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A GENERALIZED LIKELIHOOD RATIO TEST FOR MULTIVARIATE ANALYSIS OF VARIANCE IN HIGH DIMENSION

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Abstract: This paper considers in high dimensional setting a canonical testing problem, namely testing the equality of multiple mean vectors of normal distribution. Motivated by Roy's union-intersection principle, we propose a generalized likelihood ratio test. To investigate the asymptotic properties of the proposed test, we adopt a spiked covariance model which can characterize the strong correlation between variables. The limiting null distribution of the test statistic is derived and the local asymptotic power function is given. The asymptotic power function implies that the proposed test has particular high power when there are strong correlation between variables. We also carry out simulations to verify our theoretical results.

Key words and phrases:

1. Introduction Suppose there are k $(k \geq 2)$ groups of p dimensional data. Within the ith group $(1 \leq i \leq k)$, we have observations $\{X_{ij}\}_{j=1}^{n_i}$

which are independent and identically distributed (i.i.d.) as $N_p(\xi_i, \mathbf{\Sigma})$, the p dimensional normal distribution with mean vector ξ_i and common variance matrix $\mathbf{\Sigma}$. We would like to test the hypotheses

$$H_0 : \xi_1 = \xi_2 = \cdots = \xi_k \quad \text{v.s.} \quad H_1 : \xi_i \neq \xi_j \text{ for some } i \neq j. \tag{1.1}$$

This testing problem is known as one-way multivariate analysis of variance (MANOVA) and has been well studied when p is small compared to n, where $n = \sum_{i=1}^k n_i$ is the total sample size.

Let $\mathbf{H} = \sum_{i=1}^k n_i(\bar{\mathbf{X}}_i - \bar{\mathbf{X}})(\bar{\mathbf{X}}_i - \bar{\mathbf{X}})^T$ be the sum-of-squares between groups and $\mathbf{G} = \sum_{i=1}^k \sum_{j=1}^{n_i}(X_{ij} - \bar{\mathbf{X}}_i)(X_{ij} - \bar{\mathbf{X}}_i)^T$ be the sum-of-squares within groups, where $\bar{\mathbf{X}}_i = n_i^{-1} \sum_{j=1}^{n_i} X_{ij}$ is the sample mean of group i and $\bar{\mathbf{X}} = n^{-1} \sum_{i=1}^k \sum_{j=1}^{n_i} X_{ij}$ is the pooled sample mean. There are four classical test statistics for hypothesis (1.1), which are all based on the eigenvalues of $\mathbf{HG}^{-1}$.

Wilks' Lambda:	$\lvert\mathbf{G} + \mathbf{H}\rvert / \lvert\mathbf{G}\rvert$
Pillai trace:	$\mathrm{tr}[\mathbf{H}(\mathbf{G} + \mathbf{H})^{-1}]$
Hotelling-Lawley trace:	$\mathrm{tr}[\mathbf{HG}^{-1}]$
Roy's maximum root:	$\lambda_{\max}(\mathbf{HG}^{-1})$

In some modern scientific applications, people would like to test hypothesis (1.1) in high dimensional setting, i.e., p is greater than n. See, for example, Tsai and Chen (2009). Some references However, when $p \geq n$, the four classical test statistics can not be defined. Researchers have done extensive work to study the testing problem (1.1) in high dimensional setting. So far, most tests are designed for two sample case, i.e., $k = 2$. See, for example, Bai and Saranadasa (1996); Chen and Qin (2010); Srivastava (2009); Tony et al. (2013); Feng et al. (2016). For multiple sample case, Schott (2007) modified Hotelling-Lawley trace and proposed the test statistic

$$T_{SC} = \frac{1}{\sqrt{n-1}}\Big(\frac{1}{k-1}\,\mathrm{tr}\,(\mathbf{H}) - \frac{1}{n-k}\,\mathrm{tr}\,(\mathbf{G})\Big).$$

In another work, Cai and Xia (2014) proposed a test statistic

$$T_{CX} = \max_{1\leq i\leq p} \sum_{1\leq j<l\leq k} \frac{n_j n_l}{n_j + n_l} \frac{(\Omega(\bar{\mathbf{X}}_j - \bar{\mathbf{X}}_l))_i^2}{\omega_{ii}},$$

Where $\Omega = (\omega)_{ij} = \mathbf{\Sigma}^{-1}$ is the precision matrix. When Ω is unknown, they substitute it by an estimator $\hat{\Omega}$. Stitistics T_{SC} and T_{CX} are the representatives of two popular methodologies for high dimensional tests. T_{SC} is a so-called sum-of-squares type statistic as it is based on an estimation of squared Euclidean norm $\sum_{i=1}^k n_i\|\xi_i - \bar{\xi}\|^2$, where $\bar{\xi} = n^{-1}\sum_{i=1}^k n_i\xi_i$. T_{CX} is an extreme value type statistic.

Note that both sum-of-squares type statistic and extreme value type statistic are not based on likelihood function. While the likelihood ratio test (LRT), i.e., Wilks' Lambda, is not defined for $p > n - k$, it remains a problem how to construct likelihood-based tests in high dimensional setting. In a recent work, Zhao and Xu (2016) proposed a generalized likelihood ratio test in the context of one-sample mean vector test. Inspired by Roy's union-intersection principle (Roy, 1953), they wrote the null hypothesis as the intersection of a class of component hypotheses. For each component hypotheses, the likelihood ratio test is constructed. They use a least favorable argument to construct test statistic based on component tests. Their simulation results showed that their test has good power performance, especially when the variables are correlated.

Following Zhao and Xu (2016)'s methodology, we propose a generalized likelihood ratio test for hypothesis (1.1). To understand the power behavior of the new test, especially when variables are strongly correlated, the asymptotic distribution of the new statistic needs to be derived. An important correlation pattern is that the variation of variables are mainly driven by a small number of common factors. In this case, the covariance matrix has a few significantly large eigenvalues (Fan et al., 2008; Cai et al., 2013; Shen et al., 2013; Ma et al., 2015). We assume there are r significantly large eigenvalues and the other eigenvalues are bounded. We derive the asymptotic null distribution of the test statistic and give the asymptotic local power function. Our theoretical results implies that the asymptotic power of the new test is not affected by large eigenvalues, while most existing tests are negatively affected by large eigenvalues. Hence the new test is particularly powerful when there are strong correlations between variables. We also conduct a simulation study to examine the numerical performance of the test.

The rest of the paper is organized as follows. In Section 2, we propose a new test. Section 3 concerns the theoretical properties of the proposed test. In Section 4, the proposed test is compared with some existing tests. Section 5 complements our study with some numerical simulations. In Section 6, we give a short discussion. Finally, the proofs are gathered in the Appendix.

2. Methodology

2.1 Discussion about existing methods

To facilitate the discussion, we introduce some notations. Let

$$\mathbf{X} = (X_{11}, X_{12}, \ldots, X_{1n_1}, X_{21}, X_{22}, \ldots, X_{2n_2}, \ldots, X_{k1}, X_{k2}, \ldots, X_{kn_k})$$

be the pooled sample matrix. The sum-of-squares within groups $\mathbf{G}$ can be written as $\mathbf{G} = \mathbf{X}(\mathbf{I}_n - \mathbf{J}\mathbf{J}^T)\mathbf{X}^T$ where

$$\mathbf{J} = \begin{pmatrix} \frac{1}{\sqrt{n_1}}\mathbf{1}_{n_1} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \frac{1}{\sqrt{n_2}}\mathbf{1}_{n_2} & \mathbf{0} \\ \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \frac{1}{\sqrt{n_k}}\mathbf{1}_{n_k} \end{pmatrix},$$

and $\mathbf{1}_{n_i}$ is an n_i-dimensional vector with all elements equal to 1. Let

$$\tilde{\mathbf{J}} = \begin{pmatrix} \tilde{\mathbf{J}}_1 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \tilde{\mathbf{J}}_2 & \mathbf{0} \\ \vdots & \vdots & \vdots \\ \mathbf{0} & \mathbf{0} & \tilde{\mathbf{J}}_k \end{pmatrix},$$

where $\tilde{\mathbf{J}}_i$ is a $n_i \times n_{i-1}$ matrix satisfying

$$\tilde{\mathbf{J}}_i = \begin{pmatrix} \frac{\sqrt{2}}{2} & & & 0 \\ -\frac{\sqrt{2}}{2} & \frac{\sqrt{2}}{2} & & \\ & -\frac{\sqrt{2}}{2} & \ddots & \\ & & \ddots & \frac{\sqrt{2}}{2} \\ 0 & & & -\frac{\sqrt{2}}{2} \end{pmatrix}.$$

Then $\tilde{\mathbf{J}}$ is an $n \times (n-k)$ orthogonal matrix satisfying $\tilde{\mathbf{J}}\tilde{\mathbf{J}}^T = \mathbf{I}_n - \mathbf{J}\mathbf{J}^T$. Let $\mathbf{Y} = \mathbf{X}\tilde{\mathbf{J}}$. Then $\mathbf{G}$ has representation

$$\mathbf{G} = \mathbf{Y}\mathbf{Y}^T.$$

On the other hand, the sum-of-squares between groups $\mathbf{H}$ satisfies

$$\mathbf{H} = \mathbf{X}(\mathbf{J}\mathbf{J}^T - \frac{1}{n}\mathbf{1}_n\mathbf{1}_n^T)\mathbf{X}^T = \mathbf{X}\mathbf{J}(\mathbf{I}_k - \frac{1}{n}\mathbf{J}^T\mathbf{1}_n\mathbf{1}_n^T\mathbf{J})\mathbf{J}^T\mathbf{X}^T.$$

We can write $\mathbf{I}_k - \frac{1}{n}\mathbf{J}^T\mathbf{1}_n\mathbf{1}_n^T\mathbf{J} = \mathbf{C}\mathbf{C}^T$ where $\mathbf{C}$ be a $k \times (k-1)$ matrix satisfying

$$\mathbf{C} = \begin{pmatrix} \sqrt{\frac{n_2}{n_1+n_2}} & & & 0 \\ -\sqrt{\frac{n_1}{n_1+n_2}} & \sqrt{\frac{n_3}{n_2+n_3}} & & \\ & -\sqrt{\frac{n_2}{n_2+n_3}} & \ddots & \\ & & \ddots & \sqrt{\frac{n_k}{n_{k-1}+n_k}} \\ 0 & & & -\sqrt{\frac{n_{k-1}}{n_{k-1}+n_k}} \end{pmatrix}.$$

Then $\mathbf{H}$ has representation

$$\mathbf{H} = \mathbf{X}\mathbf{J}\mathbf{C}\mathbf{C}^T\mathbf{J}^T\mathbf{X}^T.$$

Define $\Xi = (\sqrt{n_1}\xi_1, \ldots, \sqrt{n_k}\xi_k)$ and the null hypothesis H_0 is equivalent to $\Xi\mathbf{C} = \mathbf{O}_{p\times(k-1)}$, where $\mathbf{O}_{p\times(k-1)}$ is a $p \times (k-1)$ matrix with all elements equal to 0. Thus the problem becomes testing hypotheses

$$H_0 : \Xi\mathbf{C} = \mathbf{O}_{p\times(k-1)} \quad \text{v.s.} \quad H_1 : \Xi\mathbf{C} \neq \mathbf{O}_{p\times(k-1)}$$

based on data matrix $\mathbf{X}$ when p is larger.

