

# The Sample Covariance Matrix and the Sample Correlation Matrix and Their Applications in the Sample Principal Component

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## Abstract

We give the properties and proofs of the sample principal component, and discuss them in two different conditions: from S on to calculate principal component and from R on to calculate principal component. From S on to calculate principal component, we give 7 properties (S1)-(S7) and their proofs, and the relationships stated by these properties get full display in [Figure 1](#). Similarly, from R on to calculate principal component, we give 7 properties (R1)-(R7) and their proofs, and the relationships stated by these properties get full display in [Figure 2](#). Finally we give two numerical simulation examples to verify the correctness of properties (S1)-(S7) and (R1)-(R7).

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## Keywords

Sample Covariance Matrix, Sample Correlation Matrix, Sample Principal Component, Properties and Proofs, R Software

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# 样本协方差矩阵和样本相关矩阵及其在样本主成分中的应用

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## 摘要

我们给出了样本主成分的性质及证明，分两种情况讨论：从  $S$  出发求主成分和从  $R$  出发求主成分。在从  $S$  出发求主成分中，给出了 7 个性质(S1)-(S7) 及它们的证明，这些性质说明的关系在图 1 中得到了充分的展现。同样，在从  $R$  出发求主成分中，给出了 7 个性质(R1)-(R7) 及它们的证明，这些性质说明的关系在图 2 中得到了充分的展现。最后我们给出了两个数值模拟的例子来验证性质(S1)-(S7) 和(R1)-(R7) 的正确性。

## 关键词

样本协方差矩阵, 样本相关矩阵, 样本主成分, 性质及证明, R 软件

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## 1. 引言

主成分分析(Principal Component Analysis, PCA)或称主分量分析，是一种降维的统计方法。通过正交变换将一组可能存在相关性的变量转换为一组线性不相关的综合变量，同时根据实际需要从中可以取出几个较少的综合变量尽可能多地反映原来变量的信息，转换后的这组综合变量叫主成分。主成分分析首先是由卡尔·皮尔森(Karl Pearson)对非随机变量引入的，尔后霍特林将此方法推广到随机向量的情形。信息的大小通常用方差来衡量。

为研究总体主成分和样本主成分的性质，需要定义总体或样本的协方差(矩阵)和相关系数(矩阵)。它们的定义及性质请参见[1]。总体主成分的性质在[2]-[10]中已有很好的总结及证明，但是他们对样本主成分的性质讨论却不多。由于总体的协方差矩阵和相关系数矩阵一般是未知的，而样本资料阵一般是已知的，人们一般采用样本主成分进行计算，从而研究样本主成分的性质就显得非常重要。本文给出了样本主成分的性质及证明，分两种情况讨论：从  $S$  出发求主成分并给出了 7 个性质(S1)-(S7) 及它们的证明；从  $R$  出发求主成分并给出了 7 个性质(R1)-(R7) 及它们的证明。

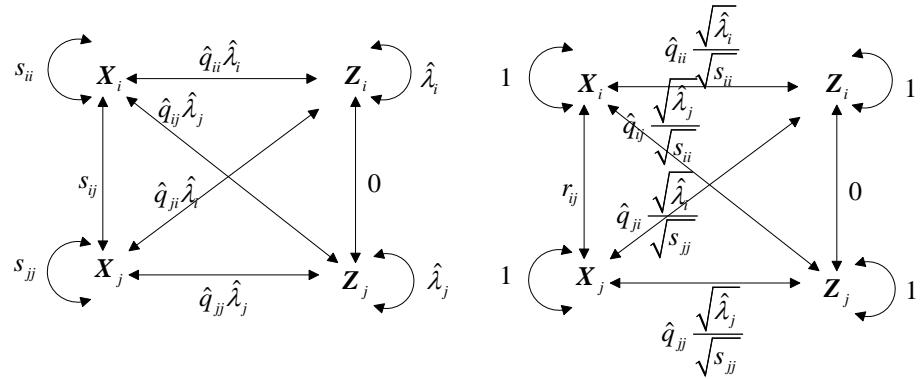
本文剩余部分安排如下：第 2 节给出样本主成分的性质及证明，分两种情况讨论：从  $S$  出发求主成分和从  $R$  出发求主成分。这些性质(S1)-(S7) 和(R1)-(R7) 说明的关系在图 1 和图 2 中得到了充分的展现。第 3 节给出了两个数值模拟的例子来验证性质(S1)-(S7) 和(R1)-(R7) 的正确性。第 4 节总结。

## 2. 样本主成分的性质及证明

有总体主成分和样本主成分，有协方差矩阵和相关矩阵，把这两个概念结合在一起形成表 1。本文讨论样本主成分的性质及证明。分两种情况讨论：从  $S$  或  $R$  出发求主成分。

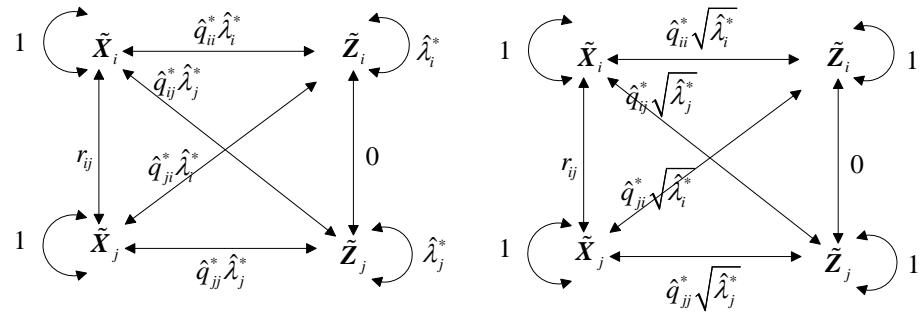
### 2.1. 从 $S$ 出发求主成分

设  $\hat{\lambda}_1 \geq \hat{\lambda}_2 \geq \dots \geq \hat{\lambda}_p \geq 0$  为样本协方差矩阵  $S$  的特征值， $\hat{a}_1, \hat{a}_2, \dots, \hat{a}_p$  为相应的两两正交的单位特征向量，即



**Figure 1.** The relationships of the sample covariances (left) and the relationships of the sample correlations (right) among  $X_i, X_j, Z_i, Z_j$

**图 1.**  $X_i, X_j, Z_i, Z_j$  的样本协方差关系图(左)和样本相关系数关系图(右)



**Figure 2.** The relationships of the sample covariances (left) and the relationships of the sample correlations (right) among  $\tilde{X}_i, \tilde{X}_j, \tilde{Z}_i, \tilde{Z}_j$

**图 2.**  $\tilde{X}_i, \tilde{X}_j, \tilde{Z}_i, \tilde{Z}_j$  的样本协方差关系图(左)和样本相关系数关系图(右)

**Table 1.** The covariance matrix and the correlation matrix of the population and the sample  
**表 1.** 总体和样本的协方差矩阵和相关矩阵

协方差矩阵		相关矩阵
总体	$\Sigma = (\sigma_{ij})_{p \times p}$	$\rho = (\rho_{ij})_{p \times p}$
样本	$S = (s_{ij})_{p \times p}$	$R = (r_{ij})_{p \times p}$

$$\begin{aligned} S\hat{\mathbf{a}}_j &= \hat{\lambda}_j \hat{\mathbf{a}}_j, \\ \hat{\mathbf{a}}_i^\top \hat{\mathbf{a}}_j &= 1, \quad j = 1, 2, \dots, p, \\ \hat{\mathbf{a}}_i^\top \hat{\mathbf{a}}_j &= 0, \quad i \neq j, \quad i, j = 1, 2, \dots, p. \end{aligned}$$

令  $\hat{\mathbf{Q}} = (\hat{\mathbf{a}}_1, \hat{\mathbf{a}}_2, \dots, \hat{\mathbf{a}}_p) = (\hat{q}_{ij})_{p \times p}$ , 它是一个正交阵,  $\hat{\Lambda} = \text{diag}(\hat{\lambda}_1, \hat{\lambda}_2, \dots, \hat{\lambda}_p)$ , 写成矩阵形式, 就是

$$S\hat{\mathbf{Q}} = \hat{\mathbf{Q}}\hat{\Lambda},$$

上式两边左乘以  $\hat{\mathbf{Q}}^\top$ , 得到

$$\hat{\mathbf{Q}}^\top S \hat{\mathbf{Q}} = \hat{\Lambda}.$$

则第  $i$  个主成分  $z_i = \hat{\mathbf{a}}_i^\top \mathbf{x}$ ,  $i = 1, 2, \dots, p$ , 其中  $\mathbf{x} = (x_1, x_2, \dots, x_p)^\top$ , 且

$$\mathbf{z} = \begin{pmatrix} z_1 \\ z_2 \\ \vdots \\ z_p \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_1^T \mathbf{x} \\ \hat{\mathbf{a}}_2^T \mathbf{x} \\ \vdots \\ \hat{\mathbf{a}}_p^T \mathbf{x} \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_1^T \\ \hat{\mathbf{a}}_2^T \\ \vdots \\ \hat{\mathbf{a}}_p^T \end{pmatrix} \mathbf{x} = (\hat{\mathbf{a}}_1, \hat{\mathbf{a}}_2, \dots, \hat{\mathbf{a}}_p)^T \mathbf{x} = \hat{\mathbf{Q}}^T \mathbf{x}.$$

下面构造样本主成分, 令

$$\mathbf{Z}_{(k)} = \hat{\mathbf{Q}}^T \mathbf{X}_{(k)}.$$

因此样本主成分为

$$\begin{aligned} \mathbf{Z} &= \begin{pmatrix} z_{11} & z_{12} & \cdots & z_{1p} \\ z_{21} & z_{22} & \cdots & z_{2p} \\ \vdots & \vdots & & \vdots \\ z_{n1} & z_{n2} & \cdots & z_{np} \end{pmatrix} = \begin{pmatrix} \mathbf{Z}_{(1)}^T \\ \mathbf{Z}_{(2)}^T \\ \vdots \\ \mathbf{Z}_{(n)}^T \end{pmatrix} = \begin{pmatrix} \mathbf{X}_{(1)}^T \hat{\mathbf{Q}} \\ \mathbf{X}_{(2)}^T \hat{\mathbf{Q}} \\ \vdots \\ \mathbf{X}_{(n)}^T \hat{\mathbf{Q}} \end{pmatrix} = \mathbf{X} \hat{\mathbf{Q}} \\ &= (\mathbf{X} \hat{\mathbf{a}}_1, \mathbf{X} \hat{\mathbf{a}}_2, \dots, \mathbf{X} \hat{\mathbf{a}}_p) = (\mathbf{Z}_1, \mathbf{Z}_2, \dots, \mathbf{Z}_p), \end{aligned}$$

其中  $\mathbf{Z}_{(k)}^T = (z_{k1}, z_{k2}, \dots, z_{kp})$  表示样本主成分的各行,  $\mathbf{Z}_j = (z_{1j}, z_{2j}, \dots, z_{nj})^T$  表示样本主成分的各列。易知

$$\bar{\mathbf{Z}} = \frac{1}{n} \sum_{k=1}^n \mathbf{Z}_{(k)} = \frac{1}{n} \sum_{k=1}^n \hat{\mathbf{Q}}^T \mathbf{X}_{(k)} = \hat{\mathbf{Q}}^T \frac{1}{n} \sum_{k=1}^n \mathbf{X}_{(k)} = \hat{\mathbf{Q}}^T \bar{\mathbf{X}}.$$

类似于数据资料阵  $\mathbf{X}$  的标准化[1], 可得到矩阵  $\mathbf{Z}$  的标准化矩阵  $\mathbf{Z}^*$  满足

$$\mathbf{Z}^* = (z_{ij}^*)_{n \times p} = \begin{pmatrix} \mathbf{Z}_{(1)}^{*T} \\ \mathbf{Z}_{(2)}^{*T} \\ \vdots \\ \mathbf{Z}_{(n)}^{*T} \end{pmatrix} = (\mathbf{Z}_1^*, \mathbf{Z}_2^*, \dots, \mathbf{Z}_p^*),$$

其中

$$\begin{aligned} \mathbf{Z}_{(k)}^* &= \left( \frac{z_{k1} - \bar{z}_1}{\sqrt{\hat{\lambda}_1}}, \frac{z_{k2} - \bar{z}_2}{\sqrt{\hat{\lambda}_2}}, \dots, \frac{z_{kp} - \bar{z}_p}{\sqrt{\hat{\lambda}_p}} \right)^T \\ &= \begin{pmatrix} \frac{1}{\sqrt{\hat{\lambda}_1}} & & & \\ & \frac{1}{\sqrt{\hat{\lambda}_2}} & & \\ & & \ddots & \\ & & & \frac{1}{\sqrt{\hat{\lambda}_p}} \end{pmatrix} \begin{pmatrix} z_{k1} - \bar{z}_1 \\ z_{k2} - \bar{z}_2 \\ \vdots \\ z_{kp} - \bar{z}_p \end{pmatrix} \\ &= \hat{\Lambda}^{-\frac{1}{2}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}}), \\ \hat{\Lambda} &= \text{diag}(\hat{\lambda}_1, \hat{\lambda}_2, \dots, \hat{\lambda}_p) = \text{cov}(\mathbf{Z}), \end{aligned}$$

上式中  $\text{diag}(\hat{\lambda}_1, \hat{\lambda}_2, \dots, \hat{\lambda}_p)$  表示由向量  $(\hat{\lambda}_1, \hat{\lambda}_2, \dots, \hat{\lambda}_p)^T$  作为对角线元素构成的对角阵。注意, 上式用到了(S2)

