



RESEARCH ARTICLE

GENERALIZED INVERSE OF K-Normal Matrix

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ABSTRACT

The generalized inverses of k-normal matrix are discussed by its schur decomposition.

Key words: Schur decomposition, k-normal, k-unitary, k-diagonal, generalized inverse.

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INTRODUCTION

Let $\square^{n \times m}$ denote the set of all complex $n \times m$ matrices. Let 'k' be a fixed product of disjoint transposition in $S_n = \{1, 2, \dots, n\}$ (hence, involutory) and let 'K' be the associated permutation matrix of 'k'. Let A^* be denote the conjugate transpose matrix $A \in \square^{n \times m}$ and by $\square_r^{n \times n}$ the set of all matrices $A \in \square^{n \times n}$ such that $rank(A) = r$. I_n denotes the unit matrix of order n. The Moore-Penrose inverse of $A \in \square^{n \times m}$, is an unique matrix X satisfying the four equations

$$AXA = A \dots \dots \dots (1)$$

$$XAX = X \dots \dots \dots (2)$$

$$(AX)^* = AX \dots \dots \dots (3)$$

$$(XA)^* = XA \dots \dots \dots (4)$$

and it is denoted by $X = A^\dagger$. Let $A\{i, j, \dots, l\}$ denote the set of matrices $X \in \square^{m \times n}$ which satisfy the corresponding above four equations. A matrix $X \in A\{i, j, \dots, l\}$ is called an $\{i, j, \dots, l\}$ -inverse of A and is denoted by $A^{(i, j, \dots, l)}$. All of these matrices are called the generalized inverse of A. In this paper, we discuss expressions for generalized inverses of a special class of matrices, k-normal matrices, using their schur decomposition.

Definition 1.1: A matrix $A \in \square^{n \times n}$ is said to be k-normal, if $AA^*K = KA^*A$.

Example 1.2: If $A = \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & i \\ -i & 0 & 0 \end{pmatrix}$ is k-normal matrix and

$$X = \begin{pmatrix} 0 & 0 & i \\ 0 & 0 & 0 \\ 0 & -i & 0 \end{pmatrix}$$

These two matrices satisfies the above four equations (1), (2), (3) and (4). Therefore X is a Moore-Penrose inverse of a singular matrix A and it is denoted by A^\dagger

Moore-Penrose inverse of k-normal matrix:

In this section $\{1\}, \{2\}, \{1,2\}, \{1,3\}, \{1,4\}, \{1,2,3\}, \{1,2,4\}, \{1,3,4\}, \{2,3\}, \{2,4\}, \{2,3,4\}$ - inverses of a k-normal matrices are discussed.

Theorem 2.1: Let $A \in \square_r^{n \times n}$ be a k-normal matrix. Then all matrices $A^{(1)}, A^{(2)}$ are given by

$$(i) A^{(1)} = V \begin{pmatrix} \Sigma^{-1} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} V^* K$$

$$(ii) A^{(2)} = V \begin{pmatrix} \Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} & \Sigma^{-1} P \begin{pmatrix} E \\ 0 \end{pmatrix} \\ (F \ 0) P^{-1} & FE \end{pmatrix} V^* K,$$

where $X_{12} \in \square^{r \times (n-r)}, X_{21} \in \square^{(n-r) \times r}, X_{22} \in \square^{(n-r) \times (n-r)}, E \in \square^{s \times (n-r)}$ and $F \in \square^{(n-r) \times s}$ are arbitrary sub matrices and $0 \leq s \leq r$.

Proof: Let $X \in \square_r^{n \times n}$ be given by

$$KV^*XV = \begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} \begin{matrix} r \\ n-r \end{matrix} \dots \dots \dots (5)$$

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(i) Using the k-unitary diagonal decomposition of A, we have that $X \in A\{1\}$ if and only if

$$\begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix}.$$

Hence $X_{11} = \Sigma^{-1}$ and X_{12}, X_{21}, X_{22} are arbitrary matrices of suitable size.

