

# Lec 4: Mathematical Economics

## Quadratic Forms

Sugata Bag

Delhi School of Economics

5th September 2013

## Definition: Bilinear Form

### Definition

A **bilinear form** on  $\mathbb{R}^n$  is a function  $L = L(x, y)$  of two arguments  $x, y \in \mathbb{R}^n$  which is linear in each argument, i.e. such that

1.  $L(x_1 + x_2, y) = L(x_1, y) + L(x_2, y)$ ;
2.  $L(x, y_1 + y_2) = L(x, y_1) + L(x, y_2)$ .

**Note (1)** If  $x = (x_1, \dots, x_n)^T$  and  $y = (y_1, \dots, y_n)^T$ , a bilinear form can be written as

$$L(x, y) = \sum_{j,k=1}^n a_{jk} x_k y_j = (Ax, y) = y^* Ax$$

where  $\mathbf{A}_{nn}$  is determined uniquely by the linear form  $L$ .

**Note (2):**  $L(x, y)$  is essentially an inner product.

# Quadratic Forms

## Fact

A quadratic form in  $n$  variables  $x_1, \dots, x_n$  is an expression

$$F = \sum \sum a_{jk} x_k x_j = a_{11}x_1x_1 + a_{12}x_1x_2 + \dots + a_{1n}x_1x_n \\ + a_{21}x_2x_1 + \dots + a_{2n}x_2x_n + \\ \dots \dots \\ + a_{n1}x_nx_1 + \dots + a_{nn}x_nx_n.$$

It is called a "quadratic" form because each term  $a_{ij}x_i x_j$  contains either the square of a variable or the product of two different variables. A QF on  $R^n$  is the "diagonal" of a bilinear form  $L$ , i.e. that any quadratic form  $Q$  is defined by  $Q[x] = L(x, x) = (Ax, x) = x^*Ax$ .

## Examples

(1) A QF  $(a_{11}x_1^2 + 2a_{12}x_1x_2 + a_{22}x_2^2)$  in matrix form

$$\begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

## Change of Variables

It is often possible to simplify a QF  $x^*Ax$  by a change of variables  $x = Sy$  or  $y = S^{-1}x$ , where  $S$  is, of course, a nonsingular matrix. We can go from  $x$  to  $y$  or from  $y$  to  $x$ . Substitution of  $x = Sy$  into  $F = x^*Ax$  gives  $F = (Sy)^*A(Sy) = y^*S^*ASy = y^*By$ , where  $B = S^*AS$ .

- Note that if  $\mathbf{A}$  is a symmetric matrix,  $\mathbf{B}$  is also symmetric.
- The  $\det A$  is called the **discriminant** of the QF  $x^*Ax$ .
- If  $B = S^*AS$  is **congruent** to  $A$ , then the discriminant of the form  $y^*By$  is  $|B| = |S^*| |A| |S| = |S|^2 |A|$ ;  
i.e. under a nonsingular change of the variables  $x = Sy$ , the discriminant of new QF assumes a magnitude of  $|S|^2$  times that of the original form.
- The  $\det S$  is often called the **modulus of the transformation**  $x = Sy$ .

### Definition

**CONGRUENCE:** A square matrix  $\mathbf{B}$  is said to be congruent to the square matrix  $\mathbf{A}$  if there exists a nonsingular matrix  $\mathbf{S}$  such that  $B = S^*AS$ .

## Theorem

If we allow  $x$  to vary over all of  $\mathbf{E}^n$ , then the set of values taken on by  $F = x^*Ax$  is called the range of the quadratic form.

### Theorem

*Under a **nonsingular transformation** of variables, the **range** of a quadratic form remains unchanged.*

### Proof.

Suppose, we have the form  $F = x^*Ax$  and transform it by the change of variables  $x = Sy$  or  $y = S^{-1}x$  to obtain the new form  $(Sy)^*A(Sy) = y^*S^*ASy = y^*By$ .

Now it is only necessary to note that for any  $x$  there is a unique  $y$  (and, similarly, for any  $y$  there is a unique  $x$ ) such that  $F = x^*Ax = y^*By$ .

Hence  $x^*Ax$  and  $y^*By$  must have the same range. In general, this property will not hold if the matrix  $S$  is singular. For example, if  $S = 0$ , the range of  $y^*By$  contains only a single number 0. □

## Definiteness of QFs - definitions

### Definitions

**Positive Definite QF:** The quadratic form  $x^*Ax$  is said to be positive definite if it is positive ( $> 0$ ) for every  $x$  except  $x = 0$ .

**Positive Semi-Definite QF:** The quadratic form  $x^*Ax$  is said to be positive semidefinite if it is non-negative ( $\geq 0$ ) for every  $x$ , and there exist points  $x \neq 0$  for which  $x^*Ax = 0$ .

**Indefinite Forms:** A quadratic form  $x^*Ax$  is said to be indefinite if the form is positive for some points  $x$  and negative for others.