的结论。从而

$$\mathbf{Z}^* = \begin{pmatrix} \mathbf{Z}_{(1)}^{*\top} \\ \mathbf{Z}_{(2)}^{*\top} \\ \vdots \\ \mathbf{Z}_{(n)}^{*\top} \end{pmatrix} = \begin{pmatrix} (\mathbf{Z}_{(1)} - \bar{\mathbf{Z}})^\top \hat{\Lambda}^{-\frac{1}{2}} \\ (\mathbf{Z}_{(2)} - \bar{\mathbf{Z}})^\top \hat{\Lambda}^{-\frac{1}{2}} \\ \vdots \\ (\mathbf{Z}_{(n)} - \bar{\mathbf{Z}})^\top \hat{\Lambda}^{-\frac{1}{2}} \end{pmatrix} = \begin{pmatrix} \mathbf{Z}_{(1)}^\top - \bar{\mathbf{Z}}^\top \\ \mathbf{Z}_{(2)}^\top - \bar{\mathbf{Z}}^\top \\ \vdots \\ \mathbf{Z}_{(n)}^\top - \bar{\mathbf{Z}}^\top \end{pmatrix} \hat{\Lambda}^{-\frac{1}{2}} = (\mathbf{Z} - \mathbf{I}_{n \times 1} \bar{\mathbf{Z}}^\top) \hat{\Lambda}^{-\frac{1}{2}}.$$

易知

$$\bar{\mathbf{Z}}^* = \frac{1}{n} \sum_{k=1}^n \mathbf{Z}_{(k)}^* = \frac{1}{n} \sum_{k=1}^n \hat{\Lambda}^{-\frac{1}{2}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}}) = \frac{1}{n} \hat{\Lambda}^{-\frac{1}{2}} (n \bar{\mathbf{Z}} - n \bar{\mathbf{Z}}) = \mathbf{0}.$$

因为  $\mathbf{Z}_{(k)} = \hat{\mathbf{Q}}^\top \mathbf{X}_{(k)}$ , 人们自然会想到  $\mathbf{Z}_{(k)}^* = \hat{\mathbf{Q}}^\top \mathbf{X}_{(k)}^*$ , 但是一般来说这是错误的。详细的证明请见本文的附录。

我们用  $\mathbf{S} \geq \mathbf{0}$  表示它是一个非负定阵, 用  $\mathbf{S} > \mathbf{0}$  表示它是一个正定阵。令  $\mathbf{X} = (x_{ij})_{n \times p}$  为数据资料矩阵,  $\mathbf{Z} = (z_{ij})_{n \times p}$  为主成分得分矩阵, 则对于由  $\mathbf{S} \geq \mathbf{0}$  出发计算的样本主成分有如下性质:

(S1).

$$\text{cov}(\mathbf{X}) = \text{cov}(\mathbf{X}, \mathbf{X}) = (\text{cov}(\mathbf{X}_i, \mathbf{X}_j))_{p \times p} = \mathbf{S} = (s_{ij})_{p \times p},$$

特别地,

$$\text{cov}(\mathbf{X}_i, \mathbf{X}_j) = s_{ij}, \quad i, j = 1, \dots, p.$$

(S2).

$$\text{cov}(\mathbf{Z}) = \text{cov}(\mathbf{Z}, \mathbf{Z}) = (\text{cov}(\mathbf{Z}_i, \mathbf{Z}_j))_{p \times p} = \hat{\Lambda},$$

特别地,

$$\begin{aligned} \text{cov}(\mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_j, \mathbf{Z}_j) = \hat{\lambda}_j, \quad j = 1, \dots, p, \\ \text{cov}(\mathbf{Z}_i, \mathbf{Z}_j) &= 0, \quad i \neq j, \quad i, j = 1, \dots, p. \end{aligned}$$

(S3).

$$\text{cov}(\mathbf{X}, \mathbf{Z}) = (\text{cov}(\mathbf{X}_i, \mathbf{Z}_j))_{p \times p} = (\hat{q}_{ij} \hat{\lambda}_j)_{p \times p} = \hat{\mathbf{Q}} \hat{\Lambda},$$

特别地,

$$\text{cov}(\mathbf{X}_i, \mathbf{Z}_j) = \hat{q}_{ij} \hat{\lambda}_j, \quad i, j = 1, \dots, p.$$

(S4).

$$\begin{aligned} \text{cor}(\mathbf{X}) &= \text{cor}(\mathbf{X}, \mathbf{X}) = (\text{cor}(\mathbf{X}_i, \mathbf{X}_j))_{p \times p} \\ &= \text{cov}(\mathbf{X}^*) = (\text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*))_{p \times p} = \mathbf{R} = (r_{ij})_{p \times p}, \end{aligned}$$

特别地,

$$\text{cor}(\mathbf{X}_i, \mathbf{X}_j) = \text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*) = r_{ij}, \quad i, j = 1, \dots, p.$$

(S5). 若  $S > \mathbf{0}$ , 则

$$\begin{aligned}\text{cor}(\mathbf{Z}) &= \text{cor}(\mathbf{Z}, \mathbf{Z}) = (\text{cor}(\mathbf{Z}_i, \mathbf{Z}_j))_{p \times p} = \text{cov}(\mathbf{Z}^*) = (\text{cov}(\mathbf{Z}_i^*, \mathbf{Z}_j^*))_{p \times p} \\ &= \mathbf{E}_{p \times p} = \text{diag}(1, 1, \dots, 1)_{p \times p},\end{aligned}$$

特别地,

$$\begin{aligned}\text{cor}(\mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_j^*) = \text{cov}(\mathbf{Z}_j^*, \mathbf{Z}_j^*) = 1, \quad j = 1, \dots, p, \\ \text{cor}(\mathbf{Z}_i, \mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_i^*, \mathbf{Z}_j^*) = 0, \quad i \neq j, \quad i, j = 1, \dots, p.\end{aligned}$$

(S6). 若  $S > \mathbf{0}$ , 则

$$\begin{aligned}\text{cor}(\mathbf{X}, \mathbf{Z}) &= (\text{cor}(\mathbf{X}_i, \mathbf{Z}_j))_{p \times p} = \text{cov}(\mathbf{X}^*, \mathbf{Z}^*) = (\text{cov}(\mathbf{X}_i^*, \mathbf{Z}_j^*))_{p \times p} \\ &= \left( \hat{q}_{ij} \frac{\sqrt{\hat{\lambda}_j}}{\sqrt{s_{ii}}} \right)_{p \times p} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}},\end{aligned}$$

其中

$$\hat{\mathbf{D}} = \text{diag}(s_{11}, s_{22}, \dots, s_{pp})$$

是  $\mathbf{S}$  的对角线元素组成的对角阵。特别地,

$$\text{cor}(\mathbf{X}_i, \mathbf{Z}_j) = \text{cov}(\mathbf{X}_i^*, \mathbf{Z}_j^*) = \hat{q}_{ij} \frac{\sqrt{\hat{\lambda}_j}}{\sqrt{s_{ii}}}, \quad i, j = 1, \dots, p.$$

(S7). 样本总方差

$$\sum_{j=1}^p \text{cov}(\mathbf{X}_j) = \sum_{j=1}^p s_{jj} = \sum_{j=1}^p \hat{\lambda}_j = \sum_{j=1}^p \text{cov}(\mathbf{Z}_j).$$

此式表明了样本  $\mathbf{X}_1, \dots, \mathbf{X}_p$  的样本(协)方差之和等于样本主成分  $\mathbf{Z}_1, \dots, \mathbf{Z}_p$  的样本(协)方差之和。

在以上 7 个性质中, (S1)显然, (S2)和(S6)的分量形式的结果和(S7)可以在[7]中找到。

注意, 在(S5)和(S6)中我们要求  $S > \mathbf{0}$ , 而其余性质只要求  $S \geq \mathbf{0}$ 。因为在(S5)和(S6)的证明中会涉及到

$$\hat{\Lambda}^{-\frac{1}{2}} = \text{diag} \left( \frac{1}{\sqrt{\hat{\lambda}_1}}, \frac{1}{\sqrt{\hat{\lambda}_2}}, \dots, \frac{1}{\sqrt{\hat{\lambda}_p}} \right),$$

若  $\mathbf{S}$  有一个 0 特征值, 即  $\hat{\lambda}_p = 0$ , 则  $1/\sqrt{\hat{\lambda}_p}$  是没有意义的, 从而结论不成立, 数值结果也证实了这一点。

由性质(S1)-(S6)归纳得到样本  $\mathbf{X}_i, \mathbf{X}_j, \mathbf{Z}_i, \mathbf{Z}_j$  的样本协方差关系图((S1)-(S3))和样本相关系数关系图((S4)-(S6)), 如图 1。

性质(S1)-(S7)的证明有些是初等的, 有些需要一定的技巧, 由于这些证明较占篇幅, 所以把它们放到了本文的附录中。

## 2.2. 从 R 出发求主成分

设  $\hat{\lambda}_1^* \geq \hat{\lambda}_2^* \geq \dots \geq \hat{\lambda}_p^* \geq 0$  为样本相关矩阵  $\mathbf{R}$  的特征值,  $\hat{\mathbf{a}}_1^*, \hat{\mathbf{a}}_2^*, \dots, \hat{\mathbf{a}}_p^*$  为相应的两两正交的单位特征向量,

即

$$\begin{aligned}\mathbf{R}\hat{\mathbf{a}}_j^* &= \hat{\lambda}_j^* \hat{\mathbf{a}}_j^*, \\ \hat{\mathbf{a}}_j^{*T} \hat{\mathbf{a}}_j^* &= 1, \quad j = 1, 2, \dots, p, \\ \hat{\mathbf{a}}_i^{*T} \hat{\mathbf{a}}_j^* &= 0, \quad i \neq j, \quad i, j = 1, 2, \dots, p.\end{aligned}$$

令  $\hat{\mathbf{Q}}^* = (\hat{\mathbf{a}}_1^*, \hat{\mathbf{a}}_2^*, \dots, \hat{\mathbf{a}}_p^*) = (\hat{q}_{ij}^*)_{p \times p}$ , 它是一个正交阵,  $\hat{\Lambda}^* = \text{diag}(\hat{\lambda}_1^*, \hat{\lambda}_2^*, \dots, \hat{\lambda}_p^*)$ , 写成矩阵形式, 就是

$$\mathbf{R}\hat{\mathbf{Q}}^* = \hat{\mathbf{Q}}^* \hat{\Lambda}^*,$$

上式两边左乘以  $\hat{\mathbf{Q}}^{*T}$ , 得到

$$\hat{\mathbf{Q}}^{*T} \mathbf{R}\hat{\mathbf{Q}}^* = \hat{\Lambda}^*.$$

则第  $i$  个主成分  $\tilde{z}_i = \hat{\mathbf{a}}_i^{*T} \tilde{\mathbf{x}}$ ,  $i = 1, 2, \dots, p$ , 其中  $\tilde{\mathbf{x}} = \mathbf{x}^* = (x_1^*, x_2^*, \dots, x_p^*)^T$ 。这是因为我们从样本相关矩阵  $\mathbf{R}$  出发, 所以变量已经标准化了。且

$$\tilde{\mathbf{z}} = \begin{pmatrix} \tilde{z}_1 \\ \tilde{z}_2 \\ \vdots \\ \tilde{z}_p \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_1^{*T} \tilde{\mathbf{x}} \\ \hat{\mathbf{a}}_2^{*T} \tilde{\mathbf{x}} \\ \vdots \\ \hat{\mathbf{a}}_p^{*T} \tilde{\mathbf{x}} \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_1^{*T} \\ \hat{\mathbf{a}}_2^{*T} \\ \vdots \\ \hat{\mathbf{a}}_p^{*T} \end{pmatrix} \tilde{\mathbf{x}} = (\hat{\mathbf{a}}_1^*, \hat{\mathbf{a}}_2^*, \dots, \hat{\mathbf{a}}_p^*)^T \tilde{\mathbf{x}} = \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{x}} = \hat{\mathbf{Q}}^{*T} \mathbf{x}^*.$$

下面构造样本主成分, 令

$$\tilde{\mathbf{Z}}_{(k)} = \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)} = \hat{\mathbf{Q}}^{*T} \mathbf{X}_{(k)}^*,$$

则

$$\tilde{\mathbf{X}}_{(k)} = \hat{\mathbf{Q}}^* \tilde{\mathbf{Z}}_{(k)}.$$

因此样本主成分为

$$\begin{aligned}\tilde{\mathbf{Z}} &= \begin{pmatrix} \tilde{z}_{11} & \tilde{z}_{12} & \cdots & \tilde{z}_{1p} \\ \tilde{z}_{21} & \tilde{z}_{22} & \cdots & \tilde{z}_{2p} \\ \vdots & \vdots & & \vdots \\ \tilde{z}_{n1} & \tilde{z}_{n2} & \cdots & \tilde{z}_{np} \end{pmatrix} = \begin{pmatrix} \tilde{\mathbf{Z}}_{(1)}^T \\ \tilde{\mathbf{Z}}_{(2)}^T \\ \vdots \\ \tilde{\mathbf{Z}}_{(n)}^T \end{pmatrix} = \begin{pmatrix} \tilde{\mathbf{X}}_{(1)}^T \hat{\mathbf{Q}}^* \\ \tilde{\mathbf{X}}_{(2)}^T \hat{\mathbf{Q}}^* \\ \vdots \\ \tilde{\mathbf{X}}_{(n)}^T \hat{\mathbf{Q}}^* \end{pmatrix} = \begin{pmatrix} \tilde{\mathbf{X}}_{(1)}^T \\ \tilde{\mathbf{X}}_{(2)}^T \\ \vdots \\ \tilde{\mathbf{X}}_{(n)}^T \end{pmatrix} \hat{\mathbf{Q}}^* \\ &= \tilde{\mathbf{X}} \hat{\mathbf{Q}}^* = \mathbf{X}^* \hat{\mathbf{Q}}^* = (\tilde{\mathbf{X}} \hat{\mathbf{a}}_1^*, \tilde{\mathbf{X}} \hat{\mathbf{a}}_2^*, \dots, \tilde{\mathbf{X}} \hat{\mathbf{a}}_p^*) = (\tilde{\mathbf{Z}}_1, \tilde{\mathbf{Z}}_2, \dots, \tilde{\mathbf{Z}}_p),\end{aligned}$$

