

where Q is an orthogonal matrix and D is a diagonal matrix,

$$D = \text{diag}(d_1, \dots, d_n),$$

with $d_i > 0$, for $i = 1, \dots, n$. If we define the matrices $B^{1/2}$ and $B^{-1/2}$ by

$$B^{1/2} = Q \text{diag}(\sqrt{d_1}, \dots, \sqrt{d_n}) Q^\top$$

and

$$B^{-1/2} = Q \text{diag}(1/\sqrt{d_1}, \dots, 1/\sqrt{d_n}) Q^\top,$$

it is clear that these matrices are symmetric, that $B^{-1/2} B B^{-1/2} = I$, and that $B^{1/2}$ and $B^{-1/2}$ are mutual inverses. Then if we make the change of variable

$$x = B^{-1/2} y,$$

the equation $x^\top B x = 1$ becomes $y^\top y = 1$, and the optimization problem

$$\begin{aligned} &\text{minimize} && x^\top A x \\ &\text{subject to} && x^\top B x = 1, \ x \in \mathbb{R}^n, \end{aligned}$$

is equivalent to the problem

$$\begin{aligned} &\text{minimize} && y^\top B^{-1/2} A B^{-1/2} y \\ &\text{subject to} && y^\top y = 1, \ y \in \mathbb{R}^n, \end{aligned}$$

where $y = B^{1/2} x$ and $B^{-1/2} A B^{-1/2}$ are symmetric.

The complex version of our basic optimization problem in which A is a Hermitian matrix also arises in computer vision. Namely, given an $n \times n$ complex Hermitian matrix A ,

$$\begin{aligned} &\text{maximize} && x^* A x \\ &\text{subject to} && x^* x = 1, \ x \in \mathbb{C}^n. \end{aligned}$$

Again by Proposition 23.10, the maximum value of $x^* A x$ on the unit sphere is equal to the largest eigenvalue λ_1 of the matrix A , and it is achieved for any unit eigenvector u_1 associated with λ_1 .

Remark: It is worth pointing out that if A is a *skew-Hermitian* matrix, that is, if $A^* = -A$, then $x^* A x$ is *pure imaginary or zero*.

Indeed, since $z = x^* A x$ is a scalar, we have $z^* = \bar{z}$ (the conjugate of z), so we have

$$\overline{x^* A x} = (x^* A x)^* = x^* A^* x = -x^* A x,$$

so $\overline{x^* A x} + x^* A x = 2\text{Re}(x^* A x) = 0$, which means that $x^* A x$ is pure imaginary or zero.