

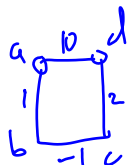
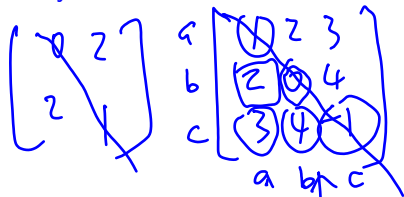
Section 7.1 Diagonalization of symmetric matrices and 7.2 Quadratic forms

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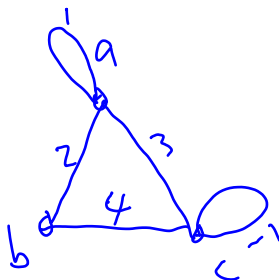
College of William and Mary

Symmetric matrix

- A symmetric matrix is a matrix A such that $A^T = A$.



$$\begin{matrix}
 a & b & c & d \\
 b & a & 0 & 10 \\
 c & 0 & -1 & 0 & 2 \\
 d & 10 & 0 & 2 & 0
 \end{matrix}$$



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- Its main diagonal entries are arbitrary, but its other entries occur in pairs on opposite sides of the main diagonal.

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$$Av_1 = \lambda_1 v_1$$

Proof: Let v_1 and v_2 be eigenvectors that correspond to distinct eigenvalues, say λ_1 and λ_2 . We show that $v_1 \cdot v_2 = 0$. Note that

$$\begin{aligned}\lambda_1 v_1 \cdot v_2 &= (\lambda_1 v_1)^T v_2 = (Av_1)^T v_2 = (v_1^T A^T) v_2 \\ &= v_1^T (A^T v_2) = v_1^T (Av_2) = v_1^T (\lambda_2 v_2) = \lambda_2 (v_1^T v_2) \\ &= \lambda_2 v_1 \cdot v_2.\end{aligned}$$

It follows that $(\lambda_1 - \lambda_2)(v_1 \cdot v_2) = 0$. So $v_1 \cdot v_2 = 0$.

Orthogonally diagonalizable matrix

- An $n \times n$ matrix A is said to be **orthogonally diagonalizable** if there are orthogonal matrix P (with $P^{-1} = P^T$) and a diagonal matrix D such that

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- **Theorem:** An $n \times n$ matrix A is orthogonally diagonalizable **if and only if** A is symmetric.

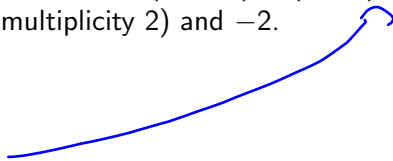
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- First of all, its characteristic equation is $\det(A - \lambda I) = (\lambda - 7)^2(\lambda + 2)$. So its eigenvalues are 7 (with multiplicity 2) and -2 .

$$\det \begin{pmatrix} 3-\lambda & -2 & 4 \\ -2 & 6-\lambda & 2 \\ 4 & 2 & 3-\lambda \end{pmatrix}$$



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- The bases for the eigenspaces are

$$\lambda = 7 : v_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}, v_2 = \begin{pmatrix} -\frac{1}{2} \\ 1 \\ 0 \end{pmatrix}; \quad \lambda = -2 : v_3 = \begin{pmatrix} -1 \\ -\frac{1}{2} \\ 1 \end{pmatrix}$$

$(A - 7I)x = 0$

$$A - 7I = \begin{bmatrix} -4 & -2 & 4 \\ -2 & -1 & 2 \\ 4 & 2 & -4 \end{bmatrix} \rightarrow \begin{bmatrix} 2 & 1 & -2 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

$x_1 = -\frac{1}{2}x_2 + x_3$

$$x = \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} = \begin{pmatrix} -\frac{1}{2}x_2 + x_3 \\ x_2 \\ x_3 \end{pmatrix} =$$

(Handwritten notes in the image show arrows pointing from the 2 in the first row of the reduced matrix to the x2 and x3 terms in the vector equation.)