其中  $\tilde{\mathbf{Z}}_{(k)}^T = (\tilde{z}_{k1}, \tilde{z}_{k2}, \dots, \tilde{z}_{kp})$  表示样本主成分的各行,  $\tilde{\mathbf{Z}}_j = (\tilde{z}_{1j}, \tilde{z}_{2j}, \dots, \tilde{z}_{nj})^T$  表示样本主成分的各列。注意到

$$\tilde{\mathbf{X}} = \begin{pmatrix} \tilde{\mathbf{X}}_{(1)}^T \\ \tilde{\mathbf{X}}_{(2)}^T \\ \vdots \\ \tilde{\mathbf{X}}_{(n)}^T \end{pmatrix} = \begin{pmatrix} \mathbf{X}_{(1)}^{*T} \\ \mathbf{X}_{(2)}^{*T} \\ \vdots \\ \mathbf{X}_{(n)}^{*T} \end{pmatrix} = \mathbf{X}^*,$$

$\mathbf{X}^*$  和  $\mathbf{X}_{(k)}^*$  可参照[1]中的数据资料矩阵  $\mathbf{X}$  的标准化部分。但是,

$$\tilde{\mathbf{Z}}_{(k)} = \hat{\mathbf{Q}}^{*T} \mathbf{X}_{(k)}^* = \hat{\mathbf{Q}}^{*T} \hat{\mathbf{D}}^{-\frac{1}{2}} (\mathbf{X}_{(k)} - \bar{\mathbf{X}}),$$

$$\mathbf{Z}_{(k)}^* = \hat{\Lambda}^{-\frac{1}{2}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}}) = \hat{\Lambda}^{-\frac{1}{2}} \hat{\mathbf{Q}}^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}),$$

所以  $\tilde{\mathbf{Z}}_{(k)} \neq \mathbf{Z}_{(k)}^*$ , 从而  $\tilde{\mathbf{Z}} \neq \mathbf{Z}^*$ 。易知

$$\overline{\tilde{\mathbf{X}}} = \overline{\mathbf{X}^*} = \mathbf{0}.$$

容易验证

$$\overline{\tilde{\mathbf{Z}}} = \frac{1}{n} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)} = \frac{1}{n} \sum_{k=1}^n \hat{\mathbf{Q}}^{*\text{T}} \tilde{\mathbf{X}}_{(k)} = \hat{\mathbf{Q}}^{*\text{T}} \frac{1}{n} \sum_{k=1}^n \tilde{\mathbf{X}}_{(k)} = \hat{\mathbf{Q}}^{*\text{T}} \overline{\tilde{\mathbf{X}}} = \mathbf{0}.$$

由  $\tilde{\mathbf{X}} = \mathbf{X}^*$  和  $\overline{\mathbf{X}^*} = \mathbf{0}$  有

$$\tilde{\mathbf{X}}^* = \mathbf{X}^{**} = (x_{ij}^{**})_{n \times p} = \begin{pmatrix} \mathbf{X}_{(1)}^{**\text{T}} \\ \mathbf{X}_{(2)}^{**\text{T}} \\ \vdots \\ \mathbf{X}_{(n)}^{**\text{T}} \end{pmatrix},$$

其中

$$\begin{aligned} \mathbf{X}_{(k)}^{**} &= \left( \frac{x_{k1}^* - \bar{x}_1^*}{\sqrt{r_{11}}}, \frac{x_{k2}^* - \bar{x}_2^*}{\sqrt{r_{22}}}, \dots, \frac{x_{kp}^* - \bar{x}_p^*}{\sqrt{r_{pp}}} \right)^T \\ &= \left( \frac{x_{k1}^* - 0}{1}, \frac{x_{k2}^* - 0}{1}, \dots, \frac{x_{kp}^* - 0}{1} \right)^T \\ &= (x_{k1}^*, x_{k2}^*, \dots, x_{kp}^*)^T = \mathbf{X}_{(k)}^*, \end{aligned}$$

注意, 上式用到了(S4)的结论  $\text{cov}(\mathbf{X}^*) = \mathbf{R}$ 。则

$$\tilde{\mathbf{X}}^* = \mathbf{X}^{**} = \mathbf{X}^* = \tilde{\mathbf{X}}.$$

易知

$$\begin{aligned} \overline{\tilde{\mathbf{X}}}^* &= \overline{\mathbf{X}^{**}} = \overline{\mathbf{X}^*} = \mathbf{0}, \\ \tilde{\mathbf{X}}_{(k)}^* &= \mathbf{X}_{(k)}^{**} = \mathbf{X}_{(k)}^* = \tilde{\mathbf{X}}_{(k)}, \quad k = 1, \dots, n. \end{aligned}$$

类似于矩阵  $\mathbf{X}$  的标准化, 可得到矩阵  $\tilde{\mathbf{Z}}$  的标准化矩阵  $\tilde{\mathbf{Z}}^*$  满足

$$\tilde{\mathbf{Z}}^* = (\tilde{z}_{ij}^*)_{n \times p} = \begin{pmatrix} \tilde{\mathbf{Z}}_{(1)}^{*\text{T}} \\ \tilde{\mathbf{Z}}_{(2)}^{*\text{T}} \\ \vdots \\ \tilde{\mathbf{Z}}_{(n)}^{*\text{T}} \end{pmatrix} = (\tilde{\mathbf{Z}}_1^*, \tilde{\mathbf{Z}}_2^*, \dots, \tilde{\mathbf{Z}}_p^*),$$

其中

$$\begin{aligned} \tilde{\mathbf{Z}}_{(k)}^* &= \begin{pmatrix} (\tilde{z}_{k1} - \bar{\tilde{z}}_1) / \sqrt{\hat{\lambda}_1^*} \\ (\tilde{z}_{k2} - \bar{\tilde{z}}_2) / \sqrt{\hat{\lambda}_2^*} \\ \vdots \\ (\tilde{z}_{kp} - \bar{\tilde{z}}_p) / \sqrt{\hat{\lambda}_p^*} \end{pmatrix} = \begin{pmatrix} 1 / \sqrt{\hat{\lambda}_1^*} & & & \bar{\tilde{z}}_{k1} - \bar{\tilde{z}}_1 \\ & 1 / \sqrt{\hat{\lambda}_2^*} & & \bar{\tilde{z}}_{k2} - \bar{\tilde{z}}_2 \\ & & \ddots & \vdots \\ & & & 1 / \sqrt{\hat{\lambda}_p^*} \end{pmatrix} \begin{pmatrix} \tilde{z}_{k1} - \bar{\tilde{z}}_1 \\ \tilde{z}_{k2} - \bar{\tilde{z}}_2 \\ \vdots \\ \tilde{z}_{kp} - \bar{\tilde{z}}_p \end{pmatrix} \\ &= (\hat{\Lambda}^*)^{-\frac{1}{2}} (\tilde{\mathbf{Z}}_{(k)} - \bar{\tilde{\mathbf{Z}}}) = (\hat{\Lambda}^*)^{-\frac{1}{2}} \tilde{\mathbf{Z}}_{(k)}, \\ \hat{\Lambda}^* &= \text{diag}(\hat{\lambda}_1^*, \hat{\lambda}_2^*, \dots, \hat{\lambda}_p^*) = \text{cov}(\tilde{\mathbf{Z}}). \end{aligned}$$

注意，上式用到了(R2)的结论。从而

$$\tilde{\mathbf{Z}}^* = \begin{pmatrix} \tilde{\mathbf{Z}}_{(1)}^{*\top} \\ \tilde{\mathbf{Z}}_{(2)}^{*\top} \\ \vdots \\ \tilde{\mathbf{Z}}_{(n)}^{*\top} \end{pmatrix} = \begin{pmatrix} \tilde{\mathbf{Z}}_{(1)}^T (\hat{\Lambda}^*)^{-\frac{1}{2}} \\ \tilde{\mathbf{Z}}_{(2)}^T (\hat{\Lambda}^*)^{-\frac{1}{2}} \\ \vdots \\ \tilde{\mathbf{Z}}_{(n)}^T (\hat{\Lambda}^*)^{-\frac{1}{2}} \end{pmatrix} = \begin{pmatrix} \tilde{\mathbf{Z}}_{(1)}^T \\ \tilde{\mathbf{Z}}_{(2)}^T \\ \vdots \\ \tilde{\mathbf{Z}}_{(n)}^T \end{pmatrix} (\hat{\Lambda}^*)^{-\frac{1}{2}} = \tilde{\mathbf{Z}} (\hat{\Lambda}^*)^{-\frac{1}{2}}.$$

易知

$$\begin{aligned} \overline{\tilde{\mathbf{Z}}}^* &= \frac{1}{n} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)}^* = \frac{1}{n} \sum_{k=1}^n (\hat{\Lambda}^*)^{-\frac{1}{2}} \tilde{\mathbf{Z}}_{(k)} \\ &= (\hat{\Lambda}^*)^{-\frac{1}{2}} \left( \frac{1}{n} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)} \right) = (\hat{\Lambda}^*)^{-\frac{1}{2}} \overline{\tilde{\mathbf{Z}}} = \mathbf{0}. \end{aligned}$$

因为  $\tilde{\mathbf{Z}}_{(k)} = \hat{\mathbf{Q}}^{*\top} \tilde{\mathbf{X}}_{(k)}$ ，人们自然会想到  $\tilde{\mathbf{Z}}_{(k)}^* = \hat{\mathbf{Q}}^{*\top} \tilde{\mathbf{X}}_{(k)}^*$ ，同样，一般来说这是错误的。详细的证明请见本文的附录。

值得一提的是，矩阵  $\tilde{\mathbf{Z}}$  和它的标准化矩阵  $\tilde{\mathbf{Z}}^*$  的推导是新的。

我们用  $\mathbf{R} \geq \mathbf{0}$  表示它是一个非负定阵， $\mathbf{R} > \mathbf{0}$  表示它是一个正定阵。令  $\tilde{\mathbf{X}} = (\tilde{x}_{ij})_{n \times p} = \mathbf{X}^*$  为数据资料矩阵， $\tilde{\mathbf{Z}} = (\tilde{z}_{ij})_{n \times p}$  为主成分得分矩阵，则对于由  $\mathbf{R} \geq \mathbf{0}$  出发计算的样本主成分有如下性质：

(R1).

$$\begin{aligned} \text{cov}(\tilde{\mathbf{X}}) &= \text{cov}(\mathbf{X}^*) = \text{cor}(\mathbf{X}) = \mathbf{R} = (r_{ij})_{p \times p} \\ &= \text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{X}}) = (\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j))_{p \times p}, \end{aligned}$$

特别地，

$$\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) = \text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*) = r_{ij}, \quad i, j = 1, \dots, p.$$

(R2).

$$\text{cov}(\tilde{\mathbf{Z}}) = \text{cov}(\tilde{\mathbf{Z}}, \tilde{\mathbf{Z}}) = (\text{cov}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j))_{p \times p} = \hat{\Lambda}^*,$$

特别地，

$$\begin{aligned} \text{cov}(\tilde{\mathbf{Z}}_j) &= \text{cov}(\tilde{\mathbf{Z}}_j, \tilde{\mathbf{Z}}_j) = \hat{\lambda}_j^*, \quad j = 1, \dots, p, \\ \text{cov}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j) &= 0, \quad i \neq j, \quad i, j = 1, \dots, p. \end{aligned}$$

(R3).

$$\text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = (\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j))_{p \times p} = (\hat{q}_{ij}^* \hat{\lambda}_j^*)_{p \times p} = \hat{\mathbf{Q}}^* \hat{\Lambda}^*,$$

特别地，

$$\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j) = \hat{q}_{ij}^* \hat{\lambda}_j^*, \quad i, j = 1, \dots, p.$$

(R4).

$$\begin{aligned}\text{cor}(\tilde{\mathbf{X}}) &= \text{cor}(\mathbf{X}^*) = \text{cov}(\mathbf{X}^{**}) = \text{cov}(\mathbf{X}^*) = \text{cor}(\mathbf{X}) = \mathbf{R} = (r_{ij})_{p \times p} \\ &= \text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{X}}) = (\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j))_{p \times p},\end{aligned}$$

特别地, 对  $i, j = 1, \dots, p$ ,

$$\begin{aligned}\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) &= \text{cor}(\mathbf{X}_i^*, \mathbf{X}_j^*) = \text{cov}(\mathbf{X}_i^{**}, \mathbf{X}_j^{**}) = \text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*) \\ &= \text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) = \text{cor}(\mathbf{X}_i, \mathbf{X}_j) = r_{ij}.\end{aligned}$$

(R5). 若  $\mathbf{R} > \mathbf{0}$ , 则

$$\begin{aligned}\text{cor}(\tilde{\mathbf{Z}}) &= \text{cor}(\tilde{\mathbf{Z}}, \tilde{\mathbf{Z}}) = (\text{cor}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j))_{p \times p} = \text{cov}(\tilde{\mathbf{Z}}^*) \\ &= \mathbf{E}_{p \times p} = \text{diag}(1, 1, \dots, 1)_{p \times p},\end{aligned}$$

特别地,

$$\begin{aligned}\text{cor}(\tilde{\mathbf{Z}}_j) &= \text{cor}(\tilde{\mathbf{Z}}_j, \tilde{\mathbf{Z}}_j) = 1, \quad j = 1, \dots, p, \\ \text{cor}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j) &= 0, \quad i \neq j, \quad i, j = 1, \dots, p.\end{aligned}$$

(R6). 若  $\mathbf{R} > \mathbf{0}$ , 则

$$\begin{aligned}\text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) &= (\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j))_{p \times p} = \text{cov}(\tilde{\mathbf{X}}^*, \tilde{\mathbf{Z}}^*) = (\text{cov}(\mathbf{X}_i^*, \tilde{\mathbf{Z}}_j^*))_{p \times p} \\ &= \hat{\mathbf{Q}}^* (\hat{\Lambda}^*)^{\frac{1}{2}} = \left( \hat{q}_{ij}^* \sqrt{\hat{\lambda}_j^*} \right)_{p \times p},\end{aligned}$$

