

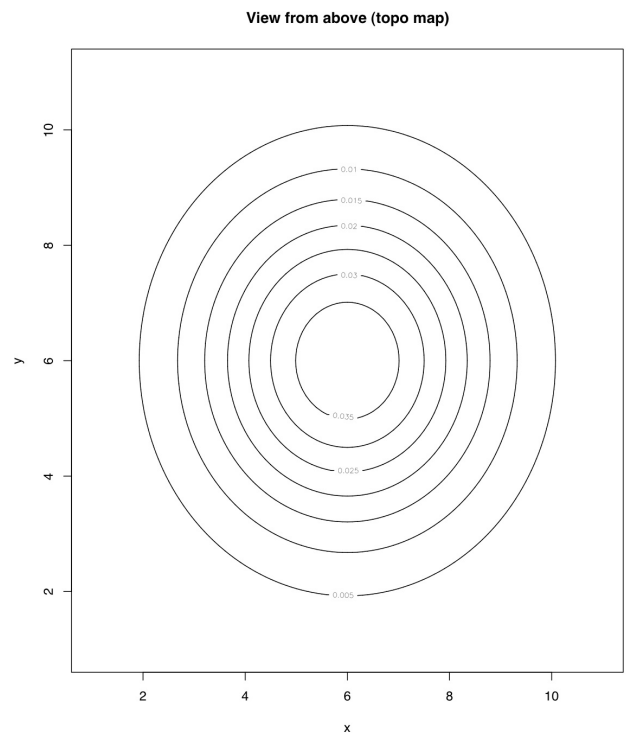
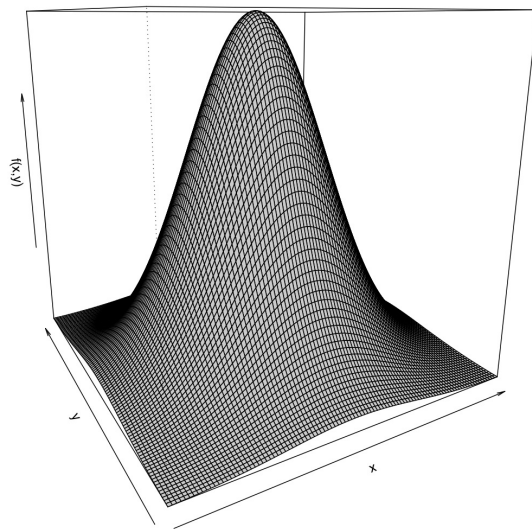
# Chapter 5: JOINT PROBABILITY DISTRIBUTIONS

## Part 3: The Bivariate Normal

Section 5-3.2

## Linear Functions of Random Variables

Section 5-4



The bivariate normal is kind of nifty because...

- The marginal distributions of  $X$  and  $Y$  are both univariate normal distributions.
- The conditional distribution of  $Y$  given  $X$  is a normal distribution.
- The conditional distribution of  $X$  given  $Y$  is a normal distribution.
- Linear combinations of  $X$  and  $Y$  (such as  $Z = 2X + 4Y$ ) follow a normal distribution.
- It's normal almost any way you slice it.

## • Bivariate Normal Probability Density Function

The parameters:  $\mu_X, \mu_Y, \sigma_X, \sigma_Y, \rho$

$$f_{XY}(x, y) = \frac{1}{2\pi\sigma_X\sigma_Y\sqrt{(1-\rho^2)}} \times \\ \exp \left\{ \frac{-1}{2(1-\rho^2)} \left[ \frac{(x-\mu_X)^2}{\sigma_X^2} - \frac{2\rho(x-\mu_X)(y-\mu_Y)}{\sigma_X\sigma_Y} + \frac{(y-\mu_Y)^2}{\sigma_Y^2} \right] \right\}$$

