

## Homework 2

1. *Max-min and min-max characterization of eigenvalues.* Let  $A$  be a symmetric  $n \times n$  matrix, with eigendecomposition

$$A = Q \mathbf{diag}(\lambda) Q^T = \sum_{i=1}^n \lambda_i q_i q_i^T.$$

The matrix  $Q$  is orthogonal ( $Q^T Q = Q Q^T = I$ ) with columns  $q_1, \dots, q_n$ , and  $\mathbf{diag}(\lambda)$  is the diagonal matrix with the eigenvalues  $\lambda_1, \dots, \lambda_n$  on its diagonal. We assume the eigenvalues are sorted as  $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$ .

We denote by  $\mu_1(X) \geq \mu_2(X) \geq \dots \geq \mu_m(X)$  the eigenvalues of  $X^T A X$ , where  $X$  is an  $n \times m$  matrix. In this problem we show that

$$\begin{bmatrix} \mu_1(X) \\ \mu_2(X) \\ \vdots \\ \mu_m(X) \end{bmatrix} \preceq \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_m \end{bmatrix} \quad (1)$$

for all matrices  $X \in \mathbf{R}^{n \times m}$  with orthonormal columns ( $X^T X = I$ ). The inequality is a component-wise vector inequality, *i.e.*, equivalent to the  $m$  scalar inequalities

$$\mu_1(X) \leq \lambda_1, \quad \mu_2(X) \leq \lambda_2, \quad \dots, \quad \mu_m(X) \leq \lambda_m.$$

- (a) Suppose  $X \in \mathbf{R}^{n \times m}$  is given and satisfies  $X^T X = I$ . We drop the argument  $X$  in  $\mu_i(X)$ , and write the eigendecomposition of the  $m \times m$  matrix  $X^T A X$  as

$$X^T A X = \sum_{i=1}^m \mu_i v_i v_i^T.$$

The vectors  $v_1, \dots, v_m$  are orthonormal eigenvectors, and  $\mu_1, \dots, \mu_m$  are the eigenvalues, sorted as  $\mu_1 \geq \mu_2 \geq \dots \geq \mu_m$ .

Suppose  $1 \leq k \leq m$ . Denote by  $V = [v_1 \ v_2 \ \dots \ v_k]$  the matrix with the first  $k$  eigenvectors  $v_1, \dots, v_k$  as its columns. Verify the following expressions for  $\mu_k$ :

$$\begin{aligned} \mu_k &= \inf_{y_1^2 + \dots + y_k^2 = 1} (\mu_1 y_1^2 + \dots + \mu_k y_k^2) \\ &= \inf_{y_1^2 + \dots + y_k^2 = 1} y^T V^T (X^T A X) V y \\ &= \inf_{y_1^2 + \dots + y_k^2 = 1} y^T V^T X^T Q \mathbf{diag}(\lambda) Q^T X V y \\ &= \inf_{y_1^2 + \dots + y_k^2 = 1} \sum_{i=1}^n \lambda_i (q_i^T X V y)^2, \end{aligned} \quad (2)$$

where  $y = (y_1, \dots, y_k) \in \mathbf{R}^k$ .

(b) From the last expression (2), show that  $\mu_k \leq \lambda_k$ .

*Hint.* Consider a vector  $\tilde{y} \in \mathbf{R}^k$  that satisfies  $\|\tilde{y}\|_2 = 1$  and

$$q_1^T X V \tilde{y} = 0, \quad q_2^T X V \tilde{y} = 0, \quad \dots, \quad q_{k-1}^T X V \tilde{y} = 0.$$

Show that

$$\mu_k \leq \sum_{i=1}^n \lambda_i (q_i^T X V \tilde{y})^2 \leq \lambda_k.$$

Since the inequality (1) holds with equality for the matrix

$$X = [ \begin{array}{cccc} q_1 & q_2 & \cdots & q_m \end{array} ], \quad (3)$$

we can conclude that the set

$$S = \{(\mu_1(X), \dots, \mu_m(X)) \mid X \in \mathbf{R}^{n \times m}, X^T X = I\}$$

has a *maximum element*, given by  $(\lambda_1, \dots, \lambda_m)$ . Applying this result to  $-A$ , we see that the set  $S$  also has a *minimum element*, given by  $(\lambda_{n-m+1}, \dots, \lambda_n)$ . This result is known as the Courant–Fischer min–max theorem.

As an application, it follows that the matrix  $X$  given in (3) is a solution of the (non-convex) optimization problem

$$\begin{array}{ll} \text{maximize} & f(X) \\ \text{subject to} & X^T X = I, \end{array}$$

with variable  $X \in \mathbf{R}^{n \times m}$ , for the following functions:

$$\begin{aligned} f(X) &= \lambda_{\max}(X^T A X) \\ &= \mu_1(X), \\ f(X) &= \lambda_{\min}(X^T A X) \\ &= \mu_m(X), \\ f(X) &= \mathbf{tr}(X^T A X) \\ &= \mu_1(X) + \cdots + \mu_m(X), \end{aligned}$$

and, more generally, any function  $f(X) = \sum_{k=1}^m h_k(\mu_k(X))$  where  $h_k$  is a nondecreasing function.

2. Exercise T3.1.
3. Exercise T3.18 (b).
4. Exercise A3.10.
5. Exercise T3.19 (a).
6. Exercise A3.20 (a).
7. Exercise A6.8.