特别地,

$$\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j) = \text{cov}(\mathbf{X}_i^*, \tilde{\mathbf{Z}}_j^*) = \hat{q}_{ij}^* \sqrt{\hat{\lambda}_j^*}, \quad i, j = 1, \dots, p.$$

(R7). 样本总方差

$$\sum_{j=1}^p \text{cov}(\tilde{\mathbf{X}}_j) = \sum_{j=1}^p 1 = p = \sum_{j=1}^p \hat{\lambda}_j^* = \sum_{j=1}^p \text{cov}(\tilde{\mathbf{Z}}_j).$$

此式表明了样本  $\tilde{\mathbf{X}}_1, \dots, \tilde{\mathbf{X}}_p$  的样本(协)方差之和等于样本主成分  $\tilde{\mathbf{Z}}_1, \dots, \tilde{\mathbf{Z}}_p$  的样本(协)方差之和。

在以上 7 个性质中, (R1)显然, (R2)和(R6)的分量形式的结果和(R7)可以在[7]中找到。

注意, 在(R5)和(R6)中我们要求  $\mathbf{R} > \mathbf{0}$ , 而其余性质只要求  $\mathbf{R} \geq \mathbf{0}$ 。因为在(R5)和(R6)的证明中会涉及到

$$(\hat{\Lambda}^*)^{-\frac{1}{2}} = \text{diag} \left( \frac{1}{\sqrt{\hat{\lambda}_1^*}}, \frac{1}{\sqrt{\hat{\lambda}_2^*}}, \dots, \frac{1}{\sqrt{\hat{\lambda}_p^*}} \right),$$

若  $\mathbf{R}$  有一个 0 特征值, 即  $\hat{\lambda}_p^* = 0$ , 则  $1/\sqrt{\hat{\lambda}_p^*}$  是没有意义的, 从而结论不成立, 数值结果也证实了这一点。

由性质(R1)-(R6)归纳得到样本  $\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j, \tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j$  的样本协方差关系图((R1)-(R3))和样本相关系数关系图((R4)-(R6)), 如图 2。

性质(R1)-(R7)的证明有些是初等的, 有些需要一定的技巧, 由于这些证明较占篇幅, 所以把它们放到了本文的附录中。

### 3. 数值模拟

此节我们在 R 软件[11]中编写程序, 通过数值模拟来验证从样本协方差矩阵  $\mathbf{S}$  出发计算的样本主成分的性质(S1)-(S7)及从样本相关矩阵  $\mathbf{R}$  出发计算的样本主成分的性质(R1)-(R7)。

在 R 软件中, 求矩阵的样本协方差矩阵的函数是 cov(), 求矩阵的样本相关矩阵的函数是 cor() [12]。性质(S1)-(S7)即是要验证

$$(S1). \text{cov}(\mathbf{X}) = \mathbf{S}, \quad (S2). \text{cov}(\mathbf{Z}) = \hat{\Lambda}, \quad (S3). \text{cov}(\mathbf{X}, \mathbf{Z}) = \hat{Q}\hat{\Lambda},$$

$$(S4). \text{cor}(\mathbf{X}) = \mathbf{R}, \quad (S5). \text{cor}(\mathbf{Z}) = \mathbf{E}_{p \times p},$$

$$(S6). \text{cor}(\mathbf{X}, \mathbf{Z}) = \hat{D}^{-\frac{1}{2}}\hat{Q}\hat{\Lambda}^{\frac{1}{2}} = (\text{Diag}(\mathbf{S}))^{-\frac{1}{2}}\hat{Q}\hat{\Lambda}^{\frac{1}{2}},$$

$$(S7). \text{tr}(\text{cov}(\mathbf{X})) = \text{tr}(\text{cov}(\mathbf{Z})).$$

注意在(S1)中的  $\mathbf{S}$  和(S4)中的  $\mathbf{R}$  分别为

$$\mathbf{S} = \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)} - \bar{\mathbf{X}})(\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T,$$

$$\mathbf{R} = \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)}^* - \bar{\mathbf{X}}^*)(\mathbf{X}_{(k)}^* - \bar{\mathbf{X}}^*)^T.$$

性质(R1)-(R7)即是要验证

$$(R1). \text{cov}(\tilde{\mathbf{X}}) = \mathbf{R}, \quad (R2). \text{cov}(\tilde{\mathbf{Z}}) = \hat{\Lambda}^*, \quad (R3). \text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \hat{Q}^*\hat{\Lambda}^*,$$

$$(R4). \text{cor}(\tilde{\mathbf{X}}) = \mathbf{R}, \quad (R5). \text{cor}(\tilde{\mathbf{Z}}) = \mathbf{E}_{p \times p},$$

$$(R6). \text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \hat{Q}^*(\hat{\Lambda}^*)^{\frac{1}{2}}, \quad (R7). \text{tr}(\text{cov}(\tilde{\mathbf{X}})) = p = \text{tr}(\text{cov}(\tilde{\mathbf{Z}})).$$

注意在(S5)和(S6)中要求  $\mathbf{S} > \mathbf{0}$ , 在(R5)和(R6)中要求  $\mathbf{R} > \mathbf{0}$ 。

下面我们举两个例子来验证(S1)-(S7)和(R1)-(R7)的正确性。

**例 1.**

$$\mathbf{X} = (x_{ij})_{n \times p}, n = 4, p = 3, x_{ij} \sim N(0, 1).$$

为重复本文的结果, 我们在 R 软件中使用 set.seed(1), 此时

$$\mathbf{X} = \begin{pmatrix} -0.6264538 & 0.3295078 & 0.5757814 \\ 0.1836433 & -0.8204684 & -0.3053884 \\ -0.8356286 & 0.4874291? & 1.5117812 \\ 1.5952808 & 0.7383247 & 0.3898432 \end{pmatrix}.$$

容易验证  $\mathbf{S} > \mathbf{0}$  且  $\mathbf{R} > \mathbf{0}$ , (S1)-(S7)和(R1)-(R7)均是正确的。详细的数值模拟结果请见本文的附录。

下面给一个  $\mathbf{S} \geq \mathbf{0}$  且  $\mathbf{R} \geq \mathbf{0}$  的例子, 即  $\mathbf{S}$  和  $\mathbf{R}$  都有 1 个 0 特征值, 此时(S5), (S6), (R5)和(R6)是不成立的, 但其余性质是成立的。

**例 2.**

$$\mathbf{X} = (x_{ij})_{n \times p}, n = p = 3, x_{ij} \sim N(0, 1).$$

为重复本文的结果, 我们在 R 软件中使用 set.seed(1), 此时

$$\mathbf{X} = \begin{pmatrix} -0.6264538 & 1.5952808 & 0.4874291 \\ 0.1836433 & 0.3295078 & 0.7383247 \\ -0.8356286 & -0.8204684 & 0.5757814 \end{pmatrix}.$$

详细的数值模拟结果请见本文的附录。

## 4. 总结

我们给出了样本主成分的性质及证明，分两种情况讨论：从  $\mathbf{S}$  出发求主成分和从  $\mathbf{R}$  出发求主成分。在从  $\mathbf{S}$  出发求主成分中，给出了 7 个性质(S1)-(S7)及它们的证明，这些性质说明的关系在图 1 中得到了充分的展现。同样，在从  $\mathbf{R}$  出发求主成分中，给出了 7 个性质(R1)-(R7)及它们的证明，这些性质说明的关系在图 2 中得到了充分的展现。最后我们给出了两个数值模拟的例子来验证性质(S1)-(S7)和(R1)-(R7)的正确性。例 1 中的  $\mathbf{S} > \mathbf{0}$  且  $\mathbf{R} > \mathbf{0}$ ，从而性质(S1)-(S7)和(R1)-(R7)均是正确的。例 2 中的  $\mathbf{S} \geq \mathbf{0}$  且  $\mathbf{R} \geq \mathbf{0}$ ，即  $\mathbf{S}$  和  $\mathbf{R}$  都有 1 个 0 特征值，数值模拟显示(S5), (S6), (R5)和(R6)是不成立的，但其余性质是成立的，与理论结果相一致。

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## 附 录

附录中包含了性质(S1)-(S7)和(R1)-(R7)的证明，还有两个例子的详细的数值模拟结果。

### A.1. 准备知识及杂项证明

#### 准备知识

样本的协方差(矩阵)和相关系数(矩阵)的定义及性质请参见[1]。[1]中有三个公式在本文中经常用到：

$$\text{cov}(\mathbf{X}, \mathbf{Y}) = \left( \text{cov}(\mathbf{X}_i, \mathbf{Y}_j) \right)_{p \times q}, \quad (\text{A.1})$$

$$\text{cor}(\mathbf{X}, \mathbf{Y}) = \left[ \text{Diag}(\text{cov}(\mathbf{X})) \right]^{-\frac{1}{2}} \text{cov}(\mathbf{X}, \mathbf{Y}) \left[ \text{Diag}(\text{cov}(\mathbf{Y})) \right]^{-\frac{1}{2}}, \quad (\text{A.2})$$

其中  $\text{Diag}(\text{cov}(\mathbf{X}))$  表示取矩阵  $\text{cov}(\mathbf{X})$  的对角线元素构成的对角阵，

$$\text{cor}(\mathbf{X}, \mathbf{Y}) = \left( \text{cor}(\mathbf{X}_i, \mathbf{Y}_j) \right)_{p \times q}. \quad (\text{A.3})$$

另外，还有

$$\mathbf{X}^{**} = \mathbf{X}^* = (x_{ij}^*)_{n \times p}. \quad (\text{A.4})$$

#### 杂项证明

因为  $\mathbf{Z}_{(k)} = \hat{\mathbf{Q}}^T \mathbf{X}_{(k)}$ ，人们自然会想到  $\mathbf{Z}_{(k)}^* = \hat{\mathbf{Q}}^T \mathbf{X}_{(k)}^*$ ，但是一般来说这是错误的。从[1]中，我们知道

$$\mathbf{X}_{(k)}^* = \hat{\mathbf{D}}^{-\frac{1}{2}} (\mathbf{X}_{(k)} - \bar{\mathbf{X}}),$$

其中，

$$\hat{\mathbf{D}} = \hat{\mathbf{D}}^X = \text{diag}(s_{11}, s_{22}, \dots, s_{pp}) = \text{Diag}(\mathbf{S}) = \text{Diag}(\text{cov}(\mathbf{X})).$$

易知

$$\hat{\mathbf{Q}}^T \mathbf{X}_{(k)}^* = \hat{\mathbf{Q}}^T \hat{\mathbf{D}}^{-\frac{1}{2}} (\mathbf{X}_{(k)} - \bar{\mathbf{X}}),$$

$$\mathbf{Z}_{(k)}^* = \hat{\Lambda}^{-\frac{1}{2}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}}) = \hat{\Lambda}^{-\frac{1}{2}} (\hat{\mathbf{Q}}^T \mathbf{X}_{(k)} - \hat{\mathbf{Q}}^T \bar{\mathbf{X}}) = \hat{\Lambda}^{-\frac{1}{2}} \hat{\mathbf{Q}}^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}).$$

则

$$\begin{aligned}
& \hat{\mathbf{Q}}^T \mathbf{X}_{(k)}^* = \mathbf{Z}_{(k)}^* \Leftrightarrow \hat{\mathbf{Q}}^T \hat{\mathbf{D}}^{-\frac{1}{2}} = \hat{\Lambda}^{-\frac{1}{2}} \hat{\mathbf{Q}}^T \\
& \Leftrightarrow \begin{pmatrix} \hat{q}_{11} & \hat{q}_{21} & \cdots & \hat{q}_{p1} \\ \hat{q}_{12} & \hat{q}_{22} & \cdots & \hat{q}_{p2} \\ \vdots & \vdots & & \vdots \\ \hat{q}_{1p} & \hat{q}_{2p} & \cdots & \hat{q}_{pp} \end{pmatrix} \begin{pmatrix} \frac{1}{\sqrt{s_{11}}} & & & \\ & \frac{1}{\sqrt{s_{22}}} & & \\ & & \ddots & \\ & & & \frac{1}{\sqrt{s_{pp}}} \end{pmatrix} \\
& = \begin{pmatrix} \frac{1}{\sqrt{\hat{\lambda}_1}} & & & \\ & \frac{1}{\sqrt{\hat{\lambda}_2}} & & \\ & & \ddots & \\ & & & \frac{1}{\sqrt{\hat{\lambda}_p}} \end{pmatrix} \begin{pmatrix} \hat{q}_{11} & \hat{q}_{21} & \cdots & \hat{q}_{p1} \\ \hat{q}_{12} & \hat{q}_{22} & \cdots & \hat{q}_{p2} \\ \vdots & \vdots & & \vdots \\ \hat{q}_{1p} & \hat{q}_{2p} & \cdots & \hat{q}_{pp} \end{pmatrix} \\
& \Leftrightarrow \begin{pmatrix} \frac{\hat{q}_{11}}{\sqrt{s_{11}}} & \frac{\hat{q}_{21}}{\sqrt{s_{22}}} & \cdots & \frac{\hat{q}_{p1}}{\sqrt{s_{pp}}} \\ \frac{\hat{q}_{12}}{\sqrt{s_{11}}} & \frac{\hat{q}_{22}}{\sqrt{s_{22}}} & \cdots & \frac{\hat{q}_{p2}}{\sqrt{s_{pp}}} \\ \vdots & \vdots & & \vdots \\ \frac{\hat{q}_{1p}}{\sqrt{s_{11}}} & \frac{\hat{q}_{2p}}{\sqrt{s_{22}}} & \cdots & \frac{\hat{q}_{pp}}{\sqrt{s_{pp}}} \end{pmatrix} = \begin{pmatrix} \frac{\hat{q}_{11}}{\sqrt{\hat{\lambda}_1}} & \frac{\hat{q}_{21}}{\sqrt{\hat{\lambda}_1}} & \cdots & \frac{\hat{q}_{p1}}{\sqrt{\hat{\lambda}_1}} \\ \frac{\hat{q}_{12}}{\sqrt{\hat{\lambda}_2}} & \frac{\hat{q}_{22}}{\sqrt{\hat{\lambda}_2}} & \cdots & \frac{\hat{q}_{p2}}{\sqrt{\hat{\lambda}_2}} \\ \vdots & \vdots & & \vdots \\ \frac{\hat{q}_{1p}}{\sqrt{\hat{\lambda}_p}} & \frac{\hat{q}_{2p}}{\sqrt{\hat{\lambda}_p}} & \cdots & \frac{\hat{q}_{pp}}{\sqrt{\hat{\lambda}_p}} \end{pmatrix} \\
& \Leftrightarrow s_{11} = s_{22} = \cdots = s_{pp} = \hat{\lambda}_1 = \hat{\lambda}_2 = \cdots = \hat{\lambda}_p.
\end{aligned}$$