for  $-\infty < x < \infty$  and  $-\infty < y < \infty$ , with

parameters  $\sigma_X > 0$ ,  $\sigma_Y > 0$ ,

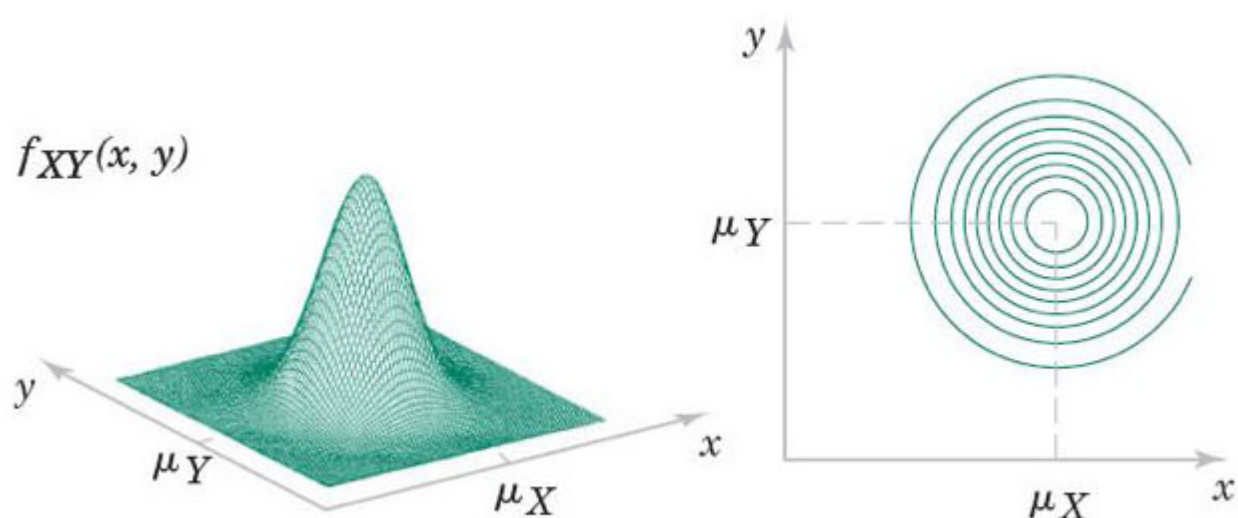
$$-\infty < \mu_X < \infty, -\infty < \mu_Y < \infty, \\ \text{and } -1 < \rho < 1.$$

Where  $\rho$  is the correlation between  $X$  and  $Y$ .

The other parameters are the needed parameters for the marginal distributions of  $X$  and  $Y$ .

## • Bivariate Normal

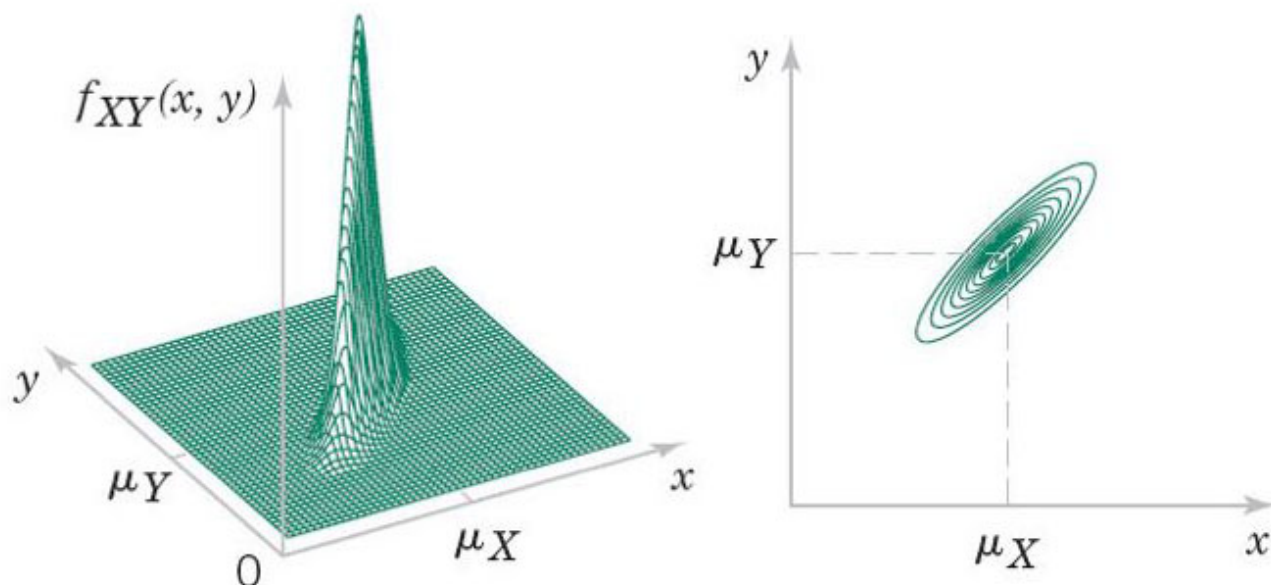
When  $X$  and  $Y$  are **independent**, the contour plot of the joint distribution looks like concentric circles (or ellipses, if they have different variances) with major/minor axes that are parallel/perpendicular to the  $x$ -axis:



The center of each circle or ellipse is at  $(\mu_X, \mu_Y)$ .

## • Bivariate Normal

When  $X$  and  $Y$  are **dependent**, the contour plot of the joint distribution looks like concentric diagonal ellipses, or concentric ellipses with major/minor axes that are NOT parallel/perpendicular to the  $x$ -axis:



The center of each ellipse is at  $(\mu_X, \mu_Y)$ .

