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Variational Principles of Functions In Matrix Analysis

Antoine Mhanna¹

1 Dept of Mathematics, Lebanese University, Hadath, Beirut, Lebanon.

tmhanat@yahoo.com

Abstract

The main result i present is extending by a very basic lemma the Ky-Fan principle to a larger set of functions satisfying certain conditions.

Keywords : Matrix Analysis, Hermitian matrices, variational characterization, Ky-Fan principle.

1 Introduction

The numerical range of a Hermitian matrix A is called the Rayleigh Quotient $R_A(v)$ which is the application (Rayleigh quotient):

$$\begin{aligned} R_A : \mathbb{C}^n \setminus \{0\} &\rightarrow \mathbb{R} \\ v &\rightarrow \frac{v^* A v}{v^* v}. \end{aligned}$$

This application is well defined because $v^* v = \|v\|^2$ is real and $v^* A v$ is real. The set of $m \times n$ complex matrices is denoted by $\mathbb{M}_{m,n}(\mathbb{C})$.

Proposition 1.1. *Let A be a square matrix, and (v_1, v_2, \dots, v_n) the orthonormal basis of eigenvectors corresponding to the set of eigenvalues λ_i , $i = 1, \dots, n$, that is $Av_i = \lambda_i v_i$. Then:*

1. $\lambda_k = R_A(v_k)$ and the range of R_A is $[\lambda_n, \lambda_1]$.

2. $\lambda_1 = \sup_v (R_A(v)) = R_A(B)$, $\lambda_n = \inf_v (R_A(v)) = R_A(C)$

where B is the subspace of eigenvectors corresponding to λ_1 and C is the subspace of eigenvectors corresponding to λ_n .

More specifically:

3. Let V_k be the subspace of \mathbb{C}^n spanned by $\{v_1, v_2, \dots, v_k\}$,

and $W_k = \text{span} \{v_{k+1}, \dots, v_n\} = V_k^\perp$

$$\lambda_k = \inf_{v \in V_k} (R_A(v)) \quad \text{and} \quad \lambda_k = \sup_{v \in W_{k-1}} (R_A(v))$$

Remark 1. Note the difference between (1) and (2) : in (2) the two eigenvalues are uniquely determined by B and C respectively. Obviously the dimension of W_{k-1} is $n - k + 1$, and $\dim(V_k)$ is equal to k .

Proof. Recall that for a Hermitian matrix A there is an orthonormal basis in which A is a diagonal matrix : $\Delta = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$ so taking any vector v in \mathbb{C}^n and writing $(\alpha_1, \alpha_2, \dots, \alpha_n)$ as its coordinates in that base:

$$v^* A v = (\alpha_1, \alpha_2, \dots, \alpha_n) \Delta \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{pmatrix} = \sum_{i=1}^n \lambda_i |\alpha_i|^2. \quad (1)$$

We get this formula:

$$R_A(v) = \frac{\sum_{i=1}^n \lambda_i |\alpha_i|^2}{\sum_{i=1}^n |\alpha_i|^2}$$

As a matter of fact this implies $R_A(\text{span}\{v_i, \dots, v_j\}) = [\lambda_i, \lambda_j]$ and that completes the proof. \square

2 Max principle

In this section let $\lambda_1 \leq \dots \leq \lambda_n$ denote the eigenvalues and (v_1, \dots, v_n) the corresponding eigenvectors of an $n \times n$ Hermitian matrix A , and let $\sigma_1 \leq \dots \leq \sigma_n$ be the singular values of A . Another yet equivalent form of Proposition 1.1 is:

Proposition 2.1. Let A be an $n \times n$ Hermitian matrix then

$$\lambda_1(A) = \max\{R_A(v)\} \text{ so } \lambda_1 = R_A(v_1) \text{ for some } v_1 \in \mathbb{C}^n.$$

$$\vdots$$

$$\lambda_k(A) = \max\{R_A(v), v \perp v_1, v_2, \dots, v_{k-1}\} \text{ and}$$

$$\lambda_k = R_A(v_k) \text{ for some } v_k \perp v_1, v_2, \dots, v_{k-1}.$$

Proof. The characterization of λ_1 is already proved, since the unit ball is a compact set of \mathbb{C}^n and every closed set in a compact is compact, the continuous function x^*Ax will attain its maximum on all described sets, we need to show the proposition for λ_2 and the rest follows easily; take any vector w such that $w \perp v_1$ i.e w orthogonal to v_1 , then $w = \sum_{i=2}^n \alpha_i v_i$ but from Proposition 1.1 $R_A(\text{span}\{v_n, \dots, v_2\}) = [\lambda_n, \lambda_2]$, thus $R_A(w) \leq R_A(v_2)$ since $v_2 \perp v_1$, this completes the proof. \square

