

Week 3 Lab (Hyperbola Tutorial + Lab #2) MAST30025

Q1) Let X be a 10×5 matrix of full rank and let
 $\star H = X(X^T X)^{-1} X^T$.

find $\text{tr}(H)$ & $r(H)$ \star Recall the exercise in Q6 Tutorial 1 (week 2)

$$\star \text{tr}(H) = \text{tr} \left(\underset{10 \times 5}{X} \underset{5 \times 10}{(X^T X)^{-1}} \underset{5 \times 10}{X^T} \right) = \text{tr} \left(X^T X (X^T X)^{-1} \right) = \text{tr} (I_5) = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\text{tr}(H) = r(H) = 5!!$$

\uparrow
 H is idempotent and symmetric!! $H = H^2$ $H = H^T$ $\star H$: hat matrix

can easily prove through definitions

Q2) Let,

$$\star A = \begin{bmatrix} 3 & 1 & 8 \\ 1 & 0 & 1 \\ 2 & 4 & -4 \end{bmatrix}, y = \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

will appear lots of times in the future.

Let $z = y^T A y$. Write out z in full, then find $\frac{\partial z}{\partial y}$ directly & using the matrix formula.

$$z = [y_1, y_2, y_3] \begin{bmatrix} 3 & 1 & 8 \\ 1 & 0 & 1 \\ 2 & 4 & -4 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$= [3y_1 + y_2 + 8y_3, y_1 + y_3, 8y_1 + y_2 - 4y_3] \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$$= 3y_1^2 + y_1 y_2 + 2y_1 y_3 + y_1 y_2 + y_2 y_3 + 8y_1 y_3 + y_2 y_3 - 4y_3^2$$

~~$$= 3y_1^2 + 2y_1 y_2 + 10y_1 y_3 + 2y_2 y_3 - 4y_3^2$$~~

$$\frac{\partial z}{\partial y} = Ay + A^T y = \begin{bmatrix} 3 & 1 & 8 \\ 1 & 0 & 1 \\ 2 & 4 & -4 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} + \begin{bmatrix} 3 & 1 & 2 \\ 1 & 0 & 1 \\ 8 & 4 & -4 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix}$$

$\star A$ is not symmetric.

$$= \begin{bmatrix} 3y_1 + y_2 + 8y_3 \\ y_1 + y_3 \\ 2y_1 + y_2 - 4y_3 \end{bmatrix} + \begin{bmatrix} 3y_1 + y_2 + 2y_3 \\ y_1 + y_3 \\ 8y_1 + y_2 - 4y_3 \end{bmatrix} - \begin{bmatrix} 6y_1 + 2y_2 + 10y_3 \\ 2y_1 + 2y_3 \\ 10y_1 + 2y_2 - 8y_3 \end{bmatrix}$$

Q.3), let $y = [y_1, y_2, y_3]^T$ be a random vector with mean $\mu = [1, 3, 2]^T$, and assume that $\text{Var}(y_i) = 4$ and $\text{Cov}(y_i, y_j) = 0$.

(a) Write down $\text{Var}y$.

$$\text{Var}y = \begin{bmatrix} y_1 & 4 & 0 & 0 \\ y_2 & 0 & 4 & 0 \\ y_3 & 0 & 0 & 4 \end{bmatrix}$$

$$\sqrt{\text{Var}y} = \text{Var}[y_1, y_2, y_3]^T$$

$$= \text{cov}(y_i, y_j) = 0 = E[(y_i - \mu_i)(y_j - \mu_j)^T]$$

$$= E[(y - \mu)(y - \mu)^T] \quad \mu = E[y] = [1, 3, 2]^T$$

~~= E[EE]~~

$$= E \left[\left(\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} - \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \right) \left(\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} - \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} \right)^T \right]$$

$$= E \left[\begin{bmatrix} y_1 - 1 \\ y_2 - 3 \\ y_3 - 2 \end{bmatrix} \begin{bmatrix} y_1 - 1 & y_2 - 3 & y_3 - 2 \end{bmatrix}^T \right]$$

$$\begin{matrix} 3 \times 1 & 1 \times 3 \\ y_1 - 1 \\ y_2 - 3 \\ y_3 - 2 \end{matrix}$$

$$= E \left[\begin{bmatrix} y_1 - 1 \\ y_2 - 3 \\ y_3 - 2 \end{bmatrix} \begin{bmatrix} y_1 - 1 & y_2 - 3 & y_3 - 2 \end{bmatrix}^T \right]$$

$$= E \left[\begin{bmatrix} (y_1 - 1)^2 & (y_1 - 1)(y_2 - 3) & (y_1 - 1)(y_3 - 2) \\ (y_2 - 3)(y_1 - 1) & (y_2 - 3)^2 & (y_2 - 3)(y_3 - 2) \\ (y_3 - 2)(y_1 - 1) & (y_3 - 2)(y_2 - 3) & (y_3 - 2)^2 \end{bmatrix} \right]$$

$$\text{Var } y_1 = 4$$

$$\text{Cov}(y_1, y_2) = 2$$

$$\text{Cov}(y_3, y_2) = 3$$

and the rest of $\text{Cov} = 0$.

