



Research on matrix problems based on Quadratic Forms

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Background

Our problem is driven from max problem of quadratic form and Bell nonlocality.

We mainly study extreme value problems, but the exact solutions were proven impossible. We break down the problem into simpler ones. The main method we use are SVD and Lagrange Multiplier.

Methods

Method I : SVD

$$M'M = V \Sigma U^t U \Sigma V^t = V \Sigma \Sigma V^t \quad (\text{U and V are orthogonal matrix})$$

$$\text{let } L = \Sigma = \begin{pmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_n \end{pmatrix} = \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$$

$$\text{Then } M^t M V = V L \quad \text{and} \quad M M^t U = U L$$

To get V, we need to solve the eigenvector of $M^t M$: $M^t M \vec{v} = \lambda \vec{v}$

$$M^t M \begin{pmatrix} \vec{v}_1 & \vec{v}_2 \end{pmatrix} = \begin{pmatrix} \vec{v}_1 & \vec{v}_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & \\ & \lambda_2 \end{pmatrix} \quad \xrightarrow{\text{blue arrow}} M^t M V = V L$$

$$M M^t \begin{pmatrix} \vec{u}_1 & \vec{u}_2 \end{pmatrix} = \begin{pmatrix} \vec{u}_1 & \vec{u}_2 \end{pmatrix} \begin{pmatrix} \lambda_1 & \\ & \lambda_2 \end{pmatrix} \quad \xrightarrow{\text{blue arrow}} M M^t U = U L$$

Method II : Lagrange Multiplier Method

$$1) \text{ Lagrangian first: } F(x, y, \lambda) = f(x, y) + \lambda \varphi(x, y)$$

$$F'x = f'(x, y) + \lambda \varphi'(x, y) = 0$$

$$F'y = f'(y, x) + \lambda \varphi'(y, x) = 0$$

$$F'\lambda = \varphi(\lambda, x) = 0$$

2) Lagrangian multiplier method for multi-constraints

$$F(x, \lambda) = f(x) + \sum_k \lambda_k \varphi_k(x)$$

$$F'_x = f'(x) + \sum_k \lambda_k \varphi'_k(x) = 0$$

$$P_{\lambda} = \varphi(\lambda, x) = 0$$

3) For matrix λ

$$q(x) = \sum_i a_{ii} x_i y_i, \quad \sum_i x_i^2 = 1, \quad \sum_i y_i^2 = 1$$

$$F(x, y, \lambda) = f(x) + \sum_i \lambda_i (x_i^2 - 1) + \sum_i \mu_i (y_i^2 - 1)$$

$$\frac{\partial F}{\partial x_i} = \sum_j a_{ij} y_j + 2 \lambda_i x_i = 0$$

$$\frac{\partial F}{\partial y_i} = \sum_j a_{ji} x_j + 2 \mu_i y_i = 0$$

$$\frac{\partial F}{\partial \mu_i} = \sum_j a_{ij} x_j - 1 = 0$$

$$\frac{\partial F}{\partial \lambda_i} = \sum_j a_{ij} y_j - 1 = 0$$

Special Stitutions

Given that $A^T = A$, $q(x) = x^T A x$ and $|x| = 1$

$$\xrightarrow{\text{Larange}} F(x_1, \dots, x_n, \lambda) = q(x) + \lambda (\sum_{i=1}^n x_i^2 - 1)$$

Last, we can get $\lambda = -q(x)$

$$\xrightarrow{\text{SVD}} A = U^t \Lambda U$$

$$q(x) = y^t \Lambda y = \lambda_1 y_1^2 + \dots + \lambda_n y_n^2$$

$$(y_1 \geq y_2 \geq \dots \geq y_n)(|y| = |x| = 1)$$

$$q(y_1 = 1, y_2 = 0, \dots, y_n = 0) = \lambda_1$$

$$q(y_1 = 0, y_2 = 0, \dots, y_n = 1) = \lambda_n$$

Given that A is any n-order real square matrix and $q(x) = x^T A y$ and $|x| = |y| = 1$

$$\xrightarrow{\text{SVD}} A = U^t \Lambda U$$

$$x^T A y = X^T \Lambda Y = \sigma_1 X_1 Y_1 + \sigma_2 X_2 Y_2 + \dots + \sigma_n X_n Y_n$$

$$(\sigma_1 \geq \sigma_2 \geq \dots \geq \sigma_n > 0)$$

$$q(X_1 = 1, Y_1 = 1, X_2 = 0, Y_2 = 0, \dots, X_r = 0, Y_r = 0) = \sigma_1$$

$$q(X_1 = -1, Y_1 = 1, X_2 = 0, Y_2 = 0, \dots, X_r = 0, Y_r = 0) = -\sigma_1$$

Derivation

Given that A is any n-order real square matrix, $q(x) = \vec{x}^T A \vec{y} = \sum_{k,j=1}^n a_{kj} \vec{x}_k \vec{y}_j$