In low dimensional setting, the problem is well studied. The difficulty occurs when $p \geq n$ where the four classical test statistics can not be defined.

As the high dimensional problem is hard to deal with, an simple idea is to reduce the problem into a class of univariate problems. Following this idea, a general strategy to propose a test statistic can be summarized as three steps.

1. Construct a class of projected univariate data $\{\mathbf{X}_\gamma : \gamma \in \Gamma\}$ which contains all the information of data $\mathbf{X}$. This induces a decomposition of the null hypothesis and the alternative hypothesis:
$$H_0 = \bigcap_{\gamma \in \Gamma} H_{0\gamma} \quad \text{v.s.} \quad H_1 = \bigcup_{\gamma \in \Gamma} H_{1\gamma}.$$
2. Construct a test statistic T_γ for $H_{0\gamma}$ against $H_{1\gamma}$ such that $H_{0\gamma}$ is rejected if T_γ is large.
3. Summarize the component test statistics $\{T_\gamma : \gamma \in \Gamma\}$ into a global test statistic.

It turns out that many tests in the literature can be derived by the above strategy. While the LRT may be the best choice of univariate problems in step 2, step 1 and step 3 are more flexible. As for step 3, Roy's union intersection principle suggest to use $\max_{\gamma \in \Gamma} T_\gamma$ as global test statistic (Roy, 1953). Another choice is to integrate T_γ according some measure $\mu(\gamma)$ and use $\int_\gamma T_\gamma \, \mu(d\gamma)$ as global test statistic. For step 1, we consider two different constructions of data projection.

i Consider the class of univariate data $\{\mathbf{X}_i = e_i^T \mathbf{X} : i = 1, \dots, p\}$, where e_i is the ith standard basis in $\mathbb{R}^p$. Hence $H_0 = \bigcap_{i=1}^p H_{0i}$ and $H_1 = \bigcup_{i=1}^p H_{1i}$, where

$$H_{0i} : e_i^T \Xi \mathbf{C} = \mathbf{O}_{1\times(k-1)} \quad \text{and} \quad H_{1a} : e_i^T \Xi \mathbf{C} \neq \mathbf{O}_{1\times(k-1)}.$$

ii Consider the class of univariate data $\{\mathbf{X}_a = a^T \mathbf{X} : i = 1, a \in \mathbb{R}^p, a^T a = 1\}$. Hence $H_0 = \bigcap_{a\in\mathbb{R}^p, a^T a=1} H_{0a}$ and $H_1 = \bigcup_{a\in\mathbb{R}^p, a^T a=1} H_{1a}$, where

$$H_{0a} : a^T \Xi \mathbf{C} = \mathbf{O}_{1\times(k-1)} \quad \text{and} \quad H_{1a} : a^T \Xi \mathbf{C} \neq \mathbf{O}_{1\times(k-1)}.$$

First, we consider the construction i in step 1. Suppose component test statistics

$$T_i = (k-1)^{-1} e_i^T \mathbf{H} e_i - (n-k)^{-1} e_i^T \mathbf{G} e_i \quad i = 1, \dots, p$$

are used in step 2, and in step 3 we integrate T_i according to the uniform measure on $1, \dots, p$. Then the resulting statistic is $p^{-1} \sum_{i=1}^p T_i$ which is equivalent to T_{SC}. If instead the likelihood ratio test statistic $e_i^T \mathbf{H} e_i / e_i^T \mathbf{G} e_i$ is used in step 2, one obtains a scalar invariant test statistic which is a direct generalization of Srivastava (2009). By using data $\Omega^{-1}\mathbf{X}$ and component test statistics

$$T_i^* = \sum_{1\le j<l\le k} \frac{n_j n_l}{n_j + n_l} \frac{(\Omega(\bar{\mathbf{X}}_j - \bar{\mathbf{X}}_l))_i^2}{\omega_{ii}},$$

we have $T_{CX} = \max_{1\le i\le p} T_i^*$. Here the component test statistic T_i^* is similar to likelihood ratio tests.

While many existing tests can be derived by the construction i in step 1, this construction has limitation in that it relies on the choice of an orthogonal basis of $\mathbb{R}^p$. In fact, test statistics resulting from this construction mostly requires certain prior information about the covariance matrix. For example, Schott (2007) requires that $\mathrm{tr}(\mathbf{\Sigma}^{2j})/p \to \tau_j \in (0,\infty)$, $j = 1, 2$, and Cai and Xia (2014) requires a consistent estimator of Ω.

Next, we consider using construction ii in step 1, which is not relies on the basis of $\mathbb{R}^p$. Suppose the likelihood ratio test statistic $T_a = a^T\mathbf{H}a/a^T\mathbf{G}a$ is used in step 2. If we use the integrating strategy in step 3 and choose μ equal to the uniform distribution on the sphere, then the test statistic becomes

$$\int_{a^Ta=1} \frac{a^T\mathbf{H}a}{a^T\mathbf{G}a}\,\mu(da).$$

Although it is hard to give an explicit form of the integration, it can be approximated by random projection. More specifically, one can randomly generate unit vectors $a_1, \ldots, a_M$ and the statistics can be approximated by $M^{-1}\sum_{i=1}^M a^T\mathbf{H}a/a^T\mathbf{G}a$. This statistic is well defined in high dimensional setting. A similar method is proposed by Lopes et al. (2015) for $k = 2$ from different point of view. Their analysis and simulations show that such random projection method has relative good performance especially when variables are correlated. On the other hand, if $n-k \geq p$, Roy's union intersection principle can be used in step 3, the resulting statistic is the well known Roy's maximum root:

$$\max_{a^T a=1} T_a = \lambda_{\max}(\mathbf{H}\mathbf{G}^{-1}).$$

In fact, this statistic is first derived in Roy (1953) as an example of his union intersection principle.

2.2 A new test statistic

Roy's maximum root is constructed from the component statistics $\{T_a : a^T a = 1\}$ and doesn't require prior knowledge of covariance matrix. However, it can only be defined when $n-k \geq p$. In fact, if $p > n-k$, G is not invertible and T_a is not defined for some a. We will follow Zhao and Xu (2016)'s idea and propose a new test statistic for $p > n-k$.

Let $L_0(a)$ and $L_1(a)$ be the maximum likelihood of $\mathbf{X}_a$ under H_{01} and H_{01}, respectively. The log likelihood ratio

$$\log \frac{L_1(a)}{L_0(a)} = \Big(\frac{a^T(\mathbf{G}+\mathbf{H})a}{a^T\mathbf{G}a}\Big)^{n/2}$$

is an increase function of T_a. From a likelihood point view, log likelihood ratio is an estimator of the Kullback-Leibler divergence between the true distribution and the null distribution. Thus, the component LRT statistic characterize the discrepancy between H_{0a} and H_{1a}. Thus, by maximizing $\log L_1(a) - \log L_0(a)$, or equivalently maximizing T_a, one obtains component hypothesis H_{0a^*}, where $a^* = \arg\max_{a^T a=1} T_a$. We shall call H_{0a^*} the least favorable hypothesis since it is the component null hypothesis most like to be not true.

While it is hard to generalize Roy's maximum root to high dimensional setting, the least favorable hypothesis a^* can be formally generalized to high dimensional setting. In what follows, we shall assume $p > n - k$. In this case, Roy's maximum root is not defined since

$$\mathcal{A} \overset{def}{=} \{a : L_1(a) = +\infty,\, a^T a = 1\} = \{a : a^T \mathbf{G} a = 0,\, a^T a = 1\}$$

is not empty. Note that

$$\{a : L_0(a) < +\infty,\, a^T a = 1\} = \{a : a^T (\mathbf{G} + \mathbf{H}) a \neq 0,\, a^T a = 1\}.$$

By the independence of $\mathbf{G}$ and $\mathbf{H}$, with probability 1, we have $\mathcal{A} \cap \{a : L_0(a) < +\infty,\, a^T a = 1\} \neq \emptyset$. This suggests that the a^* which makes the discrepancy between $L_1(a^*)$ and $L_0(a^*)$ the most should be the one which is in the set $\mathcal{A}$ and minimize $L_0(a)$. Hence we define $a^* = \arg\min_{a\in\mathcal{A}} L_0(a)$ and take H_{a^*} as the least favorable hypothesis. Equivalently

$$a^* = \arg\min_{a\in\mathcal{A}} L_0(a) = \mathop{\arg\max}_{a^T a=1, a^T G a=0} a^T \mathbf{H} a.$$

This motivates us to propose the new test statistic as

$$T(\mathbf{X}) = a^{*T}\mathbf{H}a^{*} = \max_{a^Ta=1, a^T\mathbf{G}a=0} a^T\mathbf{H}a.$$

We reject the null hypothesis when T is large enough.

