A Bootstrap Test for Testing the Equality of Two Ultra-high Dimensional Covariance Matrices

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Abstract

This paper proposes a test for testing the equality of two high-dimensional covariance matrices in the two-sample set up. This test is based on the maximum of the absolute differences between the entries of the multiplier bootstrap Jackknifed estimators of the two sample covariance matrices. The paper also contains an extension of the central limit theorem for the one-sample non-degenerate U statistics to the two sample non-degenerate U statistics. This extension is used to derive the asymptotic guarantees for level and power of the proposed test statistic under the null and some local alternative hypotheses. These results are obtained under some weak conditions on the moments of the random vectors and tails of the marginal distributions. The correlation structures of the random vectors can be arbitrary, the two sample sizes need not be equal and the multivariate dimension is allowed to grow exponentially with the two sample sizes. The test is shown to be consistent against a class of shrinking nonparametric alternatives. An extensive finite sample simulation study reveals some superiority of this test compared to some of the existing tests. Finally, we apply our test to a real-life dataset and contrast the outcome with other tests.

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1. Introduction

The problem of testing the equality of the two covariance matrices in the two sample multivariate set up is a classical problem in statistical inference. It has been well studied in the low-dimensional setting where the multivariate dimension p is fixed and smaller than the sample sizes, see, e.g., Chapter 10, Anderson [1] and the references therein.

In the context of high dimensional data where the number of components p either grows polynomially or even exponentially with increasing sample sizes, this problem has been addressed only in the last decade or so. The tests proposed by Schott [14] and Srivastava and Yanighara [15] are valid for multivariate normal distributions only. A U-statistic test based on an unbiased estimator of the Frobenius norm of the difference of the two population covariance matrices was proposed by Li and Chen [13]. Aoshima and Yata [2] proposed a test based on the difference of the traces of two high-dimensional covariance matrices. Ishii, Yata and Aoshima [12] proposed a test based on the eigenvalues of the dual of the sample covariance matrices under strongly spiked eigenvalue models. Cai, Liu and Xia [3] proposed a test based on the maximum of the standardized differences between the entries of the estimates of the two population covariance matrices. Further investigation by Cai et al. [3] revealed that the Li and Chen [13] test fails to distinguish between the null and the alternative hypotheses when the difference between the two population covariance matrices is sparse, i.e., when the number of non-zero elements in this difference matrix is small. On the other hand, the Cai et al. [3] test works well only when the difference matrix is sparse.

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Although Cai et al. [3] showed that under certain regularity conditions their test enjoys some optimality in terms of the asymptotic power, it has been pointed out by Fan, Liao and Yao [10] that one needs large sample sizes in applications to use the asymptotic null distribution for implementing the Cai et al. [3] test effectively. They also suggested some power-enhancement techniques to achieve the desired power for the test statistic of Cai et al. [3]. Chang, Zhou, Zhou and Wang [4] investigated the finite sample performance of a bootstrap version of the Cai et al. [3] test. The technique involves using multiplier bootstrap approximation result for random vectors after vectorizing the covariance matrices. Their bootstrap method is inapplicable when the two populations means are unknown and unequal because then the sample covariance matrices can no longer be expressed as sums of independent vectors. Moreover, they established consistency of their test under some restrictive conditions like sparsity and other correlational structures.

The need for U statistics based testing approach for covariance matrices can be motivated by noting the fact that the high dimensional central limit theorem fails because the sample covariance matrix can no longer be written as a vectorized sum of independent high dimensional vectors.

In this paper we propose a test for testing the equality of two population covariance matrices in the high dimensional set up when the two population means are unknown, under some mild assumptions on the moments and tails of the underlying distributions. The proposed test is based on the maximum of the absolute differences between the entries of the Jackknifed estimators of the two population covariance matrices. We actually use a multiplier bootstrap version of this test statistic. Moreover, the absence of distributional and correlational assumptions makes it applicable more broadly, compared to the above mentioned tests. The proposed test is shown to be consistent against a large class of shrinking alternatives and is argued to be constant rate-optimal against such alternatives. These results are obtained using the seminal works of Chernozhukov, Chetverikov and Kato [6], [7], [8] and Chen [5].

The rest of the article is organized as follows. Section 3 describes the testing problem, the proposed test statistic and the large sample Gaussian approximation of a class of two sample U statistics in the high dimensional set up along with the needed assumptions. This approximation in turn is used to derive the limiting null distribution of the proposed test statistic in Section 4. It is also used to prove the consistency of the test against a sequence of general nonparametric alternatives in Section 5. An extensive finite sample study reported in Section 6 exhibits some superiority of the proposed test compared to some of the existing tests in terms of the empirical level and power. An application of the proposed method to a real life example is presented in Section 7. Section 9 contains some auxiliary lemmas. The proofs of the main theorems, which use auxiliary lemmas of Section 9, appear in an Appendix.

2. Notation

We shall use the following notation and conventions in this paper. The symbol := stands for 'definition'. For a positive integer p, $\mathbb{R}^p$ denotes the p dimensional Euclidean space. $\mathbb{R} := \mathbb{R}^1$. For $x \in \mathbb{R}^p$, x^T denotes its transpose, $\|x\|$ denotes its Euclidean norm and $\|x\|_\infty$ denotes its maximum norm. For any two vectors $x = (x_1, \cdots, x_p)^T \in \mathbb{R}^p$ and $y = (y_1, \cdots, y_p)^T \in \mathbb{R}^p$, write $x \le y$ if $x_j \le y_j$ for all $j = 1, \cdots, p$. For any $x = (x_1, \cdots, x_p)^T \in \mathbb{R}^p$ and $a \in \mathbb{R}$, $x + a := (x_1 + a, \cdots, x_p + a)^T$. For any $a, b \in \mathbb{R}$, $a \vee b := \max\{a, b\}$ and $a \wedge b := \min\{a, b\}$. For any two sequences $a_{d,m,n}$, $b_{d,m,n}, d \wedge m \wedge n \ge 1$, of positive numbers, write $a_{d,m,n} \lesssim b_{d,m,n}$ if for some universal constant $C > 0$, not depending on m, n, d, $a_{d,m,n} \le C b_{d,m,n}$, for all sufficiently large $d \wedge m \wedge n$. We write $a_{d,m,n} \sim b_{d,m,n}$ if $a_{d,m,n} \lesssim b_{d,m,n}$ and $b_{d,m,n} \lesssim a_{d,m,n}$.

For a positive integer q and a random vector (r.v.) $Z = (Z_1, \cdots, Z_q)^T$ with finite expectation, set $\|Z\|_1 := \sum_{j=1}^p E(|Z_j|)$ and $Z \sim_D G$ means that the distribution function (d.f.) of Z is G. For any matrix $A = ((a_{ij}))$, $\|A\|_\infty := \max_{i,j} |a_{ij}|$. For any $p \times p$ symmetric matrix A, vec(A) denotes the $d := p(p+1)/2$-dimensional vector consisting of all of the upper-diagonal entries of A. For any function $f : \mathbb{R} \to \mathbb{R}$, $\|f\|_\infty := \sup_{z \in \mathbb{R}} |f(z)|$. For a smooth function $g : \mathbb{R}^p \to \mathbb{R}$, we adopt indices to represent the partial derivatives for brevity. For example, $\delta_j \delta_k \delta_l g = g_{jkl}$, where δ_j denotes the partial derivative with respect to the jth coordinate. Let $\psi_\alpha(x) := \exp(x^\alpha) - 1$, $x > 0, \alpha > 0$. For any r.v. X, define

$$\|\mathcal{X}\|_{\psi_\alpha} := \inf\Big\{\lambda > 0 : E\{\psi_\alpha(|\mathcal{X}|/\lambda)\} \le 1\Big\}. \tag{2.1}$$

The entity $\|\mathcal{X}\|_{\psi_\alpha}$ with $\alpha \in [1,\infty)$, is called Orlicz norm while for $0 < \alpha < 1$, it is called Orlicz quasi-norm. Also let, $\mathcal{A}^{Re}$ denote the class of hyper-rectangles in $\mathbb{R}^p$, i.e.,

$$\mathcal{A}^{Re} := \Big\{\prod_{j=1}^{d}[a_j, b_j] : -\infty \le a_j \le b_j \le \infty,\ j = 1,2,\ldots,d\Big\}.$$

3. Gaussian approximation result for U statistics

This section contains the description of the testing problem, the proposed test and the Gaussian approximation results along with the needed assumptions for a large class of the two sample U statistics.

Let F_1 and F_2 be possibly two different d.f.'s on $\mathbb{R}^p$, both having finite second moments. Let μ_j and Σ_j, $j = 1,2$ denote their mean vectors and covariance matrices, respectively. Let X^m represent the random sample $X_1,\cdots,X_m$ from F_1 and Y^n denote the random sample $Y_1,\cdots,Y_n$ from F_2. We wish to test $H_0 : \Sigma_1 = \Sigma_2$ versus the alternatives $H_{alt} : \Sigma_1 \ne \Sigma_2$.

To describe the proposed test, let

$$V_m^X := \frac{1}{m(m-1)}\sum_{1\le i\ne j\le m}\frac{\mathrm{vec}((X_i - X_j)(X_i - X_j)^T)}{2} \quad \text{and} \quad V_n^Y := \frac{1}{n(n-1)}\sum_{1\le i\ne j\le n}\frac{\mathrm{vec}((Y_i - Y_j)(Y_i - Y_j)^T)}{2},$$

be the sample covariance matrices for the X^m and Y^n samples, respectively. Let

$$T_{m,n} := \frac{\sqrt{m}(V_m^X - V_n^Y)}{2}. \tag{3.1}$$

Both V_m^X, V_n^Y are $d := p(p+1)/2$ dimensional U statistics. The proposed test rejects H_0 whenever $\|T_{m,n}\|_\infty$ is large. To implement this test in the large samples, we need to know its asymptotic null distribution. Towards that goal, we shall first analyze some asymptotic properties of a general class of two sample U statistics in the high dimensional set up.

Let $\tilde{h}$ be a kernel function from $\mathbb{R}^p \times \mathbb{R}^p \mapsto \mathbb{R}^{p\times p}$ that is symmetric under permutations, i.e., $\tilde{h}(x_1,x_2) = \tilde{h}(x_2,x_1)$, for all $x_1, x_2 \in \mathbb{R}^p$. Thus $\tilde{h}$ is a $p \times p$ symmetric matrix. Assume $\big\|\mathrm{vec}(\tilde{h}(X_1,X_2))\big\|_1 + \big\|\mathrm{vec}(\tilde{h}(Y_1,Y_2))\big\|_1 < \infty$.

Let $\delta_{m,n}$ be a sequence of real numbers and define

$$\begin{aligned}
U_m^X &:= \frac{1}{m(m-1)}\sum_{1\le i\ne j\le m}\mathrm{vec}(\tilde{h}(X_i,X_j)), \qquad U_n^Y := \frac{1}{n(n-1)}\sum_{1\le i\ne j\le n}\mathrm{vec}(\tilde{h}(Y_i,Y_j)),\\
\Omega^X &:= \mathbb{E}\Big(\mathrm{vec}(\tilde{h}(X_1,X_2))\Big), \qquad \Omega^Y := \mathbb{E}\Big(\mathrm{vec}(\tilde{h}(Y_1,Y_2))\Big),\\
W_m^X &:= \frac{\sqrt{m}(U_m^X - \Omega^X)}{2}, \qquad W_n^Y := \frac{\sqrt{n}(U_n^Y - \Omega^Y)}{2}, \qquad W_{m,n} := W_m^X + \delta_{m,n}W_n^Y.
\end{aligned}$$

Note that if $\tilde{h}(x_1,x_2) \equiv (x_1 - x_2)(x_1 - x_2)^T/2$ and $\delta_{m,n} = -(m/n)^{1/2}$, then $U_m^X \equiv V_m^X$, $U_n^Y \equiv V_n^Y$, $\Omega^X \equiv \Sigma_1$ and $\Omega^Y \equiv \Sigma_2$. Moreover, under H_0, $\Omega^X = \Omega^Y$ and $W_{m,n} = T_{m,n}$.

We further define the linear projection terms of U_m^X and U_n^Y, respectively, to be

$$\begin{aligned}
g(x) &:= \mathbb{E}\Big(\mathrm{vec}(\tilde{h}(X_1,X_2))\Big|X_1 = x\Big) - \Omega^X, \qquad x \in \mathbb{R}^p,\\
\ell(y) &:= \mathbb{E}\Big(\mathrm{vec}(\tilde{h}(Y_1,Y_2))\Big|Y_1 = y\Big) - \Omega^Y, \qquad y \in \mathbb{R}^p.
\end{aligned}$$

The $d \times d$ covariance matrices of $g(X)$ and $\ell(Y)$ are, respectively, defined as

$$\Gamma^X := \mathbb{E}\Big(g(X)g(X)^T\Big), \qquad \Gamma^Y := \mathbb{E}\Big(\ell(Y)\ell(Y)^T\Big). \tag{3.2}$$

Let $\text{vec}(h(x_1, x_2)) := \text{vec}(\tilde{h}(x_1, x_2)) - \Omega^X$ and $\text{vec}(h(y_1, y_2)) := \text{vec}(\tilde{h}(y_1, y_2)) - \Omega^Y$. Further, for $x_j, y_j \in \mathbb{R}^p$, $j = 1, 2$, let

$$f(x_1, x_2) := \text{vec}(h(x_1, x_2)) - g(x_1) - g(x_2), \qquad q(y_1, y_2) := \text{vec}(h(y_1, y_2)) - \ell(y_1) - \ell(y_2).$$

A kernel $\text{vec}(h) : \mathbb{R}^p \times \mathbb{R}^p \mapsto \mathbb{R}^d$ is said to be non-degenerate if $\text{Var}(g_a(X)) > 0$, for all $a = 1, 2, \cdots, d$. It is said to be completely degenerate if $\mathbb{P}(g(X) = 0) = 1$ or equivalently,

$$\mathbb{E}[\text{vec}(h(x_1, X_2))] = \mathbb{E}[\text{vec}(h(X_1, x_2))] = \mathbb{E}[\text{vec}(h(X_1, X_2))] = 0, \quad \forall x_1, x_2 \in \mathbb{R}^p.$$

To proceed further, we need the following additional notation and assumptions. Let

$$\begin{aligned} L_{m,n} &:= \frac{1}{\sqrt{m}} \sum_{i=1}^{m} g(X_i) + \frac{\delta_{m,n}}{\sqrt{n}} \sum_{j=1}^{n} \ell(Y_j), \\ R_{m,n} &:= \frac{1}{2\sqrt{m}(m-1)} \sum_{1 \le i \neq j \le m} f(X_i, X_j) + \frac{\delta_{m,n}}{2\sqrt{n}(n-1)} \sum_{1 \le i \neq j \le n} q(Y_i, Y_j). \end{aligned} \tag{3.3}$$

Then,

$$W_{m,n} = L_{m,n} + R_{m,n}. \tag{3.4}$$

Note that, $R_{m,n}$ is a degenerate U statistic while $L_{m,n}$ is non-degenerate. It is reasonable to expect that the distribution of $W_{m,n}$ would be well approximated by that of $L_{m,n}$.