Corollary 2.1. *Let A be an $m \times n$ matrix, and let $\sigma_1 \geq \dots \geq \sigma_n$ denotes the singular values of A , we have*

$$\sigma_1(A) = \max\{\|Ax\|, \|x\| = 1\} \text{ so } \sigma_1 = \|Ax_1\| \text{ for some } x_1 \in \mathbb{C}^n.$$

\vdots

$$\sigma_k(A) = \max\{\|Ax\|, x \perp x_1, x_2, \dots, x_{k-1}, \|x\| = 1\} \text{ and}$$

$$\sigma_k = \|Ax_k\| \text{ for some } x_k \perp x_1, x_2, \dots, x_{k-1}.$$

Proof. Since $\sigma_i^2(A)$ are the eigenvalues of A^*A , and $\|Ax\|^2 = \langle Ax, Ax \rangle = \langle A^*Ax, x \rangle$ for every $x \in \mathbb{C}^n$, we get the desired representation from Proposition 2.1. \square

Theorem 2.1. *Let $A \in \mathbb{M}_{m,n}(\mathbb{C})$ If $A = W\Sigma V$ is the singular value decomposition, $W = \begin{pmatrix} t_1 & \dots & t_m \\ \vdots & \dots & \vdots \end{pmatrix}$ and $V^* = \begin{pmatrix} s_1 & \dots & s_n \\ \vdots & \dots & \vdots \end{pmatrix}$ we have:*

$$\sigma_1(A) = \max \frac{|x^*Ay|}{\|x\|\|y\|} \quad \text{and} \quad \sigma_k(A) = \max_{\substack{x \in \text{span}\{t_1, \dots, t_{k-1}\}^\perp \\ y \in \text{span}\{s_1, \dots, s_{k-1}\}^\perp}} \frac{|x^*Ay|}{\|x\|\|y\|}$$

for all $k \leq \min(m, n)$.

Proof. Let x and y both be unit vectors, $x \in \mathbb{C}^m$ and $y \in \mathbb{C}^n$, W (respectively V) is an $m \times m$ (respectively $n \times n$) unitary matrix, we first expand the quadratic form in terms of the S.V.D of A :

$$|x^*Ay| = |x^*W\Sigma Vy| = \left| \sum_{i=1}^n \sigma_i (x^*t_i)(s_i^*y) \right| \leq \sigma_1.$$

where the last inequality holds because x and y are both unit vectors. This bound is attained by $x = t_1$ and $y = s_1$ so σ_1 is the optimal value of the optimization problem: $\max_{x,y} \frac{|x^*Ay|}{\|x\|\|y\|}$. To characterize the smaller singular values, we constrain x and y to lie

in $\text{span}\{t_1, \dots, t_{k-1}\}^\perp$ and $\text{span}\{s_1, \dots, s_{k-1}\}^\perp$ respectively. Then we can ignore the $k-1$ largest singular values and

$$|x^*Ay| = \left| \sum_{i=k}^n \sigma_i(x^*t_i)(s_i^*y) \right| \leq \sigma_k.$$

this bound is attained by $x = t_k$ and $y = s_k$ so σ_k is the optimal value of the optimization problem:

$$\max_{\substack{x \in \text{span}\{t_1, \dots, t_{k-1}\}^\perp \\ y \in \text{span}\{s_1, \dots, s_{k-1}\}^\perp}} \frac{|x^*Ay|}{\|x\|\|y\|}$$

□

3 Variational characterizations

Lemma 3.1. *Let E be a \mathbb{K} -Hilbert space ($\mathbb{K} \equiv \mathbb{R}$ or \mathbb{C}) of dimension n and let f be a continuous function from E to \mathbb{R} . If $r > 0$ is any fixed real number, Set:*

$$h_1 := \max\{f(x), \|x\|_s = r\} \text{ so } h_1 = f(v_1) \text{ for some } v_1 \in \mathbb{C}^n.$$

$$h_2 := \max\{f(x), \|x\|_s = r, x \perp v_1\} \text{ so } h_2 = f(v_2) \text{ for some } v_2 \in \mathbb{C}^n.$$