上式一般来说是不会一定成立的, 所以一般来说  $\mathbf{Z}_{(k)}^* \neq \hat{\mathbf{Q}}^T \mathbf{X}_{(k)}^*$ 。

因为  $\tilde{\mathbf{Z}}_{(k)} = \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}$ , 人们自然会想到  $\tilde{\mathbf{Z}}_{(k)}^* = \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}^*$ , 同样, 一般来说这是错误的。我们有

$$\begin{aligned}
& \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}^* = \hat{\mathbf{Q}}^{*T} \mathbf{X}_{(k)}^{**} = \hat{\mathbf{Q}}^{*T} \mathbf{X}_{(k)}^* = \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}, \\
& \tilde{\mathbf{Z}}_{(k)}^* = (\hat{\Lambda}^*)^{-\frac{1}{2}} \tilde{\mathbf{Z}}_{(k)} = (\hat{\Lambda}^*)^{-\frac{1}{2}} \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}.
\end{aligned}$$

则

$$\hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}^* = \tilde{\mathbf{Z}}_{(k)}^* \Leftrightarrow (\hat{\Lambda}^*)^{-\frac{1}{2}} = \mathbf{E}_{p \times p} \Leftrightarrow \hat{\Lambda}^* = \mathbf{E}_{p \times p}.$$

同样, 上式一般来说是不会一定成立的, 所以一般来说  $\tilde{\mathbf{Z}}_{(k)}^* \neq \hat{\mathbf{Q}}^{*T} \tilde{\mathbf{X}}_{(k)}^*$ 。

## A.2. 从 S 出发求主成分

证明:

(S1). 由数据资料阵  $\mathbf{X}$  的样本协方差矩阵的定义有

$$\text{cov}(\mathbf{X}) = \text{cov}(\mathbf{X}, \mathbf{X}) = \mathbf{S}^X = \mathbf{S} = (s_{ij})_{p \times p}.$$

由(A.1)得,

$$\text{cov}(\mathbf{X}, \mathbf{X}) = (\text{cov}(\mathbf{X}_i, \mathbf{X}_j))_{p \times p}.$$

从而,

$$\text{cov}(\mathbf{X}_i, \mathbf{X}_j) = s_{ij} = \frac{1}{n-1} \sum_{k=1}^n (x_{ki} - \bar{x}_i)(x_{kj} - \bar{x}_j), \quad i, j = 1, \dots, p.$$

(S2). 易知

$$\mathbf{Z}_{(k)} - \bar{\mathbf{Z}} = \hat{\mathbf{Q}}^T \mathbf{X}_{(k)} - \hat{\mathbf{Q}}^T \bar{\mathbf{X}} = \hat{\mathbf{Q}}^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}),$$

从而由矩阵  $\mathbf{Z}$  的样本协方差矩阵的定义有

$$\begin{aligned} \text{cov}(\mathbf{Z}) &= \text{cov}(\mathbf{Z}, \mathbf{Z}) = \frac{1}{n-1} \sum_{k=1}^n (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})(\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \\ &= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{Q}}^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}})(\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \hat{\mathbf{Q}} \\ &= \hat{\mathbf{Q}}^T \left[ \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)} - \bar{\mathbf{X}})(\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \right] \hat{\mathbf{Q}} \\ &= \hat{\mathbf{Q}}^T \mathbf{S} \hat{\mathbf{Q}} = \hat{\Lambda}. \end{aligned}$$

由(A.1)得

$$\text{cov}(\mathbf{Z}, \mathbf{Z}) = (\text{cov}(\mathbf{Z}_i, \mathbf{Z}_j))_{p \times p} = \hat{\Lambda} = \begin{pmatrix} \hat{\lambda}_1 & & & \\ & \hat{\lambda}_2 & & \\ & & \ddots & \\ & & & \hat{\lambda}_p \end{pmatrix}.$$

从而

$$\begin{aligned} \text{cov}(\mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_j, \mathbf{Z}_j) = \hat{\lambda}_j, \quad j = 1, \dots, p, \\ \text{cov}(\mathbf{Z}_i, \mathbf{Z}_j) &= 0, \quad i \neq j, \quad i, j = 1, \dots, p. \end{aligned}$$

在证明  $\text{cov}(\mathbf{Z}_j) = \hat{\lambda}_j$  时, 我们也可以利用样本协方差的定义直接来求。

$$\mathbf{Z}_j = \begin{pmatrix} z_{1j} \\ z_{2j} \\ \vdots \\ z_{nj} \end{pmatrix} = \mathbf{X} \hat{\mathbf{a}}_j = \begin{pmatrix} \mathbf{X}_{(1)}^T \\ \mathbf{X}_{(2)}^T \\ \vdots \\ \mathbf{X}_{(n)}^T \end{pmatrix} \hat{\mathbf{a}}_j = \begin{pmatrix} \mathbf{X}_{(1)}^T \hat{\mathbf{a}}_j \\ \mathbf{X}_{(2)}^T \hat{\mathbf{a}}_j \\ \vdots \\ \mathbf{X}_{(n)}^T \hat{\mathbf{a}}_j \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_j^T \mathbf{X}_{(1)} \\ \hat{\mathbf{a}}_j^T \mathbf{X}_{(2)} \\ \vdots \\ \hat{\mathbf{a}}_j^T \mathbf{X}_{(n)} \end{pmatrix},$$

从而

$$\begin{aligned} z_{kj} &= \hat{\mathbf{a}}_j^T \mathbf{X}_{(k)}, \quad k = 1, \dots, n, \\ \bar{z}_j &= \frac{1}{n} \sum_{k=1}^n z_{kj} = \frac{1}{n} \sum_{k=1}^n \hat{\mathbf{a}}_j^T \mathbf{X}_{(k)} = \hat{\mathbf{a}}_j^T \left( \frac{1}{n} \sum_{k=1}^n \mathbf{X}_{(k)} \right) = \hat{\mathbf{a}}_j^T \bar{\mathbf{X}}, \\ z_{kj} - \bar{z}_j &= \hat{\mathbf{a}}_j^T \mathbf{X}_{(k)} - \hat{\mathbf{a}}_j^T \bar{\mathbf{X}} = \hat{\mathbf{a}}_j^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) = (\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \hat{\mathbf{a}}_j. \end{aligned}$$

因此

$$\begin{aligned}
\text{cov}(\mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_j, \mathbf{Z}_j) \\
&= \frac{1}{n-1} \sum_{k=1}^n (z_{kj} - \bar{z}_j)^2 \\
&= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{a}}_j^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) (\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \hat{\mathbf{a}}_j \\
&= \hat{\mathbf{a}}_j^T \left[ \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) (\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \right] \hat{\mathbf{a}}_j \\
&= \hat{\mathbf{a}}_j^T \mathbf{S} \hat{\mathbf{a}}_j = \hat{\mathbf{a}}_j^T \hat{\lambda}_j \hat{\mathbf{a}}_j = \hat{\lambda}_j.
\end{aligned}$$

类似地, 在证明  $\text{cov}(\mathbf{Z}_i, \mathbf{Z}_j) = 0, i \neq j, i, j = 1, \dots, p$  时, 我们也可以利用样本协方差的定义直接来求。

$$\mathbf{Z}_i = \begin{pmatrix} z_{1i} \\ z_{2i} \\ \vdots \\ z_{ni} \end{pmatrix} = \mathbf{X} \hat{\mathbf{a}}_i = \begin{pmatrix} \mathbf{X}_{(1)}^T \\ \mathbf{X}_{(2)}^T \\ \vdots \\ \mathbf{X}_{(n)}^T \end{pmatrix} \hat{\mathbf{a}}_i = \begin{pmatrix} \mathbf{X}_{(1)}^T \hat{\mathbf{a}}_i \\ \mathbf{X}_{(2)}^T \hat{\mathbf{a}}_i \\ \vdots \\ \mathbf{X}_{(n)}^T \hat{\mathbf{a}}_i \end{pmatrix} = \begin{pmatrix} \hat{\mathbf{a}}_i^T \mathbf{X}_{(1)} \\ \hat{\mathbf{a}}_i^T \mathbf{X}_{(2)} \\ \vdots \\ \hat{\mathbf{a}}_i^T \mathbf{X}_{(n)} \end{pmatrix},$$

$$z_{ki} - \bar{z}_i = \hat{\mathbf{a}}_i^T \mathbf{X}_{(k)} - \hat{\mathbf{a}}_i^T \bar{\mathbf{X}} = \hat{\mathbf{a}}_i^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) = (\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \hat{\mathbf{a}}_i.$$

因此对  $i \neq j, i, j = 1, \dots, p$ ,

$$\begin{aligned}
\text{cov}(\mathbf{Z}_i, \mathbf{Z}_j) &= \frac{1}{n-1} \sum_{k=1}^n (z_{ki} - \bar{z}_i)(z_{kj} - \bar{z}_j) \\
&= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{a}}_i^T (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) (\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \hat{\mathbf{a}}_j \\
&= \hat{\mathbf{a}}_i^T \left[ \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) (\mathbf{X}_{(k)} - \bar{\mathbf{X}})^T \right] \hat{\mathbf{a}}_j \\
&= \hat{\mathbf{a}}_i^T \mathbf{S} \hat{\mathbf{a}}_j = \hat{\mathbf{a}}_i^T \hat{\lambda}_j \hat{\mathbf{a}}_j = \hat{\lambda}_j \hat{\mathbf{a}}_i^T \hat{\mathbf{a}}_j = 0.
\end{aligned}$$

由此我们发现用矩阵形式来证明比用分量形式来证明要简洁得多。

(S3). 由(A.1), 得

$$\text{cov}(\mathbf{X}, \mathbf{Z}) = \left( \text{cov}(\mathbf{X}_i, \mathbf{Z}_j) \right)_{p \times p}.$$

由  $\mathbf{Z}_{(k)} = \hat{\mathbf{Q}}^T \mathbf{X}_{(k)}$ , 得

$$\mathbf{X}_{(k)} = \hat{\mathbf{Q}} \mathbf{Z}_{(k)}, \tag{A.5}$$

即

$$\begin{pmatrix} x_{k1} \\ x_{k2} \\ \vdots \\ x_{kp} \end{pmatrix} = \left( \hat{q}_{ij} \right)_{p \times p} \begin{pmatrix} z_{k1} \\ z_{k2} \\ \vdots \\ z_{kp} \end{pmatrix},$$

则

$$x_{ki} = (\hat{q}_{i1}, \hat{q}_{i2}, \dots, \hat{q}_{ip}) \begin{pmatrix} z_{k1} \\ z_{k2} \\ \vdots \\ z_{kp} \end{pmatrix} = \sum_{r=1}^p \hat{q}_{ir} z_{kr} = \sum_{r=1}^p z_{kr} \hat{q}_{ir},$$

$$\begin{aligned} \bar{x}_i &= \frac{1}{n} \sum_{k=1}^n x_{ki} = \frac{1}{n} \sum_{k=1}^n \sum_{r=1}^p z_{kr} \hat{q}_{ir} = \frac{1}{n} \sum_{r=1}^p \sum_{k=1}^n z_{kr} \hat{q}_{ir} \\ &= \sum_{r=1}^p \left( \frac{1}{n} \sum_{k=1}^n z_{kr} \right) \hat{q}_{ir} = \sum_{r=1}^p \bar{z}_r \hat{q}_{ir}, \end{aligned}$$

$$x_{ki} - \bar{x}_i = \sum_{r=1}^p z_{kr} \hat{q}_{ir} - \sum_{r=1}^p \bar{z}_r \hat{q}_{ir} = \sum_{r=1}^p (z_{kr} - \bar{z}_r) \hat{q}_{ir}.$$

因此

$$\begin{aligned} \text{cov}(X_i, Z_j) &= \frac{1}{n-1} \sum_{k=1}^n (x_{ki} - \bar{x}_i)(z_{kj} - \bar{z}_j) \\ &= \frac{1}{n-1} \sum_{k=1}^n \left\{ \left[ \sum_{r=1}^p (z_{kr} - \bar{z}_r) \hat{q}_{ir} \right] (z_{kj} - \bar{z}_j) \right\} \\ &= \frac{1}{n-1} \sum_{k=1}^n \left\{ \sum_{r=1}^p [(z_{kr} - \bar{z}_r)(z_{kj} - \bar{z}_j) \hat{q}_{ir}] \right\} \\ &= \frac{1}{n-1} \sum_{r=1}^p \left\{ \sum_{k=1}^n [(z_{kr} - \bar{z}_r)(z_{kj} - \bar{z}_j) \hat{q}_{ir}] \right\} \\ &= \sum_{r=1}^p \left\{ \left[ \frac{1}{n-1} \sum_{k=1}^n (z_{kr} - \bar{z}_r)(z_{kj} - \bar{z}_j) \right] \hat{q}_{ir} \right\} \\ &= \sum_{r=1}^p \text{cov}(Z_r, Z_j) \hat{q}_{ir} \\ &= \text{cov}(Z_j, Z_j) \hat{q}_{ij} = \hat{q}_{ij} \hat{\lambda}_j. \end{aligned}$$