Let $T_m^{G_1}$ and $T_n^{G_2}$ be two independent r.v.'s having $\mathcal{N}_d(0, \Gamma^X)$, $\mathcal{N}_d(0, \Gamma^Y)$ distribution, respectively, and define

$$\begin{aligned} \rho_{m,n}^{**} &:= \sup_{A \in \mathcal{A}^{Re}} \left| \mathbb{P}\Big(\frac{\sqrt{m}(U_m^X - \Omega^X)}{2} + \delta_{m,n} \frac{\sqrt{n}(U_n^Y - \Omega^Y)}{2} \in A \Big) - \mathbb{P}\Big(T_m^{G_1} + \delta_{m,n} T_n^{G_2} \in A \Big) \right| \\ &= \sup_{A \in \mathcal{A}^{Re}} \left| \mathbb{P}\Big(W_m^X + \delta_{m,n} W_n^Y \in A \Big) - \mathbb{P}\Big(T_m^{G_1} + \delta_{m,n} T_n^{G_2} \in A \Big) \right|. \end{aligned}$$

The additional needed assumptions are as follows, where for any measurable function f from $\mathbb{R}^p \times \mathbb{R}^p \to \mathbb{R}^d$, f_a denotes its a^{th} coordinate, $a = 1(1)d$ and $\|\cdot\|_{\psi_1}$ is as in (2.1).

(a) There exists constants $0 < \underline{b} < \infty$ and $\delta_2 > \delta_1 > 0$ such that $\delta_1 < |\delta_{m,n}| < \delta_2$ and $\inf_{1 \le a \le d} \mathbb{E}\Big[g_a^2(X) + \delta_{m,n}^2 \ell_a^2(Y)\Big] > \underline{b}$, $\forall\, m \wedge n \ge 2$.

(b) There exists a sequence of positive constants $B_{m,n}^l, l = 1, 2$ such that the following holds with $\xi_j = X_j,\ j = 1, 2$ and $\xi_j = Y_j,\ j = 1, 2$.

$$\max_{1 \le a \le d} \mathbb{E}\Big[\Big| \{\text{vec}(h(\xi_1, \xi_2))\}_a \Big|^{2+l} \Big] \le B_{m,n}^l, \quad l = 1, 2, \forall\, m \wedge n \ge 2.$$

(c) There exists a sequence of positive constants $B_{m,n}$ such that the following holds with $\xi_j = X_j,\ j = 1, 2$ and $\xi_j = Y_j,\ j = 1, 2$.

$$\max_{1 \le a \le d} \Big\| \{\text{vec}(h(\xi_1, \xi_2))\}_a \Big\|_{\psi_1} \le B_{m,n}, \quad \forall\, m \wedge n \ge 1.$$

(d) $B_{m,n}^2 \log(md)^7 \le Km$ and $B_{m,n}^2 \log(nd)^7 \le Kn$, for some constant $K > 0$ and for all $m \wedge n \ge 2$.

We are now ready to state the following theorem which provides an approximation of the error bound estimate between the probability of interest and its Gaussian counterpart. Its proof is deferred to Section 10.

Theorem 3.1. *Under the above set up and assumptions* (a)–(d)*,*

$$\rho^{**}_{m,n} \lesssim \Big(\frac{B^2_{m,n}\log^7(md)}{m}\Big)^{1/6} + \Big(\frac{B^2_{m,n}\log^7(nd)}{n}\Big)^{1/6}. \tag{3.5}$$

Remark 1. The above assumptions (a)-(d) have roots in the works of Chernozhukov et al. [8] and Chen [5], which deal with the one sample set up. These conditions are the two sample adaptations of their conditions.

Assumption (a) specifies the restriction on the sequence of constants $\delta_{m,n}$ to be bounded away from zero and infinity. It also ensures the non-degeneracy of the kernel $\mathrm{vec}(h(X_1, X_2))$ and $\mathrm{vec}(h(Y_1, Y_2))$. Cai et al. [3] and Chang et al. [4] require the kurtosis of the observed random vectors to be bounded away from 1 in order to ensure non-degeneracy. The latter excludes some distributions like Rademacher distribution whose kurtosis equals one while our assumption (a) allows their inclusion. Li and Chen [13], Cai et al. [3] and Chang et al. [4] assumed the third order moments to be bounded whereas our assumptions (b) and (d) allow them to diverge to infinity as $m \wedge n \to \infty$. Along with the kurtosis condition both Cai et al. [3] and Chang et al. [4] require the r.v.'s X and Y to be sub-Gaussian whereas our assumption (c) only requires the tails of the given kernel h to decay exponentially without any additional restriction on the kurtosis.

Li and Chen [13] and Aoshima and Yata [2] require some structural assumptions on the traces of the two covariance matrices. In the case $\Sigma_1 = \Sigma_2 = \Sigma$, where Σ is a $p \times p$ covariance matrix, their trace condition becomes $\mathrm{trace}(\Sigma^4) = \mathrm{o}(\mathrm{trace}^2(\Sigma^2))$. This condition is not satisfied by the matrices like $\Sigma = (1-\rho)I_p + \rho 1_p 1_p^T$, where I_p is the $p \times p$ identity matrix, 1_p is the vector of p 1's and $0 < \rho < 1$. It is easy to see that in this case $\mathrm{trace}^2(\Sigma^2) = \mathrm{trace}(\Sigma^4) = O(\mathrm{p}^4)$ and hence their trace condition is not satisfied. Thus these author's results are not applicable to such matrices whereas our results are because we do not have any such assumption.

Cai et al. [3] imposed some structural assumptions like correlation and sparsity among the components of X and Y. For example, they require the maximum number of elements in each row of the correlation matrix that exceeds $1/\log p$, to be of the order of $o(p^\gamma)$, for every $\gamma > 0$. For the validity of their asymptotic results, Schott [14] and Srivastava and Yanighara [15] assumed the Gaussianity of X and Y.

In summary, our assumptions (a)–(d) are generally weaker than those appearing in the above references. They are weaker in the sense that no specific distributional assumption nor additional correlational assumption nor any uniformly bounded moment conditions are needed for the validity of the asymptotic results about the proposed test.

Although Theorem 3.1 acts as a foundational stone towards the Gaussian approximation of the distribution of $W^X_m + \delta_{m,n}W^Y_n$, but because the limiting distribution is unknown, this theorem is of little use in implementing any test based on $W^X_m + \delta_{m,n}W^Y_n$ for the large sample sizes. To circumvent this problem we are proposing a bootstrap approximation in Theorem 3.2 in the next section, which acts as a crucial step towards bridging this gap.

Instead of applying re-weighted multiplier bootstrap to estimate the unknown covariance matrices we employ the jackknifed version of multiplier bootstrap approximation with jackknifed estimators of the covariance matrices. A reason for choosing this strategy is that the i.i.d re-weighted bootstrap or naive multiplier bootstrap techniques are known to have slower rates of consistency than the jackknifed counterpart, see, e.g., Section 3 in Chen [5].

Let $e_1, e_2, \cdots, e_{m+n}$ be i.i.d. $\mathcal{N}(0,1)$ r.v.'s that are independent of $X^m, Y^n, T^{G_1}_m$ and $T^{G_2}_n$. Define the jackknife versions of W^X_m and W^Y_n , respectively, as

$$W^{eX}_m := \frac{1}{\sqrt{m}}\sum_{i=1}^m \Big[\frac{1}{m-1}\sum_{j\neq i=1}^m \mathrm{vec}(\tilde{h}(X_i, X_j)) - U^X_m\Big]e_i, \quad W^{eY}_n := \frac{1}{\sqrt{n}}\sum_{i=1}^n \Big[\frac{1}{n-1}\sum_{j\neq i=1}^n \mathrm{vec}(\tilde{h}(Y_i, Y_j)) - U^Y_n\Big]e_{i+m}.$$

Define the jackknife estimators of the corresponding covariance matrices of W_m^X and W_n^Y as

$$\hat{\Gamma}_m^{JK} := \frac{1}{(m-1)(m-2)^2} \sum_{i=1}^m \sum_{j\neq i} \sum_{k\neq i} \Big\{\mathrm{vec}(\tilde{h}(X_i, X_j)) - U_m^X\Big\}\Big\{\mathrm{vec}(\tilde{h}(X_i, X_k)) - U_m^X\Big\}^T,$$
$$\hat{\Gamma}_n^{JK} := \frac{1}{(n-1)(n-2)^2} \sum_{i=1}^n \sum_{j\neq i} \sum_{k\neq i} \Big\{\mathrm{vec}(\tilde{h}(Y_i, Y_j)) - U_n^Y\Big\}\Big\{\mathrm{vec}(\tilde{h}(Y_i, Y_k)) - U_n^Y\Big\}^T.$$

Let

$$\tilde{\Gamma}_m^{JK} := \frac{(m-2)^2}{m(m-1)}\hat{\Gamma}_m^{JK}, \quad \tilde{\Gamma}_n^{JK} := \frac{(n-2)^2}{n(n-1)}\hat{\Gamma}_n^{JK}, \;\; \hat{\Delta}_{m,n} := \Big\|(\tilde{\Gamma}_m^{JK} - \Gamma^X) + \delta_{m,n}^2(\tilde{\Gamma}_n^{JK} - \Gamma^Y)\Big\|_\infty. \tag{3.6}$$

For any two random vectors ξ, ζ, the notation $\xi|\zeta$ denotes the conditional distribution of ξ, given ζ. Note that, $W_m^{eX}|X^m$ is $\mathcal{N}_d(0, \tilde{\Gamma}_m^{JK})$ and $W_n^{eY}|Y^n$ is $\mathcal{N}_d(0, \tilde{\Gamma}_n^{JK})$. We are ready to state the following lemma which plays a crucial role towards obtaining the bootstrap approximation result. Its proof appears in Section 10.

Lemma 3.1. *Let Z^X, Z^Y be two independent r.v.'s such that $Z^X|X^m \sim_D \mathcal{N}_d(0, \tilde{\Gamma}_m^{JK})$ and $Z^Y|Y^n \sim_D \mathcal{N}_d(0, \tilde{\Gamma}_n^{JK})$. Then, for some constant $0 < C < \infty$ and every sequence of real numbers $\bar{\Delta}_{m,n} > 0$, on the event $\{\hat{\Delta}_{m,n} \leq \bar{\Delta}_{m,n}\}$,*

$$\sup_{A\in\mathcal{A}^{Re}} \Big|\mathbb{P}\Big(Z^X + \delta_{m,n}Z^Y \in A|X^m, Y^n\Big) - \mathbb{P}\Big(T_m^{G_1} + \delta_{m,n}T_n^{G_2} \in A\Big)\Big| \leq C(\bar{\Delta}_{m,n})^{1/2}\log d.$$

To proceed further, let $\mathbb{P}_{\boldsymbol{e}}$ denote the conditional distribution of $\boldsymbol{e} := \{e_1, e_2, \cdots, e_{m+n}\}$, given X^m, Y^n and define

$$\rho_{m,n}^{JK} := \sup_{A\in A^{Re}} \Big|\mathbb{P}_{\boldsymbol{e}}\Big(W_m^{eX} + \delta_{m,n}W_n^{eY} \in A\Big) - \mathbb{P}\Big(T_m^{G_1} + \delta_{m,n}T_n^{G_2} \in A\Big)\Big|.$$

Lemma 3.1 applied with $Z^X = W_m^{eX}$, $Z^Y = W_n^{eY}$, yields a preliminary upper bound for $\rho_{m,n}^{JK}$, which is instrumental in obtaining an improved rate of bootstrap approximation as is evidenced in the next theorem, under the following additional assumption.

(e) There exists a sequence of constant $\gamma_{m,n} \in (0, e^{-1})$ such that for all sufficiently large $d \wedge m \wedge n$,

$$m^{-1}B_{m,n}^2 \log^5(md)\log^2(1/\gamma_{m,n}) \leq 1, \qquad n^{-1}B_{m,n}^2 \log^5(nd)\log^2(1/\gamma_{m,n}) \leq 1. \tag{3.7}$$

We are ready to state the following theorem.

Theorem 3.2. *Under the above setup and assumptions* (a)–(c) *and* (e)*, the following holds. For a $\gamma_{m,n} < 1/56$, with probability at least $1 - 56\gamma_{m,n}$,*

$$\rho_{m,n}^{JK} \lesssim \Big(\frac{B_{m,n}^2 \log^5(md)\log^2(1/\gamma_{m,n})}{m}\Big)^{1/4} + \Big(\frac{B_{m,n}^2 \log^5(nd)\log^2(1/\gamma_{m,n})}{n}\Big)^{1/4}.$$

The entity $\rho_{m,n}^{JK}$ provides an upper bound to the error of approximation of the bootstrap distribution of the sequence of test statistics $W_m^{eX} + \delta_{m,n}W_n^{eY}$ by the Gaussian counterpart. Theorem 3.2 provides a theoretical guarantee towards the Gaussian approximation term and its jackknife covariance multiplier bootstrap counterpart. It shows that the rate of bootstrap approximation has improved from the rate $\Big(\log^5(nd)/n\Big)^{1/6}$ given in Chen [5] to $\Big(\log^5(nd)/n\Big)^{1/4}$.

Remark 2. One can choose a sequence $\gamma_{m,n}$ such that $\sum_{m,n}\gamma_{m,n} < \infty$. Then, by the Borel-Cantelli Lemma, the bootstrap convergence result holds almost surely. For example, if $\gamma_{m,n} = (m(\log m))^{-2}$ and $m = n$, then for $m \geq 11$, $\gamma_{m,n} < 1/56$. Then, the choice of $B_{m,n} = Cn^{1/6}$, for some $C > 0$ and $p = e^{n^{1/10}}$ will yield the condition (e).