try to find the maximum and the minimum of $q(x)$ and $\vec{x}_i, \vec{y}_i \in R^d$ and $|\vec{x}_i| = |\vec{y}_i| = 1$,

$$\xrightarrow{\text{Larange}} \frac{\partial q}{\partial x_{ki}} = \sum_{j=1}^n a_{kj} y_{jr} = 0, \quad k \in \{1, 2, \dots, n\}, \quad r \in \{1, 2, \dots, d\}$$

$$\text{boundary } \sum_{i=1}^d x_{ki}^2 = 1, \quad \sum_{i=1}^d y_{ki}^2 = 1, \quad k \in \{1, 2, \dots, n\}.$$

$$\text{so: } F(\vec{x}_1, \dots, \vec{x}_n, \vec{y}_1, \dots, \vec{y}_n, \lambda_1, \dots, \lambda_n, \mu_1, \dots, \mu_d) = q(x) + \sum_{k=1}^n \lambda_k (\sum_{i=1}^d x_{ki}^2 - 1) + \sum_{k=1}^n \mu_k (\sum_{i=1}^d y_{ki}^2 - 1)$$

$$\frac{\partial F}{\partial x_{ki}} = \sum_{j=1}^n a_{kj} y_{jr} + 2 \lambda_k x_{ki} = 0$$

$$\text{then we get: } \frac{\partial F}{\partial y_{ki}} = \sum_{j=1}^n a_{kj} x_{jr} + 2 \mu_k y_{ki} = 0$$

$$\frac{\partial F}{\partial \lambda_k} = \sum_{i=1}^d x_{ki}^2 - 1 = 0$$

$$\frac{\partial F}{\partial \mu_k} = \sum_{i=1}^d y_{ki}^2 - 1 = 0$$

by moving items and substituting $-2 \sum_{k=1}^n \lambda_k = q(x)$.

$$-2 \sum_{k=1}^n \mu_k = q(x).$$

$$\text{We try to represent } x_{ki}, y_{ki} \text{ like this: } x_{ki} = -\frac{1}{2 \lambda_k} \sum_{j=1}^n a_{kj} y_{jr}$$

$$\sum_{j=1}^n a_{kj} \left(-\frac{1}{2 \lambda_k} \sum_{i=1}^d a_{ij} y_{ri} \right) + 2 \mu_k y_{ki} = 0$$

$$\text{so: } \sum_{j=1}^n \left(\sum_{i=1}^d \frac{a_{ik} a_{ij}}{2 \lambda_k} \right) y_{ri} = 2 \mu_k y_{ki}$$

$$(a_{1k} \quad a_{2k} \quad \dots \quad a_{nk}) \begin{pmatrix} \frac{1}{2 \lambda_1} & & \\ & \ddots & \\ & & \frac{1}{2 \lambda_n} \end{pmatrix} A \begin{pmatrix} y_{1r} \\ y_{2r} \\ \vdots \\ y_{nr} \end{pmatrix} = 2 \mu_k y_{ki}$$

$$\text{Finally we get: } A^T \begin{pmatrix} \frac{1}{2 \lambda_1} & & \\ & \ddots & \\ & & \frac{1}{2 \lambda_n} \end{pmatrix} A \begin{pmatrix} y_{1r} \\ y_{2r} \\ \vdots \\ y_{nr} \end{pmatrix} = \begin{pmatrix} 2 \mu_1 & & \\ & \ddots & \\ & & 2 \mu_n \end{pmatrix} \begin{pmatrix} y_{1r} \\ y_{2r} \\ \vdots \\ y_{nr} \end{pmatrix} \dots \text{①}$$

$$\text{Similarly: } A \begin{pmatrix} \frac{1}{2 \mu_1} & & \\ & \ddots & \\ & & \frac{1}{2 \mu_n} \end{pmatrix} A^T \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} = \begin{pmatrix} 2 \lambda_1 & & \\ & \ddots & \\ & & 2 \lambda_n \end{pmatrix} \begin{pmatrix} x_{1r} \\ x_{2r} \\ \vdots \\ x_{nr} \end{pmatrix} \dots \text{②}$$

The equations ① and ② are called generalized singular value equation!

For the next part, we can specialize the conditions to solve the corresponding problems. we try to give verification when dimension is two and we try to assume that matrix A is a two by two matrix.