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- The projection of v_2 onto v_1 is $\frac{v_2 \cdot v_1}{v_1 \cdot v_1} v_1$, so the component of v_2 orthogonal to v_1 is $z_2 = v_2 - \frac{v_2 \cdot v_1}{v_1 \cdot v_1} v_1 = \begin{pmatrix} -\frac{1}{4} \\ 1 \\ \frac{1}{4} \end{pmatrix}$

Gram-Schmidt process (6.4)

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- So $\{v_1, z_2\}$ is an orthogonal set in the eigenspace for $\lambda = 7$.

- Normalize v_1 and z_2 to get an orthonormal basis for the eigenspace for $\lambda = 7$:

$$u_i = \frac{v_i}{\|v_i\|}$$

$$u_1 = \begin{pmatrix} 1/\sqrt{2} \\ 0 \\ 1/\sqrt{2} \end{pmatrix}, \quad u_2 = \begin{pmatrix} -1/\sqrt{18} \\ 4/\sqrt{18} \\ 1/\sqrt{18} \end{pmatrix}$$

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- Let

$$P = [u_1 \ u_2 \ u_3] = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{18}} & -\frac{2}{3} \\ 0 & \frac{4}{\sqrt{18}} & -\frac{1}{3} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{18}} & \frac{2}{3} \end{bmatrix}, \quad D = \begin{bmatrix} 7 & 0 & 0 \\ 0 & 7 & 0 \\ 0 & 0 & -2 \end{bmatrix}$$

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- then P orthogonally diagonalizes A , and $A = PDP^T$.

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 - 4 A is orthogonally diagonalizable.

Spectral decomposition

- Suppose that $A = PDP^{-1}$, where the columns of P are orthonormal eigenvectors u_1, \dots, u_n of A and the corresponding eigenvalues $\lambda_1, \dots, \lambda_n$ are in the diagonal matrix D . Then

$$A = PDP^T = [u_1 \ u_2 \ \dots \ u_n] \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & & 0 \\ \dots & & \dots & \\ 0 & & & \lambda_n \end{bmatrix} \begin{pmatrix} u_1^T \\ u_2^T \\ \dots \\ u_n^T \end{pmatrix}$$

$$= \lambda_1 u_1 u_1^T + \lambda_2 u_2 u_2^T + \dots + \lambda_n u_n u_n^T$$

$n \times n$ matrix

$$(\lambda_1 u_1 \ \lambda_2 u_2 \ \dots \ \lambda_n u_n) \begin{pmatrix} u_1^T \\ \vdots \\ u_n^T \end{pmatrix}$$

$$u_1 u_1^T = \begin{bmatrix} u_{11} \\ \vdots \\ u_{in} \end{bmatrix} \begin{bmatrix} u_{11} & \dots & u_{in} \end{bmatrix}$$

$n \times 1$ $1 \times n$

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- The expression $A = \lambda_1 u_1 u_1^T + \lambda_2 u_2 u_2^T + \dots + \lambda_n u_n u_n^T$ is called a **spectral decomposition of A** , because it breaks A into pieces determined by the spectrum (eigenvalues) of A .

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- Each term in the decomposition is an $n \times n$ matrix of rank 1.

Example

- Ex:

$$A = \begin{bmatrix} 7 & 2 \\ 2 & 4 \end{bmatrix} = \begin{bmatrix} \frac{2}{\sqrt{5}} & -\frac{1}{\sqrt{5}} \\ \frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{bmatrix} \begin{bmatrix} 8 & 0 \\ 0 & 3 \end{bmatrix} \begin{bmatrix} \frac{2}{\sqrt{5}} & \frac{1}{\sqrt{5}} \\ -\frac{1}{\sqrt{5}} & \frac{2}{\sqrt{5}} \end{bmatrix}$$

v_1 v_2

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- Then

$$A = 8u_1u_1^T + 3u_2u_2^T = \begin{bmatrix} \frac{32}{5} & \frac{16}{5} \\ \frac{16}{5} & \frac{8}{5} \end{bmatrix} + \begin{bmatrix} \frac{3}{5} & -\frac{6}{5} \\ -\frac{6}{5} & \frac{12}{5} \end{bmatrix}$$

Quadratic forms

- A **quadratic form** is a function defined on \mathbf{R}^n whose value at a vector x in \mathbf{R}^n can be computed by an expression of the form $Q(x) = x^T A x$, where A is an $n \times n$ symmetric matrix.