4. Test Procedure

In this section, we shall describe the multiplier bootstrap distribution of the test statistic $\|T_{m,n}\|_\infty$ of (3.1). This is facilitated by Theorems 3.1 and 3.2. The proposed test rejects H_0 whenever $\|T_{m,n}\|_\infty$ is large. To implement the test in the large samples, we propose to use multiplier bootstrap version of $T_{m,n}$ given by $T^{JK}_{m,n} = W^{eX}_m - \sqrt{\frac{m}{n}} W^{eY}_n$, where

$$W^{eX}_m := \sqrt{m}\Big(\frac{1}{m}\sum_{i=1}^{m}\Big[\frac{1}{m-1}\sum_{j\neq i=1}^{m}\Big(\frac{\mathrm{vec}((X_i-X_j)(X_i-X_j)^T)}{2} - U^X_m\Big)\Big]e_i\Big),$$
$$W^{eY}_n := \sqrt{n}\Big(\frac{1}{n}\sum_{i=1}^{n}\Big[\frac{1}{n-1}\sum_{j\neq i=1}^{n}\Big(\frac{\mathrm{vec}((Y_i-Y_j)(Y_i-Y_j)^T)}{2} - U^Y_n\Big)\Big]e_{i+m}\Big).$$

Let

$$c_B(\alpha) = \inf\left\{t\in\mathbb{R} : \mathbb{P}_{\boldsymbol{e}}\left(\left\|W^{eX}_m - \sqrt{\frac{m}{n}}W^{eY}_n\right\|_\infty \le t\right) \ge 1-\alpha\right\}, \quad 0<\alpha<1.$$

Corollary 4.1 below shows that the test that rejects H_0 whenever $\|T_{m,n}\|_\infty > c_B(\alpha)$ is of the asymptotic size α.

For the sake of brevity, let $h(\xi_1,\xi_2) := \mathrm{vec}((\xi_1-\xi_2)(\xi_1-\xi_2)^T)/2,\ \xi_1,\xi_2\in\mathbb{R}^d$. The following assumptions are needed for the next theorem that provides the guarantee of the asymptotic level of the above mentioned test.

(a′) For some universal constants $0<c_1<c_2<1$, $\frac{m}{m+n}\in(c_1,c_2), \forall\, m\wedge n\ge 2$.

(b′) There exists a constant $b>0$ such that $\mathbb{E}\Big[g^2_a(X) + \delta^2_{m,n}\ell^2_a(Y)\Big] \ge b$, for all $1\le a\le d$.

(c′) There exists a sequence of constants $B_{m,n}\ge 1$ such that for $l=1,2$,

$$\max_{1\le a\le d}\mathbb{E}\Big[\Big|(\mathrm{vec}(h(X_1,X_2)))_a\Big|^{2+l}\Big] \le B^l_{m,n}, \quad \max_{1\le a\le d}\mathbb{E}\Big[\Big|(\mathrm{vec}(h(Y_1,Y_2)))_a\Big|^{2+l}\Big] \le B^l_{m,n},$$

(d′) $\max_{1\le a\le d}\Big\|(\mathrm{vec}(h(X_1,X_2)))_a\Big\|_{\psi_1} \le B_{m,n}, \quad \max_{1\le a\le d}\Big\|(\mathrm{vec}(h(Y_1,Y_2)))_a\Big\|_{\psi_1} \le B_{m,n},$

(e′) $\max\left(\frac{B^2_{m,n}\log^7(dm)}{m}, \frac{B^2_{m,n}\log^7(dn)}{n}\right) \to 0$, as $m\wedge n\to\infty$.

For brevity, let $\mathcal{D} = \Sigma_1 - \Sigma_2$. The Kolmogorov distance between the two distributions of suitably centered $T_{m,n}$ and $T^{JK}_{m,n}$ is defined to be

$$KD\big(T_{m,n}, T^{JK}_{m,n}\big) = \sup_{t\ge 0}\left|P\left(\left\|\frac{\sqrt{m}(V^X_m - V^Y_n) - \sqrt{m}\,\mathrm{vec}(\mathcal{D})}{2}\right\|_\infty \le t\right) - \mathbb{P}_{\boldsymbol{e}}\left(\left\|W^{eX}_m - \sqrt{\frac{m}{n}}W^{eY}_n\right\|_\infty \le t\right)\right|.$$

Theorem 4.1. *Suppose the conditions* (a′)–(e′) *hold. Then for any non-negative definite matrices* Σ_1 *and* Σ_2 *of real numbers,* $KD(T_{m,n}, T^{JK}_{m,n}) \to 0$, *almost surely.*

Remark 3. The above conditions (a′)–(e′) are analogous to the assumptions (a)–(e) suitable for the h of the theorem. Condition (a′) specifies that the ratio of the sample sizes should stay bounded away from 0 and 1. Condition (b′) ensures the non-degeneracy of the sample covariance kernel. Condition (c′) allows the bounds on the third and fourth order moments to grow with the sample sizes m, n, unlike as in Cai et al. [3], Li and Chen [13] and Chang et al. [4]. In these papers the moments appearing in (c′) are assumed to be bounded from the above by a fixed constant, for all sample sizes. Condition (d′) allows the sub-exponential tails to grow freely with the sample sizes, which is also advantageous than the analogous conditions in Cai et al. [3] and Chang et al. [4]. The condition (e′) specifies the asymptotic regime of the test.

On a similar note, in Cai et al. [3], for the convergence of the null distribution of their test statistic to an extreme Type-I distribution or to a normal distribution as in Li and Chen [13], they assumed the sparsity or weak correlation structure among the individual components of the observed random vectors and the corresponding covariance matrices. The jackknifed multiplier bootstrap test proposed in this paper is free from any such correlational assumptions.

The proposed test rejects $H_0 : \Sigma_1 = \Sigma_2$ versus $H_{alt} : \Sigma_1 \neq \Sigma_2$, at the significance level $\alpha \in (0,1)$, whenever $\varphi_\alpha = I\Big(\|T_{m,n}\|_\infty > c_B(\alpha)\Big) = 1$. The following corollary is an immediate consequence of Theorem 4.1.

Corollary 4.1. *Under the conditions of Theorem 4.1 and under H_0,*

$$\mathbb{P}\Big(\Big\|\frac{\sqrt{m}(V_m^X - V_n^Y)}{2}\Big\|_\infty \geq c_B(\alpha)\Big) \to \alpha. \tag{4.1}$$

Consequently, the set $CR_{1-\alpha}$ is a confidence set for $\text{vec}\Big(\Sigma_1 - \Sigma_2\Big)$ of the asymptotic confidence level $(1-\alpha)$, where

$$CR_{1-\alpha} := \left\{\text{vec}(\Sigma_1 - \Sigma_2) : \left\|T_{m,n} - \frac{\sqrt{m}\text{vec}(\Sigma_1 - \Sigma_2)}{2}\right\|_\infty \leq c_B(\alpha)\right\}.$$

A computing procedure for $c_B(\alpha)$. The multiplier bootstrapped version of the critical value $c_B(\alpha)$ requires the computational cost to be of the order of $O((m^2+n^2)dB)$, where B is the number of bootstrap iterations. A procedure for computing $c_B(\alpha)$ is as follows.

Step 1: Generate N sets of size $m+n$ i.i.d. $\mathcal{N}(0,1)$ r.v.'s. Denote them by $\boldsymbol{e}_1^*, \cdots, \boldsymbol{e}_N^*$. Treat $\boldsymbol{e}_j^*$ as a copy of $\boldsymbol{e} = \{e_1, e_2, \cdots, e_{m+n}\}$, $1 \leq j \leq N$.

Step 2: Keeping X^m and Y^n fixed, using the vectors $\boldsymbol{e}_j^*$'s of Step 1, compute the bootstrapped version of the test statistic $\|T_{m,n}\|_\infty$ N times, viz., calculate $\|T_{m,n}^{JK}\|_\infty$ N times, jth time with $\boldsymbol{e}$ replaced by $\boldsymbol{e}_j^*$, $1 \leq j \leq N$. Denote these N values by $\{T_{mn1}^{JK}, T_{mn2}^{JK}, \cdots, T_{mnN}^{JK}\}$.

Step 3: The $(1-\alpha)^{\text{th}}$ quantile of $\{T_{mn1}^{JK}, T_{mn2}^{JK}, \cdots, T_{mnN}^{JK}\}$ is treated as an approximate value for $c_B(\alpha)$.

A general criticism of the maximum norm-based statistic of Cai et al. [3] is that the convergence of the null distribution to Gumbel requires relatively large sample sizes, which in turn poses some computational challenges in terms of size and power when the sample sizes are moderate to small. Fan et al. [10] suggested power enhancement techniques in this context. In contrast, the proposed jackknifed multiplier bootstrap method exhibits good power performance without any power enhancement techniques.

5. Consistency

In this section, we show that the proposed jackknifed multiplier bootstrap based test is consistent against a sequence of shrinking nonparametric alternatives. The power function of the test is

$$\mathbb{P}_{H_{alt}}(\varphi_\alpha = 1) = \mathbb{P}\left(\left\|\frac{\sqrt{m}(V_m^X - V_n^Y)}{2}\right\|_\infty \geq c_B(\alpha)|H_{alt}\right).$$

This power function is an abstract quantity because the respective covariance matrices Γ^X and Γ^Y of V_m^X and V_n^Y are unknown in practice. To circumvent this problem we define jackknifed multiplier bootstrap based power function

$$\mathbb{P}_{H_{alt}}^*(\varphi_\alpha = 1) := \mathbb{P}_{\boldsymbol{e}^*}\left(\left\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y} + \frac{\sqrt{m}(\text{vec}(\Sigma_1 - \Sigma_2))}{2}\right\|_\infty \geq c_B(\alpha)|H_{alt}\right),$$

where $\mathbb{P}_{\boldsymbol{e}^*}(.)$ denotes the conditional distribution of $\boldsymbol{e}^*$, given all the other r.v.'s. Before exploring the asymptotic theoretical aspects of the power function we shall describe the multiplier bootstrap procedure in the context of approximating the true power function as follows.

Step 1: Generate $\{\boldsymbol{e}_1^*, \boldsymbol{e}_2^*, \cdots, \boldsymbol{e}_{m+n}^*\}$ independent of $\boldsymbol{e}$ which has been used previously to calculate $c_B(\alpha)$.

Step 2: Use the $c_B(\alpha)$ from Step 1 to compute the bootstrap power function for the proposed test by computing:

$$\mathbb{P}_{\boldsymbol{e}^*}\left(\left\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y} + \frac{\sqrt{m}(\text{vec}(\Sigma_1 - \Sigma_2))}{2}\right\|_\infty \geq c_B(\alpha)\right).$$

The following theorem establishes consistency of the proposed test by approximating the true power function $\mathbb{P}_{H_{alt}}(\varphi_\alpha = 1)$, by its jackknifed multiplier bootstrap counterpart $P^*_{H_{alt}}(\varphi_\alpha = 1)$. Its proof also appears in Section 10.

Recall $\mathcal{D} := \Sigma_1 - \Sigma_2$. Let $C > 0$ be a constant and define the sequence of alternatives

$$\mathcal{M}_{m,n,d} = \left\{ \mathcal{D} \in \mathbb{R}^{p\times p} : \|\mathrm{vec}(\mathcal{D})/2\|_\infty \geq C(B_{m,n}\log(md)/m)^{1/2} \right\}.$$

Theorem 5.1. *Suppose the conditions for Theorem 4.1 hold. Then, for all $\mathcal{D} \in \mathcal{M}_{m,n,d}$,*

$$\mathbb{P}\left(\left\| \frac{\sqrt{m}(V_m^X - V_n^Y)}{2} \right\|_\infty \geq c_B(\alpha) \right) \to 1, \text{ as } n \wedge m \wedge d \to \infty.$$

Remark 4. Cai et al. [3] and Chang et al. [4] obtained similar consistency results for their test statistics under a class of sparse alternatives. The above theorem generalizes their result in the sense that it is valid for general alternatives where $B_{m,n}$ possibly diverges to infinity. This can be understood by noting that the class $\mathcal{M}_{m,n,d}$ is constructed in a manner such that Σ_1 and Σ_2 are separated by a lower bound $K\Big(\sqrt{\frac{B_{m,n}\log(md)}{m}}\Big)$. Theorem 4 in Cai et al. [3] obtained a similar bound treating $B_{m,n}$ as a constant and their separation parameter was bounded from below by $C\Big(\sqrt{\frac{\log d}{m}}\Big)$ for some universal constant $C > 0$ under the class of sparse alternatives.

6. Simulation studies

This section contains the findings of a finite sample study that compares the empirical level and power of the proposed test with those of the existing five tests for testing the equality of the two high dimensional covariance matrices.

We chose the following five competitors to contrast with the performance of the proposed test (CKK test henceforth): They are the tests of Chang et al. [4], Cai et al. [3], Schott [14], Li and Chen [13] and Ishii et al. [12] denoted by CZZW, CLX, Sc, LC and IYA tests, respectively.

The CZZW test has similar flavor to the CKK test as they derive their critical values using multiplier bootstrap without jackknifing. The CLX test uses the critical values obtained from its asymptotic Gumbel distribution. The Sc and LC tests are based on the Frobenius norm or the vectorized l_2 norm. These tests use critical values obtained from their respective asymptotic normal distributions. The power enhanced test of IYA is based on the eigenvalues of the dual of the sample covariance matrices and uses the critical values obtained from its asymptotic chi-square distribution.

The finite sample performances of the six tests are compared for the following choices of the covariance matrices and the alternatives. Let $\mathbf{1}$ denotes the $p \times 1$ vector of 1's, $\mathcal{I}_p$ denote the $p \times p$ identity matrix and define

$$\Omega_1 := 0.1\mathcal{I}_p + 0.9\mathbf{1}\mathbf{1}^T, \qquad \Omega_2 := (((0.99)^{|i-j|^{0.5}}))_{i,j=1,\cdots,p}. \tag{6.1}$$

Let $[x]$ denote the greatest integer in $x \in \mathbb{R}$. For $0 < \beta < 1$ define the r.v.'s $v_1, \cdots, v_p$ as follows:

$$v_j \sim_D \mathrm{Unif}(-1,1),\ 1 \leq j \leq [\beta p] \text{ and } v_j = 0,\ [\beta p] < j \leq p; \quad v := (v_1, \cdots, v_p)^T. \tag{6.2}$$

We did simulations for two models, M1 amd M2. Under M1, $H_0 : \Sigma_1 = \Sigma_2 = \Omega_1$ and the alternatives are $H_1 : \Sigma_2 = \Omega_1 + \delta v v^T$. Under M2, $H_0 : \Sigma_1 = \Sigma_2 = \Omega_2$ and $H_1 : \Sigma_2 = \Omega_2 + \delta v v^T$. Note that the alternatives are composite because for each choice of (v, β, δ) we have one alternative under both models M1 and M2.