Examples (2-dimension)

$$\text{Given that } q(x) = \vec{x}^T A \vec{y} = \sum_{i,j=1}^n a_{ij} \vec{x}_i \vec{y}_j$$

$$\text{Condition 1 where } \vec{y}_j = \vec{x}_j, A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, |\vec{x}_i| = 1, |\vec{y}_i| = 1, \vec{x}_i \in R^{2 \times 1}$$

We can get the result like this based on what we did before: $q(x) = -(\lambda_1 + \lambda_2)$.

$$(A + A^T) \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} = - \begin{pmatrix} 2\lambda_1 & a_{12} \\ a_{21} & 2\lambda_2 \end{pmatrix} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix}$$

$$\text{We can abstract this question that: } BX = AX, B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}, A = \begin{pmatrix} \mu_1 & \\ & \mu_2 \end{pmatrix}.$$

$$\text{so: } (b_{11} - \mu_1)(b_{22} - \mu_2) - b_{12}b_{21} = 0$$

$$\text{then we get: } \mu_1 \mu_2 - b_1 \mu_2 - b_{22} \mu_1 + b_{11} b_{22} - b_{12} b_{21} = 0$$

$$F(\mu_1, \mu_2, \lambda) = \mu_1 + \mu_2 + \lambda(\mu_1 \mu_2 - b_{11} \mu_2 - b_{22} \mu_1 + b_{11} b_{22} - b_{12} b_{21})$$

$$\text{then we have: } \begin{cases} \frac{\partial F}{\partial \mu_1} = 1 + \lambda \mu_2 - b_{22} = 0 \Rightarrow \mu_2 = \frac{b_{22} - 1}{\lambda} \dots \text{①} \\ \frac{\partial F}{\partial \mu_2} = 1 + \lambda \mu_1 - b_{11} = 0 \Rightarrow \mu_1 = \frac{b_{11} - 1}{\lambda} \dots \text{②} \\ \frac{\partial F}{\partial \lambda} = \mu_1 \mu_2 - b_{11} \mu_2 - b_{22} \mu_1 + b_{11} b_{22} - b_{12} b_{21} = 0 \dots \text{③} \end{cases}$$

If $\det(A) \neq 0, b_{11} b_{22} - b_{12} b_{21} \neq 0$, so we can get the solution of lambda,

$$f(\mu_1, \mu_2) = \frac{1}{\lambda}(b_{11} + b_{22} - 1)$$

$$\text{So we get the extreme value: } \mu_1 + \mu_2$$

$$\text{Condition 2 where } A^T = A = \begin{pmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{pmatrix}, |\vec{x}_i| = |\vec{y}_i| = 1, \vec{x}_i, \vec{y}_i \in R^{2 \times 1}.$$

$$\text{we get: } \det \left[A \begin{pmatrix} \frac{1}{2 \lambda_1} & \\ & \frac{1}{2 \lambda_2} \end{pmatrix} A \begin{pmatrix} 2 \lambda_1 & \\ & 2 \lambda_2 \end{pmatrix} \right] = 0$$

$$F(\lambda_1, \lambda_2, \mu) = \lambda_1 + \lambda_2 + \mu \frac{a_{11}^2 a_{22}^2}{4 \lambda_1 \lambda_2} + 4 \lambda_1 \lambda_2 - \frac{2 \lambda_2 a_{11}^2}{\lambda_1} - \frac{\lambda_1 a_{22}^2}{\lambda_2}$$

$$\text{then we have: } \frac{\partial F}{\partial \lambda_1} = 0, \quad \frac{\partial F}{\partial \lambda_2} = 0, \quad \frac{\partial F}{\partial \mu} = 0.$$

Using these 3 equations, we can solve $\lambda_1 = \frac{a_{11}}{2}$, $\lambda_2 = \frac{a_{22}}{2}$, then $f(\lambda_1 + \lambda_2) = \frac{a_{11} + a_{22}}{2}$,

$$\text{Condition 3 where } A \text{ is a general matrix, } |\vec{x}_i| = |\vec{y}_i| = 1, \vec{x}_i, \vec{y}_i \in R^{2 \times 1}$$

This condition is more general and complicated. We can get the result based on what we did before.

We need to construct Lagrange's Multiply equation $F(\lambda_1, \lambda_2, \mu_1, \mu_2, \lambda)$ with 6 variables, then take Partial derivative for each variable to get 6 constraint equations to solve each variables.

Finally $\lambda_1 + \lambda_2 = \mu_1 + \mu_2$ is extreme value.

Future Works

● In condition 1, we can get $(\frac{x_{11}}{x_{12}}, \frac{x_{12}}{x_{22}})$ however we can't get $x_{11}^2 + x_{12}^2 = 1, x_{21}^2 + x_{22}^2 = 1$. More work is needed.

● In condition 2, we may still try to find other λ_1, λ_2 to make satisfy the equation. At the same time, when we can't get $x_{11}^2 + x_{12}^2 = 1, x_{21}^2 + x_{22}^2 = 1, y_{11}^2 + y_{12}^2 = 1, y_{21}^2 + y_{22}^2 = 1$ whether we can find the max/min of $\lambda_1 + \lambda_2$.

● In condition 3, drawing graphs may be an effective way to solve the problem. But in this case, constraints seems to be lack that where we will try again.

Reference

1 "Grothendieck constant", Acin, Antonio; Gisin, Nicolas ; Toner, Benjamin(2006)

2 "Grothendieck's constant and local models for noisy entangled quantum states", Physical Review A, 73(6):062105.