上式最后两个等式用到了性质(S2)的结果。从而有

$$\begin{aligned} (\text{cov}(X_i, Z_j))_{p \times p} &= (\hat{q}_{ij} \hat{\lambda}_j)_{p \times p} = \begin{pmatrix} \hat{q}_{11} \hat{\lambda}_1 & \hat{q}_{12} \hat{\lambda}_2 & \cdots & \hat{q}_{1p} \hat{\lambda}_p \\ \hat{q}_{21} \hat{\lambda}_1 & \hat{q}_{22} \hat{\lambda}_2 & \cdots & \hat{q}_{2p} \hat{\lambda}_p \\ \vdots & \vdots & & \vdots \\ \hat{q}_{p1} \hat{\lambda}_1 & \hat{q}_{p2} \hat{\lambda}_2 & \cdots & \hat{q}_{pp} \hat{\lambda}_p \end{pmatrix} \\ &= (\hat{q}_{ij})_{p \times p} \begin{pmatrix} \hat{\lambda}_1 & & & \\ & \hat{\lambda}_2 & & \\ & & \ddots & \\ & & & \hat{\lambda}_p \end{pmatrix} = \hat{Q} \hat{\Lambda}. \end{aligned}$$

在证明  $\text{cov}(X, Z) = \hat{Q} \hat{\Lambda}$  时也可以利用矩阵化的方法来证明。由(A.5)，有

$$\bar{X} = \frac{1}{n} \sum_{k=1}^n X_{(k)} = \frac{1}{n} \sum_{k=1}^n \hat{Q} Z_{(k)} = \hat{Q} \left( \frac{1}{n} \sum_{k=1}^n Z_{(k)} \right) = \hat{Q} \bar{Z},$$

则

$$\mathbf{X}_{(k)} - \bar{\mathbf{X}} = \hat{\mathbf{Q}} \mathbf{Z}_{(k)} - \hat{\mathbf{Q}} \bar{\mathbf{Z}} = \hat{\mathbf{Q}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}}).$$

从而有

$$\begin{aligned} \text{cov}(\mathbf{X}, \mathbf{Z}) &= \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)} - \bar{\mathbf{X}})(\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \\ &= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{Q}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})(\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \\ &= \hat{\mathbf{Q}} \left[ \frac{1}{n-1} \sum_{k=1}^n (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})(\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \right] \\ &= \hat{\mathbf{Q}} \text{cov}(\mathbf{Z}) = \hat{\mathbf{Q}} \hat{\Lambda}. \end{aligned}$$

上式最后一个等式用到了性质(S2)的结果。由此发现矩阵化可以大大简化证明。

(S4). 由数据资料阵  $\mathbf{X}$  的样本相关矩阵的定义有

$$\text{cor}(\mathbf{X}) = \text{cov}(\mathbf{X}^*) = \mathbf{R}^X = \mathbf{R} = (r_{ij})_{p \times p},$$

由(A.1), 有

$$\text{cov}(\mathbf{X}^*) = \text{cov}(\mathbf{X}^*, \mathbf{X}^*) = (\text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*))_{p \times p},$$

由(A.3), 有

$$\text{cor}(\mathbf{X}) = \text{cor}(\mathbf{X}, \mathbf{X}) = (\text{cor}(\mathbf{X}_i, \mathbf{X}_j))_{p \times p}.$$

从而有

$$\text{cor}(\mathbf{X}_i, \mathbf{X}_j) = \text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*) = r_{ij}, \quad i, j = 1, \dots, p.$$

(S5). 由矩阵的样本相关矩阵的定义和(A.1)有

$$\text{cor}(\mathbf{Z}) = \text{cov}(\mathbf{Z}^*) = \text{cov}(\mathbf{Z}^*, \mathbf{Z}^*) = (\text{cov}(\mathbf{Z}_i^*, \mathbf{Z}_j^*))_{p \times p},$$

由(A.3)有

$$\text{cor}(\mathbf{Z}) = \text{cor}(\mathbf{Z}, \mathbf{Z}) = (\text{cor}(\mathbf{Z}_i, \mathbf{Z}_j))_{p \times p}.$$

由  $\overline{\mathbf{Z}^*} = 0$  和(S2)的结论有

$$\begin{aligned} \text{cov}(\mathbf{Z}^*) &= \frac{1}{n-1} \sum_{k=1}^n (\mathbf{Z}_{(k)}^* - \overline{\mathbf{Z}^*})(\mathbf{Z}_{(k)}^* - \overline{\mathbf{Z}^*})^T = \frac{1}{n-1} \sum_{k=1}^n \mathbf{Z}_{(k)}^* \mathbf{Z}_{(k)}^{*\top} \\ &= \frac{1}{n-1} \sum_{k=1}^n \hat{\Lambda}^{\frac{1}{2}} (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})(\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \hat{\Lambda}^{-\frac{1}{2}} \\ &= \hat{\Lambda}^{-\frac{1}{2}} \left[ \frac{1}{n-1} \sum_{k=1}^n (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})(\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \right] \hat{\Lambda}^{-\frac{1}{2}} \\ &= \hat{\Lambda}^{-\frac{1}{2}} \text{cov}(\mathbf{Z}) \hat{\Lambda}^{-\frac{1}{2}} = \hat{\Lambda}^{-\frac{1}{2}} \hat{\Lambda} \hat{\Lambda}^{-\frac{1}{2}} = \hat{\Lambda}^0 = \mathbf{E}_{p \times p} = \text{diag}(1, 1, \dots, 1)_{p \times p}. \end{aligned}$$

其实我们也可以利用(A.2)和(S2)的结论来证明

$$\begin{aligned}\text{cor}(\mathbf{Z}) &= \text{cor}(\mathbf{Z}, \mathbf{Z}) \\ &= [\text{Diag}(\text{cov}(\mathbf{Z}))]^{\frac{1}{2}} \text{cov}(\mathbf{Z}, \mathbf{Z}) [\text{Diag}(\text{cov}(\mathbf{Z}))]^{\frac{1}{2}} \\ &= \hat{\Lambda}^{-\frac{1}{2}} \hat{\Lambda} \hat{\Lambda}^{-\frac{1}{2}} = \hat{\Lambda}^0 = \mathbf{E}_{p \times p}.\end{aligned}$$

由此发现式(A.2)在求相关矩阵时非常有力，原因在于它使得我们可以利用已有的结论(S2)来简化证明。式(A.2)在(S6), (R4)-(R6)的证明中求相关矩阵时都会用到。从而

$$\begin{aligned}\text{cor}(\mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_j^*) = \text{cov}(\mathbf{Z}_j^*, \mathbf{Z}_j^*) = 1, \quad j = 1, \dots, p, \\ \text{cor}(\mathbf{Z}_i, \mathbf{Z}_j) &= \text{cov}(\mathbf{Z}_i^*, \mathbf{Z}_j^*) = 0, \quad i \neq j, \quad i, j = 1, \dots, p.\end{aligned}$$

(S6). 由(A.3)有

$$\text{cor}(\mathbf{X}, \mathbf{Z}) = (\text{cor}(\mathbf{X}_i, \mathbf{Z}_j))_{p \times p}.$$

由矩阵的样本相关矩阵的定义和(A.1)有

$$\text{cor}(\mathbf{X}, \mathbf{Z}) = \text{cov}(\mathbf{X}^*, \mathbf{Z}^*) = (\text{cov}(\mathbf{X}_i^*, \mathbf{Z}_j^*))_{p \times p}.$$

容易验证

$$\begin{aligned}\text{cov}(\mathbf{X}^*, \mathbf{Z}^*) &= \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)}^* - \bar{\mathbf{X}}^*) (\mathbf{Z}_{(k)}^* - \bar{\mathbf{Z}}^*)^T = \frac{1}{n-1} \sum_{k=1}^n \mathbf{X}_{(k)}^* \mathbf{Z}_{(k)}^{*T} \\ &= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{D}}^{-\frac{1}{2}} (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \hat{\Lambda}^{-\frac{1}{2}} \\ &= \hat{\mathbf{D}}^{-\frac{1}{2}} \left[ \frac{1}{n-1} \sum_{k=1}^n (\mathbf{X}_{(k)} - \bar{\mathbf{X}}) (\mathbf{Z}_{(k)} - \bar{\mathbf{Z}})^T \right] \hat{\Lambda}^{-\frac{1}{2}} \\ &= \hat{\mathbf{D}}^{-\frac{1}{2}} \text{cov}(\mathbf{X}, \mathbf{Z}) \hat{\Lambda}^{-\frac{1}{2}}.\end{aligned}$$

由(S3)知

$$\text{cov}(\mathbf{X}^*, \mathbf{Z}^*) = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda} \hat{\Lambda}^{-\frac{1}{2}} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}}.$$

其实我们也可以利用(A.2)和(S1)-(S3)的结论来证明

$$\begin{aligned}\text{cor}(\mathbf{X}, \mathbf{Z}) &= [\text{Diag}(\text{cov}(\mathbf{X}))]^{\frac{1}{2}} \text{cov}(\mathbf{X}, \mathbf{Z}) [\text{Diag}(\text{cov}(\mathbf{Z}))]^{\frac{1}{2}} \\ &= [\text{Diag}(\mathbf{S})]^{\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda} [\text{Diag}(\hat{\Lambda})]^{\frac{1}{2}} \\ &= \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda} \hat{\Lambda}^{-\frac{1}{2}} = \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}}.\end{aligned}$$

易知

$$\hat{D}^{-\frac{1}{2}} \hat{Q} \hat{\Lambda}^{\frac{1}{2}} = \begin{pmatrix} \frac{1}{\sqrt{s_{11}}} & & & \\ & \frac{1}{\sqrt{s_{22}}} & & \\ & & \ddots & \\ & & & \frac{1}{\sqrt{s_{pp}}} \end{pmatrix} (\hat{q}_{ij})_{p \times p} \begin{pmatrix} \sqrt{\hat{\lambda}_1} & & & \\ & \sqrt{\hat{\lambda}_2} & & \\ & & \ddots & \\ & & & \sqrt{\hat{\lambda}_p} \end{pmatrix} = \begin{pmatrix} \hat{q}_{ij} \frac{\sqrt{\hat{\lambda}_j}}{\sqrt{s_{ii}}} \\ & \ddots \\ & & \hat{q}_{ij} \end{pmatrix}_{p \times p}$$

从而有

$$\text{cor}(\mathbf{X}_i, \mathbf{Z}_j) = \text{cov}(\mathbf{X}_i^*, \mathbf{Z}_j^*) = \hat{q}_{ij} \frac{\sqrt{\hat{\lambda}_j}}{\sqrt{s_{ii}}}, \quad i, j = 1, \dots, p.$$

(S7). 由性质(S1)有

$$\sum_{j=1}^p \text{cov}(\mathbf{X}_j) = \sum_{j=1}^p \text{cov}(\mathbf{X}_j, \mathbf{X}_j) = \sum_{j=1}^p s_{jj},$$

由性质(S2)有

$$\sum_{j=1}^p \text{cov}(\mathbf{Z}_j) = \sum_{j=1}^p \text{cov}(\mathbf{Z}_j, \mathbf{Z}_j) = \sum_{j=1}^p \hat{\lambda}_j,$$

由  $\hat{Q}^\top S \hat{Q} = \hat{\Lambda}$  有

$$\sum_{j=1}^p s_{jj} = \text{tr}(S) = \text{tr}(S \hat{Q} \hat{Q}^\top) = \text{tr}(\hat{Q}^\top S \hat{Q}) = \text{tr}(\hat{\Lambda}) = \sum_{j=1}^p \hat{\lambda}_j.$$

### A.3. 从 R 出发求主成分

证明:

(R1). 由(A.1)有

$$\text{cov}(\tilde{\mathbf{X}}) = \text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{X}}) = (\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j))_{p \times p},$$

由  $\tilde{\mathbf{X}} = \mathbf{X}^*$  及性质(S4)有

$$\text{cov}(\tilde{\mathbf{X}}) = \text{cov}(\mathbf{X}^*) = \text{cor}(\mathbf{X}) = \mathbf{R} = (r_{ij})_{p \times p},$$

从而有

$$\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) = \text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*) = r_{ij}, \quad i, j = 1, \dots, p.$$

(R2). 由(A.1)有

$$\text{cov}(\tilde{\mathbf{Z}}) = \text{cov}(\tilde{\mathbf{Z}}, \tilde{\mathbf{Z}}) = (\text{cov}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j))_{p \times p}.$$

由于  $\tilde{\mathbf{Z}} = \mathbf{0}$ , 则

$$\begin{aligned}\text{cov}(\tilde{\mathbf{Z}}) &= \frac{1}{n-1} \sum_{k=1}^n (\tilde{\mathbf{Z}}_{(k)} - \bar{\tilde{\mathbf{Z}}})(\tilde{\mathbf{Z}}_{(k)} - \bar{\tilde{\mathbf{Z}}})^\top = \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^\top \\ &= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{Q}}^{*\top} \tilde{\mathbf{X}}_{(k)} \tilde{\mathbf{X}}_{(k)}^\top \hat{\mathbf{Q}}^* = \hat{\mathbf{Q}}^{*\top} \left( \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{X}}_{(k)} \tilde{\mathbf{X}}_{(k)}^\top \right) \hat{\mathbf{Q}}^* \\ &= \hat{\mathbf{Q}}^{*\top} \left( \frac{1}{n-1} \sum_{k=1}^n X_{(k)}^* X_{(k)}^{*\top} \right) \hat{\mathbf{Q}}^* = \hat{\mathbf{Q}}^{*\top} \mathbf{R} \hat{\mathbf{Q}}^* = \hat{\Lambda}^*,\end{aligned}$$

从而

$$\begin{aligned}\text{cov}(\tilde{\mathbf{Z}}_j) &= \text{cov}(\tilde{\mathbf{Z}}_j, \tilde{\mathbf{Z}}_j) = \hat{\lambda}_j^*, \quad j = 1, \dots, p, \\ \text{cov}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j) &= 0, \quad i \neq j, \quad i, j = 1, \dots, p.\end{aligned}$$

(R3). 由(A.1)有

$$\text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \left( \text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j) \right)_{p \times p}.$$