\vdots

$$h_n := \max\{f(x), \|x\|_s = r, x \perp v_1, v_2, \dots, v_{n-1}\}$$

$$\text{so } h_n = f(v_n) \text{ for some } v_n \perp v_1, \dots, v_{n-1}.$$

and set:

$$q_1 := \min\{f(x), \|x\|_s = r\} \text{ so } q_1 = f(w_1) \text{ for some } w_1 \in \mathbb{C}^n.$$

$$q_2 := \min\{f(x), \|x\|_s = r, x \perp w_1\} \text{ so } q_2 = f(w_2) \text{ for some } w_2 \in \mathbb{C}^n.$$

\vdots

$$q_n := \min\{f(x), \|x\|_s = r, x \perp w_1, w_2, \dots, w_{n-1}\}$$

$$\text{so } q_n = f(w_n) \text{ for some } w_n \perp w_1, w_2, \dots, w_{n-1}.$$

$\mathcal{A} \equiv (v_1, \dots, v_n)$ and $\mathcal{B} \equiv (w_1, \dots, w_n)$ are two orthonormal basis of E . Let $k \leq n$, and $m < z$ since we study f on the ball of radius r denoted B_r we will suppose that our function f is only defined from B_r to \mathbb{R} .

- If $f(\text{span}(v_z, \dots, v_m)) \leq rf(v_m)$ and $f(\alpha_i v_i + \alpha_{i+1} v_{i+1}) \leq \sum_{j=i}^{i+1} |\alpha_j|^2 f(v_j)$ (max condition) for all $i = 1, \dots, n$ then $\sum_{i=1}^k rh_i = \max_{B_k} \sum_{i=1}^k f(x_i)$, if f is positive valued we have also $\prod_{i=1}^k rh_i = \max_{B_k} \prod_{i=1}^k f(x_i)$.
- If $f(\text{span}(w_z, \dots, w_m)) \geq rf(w_z)$ and $f(\alpha_i w_i + \alpha_{i+1} w_{i+1}) \geq \sum_{j=i}^{i+1} |\alpha_j|^2 f(w_j)$ (min condition) for all $i = 1, \dots, n$ then $\sum_{i=1}^k rq_i = \min_{B_k} \sum_{i=1}^k f(x_i)$, if f is positive valued we have also $\prod_{i=1}^k rq_i = \min_{B_k} \prod_{i=1}^k f(x_i)$.

where $B_k = (x_1, \dots, x_k)$ denotes an orthogonal basis of dimension k such that $\|x_i\|_s = r$ for $1 \leq i \leq k$ and $\alpha_i \in \mathbb{C}$, $\beta_i \in \mathbb{C}$ for all $i = 1, \dots, k$.

Proof. It suffices to prove the maximum version as the other has a similar proof, we will take r to be 1, as the same proof holds if $r \neq 1$. Let us suppose first that E is of dimension $n = 2$, take two orthonormal vectors x_1 and x_2 and since (v_1, v_2) is a basis, necessarily we have

$$\left\{ \begin{array}{l} x_1 = \alpha v_1 + \beta v_2 \\ x_2 = i v_1 + j v_2 \\ |\alpha|^2 + |\beta|^2 = 1 \quad (\|x_1\|_s = 1) \\ |i|^2 + |j|^2 = 1 \quad (\|x_2\|_s = 1) \\ \alpha \bar{i} = -\beta \bar{j} \quad (x_1 \perp x_2) \\ |\alpha|^2 |i|^2 = |\beta|^2 |j|^2 \end{array} \right. \implies \left\{ \begin{array}{l} |\alpha|^2 |i|^2 + |\beta|^2 |i|^2 = i^2 \\ |\beta|^2 (|i|^2 + |j|^2) = |i|^2 \\ |\beta|^2 = |i|^2 \\ |\alpha|^2 = |j|^2 \end{array} \right.$$

The max condition let us write

$$\begin{aligned} f(x_1) &\leq |\alpha|^2 f(v_1) + |\beta|^2 f(v_2) \\ f(x_2) &\leq |i|^2 f(v_1) + |j|^2 f(v_2) = |\beta|^2 f(v_1) + |\alpha|^2 f(v_2) \end{aligned}$$

adding both inequalities yields to $f(x_1) + f(x_2) \leq f(v_1) + f(v_2)$ and we have equality if $v_1 = x_1$ and $x_2 = v_2$. For any n , $n > 2$ we can write:

$$\left\{ \begin{array}{l} x_1 = \alpha_{1,1}v_1 + \alpha_{2,1}v_2 + \cdots + \alpha_{n,1}v_n \\ x_2 = \alpha_{1,2}v_1 + \alpha_{2,2}v_2 + \cdots + \alpha_{n,2}v_n \\ \vdots \\ x_k = \alpha_{1,k}v_1 + \alpha_{2,k}v_2 + \cdots + \alpha_{n,k}v_n \\ |\alpha_{1,1}|^2 + \cdots + |\alpha_{n,1}|^2 = 1 \quad (\|x_1\|_s = 1) \\ |\alpha_{1,2}|^2 + \cdots + |\alpha_{n,2}|^2 = 1 \quad (\|x_2\|_s = 1) \\ \vdots \\ |\alpha_{1,k}|^2 + \cdots + |\alpha_{n,k}|^2 = 1 \quad (\|x_k\|_s = 1) \end{array} \right.$$