Next we derive the explicit forms of the test statistic. Let $\mathbf{Y} = \mathbf{U_Y}\mathbf{D_Y}\mathbf{V_Y}^T$ be the singular value decomposition of $\mathbf{Y}$, where $\mathbf{U_Y}$ and $\mathbf{V_Y}$ are $p\times(n-k)$ and $(n-k)\times(n-k)$ both column orthogonal matrices, $\mathbf{D}_Y$ is an $(n-k)\times(n-k)$ diagonal matrix. Let $\mathbf{P_Y} = \mathbf{U_Y}\mathbf{U_Y}^T$ be the projection matrix on the column space of $\mathbf{Y}$. Then Proposition 4 implies that

$$T(\mathbf{X}) = \lambda_{\max}\big(\mathbf{C}^T\mathbf{J}^T\mathbf{X}^T(\mathbf{I}_p - \mathbf{P_Y})\mathbf{XJC}\big). \tag{2.2}$$

Next we introduce another form of T. By the relationship

$$\begin{pmatrix} \mathbf{J}^T\mathbf{X}^T\mathbf{XJ} & \mathbf{J}^T\mathbf{X}^T\mathbf{X}\tilde{\mathbf{J}} \\ \tilde{\mathbf{J}}^T\mathbf{X}^T\mathbf{XJ} & \tilde{\mathbf{J}}^T\mathbf{X}^T\mathbf{X}\tilde{\mathbf{J}} \end{pmatrix}^{-1} = \left(\begin{pmatrix} \mathbf{J}^T \\ \tilde{\mathbf{J}}^T \end{pmatrix} \mathbf{X}^T\mathbf{X} \begin{pmatrix} \mathbf{J} & \tilde{\mathbf{J}} \end{pmatrix} \right)^{-1} = \begin{pmatrix} \mathbf{J}^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{J} & \mathbf{J}^T(\mathbf{X}^T\mathbf{X})^{-1}\tilde{\mathbf{J}} \\ \tilde{\mathbf{J}}^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{J} & \tilde{\mathbf{J}}^T(\mathbf{X}^T\mathbf{X})^{-1}\tilde{\mathbf{J}} \end{pmatrix}$$

and matrix inverse formula, we have that

$$\big(\mathbf{J}^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{J}\big)^{-1} = \mathbf{J}^T\mathbf{X}^T\mathbf{XJ} - \mathbf{J}^T\mathbf{X}^T\mathbf{X}\tilde{\mathbf{J}}(\tilde{\mathbf{J}}^T\mathbf{X}^T\mathbf{X}\tilde{\mathbf{J}})^{-1}\tilde{\mathbf{J}}^T\mathbf{X}^T\mathbf{XJ} = \mathbf{J}^T\mathbf{X}^T(\mathbf{I}_p - \mathbf{P_Y})\mathbf{XJ}.$$

Thus,

$$T(\mathbf{X}) = \lambda_{\max}\Big(\mathbf{C}^T\big(\mathbf{J}^T(\mathbf{X}^T\mathbf{X})^{-1}\mathbf{J}\big)^{-1}\mathbf{C}\Big). \tag{2.3}$$

While (2.2) is convenient for theoretical analysis, (2.3) is suitable for computation.

3. Main results

We shall derive the asymptotic distribution of $T(\mathbf{X})$. We are specially interested in the case when variables are correlated. For some real world problems, variables are heavily correlated with common factors, then the covariance matrix $\mathbf{\Sigma}$ is spiked in the sense that a few eigenvalues of $\mathbf{\Sigma}$ are significantly larger than the others (Fan et al., 2008; Cai et al., 2013; Shen et al., 2013; Ma et al., 2015). To characterize this correlation, we make the following assumption for the eigenvalues of $\mathbf{\Sigma}$.

Assumption 1. *Let $\boldsymbol{\lambda}_1 \geq \boldsymbol{\lambda}_2 \geq \cdots \geq \boldsymbol{\lambda}_p$ be the eigenvalues of $\mathbf{\Sigma}$. Suppose the first r $(r \geq 0)$ eigenvalues are significantly larger than the others. We assume $r = o(n)$. We assume $c_1 \geq \boldsymbol{\lambda}_{r+1} \geq \ldots \geq \boldsymbol{\lambda}_p \geq c_2$ for some absolute constants c_1 and c_2. For large eigenvalues $\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_r$, we assume*

$$\frac{\boldsymbol{\lambda}_r n}{p} \to \infty, \quad \frac{\boldsymbol{\lambda}_1^2 p r^2}{\boldsymbol{\lambda}_r^2 n^2} \to 0.$$

Remark 1. The spiked covariance model is commonly assumed in the study of PCA theory. Most existing work assumed r is fixed. Here we allow r to vary as a smaller order of n. The condition $\boldsymbol{\lambda}_r n/p \to \infty$ requires $\boldsymbol{\lambda}_r$ to be much larger than p/n. This is satisfied, for example, for the factor model adopted by Ma et al. (2015). The most harsh condition is $\boldsymbol{\lambda}_1^2 p r^2/(\boldsymbol{\lambda}_r^2 n^2) \to 0$. If $\boldsymbol{\lambda}_1$ and $\boldsymbol{\lambda}_r$ are of same order and r is fixed, this condition is equivalent to $p/n^2 \to 0$. We require this condition since the PCA consistency results are not valid when p is too large. See, for example, (Cai et al., 2013). This condition is unavoidable and the asymptotic behavior of $T(\mathbf{X})$ is different if this condition is violated.

To establish the asymptotic distribution of $T(\mathbf{X})$ under Assumption 1, we need following notations. Let $\mathbf{W}_{k-1}$ be a $(k-1)\times(k-1)$ symmetric random matrix whose entries above the main diagonal are i.i.d. $N(0,1)$ and the entries on the diagonal are i.i.d. $N(0,2)$. Let $\mathbf{\Sigma} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^T$ be the eigenvalue decomposition of $\mathbf{\Sigma}$, where $\mathbf{\Lambda} = \operatorname{diag}(\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_p)$. Let $\mathbf{U} = (\mathbf{U}_1, \mathbf{U}_2)$ where $\mathbf{U}_1$ is $p \times r$ and $\mathbf{U}_2$ is $p \times (p-r)$. Let $\mathbf{\Lambda}_1 = \operatorname{diag}(\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_r)$ and $\mathbf{\Lambda}_2 = \operatorname{diag}(\boldsymbol{\lambda}_{r+1}, \ldots, \boldsymbol{\lambda}_p)$. Then $\mathbf{\Sigma} = \mathbf{U}_1\mathbf{\Lambda}_1\mathbf{U}_1^T + \mathbf{U}_2\mathbf{\Lambda}_2\mathbf{U}_2^T$.

The following theorem establishes the asymptotic distribution of $T(\mathbf{X})$ under spiked covariance.

Theorem 1. *Under Assumption* (1)*, suppose $p/n \to \infty$ and*

$$\operatorname{tr}\Big(\mathbf{\Lambda}_2 - \frac{1}{p-r}(\operatorname{tr}\mathbf{\Lambda}_2)\mathbf{I}_{p-r}\Big)^2 = o\big(\frac{p}{n}\big).$$

Then under local alternative

$$\frac{1}{\sqrt{p}}\|\Xi\mathbf{C}\|_F^2 = O(1),$$

we have

$$\frac{T(\mathbf{X}) - \frac{p-r-n+k}{p-r}\operatorname{tr}(\mathbf{\Lambda}_2)}{\sqrt{\operatorname{tr}(\mathbf{\Lambda}_2^2)}} \sim \lambda_{\max}\Big(\mathbf{W}_{k-1} + \frac{1}{\sqrt{\operatorname{tr}(\mathbf{\Lambda}_2^2)}}\mathbf{C}^T\Xi^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\Xi\mathbf{C}\Big) + o_P(1).$$

3.1 Variance estimation

We use the following statistic to estimate r:

$$\hat{r} = \arg\max_{0 \le i \le n-k} \frac{\lambda_i(\mathbf{Y}^T\mathbf{Y})}{\lambda_{i+1}(\mathbf{Y}^T\mathbf{Y})} \ge \gamma_n,$$

where γ_n slowly tends to $+\infty$ as $n \to \infty$. We use the following statistic to estimate $\mathrm{tr}(\mathbf{\Lambda}_2)$:

$$\widehat{\mathrm{tr}(\mathbf{\Lambda}_2)} = \frac{1}{n-k} \sum_{i=\hat{r}+1}^{n-k} \lambda_i(\mathbf{Y}^T\mathbf{Y}).$$

Proposition 1. *Under Assumption 1, suppose $p/n \to \infty$, $\gamma_n \to \infty$ and $\gamma_n = o(n\boldsymbol{\lambda}_r/p)$, then*

$$\widehat{\mathrm{tr}(\mathbf{\Lambda}_2)} = \mathrm{tr}(\Lambda_2) + o_P(\sqrt{p}).$$

Proof. Lemma 2 and Assumption 1 imply that

$$\frac{1}{n-k} \sum_{i=r+1}^{n-k} \lambda_i(\mathbf{Y}^T\mathbf{Y}) = \mathrm{tr}(\mathbf{\Lambda}_2) + O_P\big(\frac{rp}{n}\big) = \mathrm{tr}(\mathbf{\Lambda}_2) + o_P(\sqrt{p}).$$

It only remains to prove $\hat{r}$ is a consistent estimator of r. $\Pr(\hat{r} = r) \to 1$. Note that

$$\{\hat{r} = r\} \supseteq \{\frac{\lambda_r(\mathbf{Y}^T\mathbf{Y})}{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})} \ge \gamma_n\} \cap \{\frac{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})}{\lambda_{n-k}(\mathbf{Y}^T\mathbf{Y})} \le \gamma_n\}.$$

Suppose $0 < \epsilon < 1$ is a fixed number. By assumption, there exists an n_0^*, for $n \ge n_0^*$, $\gamma_n \le (1-\epsilon)n\boldsymbol{\lambda}_r/(c_1 p)$ and $\gamma_n \ge (1+\epsilon)c_1/c_2$. Thus

$$\{\hat{r} = r\} \supseteq \{\frac{\lambda_r(\mathbf{Y}^T\mathbf{Y})}{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})} \ge (1-\epsilon)\frac{n\boldsymbol{\lambda}_r}{c_1 p}\} \cap \{\frac{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})}{\lambda_{n-k}(\mathbf{Y}^T\mathbf{Y})} \le (1+\epsilon)\frac{c_1}{c_2}\}.$$

Lemma 2 implies that almost surely, there exists an n_0, for $n \geq n_0$, we have

$$\frac{\lambda_r(\mathbf{Y}^T\mathbf{Y})}{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})} \geq (1-\epsilon)\frac{n\boldsymbol{\lambda}_r}{c_1 p}, \quad \frac{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})}{\lambda_{n-k}(\mathbf{Y}^T\mathbf{Y})} \leq (1+\epsilon)\frac{c_1}{c_2}.$$

This yields $\Pr(\hat{r} = r) \to 1$, which completes the proof. $\square$

Under non-spiked covariance, an unbiased estimator of $\mathrm{tr}(\boldsymbol{\Sigma}^2)$ is

$$\widehat{\mathrm{tr}(\boldsymbol{\Sigma}^2)} = \frac{2}{(n-k)(n-k-1)} \sum_{1 \leq i < j \leq n-k} (Y_i^T Y_j)^2.$$

Proposition 2. *As $n \to \infty$,*

$$\frac{\widehat{\mathrm{tr}(\boldsymbol{\Sigma}^2)}}{\mathrm{tr}(\boldsymbol{\Sigma}^2)} \xrightarrow{P} 1.$$

