

Chapter 5 Notes - LA

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April 5, 2022

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5 Orthogonality

5.1 Orthogonality in \mathbb{R}^n

- A set of vectors $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ in \mathbb{R}^n is called an orthogonal set if all pairs of distinct vectors in the set are orthogonal; that is, if

$$\mathbf{v}_i \cdot \mathbf{v}_j = 0 \quad \text{whenever} \quad i \neq j \quad \text{for } i, j = 1, 2, \dots, k$$

- The standard basis of \mathbb{R}^n is an orthogonal set.
- If $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ is an orthogonal set of nonzero vectors in \mathbb{R}^n , then these vectors are linearly independent.
- An orthogonal basis for a subspace W of \mathbb{R}^n is a basis of W that is an orthogonal set.
- Let $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ be an orthogonal basis for a subspace W of \mathbb{R}^n and let \mathbf{w} be any vector in W . Then the unique scalars c_1, \dots, c_k such that

$$\mathbf{w} = c_1 \mathbf{v}_1 + \dots + c_k \mathbf{v}_k$$

are given by

$$c_i = \frac{\mathbf{w} \cdot \mathbf{v}_i}{\mathbf{v}_i \cdot \mathbf{v}_i} \quad \text{for } i = 1, \dots, k$$

- A set of vectors \mathbb{R}^n is an orthonormal set if it is an orthogonal set of unit vectors. An orthonormal basis for a subspace W of \mathbb{R}^n is a basis of W that is an orthonormal set.
- Let $\{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_k\}$ be an orthogonal basis for a subspace W of \mathbb{R}^n and let \mathbf{w} be any vector in W . Then

$$\mathbf{w} = (\mathbf{w} \cdot \mathbf{q}_1) \mathbf{q}_1 + (\mathbf{w} \cdot \mathbf{q}_2) \mathbf{q}_2 + \dots + (\mathbf{w} \cdot \mathbf{q}_k) \mathbf{q}_k$$

and this representation is unique.

- The columns of an $m \times n$ matrix Q form an orthonormal set IFF $Q^T Q = I_n$
- An $n \times n$ matrix Q whose columns form an orthonormal set is called an orthogonal matrix.

- A square matrix Q is orthogonal IFF $Q^{-1} = Q^T$
- Let Q be an $n \times n$ matrix. The following are equivalent:
 - Q is orthogonal.
 - $\|Q\mathbf{x}\| = \|\mathbf{x}\|$ for every \mathbf{x} in \mathbb{R}^n
 - $Q\mathbf{x} \cdot Q\mathbf{y} = \mathbf{x} \cdot \mathbf{y}$ for every \mathbf{x} and \mathbf{y} in \mathbb{R}^n
- If Q is an orthogonal matrix, then its rows form an orthonormal set.
- Let Q be an orthogonal matrix.
 - Q^{-1} is orthogonal.
 - $\det Q = \pm 1$
 - If λ is an eigenvalue of Q , then $|\lambda| = 1$
 - If Q_1 and Q_2 are orthogonal $n \times n$ matrices, then so is $Q_1 Q_2$.

5.2 Orthogonal Complements and Orthogonal Projections

- Let W be a subspace of \mathbb{R}^n . We say that a vector \mathbf{v} in \mathbb{R}^n is orthogonal to W if \mathbf{v} is orthogonal to every vector in W . The set of all vectors that are orthogonal to W is called the orthogonal complement of W , denoted W^\perp . That is,

$$W^\perp = \{\mathbf{v} \text{ in } \mathbb{R}^n : \mathbf{v} \cdot \mathbf{w} = 0 \text{ for all } \mathbf{w} \text{ in } W\}$$

- Let W be a subspace of \mathbb{R}^n .
 - W^\perp is a subspace of \mathbb{R}^n
 - $(W^\perp)^\perp = W$
 - $W \cap W^\perp = \{\mathbf{0}\}$
 - If $W = \text{span}(\mathbf{w}_1, \dots, \mathbf{w}_k)$, then \mathbf{v} is in W^\perp IFF $\mathbf{v} \cdot \mathbf{w}_i = 0$ for all $i = 1, \dots, k$.
- Let A be an $m \times n$ matrix. Then the orthogonal complement of the row space of A is the null space of A , and the orthogonal complement of the column space of A is the null space of A^T :

$$(\text{row}(A))^\perp = \text{null}(A) \quad \text{and} \quad (\text{col}(A))^\perp = \text{null}(A^T)$$