For the two sample sizes and the dimension, we choose the following scenarios:

- $m = 60, n = 40, p = 1000$, (See Tables 1 and 2).
- $m = 60, n = 60, p = 1000$. (See Tables 3 and 4).

For the distributions of the two samples, we used the following three choices.

- D1: $(X_0)_{ij}, (Y_0)_{ij} \overset{iid}{\sim} N(0,1)$ and $X = \Sigma_1^{1/2} X_0,\ \ Y = \Sigma_2^{1/2} Y_0$.
- D2: $(X_0)_{ij}, (Y_0)_{ij} \overset{iid}{\sim} t_{10}$ and $X = \Sigma_1^{1/2} X_0, Y = \Sigma_2^{1/2} Y_0$.
- D3: $(X_0)_{ij}, (Y_0)_{ij} \overset{iid}{\sim} \chi^2_{10} - 10$ and $X = \Sigma_1^{1/2} X_0, Y = \Sigma_2^{1/2} Y_0$.

To assess the sensitivity of these tests to the variances in the base distributions, we chose the variances of the base distributions in D1, D2 and D3 to be 1, 1.25 and 20, respectively. For the evaluation of the empirical sizes of the tests, we chose $\Sigma_1 = \Sigma_2 = \Omega_1$ or Ω_2. In the alternatives specified under models M1 and M2, we chose to assess the performance of the empirical power from both the light of how sparse the difference is and how dense the signal is. The variable β is the sparsity parameter with smaller values indicating the larger sparsity and the larger values correspond to the dense scenarios while δ measures the distance of the alternative from the null. Larger the value of δ farther is the alternative from the null. In the simulation, we chose $\beta = 0.2, 0.5, 0.8$ and $\delta = 0, 0.5, 1$. The entries in all the tables below for $\delta = 0\,(\delta > 0)$ represent the empirical levels (the empirical powers) of these tests. These entries are based on 2000 iterations. For the CKK and CZZW tests, in each empirical iteration a bootstrap sample of size 1000 was used. The nominal level of significance used in the simulation is 0.05 and Ω_1, Ω_2 and v are defined at (6.1) and (6.2).

Next, we summarize the findings in these four tables. Overall, when looked at from a comparative viewpoint across the 6 methods, the tables show somewhat similar pattern although the differences are mild or stark depending on the data generating distribution $D1$, $D2$ or $D3$, model $M1$ or $M2$, sample sizes m or n and parameter dimensions p. First, we discuss general patterns for all the tables and then specifically delve into the differences that arise due to different m, n, p combinations. Although the LC test does not meet the theoretical assumptions required for $M1$ and $M2$, we nevertheless include it due to its prevalence in the existing literature.

In terms of the empirical level ($\delta = 0$), we find that the empirical level of the CKK test is somewhat uniformly close to the nominal level of 0.05 across the chosen values of the sparsity parameter β, distributions, models, sample sizes and parameter sizes for $D1$. Notable exceptions are probably a few conservative values for the model $M1$ at $D2$ or $D3$ for both $m = 60, n = 40, p = 1000$ and $m = n = 60, p = 1000$ cases in Tables 1 and 3 respectively. In contrast, other than the CZZW test, the empirical levels of all other tests are quite far off. The CLX test fails to reject almost everywhere whereas the Sc and LC tests tend to be liberal, i.e., their empirical levels are significantly higher than the nominal level of 0.05, almost everywhere across the four tables. The CZZW and IYA tests are the most competitive with the CKK test in terms of the closeness of the empirical level to the nominal level 0.05 across all the settings in this extensive simulation study. The CZZW test sometimes tend to be slightly liberal across all distributions for smaller sample sizes as seen in Tables 1 and 2, while IYA tends to be slightly liberal for $D2$ and $D3$.

As far as the empirical power is concerned, we observe a general increasing pattern for every methods in all the tables. The empirical power of all tests has an increasing trend with the increasing chosen δ values or sparsity parameters for all distributions $D1 - D3$ and models M1 and M2. However, the empirical power of the CKK test is much higher than that of CLX, Sc and LC tests across all 4 tables, 3 distributions and 2 models.

Remaining consistent with the low empirical level, the CLX test has the lowest empirical power almost everywhere and for the Sc and LC tests, one sees that despite starting with relatively higher empirical levels, their empirical powers do not scale properly as δ increases and remain below those of the CKK, CZZW and IYA tests, uniformly for all chosen distributions $D1 - D3$, sparsity levels β, distance δ from the null and the models M1 and M2. Coming to the CZZW test, albeit significantly faring better than CLX, Sc or LC tests, the empirical power of the CKK test is generally larger or quite similar to that of the CZZW test with very few exceptions. The IYA test shows higher empirical power. However, it is important to note that for covariance structure M2 and for lower values of sparsity parameter β, the power of the CKK test is significantly higher than that of the IYA test as seen in Tables 2 and 4 across all the three distributions.

In conclusion, it can be said that although there are some qualitative differences between these 4 tables and more specifically when (m, n, p) changes but across all of them CKK fares reasonably well both in terms of empirical level

	D1			D2			D3		
β	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8
CKK									
$\delta = 0$	0.050	0.045	0.044	0.039	0.034	0.031	0.026	0.029	0.033
$\delta = 0.5$	0.326	0.357	0.342	0.192	0.219	0.207	0.214	0.228	0.227
$\delta = 1$	0.795	0.804	0.832	0.572	0.583	0.574	0.627	0.659	0.625
CZZW									
$\delta = 0$	0.071	0.062	0.079	0.054	0.057	0.082	0.076	0.056	0.080
$\delta = 0.5$	0.316	0.370	0.403	0.272	0.321	0.310	0.242	0.323	0.352
$\delta = 1$	0.679	0.771	0.816	0.623	0.649	0.690	0.674	0.712	0.742
CLX									
$\delta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\delta = 0.5$	0.009	0.016	0.025	0.001	0.009	0.005	0.002	0.009	0.031
$\delta = 1$	0.050	0.072	0.131	0.027	0.052	0.081	0.059	0.058	0.054
Sc									
$\delta = 0$	0.081	0.077	0.090	0.109	0.137	0.127	0.140	0.145	0.154
$\delta = 0.5$	0.099	0.102	0.119	0.145	0.165	0.152	0.141	0.168	0.172
$\delta = 1$	0.059	0.097	0.222	0.172	0.223	0.294	0.145	0.183	0.294
LC									
$\delta = 0$	0.113	0.010	0.111	0.100	0.131	0.131	0.140	0.151	0.145
$\delta = 0.5$	0.125	0.129	0.143	0.131	0.155	0.144	0.138	0.145	0.168
$\delta = 1$	0.063	0.124	0.262	0.172	0.204	0.290	0.145	0.181	0.394
IYA									
$\delta = 0$	0.038	0.048	0.031	0.0925	0.088	0.099	0.083	0.090	0.075
$\delta = 0.5$	0.7905	0.946	0.974	0.843	0.96	0.9845	0.817	0.953	0.973
$\delta = 1$	0.943	0.988	0.986	0.952	0.983	0.993	0.941	0.976	0.992

Table 1: Empirical level and power of 6 tests, $m = 60, n = 40, p = 1000$ and model M1: $H_0 : \Sigma_1 = \Sigma_2 = \Omega_1$, $H_1 : \Sigma_2 = \Omega_1 + \delta v v^T$

and power. However, it is important to note that the performance of the CKK test is suboptimal under the relatively heavy-tailed t_{10} distribution. This is likely due to the fact that Gaussian or bootstrap approximations for heavy-tailed distributions typically require larger sample sizes in high-dimensional settings. Additionally, for higher sparsity levels, such as $\beta = 0.8$, the CKK test tends to be slightly conservative, particularly for smaller sample sizes, as observed for D_2 and D_3 in Tables 1 and 2. The performance improves modestly with larger sample sizes, as shown in Tables 3 and 4. The CZZW and IYA tests are probably the most competitive ones as compared to CKK and their empirical power only matches that of CKK at dense (larger β) and/or farther away from null (larger δ).

	D1			D2			D3		
β	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8
CKK									
$\delta = 0$	0.044	0.048	0.049	0.031	0.037	0.035	0.046	0.045	0.040
$\delta = 0.5$	0.301	0.358	0.373	0.189	0.206	0.222	0.270	0.312	0.313
$\delta = 1$	0.810	0.819	0.834	0.575	0.592	0.602	0.687	0.711	0.717
CZZW									
$\delta = 0$	0.095	0.070	0.084	0.054	0.057	0.090	0.068	0.082	0.079
$\delta = 0.5$	0.263	0.366	0.427	0.227	0.321	0.353	0.233	0.292	0.387
$\delta = 1$	0.570	0.761	0.792	0.620	0.650	0.719	0.584	0.717	0.778
CLX									
$\delta = 0$	0.000	0.000	0.000	0.000	0.000	0.005	0.000	0.000	0.000
$\delta = 0.5$	0.005	0.016	0.014	0.007	0.009	0.021	0.012	0.012	0.011
$\delta = 1$	0.036	0.059	0.136	0.027	0.052	0.045	0.063	0.039	0.054
Sc									
$\delta = 0$	0.100	0.084	0.098	0.109	0.136	0.154	0.131	0.129	0.136
$\delta = 0.5$	0.109	0.104	0.095	0.145	0.165	0.175	0.152	0.131	0.149
$\delta = 1$	0.109	0.131	0.217	0.172	0.222	0.317	0.127	0.195	0.308
LC									
$\delta = 0$	0.122	0.100	0.111	0.100	0.132	0.136	0.127	0.132	0.134
$\delta = 0.5$	0.118	0.127	0.122	0.131	0.236	0.152	0.113	0.127	0.148
$\delta = 1$	0.118	0.161	0.285	0.172	0.204	0.290	0.109	0.190	0.312
IYA									
$\delta = 0$	0.052	0.052	0.053	0.119	0.125	0.118	0.094	0.084	0.090
$\delta = 0.5$	0.059	0.168	0.329	0.119	0.259	0.433	0.108	0.189	0.368
$\delta = 1$	0.115	0.414	0.7	0.185	0.53	0.749	0.118	0.514	0.680

Table 2: Empirical level and power of 6 tests, $m = 60, n = 40, p = 1000$ and model M2: $H_0 : \Sigma_1 = \Sigma_2 = \Omega_2$, $H_1 : \Sigma_2 = \Omega_2 + \delta vv^T$

7. Data Study

We analyze the following dataset obtained from the UCI Machine Learning Repository (`https://archive.ics.uci.edu/dataset/121/eeg+database`). Our data set consists of 93 individuals, divided into two groups: the alcoholic group, comprising 60 individuals ($m = 60$), and the control group, consisting of 33 individuals ($n = 33$). The 1980 Snodgrass and Vanderwart picture set was used as the stimulus for the experiment, providing an image of an object presented to each subject.

For each individual, EEG measurements were sampled at 256 Hz (3.9 ms epoch) for one second, recorded from

	D1			D2			D3		
β	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8
CKK									
$\delta = 0$	0.051	0.047	0.043	0.035	0.030	0.037	0.035	0.034	0.028
$\delta = 0.5$	0.436	0.458	0.485	0.251	0.282	0.284	0.283	0.332	0.327
$\delta = 1$	0.942	0.949	0.950	0.728	0.759	0.760	0.803	0.818	0.799
CZZW									
$\delta = 0$	0.050	0.066	0.068	0.032	0.052	0.036	0.045	0.048	0.068
$\delta = 0.5$	0.353	0.422	0.487	0.233	0.343	0.353	0.337	0.378	0.421
$\delta = 1$	0.891	0.930	0.946	0.661	0.787	0.801	0.805	0.860	0.842
CLX									
$\delta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\delta = 0.5$	0.005	0.012	0.014	0.000	0.005	0.003	0.000	0.009	0.007
$\delta = 1$	0.077	0.118	0.154	0.045	0.07	0.054	0.054	0.077	0.086
Sc									
$\delta = 0$	0.086	0.100	0.077	0.154	0.000	0.104	0.127	0.149	0.176
$\delta = 0.5$	0.095	0.110	0.098	0.136	0.139	0.176	0.143	0.138	0.165
$\delta = 1$	0.095	0.134	0.267	0.176	0.222	0.326	0.140	0.167	0.294
LC									
$\delta = 0$	0.113	0.116	0.095	0.149	0.156	0.086	0.131	0.122	0.163
$\delta = 0.5$	0.116	0.125	0.127	0.125	0.134	0.147	0.140	0.136	0.159
$\delta = 1$	0.122	0.172	0.353	0.149	0.202	0.285	0.154	0.186	0.276
IYA									
$\delta = 0$	0.042	0.035	0.044	0.096	0.092	0.089	0.082	0.095	0.084
$\delta = 0.5$	0.796	0.949	0.967	0.856	0.975	0.983	0.814	0.952	0.976
$\delta = 1$	0.917	0.972	0.996	0.951	0.989	0.991	0.944	0.982	0.993

Table 3: Empirical level and power of 6 tests, $m = 60, n = 60, p = 1000$ and model M1: $H_0 : \Sigma_1 = \Sigma_2 = \Omega_1$, $H_1 : \Sigma_2 = \Omega_1 + \delta v v^T$

64 electrodes placed on the scalp. In line with standard data reduction practices (e.g., [11], [17]), we aggregated the data by averaging the four proximal grid points for each electrode, reducing the number of data points from 256 to 64. Additionally, we pooled the data from the 64 electrodes by averaging every four adjacent electrodes, resulting in 16 electrodes. Consequently, the dimensionality of the dataset became $p = 64 \times 16 = 1024$, which is considerably large relative to the sample sizes m and n.

