

## Multivariate probability distributions

- Often we are interested in more than 1 aspect of an experiment/trial
- Will have more than 1 random variable
- Interest the probability of a combination of events (results of the different aspects of the experiment)

Examples include:

- Price of crude oil (per barrel) and price per gallon of unleaded gasoline at your local station (per gallon)
- Level of different chemical contaminants in soil samples
- Probability of obtaining a certain sample mean and sample variance in a sample from a population

## Bivariate and discrete

Assume that  $X_1$  and  $X_2$  are discrete random variables. The joint (bivariate) probability distribution for  $X_1$  and  $X_2$  is  $p(x_1, x_2) = P(X_1 = x_1, X_2 = x_2)$ .

- $p(x_1, x_2) \geq 0$  for all  $x_1$  and  $x_2$
- $\sum_{x_1} \sum_{x_2} p(x_1, x_2) = 1$
- C.d.f given by  $F(x_1, x_2) = P(X_1 \leq x_1, Y_1 \leq x_1)$

## Simple bivariate example

Have one die with 3 “1” faces and 3 “2” faces. Each face is equally likely to come up. The second die has 2 “1” faces, 2 “2” faces, and 2 “3” faces, also with equally weighted sides.

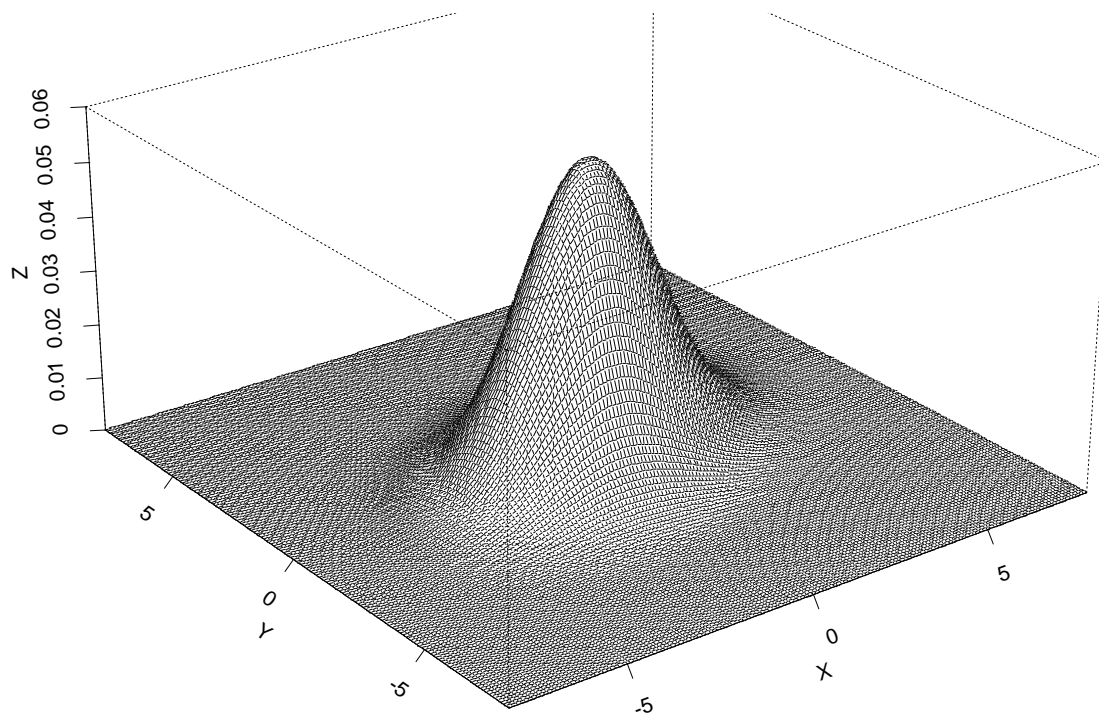
$X$ : how many “2”’s rolled

$Y$ : sum of the these dice

Find  $p(x, y) = P(X = x, Y = y)$ . Also find the c.d.f.

# Multivariate and continuous

- Random variables  $Y_1$  and  $Y_2$  are jointly continuous if their joint c.d.f is continuous in both arguments
- Joint density function is given by  $f(y_1, y_2)$ ; the function is non-negative for all  $y_1$  and  $y_2$
- Volume under the surface must be 1:  
$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f(y_1, y_2) dy_1 dy_2 = 1$$
- Some calculations will require multiple integrals



## Marginal distributions

If we're given the joint distribution for 2 or more variables, how can we find the distribution for just one of them?