- **Marginal distributions of  $X$  and  $Y$  in the Bivariate Normal**

Marginal distributions of  $X$  and  $Y$  are normal:

$$X \sim N(\mu_X, \sigma_X^2) \quad \text{and} \quad Y \sim N(\mu_Y, \sigma_Y^2)$$

Know how to take the parameters from the bivariate normal and calculate probabilities in a univariate  $X$  or  $Y$  problem.

- **Conditional distribution of  $Y|x$  in the Bivariate Normal**

The conditional distribution of  $Y|x$  is also normal:

$$Y|x \sim N(\mu_{Y|x}, \sigma_{Y|x}^2)$$

$$Y|x \sim N(\mu_{Y|x}, \sigma_{Y|x}^2)$$

where the “mean of  $Y|x$ ” or  $\mu_{Y|x}$  depends on the given  $x$ -value as

$$\mu_{Y|x} = \mu_Y + \rho \frac{\sigma_Y}{\sigma_X}(x - \mu_X)$$

and “variance of  $Y|x$ ” or  $\sigma_{Y|x}^2$  depends on the correlation as

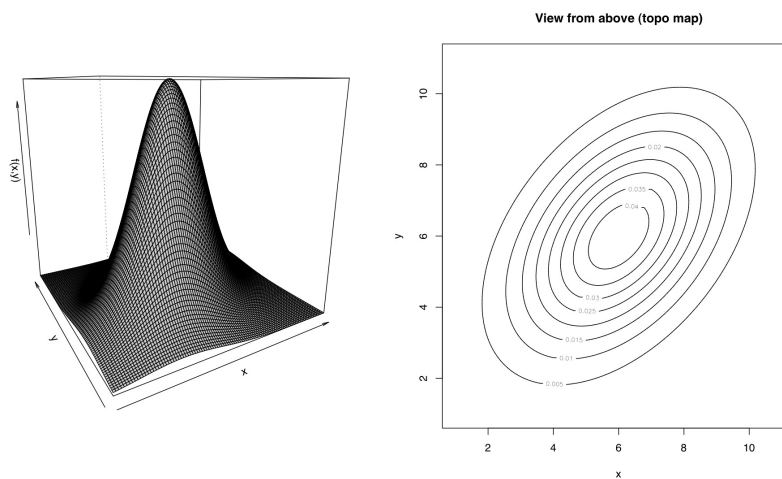
$$\sigma_{Y|x}^2 = \sigma_Y^2(1 - \rho^2).$$

Know how to take the parameters from the bivariate normal and get a conditional distribution for a given  $x$ -value, and then calculate probabilities for the conditional distribution of  $Y|x$  (which is a univariate distribution).

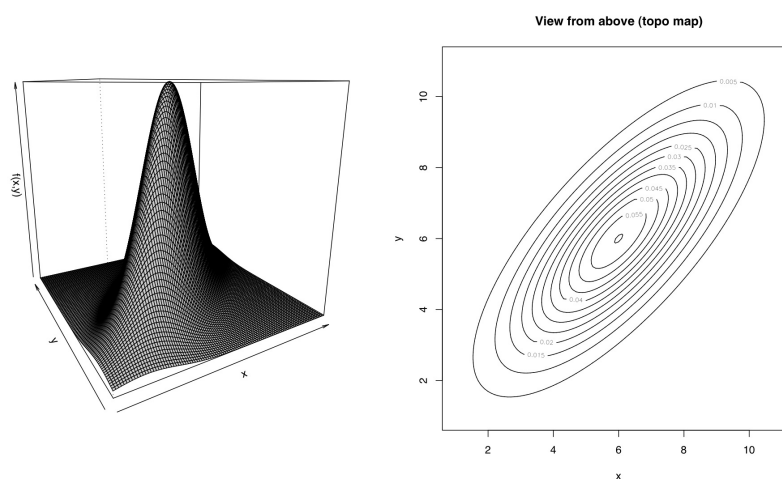
Remember that probabilities in the normal case will be found using the  $z$ -table.

Notice what happens to the joint distribution (and conditional) as  $\rho$  gets closer to  $+1$ :

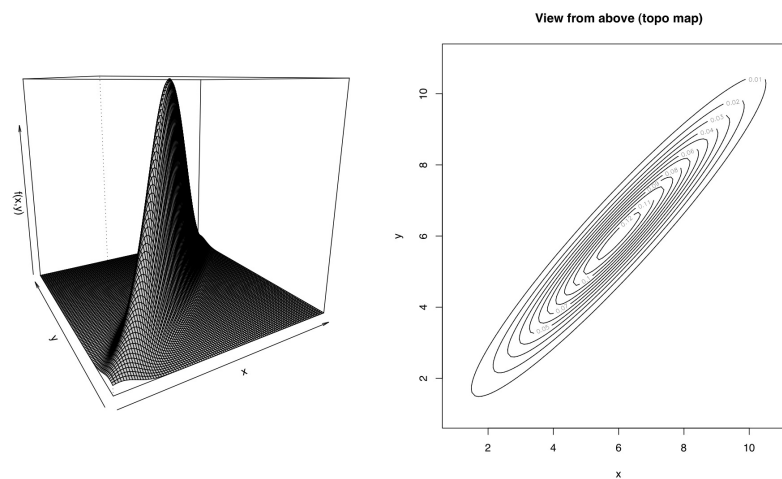
$$\rho = 0.45$$



$$\rho = 0.75$$



$$\rho = 0.95$$





As a last note on the bivariate normal...