Let Σ_a and Σ_c denote the population covariance matrices for the alcoholic and control groups, respectively. To assess potential differences between the two covariance matrices, we conduct hypothesis testing for $H_0 : \Sigma_a = \Sigma_c$

	D1			D2			D3		
β	0.2	0.5	0.8	0.2	0.5	0.8	0.2	0.5	0.8
CKK									
$\delta = 0$	0.045	0.052	0.047	0.038	0.036	0.027	0.040	0.051	0.040
$\delta = 0.5$	0.406	0.479	0.552	0.262	0.290	0.307	0.347	0.400	0.419
$\delta = 1$	0.937	0.953	0.965	0.750	0.798	0.779	0.837	0.873	0.874
CZZW									
$\delta = 0$	0.068	0.066	0.041	0.059	0.061	0.054	0.050	0.057	0.086
$\delta = 0.5$	0.315	0.423	0.523	0.224	0.336	0.405	0.254	0.378	0.489
$\delta = 1$	0.842	0.930	0.968	0.692	0.781	0.855	0.774	0.853	0.873
CLX									
$\delta = 0$	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
$\delta = 0.5$	0.005	0.005	0.009	0.000	0.001	0.010	0.000	0.006	0.018
$\delta = 1$	0.059	0.122	0.158	0.036	0.048	0.063	0.045	0.057	0.100
Sc									
$\delta = 0$	0.063	0.082	0.068	0.154	0.1495	0.163	0.081	0.127	0.154
$\delta = 0.5$	0.105	0.089	0.104	0.116	0.172	0.188	0.100	0.121	0.168
$\delta = 1$	0.095	0.143	0.303	0.176	0.220	0.398	0.145	0.154	0.335
LC									
$\delta = 0$	0.100	0.098	0.086	0.136	0.138	0.176	0.081	0.125	0.154
$\delta = 0.5$	0.120	0.107	0.131	0.109	0.148	0.167	0.115	0.118	0.188
$\delta = 1$	0.127	0.179	0.367	0.163	0.204	0.398	0.145	0.170	0.317
IYA									
$\delta = 0$	0.05	0.05	0.05	0.119	0.125	0.118	0.100	0.096	0.096
$\delta = 0.5$	0.061	0.174	0.343	0.119	0.259	0.433	0.096	0.192	0.386
$\delta = 1$	0.113	0.475	0.687	0.191	0.552	0.737	0.144	0.515	0.699

Table 4: Empirical level and power of 6 tests, $m = 60, n = 60, p = 1000$ and model M2: $H_0 : \Sigma_1 = \Sigma_2 = \Omega_2$, $H_1 : \Sigma_2 = \Omega_2 + \delta vv^T$

against $H_a : \Sigma_a \neq \Sigma_c$. The nominal level considered here was $\alpha = 0.05$. We performed the six different tests, as considered in our simulation studies, and found that only the CKK, Sc and IYA tests rejected the null hypothesis. Although Sc test is only valid for normal distribution, we still decided to report its p-value here. Out of the l_∞ norm based tests only CKK could reject the null hypothesis. The p-values for all tests are summarized in Table 5. Previous studies in [11] and [17] observed differences between the two groups based on ranks and means, respectively, and our findings are consistent with these earlier results.

Test	CKK	CZZW	CLX	Sc	LC	IYA
p-value	0.035	0.555	1	0.002	0.336	0.001

Table 5: p-value for the 6 tests

8. Discussion

This paper proposes a test for testing the equality of the two population covariance matrices in an ultra-high dimensional regime, where the dimension is generally much larger than the sample sizes. The proposed test is based on the maximum of the absolute differences between the entries of the Jackknifed multiplier bootstrap estimators of the two population covariance matrices. The paper contains the proof of the asymptotic normality of the test statistic under the null hypothesis and the consistency of the sequence of the proposed tests against a sequence of shrinking alternatives. A finite sample simulation exhibits some superiority of the proposed test in terms of the empirical level and power, compared to the currently popular four tests. Several further works can be considered following the spirit of the current paper. Sometimes researchers are interested in testing the equality of correlation matrices via Kendall's tau for two populations see for instance Zhou, Han, Zhang and Liu [18]. The methodology proposed in this paper can be extended to those situations, which we leave for future research.

9. Some Useful Auxiliary Lemmas

Before stating the next lemma we need some definitions. For any functions f, q from $\mathbb{R}^p \times \mathbb{R}^p$ to $\mathbb{R}^p \times \mathbb{R}^p$, define

$$\begin{aligned}
\mathcal{V}_m^X &= \frac{1}{m(m-1)} \sum_{1\le i\ne j\le m} f(X_i, X_j), \qquad \mathcal{V}_n^Y = \frac{1}{n(n-1)} \sum_{1\le i\ne j\le n} q(Y_i, Y_j),\\
M^X &= \max_{1\le i\ne j\le m} \max_{1\le a\le d} \left|f_a(X_i, X_j)\right|, \qquad M^Y = \max_{1\le i\ne j\le n} \max_{1\le a\le d} \left|q_a(Y_i, Y_j)\right|,\\
D_r^X &= \max_{1\le a\le d} \left(\mathbb{E}|f_a(X_1, X_2)|^r\right)^{\frac{1}{r}}, \qquad D_r^Y = \max_{1\le a\le d} \left(\mathbb{E}|q_a(Y_1, Y_2)|^r\right)^{\frac{1}{r}}, \quad r > 0.
\end{aligned}$$

The following lemma will provide a bound for $R_{m,n}$ in (3.3). The claim (9.1) of this lemma is Theorem 5.1 of Chen [5] while (9.2) follows from (9.1) by applying it to each of the two samples.

Lemma 9.1. *Let $X^m = (X_1, \cdots, X_m)$ and $Y^n = (Y_1, \cdots, Y_n)$ be two independent random samples from F_1, F_2, respectively. Let $f, q : \mathbb{R}^p \times \mathbb{R}^p \mapsto \mathbb{R}^d$ be measurable symmetric functions such that $\mathbb{E}\left|f_a(X_1, X_2)\right| + \mathbb{E}\left|q_a(Y_1, Y_2)\right| < \infty$. If $2 \le d \le \exp(\underline{b}(m \vee n))$, for some constant $\underline{b} > 0$, then $\exists$ a constant $0 < C^X < \infty$ such that*

$$\mathbb{E}\left\|\mathcal{V}_m^X\right\|_\infty \le C^X(1 + \sqrt{\underline{b}})\Big[\Big(\frac{\log(d)}{m}\Big)^{\frac{3}{2}} \|M^X\|_4 + \frac{\log(d)}{m} D_2^X + \Big(\frac{\log(d)}{m}\Big)^{\frac{5}{4}} D_4^X\Big]. \tag{9.1}$$

Consequently, with $C = \max\{C^X, C^Y\} > 0$, we obtain that

$$\begin{aligned}
\mathbb{E}\Big[\left\|\mathcal{V}_m^X - \delta_{m,n}\mathcal{V}_n^Y\right\|_\infty\Big] \le K(1 + \sqrt{\underline{b}}) &\left(\left(\frac{\log d}{m}\right)^{\frac{3}{2}} \|M^X\|_4 + \frac{\log(d)}{m} D_2^X + \left(\frac{\log(d)}{m}\right)^{\frac{5}{4}} D_4^X\right)\\
&+ \delta_{m,n}\left(\left(\frac{\log(d)}{n}\right)^{\frac{3}{2}} \|M^Y\|_4 + \frac{\log(d)}{n} D_2^Y + \left(\frac{\log(d)}{n}\right)^{\frac{5}{4}} D_4^Y\right).
\end{aligned} \tag{9.2}$$

To proceed further we need more notation. For $r > 0$ and any sequences of real numbers $\phi_m, \phi_n \geq 1$, define

$$D^X_{g,r} = \max_{1\leq a\leq d} \mathbb{E}|g_a(X-\mu^X)|^r, \qquad D^Y_{\ell,r} = \max_{1\leq a\leq d} \mathbb{E}|\ell_a(Y-\mu^Y)|^r,$$

$$M^X_{g,r}(\phi_m) = \mathbb{E}\Big[\max_{1\leq a\leq d}\big|g_a(X-\mu^X)\big|^r \mathrm{I}\Big(\max_{1\leq a\leq d}\big|g_a(X-\mu^X)\big| > \frac{\sqrt{n}}{4\phi_m\log d}\Big)\Big],$$

$$M^Y_{\ell,r}(\phi_n) = \mathbb{E}\Big[\max_{1\leq a\leq d}\big|\ell_a(Y-\mu^Y)|^r \mathrm{I}\Big(\max_{1\leq a\leq d}\big|\ell_a(Y-\mu^Y)\big| > \frac{\sqrt{n}}{4\phi_n\log d}\Big)\Big],$$

$$M^{G_1}_r(\phi_m) = \mathbb{E}\Big[\max_{1\leq a\leq d}|T^{G_1}_{ma}|^r \mathrm{I}\Big(\max_{1\leq a\leq d}|T^{G_1}_{ma}| > \frac{\sqrt{n}}{4\phi_m\log d}\Big)\Big],\ \ M^{G_2}_r(\phi_n) = \mathbb{E}\Big[\max_{1\leq a\leq d}|T^{G_2}_{na}|^r \mathrm{I}\Big(\max_{1\leq a\leq d}|T^{G_2}_{na}| > \frac{\sqrt{n}}{4\phi_n\log d}\Big)\Big],$$

$$M^X_r(\phi_m) = M^X_{g,r}(\phi_m) + M^{G_1}_r(\phi_m), \quad M^Y_r(\phi_n) = M^Y_{\ell,r}(\phi_n) + M^{G_2}_r(\phi_n),$$

$$M^X_{h,r} = \mathbb{E}\Big[\max_{1\leq i\neq j\leq m}\max_{1\leq a\leq d}\Big|\big(\mathrm{vec}(h(X_i,X_j))\big)_a\Big|^r\Big],\ \ M^Y_{h,r} = \mathbb{E}\Big[\max_{1\leq i\neq j\leq m}\max_{1\leq a\leq d}\Big|\big(\mathrm{vec}(h(Y_i,Y_j))\big)_a\Big|^r\Big].$$

We are ready to state the following lemma. Recall $\underline{b}$ appears in condition (a).

Lemma 9.2. *Suppose condition* (a) *holds and* $\log(d) \leq \bar{b}(m \vee n)$*, for some constant* $\bar{b} > 0$*. Then, for some constants* $C_i := C_i(\underline{b}, \bar{b}) > 0, i = 1, 2$ *and for any two sequences* $\bar{D}^X_{g,3}$ *and* $\bar{D}^Y_{\ell,3}$ *of real numbers satisfying* $D^X_{g,3} \leq \bar{D}^X_{g,3}$ *and* $D^Y_{\ell,3} \leq \bar{D}^Y_{\ell,3}$,

$$\begin{aligned}\rho^{**}_{m,n} \leq C_3\Big[&\Big(\frac{(\bar{D}^X_{g,3})^2\log^7 d}{m}\Big)^{\frac{1}{6}} + \frac{M^X_3(\phi_m)}{\bar{D}^X_{g,3}} + \Big(\frac{(\bar{D}^Y_{\ell,3})^2|\delta_{m,n}|^6\log^7 d}{n}\Big)^{\frac{1}{6}} + \frac{M^Y_3(\phi_n)}{\bar{D}^Y_{\ell,3}} \\ &+ \phi^*\Big(\frac{\log^{3/2} d}{m}(M^X_{h,4})^{1/4} + \frac{\log(d)}{m^{1/2}}(D^X_2)^{1/2} + \frac{\log^{5/4} d}{m^{3/4}}(D^X_4)^{1/4} \\ &+ \frac{\log^{3/2} d}{m}(M^Y_{h,4})^{1/4} + \frac{\log(d)}{m^{1/2}}(D^Y_2)^{1/2} + \frac{\log^{5/4} d}{m^{3/4}}(D^Y_4)^{1/4}\Big)\Big].\end{aligned} \tag{9.3}$$

where, $C_3 = \max\{C_1, C_2\}$*,* $\phi^* = \max\{\phi_m, \phi_n\}$*, with*

$$\phi_m = C_1\left(\frac{(\bar{D}^X_{g,3})^2\log^4 d}{m}\right)^{-1/6}, \quad \phi_n = C\left(\frac{(\bar{D}^Y_{\ell,3})^2\log^4 d}{n}\right)^{-1/6}. \tag{9.4}$$

Proof. This lemma is analogous to Proposition 5.3 of Chen [5]. We provide details to clearly address the additional changes needed in the proof of Proposition 5.3 to prove the stated lemma. Fix a $y \in \mathbb{R}^p$ and define

$$F_\beta(w) = \frac{1}{\beta}\log\Big(\sum_{j=1}^d \exp\big(\beta(w_j - y_j)\big)\Big), \quad \beta \in \mathbb{R}, w \in \mathbb{R}^p.$$

We shall often use this function with $\beta = \phi\log(d)$, where $\phi \geq 1$. In this case,

$$0 \leq F_\beta(w) - \max_{1\leq j\leq d}(w_j - y_j) \leq \frac{\log(d)}{\beta} = \phi^{-1}, \quad \forall\, w \in \mathbb{R}^d,\ \phi \geq 1.$$

Next, let $u_0 : \mathbb{R} \to [0, 1]$ be a function such that $u_0(t) = 1$, if $t < 0$, $u_0(t) = 0$, if $t > 1$ and $u_0(t)$, $t \in [0, 1]$, is five times continuously differentiable with bounded derivatives. Let

$$u(t) := u_0(\phi t), \qquad \Psi(w) = u(\phi F_\beta(w)), \qquad t \in \mathbb{R}, \phi \geq 1, w \in \mathbb{R}^p.$$

Note that, $\Psi(w) : \mathbb{R}^d \to [0, 1]$. For the later use, we note that when $\beta = \phi\log(d)$,

$$I(t \leq 0) \leq u(t) \leq I(t \leq \phi^{-1}), \quad t \in \mathbb{R}.$$

Let $G_{1i}, H_{1i}, 1 \le i \le m$ be i.i.d. $\mathcal{N}_d(0, \Gamma^X)$ r.v.'s and $G_{2j}, H_{2j}, 1 \le j \le n$ be i.i.d. $\mathcal{N}_d(0, \Gamma^Y)$ r.v.'s, independent of $G_{1i}, H_{1i}, 1 \le i \le m$, where $\Gamma^X = \mathrm{Cov}(g(X))$, $\Gamma^Y := \mathrm{Cov}(\ell(Y))$. Let

$$
\begin{aligned}
Z_i^*(t) &:= \frac{1}{\sqrt{m}}\Big[\sqrt{t}\Big\{\sqrt{v}g(X_i) + \sqrt{1-v}G_{1i}\Big\} + \sqrt{1-t}H_{1i}\Big], \quad 1 \le i \le m,\\
Z_j^{**}(t) &:= \frac{1}{\sqrt{n}}\delta_{m,n}\Big[\sqrt{t}\Big\{\sqrt{v}\ell(Y_j) + \sqrt{1-v}G_{2j}\Big\} + \sqrt{1-t}H_{2j}\Big], \quad 1 \le j \le n,\\
Z^*(t) &:= \sum_{i=1}^m Z_i(t), \quad Z^{**}(t) := \sum_{j=1}^n Z_j^{**}(t), \quad Z(t) = Z^*(t) + Z^{**}(t), \quad v, t \in [0,1].
\end{aligned}
$$