- Let W be a subspace of \mathbb{R}^n and let $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ be an orthogonal basis for W . For any vector \mathbf{v} in \mathbb{R}^n , the orthogonal projection of \mathbf{v} onto W is defined as

$$\text{proj}_W(\mathbf{v}) = \left(\frac{\mathbf{u}_1 \cdot \mathbf{v}}{\mathbf{u}_1 \cdot \mathbf{u}_1} \right) \mathbf{u}_1 + \dots + \left(\frac{\mathbf{u}_k \cdot \mathbf{v}}{\mathbf{u}_k \cdot \mathbf{u}_k} \right) \mathbf{u}_k$$

The complement of \mathbf{v} orthogonal to W is the vector

$$\text{perp}_W(\mathbf{v}) = \mathbf{v} - \text{proj}_W(\mathbf{v})$$

- $\text{proj}_W(\mathbf{v}) = \text{proj}_{\mathbf{u}_1}(\mathbf{v}) + \dots + \text{proj}_{\mathbf{u}_k}(\mathbf{v})$
- The orthogonal decomposition theorem: Let W be a subspace of \mathbb{R}^n and let \mathbf{v} be a vector in \mathbb{R}^n . Then there are unique vectors \mathbf{w} in W and \mathbf{w}^\perp in W^\perp such that

$$\mathbf{v} = \mathbf{w} + \mathbf{w}^\perp$$

- If W is a subspace of \mathbb{R}^n then

$$(W^\perp)^\perp = W$$

- If W is a subspace of \mathbb{R}^n then

$$\dim W + \dim W^\perp = n$$

- The Rank Theorem: If A is an $m \times n$ matrix, then

$$\text{rank}(A) + \text{nullity}(A) = n$$

5.3 The Gram-Schmidt Process and the QR Factorization

- The Gram-Schmidt Process: Let $\{\mathbf{x}_1, \dots, \mathbf{x}_k\}$ be a basis for a subspace W of \mathbb{R}^n and define the following:

$$\begin{aligned} \mathbf{v}_1 &= \mathbf{x}_1; & W_1 &= \text{span}(\mathbf{x}_1) \\ \mathbf{v}_2 &= \mathbf{x}_2 - \left(\frac{\mathbf{v}_1 \cdot \mathbf{x}_2}{\mathbf{v}_1 \cdot \mathbf{v}_1} \right) \mathbf{v}_1, & W_2 &= \text{span}(\mathbf{x}_1, \mathbf{x}_2) \\ \mathbf{v}_3 &= \mathbf{x}_3 - \left(\frac{\mathbf{v}_1 \cdot \mathbf{x}_3}{\mathbf{v}_1 \cdot \mathbf{v}_1} \right) \mathbf{v}_1 - \left(\frac{\mathbf{v}_2 \cdot \mathbf{x}_3}{\mathbf{v}_2 \cdot \mathbf{v}_2} \right) \mathbf{v}_2, & W_3 &= \text{span}(\mathbf{x}_1, \mathbf{x}_2, \mathbf{x}_3) \\ & \vdots & & \\ \mathbf{v}_k &= \mathbf{x}_k - \left(\frac{\mathbf{v}_1 \cdot \mathbf{x}_k}{\mathbf{v}_1 \cdot \mathbf{v}_1} \right) \mathbf{v}_1 - \left(\frac{\mathbf{v}_2 \cdot \mathbf{x}_k}{\mathbf{v}_2 \cdot \mathbf{v}_2} \right) \mathbf{v}_2 - \dots - \left(\frac{\mathbf{v}_{k-1} \cdot \mathbf{x}_k}{\mathbf{v}_{k-1} \cdot \mathbf{v}_{k-1}} \right) \mathbf{v}_{k-1}, & W_k &= \text{span}(\mathbf{x}_1, \dots, \mathbf{x}_k) \end{aligned}$$

Then for each $i = 1, \dots, k$, $\{\mathbf{v}_1, \dots, \mathbf{v}_i\}$ is an orthogonal basis for W_i . In particular, $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is an orthogonal basis for W .

