

Independence,  
Covariance and Correlation  
18.05 Spring 2018

$X \backslash Y$	1	2	3	4	5	6
1	1/36	1/36	1/36	1/36	1/36	1/36
2	1/36	1/36	1/36	1/36	1/36	1/36
3	1/36	1/36	1/36	1/36	1/36	1/36
4	1/36	1/36	1/36	1/36	1/36	1/36
5	1/36	1/36	1/36	1/36	1/36	1/36
6	1/36	1/36	1/36	1/36	1/36	1/36

# Independence, Covariance, Correlation

Events  $A$  and  $B$  are independent if

$$P(A \cap B) = P(A)P(B).$$

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

$$F(x, y) = F_X(x)F_Y(y).$$

Discrete random variables  $X$  and  $Y$  are independent if

$$p(x_i, y_j) = p_X(x_i)p_Y(y_j).$$

Continuous random variables  $X$  and  $Y$  are independent if

$$f(x, y) = f_X(x)f_Y(y).$$

## Concept question: independence I

Roll two dice:  $X$  = value on first,  $Y$  = value on second

$X \backslash Y$	1	2	3	4	5	6	$p(x_i)$
1	1/36	1/36	1/36	1/36	1/36	1/36	1/6
2	1/36	1/36	1/36	1/36	1/36	1/36	1/6
3	1/36	1/36	1/36	1/36	1/36	1/36	1/6
4	1/36	1/36	1/36	1/36	1/36	1/36	1/6
5	1/36	1/36	1/36	1/36	1/36	1/36	1/6
6	1/36	1/36	1/36	1/36	1/36	1/36	1/6
$p(y_j)$	1/6	1/6	1/6	1/6	1/6	1/6	1

Are  $X$  and  $Y$  independent?      1. Yes      2. No

**answer:** 1. Yes. Every cell probability is the product of the marginal probabilities.

## Concept question: independence II

Roll two dice:  $X$  = value on first,  $T$  = sum

$X \backslash T$	2	3	4	5	6	7	8	9	10	11	12	$p(x_i)$
1	1/36	1/36	1/36	1/36	1/36	1/36	0	0	0	0	0	1/6
2	0	1/36	1/36	1/36	1/36	1/36	1/36	0	0	0	0	1/6
3	0	0	1/36	1/36	1/36	1/36	1/36	1/36	0	0	0	1/6
4	0	0	0	1/36	1/36	1/36	1/36	1/36	1/36	0	0	1/6
5	0	0	0	0	1/36	1/36	1/36	1/36	1/36	1/36	0	1/6
6	0	0	0	0	0	1/36	1/36	1/36	1/36	1/36	1/36	1/6
$p(y_j)$	1/36	2/36	3/36	4/36	5/36	6/36	5/36	4/36	3/36	2/36	1/36	1

Are  $X$  and  $Y$  independent?      1. Yes      2. No

**answer:** 2. No. The cells with probability zero are clearly not the product of the marginal probabilities.

## Concept Question

Among the following pdf's which are independent? (Each of the ranges is a rectangle chosen so that  $\int \int f(x, y) dx dy = 1$ .)

(i)  $f(x, y) = 4x^2y^3$ .

(ii)  $f(x, y) = \frac{1}{2}(x^3y + xy^3)$ .

(iii)  $f(x, y) = 6e^{-3x-2y}$

Put a 1 for independent and a 0 for not-independent.

(a) 111    (b) 110    (c) 101    (d) 100

(e) 011    (f) 010    (g) 001    (h) 000

answer: (c). *Explanation on next slide.*

## Solution

- (i) Independent. The variables can be separated: the marginal densities are  $f_X(x) = ax^2$  and  $f_Y(y) = by^3$  for some constants  $a$  and  $b$  with  $ab = 4$ .
- (ii) Not independent.  $X$  and  $Y$  are not independent because there is no way to factor  $f(x, y)$  into a product  $f_X(x)f_Y(y)$ .
- (iii) Independent. The variables can be separated: the marginal densities are  $f_X(x) = ae^{-3x}$  and  $f_Y(y) = be^{-2y}$  for some constants  $a$  and  $b$  with  $ab = 6$ .

# Covariance

Measures the degree to which two random variables **vary together**, e.g. height and weight of people.

$X$ ,  $Y$  random variables with means  $\mu_X$  and  $\mu_Y$ .

$$\text{Cov}(X, Y) =_{\text{def}} E((X - \mu_X)(Y - \mu_Y)).$$

- **Vary together** might mean  $X$  is usually bigger than  $\mu_X$  when  $Y$  is bigger than  $\mu_Y$ , and vice versa. In this case  $(X - \mu_X)(Y - \mu_Y)$  is usually **positive**, so  $\text{Cov}(X, Y)$  is **positive**.
- **Vary together** might mean  $X$  is usually bigger than  $\mu_X$  when  $Y$  is smaller than  $\mu_Y$ , and vice versa. In this case  $(X - \mu_X)(Y - \mu_Y)$  is usually **negative**, so  $\text{Cov}(X, Y)$  is **negative**.
- If  $X$  and  $Y$  don't vary together, then sign of  $(X - \mu_X)$  tells nothing about sign of  $(Y - \mu_Y)$ . In this case  $(X - \mu_X)(Y - \mu_Y)$  can be **both positive and negative**, so  $\text{Cov}(X, Y)$  might be **zero or small**.