Let

$$
\begin{aligned}
I_{m,n} &:= \Psi\Big(\sqrt{v}\frac{1}{\sqrt{m}}\sum_{i=1}^n g(X_i) + \sqrt{1-v}\frac{1}{\sqrt{m}}\sum_{i=1}^n G_{1i} + \sqrt{v}\delta_{m,n}\frac{1}{\sqrt{n}}\sum_{j=1}^n \ell(Y_j)\\
&\qquad + \sqrt{1-v}\delta_{m,n}\frac{1}{\sqrt{n}}\sum_{j=1}^n G_{2j}\Big) - \Psi\Big(\frac{1}{\sqrt{m}}\sum_{i=1}^n H_{1i} + \delta_{m,n}\frac{1}{\sqrt{n}}\sum_{j=1}^n H_{2j}\Big)\\
&= \Psi(Z(1)) - \Psi(Z(0)).
\end{aligned}
$$

Recall (9.4). From Xue and Yao [17], (Lemma 2, eqn. (99)) we obtain

$$
\begin{aligned}
\Big|\mathbb{E}[I_{m,n}(v)]\Big| &\lesssim C_1(\underline{b})\Big\{\frac{\phi_m^2 \log^2 d}{\sqrt{m}}\Big[\phi_m D_{g,3}^X \rho_{m,n}^1 + D_{g,3}^X\sqrt{\log(d)} + \phi_m M_3^X(\phi_m)\Big]\\
&\qquad + \frac{\phi_n^2 \log^2 d}{\sqrt{n}}|\delta_{m,n}|^3\left(\phi_2 D_{\ell,3}^Y \rho_{m,n}^1 + D_{\ell,3}^Y\sqrt{\log(d)} + \phi_n M_3^Y(\phi_n)\right)\Big\}.
\end{aligned}
$$

To proceed further, define

$$
\begin{aligned}
\rho_{m,n}^1 := \sup_{v\in[0,1]}\sup_{y\in\mathbb{R}^d}\Big|&\mathbb{P}\Big(\sqrt{v}\Big\{\frac{1}{\sqrt{m}}\sum_{i=1}^n g(X_i) + \delta_{m,n}\frac{1}{\sqrt{n}}\sum_{j=1}^n \ell(Y_j)\Big\} + \sqrt{1-v}\Big\{\frac{1}{\sqrt{m}}\sum_{i=1}^m G_{1i} + \delta_{m,n}\frac{1}{\sqrt{n}}\sum_{j=1}^n G_{2j}\Big\} \le y\Big)\\
&- \mathbb{P}\Big(\frac{1}{\sqrt{m}}\sum_{i=1}^n G_{1i} + \delta_{m,n}\frac{1}{\sqrt{n}}\sum_{j=1}^n G_{2j} \le y\Big)\Big|.
\end{aligned}
$$

Note that

$$
\rho_{m,n}^1 = \sup_{v\in[0,1]}\sup_{y\in\mathbb{R}^d}\Big|\mathbb{P}\Big(Z(1) \le y\Big) - \mathbb{P}\Big(Z(0) \le y\Big)\Big|.
$$

Recall from (3.3) and (3.4) that $W_{m,n} - L_{m,n} = R_{m,n}$. Write $R_{m,n} = (R_{m,n,1}, \cdots, R_{m,n,d})^T$. By the Mean Value Theorem,

$$
\Psi(W_{m,n}) - \Psi(L_{m,n}) = \sum_{a=1}^d \partial_a \Psi(\xi) R_{m,n,a} = \sum_{a=1}^d u'(F_\beta(\xi))\eta_a(\xi) R_{m,n,a}
$$

where $\eta_a(w) = \partial F_\beta(w)/\partial w_a$ is defined to be the first order partial derivative of $F_\beta(w)$ w.r.t w_a and $\eta := (\eta_1, \cdots, \eta_d)^T$ is a $d \times 1$ random vector on the line segment joining $L_{m,n}$ and $T_{m,n}$. Following the arguments in Xue and Yao [17], we can verify that $\eta_a(w) \ge 0, \sum_{a=1}^d \eta_a(w) = 1$, for any $w \in \mathbb{R}^d$ and there is a constat $K_1(\phi^*)$ such that $\sup_{t\in\mathbb{R}} |u'(t)| \le K_1(\phi^*)$, where $\phi^* = \max\{\phi_m, \phi_n\}$. Therefore, with $|R_{m,n}|_\infty = \max_{1\le a\le d} |R_{m,n,a}|$, we obtain that

$$
\Big|\mathbb{E}[\Psi(T_{m,n}) - \Psi(L_{m,n})]\Big| \le K_1 \phi^* \mathbb{E}|R_{m,n}|_\infty.
$$

Proceeding as in Xue and Yao [17] (eqn. (99)) with $\phi = \min\{\phi_m, \phi_n\}$, we conclude that

$$
\begin{aligned}
\mathbb{P}\Big(Z(1) \le y - \phi^{-1}\Big) &\le \mathbb{P}\Big(Z(0) \le y - \phi^{-1}\Big) + C(\underline{b})\phi^{-1}\sqrt{\log(d)} + |\mathbb{E}[I_{m,n}]| + K_1\phi^*\mathbb{E}\Big(|R_{m,n}|_\infty\Big),\\
\mathbb{P}\Big(Z(0) \le y + \phi^{-1}\Big) &\ge \mathbb{P}\Big(Z(1) \le y + \phi^{-1}\Big) + C(\underline{b})\phi^{-1}\sqrt{\log(d)} + |\mathbb{E}[I_{m,n}]| + K_1\phi^*\mathbb{E}\Big(|R_{m,n}|_\infty\Big).
\end{aligned}
$$

Combining these bounds with the previous equations, we conclude that

$$\rho^1_{m,n} \le K_1\phi^*\mathbb{E}|R_{m,n}|_\infty + C(\underline{b})\phi^{-1}\log^{\frac{1}{2}} d + C_1(\underline{b})\Big[\frac{(\phi_m)^2\log^2 d}{\sqrt{m}}\Big(\phi_m D^X_{g,3}\rho^1_{m,n} + D^X_{g,3}\sqrt{\log(d)} + \phi_m M^X_3(\phi_m)\Big)$$
$$+\frac{|\delta_{m,n}|^3\phi_n^2\log^2 d}{\sqrt{n}}\Big(\phi_n D^Y_{\ell,3}\rho^1_{m,n} + D^Y_{\ell,3}\sqrt{\log(d)} + \phi_n M^Y_3(\phi_n)\Big)\Big].$$

By similar arguments as used in Lemma 4 of Xue and Yao [17] and choosing $\phi^X_m, \phi^Y_n \ge 1$ we conclude that for any two sequence of real numbers $(\bar{D}^X_{g,3})^2, (\bar{D}^Y_{\ell,3})^2$ such that $(\bar{D}^X_{g,3})^2 \ge D^X_{g,3}$ and $(\bar{D}^Y_{\ell,3})^2 \ge D^Y_{\ell,3}$, $\rho^1_{m,n}$ is bounded from the above by $C_3(\underline{b})$ multiplied by

$$\left[\phi\,\mathbb{E}|R_{m,n}|_\infty + \left(\frac{(\bar{D}^X_{g,3})^2\log^7 d}{m}\right)^{\frac{1}{6}} + \frac{M^X_3(\phi_m)}{\bar{D}^X_{g,3}} + \left(\frac{(\bar{D}^Y_{\ell,3})^2|\delta_{m,n}|^6\log^7 d}{n}\right)^{\frac{1}{6}} + \frac{M^Y_3(\phi_n)}{\bar{D}^Y_{g,3}}\right].$$

By similar arguments as used in Chen [5], Lemma A.1 and Jensen's inequality, there exist universal positive constants K_2, K_3 such that the following inequalities hold.

$$\mathbb{E}\Big[\max_{1\le a\le d}\max_{1\le i\ne j\le m} f^4_a(X_i,X_j)\Big] \le K_2\mathbb{E}\Big[\max_{1\le a\le d}\max_{1\le i\ne j\le n}(\mathrm{vec}(h(X_i,X_j)))^4_a\Big],$$
$$\mathbb{E}\Big[\max_{1\le a\le d}\max_{1\le i\ne j\le m} q^4_a(Y_i,Y_j)\Big] \le K_3\mathbb{E}\Big[\max_{1\le a\le d}\max_{1\le i\ne j\le n}(\mathrm{vec}(h(Y_i,Y_j)))^4_a\Big].$$

By Lemma 9.1, we obtain that

$$\mathbb{E}[\|R_{m,n}\|_\infty] \le K_3(\bar{b}^{\frac{1}{2}}+1)\Big[\frac{\log^{3/2} d}{m}(M^X_{h,4})^{1/4} + \frac{\log(d)}{m^{1/2}}(D^X_2)^{1/2} + \frac{\log^{5/4} d}{m^{3/4}}(D^X_4)^{1/4}$$
$$+\frac{|\delta_{m,n}|\log^{3/2} d}{m}(M^Y_{h,4})^{1/4} + \frac{\log(d)}{m^{1/2}}(D^Y_2)^{1/2} + \frac{\log^{5/4} d}{m^{3/4}}(D^Y_4)^{1/4}\Big].$$

Finally by using Xue and Yao [17] Lemma 3 and Lemma 4, we conclude the proof of this lemma, since

$$\rho^{**}_{m,n} \le C_3\Big[\Big(\frac{(\bar{D}^X_{g,3})^2\log^7 d}{m}\Big)^{\frac{1}{6}} + \frac{M^X_3(\phi_m)}{\bar{D}^X_{g,3}} + \Big(\frac{(\bar{D}^Y_{\ell,3})^2|\delta_{m,n}|^6\log^7 d}{n}\Big)^{\frac{1}{6}} + \frac{M^Y_3(\phi_n)}{\bar{D}^Y_{g,3}}$$
$$+\phi^*\Big(\frac{\log^{3/2} d}{m}(M^X_{h,4})^{1/4} + \frac{\log(d)}{m^{1/2}}(D^X_2)^{1/2} + \frac{\log^{5/4} d}{m^{3/4}}(D^X_4)^{1/4}$$
$$+\frac{\log^{3/2} d}{m}(M^Y_{h,4})^{1/4} + \frac{\log(d)}{m^{1/2}}(D^Y_2)^{1/2} + \frac{\log^{5/4} d}{m^{3/4}}(D^Y_4)^{1/4}\Big)\Big]. \qquad \square$$

10. Appendix

This section contains the proofs of Theorems 3.1, 3.2, 4.1, 5.1, Lemma 3.1 and Corollary 4.1. In the proofs below, C denotes a large enough finite positive constant, not depending on m, n, d and that may be different in different context.

Proof of Theorem 3.1. This theorem is a two sample version of the Theorem 2.1 of Chen [5]. Some detailed calculations are still needed so we provide the proof for the sake of completeness. The objective of the proof is to quantify the bounds obtained in (9.3) in terms of d, m and n. First, we obtain explicit rates for each summand of the upper bound of (9.3). Then, these rates are combined to obtain an overall rate bound for $\rho^{**}_{m,n}$.

Recall $g_a(x) = \mathbb{E}\Big[(\mathrm{vec}(h(\xi,\xi_2)))_a\Big|\xi = x\Big]$, $x\in\mathbb{R}$. For any random vectors ξ,ξ_1,ξ_2, let

$$D^\xi_2 := \max_{1\le a\le d}\mathbb{E}\Big|(\mathrm{vec}(h(\xi_1,\xi_2)))_a\Big|^2, \qquad D^\xi_{g,3} := \max_{1\le a\le d}\mathbb{E}\Big|g_a(\xi)\Big|^3, \qquad D^\xi_4 := \max_{1\le a\le d}\mathbb{E}\Big|(\mathrm{vec}(h(\xi_1,\xi_2)))_a\Big|^4.$$

The Jensen's inequality and the assumption (b) yield that

$$D_2^{\xi} = \max_{1\le a\le d} \mathbb{E}\left|(\mathrm{vec}(h(\xi_1,\xi_2)))_a\right|^2 \le \max_{1\le a\le d} (\mathbb{E}\left|(\mathrm{vec}(h(\xi_1,\xi_2)))_a\right|^3)^{\frac{2}{3}} \le B_{m,n}^{\frac{2}{3}}.$$

To analyse $D_{g,3}^{\xi}$, assumption (b) implies that

$$\begin{aligned} \mathbb{E}\left|g_a(\xi)\right|^3 &\le \mathbb{E}\Big(\mathbb{E}[\left|(\mathrm{vec}(h(\xi_1,\xi_2)))_a\right|^3 \big|\xi_1]\Big) = \mathbb{E}[\left|(\mathrm{vec}(h(\xi_1,\xi_2)))_a\right|^3] \le B_{m,n}, \ \forall\, 1\le a\le d,\\ D_{g,3}^{\xi} &\le B_{m,n}. \end{aligned}$$

Again, by the condition (b), we readily obtain $D_4^{\xi} \le B_{m,n}^2$.