Proof. Since $\mathrm{E}(Y_i^T Y_j)^2 = \mathrm{tr}(\boldsymbol{\Sigma}^2)$, $i \leq j$, we have

$$\mathrm{E}\left(\widehat{\mathrm{tr}(\boldsymbol{\Sigma}^2)}\right) = \mathrm{tr}(\boldsymbol{\Sigma}^2).$$

To prove the proposition, we only need to show that

$$\mathrm{Var}\left(\widehat{\mathrm{tr}(\boldsymbol{\Sigma}^2)}\right) = o(\mathrm{tr}^2(\boldsymbol{\Sigma}^2)).$$

Note that

$$\mathrm{E}\left(\widehat{\mathrm{tr}(\mathbf{\Sigma}^2)}\right)^2 = \frac{4}{(n-k)^2(n-k-1)^2}\Big(\sum_{1\le i<j\le n-k}(Y_i^TY_j)^2\Big)^2$$

$$=\frac{4}{(n-k)^2(n-k-1)^2}\,\mathrm{E}\Big(\sum_{i<j}(Y_i^TY_j)^4+\sum_{i<j,k<l:\{i,j\}\{k,l\}=\emptyset}(Y_i^TY_j)^2(Y_k^TY_l)^2$$

$$+2\sum_{i<j<k}\big((Y_i^TY_j)^2(Y_iY_k)^2+(Y_i^TY_j)^2(Y_jY_k)^2+(Y_i^TY_k)^2(Y_jY_k)^2\big)\Big)$$

$$=\frac{4}{(n-k)^2(n-k-1)^2}\Big(\frac{(n-k)(n-k-1)}{2}\big(6\,\mathrm{tr}(\mathbf{\Sigma}^4)+3\,\mathrm{tr}^2(\mathbf{\Sigma}^2)\big)$$

$$+\frac{(n-k)(n-k-1)(n-k-2)(n-k-3)}{4}\,\mathrm{tr}^2(\mathbf{\Sigma}^2)$$

$$+(n-k)(n-k-1)(n-k-2)\big(2\,\mathrm{tr}(\mathbf{\Sigma}^4)+\mathrm{tr}^2(\mathbf{\Sigma}^2)\big)\Big)$$

$$=\mathrm{tr}^2(\mathbf{\Sigma}^2)(1+o(1)).$$

Then

$$\mathrm{Var}\left(\widehat{\mathrm{tr}(\mathbf{\Sigma}^2)}\right)=\mathrm{E}\left(\widehat{\mathrm{tr}(\mathbf{\Sigma}^2)}\right)^2-\left(\mathrm{E}\left(\widehat{\mathrm{tr}(\mathbf{\Sigma}^2)}\right)\right)^2=o(\mathrm{tr}^2(\mathbf{\Sigma}^2)).$$

This completes the proof. □

We use a leave-two-out estimator to estimate $\mathrm{tr}(\mathbf{\Lambda}_2^2)$. Let w_{ij} be the (i,j)th element of $\mathbf{Y}^T\mathbf{U}_{\mathbf{Y},2;(i,j)}\mathbf{U}_{\mathbf{Y},2;(i,j)}^T\mathbf{Y}$. We use

$$\widehat{\mathrm{tr}(\mathbf{\Lambda}_2^2)}=\frac{2}{(n-k)(n-k-1)}\sum_{1\le i<j\le n-k}w_{ij}^2$$

to estimate $\mathrm{tr}(\mathbf{\Lambda}_2^2)$.

Proposition 3. *Under Assumption* (1) *and $p/n\to\infty$, we have*

$$\frac{\widehat{\mathrm{tr}(\mathbf{\Lambda}_2^2)}}{\mathrm{tr}(\mathbf{\Lambda}_2^2)}\xrightarrow{P}1.$$

Proof. For $1 \le i < j \le n-k$, we have

$$
\begin{aligned}
w_{ij} - Y_i^T \mathbf{U}_2 \mathbf{U}_2^T Y_j =& Y_i^T (\mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T - \mathbf{U}_2 \mathbf{U}_2^T) Y_j \\
=& Y_i^T \mathbf{U}_2 \mathbf{U}_2^T (\mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T - \mathbf{U}_2 \mathbf{U}_2^T) \mathbf{U}_2 \mathbf{U}_2^T Y_j \\
&+ Y_i^T \mathbf{U}_1 \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_2 \mathbf{U}_2^T Y_j \\
&+ Y_i^T \mathbf{U}_2 \mathbf{U}_2^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_1 \mathbf{U}_1^T Y_j \\
&+ Y_i^T \mathbf{U}_1 \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_1 \mathbf{U}_1^T Y_j
\end{aligned}
$$

For the first term, we have

$$
\begin{aligned}
& Y_i^T \mathbf{U}_2 \mathbf{U}_2^T (\mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T - \mathbf{U}_2 \mathbf{U}_2^T) \mathbf{U}_2 \mathbf{U}_2^T Y_j \\
=& O_P(1) \sqrt{p} \lambda_1 (\mathbf{\Lambda}_2^{1/2} \mathbf{U}_2^T (\mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T - \mathbf{U}_2 \mathbf{U}_2^T) \mathbf{U}_2 \mathbf{\Lambda}_2^{1/2}) \\
=& O_P(1) \sqrt{p} \lambda_1 (\mathbf{U}_2^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_2 - \mathbf{I}_{p-r}) = O_P(\sqrt{p} \frac{p}{\lambda_r n}).
\end{aligned}
$$

For the second term, we have

$$
\begin{aligned}
& Y_i^T \mathbf{U}_1 \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_2 \mathbf{U}_2^T Y_j \\
=& O_P(1) \sqrt{r} \| \mathbf{\Lambda}_1^{1/2} \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_2 \mathbf{\Lambda}_2^{1/2} \| \\
=& O_P(1) \sqrt{r \lambda_1} \| \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \| \\
=& O_P(1) \sqrt{r \lambda_1} \sqrt{\frac{p}{\lambda_r n}} \\
=& O_P(\sqrt{\frac{p r \lambda_1}{\lambda_r n}}).
\end{aligned}
$$

For the third term, we have

$$\begin{aligned}
& Y_i^T \mathbf{U}_1 \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_1 \mathbf{U}_1^T Y_j \\
=& O_P(1)\sqrt{r} \|\mathbf{\Lambda}_1^{1/2} \mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_1 \mathbf{\Lambda}_1^{1/2}\| \\
=& O_P(1)\sqrt{r}\lambda_1 \|\mathbf{U}_1^T \mathbf{U}_{\mathbf{Y},2;(i,j)} \mathbf{U}_{\mathbf{Y},2;(i,j)}^T \mathbf{U}_1\| \\
=& O_P(\sqrt{r}\lambda_1 \frac{p}{\lambda_r n}).
\end{aligned}$$

Thus,

$$w_{ij} = Y_i^T \mathbf{U}_2 \mathbf{U}_2^T Y_j + O_P(\frac{p\sqrt{p}}{\lambda_r n} + \sqrt{\frac{pr\lambda_1}{\lambda_r n}} + \frac{\sqrt{r}\lambda_1 p}{\lambda_r n}) = Y_i^T \mathbf{U}_2 \mathbf{U}_2^T Y_j + o_P(\sqrt{p})$$

It follows that $w_{ij}^2 = (Y_i^T \mathbf{U}_2 \mathbf{U}_2^T Y_j)^2 + o_P(p)$. Thus

$$\widehat{\operatorname{tr}(\mathbf{\Lambda}_2^2)} = \frac{2}{(n-k)(n-k-1)} \sum_{1 \le i < j \le n-k} (Y_i^T \mathbf{U}_2 \mathbf{U}_2^T Y_j)^2 + o_P(p).$$

Then the conclusion follows from Proposition 2. □

4. Comparison with existing tests

4.1 Permutation method

Permutation method is a powerful tool to determine the critical value of a test statistic. The test procedure resulting from permutation method is exact as long as the null distribution of observations are exchangeable (Romano, 1990). The major down-side to permutation method is that it can be computationally intensive. Fortunately, the permutation method can be computationally fast. By expression (2.3), a permuted statistic can be written as

$$T(\mathbf{X}\Gamma) = \lambda_{\max}\Big(\mathbf{C}^T\big(\mathbf{J}^T\Gamma^T(\mathbf{X}^T\mathbf{X})^{-1}\Gamma\mathbf{J}\big)^{-1}\mathbf{C}\Big), \tag{4.4}$$

where Γ is an $n \times n$ permutation matrix. Note that $(\mathbf{X}^T\mathbf{X})^{-1}$, the most time-consuming component, can be calculated aforehand. The permutation procedure for our statistic can be summarized as:

1. Calculate $T(\mathbf{X})$ according to (2.3), hold intermediate result $(\mathbf{X}^T\mathbf{X})^{-1}$.
2. For a large M, independently generate M random permutation matrix $\Gamma_1, \ldots, \Gamma_M$ and calculate $T(\mathbf{X}\Gamma_1), \ldots, T(\mathbf{X}\Gamma_M)$ according to (4.4).
3. Calculate the p-value by $\tilde{p} = (M+1)^{-1}\big[1+\sum_{i=1}^M I\{T(\mathbf{X}\Gamma_i) \geq T(\mathbf{X})\}\big]$. Reject the null hypothesis if $\tilde{p} \leq \alpha$.

Here M is the permutation times. It can be seen that step 1 and step 2 cost $O(n^2p+n^3)$ and $O(n^2M)$ operations respectively. In large sample or high dimensional setting, step 2 has negligible effect on total computational complexity.

Our new test statistic comes from construction ii in step 1, the likelihood ratio test statistics in step 2 and strategy II in step 3. Theorems **??** and 1 allow us to analyze the properties of the proposed test. Suppose $\sqrt{n_i}\mu_i$ is from prior distribution $N_p(0, \psi \mathbf{I}_p)$, $i = 1, \ldots, k$. Then $\psi^{-1}\mathbf{C}^T\Xi^T\Xi\mathbf{C}$ is distributed as $\text{Wishart}_{k-1}(p, \mathbf{I}_{k-1})$ (Wishart distribution with freedom p and parameter $\mathbf{I}_{k-1}$) and $\psi^{-1}\mathbf{C}^T\Xi^T\mathbf{P}_{\mathbf{Y}}\Xi\mathbf{C}$ is distributed as $\text{Wishart}_{k-1}(n-k, \mathbf{I}_{k-1})$. In this case, we have

$$\psi^{-1}\mathbf{C}^T\Xi^T(\mathbf{I}_P - \mathbf{P}_{\mathbf{Y}})\Xi\mathbf{C} = (1 + o_P(1))\psi^{-1}\mathbf{C}^T\Xi^T\Xi\mathbf{C}.$$

If the conditions of Theorem **??** hold and $k = 2$, the asymptotic power of the proposed test is the same as that of Bai and Saranadasa (1996)and Chen and Qin (2010)'s method. Since the method of Schott (2007) is a direct generalization of Bai and Saranadasa (1996)'s method, it can be shown the asymptotic power of the proposed test is the same as that of Schott (2007) for general k. Next, suppose the covariance matrix is spiked and the conditions of Theorem 1 hold. Theorem 1 implies that the proposed test does not depend on large eigenvalues $\lambda_1, \ldots, \lambda_r$ while other existing test procedures are negatively affected by large eigenvalues $\lambda_1, \ldots, \lambda_r$. Thus, the new test has particular good power behavior when $\lambda_1, \ldots, \lambda_r$ are large. This property is not surprising since our statistic is from construction ii. As a result, our statistic has a wider applicable range compared to the tests from construction i.