### Fact

*Negative definite and semidefinite forms are defined by interchanging words "negative" and "positive" in the above definitions. If  $x^*Ax$  is positive definite (semidefinite), then  $x^*(-A)x$  is negative definite (semidefinite).*

*A symmetric matrix  $A$  is often said to be positive definite, positive semidefinite, negative definite, etc., if the respective QF:  $x^*Ax$  is positive definite, positive semidefinite, negative definite, etc.*

## Another set of necessary and sufficient conditions for Definiteness:

A set of necessary and sufficient conditions for the form  $x^*Ax$  to be positive definite is

$$a_{11} > 0, \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix} > 0, \begin{pmatrix} a_{11} & a_{12} & a_{23} \\ a_{21} & a_{22} & a_{32} \\ a_{31} & a_{32} & a_{33} \end{pmatrix} > 0, \dots, |A| > 0;$$

If these  $n$  minors of  $A$  are positive,  $x^*Ax$  is positive definite; and  $x^*Ax$  is positive definite only if these minors are positive.

### Fact

- (1)**  $x^*Ax$  is positive (negative) definite iff every eigenvalue of  $A$  is positive (negative).
- (2)**  $x^*Ax$  is positive (negative) semidefinite iff all eigenvalues of  $A$  are non-negative (nonpositive), and at least one of the eigenvalues vanishes.
- (3)**  $x^*Ax$  is indefinite iff  $A$  has both positive and negative eigenvalues.

## Examples

(1).  $F = 3x_1^2 + 5x_2^2$ ,  $F = 2x_1^2 + 3x_2^2 + x_3^2$ ,  $F = x_1^2$  are positive definite forms in two, three, and one variable, respectively.

(2).  $F = 4x_1^2 + x_2^2 - 4x_1x_2 + 3x_3^2 = (2x_1 - x_2)^2 + 3x_3^2$  is positive semidefinite since it is never negative and vanishes if  $x_2 = 2x_1$ ,  $x_3 = 0$ .

(3)  $F = -2x_1^2 - x_2^2$ ,  $F = -x_1^2 - x_2^2$ ,  $F = -x_1^2$  are negative definite forms in two, two, and one variable, respectively.

(4)  $F = 4x_1^2 - 3x_2^2$  is indefinite since it is positive when  $x_1 = 1$ ,  $x_2 = 1$  and negative when  $x_1 = 0$ ,  $x_2 = 1$ .

**Note:** *A positive (negative) definite form remains positive (negative) definite when expressed in terms of a new set of variables provided the transformation of the variables is nonsingular.*

Thus if  $x^*Ax$  is positive (negative) definite and  $S$  is nonsingular, then  $(Sy)^*A(Sy) = y^*S^*ASy = y^*By$  ( $x = Sy$ ) is positive (negative) definite. Try to prove this statement given the previous theorem.

# Diagonalisation of QFs

## Theorem

*By an orthogonal transformation of variables every QF  $x^*Ax$  may be reduced to a diagonal form.*

**Proof.** Given a QF  $x^*Ax$ , consider a nonsingular transformation of variables  $x = Qy$ , the matrix  $Q$  has as its columns a set of **orthonormal** eigenvectors of  $A$  which span  $E^n$ . The matrix  $Q$  is therefore an orthogonal matrix, and the transformation of variables is called an orthogonal transformation. In the diagonal form, the coefficient of  $y_j^2$  is the eigenvalue  $\lambda_j$  of  $A$ . In terms of the variables  $y$ , the  $F$  becomes

$$y^*Q^*AQy = y^*Dy, \quad \text{and} \quad D = \|\lambda_j\delta_{ij}\|$$

is a diagonal matrix whose diagonal elements are the eigenvalues of  $A$ .

Thus  $y^*Dy = \sum_{j=1}^n \lambda_j y_j^2$ . Only the squares of the variables appear; there are no cross products  $y_i y_j$ . A QF containing only the squares of the variables is said to be in diagonal form. Furthermore, we say that the transformation of variables  $x = Qy$  has diagonalized the QF  $x^*Ax$ .

## Examples

Consider the QF:  $F = 2x_1^2 + 2\sqrt{2}x_1x_2 + x_2^2 = x^*Ax$

the symmetric matrix  $A$  is then  $\begin{pmatrix} 2 & \sqrt{2} \\ \sqrt{2} & 1 \end{pmatrix}$ .

To diagonalise the form, we transform  $x = Qy$ , where columns of  $Q$  are -  
 $u_1 = [-\frac{1}{\sqrt{3}}, \sqrt{\frac{2}{3}}]^T$  and  $u_2 = [\sqrt{\frac{2}{3}}, \frac{1}{\sqrt{3}}]^T$  are orthonormal e.v.s of  $A$ .

Thus the transformation variables are -

$$\begin{aligned} x_1 &= \frac{1}{\sqrt{3}}(-y_1 + \sqrt{2}y_2), & y_1 &= \frac{1}{\sqrt{3}}(-x_1 + \sqrt{2}x_2) \\ x_2 &= \frac{1}{\sqrt{3}}(\sqrt{2}y_1 + y_2), & y_2 &= \frac{1}{\sqrt{3}}(\sqrt{2}x_1 + x_2). \end{aligned}$$

**Note** that  $Q^{-1} = Q^*$ ; hence it is very easy to find the inverse transformation for an orthogonal transformation of variables. Since the eigenvalues of  $A$  are  $\lambda_1 = 0$ ,  $\lambda_2 = 3$ , the form  $F$  becomes  $F = 3y_2^2$  under this transformation of variables. The form is therefore positive semidefinite. The point  $y = [2, 0]$  causes the form to vanish. The  $x$  corresponding to this  $y$  is  $x = [\frac{2}{\sqrt{3}}, 2 - 2\sqrt{\frac{2}{3}}]$ , and of course,  $F$  vanishes for this value of  $x$ .