Next, consider $M_{h,4}^{\xi}$. Using a property of Orlicz norm, see Van der Vaart and Wellner [16] (page-96), we obtain

$$M_{h,4}^{\xi} = \mathbb{E}\Big[\max_{1\le i\ne j\le n}\max_{1\le a\le d}\left|(\mathrm{vec}(h(\xi_i,\xi_j)))_a\right|^4\Big] \le C\Big\|\max_{1\le i\ne j\le n}\max_{1\le a\le d}(\mathrm{vec}(h(\xi_i,\xi_j)))_a\Big\|_{\psi_1}^4.$$

This bound, Lemma 2.2.2 of Van der Vaart and Wellner [16] and (c) together yield that

$$M_{h,4}^{\xi} \le C\log^4(md)\Big[\max_{1\le i\ne j\le n}\max_{1\le a\le d}\left\|(\mathrm{vec}(h(\xi_i,\xi_j)))_a\right\|_{\psi_1}\Big]^4 \le C\log^4(md) B_{m,n}^4. \tag{10.1}$$

We are now ready to obtain the overall rates for the upper bound of $\rho_{m,n}^{**}$ of (9.3). Recall ϕ_m from (9.4) and take $B_{m,n} = \bar{D}_{g,3}^{\xi}$. Let $\varpi_{m,n}^{\xi} := \Big(\frac{B_{m,n}^2\log^7(md)}{m}\Big)^{1/6}$, if $\xi = X$ and $\varpi_{m,n}^{\xi} := \Big(\frac{B_{m,n}^2\log^7(nd)}{n}\Big)^{1/6}$, if $\xi = Y$.

By (10.1) and the definitions of the entities involved,

$$\begin{aligned} \frac{\phi_m(\log d)^{\frac{3}{2}}(M_{h,4}^{\xi})^{\frac{1}{4}}}{m} &\le C\Big(\frac{(\bar{D}_{g,3}^{\xi})^2\log^4 d}{m}\Big)^{-1/6}\Big(\frac{\log d}{m}\Big)^{\frac{3}{2}}(M_{h,4}^{\xi})^{\frac{1}{4}} \le C\Big(\frac{B_{m,n}^2(\log(md))^7}{m}\Big)^{\frac{1}{6}}\Big(\frac{\log(md)}{m}\Big)^{\frac{4}{6}} \le C\varpi_{m,n}^{\xi},\\ \phi_m\,\frac{\log(d)}{\sqrt{m}}D_2^{1/2} &\le \Big(\frac{D_{g,3}^2\log^4 d}{m}\Big)^{-1/6}\,\frac{\log(d)}{\sqrt{m}}\,B_{m,n}^{1/3} \le \Big(\frac{B_{m,n}^2(\log(nd))^7}{n}\Big)^{1/6}\Big(\frac{1}{B_{m,n}^2\log^5(dm)}\Big)^{1/6} \le C\varpi_{m,n}^{\xi},\\ \phi_m\,\frac{\log^{5/4} d}{n^{3/4}}D_4^{1/4} &\le C\Big(\frac{D_{g,3}^2\log^4 d}{m}\Big)^{-1/6}\,\frac{\log^{5/4} d}{m^{3/4}}\,B_{m,n}^{1/2} \le \Big(\frac{B_{m,n}^2(\log(nd))^7}{n}\Big)^{1/6}\Big(\frac{\log(d)}{m}\Big)^{7/12}\Big(\frac{1}{B_{m,n}^2}\Big)^{1/12} \le C\varpi_{m,n}^{\xi}. \end{aligned}$$

Next, we shall obtain a bound for $M_3^{\xi}(\phi_m)$. By Lemma C.1 of Chernozhukov et al. [8], applied with $B_{m,n} = \bar{D}_{g,3}^{\xi}$, we obtain that for some universal constant $c^* > 0$,

$$M_3^{\xi}(\phi_m) \lesssim \Big(\frac{\sqrt{m}}{\phi_m\log(d)} + B_{m,n}\log(d)\Big)^3 + \exp\Big[-\frac{\sqrt{m}}{\Big(4c^*\phi_m B_{m,n}(\log(d))^2\Big)}\Big].$$

Since $\phi_m \ge 2$, $\frac{\sqrt{m}}{\phi_m\log(d)} \lesssim \frac{\sqrt{m}}{\log(d)} \lesssim \sqrt{m}$ and $B_{m,n}\log(d) \lesssim \sqrt{m}$ together yield that

$$\Big(\frac{\sqrt{m}}{4c^1\phi_m B_{m,n}(\log(d))^2}\Big) \gtrsim \left(\frac{(B_{m,n})^2(\log^7(dm))}{m}\right)^{-1/3}\log(dm) \gtrsim c^*\log(dm).$$

Combine these bounds to obtain that $M_{g,3}^{\xi}(\phi_m) \lesssim m^{3/2}(md)^{-c^*} \lesssim m^{-1/2}$. Similar arguments yield that $M_3^{G_1}(\phi_m) \lesssim m^{-1/2}$. The last two facts used with $\xi = X$ in turn yield that

$$M_3^X(\phi_m) = M_{g,3}^X(\phi_m) + M_3^{G_1}(\phi_m) \lesssim m^{-1/2}.$$

Finally we have that,

$$\Big(\frac{(\bar{D}_{g,3}^X)^2\log^7 d}{m}\Big)^{1/6} + \frac{M_3^X(\phi_m)}{\bar{D}_{g,3}^X} \le \Big(\frac{B_{m,n}^2\log^7 d}{m}\Big)^{1/6} + \frac{1}{\sqrt{m}B_{m,n}} \lesssim \Big(\frac{B_{m,n}^2\log^7(md)}{m}\Big)^{1/6}.$$

Similar calculations as the above used with $\xi = Y$ and the assumption (a) yield that

$$\Big(\frac{(\bar{D}^Y_{g,3})^2(\log^7 d)|\delta_{m,n}|^6}{n}\Big)^{1/6} + \frac{M_3^Y(\phi_n)}{\bar{D}^Y_{g,3}} \le \Big(\frac{B^2_{m,n}(\log^7 d)|\delta_{m,n}|^6}{n}\Big)^{1/6} + \frac{1}{\sqrt{n}B_{m,n}} \lesssim \Big(\frac{B^2_{m,n}\log^7(nd)}{n}\Big)^{1/6}.$$

The above bounds combined with (9.3) readily yield the bound (3.5), thereby completing the proof of Theorem 3.1.

Proof of Lemma 3.1. The proof is an immediate consequence of Theorem 5.1, Chernozhukov et al. [9] applied with $Z = T_m^{G_1} + \delta_{m,n}T_n^{G_2} \sim \mathcal{N}_d(0, \Gamma^X + \delta^2_{m,n}\Gamma^Y)$ and $V = (Z_1^X + \delta_{m,n}Z_2^Y)\big|(X^m, Y^n) \sim \mathcal{N}_d(0, \tilde{\Gamma}_m^{JK} + \delta^2_{m,n}\tilde{\Gamma}_n^{JK})$.

Proof of Theorem 3.2. Throughout the proof below, m, n, d are large enough so that $\log(md) > 1, \log(nd) > 1$. Recall the definition of $\hat{\Delta}_{m,,n}$ from (3.6). By Lemma 3.1, for any sequence of constants $\bar{\Delta}_{m,n} > 0$, on the event $\{\hat{\Delta}_{m,n} \le \bar{\Delta}_{m,n}\}$, $\rho^{JK}_{m,n} \lesssim (\bar{\Delta}_{m,n})^{1/2}\log d$.

The goal here is to find a real sequence $\bar{\Delta}_{m,n}$ such that $\mathbb{P}(\hat{\Delta}_{m,n} \ge \bar{\Delta}_{m,n}) \le \gamma_{m,n}$, and then obtain a bound for the upper bound $(\bar{\Delta}_{m,n})^{1/2}\log d$. Towards this goal, we shall first bound obtain a rate bound for $\hat{\Delta}_{m,n}$.

For the sake of brevity, let $m_1 := m(m-1)^2$. To bound $\hat{\Delta}_{m,n}$, rewrite $\tilde{\Gamma}_m^{JK}$ as,

$$\begin{aligned}
\tilde{\Gamma}_m^{JK} &= \frac{1}{m_1}\sum_{i=1}^m\sum_{j\neq i}\sum_{k\neq i}\Big\{\mathrm{vec}(\tilde{h}(X_i,X_j)) - U_m^X\Big\}\Big\{\mathrm{vec}(\tilde{h}(X_i,X_k)) - U_m^X\Big\}^T,\\
&= \frac{1}{m_1}\sum_{i=1}^m\sum_{j\neq i}\sum_{k\neq i}\Big\{\mathrm{vec}(h(X_i,X_j)) - (U_m^X - \Sigma^X)\Big\}\Big\{\mathrm{vec}(h(X_i,X_k)) - (U_m^X - \Sigma^X)\Big\}^T,\\
&= \frac{1}{m_1}\Big(1-\frac{1}{m}\Big)\Bigg[\sum_{1\le i\neq j\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_j))\}^T + \sum_{1\le i\neq j\neq k\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_k))\}^T\Bigg]\\
&\quad - \frac{1}{m_1}\frac{1}{m}\Bigg[\sum_{1\le i\neq j\neq l\le m}\Big\{\mathrm{vec}(h(X_i,X_j))\Big\}\{\mathrm{vec}(h(X_l,X_j))\}^T + \sum_{1\le i\neq j\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_j))\}^T\\
&\qquad + \sum_{1\le i\neq j\neq k\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_j,X_k))\}^T + \sum_{1\le i\neq j\neq l\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_l))\}^T\\
&\qquad + \sum_{1\le i\neq j\neq l\neq k\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_l,X_k))\}^T\Bigg],\\
&= \tilde{\Gamma}^{JK}_{m1} - \tilde{\Gamma}^{JK}_{m2}, \qquad \text{(say)}.
\end{aligned}$$

Thus to obtain a bound for $\|\tilde{\Gamma}_m^{JK} - \Gamma^X\|_\infty$, it suffices to obtain bounds for $\|\tilde{\Gamma}^{JK}_{m2}\|_\infty$ and $\|\tilde{\Gamma}^{JK}_{m1} - \Gamma^X\|_\infty$. Define the approximation rates

$$\varpi_m^{BX}(\gamma_{m,n}) := \Big(\frac{B^2_{m,n}\log^5(md)\log^2(1/\gamma_{m,n})}{m}\Big)^{1/4}, \qquad \varpi_n^{BY}(\gamma_{m,n}) := \Big(\frac{B^2_{m,n}\log^5(nd)\log^2(1/\gamma_{m,n})}{n}\Big)^{1/4}. \tag{10.2}$$

To obtain the rate bound for $\tilde{\Gamma}^{JK}_{m2}$, we begin with the decomposition

$$\tilde{\Gamma}^{JK}_{m2} = \frac{(m-2)(m-3)}{m(m-1)}\,\tilde{\Gamma}^{JK}_{m,2,4} + \frac{3(m-2)}{m(m-1)}\,\tilde{\Gamma}^{JK}_{m,2,3} + \frac{1}{m(m-1)}\,\tilde{\Gamma}^{JK}_{m,2,2}, \tag{10.3}$$

where

$$\begin{aligned}
\tilde{\Gamma}^{JK}_{m,2,4} &:= \frac{(m-4)!}{m!}\sum_{1\le i\neq j\neq k\neq l\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_k,X_l))\}^T,\\
\tilde{\Gamma}^{JK}_{m,2,3} &:= \frac{(m-3)!}{m!}\sum_{1\le i\neq j\neq k\le m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_k))\}^T,\\
\tilde{\Gamma}^{JK}_{m,2,2} &:= \frac{(m-2)!}{m!}\sum_{1\le i\neq j\le n}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_j))\}^T.
\end{aligned}$$

Let $H(x_1,x_2,x_3,x_4) = \mathrm{vec}(h(x_1,x_2))\mathrm{vec}(h(x_3,x_4))^T$. Then,

$$\tilde{\Gamma}^{JK}_{m,2,4} = \frac{(m-4)!}{m!}\sum_{1\le i\ne j\ne k\ne l\le m} H(X_i,X_j,X_k,X_l).$$

Note that, $\tilde{\Gamma}^{JK}_{m,2,4}$ is a U statistics of order four and $\mathbb{E}[\tilde{\Gamma}^{JK}_{m,2,4}] = 0$. Let $r = [m/4]$ and define

$$\begin{aligned}
&Z^X_{m,2,4} := r\|\tilde{\Gamma}^{JK}_{m,2,4}\|_\infty, \qquad M^X_{m,2,4} = \max_{0\le i\le r-1}\max_{1\le a\le d}\Big|H_a\Big(X_{4i+1},X_{4i+2},X_{4i+3},X_{4i+4}\Big)\Big|,\\
&(\bar{\varsigma}^X_{m,2,4})^2 := \max_a \sum_{i=0}^{r-1}\mathbb{E}\Big[H_a^2\Big(X_{4i+1},X_{4i+2},X_{4i+3},X_{4i+4}\Big)\Big],\ \bar{Z}^X_{m,2,4} := \max_a\Big|\sum_{i=0}^{r-1}\Big[\bar{H}_a(X_{4i+1},X_{4i+2},X_{4i+3},X_{4i+4}) - \mathbb{E}\bar{H}_a\Big]\Big|,\\
&\bar{H}_a\Big((X)_1^4\Big) := H_a((X)_1^4)I\Big(\max_a\Big|H_a((X)_1^4)\Big| \le \tau\Big), \quad \tau\ge 0,
\end{aligned}$$

where $a := (a_1,a_2)^T$, $a_1,a_2 = 1,\cdots,d$. By Lemma (E.1) of Chen [5] applied with $\alpha = \frac{1}{2}, \eta = 1, \delta = \frac{1}{2}$ and $\tau = \mathbb{E}[M^X_{m,2,4}]$,

$$\mathbb{P}\Big(Z^X_{m,2,4} \ge \mathbb{E}[\bar{Z}^X_{m,2,4}] + t\Big) \le \exp\Big(-\frac{t^2}{3(\bar{\varsigma}^X_{m,2,4})^2}\Big) + 3\exp\Big[-\Big(\frac{t}{C\|M^X_{m,2,4}\|_{\psi_{\frac{1}{2}}}}\Big)^{1/2}\Big],\ \ \forall\, t>0.$$

Moreover,

$$\begin{aligned}
\mathbb{E}[\bar{Z}^X_{m,2,4}] &\le C\Big\{(\log(d)^{1/2}\Big[\max_a\sum_{i=0}^{r-1}\Big[\mathbb{E}\Big(\bar{H}_a(X_{4i+1},X_{4i+2},X_{4i+3},X_{4i+4}) - \mathbb{E}\bar{H}_a\Big)^2\Big]^{\frac{1}{2}}\\
&\qquad + (\log(d))[\mathbb{E}\Big[\max_{i,a}\Big|\bar{H}_a(X_{4i+1},X_{4i+2},X_{4i+3},X_{4i+4}) - \mathbb{E}[\bar{H}_a]\Big|^2\Big]^{1/2}\Big\},\\
&\le C\{(\log(d))^{1/2}\bar{\varsigma}^X_{m,2,4} + (\log(d))\|M^X_{m,2,4}\|_{\psi_{1/2}}.
\end{aligned}$$