5. Simulation Results

In this section, we evaluate the numerical performance of the new test. For comparison, we also carry out simulations for the test of Cai and Xia (2014) and the test of Schott (2007). These tests are denoted respectively by NEW, CX and SC. Since the critical value of CX and SC may not be valid under spiked covariance model, we use permutation method to determine the critical value for all three test. The empirical power is computed based on 1000 simulations.

In the simulations, we set $k = 3$. Note that the new test is invariant under orthogonal transformation. Without loss of generality, we only consider diagonal $\mathbf{\Sigma}$. We consider two different structure of $\mathbf{\Sigma}$.

- Covariance structure I: $\mathbf{\Sigma} = \operatorname{diag}(p, 1, \ldots, 1)$.
- Covariance structure II: $\mathbf{\Sigma} = \operatorname{diag}(\rho_1, \ldots, \rho_p)$, where $\rho_1 \geq \cdots \geq \rho_p$ are order statistics of p i.i.d. random variables which have uniform distribution between 0 and 1.

Define signal-to-noise ratio (SNR) as

$$\mathrm{SNR} = \frac{\|\xi_f\|_F^2}{\sqrt{\sum_{i=2}^p \lambda_i(\mathbf{\Sigma})^2}}.$$

We use SNR to characterize the signal strength. We consider two structure of alternative hypotheses: the non-sparse alternative and the sparse alternative. In the non-sparse case, we set $\xi_1 = \kappa 1_p$, $\xi_2 = -\kappa 1_p$ and $\xi_3 = \mathbf{0}_p$, where κ is selected to make the SNR equal to the given value. In the sparse case, we set $\xi_1 = \kappa(1_{p/5}^T, \mathbf{0}_{4p/5}^T)^T$, $\xi_2 = \kappa(\mathbf{0}_{p/5}^T, 1_{p/5}^T, \mathbf{0}_{3p/5}^T)^T$ and $\xi_3 = \mathbf{0}_p$. Again, κ is selected to make the SNR equal to the given value.

The simulation results are summarized in Tables 1-6. It can be seen from the results that under spiked covariance, the proposed test outperforms the other two tests for both non-sparse and sparse alternatives. Under non-spiked covariance, the power of the new test is a little lower than that of SC. As p increase, the power of the new test approaches to that of SC.

6. Concluding remarks

In this paper, motivated by Roy's union intersection principle, we proposed a generalized likelihood ratio statistic for MANOVA in high dimensional setting. We proved that the proposed test has similar asymptotic power with T_{SC} under non-spiked covariance. On the other hand, if covariance matrix is spiked, the asymptotic power of the proposed test is not affected by the large eigenvalues. We give a discussion of existing MANOVA tests from union intersection principle point of view, this explains why the proposed test has good power behavior.

Table 1: Empirical powers of tests under covariance structure I and non-sparse alternative. $\alpha = 0.05$, $k = 3$, $n_1 = n_2 = n_3 = 10$.

SNR	$p = 50$			$p = 75$			$p = 100$		
	CX	SC	NEW	CX	SC	NEW	CX	SC	NEW
0	0.035	0.048	0.052	0.057	0.052	0.057	0.053	0.048	0.045
1	0.060	0.049	0.096	0.081	0.050	0.092	0.063	0.062	0.085
2	0.100	0.058	0.140	0.073	0.045	0.169	0.086	0.055	0.171
3	0.145	0.066	0.234	0.119	0.070	0.266	0.117	0.056	0.307
4	0.126	0.064	0.317	0.121	0.059	0.380	0.122	0.061	0.402
5	0.179	0.072	0.392	0.178	0.068	0.541	0.141	0.071	0.579
6	0.198	0.070	0.513	0.189	0.071	0.639	0.143	0.066	0.717
7	0.249	0.085	0.629	0.227	0.084	0.777	0.206	0.073	0.822
8	0.268	0.092	0.685	0.252	0.084	0.822	0.217	0.078	0.894
9	0.324	0.100	0.786	0.256	0.090	0.911	0.246	0.074	0.949
10	0.342	0.115	0.828	0.303	0.097	0.937	0.270	0.075	0.973

Table 2: Empirical powers of tests under covariance structure I and non-sparse alternative. $\alpha = 0.05$, $k = 3$, $n_1 = n_2 = n_3 = 25$.

SNR	$p = 100$			$p = 150$			$p = 200$		
	CX	SC	NEW	CX	SC	NEW	CX	SC	NEW
0	0.050	0.043	0.050	0.056	0.066	0.048	0.062	0.045	0.054
1	0.069	0.048	0.063	0.046	0.052	0.091	0.068	0.048	0.095
2	0.097	0.046	0.131	0.086	0.053	0.164	0.068	0.057	0.173
3	0.113	0.061	0.200	0.117	0.057	0.270	0.101	0.045	0.313
4	0.135	0.053	0.247	0.130	0.054	0.402	0.118	0.066	0.485
5	0.158	0.065	0.357	0.134	0.066	0.526	0.134	0.073	0.616
6	0.198	0.081	0.433	0.161	0.052	0.668	0.138	0.067	0.765
7	0.217	0.068	0.514	0.191	0.067	0.759	0.174	0.068	0.862
8	0.229	0.063	0.582	0.223	0.075	0.853	0.187	0.060	0.927
9	0.264	0.094	0.680	0.218	0.080	0.918	0.227	0.067	0.966
10	0.298	0.091	0.758	0.245	0.076	0.934	0.228	0.052	0.982

Table 3: Empirical powers of tests under covariance structure I and sparse alternative. $\alpha = 0.05$, $k = 3$, $n_1 = n_2 = n_3 = 10$.

SNR	$p = 50$			$p = 75$			$p = 100$		
	CX	SC	NEW	CX	SC	NEW	CX	SC	NEW
0	0.063	0.056	0.052	0.048	0.049	0.048	0.057	0.047	0.042
1	0.087	0.058	0.071	0.069	0.044	0.096	0.076	0.051	0.080
2	0.091	0.066	0.116	0.113	0.037	0.133	0.080	0.058	0.139
3	0.155	0.065	0.177	0.131	0.062	0.228	0.113	0.058	0.218
4	0.184	0.065	0.246	0.174	0.076	0.308	0.144	0.061	0.310
5	0.225	0.081	0.337	0.214	0.075	0.386	0.176	0.083	0.417
6	0.270	0.088	0.425	0.266	0.085	0.507	0.228	0.071	0.508
7	0.364	0.080	0.501	0.307	0.078	0.571	0.302	0.087	0.629
8	0.405	0.105	0.549	0.381	0.080	0.698	0.362	0.089	0.721
9	0.470	0.121	0.634	0.408	0.078	0.774	0.391	0.070	0.797
10	0.547	0.128	0.702	0.484	0.109	0.819	0.415	0.088	0.877

Table 4: Empirical powers of tests under covariance structure I and sparse alternative. $\alpha = 0.05$, $k = 3$, $n_1 = n_2 = n_3 = 25$.

SNR	$p = 100$			$p = 150$			$p = 200$		
	CX	SC	NEW	CX	SC	NEW	CX	SC	NEW
0	0.048	0.045	0.046	0.053	0.046	0.043	0.051	0.034	0.046
1	0.079	0.055	0.082	0.066	0.063	0.079	0.063	0.059	0.100
2	0.097	0.054	0.119	0.088	0.055	0.138	0.085	0.055	0.160
3	0.133	0.069	0.167	0.113	0.066	0.223	0.114	0.054	0.235
4	0.149	0.062	0.212	0.126	0.084	0.298	0.132	0.057	0.344
5	0.204	0.060	0.281	0.169	0.066	0.427	0.154	0.057	0.469
6	0.252	0.060	0.352	0.227	0.070	0.548	0.195	0.072	0.641
7	0.310	0.072	0.429	0.252	0.059	0.614	0.220	0.061	0.711
8	0.372	0.088	0.529	0.314	0.085	0.719	0.297	0.060	0.800
9	0.427	0.083	0.547	0.362	0.085	0.794	0.300	0.057	0.881
10	0.449	0.093	0.619	0.396	0.072	0.853	0.340	0.076	0.911

Table 5: Empirical powers of tests under covariance structure II and non-sparse alternative. $\alpha = 0.05$, $k = 3$, $n_1 = n_2 = n_3 = 25$.

SNR	$p = 100$			$p = 150$			$p = 200$		
	CX	SC	NEW	CX	SC	NEW	CX	SC	NEW
0	0.063	0.054	0.058	0.052	0.040	0.042	0.045	0.049	0.070
1	0.141	0.120	0.115	0.126	0.120	0.112	0.103	0.110	0.102
2	0.181	0.209	0.169	0.330	0.260	0.210	0.200	0.227	0.201
3	0.692	0.367	0.244	0.759	0.385	0.341	0.468	0.413	0.394
4	0.753	0.539	0.420	0.744	0.573	0.515	0.516	0.554	0.561
5	0.828	0.690	0.509	0.871	0.697	0.693	0.556	0.724	0.727
6	0.809	0.812	0.622	0.822	0.824	0.766	0.959	0.838	0.859
7	1.000	0.882	0.780	0.979	0.916	0.903	0.990	0.923	0.947
8	0.993	0.955	0.789	1.000	0.965	0.954	0.999	0.972	0.971
9	1.000	0.979	0.911	0.999	0.981	0.979	0.964	0.986	0.987
10	1.000	0.991	0.877	0.989	0.996	0.988	0.996	0.996	0.997

Table 6: Empirical powers of tests under covariance structure II and sparse alternative. $\alpha = 0.05$, $k = 3$, $n_1 = n_2 = n_3 = 25$.