$$\Sigma = \begin{bmatrix} y_1 & y_2 & y_3 \\ y_2 & 4 & 2 & 0 \\ y_3 & 2 & 4 & 3 \\ y_1 & 0 & 3 & 4 \end{bmatrix}$$

symmetric

$$\cancel{\text{Cov}(y_1, y_2) = \text{Cov}(y_2, y_1)}$$

off-diagonals: Cov
diagonals: Var

$$\text{Var} \mathbf{y} = \text{Var} \begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} \text{Var}[y_1] \\ \text{Var}[y_2] \\ \text{Var}[y_3] \end{bmatrix}$$

given $\text{Var}[y_i] = 4$
 $\text{Cov}[y_i, y_j] = 0$

$\Rightarrow \text{Var} y_i = 4$, assume it is independent
 given, $\text{Cov}[y_i, y_j] = 0$.

$$\Sigma = \text{Var} \mathbf{y} = \begin{bmatrix} 4 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 4 \end{bmatrix} \stackrel{\sigma^2=4}{=} 4 I_3$$

Answer? \rightarrow correct. See 10 linear statistical models

Solution

(Q3b). Let, $A = \begin{bmatrix} 2 & -3 & 1 \\ -1 & 2 & 0 \\ -1 & 6 & 1 \end{bmatrix}$,

and find $\text{Var} A \mathbf{y}$ and $E[\mathbf{y}^T A \mathbf{y}]$.

Attempt 1

$\text{Var} A \mathbf{y} = A \mathbf{V} A^T$ * Variance properties.

$$= \begin{bmatrix} 2 & -3 & 1 \\ -1 & 2 & 0 \\ -1 & 6 & 1 \end{bmatrix} \begin{bmatrix} 4 & 0 & 0 \\ 0 & 4 & 0 \\ 0 & 0 & 4 \end{bmatrix} \begin{bmatrix} 2 & 1 & -1 \\ -3 & 2 & 6 \\ 1 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 8 & -12 & 4 \\ 4 & 8 & 0 \\ 4 & 24 & 4 \end{bmatrix} \begin{bmatrix} 2 & 1 & -1 \\ -3 & 2 & 6 \\ 1 & 0 & 1 \end{bmatrix}$$

$$= \begin{bmatrix} 16+8+4=32 & 8-24+0=-16 & -8-72+4=-76 \\ 8-24+0=-16 & 4+16+0=20 & -4+48+0=44 \\ -8-72+4=-76 & -4+48+0=44 & 4+144+4=152 \end{bmatrix}$$

$$= \begin{bmatrix} 32 & -16 & -76 \\ -16 & 20 & 44 \\ -76 & 44 & 152 \end{bmatrix}$$

Ch 10 (1/2)

$$\mathbb{E}[y^T A y] = \underbrace{\text{tr}(AV)}_{(1)} + \underbrace{\mu^T A \mu}_{(2)}$$

$$AV = \begin{bmatrix} 8 & -12 & 4 \\ 8 & 0 & 0 \\ -4 & 24 & 4 \end{bmatrix}, \text{tr}(AV) = 8 + 8 + 4 = 20 \quad (1)$$

$$\mu^T = [1 \ 3 \ 2]^T = [1 \ 3 \ 2]$$

$$\mu^T A \mu = [1 \ 3 \ 2] \begin{bmatrix} 2 & -3 & 1 \\ 1 & 2 & 0 \\ -1 & 6 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix}$$

$$= [2+3-2 \quad -3+6+12 \quad 1+0+2] \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix}$$

$$= [3 \quad 15 \quad 3] \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} = 3 + 45 + 6 = \underline{48+6=54} \quad (2)$$

$$\Rightarrow (1) + (2) = 20 + 54 = 74 \checkmark$$

(Q4) Prove corollaries 3.6 and 3.7 from the lectures.

See next page.