由于

$$\bar{\tilde{\mathbf{X}}} = \bar{\tilde{\mathbf{Z}}} = \mathbf{0},$$

从而

$$\begin{aligned}\text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) &= \frac{1}{n-1} \sum_{k=1}^n (\tilde{\mathbf{X}}_{(k)} - \bar{\tilde{\mathbf{X}}})(\tilde{\mathbf{Z}}_{(k)} - \bar{\tilde{\mathbf{Z}}})^\top = \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{X}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^\top \\ &= \frac{1}{n-1} \sum_{k=1}^n \hat{\mathbf{Q}}^* \tilde{\mathbf{Z}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^\top = \hat{\mathbf{Q}}^* \left( \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^\top \right) = \hat{\mathbf{Q}}^* \text{cov}(\tilde{\mathbf{Z}}),\end{aligned}$$

上式的最后一个等式在(R2)中已证明，从而由(R2)的结果有

$$\text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \hat{\mathbf{Q}}^* \hat{\Lambda}^* = \left( \hat{q}_{ij}^* \right)_{p \times p} \begin{pmatrix} \hat{\lambda}_1^* & & & \\ & \hat{\lambda}_2^* & & \\ & & \ddots & \\ & & & \hat{\lambda}_p^* \end{pmatrix} = \left( \hat{q}_{ij}^* \hat{\lambda}_j^* \right)_{p \times p},$$

从而

$$\text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j) = \hat{q}_{ij}^* \hat{\lambda}_j^*, \quad i, j = 1, \dots, p.$$

(R4). 由(A.3)有

$$\text{cor}(\tilde{\mathbf{X}}) = \text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{X}}) = \left( \text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) \right)_{p \times p}.$$

由  $\tilde{\mathbf{X}} = \mathbf{X}^*$  及矩阵的样本相关阵的定义有

$$\text{cor}(\tilde{\mathbf{X}}) = \text{cor}(\mathbf{X}^*) = \text{cov}(\mathbf{X}^{**}).$$

由性质(S4)有

$$\text{cov}(\mathbf{X}^*) = \text{cor}(\mathbf{X}) = \mathbf{R} = \left( r_{ij} \right)_{p \times p}.$$

由(A.4)有

$$\text{cov}(\mathbf{X}^{**}) = \text{cov}(\mathbf{X}^*).$$

其实我们也可以利用(A.2)和(R1)的结论来证明

$$\begin{aligned}\text{cor}(\tilde{\mathbf{X}}) &= \text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{X}}) \\ &= [\text{Diag}(\text{cov}(\tilde{\mathbf{X}}))]^{-\frac{1}{2}} \text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{X}}) [\text{Diag}(\text{cov}(\tilde{\mathbf{X}}))]^{-\frac{1}{2}} \\ &= [\text{Diag}(\mathbf{R})]^{-\frac{1}{2}} \mathbf{R} [\text{Diag}(\mathbf{R})]^{-\frac{1}{2}} = \mathbf{E}^{-\frac{1}{2}} \mathbf{R} \mathbf{E}^{-\frac{1}{2}} = \mathbf{R}.\end{aligned}$$

从而对  $i, j = 1, \dots, p$ ,

$$\begin{aligned}\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) &= \text{cor}(\mathbf{X}_i^*, \mathbf{X}_j^*) = \text{cov}(\mathbf{X}_i^{**}, \mathbf{X}_j^{**}) = \text{cov}(\mathbf{X}_i^*, \mathbf{X}_j^*) \\ &= \text{cov}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{X}}_j) = \text{cor}(\mathbf{X}_i, \mathbf{X}_j) = r_{ij}.\end{aligned}$$

(R5). 由(A.3)有

$$\text{cor}(\tilde{\mathbf{Z}}) = \text{cor}(\tilde{\mathbf{Z}}, \tilde{\mathbf{Z}}) = (\text{cor}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j))_{p \times p}.$$

由矩阵的样本相关阵的定义有

$$\text{cor}(\tilde{\mathbf{Z}}) = \text{cov}(\tilde{\mathbf{Z}}^*).$$

容易验证

$$\begin{aligned}\text{cov}(\tilde{\mathbf{Z}}^*) &= \frac{1}{n-1} \sum_{k=1}^n (\tilde{\mathbf{Z}}_{(k)}^* - \bar{\tilde{\mathbf{Z}}^*})(\tilde{\mathbf{Z}}_{(k)}^* - \bar{\tilde{\mathbf{Z}}^*})^T = \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^{*T} \\ &= \frac{1}{n-1} \sum_{k=1}^n (\hat{\Lambda}^*)^{-\frac{1}{2}} \tilde{\mathbf{Z}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^T (\hat{\Lambda}^*)^{-\frac{1}{2}} = (\hat{\Lambda}^*)^{-\frac{1}{2}} \left( \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{Z}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^T \right) (\hat{\Lambda}^*)^{-\frac{1}{2}} \\ &= (\hat{\Lambda}^*)^{-\frac{1}{2}} \text{cov}(\tilde{\mathbf{Z}})(\hat{\Lambda}^*)^{-\frac{1}{2}}.\end{aligned}$$

由性质(R2)的结果有

$$\text{cov}(\tilde{\mathbf{Z}}^*) = (\hat{\Lambda}^*)^{-\frac{1}{2}} \hat{\Lambda}^* (\hat{\Lambda}^*)^{-\frac{1}{2}} = (\hat{\Lambda}^*)^0 = \mathbf{E}_{p \times p} = \begin{pmatrix} 1 & & & \\ & 1 & & \\ & & \ddots & \\ & & & 1 \end{pmatrix}_{p \times p}.$$

其实我们也可以利用(A.2)和(R2)的结论来证明

$$\begin{aligned}\text{cor}(\tilde{\mathbf{Z}}) &= \text{cor}(\tilde{\mathbf{Z}}, \tilde{\mathbf{Z}}) \\ &= [\text{Diag}(\text{cov}(\tilde{\mathbf{Z}}))]^{-\frac{1}{2}} \text{cov}(\tilde{\mathbf{Z}}, \tilde{\mathbf{Z}}) [\text{Diag}(\text{cov}(\tilde{\mathbf{Z}}))]^{-\frac{1}{2}} \\ &= (\hat{\Lambda}^*)^{-\frac{1}{2}} \hat{\Lambda}^* (\hat{\Lambda}^*)^{-\frac{1}{2}} = (\hat{\Lambda}^*)^0 = \mathbf{E}_{p \times p}.\end{aligned}$$

从而

$$\begin{aligned}\text{cor}(\tilde{\mathbf{Z}}_j) &= \text{cor}(\tilde{\mathbf{Z}}_j, \tilde{\mathbf{Z}}_j) = 1, \quad j = 1, \dots, p, \\ \text{cor}(\tilde{\mathbf{Z}}_i, \tilde{\mathbf{Z}}_j) &= 0, \quad i \neq j, \quad i, j = 1, \dots, p.\end{aligned}$$

(R6). 由(A.3)有

$$\text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = (\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j))_{p \times p}.$$

由  $\tilde{\mathbf{X}} = \mathbf{X}^*$ , (A.4)和(A.1)有

$$\text{cov}(\tilde{\mathbf{X}}^*, \tilde{\mathbf{Z}}^*) = \text{cov}(\mathbf{X}^{**}, \tilde{\mathbf{Z}}^*) = \text{cov}(\mathbf{X}^*, \tilde{\mathbf{Z}}^*) = (\text{cov}(\mathbf{X}_i^*, \tilde{\mathbf{Z}}_j^*))_{p \times p}.$$

由矩阵的样本相关阵的定义有

$$\text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \text{cov}(\tilde{\mathbf{X}}^*, \tilde{\mathbf{Z}}^*).$$

容易验证

$$\begin{aligned} \text{cov}(\tilde{\mathbf{X}}^*, \tilde{\mathbf{Z}}^*) &= \frac{1}{n-1} \sum_{k=1}^n (\tilde{\mathbf{X}}_{(k)}^* - \bar{\tilde{\mathbf{X}}}^*) (\tilde{\mathbf{Z}}_{(k)}^* - \bar{\tilde{\mathbf{Z}}}^*)^\top = \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{X}}_{(k)}^* \tilde{\mathbf{Z}}_{(k)}^{*\top} \\ &= \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{X}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^\top (\hat{\Lambda}^*)^{-\frac{1}{2}} = \left( \frac{1}{n-1} \sum_{k=1}^n \tilde{\mathbf{X}}_{(k)} \tilde{\mathbf{Z}}_{(k)}^\top \right) (\hat{\Lambda}^*)^{-\frac{1}{2}} \\ &= \text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) (\hat{\Lambda}^*)^{-\frac{1}{2}}. \end{aligned}$$

再由性质(R3)的结果有

$$\text{cov}(\tilde{\mathbf{X}}^*, \tilde{\mathbf{Z}}^*) = \hat{\mathbf{Q}}^* \hat{\Lambda}^* (\hat{\Lambda}^*)^{-\frac{1}{2}} = \hat{\mathbf{Q}}^* (\hat{\Lambda}^*)^{\frac{1}{2}}.$$

其实我们也可以利用(A.2)和(R1)-(R3)的结论来证明

$$\begin{aligned} \text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) &= [\text{Diag}(\text{cov}(\tilde{\mathbf{X}}))]^{-\frac{1}{2}} \text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) [\text{Diag}(\text{cov}(\tilde{\mathbf{Z}}))]^{-\frac{1}{2}} \\ &= [\text{Diag}(\mathbf{R})]^{-\frac{1}{2}} \hat{\mathbf{Q}}^* \hat{\Lambda}^* [\text{Diag}(\hat{\Lambda}^*)]^{-\frac{1}{2}} \\ &= \mathbf{E}^{-\frac{1}{2}} \hat{\mathbf{Q}}^* \hat{\Lambda}^* (\hat{\Lambda}^*)^{-\frac{1}{2}} = \hat{\mathbf{Q}}^* (\hat{\Lambda}^*)^{\frac{1}{2}}. \end{aligned}$$

易知

$$\hat{\mathbf{Q}}^* (\hat{\Lambda}^*)^{\frac{1}{2}} = (\hat{q}_{ij}^*)_{p \times p} \begin{pmatrix} \sqrt{\hat{\lambda}_1^*} & & & \\ & \sqrt{\hat{\lambda}_2^*} & & \\ & & \ddots & \\ & & & \sqrt{\hat{\lambda}_p^*} \end{pmatrix} = (\hat{q}_{ij}^* \sqrt{\hat{\lambda}_j^*})_{p \times p}.$$

从而有

$$\text{cor}(\tilde{\mathbf{X}}_i, \tilde{\mathbf{Z}}_j) = \text{cov}(\tilde{\mathbf{X}}_i^*, \tilde{\mathbf{Z}}_j^*) = \text{cov}(\mathbf{X}_i^*, \tilde{\mathbf{Z}}_j^*) = \hat{q}_{ij}^* \sqrt{\hat{\lambda}_j^*}, \quad i, j = 1, \dots, p.$$

(R7). 由(R1)有

$$\sum_{j=1}^p \text{cov}(\tilde{\mathbf{X}}_j) = \sum_{j=1}^p \text{cov}(\tilde{\mathbf{X}}_j, \tilde{\mathbf{X}}_j) = \sum_{j=1}^p r_{jj} = \sum_{j=1}^p 1 = p.$$

由(R2)有

$$\sum_{j=1}^p \text{cov}(\tilde{\mathbf{Z}}_j) = \sum_{j=1}^p \text{cov}(\tilde{\mathbf{Z}}_j, \tilde{\mathbf{Z}}_j) = \sum_{j=1}^p \hat{\lambda}_j^*.$$

由  $\hat{\mathbf{Q}}^{*\top} \mathbf{R} \hat{\mathbf{Q}}^* = \hat{\Lambda}^*$  有

$$p = \sum_{j=1}^p r_{jj} = \text{tr}(\mathbf{R}) = \text{tr}(\mathbf{R} \hat{\mathbf{Q}}^* \hat{\mathbf{Q}}^{*\top}) = \text{tr}(\hat{\mathbf{Q}}^{*\top} \mathbf{R} \hat{\mathbf{Q}}^*) = \text{tr}(\hat{\Lambda}^*) = \sum_{j=1}^p \hat{\lambda}_j^*.$$

#### A.4. 数值模拟

在这里给出例 1 和例 2 的详细的数值模拟结果。

下面我们举两个例子来验证(S1)-(S7)和(R1)-(R7)的正确性。

**例 1.**

$$\mathbf{X} = (x_{ij})_{n \times p}, n = 4, p = 3, x_{ij} \sim N(0, 1).$$

为重复本文的结果, 我们在 R 软件中使用 `set.seed(1)`, 此时

$$\mathbf{X} = \begin{pmatrix} -0.6264538 & 0.3295078 & 0.5757814 \\ 0.1836433 & -0.8204684 & -0.3053884 \\ -0.8356286 & 0.4874291? & 1.5117812 \\ 1.5952808 & 0.7383247 & 0.3898432 \end{pmatrix}$$

$$\mathbf{S} = \begin{pmatrix} 1.2147560 & 0.1184091 & -0.4100692 \\ 0.1184091 & 0.4764913 & 0.3553357 \\ -0.4100692 & 0.3553357 & 0.5609438 \end{pmatrix},$$

$$\mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1556371 & -0.4967672 \\ 0.1556371 & 1.0000000 & 0.6873084 \\ -0.4967672 & 0.6873084 & 1.0000000 \end{pmatrix},$$

$$\hat{\Lambda} = \begin{pmatrix} \hat{\lambda}_1 & & \\ & \hat{\lambda}_2 & \\ & & \hat{\lambda}_3 \end{pmatrix} = \begin{pmatrix} 1.41507491 & & \\ & 0.79365619 & \\ & & 0.04346005 \end{pmatrix},$$

$$\hat{\mathbf{Q}} = (\hat{\mathbf{a}}_1, \hat{\mathbf{a}}_2, \hat{\mathbf{a}}_3) = \begin{pmatrix} 0.89017519 & 0.3354400 & 0.3083312 \\ -0.05874925 & 0.7555882 & -0.6524070 \\ -0.45181485 & 0.5626423 & 0.6923128 \end{pmatrix}.$$