Here we assume that $k < n$, let us take any two vectors from the orthonormal basis (x_1, \dots, x_k) , we take the first x to have the minimum j with $\alpha_{j,i} \neq 0$ suppose $j = 1$ and without loss of generality let it be x_1 and the other one x_i for a certain $i < n$, from $x_1 \perp x_i$ and $\|x_i\|_s = 1$ we obtain

$$\left\{ \begin{array}{l} |\alpha_{1,i}|^2 + \cdots + |\alpha_{n,i}|^2 = 1 \\ |\alpha_{1,1}|^2 + \cdots + |\alpha_{n,1}|^2 = 1 \\ \overline{\alpha_{1,1}}\alpha_{1,i} = -(\overline{\alpha_{2,1}}\alpha_{2,i} + \cdots + \overline{\alpha_{n,1}}\alpha_{n,i}) \end{array} \right.$$

Thus we get:

$$\left\{ \begin{array}{l} |\alpha_{1,1}\alpha_{1,i}|^2 = |(\overline{\alpha_{2,1}}\alpha_{2,i} + \cdots + \overline{\alpha_{n,1}}\alpha_{n,i})|^2 \\ |(\overline{\alpha_{2,1}}\alpha_{2,i} + \cdots + \overline{\alpha_{n,1}}\alpha_{n,i})|^2 + |\alpha_{2,i}|^2|\alpha_{1,1}|^2 \cdots + |\alpha_{n,i}|^2|\alpha_{1,1}|^2 = |\alpha_{1,1}|^2 \\ |(\overline{\alpha_{2,1}}\alpha_{2,i} + \cdots + \overline{\alpha_{n,1}}\alpha_{n,i})|^2 + |\alpha_{1,1}|^2(|\alpha_{2,i}|^2 + |\alpha_{3,i}|^2 + \cdots - 1) = 0 \\ |\alpha_{1,i}|^2 = 0. \end{array} \right.$$

By iterating the same process this time applied to another vector say x_2 instead of x_1 we see that the family of orthonormal vectors we have taken (x_1, \dots, x_k) is of this

form

$$\begin{cases} x_1 = \alpha_{1,1}v_1 + \alpha_{2,1}v_2 + \cdots + \alpha_{n,1}v_n \\ x_2 = \alpha_{2,2}v_2 + \cdots + \alpha_{n,2}v_n \\ \vdots \\ x_{k-1} = \alpha_{k-1,k-1}v_{k-1} + \cdots + \alpha_{n,k-1}v_n \\ x_k = \alpha_{k,k}v_k + \cdots + \alpha_{n,k}v_n \end{cases}$$

where any of the indexed α could be equal zero. Consider $k < n$, by hypothesis we get $f(x_i) \leq f(v_i)$ summing over i we get the required result, if $k = n$ we see that we can have $x_{n-1} = \alpha_{n-1,n-1}v_{n-1} + \alpha_{n-1,n}v_n$ and $x_n = \alpha_{n,n-1}v_{n-1} + \alpha_{n,n}v_n$ again by hypothesis and the case we discussed earlier; that is, when the dimension of E equals 2 we get $f(x_n) + f(x_{n-1}) \leq f(v_{n-1}) + f(v_n)$ and that completes the proof. \square

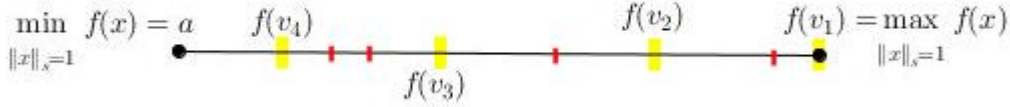


Figure 1: The max condition for a function f over a 4 dimensional space E , where the red marks are the possible $f(x_i), i = 1, \dots, 4$ if (x_1, \dots, x_4) is an orthonormal basis.

