Lecture #2 Notes Summary

Cone \mathbb{S}^n_+ , generalized inverses

Semidefinite positive matrices and generalized inverses

Definition 1 (cone \mathbb{S}^n_+). A symmetric matrix A is called positive semidefinite if $x^T A x \ge 0$ for all $x \in \mathbb{R}^n$, and positive definite if $x^T A x > 0$ for all $x \ne 0 \in \mathbb{R}^n$. The set of $n \times n$ symmetric matrices (resp. positive semidefinite, positive definite) is \mathbb{S}^n (resp. $\mathbb{S}^n_+, \mathbb{S}^n_{++}$).

Proposition 1. The set \mathbb{S}^n_+ is a closed, convex, pointed cone.

We recall that the eigenvalues of a symmetric matrix are real, and any symmetric matrix can be diagonalized by an orthogonal transformation (that is, a kind of rotation):

Theorem 2 (Spectral decomposition). Let A be a symmetric matrix. Then, there exists an orthogonal matrix U (i.e., $U^T U = UU^T = I$) such that

 $A = U\Sigma U^T,$

where the matrix Σ is diagonal and contains the eigenvalues $\lambda_i \in \mathbb{R}$ of A.

Definition 2 (Löwner ordering). The space \mathbb{S}^n is equipped with a partial ordering \succeq , defined as

$$A \succeq B \iff A - B \in \mathbb{S}^n_+.$$

In particular, we write $A \succeq 0$ if A is positive semidefinite (and $A \succ 0$ if A is positive definite).

Characterization of positive semidefinite matrices:

Theorem 3. The following statements are equivalent

- (i) $A \in \mathbb{S}^n_+$.
- (ii) All eigenvalues of A are ≥ 0 .
- (*iii*) $A \in \text{convex-hull}\{\boldsymbol{x}\boldsymbol{x}^T, \ \boldsymbol{x} \in \mathbb{R}^n\}.$
- (iv) There exists a $n \times n$ -matrix B such that $A = BB^T$.

and the equivalent theorem for positive definite matrices:

Theorem 4. The following statements are equivalent

- (i) $A \in \mathbb{S}^n_{++}$.
- (ii) All eigenvalues of A are > 0.
- (iii) There exists an invertible $n \times n$ -matrix B such that $A = BB^T$.

Some useful properties

Proposition 5 (Congruent transformations). Let P be an $m \times n$ -matrix. Then,

$$A \succeq 0 \Longrightarrow PAP^T \succeq 0.$$

Moreover, if P is square and invertible the converse relation holds $(PAP^T \succeq 0 \Longrightarrow A \succeq 0)$.

Proposition 6. Let $A \in \mathbb{S}^n_+$. Then,

- All principal submatrices of A are $\succeq 0$;
- All diagonal elements of A are ≥ 0 ;
- $\forall i, j, |A_{ij}| \leq \sqrt{A_{ii}A_{jj}} \leq \frac{1}{2}(A_{ii} + A_{jj}).$

Proposition 7 (Schur complement). Let $A \succ 0$. Then the following holds:

$$\left(\begin{array}{cc}A & B\\B^T & C\end{array}\right) \succeq 0 \Longleftrightarrow C \succeq B^T A^{-1} B.$$

There is also use a stronger version of this proposition, for the case where we only have $A \succeq 0$. But this requires the concept of *generalized inverses*.

Definition 3 (Generalized inverse). Let M be an $n \times m$ -matrix. The matrix G is called a *generalized* inverse of M if MGM = M.

Proposition 8. Let $M \in \mathbb{S}^n$. Let K_1 and K_2 be matrices whose colums are included in the range of M (i.e., $\operatorname{im} K_1 \subseteq \operatorname{im} M$, $\operatorname{im} K_2 \subseteq \operatorname{im} M$). Then, the matrix $K_1^T G K_2$ does not depend on the choice of a generalized inverse G of M. We denote this matrix by $K_1^T M^- K_2$.

Definition 4 (Moore-Penrose pseudoinverse). Let M be an $n \times m$ -matrix. The matrix

$$M^{\dagger} := \lim_{\epsilon \to 0^+} (M^T M + \epsilon \boldsymbol{I}_m)^{-1} M^T$$

is a generalized inverse of M, called the *Moore-Penrose pseudoinverse* of M. In practice, M^{\dagger} can be computed by taking a singular value decomposition of M, and inverting the nonzero singular values.

Proposition 9 (Generalized Schur complement). Let $A \succeq 0$, and let B be a matrix satisfying the range inclusion condition im $B \subseteq \text{im } A$. Then the following holds:

$$\left(\begin{array}{cc} A & B \\ B^T & C \end{array}\right) \succeq 0 \Longleftrightarrow C \succeq B^T A^- B.$$

Exercises

1. Let $A \succ 0$. Show that the set $E = \{ \boldsymbol{x} : \boldsymbol{x}^T A \boldsymbol{x} \leq 1 \}$ is an ellipsoid. More precisely, show that E is the image by an orthogonal transformation of a set of the form

$$\{ \boldsymbol{y} : \sum_{i} \left(\frac{yi}{r_i} \right)^2 \le 1 \}.$$

What are the semi-axis of E ?

2. Let $A \succeq 0$ and $B \succeq 0$, and consider the ellipsoids $E_A = \{ \boldsymbol{x} : \boldsymbol{x}^T A \boldsymbol{x} \le 1 \}, E_B = \{ \boldsymbol{x} : \boldsymbol{x}^T B \boldsymbol{x} \le 1 \}$. Show the equivalence

$$E_A \subseteq E_B \Longleftrightarrow A \succeq B.$$

- 3. Let A be a $n \times n$ -symmetrix matrix, satisfying $A \preceq \lambda I$. Show that we have $\lambda \geq \lambda_{max}$, where λ_{max} is the largest eigenvale of A. Show that $A \preceq \lambda_{max} I_n$.
- 4. Let $A \succ 0$, and B be an arbitrary matrix. Use a congruence transformation with the matrix $\begin{pmatrix} I & 0 \\ B^T A^{-1} & I \end{pmatrix}$ to prove the Schur complement lemma.
- 5. Let $A \succeq 0$. Show that A admits a square root, i.e., a matrix $X \succeq 0$ such that $A = X^2$.
- 6. (Geometric mean of two positive definite matrices). Let $A, B \succ 0$. We admit that for all $Y, Z \succeq 0$, $Y \preceq Z \Longrightarrow Y^{1/2} \preceq Z^{1/2}$ (NB: the converse is not true !). Let X be a symmetrix matrix satisfying $\begin{pmatrix} A & X \\ X & B \end{pmatrix} \succeq 0$. Show that

$$X \preceq A \# B := A^{1/2} (A^{-1/2} B A^{-1/2})^{1/2} A^{1/2}.$$