* Use Theorem 3.5. : $y \sim MVN(\mu, I)$, A is symmetric $\Rightarrow y^T A y \sim \chi_{k,\lambda}^2$
 $\lambda = \frac{1}{2} \mu^T A \mu$

* Corollary 3.6

$$y \sim MVN(0, I_n)$$

\hookrightarrow $n \times 1$ vector, let A be a $n \times n$ symmetric matrix.

$y^T A y$ has a
corollary χ^2

Outline

$$\mu = 0$$

Let $y \sim MVN(0, I_n)$ be a $n \times 1$ random vector and let A be a $n \times n$ symmetric matrix. Then $y^T A y$ has a (corollary) χ^2 distribution with k degrees of freedom if and only if A is idempotent and has a rank k .

$$\lambda = \frac{1}{2} \mu^T A \mu$$

$$\lambda = 0$$

$$\chi_{k,0}^2 = \chi_k^2$$

$$y \sim MVN(0, I_n)$$

With $\mu = 0$, then $\lambda = \frac{1}{2} \mu^T A \mu = 0$. ✓

from definition of distributions.

Q46) Corollary 3.7 III

From the distribution of y , we know that $\frac{1}{\sigma} y \sim MVN\left(\frac{1}{\sigma} \mu, I\right)$.

$$\therefore \left(\frac{1}{\sigma} y^T\right) A \left(\frac{1}{\sigma} y\right) = \frac{1}{\sigma^2} y^T A y \text{ has a noncentral}$$

χ^2 distribution with k degrees of freedom and non-centrality parameter,

$$\lambda = \frac{1}{2} \mu^T A \mu$$

$$\therefore \lambda = \frac{1}{2} \left(\frac{1}{\sigma} \mu\right)^T A \left(\frac{1}{\sigma} \mu\right) = \frac{1}{2\sigma^2} \mu^T A \mu$$

if and only if A is idempotent and has rank k .

$$\chi_{k,\lambda}^2$$

Note that $y \sim MVN(\mu, V) \Rightarrow y^T A y, y^T B y$
are χ^2

Q5) Let $y = [y_1, y_2]^T$ be a normal random vector with mean & variance.

\rightarrow df depends on rank of A, B .

$$\lambda = \frac{1}{2} \mu^T A \mu$$

$$\mu = \begin{bmatrix} 2 \\ 4 \end{bmatrix}, \text{ and } V = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

idempotent

$$\text{let } A = \frac{1}{2} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}, B = \frac{1}{2} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

slide 46

a) Find the distributions of $y^T A y$ and $y^T B y$.

Attempt 1

$$y^T A y = \frac{1}{2} \begin{bmatrix} y_1 & y_2 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$= \frac{1}{2} \left[2y_1 y_2 + y_1 + y_2 \right] \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$= \frac{1}{2} \left[y_1^2 + y_1 y_2 + y_2 y_1 + y_2^2 \right]$$

$$= \frac{1}{2} (y_1^2 + 2y_1 y_2 + y_2^2) = \frac{1}{2} (y_1 + y_2)^2$$

$$y^T B y = \frac{1}{2} \begin{bmatrix} y_1 & y_2 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$= \frac{1}{2} \begin{bmatrix} y_1 - y_2 & -y_1 + y_2 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$= \frac{1}{2} (y_1^2 - y_1 y_2 - y_1 y_2 + y_2^2)$$

$$= \frac{1}{2} (y_1^2 - 2y_1 y_2 + y_2^2) = \frac{1}{2} (y_1 - y_2)^2$$

MISSING,

Both have non central χ^2 distribution w/ 1 degree of freedom & noncentrality parameter,

where A and B has rank 1 (Both symmetric & idempotent)

eigenvalue

$$\lambda = \frac{1}{2} \mu^T A \mu \quad & \quad \lambda = \frac{1}{2} \mu^T B \mu$$

(1) (2)

$$\lambda = \frac{1}{2} \begin{bmatrix} 2 & 4 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix}$$

$$= \frac{1}{2} \times \frac{1}{2} \begin{bmatrix} 6 & 6 \\ 6 & 4 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \frac{1}{4} (12 + 24) = 9$$

(1)

$$\lambda = \frac{1}{2} \begin{bmatrix} 2 & 4 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix}$$

$y^T A y \sim X_k, \lambda$
where $k=1$,
 $\lambda = 9$

$$= \frac{1}{4} \begin{bmatrix} -2 & 2 \\ 2 & 4 \end{bmatrix} \begin{bmatrix} 2 \\ 4 \end{bmatrix} = \frac{1}{4} (-4 + 8) = \frac{4}{4} = 1$$

(2)

(Q5b) Are $y^T A y$ and $y^T B y$ independent?