# Properties of covariance

## Properties

1.  $\text{Cov}(aX + b, cY + d) = ac\text{Cov}(X, Y)$  for constants  $a, b, c, d$ .
2.  $\text{Cov}(X_1 + X_2, Y) = \text{Cov}(X_1, Y) + \text{Cov}(X_2, Y)$ .
3.  $\text{Cov}(X, X) = \text{Var}(X)$
4.  $\text{Cov}(X, Y) = E(XY) - \mu_X\mu_Y$ .
5. If  $X$  and  $Y$  are independent then  $\text{Cov}(X, Y) = 0$ .
6. **Warning** The converse is not true: if covariance is 0, the variables might not be independent.



## Concept question

Suppose we have the following joint probability table.

$Y \backslash X$	-1	0	1	$p(y_j)$
0	0	$1/2$	0	$1/2$
1	$1/4$	0	$1/4$	$1/2$
$p(x_i)$	$1/4$	$1/2$	$1/4$	1

At your table work out the covariance  $\text{Cov}(X, Y)$ .

Because the covariance is 0 we know that  $X$  and  $Y$  are independent

1. True
2. False

Key point: covariance measures the linear relationship between  $X$  and  $Y$ . It can completely miss a quadratic or higher order relationship.

## Board question: computing covariance

Flip a fair coin 12 times.

Let  $X$  = number of heads in the first 7 flips

Let  $Y$  = number of heads on the last 7 flips.

Compute  $\text{Cov}(X, Y)$ ,

## Solution

Use the properties of covariance.

$X_i$  = the number of heads on the  $i^{\text{th}}$  flip. (So  $X_i \sim \text{Bernoulli}(.5)$ .)

$$X = X_1 + X_2 + \dots + X_7 \quad \text{and} \quad Y = X_6 + X_7 + \dots + X_{12}.$$

We know  $\text{Var}(X_i) = 1/4$ . Therefore using Property 2 (linearity) of covariance



$$\begin{aligned}\text{Cov}(X, Y) &= \text{Cov}(X_1 + X_2 + \dots + X_7, X_6 + X_7 + \dots + X_{12}) \\ &= \text{Cov}(X_1, X_6) + \text{Cov}(X_1, X_7) + \text{Cov}(X_1, X_8) + \dots + \text{Cov}(X_7, X_{12})\end{aligned}$$

Since the different tosses are independent we know

$$\text{Cov}(X_1, X_6) = 0, \text{Cov}(X_1, X_7) = 0, \text{Cov}(X_1, X_8) = 0, \text{etc.}$$

Looking at the expression for  $\text{Cov}(X, Y)$  there are only two non-zero terms

$$\text{Cov}(X, Y) = \text{Cov}(X_6, X_6) + \text{Cov}(X_7, X_7) = \text{Var}(X_6) + \text{Var}(X_7) = \boxed{\frac{1}{2}}.$$

## Correlation

Like covariance, but removes scale.

The *correlation coefficient* between  $X$  and  $Y$  is defined by

$$\text{Cor}(X, Y) = \rho = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}.$$

1.  $\rho$  = covariance of standardized versions of  $X$  and  $Y$ .
2.  $\rho$  is dimensionless (it's a ratio).
3.  $-1 \leq \rho \leq 1$ .
4.  $\rho = 1$  if and only if  $Y = aX + b$  with  $a > 0$ .
5.  $\rho = -1$  if and only if  $Y = aX + b$  with  $a < 0$ .

## Real-life correlations

- Over time, amount of ice cream consumption is correlated with number of pool drownings.
- In 1685 (and today) being a student is the most dangerous profession.
- In 90% of bar fights ending in a death the person who started the fight died.
- Hormone replacement therapy (HRT) is correlated with a lower rate of coronary heart disease (CHD).

*Discussion is on the next slides.*

## Real-life correlations discussion

- Ice cream does not cause drownings. Both are correlated with summer weather.
- In a study in 1685 of the ages and professions of deceased men, it was found that the profession with the lowest average age of death was “student.” But, being a student does not cause you to die at an early age. Being a student means you *are* young. This is what makes the average of those that die so low.
- A study of fights in bars in which someone was killed found that, in 90% of the cases, the person who started the fight was the one who died.  
Of course, it's the person who survived telling the story.

