

Multiple Random Variables

Multiple random variables

We essentially always consider multiple random variables at once.

- The key concepts: Joint, conditional and marginal distributions, and independence of RVs.

Let X and Y be discrete random variables.

- **Joint distribution:**

$$p_{XY}(x,y) = \Pr(X = x \text{ and } Y = y)$$

- **Marginal distributions:**

$$p_X(x) = \Pr(X = x) = \sum_y p_{XY}(x,y)$$

$$p_Y(y) = \Pr(Y = y) = \sum_x p_{XY}(x,y)$$

- **Conditional distributions:**

$$p_{X|Y=y}(x) = \Pr(X = x \mid Y = y) = p_{XY}(x,y) / p_Y(y)$$

Example

Sample a couple who are both carriers of some disease gene.

X = number of children they have

Y = number of affected children they have

		x						
$p_{XY}(x,y)$		0	1	2	3	4	5	$p_Y(y)$
y	0	0.160	0.248	0.124	0.063	0.025	0.014	0.634
	1	0	0.082	0.082	0.063	0.034	0.024	0.285
	2	0	0	0.014	0.021	0.017	0.016	0.068
	3	0	0	0	0.003	0.004	0.005	0.012
	4	0	0	0	0	0.000	0.001	0.001
	5	0	0	0	0	0	0.000	0.000
$p_X(x)$		0.160	0.330	0.220	0.150	0.080	0.060	

Pr($Y = y$ | $X = 2$)

		x						
$p_{XY}(x,y)$		0	1	2	3	4	5	$p_Y(y)$
y	0	0.160	0.248	0.124	0.063	0.025	0.014	0.634
	1	0	0.082	0.082	0.063	0.034	0.024	0.285
	2	0	0	0.014	0.021	0.017	0.016	0.068
	3	0	0	0	0.003	0.004	0.005	0.012
	4	0	0	0	0	0.000	0.001	0.001
	5	0	0	0	0	0	0.000	0.000
$p_X(x)$		0.160	0.330	0.220	0.150	0.080	0.060	

		y					
$\text{Pr}(Y=y X=2)$		0	1	2	3	4	5
		0.564	0.373	0.064	0.000	0.000	0.000

Pr(X = x | Y = 1)

		x						p _Y (y)
		0	1	2	3	4	5	
y	0	0.160	0.248	0.124	0.063	0.025	0.014	0.634
	1	0	0.082	0.082	0.063	0.034	0.024	0.285
	2	0	0	0.014	0.021	0.017	0.016	0.068
	3	0	0	0	0.003	0.004	0.005	0.012
	4	0	0	0	0	0.000	0.001	0.001
	5	0	0	0	0	0	0.000	0.000
p _X (x)		0.160	0.330	0.220	0.150	0.080	0.060	

		x					
		0	1	2	3	4	5
Pr(X=x Y=1)		0.000	0.288	0.288	0.221	0.119	0.084

Independence

Random variables X and Y are **independent** if

→ $p_{XY}(x,y) = p_X(x) p_Y(y)$

for every pair x,y .

In other words/symbols:

→ $\Pr(X = x \text{ and } Y = y) = \Pr(X = x) \Pr(Y = y)$

for every pair x,y .

Equivalently,

→ $\Pr(X = x | Y = y) = \Pr(X = x)$

for all x,y .

Example

Sample a random rat from Baltimore.

$X = 1$ if the rat is infected with virus A, and $= 0$ otherwise

$Y = 1$ if the rat is infected with virus B, and $= 0$ otherwise

		x		
$p_{XY}(x,y)$		0	1	$p_Y(y)$
y	0	0.72	0.18	0.90
	1	0.08	0.02	0.10
	$p_X(x)$	0.80	0.20	

Continuous random variables

Continuous random variables have joint densities, $f_{XY}(x,y)$.

→ The **marginal densities** are obtained by integration:

$$f_X(x) = \int f_{XY}(x,y) dy \quad \text{and} \quad f_Y(y) = \int f_{XY}(x,y) dx$$

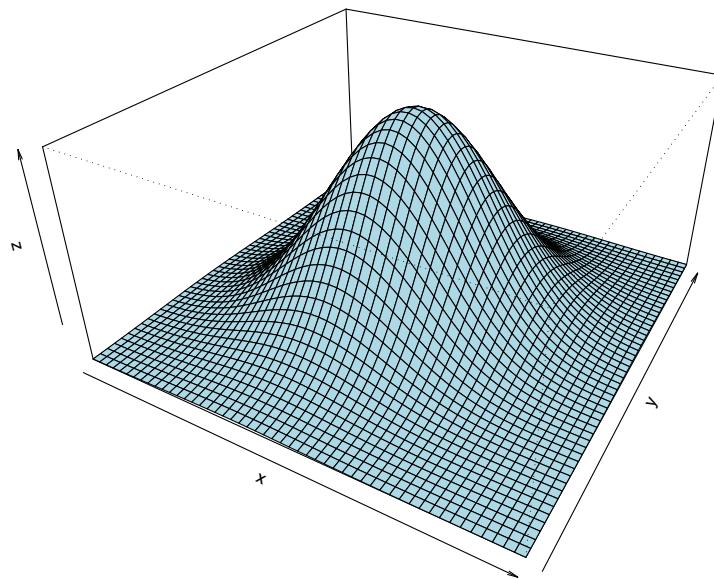
→ **Conditional density**:

$$f_{X|Y=y}(x) = f_{XY}(x,y)/f_Y(y)$$

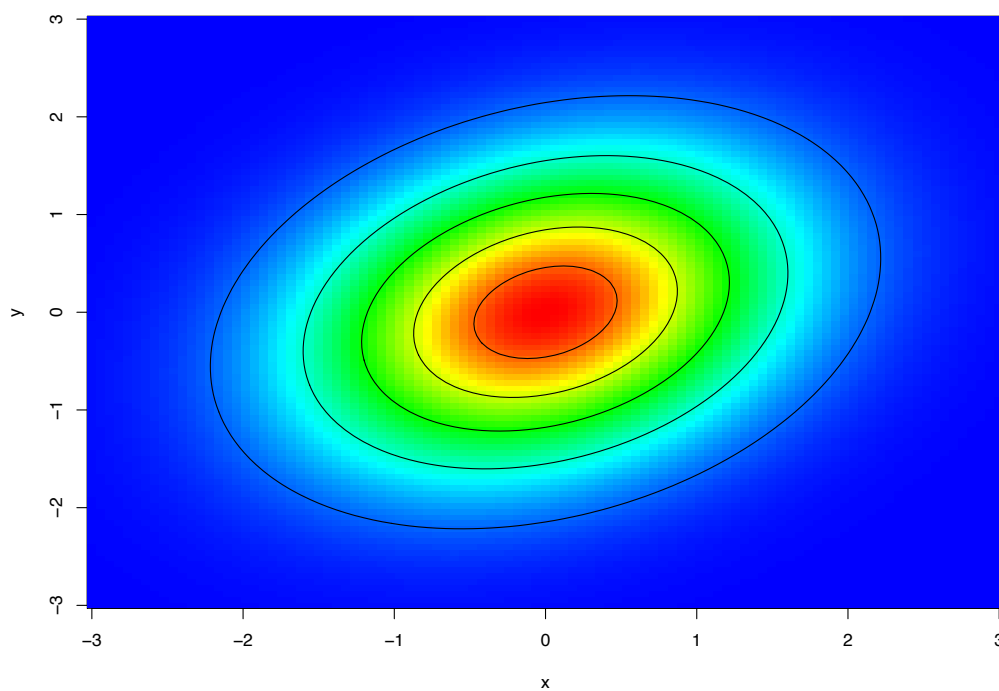
→ X and Y are **independent** if:

$$f_{XY}(x,y) = f_X(x) f_Y(y) \quad \text{for all } x,y.$$

The bivariate normal distribution



The bivariate normal distribution



iid

More jargon:

Random variables $X_1, X_2, X_3, \dots, X_n$ are said to be independent and identically distributed (iid) if

- they are independent,
- they all have the same distribution.

Usually such RVs are generated by

- repeated independent measurements, or
- random sampling from a large population.

Means and SDs

→ Mean and SD of **sums** of random variables:

$$E(\sum_i X_i) = \sum_i E(X_i) \quad \text{no matter what}$$

$$SD(\sum_i X_i) = \sqrt{\sum_i \{SD(X_i)\}^2} \quad \text{if the } X_i \text{ are independent}$$

→ Mean and SD of **means** of random variables:

$$E(\sum_i X_i / n) = \sum_i E(X_i) / n \quad \text{no matter what}$$

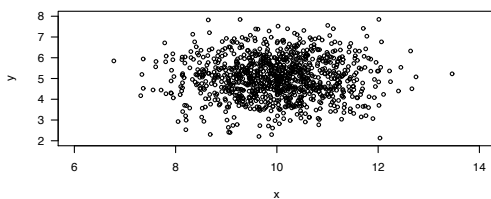
$$SD(\sum_i X_i / n) = \sqrt{\sum_i \{SD(X_i)\}^2} / n \quad \text{if the } X_i \text{ are independent}$$

→ If the X_i are iid with mean μ and SD σ :

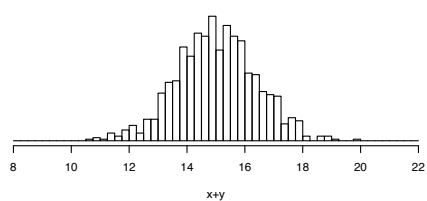
$$E(\sum_i X_i / n) = \mu \quad \text{and} \quad SD(\sum_i X_i / n) = \sigma / \sqrt{n}$$

Example

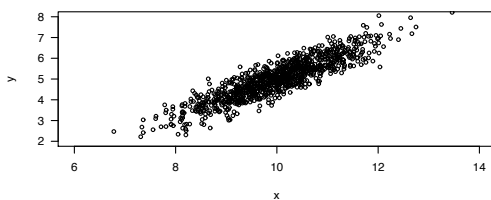
Independent



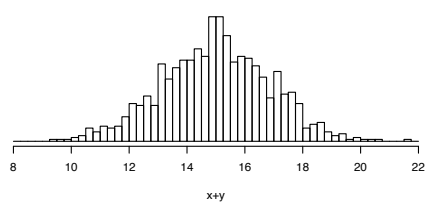
$SD(X + Y) = 1.4$



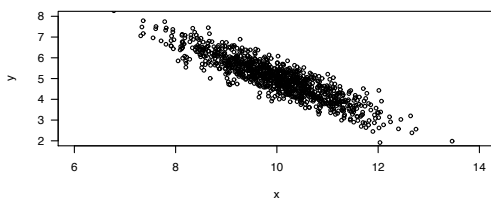
Positively correlated



$SD(X + Y) = 1.9$



Negatively correlated



$SD(X + Y) = 0.4$