- QR Factorization: Let A be an $m \times n$ matrix with linearly independent columns. Then A can be factored as $A = QR$, where Q is an $m \times n$ matrix with orthonormal columns and R is an invertible upper triangular matrix.
- Finding the QR factorization: find an orthonormal basis for $\text{col}(A)$ using the Gram-Schmidt Process. Then, $Q = [\mathbf{q}_1, \mathbf{q}_2, \dots, \mathbf{q}_k]$. Then, use the fact that $A = QR$ and $Q^T Q = I$ since Q has orthonormal columns. Therefore $Q^T A = Q^T QR = IR = R$

5.4 Orthogonal Diagonalization of Symmetric Matrices

- A square matrix A is orthogonally diagonalizable if there exists an orthogonal matrix Q and a diagonal matrix D such that $Q^T A Q = D$
- If A is orthogonally diagonalizable, then A is symmetric.
- If A is a real symmetric matrix, then the eigenvalues of A are real.
- If A is a symmetric matrix, then any two eigenvectors corresponding to distinct eigenvalues of A are orthonormal.
- The spectral theorem: Let A be an $n \times n$ real matrix. Then A is symmetric IFF it is orthogonally diagonalizable.
- Spectral decomposition:

$$A = \lambda_1 \mathbf{q}_1 \mathbf{q}_1^T + \lambda_2 \mathbf{q}_2 \mathbf{q}_2^T + \dots + \lambda_n \mathbf{q}_n \mathbf{q}_n^T$$

5.5 Applications

- A quadratic form in n variables is a function $f : \mathbb{R}^n \rightarrow \mathbb{R}$ of the form

$$f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x}$$

where A is a symmetric $n \times n$ matrix and \mathbf{x} is in \mathbb{R}^n . We refer to A as the matrix associated with f .

- The principal axes theorem: Every quadratic form can be diagonalized. Specifically, if A is the $n \times n$ symmetric matrix associated with the quadratic form $\mathbf{x}^T A \mathbf{x}$ and if Q is an orthogonal matrix such that $Q^T A Q = D$ is a diagonal matrix, then the change of variable $\mathbf{x} = Q \mathbf{y}$ transforms the quadratic form $\mathbf{x}^T A \mathbf{x}$ into the quadratic form $\mathbf{y}^T D \mathbf{y}$, which has no cross-product terms. If the eigenvalues of A are $\lambda_1, \dots, \lambda_n$ and $\mathbf{y} = [y_1 \dots y_n]^T$, then

$$\mathbf{x}^T A \mathbf{x} = \mathbf{y}^T D \mathbf{y} = \lambda_1 y_1^2 + \dots + \lambda_n y_n^2$$

- A quadratic form $f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x}$ is classified as one of the following:
 - positive definite if $f(\mathbf{x}) > 0$ for all $\mathbf{x} \neq \mathbf{0}$
 - positive semidefinite if $f(\mathbf{x}) \geq 0$ for all \mathbf{x}
 - negative definite if $f(\mathbf{x}) < 0$ for all $\mathbf{x} \neq \mathbf{0}$
 - negative semidefinite if $f(\mathbf{x}) \leq 0$ for all \mathbf{x}
 - indefinite if $f(\mathbf{x})$ takes on both positive and negative values
- A symmetric matrix A is called positive definite, positive semidefinite, negative definite, negative semidefinite, or indefinite if the associated quadratic form $f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x}$ has the corresponding property.
- Let A be an $n \times n$ symmetric matrix. The quadratic form $f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x}$ is
 - Positive definite IFF all eigenvalues of A are positive.
 - positive semidefinite IFF all eigenvalues are nonnegative.
 - negative definite IFF all eigenvalues are negative
 - negative semidefinite IFF all eigenvalues are nonpositive.
 - indefinite IFF A has both positive and negative eigenvalues.
- Let $f(\mathbf{x}) = \mathbf{x}^T A \mathbf{x}$ be a quadratic form with associated $n \times n$ symmetric matrix A . Let the eigenvalues of A be $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$. Then the following are true, with the constraint of $\|\mathbf{x}\| = 1$:
 - $\lambda_1 \geq f(\mathbf{x}) \geq \lambda_n$
 - The max value of $f(\mathbf{x})$ is λ_1 and occurs when \mathbf{x} is a unit eigenvector corresponding to λ_1
 - The min value of $f(\mathbf{x})$ is λ_n and occurs when \mathbf{x} is a unit eigenvector corresponding to λ_n
- The general form of a quadratic equation in two variables x and y is

$$ax^2 + by^2 + cxy + dx + ey + f = 0$$

- The general form of a quadratic equation in three variables x , y , and z is

$$ax^2 + by^2 + cz^2 + dxy + exz + fyz + gx + hy + iz + j = 0$$