SNR	$p = 100$			$p = 150$			$p = 200$		
	CX	SC	NEW	CX	SC	NEW	CX	SC	NEW
0	0.052	0.055	0.047	0.055	0.057	0.053	0.044	0.055	0.057
1	0.068	0.124	0.065	0.070	0.130	0.085	0.049	0.116	0.087
2	0.085	0.233	0.112	0.076	0.239	0.149	0.067	0.241	0.161
3	0.110	0.388	0.161	0.090	0.408	0.215	0.097	0.417	0.227
4	0.120	0.530	0.184	0.112	0.552	0.282	0.103	0.556	0.309
5	0.167	0.708	0.238	0.142	0.699	0.387	0.140	0.687	0.394
6	0.196	0.807	0.261	0.168	0.820	0.472	0.162	0.823	0.547
7	0.217	0.875	0.318	0.177	0.892	0.505	0.173	0.896	0.646
8	0.234	0.935	0.378	0.220	0.951	0.625	0.195	0.948	0.749
9	0.312	0.965	0.407	0.222	0.970	0.672	0.224	0.979	0.809
10	0.334	0.976	0.505	0.292	0.987	0.773	0.254	0.989	0.881

Appendix

Proposition 4. *Suppose* $\mathbf{A}$ *is a* $p \times r$ *matrix with rank* r *and* $\mathbf{B}$ *is a* $p \times p$ *non-zero semi-definite matrix. Denote by* $\mathbf{A} = \mathbf{U_A D_A V_A^T}$ *the singular value decomposition of* $\mathbf{A}$*, where* $\mathbf{U_A}$ *and* $\mathbf{V_A}$ *are* $p \times r$ *and* $r \times r$ *column orthogonal matrix,* $\mathbf{D_A}$ *is a* $r \times r$ *diagonal matrix. Let* $\mathbf{P_A} = \mathbf{U_A U_A^T}$ *be the projection on the column space of* $\mathbf{A}$*. Then*

$$\max_{a^T a=1, a^T \mathbf{A}\mathbf{A}^T a=0} a^T \mathbf{B} a = \lambda_{\max}\big(\mathbf{B}(\mathbf{I}_p - \mathbf{P_A})\big). \tag{6.5}$$

Proof. Note that $a^T \mathbf{A}\mathbf{A}^T a = 0$ is equivalent to $\mathbf{P_A} a = 0$ which in turn is equivalent to $a = (\mathbf{I}_p - \mathbf{P_A})a$. Then

$$\max_{a^T a=1, a^T \mathbf{A}\mathbf{A}^T a=0} a^T \mathbf{B} a = \max_{a^T a=1, \mathbf{P_A} a=0} a^T (\mathbf{I}_p - \mathbf{P_A})\mathbf{B}(\mathbf{I}_p - \mathbf{P_A})a, \tag{6.6}$$

which is obviously no greater than $\lambda_{\max}\big((\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})\big)$. To prove that they are equal, without loss of generality, we can assume $\lambda_{\max}\big((\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})\big) > 0$. Let α_1 be one eigenvector corresponding to the largest eigenvalue of $(\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})$. Since $(\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})\mathbf{P_A} = (\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{P_A} - \mathbf{P_A}) = \mathbf{O}_{p\times p}$ and $\mathbf{P_A}$ is symmetric, the rows of $\mathbf{P_A}$ are eigenvetors of $(\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})$ corresponding to eigenvalue 0. It follows that $\mathbf{P_A}\alpha_1 = 0$. Therefore, α_1 satisfies the constraint of (6.6) and (6.6) is no less than $\lambda_{\max}\big((\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})\big)$. The conclusion now follows by noting that $\lambda_{\max}\big((\mathbf{I} - \mathbf{P_A})\mathbf{B}(\mathbf{I} - \mathbf{P_A})\big) = \lambda_{\max}\big(\mathbf{B}(\mathbf{I} - \mathbf{P_A})\big)$.

$\square$

Lemma 1 (Davidson and Szarek (2001) Theorem II.7)**.** *Let* $\mathbf{A}$ *be* $m \times n$ *with iid* $N(0,1)$ *entries. If* $m > n$*, then for any* $t > 0$*,*

$$\Pr(\sqrt{\lambda_1(\mathbf{A}\mathbf{A}^T)} > \sqrt{m} + \sqrt{n} + t) \leq \exp(-t^2/2),$$
$$\Pr(\sqrt{\lambda_n(\mathbf{A}\mathbf{A}^T)} < \sqrt{m} - \sqrt{n} - t) \leq \exp(-t^2/2).$$

Proves of the main results It can be seen that $\mathbf{XJC}$ is independent of $\mathbf{Y}$. Since $\mathrm{E}\,\mathbf{Y} = \mathbf{O}_{p\times(n-k)}$, we can write $\mathbf{Y} = \mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_1$, where $\mathbf{G}_1$ is a $p\times(n-k)$ matrix with i.i.d. $N(0,1)$ entries. We write $\mathbf{XJC} = \xi_f + \mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2$, where $\mathbf{G}_2$ is a $p \times (k-1)$ matrix with i.i.d. $N(0,1)$ entries.

Then

$$\begin{aligned}\mathbf{C}^T\mathbf{J}^T\mathbf{X}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{XJC} =& \mathbf{G}_2^T\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2 + \xi_f^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\xi_f + \\ & \xi_f^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2 + \mathbf{G}_2^T\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\xi_f.\end{aligned} \tag{6.7}$$

The first term of (6.7) can be represented as

$$\mathbf{G}_2^T\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2 = \sum_{i=1}^p \lambda_i(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2})\xi_i\xi_i^T, \tag{6.8}$$

where $\xi_i \overset{i.i.d.}{\sim} N(0, \mathbf{I}_{k-1})$.

Let $\mathbf{G}_1 = (\mathbf{G}_{1A}^T, \mathbf{G}_{1B}^T)^T$, where $\mathbf{G}_{1A}$ is the first r rows of $\mathbf{G}_1$ and $\mathbf{G}_{1B}$ is the last $p-r$ rows of $\mathbf{G}_1$. The following lemma gives the asymptotic property of $\lambda_i(\mathbf{Y}^T\mathbf{Y})$, $i=1,\ldots,r$.

Lemma 2. *Under the Assumptions of Theorem 1, $r=o(n)$, we have*

$$\sup_{1\le i\le r}\Big|\frac{\lambda_i(\mathbf{Y}^T\mathbf{Y})}{n\boldsymbol{\lambda}_i}-1\Big|\to 0, \tag{6.9}$$

$$\limsup_{n\to+\infty}\frac{\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y})}{p}\le c_1, \tag{6.10}$$

$$\liminf_{n\to+\infty}\frac{\lambda_{n-k}(\mathbf{Y}^T\mathbf{Y})}{p}\ge c_2, \tag{6.11}$$

almost surely. And

$$\frac{1}{n-k}\sum_{i=r+1}^{n-k}\lambda_i(\mathbf{Y}^T\mathbf{Y})=\operatorname{tr}(\boldsymbol{\Lambda}_2)+O_P(\frac{rp}{n}). \tag{6.12}$$

Proof. Note that

$$\mathbf{Y}^T\mathbf{Y}=\mathbf{G}_1^T\boldsymbol{\Lambda}\mathbf{G}_1=\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1\mathbf{G}_{1A}+\mathbf{G}_{1B}^T\boldsymbol{\Lambda}_2\mathbf{G}_{1B}.$$

For $1\le i\le r$, we have

$$\lambda_i(\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1\mathbf{G}_{1A})\le\lambda_i(\mathbf{Y}^T\mathbf{Y})\le\lambda_i(\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1\mathbf{G}_{1A})+c_1\lambda_1(\mathbf{G}_{1B}^T\mathbf{G}_{1B}). \tag{6.13}$$

Using Weyl's inequality, we can derive a lower bound for $\lambda_i(\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1\mathbf{G}_{1A})$, $i=1,\ldots,r$.

$$\begin{aligned}
&\lambda_i(\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1\mathbf{G}_{1A})\ge\lambda_i(\mathbf{G}_{1A}^T\operatorname{diag}(\boldsymbol{\lambda}_i\mathbf{I}_i,\mathbf{O}_{(r-i)\times(r-i)})\mathbf{G}_{1A})\\
=&\lambda_i\Big(\boldsymbol{\lambda}_i\mathbf{G}_{1A}^T\mathbf{G}_{1A}-\boldsymbol{\lambda}_i\mathbf{G}_{1A}^T\operatorname{diag}(\mathbf{O}_{i\times i},\mathbf{I}_{r-i})\mathbf{G}_{1A}\Big)\\
\ge&\lambda_r\Big(\boldsymbol{\lambda}_i\mathbf{G}_{1A}^T\mathbf{G}_{1A}\Big)+\lambda_{p+i-r}\Big(-\boldsymbol{\lambda}_i\mathbf{G}_{1A}^T\operatorname{diag}(\mathbf{O}_{i\times i},\mathbf{I}_{r-i})\mathbf{G}_{1A}\Big)\\
=&\boldsymbol{\lambda}_i\lambda_r(\mathbf{G}_{1A}\mathbf{G}_{1A}^T).
\end{aligned} \tag{6.14}$$

Similarly, we can obtain the upper bound.

$$\begin{aligned}
&\lambda_i(\mathbf{G}_{1A}^T \boldsymbol{\Lambda}_1 \mathbf{G}_{1A}) \\
=&\lambda_i\Big(\mathbf{G}_{1A}^T\big(\operatorname{diag}(\boldsymbol{\lambda}_1, \ldots, \boldsymbol{\lambda}_{i-1}, \mathbf{O}_{(r-i+1)\times(r-i+1)}) + \operatorname{diag}(\mathbf{O}_{(i-1)\times(i-1)}, \boldsymbol{\lambda}_i, \ldots, \boldsymbol{\lambda}_r)\big)\mathbf{G}_{1A}\Big) \\
\leq&\lambda_1(\mathbf{G}_{1A}^T \operatorname{diag}(\mathbf{O}_{(i-1)\times(i-1)}, \boldsymbol{\lambda}_i \mathbf{I}_{r-i+1})\mathbf{G}_{1A}) \leq \boldsymbol{\lambda}_i \lambda_1(\mathbf{G}_{1A}\mathbf{G}_{1A}^T).
\end{aligned} \tag{6.15}$$

The inequality (6.13), (6.14) and (6.15) implies that

$$\sup_{1\leq i\leq r}\left|\frac{\lambda_i(\mathbf{Y}^T\mathbf{Y})}{n\boldsymbol{\lambda}_i} - 1\right| \leq \max\left(\left|\frac{\lambda_1(\mathbf{G}_{1A}\mathbf{G}_{1A}^T)}{n} - 1\right|, \left|\frac{\lambda_r(\mathbf{G}_{1A}\mathbf{G}_{1A}^T)}{n} - 1\right|\right) + \frac{c_1}{n\boldsymbol{\lambda}_r}\lambda_1(\mathbf{G}_{1B}^T\mathbf{G}_{1B}).$$

We only need to prove the right hand side converges to 0 almost surely.