(ii) Similarly, X satisfying $XAX=X$ if and only if

$$\begin{pmatrix} X_{11}\Sigma X_{11} & X_{11}\Sigma X_{12} \\ X_{21}\Sigma X_{11} & X_{21}\Sigma X_{12} \end{pmatrix} = \begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix}$$

$$X_{11}\Sigma X_{11} = X_{11} \dots \dots \dots (5)$$

$$X_{11}\Sigma X_{12} = X_{12} \dots \dots \dots (6)$$

$$X_{21}\Sigma X_{11} = X_{21} \dots \dots \dots (7)$$

$$X_{21}\Sigma X_{12} = X_{22} \dots \dots \dots (8)$$

Pre multiplying both sides Σ in equation (5), we get $\Sigma X_{11}\Sigma X_{11} = \Sigma X_{11}$

$$\Rightarrow (\Sigma X_{11})^2 = \Sigma X_{11} \dots \dots \dots (9)$$

A matrix $\Sigma X_{11} \in \mathbb{R}^{r \times r}$, satisfies (9) if and only if then their exist nonsingular matrix $P \in \mathbb{R}^{r \times r}$ such that

$$\Sigma X_{11} = P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}, \text{ where } 0 \leq s = \text{rank}(X_{11}) \leq r.$$

Hence $X_{11} = \Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}.$

Now, equations (6) and (7) have the form,

$$(6) \Rightarrow X_{11}\Sigma X_{12} = X_{12} \Rightarrow$$

$$\Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} \Sigma X_{12} = X_{12} \Rightarrow P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} \Sigma X_{12} = \Sigma X_{12}$$

$$\Rightarrow \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} \Sigma X_{12} = P^{-1} \Sigma X_{12}$$

And (7) $\Rightarrow X_{21}\Sigma X_{11} = X_{21} \Rightarrow X_{21} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} = X_{21}$

$\Rightarrow X_{21} P = X_{21} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix}$ from which we conclude that

$$P^{-1} \Sigma X_{12} = \begin{pmatrix} E & \\ & 0 \end{pmatrix} \begin{matrix} s \\ r-s \end{matrix} \text{ and}$$

$$X_{21} P = \begin{pmatrix} F & 0 \end{pmatrix}$$

$\Rightarrow X_{12} = \Sigma^{-1} P \begin{pmatrix} E \\ 0 \end{pmatrix}$ and $X_{21} = (F \ 0) P^{-1}$, where E, F

are arbitrary sub matrices of suitable size. Substituting (8), we have $X_{22} = X_{21}\Sigma X_{12} = (F \ 0) P^{-1} \Sigma \Sigma^{-1} P \begin{pmatrix} E \\ 0 \end{pmatrix}$

$$\Rightarrow X_{22} = (F \ 0) P^{-1} P \begin{pmatrix} E \\ 0 \end{pmatrix} \Rightarrow X_{22} = (F \ 0) \begin{pmatrix} E \\ 0 \end{pmatrix} \Rightarrow$$

$$X_{22} = FE.$$

Corollary 2.2: Let $A \in \mathbb{R}^{n \times n}$ be a k-normal matrix. Then any

{1, 2}-inverse is given by $A^{(1,2)} = V \begin{pmatrix} \Sigma^{-1} & \Sigma^{-1}PE \\ FP^{-1} & FE \end{pmatrix} V^* K,$

where $P \in \mathbb{R}^{r \times r}, E \in \mathbb{R}^{r \times (n-r)}$ and $F \in \mathbb{R}^{(n-r) \times r}$ are arbitrary matrices.

Proof: Considering the expressions for $A^{(1)}$ and $A^{(2)}$. From

Theorem 2.1, we get that $\Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} = \Sigma^{-1}$ holds if

and only if $s=r$, which implies that $X_{12} = \Sigma^{-1}PE, X_{21} = FP^{-1}$ and $X_{22} = FP^{-1}\Sigma \Sigma^{-1}PE = FE$.

Lemma 2.3: Let $A \in \mathbb{R}^{n \times n}$ be a k-normal matrix.

