}(0, 1)$

the joint  $\overset{m}{p.f.}/\overset{p.f.}{p.f.}$  of  $(X, \theta)$  would be

$$f_{X, \theta}(x, \theta) = \begin{cases} \theta^x (1-\theta)^{1-x} & \text{for } \begin{cases} x=0, 1 \\ 0 < \theta < 1 \end{cases} \\ 0 & \text{else} \end{cases}$$

$\overset{p.f.}{p.f.}/\overset{p.f.}{p.f.} \uparrow$

Then (e.g.)  $P(X=1) = P(X=1 \text{ and } \theta \text{ is anything between } 0 \text{ and } 1)$

$$= \int_0^1 \theta^1 (1-\theta)^{1-1} d\theta = \int_0^1 \theta d\theta = \frac{1}{2}.$$

(2 May 19)

Bivariate CDFs Def. The joint CDF of two rvs  $X$  and  $Y$  is the function  $F_{XY}(x, y)$

satisfying  $F_{XY}(x, y) = P(X \leq x \text{ and } Y \leq y)$

for all  $-\infty < x < \infty$  and  $-\infty < y < \infty$