* Thm 5.11

I

Show that C, D
is not indep.

$$AVB = \frac{1}{4} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

$CVD \neq 0$

\therefore not indep.

$$= \frac{1}{4} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 1 & -1 \\ -1 & 1 \end{bmatrix}$$

$$AIB = AB$$

$$= \frac{1}{4} \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} = \textcircled{0}$$

$\therefore y^T A y$ & $y^T B y$ are independent

in answer you can go straight to AB ~~or C~~
where $AB = \textcircled{0}$ ✓

Q5c) What is the distribution of $y^T A y + y^T B y$?

$\text{degree of freedom} + \text{degree of freedom} = 2 \text{ degrees of freedom?}$

$$\begin{aligned}
 y^T A y + y^T B y &= \frac{1}{2} (y_1 + y_2)^2 + \frac{1}{2} (y_1 - y_2)^2 \\
 &= \frac{1}{2} (y_1^2 + 2y_1 y_2 + y_2^2) + \frac{1}{2} (y_1^2 - 2y_1 y_2 + y_2^2) \\
 &= \frac{1}{2} (2y_1^2 + 2y_2^2) = y_1^2 + y_2^2.
 \end{aligned}$$

Yeah!

distribution.

has a non central χ^2 distribution with λ^2 degrees of freedom and non centrality parameter λ w/ rank 1, A, B are idempotents both have rank 1!!

$$\lambda = 9 + 1 = 10$$

that was wrong?

Prove that: $X_1 \sim \chi_{k_1, \lambda_1}^2$; $X_2 \sim \chi_{k_2, \lambda_2}^2$ leads to $X_1 + X_2 \sim \chi_{k_1+k_2, \lambda_1+\lambda_2}^2$

Q6) let y_1, \dots, y_n be an i.i.d. normal sample. Show that

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i \text{ and, } s^2 = \frac{1}{n-1} \sum_{i=1}^n (y_i - \bar{y})^2$$

are independent. (HINT: Express them as a random "vector" and quadratic form respectively.)

Attempt 1

$$\bar{y} = \frac{1}{n} \sum_{i=1}^n y_i = \cancel{\frac{1}{n} \sum_{i=1}^n 1^T} y$$

get comfortable with $\mathbb{1}$

$$y - \bar{y} \mathbb{1} = (I - \frac{1}{n} \mathbb{1} \mathbb{1}^T) y$$

$$\begin{aligned}
 &\Rightarrow \frac{1}{n} [\mathbb{1} \cdots \mathbb{1}] \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \\
 &= \frac{1}{n} (y_1 + \cdots + y_n)
 \end{aligned}$$

$$s^2 = \frac{1}{n-1} [(I - \frac{1}{n} \mathbb{1} \mathbb{1}^T) y]^T (I - \frac{1}{n} \mathbb{1} \mathbb{1}^T) y$$

$$= \frac{1}{n-1} y^T (I - \frac{1}{n} \mathbb{1} \mathbb{1}^T)^T (I - \frac{1}{n} \mathbb{1} \mathbb{1}^T) y$$

$$= \frac{1}{n-1} y^T (I - \frac{1}{n} \mathbb{1} \mathbb{1}^T) y$$

$I - \frac{1}{n} \mathbb{1} \mathbb{1}^T$ is symmetric & idempotent.

$$y - \bar{y} \mathbf{1} = (\underbrace{\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T}_{n \times 1} \underbrace{y}_{1 \times n}) = A$$

$$A^2 = A^T A$$

$$\frac{1}{n} \mathbf{1} \mathbf{1}^T = \frac{1}{n} \begin{bmatrix} 1 \\ \vdots \\ 1 \end{bmatrix} \begin{bmatrix} 1 & \cdots & 1 \end{bmatrix}$$

$$= \frac{1}{n} \begin{bmatrix} 1 & 1 & \cdots & 1 \\ \cdot & \cdot & \cdot & \cdot \\ 1 & 1 & \cdots & 1 \end{bmatrix}$$

$$\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T = \begin{bmatrix} 1 - \frac{1}{n} & -\frac{1}{n} & \cdots & -\frac{1}{n} \\ -\frac{1}{n} & 1 - \frac{1}{n} & \cdots & -\frac{1}{n} \\ \vdots & \vdots & \ddots & \vdots \end{bmatrix}$$