(i) Solutions of the equation (3) are given by the following general expression

$$X = V \begin{pmatrix} X_{11} & 0 \\ X_{21} & X_{22} \end{pmatrix} V^* K, \text{ where}$$

$$X_{11} = D_1 + U_1 + \Sigma^{-1}(\Sigma U_1)^*,$$

$$D_1 = \text{diag}(x_{k(1)k(1)}, \dots, x_{k(r)k(r)}).$$

$$y_{k(i)k(i)} = \begin{cases} i y_{k(i)k(i)}, & \lambda_{k(i)}^2 < 0 \\ y_{k(i)k(i)}, & \lambda_{k(i)}^2 > 0 \\ y_{k(i)k(i)} - \frac{i \lambda_{k(i)}^{(2)}}{\lambda_{k(i)}^{(1)}} y_{k(i)k(i)}, & \lambda_{k(i)}^2 \notin R \end{cases} \dots \dots (10),$$

$y_{k(i)k(i)} \in R, i = 1, 2, \dots, r, U_1 \in \mathbb{R}^{r \times r}$ is an arbitrary strictly upper triangle matrix and X_{21}, X_{22} are arbitrary matrices of suitable size.

(ii) Solutions of the equation (4) are given by the following

general expression $X = V \begin{pmatrix} \tilde{X}_{11} & \tilde{X}_{12} \\ 0 & \tilde{X}_{22} \end{pmatrix} V^* K,$ where

$$\tilde{X}_{11} = D_2 + U_2 + (U_2 \Sigma)^* \Sigma^{-1},$$

$$D_2 = \text{diag}(\tilde{x}_{k(1)k(1)}, \dots, \tilde{x}_{k(r)k(r)}).$$

$$\tilde{x}_{k(i)k(i)} = \begin{cases} i y_{k(i)k(i)} & \lambda_{k(i)}^2 < 0 \\ y_{k(i)k(i)} & \lambda_{k(i)}^2 > 0 \\ y_{k(i)k(i)} - \frac{i \lambda_{k(i)}^{(2)}}{\lambda_{k(i)}^{(1)}} y_{k(i)k(i)} & \lambda_{k(i)}^2 \notin R \end{cases},$$

$y_{k(i)k(i)} \in R, i = 1, 2, \dots, r, U_2 \in \mathbb{R}^{r \times r}$ is an arbitrary strictly upper triangle matrix and $\tilde{X}_{21}, \tilde{X}_{22}$ are arbitrary matrices of suitable size.

Proof: If X satisfies the equation (1), then

$$(KV^* X V)^* \begin{pmatrix} \Sigma^* & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} (KV^* X V) \text{ using the}$$

decomposition of X given by (5), we get

$$\begin{aligned} & \begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} \begin{pmatrix} \Sigma^* & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} \\ \Rightarrow & \begin{pmatrix} X_{11}^* & X_{12}^* \\ X_{21}^* & X_{22}^* \end{pmatrix} \begin{pmatrix} \Sigma^* & 0 \\ 0 & 0 \end{pmatrix} = \begin{pmatrix} \Sigma & 0 \\ 0 & 0 \end{pmatrix} \begin{pmatrix} X_{11} & X_{12} \\ X_{21} & X_{22} \end{pmatrix} \\ \Rightarrow & \begin{pmatrix} X_{11}^* \Sigma^* & 0 \\ X_{21}^* \Sigma^* & 0 \end{pmatrix} = \begin{pmatrix} \Sigma X_{11} & \Sigma X_{12} \\ 0 & 0 \end{pmatrix} \end{aligned}$$

So, $X_{11}^* \Sigma^* = \Sigma X_{11} \Rightarrow (\Sigma X_{11})^* = \Sigma X_{11} \dots \dots \dots (11)$ and $X_{12} = 0$.