Though  $\rho = 0$  does not mean  $X$  and  $Y$  are independent in all cases, for the bivariate normal, this does hold.

## **For the Bivariate Normal, Zero Correlation Implies Independence**

If  $X$  and  $Y$  have a bivariate normal distribution (so, we know the shape of the joint distribution), then with  $\rho = 0$ , we have  $X$  and  $Y$  as independent.

- **Example:** From book problem 5-54.

Assume  $X$  and  $Y$  have a bivariate normal distribution with..

$$\mu_X = 120, \sigma_X = 5$$

$$\mu_Y = 100, \sigma_Y = 2$$

$$\rho = 0.6$$

Determine:

(i) Marginal probability distribution of  $X$ .

(ii) Conditional probability distribution of  $Y$  given that  $X = 125$ .

# Linear Functions of Random Variables

## Section 5-4

- **Linear Combination**

Given random variables  $X_1, X_2, \dots, X_p$  and constants  $c_1, c_2, \dots, c_p$ ,

$$Y = c_1X_1 + c_2X_2 + \dots + c_pX_p$$

is a linear combination of  $X_1, X_2, \dots, X_p$ .

- **Mean of a Linear Function**

If  $Y = c_1X_1 + c_2X_2 + \dots + c_pX_p$ ,

$$E(Y) = c_1E(X_1) + c_2E(X_2) + \dots + c_pE(X_p)$$

## • Variance of a Linear Function

If  $X_1, X_2, \dots, X_p$  are random variables, and  
 $Y = c_1X_1 + c_2X_2 + \dots + c_pX_p$ , then  
in general

$$V(Y) = c_1^2V(X_1) + c_2^2V(X_2) + \dots + c_p^2V(X_p) \\ + 2 \sum_{i < j} \sum c_i c_j \text{cov}(X_i, X_j)$$

In this class, all our linear combinations of random variables will be done with independent random variables.

If  $X_1, X_2, \dots, X_p$  are independent,

$$V(Y) = c_1^2V(X_1) + c_2^2V(X_2) + \dots + c_p^2V(X_p)$$

The most common mistake for finding the variance of a linear combination is to forget to square the coefficients.

- **Example:** Semiconductor product (example 5-31)

A semiconductor product consists of three layers. The variance of the thickness of the first, second, third layers are 25, 40, and 30 nanometers<sup>2</sup>.

What is the variance of the thickness of the final product?

ANS:

## • Mean and Variance of an Average

$$\text{If } \bar{X} = \frac{(X_1 + X_2 + \cdots + X_p)}{p}$$

with  $E(X_i) = \mu$  for  $i = 1, 2, \dots, p$  then

$$E(\bar{X}) = \mu.$$

*The expected value of the average of  $p$  random variables, all with the same mean  $\mu$ , is just  $\mu$  again.*

If  $X_1, X_2, \dots, X_p$  are also independent with  $V(X_i) = \sigma^2$  for  $i = 1, 2, \dots, p$  then

$$V(\bar{X}) = \frac{\sigma^2}{p}$$

*The variance of the average of  $p$  random variables is smaller than the variance of a single random variable.*

- **Reproductive Property of the Normal Distribution**

If  $X_1, X_2, \dots, X_p$  are independent, normal random variables with  $E(X_i) = \mu_i$  and  $V(X_i) = \sigma_i^2$  for  $i = 1, 2, \dots, p$ ,

$$Y = c_1X_1 + c_2X_2 + \dots + c_pX_p$$

is a normal random variable with

$$\mu_Y = E(Y) = c_1\mu_1 + c_2\mu_2 + \dots + c_p\mu_p$$

and

$$\sigma_Y^2 = V(Y) = c_1^2\sigma_1^2 + c_2^2\sigma_2^2 + \dots + c_p^2\sigma_p^2$$

i.e.  $Y \sim N(\mu_Y, \sigma_Y^2)$  as described above.

A linear combination of normal r.v.'s is also normal.
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- **Example:** Weights of people

Assume that the weights of individuals are independent and normally distributed with a mean of 160 pounds and a standard deviation of 30 pounds. Suppose that 25 people squeeze into an elevator that is designed to hold 4300 pounds.

a) What is the probability that the load exceeds the design limit?