By Lemma 1, for every $t > 0$, we have

$$\begin{aligned}
&\Pr\left(\sqrt{1-\frac{k}{n}} - \sqrt{\frac{r}{n}} - \frac{t}{\sqrt{n}} \leq \sqrt{\frac{\lambda_r(\mathbf{G}_{1A}\mathbf{G}_{1A}^T)}{n}} \leq \sqrt{\frac{\lambda_1(\mathbf{G}_{1A}\mathbf{G}_{1A}^T)}{n}} \leq \sqrt{1-\frac{k}{n}} + \sqrt{\frac{r}{n}} + \frac{t}{\sqrt{n}}\right) \\
&\geq 1 - 2\exp(-\frac{t^2}{2}).
\end{aligned}$$

Let $t = n^{1/4}$, then Borel-Cantelli lemma implies

$$\frac{\lambda_r(\mathbf{G}_{1A}\mathbf{G}_{1A}^T)}{n} \to 1 \quad \frac{\lambda_1(\mathbf{G}_{1A}\mathbf{G}_{1A}^T)}{n} \to 1,$$

almost surely. As for $\lambda_1(\mathbf{G}_{1B}^T\mathbf{G}_{1B})$, by Lemma 1, we have

$$\Pr\left(\frac{c_1}{n\boldsymbol{\lambda}_r}\lambda_1(\mathbf{G}_{1B}\mathbf{G}_{1B}^T) \leq \frac{c_1}{n\boldsymbol{\lambda}_r}(\sqrt{n-k} + \sqrt{p-r} + t)^2\right) \geq 1 - \exp(-\frac{t^2}{2}).$$

Let $t = n^{1/2}$, since we have assumed $\boldsymbol{\lambda}_r n/p \to \infty$, we have

$$\frac{c_1}{n\boldsymbol{\lambda}_r}\lambda_1(\mathbf{G}_{1B}\mathbf{G}_{1B}^T) \to 0$$

almost surely. Then (6.9) follows.

Inequality (6.10) and (6.11) follows from the fact

$$\lambda_{r+1}(\mathbf{Y}^T\mathbf{Y}) \le \lambda_1(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}) \le c_1\lambda_1(\mathbf{G}_{1B}^T\mathbf{G}_{1B}),$$

$$\lambda_{n-k}(\mathbf{Y}^T\mathbf{Y}) \ge \lambda_{n-k}(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}) \ge c_2\lambda_{n-k}(\mathbf{G}_{1B}^T\mathbf{G}_{1B}),$$

and Lemma 1.

Now we prove (6.12). By Weyl's inequality, for $i = r+1,\dots,n-k$, we have

$$\lambda_i(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}) \le \lambda_i(\mathbf{Y}^T\mathbf{Y}) \le \lambda_{i-r}(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}).$$

It follows that

$$\sum_{i=r+1}^{n-k}\lambda_i(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}) \le \sum_{i=r+1}^{n-k}\lambda_i(\mathbf{Y}^T\mathbf{Y}) \le \sum_{i=1}^{n-k-r}\lambda_i(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}).$$

Hence

$$\Big|\sum_{i=r+1}^{n-k}\lambda_i(\mathbf{Y}^T\mathbf{Y}) - \mathrm{tr}(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B})\Big| \le r\lambda_1(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}) = O_P(rp).$$

But central limit theorem implies that

$$\mathrm{tr}(\mathbf{G}_{1B}^T\mathbf{\Lambda}_2\mathbf{G}_{1B}) - (n-k)\,\mathrm{tr}(\mathbf{\Lambda}_2) = O_P(\sqrt{np}).$$

Thus

$$\Big|\sum_{i=r+1}^{n-k}\lambda_i(\mathbf{Y}^T\mathbf{Y}) - (n-k)\,\mathrm{tr}(\mathbf{\Lambda}_2)\Big| = O_P(rp).$$

This completes the proof.

$\square$

Let $\mathbf{U_Y} = (\mathbf{U_{Y,1}}, \mathbf{U_{Y,2}})$, where $\mathbf{U_{Y,1}}$ and $\mathbf{U_{Y,2}}$ are the first r and last $p-r$ columns of $\mathbf{U_Y}$ respectively.

Lemma 3. *Under the Assumptions of Theorem 1, we have*

$$\lambda_{\max}(\mathbf{I}_r - \mathbf{U}_1^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_1) = O_P(\frac{p}{\boldsymbol{\lambda}_r n}).$$

Proof. From $\mathbf{U}\boldsymbol{\Lambda}^{1/2}\mathbf{G}_1\mathbf{G}_1^T\boldsymbol{\Lambda}^{1/2}\mathbf{U}^T = \mathbf{U_Y}\mathbf{D_Y^2}\mathbf{U_Y^T}$, we have

$$\begin{pmatrix} \boldsymbol{\Lambda}_1^{\frac{1}{2}}\mathbf{G}_{1A}\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1^{\frac{1}{2}} & \boldsymbol{\Lambda}_1^{\frac{1}{2}}\mathbf{G}_{1A}\mathbf{G}_{1B}^T\boldsymbol{\Lambda}_2^{\frac{1}{2}} \\ \boldsymbol{\Lambda}_2^{\frac{1}{2}}\mathbf{G}_{1B}\mathbf{G}_{1A}^T\boldsymbol{\Lambda}_1^{\frac{1}{2}} & \boldsymbol{\Lambda}_2^{\frac{1}{2}}\mathbf{G}_{1B}\mathbf{G}_{1B}^T\boldsymbol{\Lambda}_2^{\frac{1}{2}} \end{pmatrix} = \begin{pmatrix} \mathbf{U}_1^T\mathbf{U_Y}\mathbf{D_Y^2}\mathbf{U_Y^T}\mathbf{U}_1 & \mathbf{U}_1^T\mathbf{U_Y}\mathbf{D_Y^2}\mathbf{U_Y^T}\mathbf{U}_2 \\ \mathbf{U}_2^T\mathbf{U_Y}\mathbf{D_Y^2}\mathbf{U_Y^T}\mathbf{U}_1 & \mathbf{U}_2^T\mathbf{U_Y}\mathbf{D_Y^2}\mathbf{U_Y^T}\mathbf{U}_2 \end{pmatrix}$$

It follows that

$$\boldsymbol{\Lambda}_2^{\frac{1}{2}}\mathbf{G}_{1B}\mathbf{G}_{1B}^T\boldsymbol{\Lambda}_2^{\frac{1}{2}} \geq \lambda_r(\mathbf{Y}^T\mathbf{Y})\mathbf{U}_2^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_2.$$

Hence

$$\lambda_1(\mathbf{U}_2^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_2) \leq \frac{c_1}{\lambda_r(\mathbf{Y}^T\mathbf{Y})}\lambda_1(\mathbf{G}_{1B}\mathbf{G}_{1B}^T). \tag{6.16}$$

By Lemma 1, for every $t > 0$, we have

$$\Pr\left(\frac{1}{p}(\sqrt{p-r}-\sqrt{n-k}-t)^2 \leq \frac{1}{p}\lambda_1(\mathbf{G}_{1B}\mathbf{G}_{1B}^T) \leq \frac{1}{p}(\sqrt{p-r}+\sqrt{n-k}+t)^2\right) \geq 1-2\exp(-\frac{t^2}{2}).$$

Let $t = n^{1/2}$, then Borel-Cantelli lemma implies that

$$\frac{1}{p}\lambda_1(\mathbf{G}_{1B}\mathbf{G}_{1B}^T) \to 1 \tag{6.17}$$

almost surely. Then (6.17), (6.16) and Lemma 2 implies that

$$\lambda_1(\mathbf{U}_2^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_2) = O_P(\frac{p}{\boldsymbol{\lambda}_r n}).$$

The conclusion then follows by the following simple relationship

$$
\begin{aligned}
&\lambda_{\max}(\mathbf{U}_2^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_2) = \lambda_{\max}(\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_2\mathbf{U}_2^T\mathbf{U}_{\mathbf{Y},1})\\
=&\lambda_{\max}(\mathbf{U}_{\mathbf{Y},1}^T(\mathbf{I}_p - \mathbf{U}_1\mathbf{U}_1^T)\mathbf{U}_{\mathbf{Y},1}) = \lambda_{\max}(\mathbf{I}_r - \mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_1\mathbf{U}_1^T\mathbf{U}_{\mathbf{Y},1})\\
=&1 - \lambda_{\min}(\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_1\mathbf{U}_1^T\mathbf{U}_{\mathbf{Y},1}) = 1 - \lambda_{\min}(\mathbf{U}_1^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_1)\\
=&\lambda_{\max}(\mathbf{I}_r - \mathbf{U}_1^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_1).
\end{aligned}
$$

□

Lemma 4. *Under Assumption xxx, we have the following upper and lower bound for* $\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}$.

$$
\lambda_i(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}) \geq \boldsymbol{\lambda}_{i+n-k}, \quad i = 1, \dots, p-n+k, \tag{6.18}
$$

$$
\lambda_i\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\big) = O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n}) + c_1, \quad i = 1, \dots, r, \tag{6.19}
$$

$$
\lambda_i(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}) \leq \boldsymbol{\lambda}_i, \quad i = r+1, \dots, p. \tag{6.20}
$$

Proof. The inequality (6.20) follows from the fact $\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}} \leq \mathbf{I}_p$. The inequality (6.18) follows from the fact that $\mathrm{Rank}(\mathbf{P}_{\mathbf{Y}}) \leq n-k$ and Weyl's inequality. As for inequality (6.19), note that the positive eigenvalues of $\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}$ equal to the positive eigenvalues of $(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})$. We write $(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})$ as the sum of two terms

$$
\begin{aligned}
&(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\\
=&(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}_1\mathbf{\Lambda}_1\mathbf{U}_1^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}}) + (\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}})\mathbf{U}_2\mathbf{\Lambda}_2\mathbf{U}_2^T(\mathbf{I}_p - \mathbf{P}_{\mathbf{Y}}) \overset{def}{=} \mathbf{R}_1 + \mathbf{R}_2.
\end{aligned}
$$