$$1 - \frac{1}{n} = \frac{n-1}{n}$$

$$\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T = \frac{1}{n} \begin{bmatrix} n-1 & -1 & -1 & \cdots & -1 \\ -1 & n-1 & & & \\ & & n-1 & & \\ & & & n-1 & \ddots \end{bmatrix}$$

$$s^2 = \frac{1}{n-1} [(\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) y]^T (\mathbf{I} - \frac{1}{n} \mathbf{1} \mathbf{1}^T) y$$

$$s^2 = \frac{1}{n-1} \sum (y - \bar{y})^2$$

2020

Prove that: $X_1 \sim \chi^2_{k_1, \lambda_1}$; $X_2 \sim \chi^2_{k_2, \lambda_2}$ leads to $X_1 + X_2 \sim \chi^2_{k_1+k_2, \lambda_1+\lambda_2}$

$$X_1 = y_1^T y_1 \text{ where } y_1 \sim \text{MVN}(\mu_1, \mathbb{I}) \Rightarrow \lambda_1 = \frac{1}{2} \mu_1^T \mu_1$$

$$X_2 = y_2^T y_2 \text{ where } y_2 \sim \text{MVN}(\mu_2, \mathbb{I}) \Rightarrow \lambda_2 = \frac{1}{2} \mu_2^T \mu_2$$

$$X_1 + X_2 = y_1^T y_1 + y_2^T y_2 = \sum_{i=1}^{k_1} y_i^2 + \sum_{j=1}^{k_2} y_j^2 = \sum_{i=1}^{k_1+k_2} y_i^2$$

squares

: since $X_1 + X_2$ is the sum of $k_1 + k_2$ indep. normals,
d.f. of $X_1 + X_2$ is
then $\lambda = k_1 + k_2$

$$X_1 + X_2 = \sum_{i=1}^{k_1+k_2} y_i^2 = (y_1 + y_2)^T (y_1 + y_2)$$

$$(y_1 + y_2) \sim \text{MVN}(\mu_1 + \mu_2, \mathbb{I})$$

$$\lambda = \frac{1}{2} \mu^T \mu$$

$$= \frac{1}{2} (\mu_1 + \mu_2)^T (\mu_1 + \mu_2)$$

$$4y_1 + 3y_2 \sim \text{MVN}(4\mu_1 + 3\mu_2, \mathbb{I})$$

$$= \frac{1}{2} (\mu_1^T \mu_1 + \mu_2^T \mu_1 + \mu_1^T \mu_2 + \mu_2^T \mu_2)$$

$$\vdots \\ \vdots \\ = \frac{1}{2} \mu_1^T \mu_1 + \frac{1}{2} \mu_2^T \mu_2$$

$$\mu_1 = \begin{bmatrix} \mu_{11} \\ \vdots \\ \mu_{1, k_1} \end{bmatrix}$$

$$\mu_2 = \begin{bmatrix} \mu_{21} \\ \vdots \\ \mu_{2, k_2} \end{bmatrix}$$

$$\mu_2^T \mu_1 = \begin{bmatrix} \mu_{21} & \dots & \mu_{2, k_2} \end{bmatrix} \begin{bmatrix} \mu_{11} \\ \vdots \\ \mu_{1, k_1} \end{bmatrix}$$

$$= \mu_{21} \mu_{11} + \dots + \mu_{2, k_2} \mu_{1, k_1}$$

$$\mu_1^T \mu_2 = \begin{bmatrix} \mu_{11} & \dots & \mu_{1, k_1} \end{bmatrix} \begin{bmatrix} \mu_{21} \\ \vdots \\ \mu_{2, k_2} \end{bmatrix}$$

$$= \mu_{11} \mu_{21} + \dots + \mu_{1, k_1} \mu_{2, k_2}$$

$$\mu_1 = \begin{bmatrix} \mu_{11} \\ \vdots \\ \mu_{1, k_1} \\ \hline 0 \\ \vdots \\ 0 \end{bmatrix}, \mu_2 = \begin{bmatrix} 0 \\ \vdots \\ 0 \\ \hline \mu_{21} \\ \vdots \\ \mu_{2, k_2} \end{bmatrix}$$

$$\mu_1 + \mu_2 = \begin{bmatrix} \mu_{11} \\ \vdots \\ \mu_{1, k_1} \\ \hline \mu_{21} \\ \vdots \\ \mu_{2, k_2} \end{bmatrix}$$

$$\mu_2^T \mu_1 = 0 \\ \mu_1^T \mu_2 = 0$$