Let $X_{11} = (x_{k(i)k(j)})_{r \times r}$. Then the equation (11) is equivalent to $\overline{\lambda_{k(j)} x_{k(j)k(i)}} = \lambda_{k(i)} x_{k(i)k(j)}$, $i, j = 1, 2, \dots, r$. this holds if $\overline{\lambda_{k(i)} x_{k(i)k(i)}} = \lambda_{k(i)} x_{k(i)k(i)}$, $i = 1, 2, \dots, r \dots \dots \dots (12)$

$$x_{k(j)k(i)} = \frac{1}{\lambda_{k(j)}} \overline{\lambda_{k(i)} x_{k(i)k(j)}}, \quad i < j, \quad i, j = 1, 2, \dots, r \dots \dots \dots (13)$$

Let $X_{11} = D_1 + U_1 + L_1$, where D_1 , U_1 and L_1 are the k-diagonal, strictly upper triangle and strictly lower triangle part of X_{11} , respectively. The equation (12) holds if and only if D_1 has the form given by (10). The equation (13) is equivalent to $L_1 = \Sigma^{-1}(\Sigma U_1)^*$.

The proof of part (ii) is analogous.

Lemma 2.4: Let $A \in \square_r^{n \times n}$ be a k-normal matrix. Solutions of the equation (3) and (4) are given by the following general expression $X = V \begin{pmatrix} D & 0 \\ 0 & X_{22} \end{pmatrix} V^* K$, where

$$D = \text{diag}(d_{k(1)k(1)}, \dots, d_{k(r)k(r)}).$$

$$d_{k(i)k(i)} = \begin{cases} i y_{k(i)k(i)} & \lambda_{k(i)}^2 < 0 \\ y_{k(i)k(i)} & \lambda_{k(i)}^2 > 0 \\ y_{k(i)k(i)} - \frac{i \lambda_{k(i)}^{(2)}}{\lambda_{k(i)}^{(1)}} y_{k(i)k(i)} & \lambda_{k(i)}^2 \notin R \end{cases}$$

$y_{k(i)k(i)} \in R, i = 1, 2, \dots, r$, and $X_{22} \in \square_{(n-r) \times (n-r)}$ is an arbitrary matrix.

Proof: If $X \in \square_r^{n \times n}$. By lemma (2.3), X satisfies the equation (3) and (4) if and only if $X_{21} = 0, \tilde{X}_{12} = 0, X_{22} = \tilde{X}_{22}, D_1 = D_2, U_1 = U_2, \Sigma^{-1}(\Sigma U_1)^* = (U_2 \Sigma)^* \Sigma^{-1} \dots \dots \dots (14)$.

Now, we have $U = (\Sigma^* \Sigma)^{-1} U \Sigma \Sigma^*$, where $U = U_1 = U_2$, that is

$$U = \text{diag}(|\lambda_{k(1)}|^{-2}, \dots, |\lambda_{k(r)}|^{-2}) U \text{diag}(|\lambda_{k(1)}|^2, \dots, |\lambda_{k(r)}|^2) \dots \dots \dots (15)$$

This equation holds if and only if U is a k-diagonal matrix. However, U is a strictly upper triangle matrix, so a necessary and sufficient condition for (15) is $U=0$. Taking in (10),

$$\begin{cases} y_{k(i)k(i)} = \frac{-1}{\lambda_{k(i)}^{(2)}}, & \lambda_{k(i)}^2 < 0, \\ y_{k(i)k(i)} = \frac{1}{\lambda_{k(i)}^{(1)}}, & \lambda_{k(i)}^2 > 0, \\ y_{k(i)k(i)} = \frac{\lambda_{k(i)}^{(1)}}{|\lambda_{k(i)}|^2}, & \lambda_{k(i)}^2 \notin R \end{cases}$$

$$y_{k(i)k(i)} \in R, \quad i = 1, 2, \dots, r,$$

We get that $D_1 = \Sigma^{-1}$, so for $U_1 = 0$. We obtain that any such solution of the equation (3) satisfies $AXA=A$.

Therefore, we may now pass on to expressions for the elements of $A\{1, 3\}$ and $A\{1, 4\}$.