*Continued on next slide*

## (continued)

- In a widely studied example, numerous epidemiological studies showed that women who were taking combined hormone replacement therapy (HRT) also had a lower-than-average incidence of coronary heart disease (CHD), leading doctors to propose that HRT was protective against CHD. But randomized controlled trials showed that HRT caused a small but statistically significant increase in risk of CHD. Re-analysis of the data from the epidemiological studies showed that women undertaking HRT were more likely to be from higher socio-economic groups (ABC1), with better-than-average diet and exercise regimens. The use of HRT and decreased incidence of coronary heart disease were coincident effects of a common cause (i.e. the benefits associated with a higher socioeconomic status), rather than cause and effect, as had been supposed.

# Correlation is not causation

Edward Tufte: "Empirically observed covariation is a necessary but not sufficient condition for causality."



# Overlapping sums of uniform random variables

We made two random variables  $X$  and  $Y$  from overlapping sums of uniform random variables

For example:

$$X = X_1 + X_2 + X_3 + X_4 + X_5$$

$$Y = X_3 + X_4 + X_5 + X_6 + X_7$$

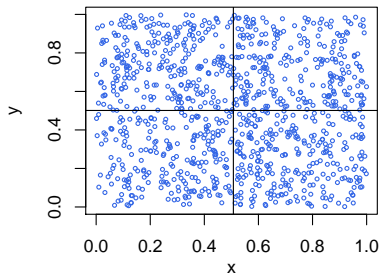
These are sums of 5 of the  $X_i$  with 3 in common.

If we sum  $r$  of the  $X_i$  with  $s$  in common we name it  $(r, s)$ .

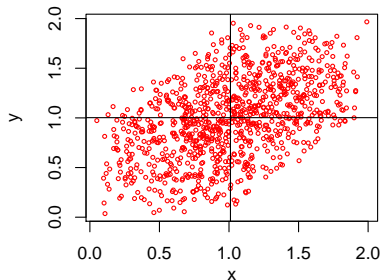
Below are a series of scatterplots produced using R.

# Scatter plots

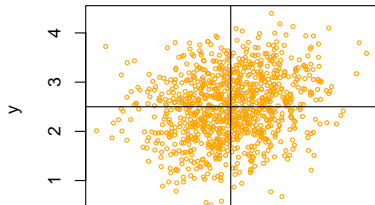
**(1, 0) cor=0.00, sample\_cor=-0.07**



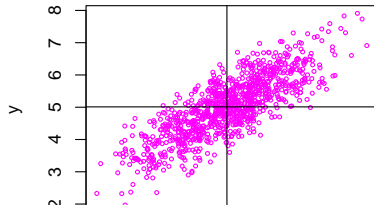
**(2, 1) cor=0.50, sample\_cor=0.48**



**(5, 1) cor=0.20, sample\_cor=0.21**



**(10, 8) cor=0.80, sample\_cor=0.81**



## Concept question

Toss a fair coin  $2n + 1$  times. Let  $X$  be the number of heads on the first  $n + 1$  tosses and  $Y$  the number on the last  $n + 1$  tosses.

If  $n = 1000$  then  $\text{Cov}(X, Y)$  is:

- (a) 0      (b)  $1/4$     (c)  $1/2$       (d) 1  
(e) More than 1      (f) tiny but not 0

**answer:** 2.  $1/4$ . This is computed in the answer to the next table question.

## Board question

Toss a fair coin  $2n + 1$  times. Let  $X$  be the number of heads on the first  $n + 1$  tosses and  $Y$  the number on the last  $n + 1$  tosses.

Compute  $\text{Cov}(X, Y)$  and  $\text{Cor}(X, Y)$ .

As usual let  $X_i$  = the number of heads on the  $i^{\text{th}}$  flip, i.e. 0 or 1. Then

$$X = \sum_{i=1}^{n+1} X_i, \quad Y = \sum_{i=n+1}^{2n+1} X_i$$

$X$  is the sum of  $n + 1$  independent Bernoulli( $1/2$ ) random variables, so

$$\mu_X = E(X) = \frac{n+1}{2}, \quad \text{and} \quad \text{Var}(X) = \frac{n+1}{4}.$$

Likewise,  $\mu_Y = E(Y) = \frac{n+1}{2}$ , and  $\text{Var}(Y) = \frac{n+1}{4}$ .

*Continued on next slide.*

## Solution continued

Now,

$$\text{Cov}(X, Y) = \text{Cov} \left( \sum_1^{n+1} X_i \sum_{n+1}^{2n+1} X_j \right) = \sum_{i=1}^{n+1} \sum_{j=n+1}^{2n+1} \text{Cov}(X_i X_j).$$

Because the  $X_i$  are independent the only non-zero term in the above sum is  $\text{Cov}(X_{n+1} X_{n+1}) = \text{Var}(X_{n+1}) = \frac{1}{4}$ . Therefore,

$$\text{Cov}(X, Y) = \frac{1}{4}.$$

We get the correlation by dividing by the standard deviations.

$$\text{Cor}(X, Y) = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{1/4}{(n+1)/4} = \frac{1}{n+1}.$$

This makes sense: as  $n$  increases the correlation should decrease since the contribution of the one flip they have in common becomes less important.