Notice that $f(v_n) \leq \cdots \leq f(v_1)$ and $f(w_n) \geq \cdots \geq f(w_1)$. The proof of Lemma 3.1 suggests that we can relax the max and min conditions, keeping the same terminology, we obtain

Corollary 3.1. *Let $k \leq n$, $m < z$ and f the function considered defined from B_r to \mathbb{R} .*

- *If $f(\text{span}(v_z, \dots, v_m)) \leq r f(v_m)$ and*

$$f(\alpha_{n-1}v_{n-1} + \alpha_n v_n) + f(\beta_{n-1}v_{n-1} + \beta_n v_n) \leq r(f(v_{n-1}) + f(v_n))$$

then $\sum_{i=1}^k r h_i = \max_{B_k} \sum_{i=1}^k f(x_i)$. In addition if f is positive valued we have also

$$\prod_{i=1}^k r h_i = \max_{B_k} \prod_{i=1}^k f(x_i).$$

- If $f(\text{span}(v_z, \dots, v_m)) \leq f(v_m)$ and

$$f(\alpha_{n-1}v_{n-1} + \alpha_nv_n) + f(\beta_{n-1}v_{n-1} + \beta_nv_n) \leq f(v_{n-1}) + f(v_n)$$

then $\sum_{i=1}^k h_i = \max_{B_k} \sum_{i=1}^k f(x_i)$. In addition if f is positive valued we have also

$$\prod_{i=1}^k h_i = \max_{B_k} \prod_{i=1}^k f(x_i).$$

- If $f(\text{span}(w_z, \dots, w_m)) \geq rf(w_z)$ and

$$f(\alpha_{n-1}w_{n-1} + \alpha_nw_n) + f(\beta_{n-1}w_{n-1} + \beta_nw_n) \geq r(f(w_{n-1}) + f(w_n))$$

then $\sum_{i=1}^k rq_i = \min_{B_k} \sum_{i=1}^k f(x_i)$. In addition if f is positive valued we have also

$$\prod_{i=1}^k rq_i = \min_{B_k} \prod_{i=1}^k f(x_i).$$

- If $f(\text{span}(w_z, \dots, w_m)) \geq f(w_z)$ and

$$f(\alpha_{n-1}w_{n-1} + \alpha_nw_n) + f(\beta_{n-1}w_{n-1} + \beta_nw_n) \geq f(w_{n-1}) + f(w_n)$$

then $\sum_{i=1}^k q_i = \min_{B_k} \sum_{i=1}^k f(x_i)$. In addition if f is positive valued then we have also

$$\prod_{i=1}^k q_i = \min_{B_k} \prod_{i=1}^k f(x_i).$$

where $B_k = (x_1, \dots, x_k)$ denotes an orthogonal basis of dimension k such that $\|x_i\|_s = r$ for $1 \leq i \leq k$ and $\alpha_i \in \mathbb{C}$, $\beta_i \in \mathbb{C}$ for $i = n-1, n$.

Here is an example showing that the conditions in Lemma 3.1 are necessary.

Example 3.1. Let

$$\begin{aligned} f : \mathbb{R}^2 &\rightarrow \mathbb{R} \\ u = (x, y) &\rightarrow \ln(|x + \epsilon|). \end{aligned}$$

where ϵ is a strictly positive number to be fixed, we verify then that $h_1 = \ln(|1 + \epsilon|)$
 $= \max_{\|x\|_s=1} \ln(|x + \epsilon|) = f(v_1)$, by taking $v_1 = (1, 0)$, $v_2 = (0, \pm 1)$, $x_1 = \left(\frac{\sqrt{2}}{2}, \frac{\sqrt{2}}{2}\right)$ and
 $x_2 = \left(\frac{\sqrt{2}}{2}, -\frac{\sqrt{2}}{2}\right)$ we have $v_1 \perp v_2$, $x_1 \perp x_2$ but

$$f(v_1) + f(v_2) = \ln(\epsilon(1 + \epsilon)) = h_1 + h_2 < f(x_1) + f(x_2) = \ln(\sqrt{2} + 0.5 + \epsilon^2)$$

whenever $\epsilon < 0.5 + \sqrt{2}$.