Theorem 2.5: Let $A \in \square_r^{n \times n}$ be a k-normal matrix. Then the elements of $A\{1, 3\}, A\{1, 4\}$ are given by $A^{(1,3)} = V \begin{pmatrix} \Sigma^{-1} & 0 \\ X_{21} & X_{22} \end{pmatrix} V^* K, A^{(1,4)} = V \begin{pmatrix} \Sigma^{-1} & \tilde{X}_{12} \\ 0 & \tilde{X}_{22} \end{pmatrix} V^* K,$

respectively, where $X_{21}, X_{22}, \tilde{X}_{12}, \tilde{X}_{22}$, are arbitrary matrices of suitable size.

Proof: The proof is analogous.

Theorem 2.6: Let $A \in \square_r^{n \times n}$ be a k-normal matrix. Then the general forms of the elements of $A\{1,2, 3\}, A\{1,2, 4\}, A\{1,3, 4\}$ are given by $A^{(1,2,3)} = V \begin{pmatrix} \Sigma^{-1} & 0 \\ FP^{-1} & 0 \end{pmatrix} V^* K,$

$$A^{(1,2,4)} = V \begin{pmatrix} \Sigma^{-1} & \Sigma^{-1} \tilde{P} E \\ 0 & 0 \end{pmatrix} V^* K,$$

$$A^{(1,3,4)} = V \begin{pmatrix} \Sigma^{-1} & 0 \\ 0 & X_{22} \end{pmatrix} V^* K, \text{ respectively, where}$$

$P, \tilde{P} \in \square_r^{r \times r}, F \in \square_{(n-r) \times r}, E \in \square_{r \times (n-r)}, X_{22} \in \square_{(n-r) \times (n-r)}$, are arbitrary matrices.

Proof: The proof is analogous.

Theorem 2.7: Let $A \in \square_r^{n \times n}$ be a k-normal matrix. Then $\{2, 3\}, \{2, 4\}$ -inverse of A are given by

$$A^{(2,3)} = V \begin{pmatrix} \Sigma^{-1} M_1 M_1^* & 0 \\ FM_1^* & 0 \end{pmatrix} V^* K,$$

$$A^{(2,4)} = V \begin{pmatrix} N_1 N_1^* \Sigma^{-1} & N_1 E \\ 0 & 0 \end{pmatrix} V^* K \text{ respectively.}$$

Where $M_1, N_1 \in \square_{r \times s}$ satisfy $M_1^* M_1 = I_s, N_1^* N_1 = I_s$ and $F \in \square_{(n-r) \times s}, E \in \square_{s \times (n-r)}$ are arbitrary matrices.

Proof: Let $X \in \square_r^{n \times n}$. By Theorem 2.1 (ii) and Lemma 2.3 (i), we have that $X \in A\{2,3\}$ if and only if

$$D_1 + U_1 + \Sigma^{-1}(\Sigma U_1)^* = \Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} \dots \dots \dots (16)$$

$$\left. \begin{aligned} \Sigma^{-1}P \begin{pmatrix} E \\ 0 \end{pmatrix} &= 0 \\ (F \ 0)P^{-1} &= X_{21} \\ FE &= X_{22} \end{aligned} \right\} \dots\dots\dots(17)$$

First, we will prove that there exist D_1, U_1, P such that (16) holds. If we multiply the equation (16) from the left side by Σ ,

We get,

$$\Sigma D_1 + \Sigma U_1 + (\Sigma U_1)^* = P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} \dots\dots\dots(18)$$

$$\Sigma D_1 = (\gamma_{k(i)k(i)})_{r \times r} = \begin{cases} -\lambda_{k(i)}^{(2)} \gamma_{k(i)k(i)} & \lambda_{k(i)}^2 < 0, \\ \lambda_{k(i)}^{(1)} \gamma_{k(i)k(i)} & \lambda_{k(i)}^2 > 0, \\ \frac{|\lambda_{k(i)}|}{\lambda_{k(i)}^{(1)}} \gamma_{k(i)k(i)} & \lambda_{k(i)}^2 \notin R \end{cases}$$