由于  $\mathbf{S}$  的特征值全为正, 故  $\mathbf{S} > \mathbf{0}$ 。

(S1).

$$\text{cov}(\mathbf{X}) = \mathbf{S} = \begin{pmatrix} 1.2147560 & 0.1184091 & -0.4100692 \\ 0.1184091 & 0.4764913 & 0.3553357 \\ -0.4100692 & 0.3553357 & 0.5609438 \end{pmatrix},$$

(S2).

$$\text{cov}(\mathbf{Z}) = \hat{\Lambda} = \begin{pmatrix} 1.41507491 & & \\ & 0.79365619 & \\ & & 0.04346005 \end{pmatrix},$$

(S3).

$$\text{cov}(\mathbf{X}, \mathbf{Z}) = \hat{\mathbf{Q}}\hat{\Lambda} = \begin{pmatrix} 1.25966458 & 0.2662241 & 0.01340009 \\ -0.08313458 & 0.5996773 & -0.02835364 \\ -0.63935186 & 0.4465446 & 0.03008795 \end{pmatrix},$$

(S4).

$$\text{cor}(\mathbf{X}) = \mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1556371 & -0.4967672 \\ 0.1556371 & 1.0000000 & 0.6873084 \\ -0.4967672 & 0.6873084 & 1.0000000 \end{pmatrix},$$

(S5).

$$\text{cor}(\mathbf{Z}) = \mathbf{E}_{3 \times 3} = \begin{pmatrix} 1 & & \\ & 1 & \\ & & 1 \end{pmatrix},$$

(S6).

$$\begin{aligned} \text{cor}(\mathbf{X}, \mathbf{Z}) &= \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}} = (\text{Diag}(\mathbf{S}))^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}} \\ &= \begin{pmatrix} 0.9607727 & 0.2711356 & 0.05832007 \\ -0.1012429 & 0.9751556 & -0.19703176 \\ -0.7176134 & 0.6692508 & 0.19270268 \end{pmatrix}, \end{aligned}$$

(S7).

$$\text{tr}(\text{cov}(\mathbf{X})) = \text{tr}(\text{cov}(\mathbf{Z})) = 2.252191.$$

此时

$$\begin{aligned} \tilde{\mathbf{X}} = \mathbf{X}^* &= \begin{pmatrix} -0.64025588 & 0.2112313 & 0.04376326 \\ 0.09475296 & -1.4547163 & -1.13275832 \\ -0.83004217 & 0.4400087 & 1.29349294 \\ 1.37554509 & 0.8034763 & -0.20449788 \end{pmatrix}, \\ \hat{\Lambda}^* &= \begin{pmatrix} \hat{\lambda}_1^* & & \\ & \hat{\lambda}_2^* & \\ & & \hat{\lambda}_3^* \end{pmatrix} = \begin{pmatrix} 1.77908842 & & \\ & 1.14726052 & \\ & & 0.07365107 \end{pmatrix}, \\ \hat{\mathbf{Q}}^* = (\hat{\mathbf{a}}_1^*, \hat{\mathbf{a}}_2^*, \hat{\mathbf{a}}_3^*) &= \begin{pmatrix} -0.3534130 & 0.81512585 & 0.4589870 \\ 0.5781696 & 0.57604641 & -0.5778326 \\ 0.7354041 & -0.06115876 & 0.6748633 \end{pmatrix}. \end{aligned}$$

由于  $\mathbf{R}$  的特征值全为正, 故  $\mathbf{R} > \mathbf{0}$ 。

(R1).

$$\text{cov}(\tilde{\mathbf{X}}) = \mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1556371 & -0.4967672 \\ 0.1556371 & 1.0000000 & 0.6873084 \\ -0.4967672 & 0.6873084 & 1.0000000 \end{pmatrix},$$

(R2).

$$\text{cov}(\tilde{\mathbf{Z}}) = \hat{\Lambda}^* = \begin{pmatrix} 1.77908842 & & \\ & 1.14726052 & \\ & & 0.07365107 \end{pmatrix},$$

(R3).

$$\text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \hat{\mathbf{Q}}^* \hat{\Lambda}^* = \begin{pmatrix} -0.628753 & 0.93516170 & 0.03380488 \\ 1.028615 & 0.66087530 & -0.04255799 \\ 1.308349 & -0.07016503 & 0.04970440 \end{pmatrix},$$

(R4).

$$\text{cor}(\tilde{\mathbf{X}}) = \mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1556371 & -0.4967672 \\ 0.1556371 & 1.0000000 & 0.6873084 \\ -0.4967672 & 0.6873084 & 1.0000000 \end{pmatrix},$$

(R5).

$$\text{cor}(\tilde{\mathbf{Z}}) = \mathbf{E}_{3 \times 3} = \begin{pmatrix} 1 & & \\ & 1 & \\ & & 1 \end{pmatrix},$$

(R6).

$$\text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \hat{\mathbf{Q}}^* (\hat{\Lambda}^*)^{\frac{1}{2}} = \begin{pmatrix} -0.4713911 & 0.8730833 & 0.1245632 \\ 0.7711769 & 0.6170047 & -0.1568164 \\ 0.9809002 & -0.0655073 & 0.1831493 \end{pmatrix},$$

(R7).

$$\text{tr}(\text{cov}(\tilde{\mathbf{X}})) = 3 = \text{tr}(\text{cov}(\tilde{\mathbf{Z}})).$$

由数值结果可以看出, (S1)-(S7)和(R1)-(R7)均是正确的。

下面给一个  $\mathbf{S} \geq \mathbf{0}$  且  $\mathbf{R} \geq \mathbf{0}$  的例子, 即  $\mathbf{S}$  和  $\mathbf{R}$  都有 1 个 0 特征值, 此时(S5), (S6), (R5)和(R6)是不成立的, 但其余性质是成立的。**例 2.**

$$\mathbf{X} = (x_{ij})_{n \times p}, n = p = 3, x_{ij} \sim N(0, 1).$$

为重复本文的结果, 我们在 R 软件中使用 `set.seed(1)`, 此时

$$\mathbf{X} = \begin{pmatrix} -0.6264538 & 1.5952808 & 0.4874291 \\ 0.1836433 & 0.3295078 & 0.7383247 \\ -0.8356286 & -0.8204684 & 0.5757814 \end{pmatrix}$$

$$\mathbf{S} = \begin{pmatrix} 0.28982112 & 0.10867553 & 0.05840744 \\ 0.10867553 & 1.46007844 & -0.05734883 \\ 0.05840744 & -0.05734883 & 0.01619585 \end{pmatrix},$$

$$\mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1670624 & 0.8525136 \\ 0.1670624 & 1.0000000 & -0.3729362 \\ 0.8525136 & -0.3729362 & 1.0000000 \end{pmatrix},$$

$$\hat{\Lambda} = \begin{pmatrix} \hat{\lambda}_1 & & \\ & \hat{\lambda}_2 & \\ & & \hat{\lambda}_3 \end{pmatrix} = \begin{pmatrix} 1.471929 & & \\ & 0.2941663 & \\ & & -7.139463e-17 \end{pmatrix},$$

$$\hat{Q} = (\hat{a}_1, \hat{a}_2, \hat{a}_3) = \begin{pmatrix} -0.08974467 & 0.97207413 & -0.21683584 \\ -0.99532799 & -0.07975163 & 0.05442315 \\ 0.03561033 & 0.22070697 & 0.97468987 \end{pmatrix}.$$

由于  $\hat{\lambda}_3 = 0$ , 故  $\mathbf{S} \geq \mathbf{0}$ 。

(S1).

$$\text{cov}(\mathbf{X}) = \mathbf{S} = \begin{pmatrix} 0.28982112 & 0.10867553 & 0.05840744 \\ 0.10867553 & 1.46007844 & -0.05734883 \\ 0.05840744 & -0.05734883 & 0.01619585 \end{pmatrix},$$

(S2).

$$\text{cov}(\mathbf{Z}) = \hat{\Lambda} = \begin{pmatrix} 1.471929 & & \\ & 0.2941663 & \\ & & 0 \end{pmatrix},$$

(S3).

$$\text{cov}(\mathbf{X}, \mathbf{Z}) = \hat{Q}\hat{\Lambda} = \begin{pmatrix} -0.13209779 & 0.28595150 & 0 \\ -1.46505219 & -0.02346024 & 0 \\ 0.05241588 & 0.06492456 & 0 \end{pmatrix},$$

(S4).

$$\text{cor}(\mathbf{X}) = \mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1670624 & 0.8525136 \\ 0.1670624 & 1.0000000 & -0.3729362 \\ 0.8525136 & -0.3729362 & 1.0000000 \end{pmatrix},$$

(S5).

$$\text{cor}(\mathbf{Z}) = \begin{pmatrix} 1 & 0 & -0.7037615 \\ 0 & 1 & -0.4139885 \\ -0.7037615 & -0.4139885 & 1 \end{pmatrix} \neq \begin{pmatrix} 1 & 1 & 1 \end{pmatrix} = \mathbf{E}_{3 \times 3},$$

(S6).

$$\begin{aligned}\text{cor}(\mathbf{X}, \mathbf{Z}) &= \begin{pmatrix} -0.2022493 & 0.97933406 & -0.2630977 \\ -0.9993591 & -0.03579711 & 0.7181300 \\ 0.3394826 & 0.94061233 & -0.6283174 \end{pmatrix} \\ &\neq \begin{pmatrix} -0.2022493 & 0.97933406 & \text{NaN} \\ -0.9993591 & -0.03579711 & \text{NaN} \\ 0.3394826 & 0.94061233 & \text{NaN} \end{pmatrix} \\ &= \hat{\mathbf{D}}^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}} = (\text{Diag}(\mathbf{S}))^{-\frac{1}{2}} \hat{\mathbf{Q}} \hat{\Lambda}^{\frac{1}{2}},\end{aligned}$$

(S7).

$$\text{tr}(\text{cov}(\mathbf{X})) = \text{tr}(\text{cov}(\mathbf{Z})) = 1.766095.$$

此时

$$\begin{aligned}\tilde{\mathbf{X}} &= \mathbf{X}^* = \begin{pmatrix} -0.3720764 & 1.01558921 & -0.8885750 \\ 1.1327004 & -0.03194387 & 1.0828999 \\ -0.7606241 & -0.98364534 & -0.1943249 \end{pmatrix}, \\ \hat{\Lambda}^* &= \begin{pmatrix} \hat{\lambda}_1^* & & \\ & \hat{\lambda}_2^* & \\ & & \hat{\lambda}_3^* \end{pmatrix} = \begin{pmatrix} 1.879171 & & \\ & 1.120829 & \\ & & 0 \end{pmatrix}, \\ \hat{\mathbf{Q}}^* &= (\hat{\mathbf{a}}_1^*, \hat{\mathbf{a}}_2^*, \hat{\mathbf{a}}_3^*) = \begin{pmatrix} 0.6669312 & -0.3826931 & 0.6393346 \\ -0.1799815 & -0.9153613 & -0.3601670 \\ 0.7230556 & 0.1251382 & -0.6793607 \end{pmatrix}.\end{aligned}$$

由于  $\hat{\lambda}_3^* = 0$ , 故  $\mathbf{R} \geq \mathbf{0}$ 。

(R1).

$$\text{cov}(\tilde{\mathbf{X}}) = \mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1670624 & 0.8525136 \\ 0.1670624 & 1.0000000 & -0.3729362 \\ 0.8525136 & -0.3729362 & 1.0000000 \end{pmatrix},$$

(R2).

$$\text{cov}(\tilde{\mathbf{Z}}) = \hat{\Lambda}^* = \begin{pmatrix} 1.879171 & & \\ & 1.120829 & \\ & & 0 \end{pmatrix},$$

(R3).

$$\text{cov}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) = \hat{\mathbf{Q}}^* \hat{\Lambda}^* = \begin{pmatrix} 1.253278 & -0.4289336 & 0 \\ -0.338216 & -1.0259635 & 0 \\ 1.358745 & 0.1402585 & 0 \end{pmatrix},$$

(R4).

$$\text{cor}(\tilde{\mathbf{X}}) = \mathbf{R} = \begin{pmatrix} 1.0000000 & 0.1670624 & 0.8525136 \\ 0.1670624 & 1.0000000 & -0.3729362 \\ 0.8525136 & -0.3729362 & 1.0000000 \end{pmatrix},$$

(R5).

$$\text{cor}(\tilde{\mathbf{Z}}) = \begin{pmatrix} 1 & 0 & -0.4178971 \\ 0 & 1 & -0.9084944 \\ -0.4178971 & -0.9084944 & 1 \end{pmatrix} \neq \begin{pmatrix} 1 & 1 & 1 \end{pmatrix} = \mathbf{E}_{3 \times 3},$$

(R6).

$$\begin{aligned} \text{cor}(\tilde{\mathbf{X}}, \tilde{\mathbf{Z}}) &= \begin{pmatrix} 0.9142484 & -0.4051542 & -0.01398142 \\ -0.2467238 & -0.9690858 & 0.98351419 \\ 0.9911853 & 0.1324828 & -0.53457336 \end{pmatrix} \\ &\neq \begin{pmatrix} 0.9142484 & -0.4051542 & 0 \\ -0.2467238 & -0.9690858 & 0 \\ 0.9911853 & 0.1324828 & 0 \end{pmatrix} = \hat{\mathbf{Q}}^* (\hat{\Lambda}^*)^{\frac{1}{2}}, \end{aligned}$$

(R7).

$$\text{tr}(\text{cov}(\tilde{\mathbf{X}})) = 3 = \text{tr}(\text{cov}(\tilde{\mathbf{Z}})).$$

由数值结果可以看出, 除了(S5), (S6), (R5)和(R6)之外, (S1)-(S4), (S7)和(R1)-(R4), (R7)均是正确的。

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