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- The matrix A is called the **matrix of the quadratic form**.

$$2x_1^2 + 3x_1x_2 - 2x_1x_3 + 4x_2x_3 + x_2^2 + 5x_3^2$$

↓

$$A = \begin{pmatrix} 2 & 3/2 & -1 \\ 3/2 & 1 & 2 \\ -1 & 2 & 5 \end{pmatrix}$$

$x_1 \quad x_2 \quad x_3$

$$x^T A x$$
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- The matrix A is called the **matrix of the quadratic form**.
- Ex: let $x = \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$. Compute $x^T A x$ for the following matrices:

$$x^T A x \quad A = \begin{bmatrix} 4 & 0 \\ 0 & 3 \end{bmatrix}, \quad B = \begin{bmatrix} 3 & -2 \\ -2 & 7 \end{bmatrix}$$
$$= \begin{pmatrix} x_1 & x_2 \end{pmatrix} \begin{pmatrix} 4 & 0 \\ 0 & 3 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$
$$\equiv (4x_1 \quad 3x_2) \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = 4x_1^2 + 3x_2^2$$

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- $x^T Ax = 4x_1^2 + 3x_2^2$
- $x^T Bx = 3x_1^2 - 4x_1x_2 + 7x_2^2$.
- The term $-4x_1x_2$ is called a **cross-product term**.

Change of variable in a quadratic form

- If x represents a variable vector in \mathbf{R}^n , then a **change of variable** is an equation of the form $x = Py$, or $y = P^{-1}x$, where P is an invertible matrix and y is a new variable vector in \mathbf{R}^n .

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- By make a change of variable on $x^T Ax$, we have

$$x^T Ax = (Py)^T A(Py) = y^T P^T APy = y^T (P^T AP)y$$

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- Since A is symmetric, there is an orthogonal matrix P such that $P^T AP$ is a diagonal matrix D , and the quadratic form above becomes $y^T Dy$, which contains no cross-product terms.
- **Theorem:** Let A be an $n \times n$ symmetric matrix. Then there is an orthogonal change of variable, $x = Py$, that transforms the quadratic form $x^T Ax$ into a quadratic form $y^T Dy$ with no cross-product term.

Example

- Ex: Make a change of variable that transforms the quadratic form $Q(x) = x_1^2 - 8x_1x_2 - 5x_2^2$ into a quadratic form with no cross-product term.

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- Orthogonally diagonalize A : the eigenvalues of A are 3 and -7 , and the associated unit eigenvectors are $\lambda = 3 : \left[\frac{2}{\sqrt{5}} \quad -\frac{1}{\sqrt{5}}\right]^T$ and $\lambda = -7 : \left[\frac{1}{\sqrt{5}} \quad \frac{2}{\sqrt{5}}\right]^T$.

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Example

- Ex: Make a change of variable that transforms the quadratic form $Q(x) = x_1^2 - 8x_1x_2 - 5x_2^2$ into a quadratic form with no cross-product term.
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- then $A = PDP^T$ and $D = P^TAP$. Let $x = Py$, then

$$x_1^2 - 8x_1x_2 - 5x_2^2 = y^T D y = 3y_1^2 - 7y_2^2$$

The principal axes theorem

- The columns of P in the theorem are called the **principal axes** of the quadratic form $x^T Ax$.

The principal axes theorem

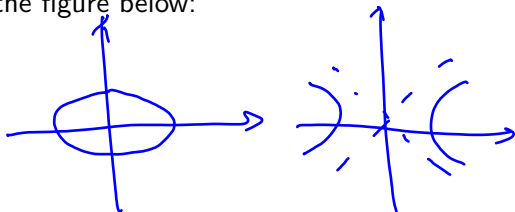
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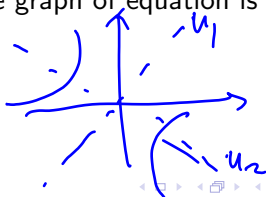
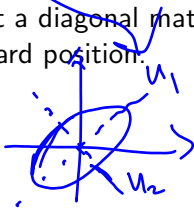
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