- Assume we have  $p(x, y)$  for the random variables  $X$  and  $Y$ , want  $p(x)$
- We want the probability for a union of mutually exclusive events:  
 $(x \cap y_1) \cup (x \cap y_2) \dots \cup (x \cap y_n) \rightarrow x$
- Since they're mutually exclusive, we sum the probabilities for all the different possible values of  $Y$  that can occur with  $X = x$
- In the discrete case, this leads to  $p(x) = \sum_y p(x, y)$  and  $p(y) = \sum_x p(x, y)$
- In the continuous case, this leads to  $p(x) = \int_{-\infty}^{\infty} p(x, y) dy$  and  $p(y) = \int_{-\infty}^{\infty} p(x, y) dx$

## Dice example continued

What are the marginal distributions for  $X$  and  $Y$  in our earlier dice example?

$X$ : how many “2”’s rolled

$Y$ : sum of the these dice

	$Y$			
$X$	2	3	4	5
0	1/6	0	1/6	0
1	0	1/3	0	1/6
2	0	0	1/6	0

## Conditional distributions

Let's say we have two random variables  $X$  and  $Y$  with a joint probability function or density function, and we want to know the probability function or density function of one given the value of the other.

Discrete case:

- Use the definition of conditional probability

$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

- $P(X = x|Y = y) = \frac{P(X=x, Y=y)}{P(Y=y)} = \frac{p(x,y)}{p(y)}$

Continuous case:

- Want to have the conditional probability density function rather than a probability function

- $f(x|y) = \frac{f(x,y)}{f(y)}$

## Dice example revisited

$X$ : how many “2”’s rolled

$Y$ : sum of the these dice

	$Y$			
$X$	2	3	4	5
0	1/6	0	1/6	0
1	0	1/3	0	1/6
2	0	0	1/6	0

Give the conditional probability distribution of  $Y$  given  $X$  and  $X$  given  $Y$  in our dice example.



## Independence revisited

In chapter 2, we discussed briefly independence and dependence of events  $A$  and  $B$ .

- These are independent if  $P(A|B) = P(A)$  or  $P(B|A) = P(B)$  or  $P(A \cap B) = P(A)P(B)$
- Otherwise, knowing that  $A$  happened gives you info about  $P(B)$  (or vice-versa) and the events are dependent

Extend this principle to random variables and their probability distributions/densities.

- Two discrete random variables  $X$  and  $Y$  are independent if  $p(x, y) = p(x)p(y)$  for all  $x$  and  $y$ .
- Two continuous random variables  $X$  and  $Y$  are independent if  $f(x, y) = f(x)f(y)$

## Independence and our dice example

$X$ : how many “2”’s rolled

$Y$ : sum of the these dice

	$Y$			
$X$	2	3	4	5
0	1/6	0	1/6	0
1	0	1/3	0	1/6
2	0	0	1/6	0

In our dice example, were  $X$  and  $Y$  independent?

## Expected value

We just extend our ideas about expected value to more than one variable. If  $g(X_1, X_2, \dots, X_n)$  is the function of random variables  $X_1, X_2, \dots, X_n$  for which we are interested in finding the expected value:

Discrete case:

$$E[g(X_1, X_2, \dots, X_n)] = \sum_{x_1} \sum_{x_2} \dots \sum_{x_n} g(x_1, x_2, \dots, x_n) p(x_1, x_2, \dots, x_n)$$

Continuous case:

$$E[g(X_1, X_2, \dots, X_n)] = \int_{x_1} \int_{x_2} \dots \int_{x_n} g(x_1, x_2, \dots, x_n) f(x_1, x_2, \dots, x_n) dx_n \dots dx_2 dx_1$$

## Properties of expected value remain the same

Also, we still have the same properties for expected values that we discussed before:

- $E(c) = c$  where  $c$  is a constant
- $E[cg(X_1, X_2, \dots, X_n)] = cE[g(X_1, X_2, \dots, X_n)]$
- $E[g_1(X_1, X_2, \dots, X_n) + g_2(X_1, X_2, \dots, X_n)] = E[g_1(X_1, X_2, \dots, X_n)] + E[g_2(X_1, X_2, \dots, X_n)]$

## Covariance

For two random variables  $X$  and  $Y$ :

- Denote their means as  $E(X) = \mu_X$  and  $E(Y) = \mu_Y$
- Covariance is an expected value:

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

The covariance calculation can be simplified (similar to simplification for variance):

## Covariance

$X$ : how many “2”’s rolled

$Y$ : sum of the these dice

	$Y$			
$X$	2	3	4	5
0	1/6	0	1/6	0
1	0	1/3	0	1/6
2	0	0	1/6	0

In our dice example, find  $Cov(X, Y)$ .