Lemma 3.1 and the previous results will entail important variational representations concerning the sum and product of eigenvalues and singular values:

Corollary 3.2 (Ky-Fan principle). *Let H be an $n \times n$ Hermitian matrix such that $\lambda_1 \geq \dots, \geq \lambda_n$ are the eigenvalues of H in decreasing order. For any $1 \leq k \leq n$*

$$\sum_{i=1}^k \lambda_i(H) = \max_{U^*U=I_k} \text{tr}(U^*HU) \quad (2)$$

$$\sum_{i=1}^k \lambda_{n-i+1}(H) = \min_{U^*U=I_k} \text{tr}(U^*HU) \quad (3)$$

And if H is P.S.D that is λ_n is nonnegative we have

$$\prod_{i=1}^k \lambda_i(H) = \max_{U^*U=I_k} \det(U^*HU) \quad (4)$$

$$\prod_{i=1}^k \lambda_{n-i+1}(H) = \min_{U^*U=I_k} \det(U^*HU). \quad (5)$$

Proof. It suffices to notice that $\max_{U^*U=I_k} \text{tr}(U^*HU) = \max_{x_i^*x_j=\delta_{ij}} \sum_{i=1}^k x_i^*Hx_i$ applying Proposition 2.1 and Lemma 3.1 to the function $f(x) = x^*Hx$ completes the proof, since $f(\text{span}(v_z, \dots, v_m)) \leq f(v_m)$ when $m < z$ (see Proposition 1.1) and for all i we have $f(\alpha_i v_i + \alpha_{i+1} v_{i+1}) = |\alpha_i|^2 f(v_i) + |\alpha_{i+1}|^2 f(v_{i+1})$. For the product assertion if H is P.S.D we have $\max_{U^*U=I_k} \det(U^*HU) = \max_{x_i^*x_j=\delta_{ij}} (x_i^*Hx_j)$ but since U^*HU is Hermitian we can suppose that it is a diagonal matrix we apply again Proposition 2.1 and Lemma 3.1 to the positive valued function $f(x) := x^*Hx$ to complete the proof. The minimum versions are similarly proven. \square

Definition 3.1. A matrix $P \in \mathbb{M}_{m,n}$ is said to be a rank k partial isometry or a k partial isometry if $\sigma_1(P) = \dots = \sigma_k(P) = 1$ and all other singular values are equal to zero.

Let us denote the set of the rank k partial isometries in $\mathbb{M}_{m,n}$ by $L_{m,n}^k$.

Corollary 3.3. Let $A \in \mathbb{M}_{m,n}$ have singular values $\sigma_1(A) \geq \dots \geq \sigma_q(A) \geq 0$, where

$q = \min\{m, n\}$. For each $k = 1, \dots, q$ we have :

$$\sum_{i=1}^k \sigma_i(A) = \max \left\{ |\operatorname{tr} X^* A Y| : X \in \mathbb{M}_{m,k}, Y \in \mathbb{M}_{n,k}, X^* X = I = Y^* Y \right\} \quad (6)$$

$$= \max \left\{ \operatorname{Re}(\operatorname{tr} X^* A Y) : X \in \mathbb{M}_{m,k}, Y \in \mathbb{M}_{n,k}, X^* X = I = Y^* Y \right\} \quad (7)$$

$$= \max \left\{ |\operatorname{tr} A P| : P \in L_{n,m}^k \right\} \quad (8)$$

Proof. (6) and (7) representations will follow from Theorem 2.1 and a direct generalization of Lemma 3.1. Let us show first that they are equivalent to the last one. If $X \in \mathbb{M}_{m,k}$ and $Y \in \mathbb{M}_{n,k}$ satisfy $Y^* Y = I = X^* X$, $\operatorname{tr} X^* A Y = \operatorname{tr} A Y X^*$ and $C := Y X^* \in \mathbb{M}_{n,m}$ has $C^* C = X Y^* Y X^* = X X^*$. Since the k largest singular values of $X X^*$ are the same as those of $X^* X = I \in \mathbb{M}_k$, we conclude that $C = Y X^*$ is a rank k partial isometry. Conversely, if $C \in \mathbb{M}_{n,m}$ is a given rank k partial isometry, then the singular value decomposition of C is

$$C = W \Sigma V = \begin{pmatrix} W_{n,k} & * \end{pmatrix} \begin{pmatrix} I_k & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} V_{m,k} \\ * \end{pmatrix} = W_{n,k} V_{k,m} = W_{n,k} (V_{k,m}^*)^*$$

and we verify that $W_{n,k}^* W_{n,k} = I_k = V_{k,m}^* V_{k,m}$. Thus the asserted variational formulas are equivalent. For (6) and (7), recall from Theorem 2.1 that

$$\sigma_k(A) = \max_{\substack{x \in \operatorname{span}\{t_1, \dots, t_{k-1}\}^\perp \\ y \in \operatorname{span}\{s_1, \dots, s_{k-1}\}^\perp}} \frac{x^* A y}{\|x\| \|y\|}$$