Lemma 3 can be applied to control the largest eigenvalue of $\mathbf{R}_1$:

$$\lambda_1\big(\mathbf{R}_1\big) = \lambda_1\big(\mathbf{\Lambda}_1^{1/2}\mathbf{U}_1^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}_1\mathbf{\Lambda}_1^{1/2}\big) \leq \lambda_1\big(\mathbf{\Lambda}_1^{1/2}\mathbf{U}_1^T(\mathbf{I}_p - \mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T)\mathbf{U}_1\mathbf{\Lambda}_1^{1/2}\big)$$
$$\leq \boldsymbol{\lambda}_1\lambda_1\big(\mathbf{U}_1^T(\mathbf{I}_p - \mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T)\mathbf{U}_1\big) = \boldsymbol{\lambda}_1\lambda_1\big(\mathbf{I}_r - \mathbf{U}_1^T\mathbf{U}_{\mathbf{Y},1}\mathbf{U}_{\mathbf{Y},1}^T\mathbf{U}_1\big) = O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n}).$$

Thus, for $i = 1, \dots, r$, we have

$$\lambda_i(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}) \leq \lambda_1(\mathbf{R}_1) + \lambda_1(\mathbf{R}_2) = O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n}) + c_1.$$

□

Lemma 5. *Under Assumption xxx, we have*

$$\operatorname{tr}\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\big) = \frac{p-r-n+k}{p-r}\operatorname{tr}(\mathbf{\Lambda}_2) + o_P(\sqrt{p}), \tag{6.21}$$

and

$$\operatorname{tr}\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\big)^2 = (1 + o_P(1))\operatorname{tr}(\mathbf{\Lambda}_2^2). \tag{6.22}$$

Proof. By Lemma 4, we have

$$\sum_{i=n-k+1}^{p}\boldsymbol{\lambda}_i^2 \leq \operatorname{tr}\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\big)^2 \leq r(O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n}) + c_1)^2 + \sum_{i=r+1}^{p}\boldsymbol{\lambda}_i^2.$$

Hence

$$\begin{aligned}&\big|\operatorname{tr}\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p - \mathbf{P}_\mathbf{Y})\mathbf{U}\mathbf{\Lambda}^{1/2}\big)^2 - \sum_{i=r+1}^{p}\boldsymbol{\lambda}_i^2\big|\\ \leq&\max\Big(\sum_{i=r+1}^{n-k}\boldsymbol{\lambda}_i^2, r(O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n}) + c_1)^2\Big)\\ \leq& r(O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n}) + c_1)^2 + O(n) = o_P(p).\end{aligned}$$

Then (6.22) holds.

Now we prove (6.21). Note that

$$\operatorname{tr}\left(\boldsymbol{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\boldsymbol{\Lambda}^{1/2}\right)=\operatorname{tr}\left(\boldsymbol{\Lambda}_1^{1/2}\mathbf{U}_1^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}_1\boldsymbol{\Lambda}_1^{1/2}\right)+\operatorname{tr}\left(\boldsymbol{\Lambda}_2^{1/2}\mathbf{U}_2^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}_2\boldsymbol{\Lambda}_2^{1/2}\right).$$

By Lemma 4, we have

$$\operatorname{tr}\left(\boldsymbol{\Lambda}_1^{1/2}\mathbf{U}_1^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}_1\boldsymbol{\Lambda}_1^{1/2}\right)=O_P\left(\frac{\boldsymbol{\lambda}_1 pr}{\boldsymbol{\lambda}_r n}\right)=o_P(\sqrt{p}).$$

The second term can be written as $\operatorname{tr}\left(\boldsymbol{\Lambda}_2^{1/2}\mathbf{U}_2^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}_2\boldsymbol{\Lambda}_2^{1/2}\right)=\operatorname{tr}(\boldsymbol{\Lambda}_2)-\operatorname{tr}(\mathbf{P}_{\mathbf{Y}}\mathbf{U}_2\boldsymbol{\Lambda}_2\mathbf{U}_2^T)$. For $\operatorname{tr}(\mathbf{P}_{\mathbf{Y}}\mathbf{U}_2\boldsymbol{\Lambda}_2\mathbf{U}_2^T)$, we have

$$\begin{aligned}&\left|\operatorname{tr}(\mathbf{P}_{\mathbf{Y}}\mathbf{U}_2\boldsymbol{\Lambda}_2\mathbf{U}_2^T)-\frac{n-k}{p-r}\operatorname{tr}(\boldsymbol{\Lambda}_2)\right|=\left|\operatorname{tr}\left(\mathbf{P}_{\mathbf{Y}}\mathbf{U}\left(\boldsymbol{\Lambda}_2-\frac{1}{p-r}(\operatorname{tr}\boldsymbol{\Lambda}_2)\mathbf{I}_{p-r}\right)\mathbf{U}^T\right)\right|\\ \le&\sqrt{\operatorname{tr}\left(\mathbf{P}_{\mathbf{Y}}^2\right)}\sqrt{\operatorname{tr}\left(\boldsymbol{\Lambda}_2-\frac{1}{p-r}\left(\operatorname{tr}\boldsymbol{\Lambda}_2\right)\mathbf{I}_{p-r}\right)^2}=\sqrt{(n-k)\operatorname{tr}\left(\boldsymbol{\Lambda}_2-\frac{1}{p-r}\left(\operatorname{tr}\boldsymbol{\Lambda}_2\right)\mathbf{I}_{p-r}\right)^2}=o(\sqrt{p}).\end{aligned}$$

Hence

$$\operatorname{tr}\left(\boldsymbol{\Lambda}_2^{1/2}\mathbf{U}_2^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}_2\boldsymbol{\Lambda}_2^{1/2}\right)=\frac{p-r-n+k}{p-r}\operatorname{tr}(\boldsymbol{\Lambda}_2)+o(\sqrt{p}).$$

Then (6.21) holds. □

Proof of Theorem 1. We deal with the three terms of (6.7) separately. Lemma (4) implies that the first term satisfies the Lyapunov condition

$$\frac{\lambda_1\left(\left(\boldsymbol{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\boldsymbol{\Lambda}^{1/2}\right)^2\right)}{\operatorname{tr}\left(\left(\boldsymbol{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\boldsymbol{\Lambda}^{1/2}\right)^2\right)}=\frac{\left(O_P(\frac{\boldsymbol{\lambda}_1 p}{\boldsymbol{\lambda}_r n})+c_1\right)^2}{(1+o_P(1))\operatorname{tr}(\boldsymbol{\Lambda}_2)}\xrightarrow{P}0.$$

Apply Lyapunov central limit theorem conditioning on $\mathbf{P}_{\mathbf{Y}}$, we have

$$\Big(\operatorname{tr}\Big(\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\big)^2\Big)\Big)^{-1/2}$$

$$\big(\mathbf{G}_2^T\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2-\operatorname{tr}\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\big)\mathbf{I}_{k-1}\big)\xrightarrow{\mathcal{L}}\mathbf{W}_{k-1},$$

where $\mathbf{W}_{k-1}$ is a $(k-1)\times(k-1)$ symmetric random matrix whose entries above the main diagonal are i.i.d. $N(0,1)$ and the entries on the diagonal are i.i.d. $N(0,2)$. This, combined with Lemma 5 and Slutsky's theorem, yields

$$\frac{1}{\sqrt{\operatorname{tr}(\mathbf{\Lambda}_2^2)}}\big(\mathbf{G}_2^T\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2-\tfrac{p-r-n+k}{p-r}\operatorname{tr}(\mathbf{\Lambda}_2)\mathbf{I}_{k-1}\big)\xrightarrow{\mathcal{L}}\mathbf{W}_{k-1}.$$

Next we show that the cross term of (6.7) is negligible. Note that

$$\begin{aligned}
&\mathrm{E}[\|\mathbf{C}^T\Xi^T(\mathbf{I}_p-\mathbf{P}_{Z\tilde{J}})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2\|_F^2|\mathbf{Y}]\\
=&(k-1)\operatorname{tr}(\mathbf{C}^T\Xi^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\Xi\mathbf{C})\\
\le&(k-1)\lambda_1\big((\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\big)\|\Xi\mathbf{C}\|_F^2\\
\le&(k-1)\lambda_1\big(\mathbf{\Lambda}^{1/2}\mathbf{U}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\big)\|\Xi\mathbf{C}\|_F^2\\
=&(k-1)O_P(\frac{\lambda_1 p}{\lambda_r n}+c_1)\|\Xi\mathbf{C}\|_F^2\\
=&(k-1)O_P\big(\frac{\lambda_1\sqrt{p}}{\lambda_r n}+\frac{c_1}{\sqrt{p}}\big)\sqrt{p}\|\Xi\mathbf{C}\|_F^2=o_P(p),
\end{aligned}$$

where the last equality holds since we have assumed $\frac{1}{\sqrt{p}}\|\Xi\mathbf{C}\|_F^2=O(1)$. Hence $\|\mathbf{C}^T\Xi^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{U}\mathbf{\Lambda}^{1/2}\mathbf{G}_2\|_F^2=o_P(p)$. Now,

$$\frac{1}{\sqrt{\operatorname{tr}(\mathbf{\Lambda}_2^2)}}\big(\mathbf{C}^T\mathbf{Y}^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\mathbf{Y}\mathbf{C}-\tfrac{p-r-n+k}{p-r}\operatorname{tr}(\mathbf{\Lambda}_2)\mathbf{I}_{k-1}-\mathbf{C}^T\Xi^T(\mathbf{I}_p-\mathbf{P}_{\mathbf{Y}})\Xi\mathbf{C}\big)\xrightarrow{\mathcal{L}}\mathbf{W}_{k-1}.$$

Equivalently,

$$\frac{1}{\sqrt{\mathrm{tr}(\mathbf{\Lambda}_2^2)}}\Big(\mathbf{C}^T\mathbf{Y}^T(\mathbf{I}_p-\mathbf{P}_\mathbf{Y})\mathbf{Y}\mathbf{C}-\frac{p-r-n+k}{p-r}\,\mathrm{tr}(\mathbf{\Lambda}_2)\mathbf{I}_{k-1}\Big)$$
$$\sim\frac{1}{\sqrt{\mathrm{tr}(\mathbf{\Lambda}_2^2)}}\mathbf{C}^T\Xi^T(\mathbf{I}_p-\mathbf{P}_\mathbf{Y})\Xi\mathbf{C}+\mathbf{W}_{k-1}+o_P(1).$$

The conclusion follows by taking the maximum eigenvalue. □

Supplementary Materials

Contain the brief description of the online supplementary materials.

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