## Implications of covariance

- If  $X$  and  $Y$  are independent,  $Cov(X, Y) = 0$
- If  $Cov(X, Y) = 0$ , this does *not* necessarily mean that  $X$  and  $Y$  are independent
- It is possible for the  $X$  and  $Y$  to be dependent (according to definition,  $p(x, y) \neq p(x)p(y)$ ), yet have  $Cov(X, Y) = 0$

## Coefficient of correlation

Let  $X$  be a random variable with  $Var(X) = \sigma_X^2$  and  $Y$  be a random variable with  $Var(Y) = \sigma_Y^2$ . Then the coefficient of correlation is

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

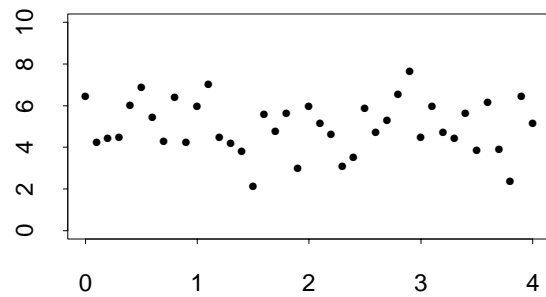
- Coefficient of correlation measures strength of *linear* relationship
- $-1 \leq \rho \leq 1$ , where the extremes denote perfect linear relationships (positive or negative)
- There can be a perfect non-linear relationship between  $X$  and  $Y$ , but this won't give you  $\rho = -1$  or  $\rho = 1$



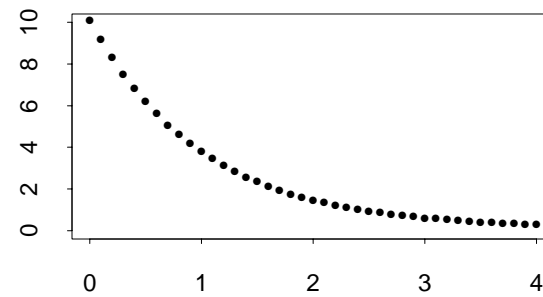
## More about $\rho$

- $\rho = 1$  denotes perfect positive linear relationship (where line has positive slope)
- $\rho = -1$  denotes perfect negative linear relationship (where line has negative slope)
- $\rho = 0$  means 0 linear correlation, 0 covariance

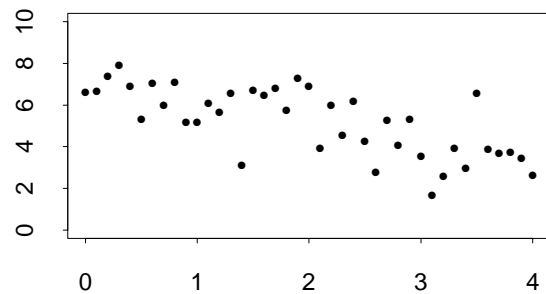
## How do various values of $\rho$ look?



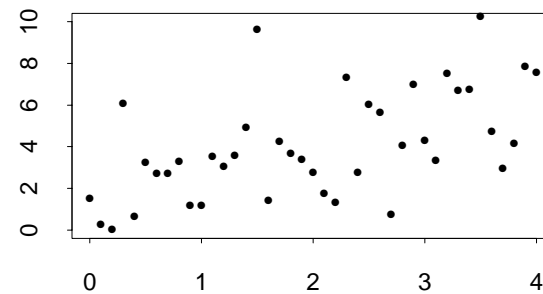
$\rho = -0.07$



$y = 10/\exp(x)$ ,  $\rho = -0.89$



$\rho = -0.71$



$\rho = 0.56$

## Correlation in the dice example

In the previous slide about covariance, we found

$$\text{Cov}(X, Y) = 0.25$$

$$E(X) = \frac{5}{6}$$

$$E(Y) = \frac{21}{6}$$

Find the coefficient of correlation  $\rho$ .

## Variance for a linear function

Let's say we have two random variables  $X$  and  $Y$ , and we are interested in the variance of a linear combination  $aX + bY$  of these two.

$$\text{Var}[aX + bY] = a^2\text{Var}(X) + b^2\text{Var}(Y) + 2ab\text{Cov}(X, Y)$$

This can be extended to the case of a linear combination of  $n > 2$  variables, using the same procedure. (See p. 228 for details.)