for all $k \leq \min(m, n)$, where we had $x^* A y = x^* W \Sigma V y = \sum_{i=1}^n \sigma_i(x^* t_i)(s_i^* y)$. This summation makes sense since $\sigma_i = 0$ if $i > \min(m, n)$. If we consider adopting the proof of the max condition in Lemma 3.1 to $f(x, y) = |x^* A y|$, the max condition would be slightly different, if $f(x)$ is the function defined from $B_1 \times B_1$ to \mathbb{R} by $f(x, y) = |x^* A y|$ then we have from the expression of $f(x)$ that whenever $z < l$ and $p < j$ $f(\operatorname{span}(t_z, \dots, t_l), \operatorname{span}(s_p, \dots, s_j)) \leq f(t_u, s_u)$ where $u := \min(z, p)$, we only need to show that

$$f(ct_i + et_{i+1}, ds_i + as_{i+1}) + f(wt_i + rt_{i+1}, ls_i + os_{i+1}) \leq f(t_i, s_i) + f(t_{i+1}, s_{i+1})$$

for any complex numbers c, e, d, r, o, w, a, l and all $i, i = 1, \dots, \min(m, n)$. Now fix $x_1 = ct_i + et_{i+1}$, $y_1 = ds_i + as_{i+1}$, $x_2 = wt_i + rt_{i+1}$ and $y_2 = ls_i + os_{i+1}$, $y_2 \perp y_1$

and $x_2 \perp x_1$, $\|x_1\|_s = \|y_1\|_s = \|y_2\|_s = \|x_2\|_s = 1$, similarly to Lemma 3.1 from the orthogonality-norm conditions

$$\begin{cases} |d|^2 = |o|^2 \\ |l|^2 = |a|^2 \\ |c|^2 = |r|^2 \\ |w|^2 = |e|^2 \end{cases}$$

and by the Cauchy-Schwartz inequality i will assume that all our complex scalars are real 'positive' because $f(ct_i + et_{i+1}, ds_i + rs_{i+1}) + f(wt_i + rt_{i+1}, ls_i + os_{i+1}) \leq f(|c|t_i + |e|t_{i+1}, |d|s_i + |r|s_{i+1}) + f(|w|t_i + |r|t_{i+1}, |l|s_i + |o|s_{i+1})$ and the upper bound is well in the range of the function f which is restricted to $B_1 \times B_1$. The assumption tells us that $c = r, a = l, o = d, w = e$, compute to get

$$f(x_1, y_1) + f(x_2, y_2) = (\sigma_i + \sigma_{i+1})(cd + ea) \leq f(t_i, s_i) + f(t_{i+1}, s_{i+1}) = \sigma_i + \sigma_{i+1}$$

if and only if $cd + ea \leq 1$, but $c^2 + e^2 = d^2 + a^2 = 1$ thus if $m := a - c$

$$\sqrt{1 - e^2}\sqrt{1 - a^2} + ea \leq 1 \iff (1 - c^2)(1 - a^2) \leq (1 - ac)^2 \quad (9)$$

$$\iff (1 - c)(1 + a)(1 - a)(1 + c) \leq (1 - ca)^2 \quad (10)$$

$$\iff (1 - ca - m)(1 - ca + m) \leq (1 - ca)^2 \quad (11)$$

$$\iff (1 - ca)^2 - m^2 \leq (1 - ac)^2 \quad (12)$$

By using Theorem 2.1 and applying Lemma 3.1 the proof is completed. \square

Since $f(x, y)$ is positive valued, a direct consequence of this characterization is that for any $k \leq \min(m, n)$, $\prod_{i=1}^k \sigma_i = \max_{B_k, C_k} \prod_{i=1}^k f(x_i, y_i)$, where $B_k = (x_1, \dots, x_k)$ and $C_k = (y_1, \dots, y_k)$ are two orthonormal basis of \mathbb{C}^k . We can do a similar generalization to the min condition for the function $f(x, y)$ as the following corollary shows:

Corollary 3.4. *For $k \leq \min(m, n)$, $A \in \mathbb{M}_{m,n}(\mathbb{C})$ fixed, define f_A as:*

$$\begin{aligned} f_A : \{ (x, y) \in \mathbb{C}^m \times \mathbb{C}^n; \|x\|_s = \|y\|_s = 1 \} &\rightarrow \mathbb{R} \\ (x, y) &\rightarrow |x^* Ay| \end{aligned}$$

and

$$\mathbf{q}_1 := \min\{f_A(x, y), \|x\|_s = \|y\|_s = 1\} \text{ so } \mathbf{q}_1 = f_A(d_1, e_1) \text{ for some } (d_1, e_1) \in \mathbb{C}^m \times \mathbb{C}^n.$$

$$\mathbf{q}_2 := \min\{f_A(x, y), \|x\|_s = \|y\|_s = 1, x \perp d_1, y \perp e_1\}$$

$$\text{so } \mathbf{q}_2 = f_A(d_2, e_2) \text{ for some } (d_2, e_2) \in \mathbb{C}^m \times \mathbb{C}^n.$$

\vdots

$$\mathbf{q}_k := \min\{f(x, y), \|x\|_s = \|y\|_s = 1, x \perp d_1, \dots, d_{k-1}, y \perp e_1, \dots, e_{k-1}\}$$

$$\text{so } \mathbf{q}_k = f(d_k, e_k) \text{ for some } (d_k, e_k) \in \mathbb{C}^m \times \mathbb{C}^n.$$

then we have

$$\sum_{i=1}^k \mathbf{q}_i = \min \{ |tr X^* A Y| : X \in \mathbb{M}_{m,k}, Y \in \mathbb{M}_{n,k}, X^* X = I = Y^* Y \} \quad (13)$$

$$= \min_{B_k, C_k} \sum_{i=1}^k f(x_i, y_i) := \mathfrak{w} = 0 \quad (14)$$

where x_i is a column of X , y_i a column of Y , $B_k = (x_1, \dots, x_k)$ and $C_k = (y_1, \dots, y_k)$

Proof. Since $f_A(x, y)$ is positive, if we showed that for all $k \leq \min(m, n)$ we have $\sum_{i=1}^k \mathbf{q}_i = 0$, then $\sum_{\mathfrak{B}_k, \mathfrak{C}_k, i=1}^k f(x_i, y_i)$ is necessarily nothing but \mathfrak{w} where $\mathfrak{B}_k \equiv (d_1, \dots, d_k)$ and $\mathfrak{C}_k \equiv (e_1, \dots, e_k)$. Recall from Theorem 2.1 that

$$f_A = |x^* A y| = |x^* W \Sigma V y| = \left| \sum_{i=1}^n \sigma_i(x^* t_i)(s_i^* y) \right|$$

We seek the minimum: \mathbf{q}_1 of f_A over $B_1 \times B_1$, let us take the two orthonormal basis of dimension k , $T_k = (t_1, \dots, t_k)$ and $S_k = (s_1, \dots, s_k)$ where (t_1, \dots, t_k) are the columns of W and (s_1, \dots, s_k) are the columns of V^* , set $S_{\mathfrak{d}(k)}$ to be the orthonormal basis $(s_{\mathfrak{d}(1)}, \dots, s_{\mathfrak{d}(k)}) = (\mathfrak{a}_1, \dots, \mathfrak{a}_k)$ where \mathfrak{d} is a permutation with no fixed point then by a direct computation we can take explicitly \mathfrak{B}_k to be the basis (t_1, \dots, t_k) , \mathfrak{C}_k to be $S_{\mathfrak{d}(k)}$ which is previously defined and get

$$\mathbf{q}_1 = f_A(t_1, \mathfrak{a}_1) = 0 \quad (15)$$

$$\mathbf{q}_2 = f_A(t_2, \mathfrak{a}_2) = 0 \quad (16)$$

$$\vdots \quad \quad \quad \vdots \quad (17)$$

$$\mathbf{q}_k = f_A(t_k, \mathfrak{a}_k) = 0 \quad (18)$$

Another way to see the result is to apply the generalization form of Corollary 3.1; that is, when the function is defined on a product space $\mathbb{C}^m \times \mathbb{C}^n$; we need to show, first if $z < l$, $p < j$ and $o = \max(l, j)$ that

$$f_A(\text{span}(d_z, \dots, d_l), \text{span}(e_p, \dots, e_j)) \geq f(d_o, e_o) = 0$$

which is true, second if we consider without loss of generality that $m \leq n$ we should have for any $\alpha_i \in \mathbb{C}$, $\beta_i \in \mathbb{C}$ with $m - 1 \leq i \leq n$:

$$f_A(\alpha_{m-1}d_{m-1} + \alpha_md_m, \sum_{i=m-1}^n \beta_ie_i) \geq f_A(d_{m-1}, e_{m-1}) + f_A(d_m, e_m) := 0 + 0 = 0$$

which is also true and that completes the proof. □

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