From the equation (18) we conclude the following

- (i) ΣD_1 is real k-diagonal matrix.
- (ii) $\Sigma D_1 + \Sigma U_1 + (\Sigma U_1)^*$ is a k-hermitian matrix.
- (iii) The k-eigen value set of $P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}$ is $\{1, 0\}$. That is, $\Sigma D_1 + \Sigma U_1 + (\Sigma U_1)^*$ that is, $P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}$

must be k-hermitian positive semi-definite matrix with k-eigen values 0 and 1. Because of that, the matrix P can be replaced by the k-unitary matrix M such that

$$M \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} M^* = \Sigma D_1 + \Sigma U_1 + (\Sigma U_1)^* = P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}$$

Let $M = (M_1 \ M_2)$.

$$\text{Then } M \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} M^* = M_1 M_1^*$$

Denoted by $M_1 M_1^* = (m_{k(i)k(i)})_{r \times r} = \Lambda_M + L_M + L_M^*$, where $\Lambda_M = \Sigma D_1, L_M = \Sigma U_1$

$$\text{When } \gamma_{k(i)k(i)} = \begin{cases} \frac{-m_{k(i)k(i)}}{\lambda_{k(i)}^{(2)}}, & \lambda_{k(i)}^2 < 0 \\ \frac{m_{k(i)k(i)}}{\lambda_{k(i)}^{(1)}}, & \lambda_{k(i)}^2 > 0 \\ \frac{\lambda_{k(i)}^{(1)} m_{k(i)k(i)}}{|\lambda_{k(i)}|^2}, & \lambda_{k(i)}^2 \notin R \end{cases}$$

So, we have found $P(M), U_1, D_1$ such that the equation (16) holds.

If we put the k-unitary matrix M in (17) instead of P, we obtain that $E = 0, X_{22} = 0$ and $X_{21} = FM_1^*$, where F is an arbitrary matrix of suitable size.

The proof for the $\{2, 4\}$ -inverse is analogous.

Theorem 2.8: let $A \in \square_{r}^{n \times n}$ be a k-normal matrix. The every $\{2, 3, 4\}$ -inverse of A is of the form

$$A^{(2,3,4)} = V \begin{pmatrix} \Sigma^{-1} T \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} T^T & 0 \\ 0 & 0 \end{pmatrix} V^* K, \text{ where } T \text{ is a}$$

permutation matrix, $S \in \{0, 1, \dots, r\}$.

Proof: Let $X \in \square^{n \times n}$ be a $\{2, 3, 4\}$ -inverse of A. then $X \in A\{2\}$ and by Lemma (2.4), we get that

$$D = \Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1} \dots\dots\dots(19)$$

$$\left. \begin{aligned} 0 &= \Sigma^{-1} P \begin{pmatrix} E \\ 0 \end{pmatrix} \\ 0 &= (F \ 0) P^{-1} \\ X_{22} &= FE \end{aligned} \right\} \dots\dots\dots(20) \text{ from (20) it follows}$$

that $E = 0, F = 0$ and $X_{22} = 0$.

Now, we have to prove that there exist D and a non-singular matrix P such that the equation (19) holds.

By (19), we have that $\Sigma D = \Sigma^{-1} P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}$, so ΣD , that

is, $P \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} P^{-1}$ is a k-diagonal matrix with k-eigen values 0 or 1 and $rank(D) = s$.

Therefore, there exists a permutation matrix T such that $\Sigma D = T \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} T^T$.

$$\text{Denote by } \Gamma = (\gamma_{k(i)k(i)})_r = T \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} T^T.$$

$$\Sigma D = \Gamma \text{ holds if } \gamma_{k(i)k(i)} = \begin{cases} \frac{-\gamma_{k(i)}}{\lambda_{k(i)}^{(2)}} & \lambda_{k(i)}^2 < 0, \\ \frac{\gamma_{k(i)}}{\lambda_{k(i)}^{(1)}} & \lambda_{k(i)}^2 > 0, \\ \frac{\lambda_{k(i)}^{(1)} \gamma_{k(i)}}{|\lambda_{k(i)}|^2} & \lambda_{k(i)}^2 \notin R, \end{cases}$$

Finally, we get $D = \Sigma^{-1} T \begin{pmatrix} I_s & 0 \\ 0 & 0 \end{pmatrix} T^T$. Hence the proof.

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