By the Cauchy-Schwarz inequality inequality and Condition (b),

$$\mathbb{E}\Big[H_a^2(X_{4i+1},X_{4i+2},X_{4i+3},X_{4i+4})\Big] \le \Big[\mathbb{E}\Big\{\mathrm{vec}\Big(h(X_{4i+1},X_{4i+2})\Big)\Big\}^4_{a_1}\Big]^{\frac{1}{2}}\Big[\mathbb{E}\Big\{\mathrm{vec}\Big(h(X_{4i+3},X_{4i+4})\Big)\Big\}^4_{a_2}\Big]^{\frac{1}{2}} \le B^2_{m,n}.$$

Thus, we have $\bar{\varsigma}^X_{m,2,4} \le \sqrt{r}B_{m,n} \le \sqrt{m}B_{m,n}$. By Condition (b) and Lemma 2.2.2 of Van der Waart and Wellner [16],

$$\|M^X_{m,2,4}\|_{\psi_{1/2}} \le C\log^2(rd)\max_{i,a}\Big\|\Big\{\mathrm{vec}\Big(h(X_{4i+1},X_{4i+2})\Big)\Big\}_a\Big\|^2_{\psi_{1/2}} \le CB^2_{m,n}\log(md)^2.$$

This bound together with condition (e) yield the following facts.

$$\begin{aligned}
&\mathbb{E}\bar{Z}^X_{m,2,4} \le C\Big\{(mB^2_{m,n}\log(d))^{1/2} + B^2_n(\log(d))\log(md)^2\Big\} \le 2C(mB^2_{m,n}\log(md))^{1/2},\\
&\mathbb{P}\Big(\|\tilde{\Gamma}^{JK}_{m,2,4}\|_\infty \ge C(m^{-1}B^2_{m,n}\log(md))^{1/2} + t)\Big) \le \exp\Big(-\frac{(mt)^2}{C3mB^2_{m,n}}\Big) + 3\exp\Big[-\Big(\frac{mt}{CB^2_{m,n}\log^2(md)}\Big)^{1/2}\Big],\\
&\qquad\qquad\qquad\qquad \le \exp\Big(-\frac{(mt)^2}{C3mB^2_{m,n}}\Big) + 3\exp\Big[-\Big(\frac{\sqrt{mt}}{CB_{m,n}\log(md)}\Big)\Big].
\end{aligned}$$

Let

$$t = C\sqrt{\frac{B^2_{m,n}\log(md)\log^2(\frac{1}{\gamma_{m,n}})}{m}}. \tag{10.4}$$

Apply the above bound with this t to obtain that

$$\mathbb{P}\Big(\|\tilde{\Gamma}^{JK}_{m,2,4}\|_\infty \ge 2t\Big) \le \exp\Big(-C\log(md)\log^2(\frac{1}{\gamma_{m,n}})\Big) + 3\exp\Big(-Cn^{1/4}\log^{\frac{1}{2}}(1/\gamma_{m,n})\log^{-\frac{3}{4}}(md)B^{-\frac{1}{2}}_{m,n}\Big). \tag{10.5}$$

Since $0 < \gamma_{m,n} < e^{-1}$, $\log(1/\gamma_{m,n}) > 1$ and $\log(md) > 1$. This fact and (e) reduces (10.5) to

$$\mathbb{P}\Big(\|\tilde{\Gamma}^{JK}_{m,2,4}\|_\infty \geq 2t\Big) \leq 4\gamma^{C}_{m,n} \leq 4\gamma_{m,n}. \tag{10.6}$$

Therefore,

$$\mathbb{P}\left(\|\tilde{\Gamma}^{JK}_{m,2,4}\|_\infty^{1/2} \geq C\left(\frac{B^2_{m,n}\log(md)\log^2(\frac{1}{\gamma_{m,n}})}{m}\right)^{1/4}\right) \leq 4\gamma_{m,n}$$

which implies that,

$$\mathbb{P}\left(\|\tilde{\Gamma}^{JK}_{m,2,4}\|_\infty^{1/2}\log(md) \geq C\varpi^{BX}_m(\gamma_{m,n})\right) \leq 4\gamma_{m,n}, \tag{10.7}$$

where ϖ^{BX}_m is defined as in (10.2). In the rest of this proof, the t is as in (10.4), unless specified otherwise and arguing as for (10.6), for the other terms in (10.3), to obtain the following bounds.

$$\mathbb{P}\Big(\frac{(m-2)}{m(m-1)}\|\tilde{\Gamma}^{JK}_{m,2,3}\|_\infty \geq 2t\Big) \leq 4\gamma_{m,n} \quad \text{and} \quad \mathbb{P}\Big(\frac{1}{m(m-1)}\|\tilde{\Gamma}^{JK}_{m,2,2}\|_\infty \geq 2t\Big) \leq 4\gamma_{m,n}. \tag{10.8}$$

Combine (10.7) and (10.8) with (10.3) we obtain that

$$\mathbb{P}\Big(\|\tilde{\Gamma}^{JK}_{m2}\|_\infty^{1/2}\log(md) \geq C\varpi^{BX}_m(\gamma_{m,n})\Big) \leq 12\gamma_{m,n}. \tag{10.9}$$

Next, we obtain the rate bound for $\tilde{\Gamma}^{JK}_{m1} - \Gamma^X$. Towards this goal, let

$$\tilde{\Gamma}^{JK}_{m,1,2} := \frac{(m-2)!}{m!}\sum_{1\leq i\neq j\leq n}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_j))\}^T,$$
$$\tilde{\Gamma}^{JK}_{m,1,3} := \frac{(m-3)!}{m!}\sum_{1\leq i\neq j\neq k\leq m}\{\mathrm{vec}(h(X_i,X_j))\}\{\mathrm{vec}(h(X_i,X_k))\}^T.$$

Then, we have the decomposition

$$\tilde{\Gamma}^{JK}_{m1} = \frac{1}{m}\,\tilde{\Gamma}^{JK}_{m,1,2} + \frac{(m-2)}{m}\,\tilde{\Gamma}^{JK}_{m,1,3}.$$

Write $\Gamma^X = \mathbb{E}\Big[\{\mathrm{vec}(h(X_1,X_2))\}\{\mathrm{vec}(h(X_1,X_3))\}^T\Big]$ and define $\Gamma^X_{1,2} := \mathbb{E}\Big[\{\mathrm{vec}(h(X_1,X_2))\}\{\mathrm{vec}(h(X_1,X_2))\}^T\Big]$.

The entities $\tilde{\Gamma}^{JK}_{m,1,3} - \Gamma^X$ and $\Gamma^{JK}_{m,1,2} - \Gamma^X_{1,2}$ are U statistics of degree three and two respectively. By using arguments similar to those used for $\tilde{\Gamma}^{JK}_{m,2,4}$ for U statistics of degree three and two, we obtain that

$$\mathbb{P}\Big(\Big(\|\tilde{\Gamma}^{JK}_{m,1,3} - \Gamma^X\|_\infty\log^2(md)\Big)^{1/2} \geq C\varpi^{BX}_m(\gamma_{m,n})\Big) \leq 4\gamma_{m,n},\ \mathbb{P}\Big(\Big(\|\tilde{\Gamma}^{JK}_{m,1,2} - \Gamma^X_{1,2}\|_\infty\log^2(md)\Big)^{1/2} \geq C\varpi^{BX}_m(\gamma_{m,n})\Big) \leq 4\gamma_{m,n}. \tag{10.10}$$

By the Cauchy-Schwarz and Lyapounov's inequalities and condition (b), $\|\Gamma^X_{1,2}\|_\infty \leq B^{2/3}_{m,n}$, from which we obtain that $m^{-1}\|\Gamma^X_{1,2}\|_\infty \leq t/2$. Hence, by the triangle inequality, $\|\tilde{\Gamma}^{JK}_{m,1,2}\|_\infty \leq \|\tilde{\Gamma}^{JK}_{m,1,2} - \Gamma^X_{1,2}\|_\infty + \|\Gamma^X_{1,2}\|_\infty$, $\Big\{m^{-1}\|\tilde{\Gamma}^{JK}_{m,1,2}\|_\infty \geq \frac{3t}{2}\Big\} \subseteq \Big\{m^{-1}\|\tilde{\Gamma}^{JK}_{m,1,2} - \Gamma^X_{1,2}\|_\infty \geq t\Big\}$, and by (10.10),

$$\mathbb{P}\Big(m^{-1}\|\tilde{\Gamma}^{JK}_{m,1,2}\|_\infty \geq \frac{3t}{2}\Big) \leq \mathbb{P}\Big(m^{-1}\|\tilde{\Gamma}^{JK}_{m,1,2} - \Gamma^X_{1,2}\|_\infty \geq t\Big) \leq 4\gamma_{m,n}.$$

Finally by (10.9) and (10.10),

$$\mathbb{P}\Big(\|\tilde{\Gamma}^{JK}_{m} - \Gamma^X\|_\infty^{1/2}\log(md) \geq C\varpi^{BX}_1(\gamma_{m,n})\Big) \leq 28\gamma_{m,n}.$$

Similarly for ${Y_1}^n$ we have the decomposition $\tilde{\Gamma}_n^{JK} = \tilde{\Gamma}_{n1}^{JK} - \tilde{\Gamma}_{n2}^{JK}$. Recall the definition of Γ^Y from (3.2). By using the similar arguments as above,

$$\mathbb{P}\Big(\|\tilde{\Gamma}_n^{JK} - \Gamma^Y\|_\infty^{1/2} \log(nd) \geq C\varpi_n^{BY}(\gamma_{m,n})\Big) \leq 28\gamma_{m,n}.$$

Finally, choosing $\bar{\Delta}_{m,n} = C\left(\sqrt{\frac{B_{m,n}^2 \log(md)\log^2(\frac{1}{\gamma_{m,n}})}{m}} + \sqrt{\frac{B_{m,n}^2 \log(nd)\log^2(\frac{1}{\gamma_{m,n}})}{n}}\right)$ and combining all the previous inequalities with this choice of $\bar{\Delta}_{m,n}$, it readily follows that

$$\begin{aligned}
\mathbb{P}(\hat{\Delta}_{m,n} \leq \bar{\Delta}_{m,n}) &= \mathbb{P}\Big(\|\tilde{\Gamma}_m^{JK} - \Gamma^X + \delta_{m,n}^2(\tilde{\Gamma}_n^{JK} - \Gamma^Y)\|_\infty \leq \bar{\Delta}_{m,n}\Big) = 1 - \mathbb{P}\Big(\|\tilde{\Gamma}_m^{JK} - \Gamma^X + \delta_{m,n}^2(\tilde{\Gamma}_n^{JK} - \Gamma^Y\|_\infty > \bar{\Delta}_{m,n}\Big) \\
&\geq 1 - \Big\{\mathbb{P}\Big(\|\tilde{\Gamma}_m^{JK} - \Gamma^X\|_\infty^{1/2}\log(md) \geq \frac{C}{2}\varpi_1^{BX}(\gamma_{m,n})\Big) + \mathbb{P}\Big(\|\tilde{\Gamma}_n^{JK} - \Gamma^Y\|_\infty^{1/2}\log(nd) \geq \frac{C}{2}\varpi_1^{BY}(\gamma_{m,n})\Big)\Big\} \\
&\geq 1 - \Big(28\gamma_{m,n} + 28\gamma_{m,n}\Big) = 1 - 56\gamma_{m,n}.
\end{aligned}$$

Thus the final conclusion follows from Lemma 3.1, by setting $W_m^{eX}|X_1^m = Z_1^X|X^m$ and $W_n^{eY}|Y_1^n = Z_2^Y|Y^n$.
This also completes the proof of Theorem 3.2.

Proof of Theorem 4.1. The proof uses the results of the previous section with $\delta_{m,n} = -m^{1/2}n^{-1/2}$.
From condition (a′), we readily obtain the bounds

$$\Big\{\frac{c_1}{(1-c_1)}\Big\}^{1/2} = \delta_1 < |\delta_{m,n}| < \delta_2 = \Big\{\frac{c_2}{(1-c_2)}\Big\}^{1/2}, \tag{10.11}$$

It follows from assumption (b′) that,

$$\min_{1\leq a\leq d} \mathbb{E}[g_a^2(X) + \delta_{m,n}^2 g_a^2(Y)] \geq \min\{1, \delta_1^2\}b. \tag{10.12}$$

Recall that, $T_{m,n}^G = T_m^{G_1} + \delta_{m,n}T_n^{G_2}$. By combining (10.11), (10.12), (a′), (e′) along with Theorem 3.1 with $\Omega^X = \mathrm{vec}(\Sigma_1), \Omega^Y = \mathrm{vec}(\Sigma_2)$ we obtain that

$$KD(T_{m,n}, T_{m,n}^G) \leq \rho_{m,n}^{**} \lesssim \Big(\frac{B_{m,n}^2(\log^7(dm))}{m}\Big)^{1/6},$$

where

$$KD(T_{m,n}, T_{m,n}^G) := \sup_{t\geq 0}\Big|P\Big(\Big\|\frac{\sqrt{m}(U_m^X - U_n^Y)}{2} - \frac{\sqrt{m}\,\mathrm{vec}(\Sigma_1 - \Sigma_2)}{2}\Big\|_\infty \leq t\Big) - \mathbb{P}\Big(\|T_m^{G_1} + \delta_{m,n}T_n^{G_2}\|_\infty \leq t\Big)\Big|.$$

Choose $\gamma_{m,n}$ in condition (e) of Theorem 3.2 to be $\gamma_{m,n} = 1/(m(\log m)^2)$. From (a′) and (e′) it can be easily verified that

$$\frac{B_{m,n}^2 \log^5(dm)\log^2(1/\gamma_{m,n})}{m} \sim \frac{B_{m,n}^2 \log^5(dn)\log^2(1/\gamma_{m,n})}{n} \to 0, \quad \text{as } m, n \to \infty. \tag{10.13}$$

Combining (10.11), (10.12), (10.13) and Theorem 3.2 we conclude that,

$$KD(T_{m,n}^{JK}, T_{m,n}^G) \leq \rho_{m,n}^{JK} \lesssim \Big\{\frac{B_{m,n}^2 \log^5(dm)\log^2(1/\gamma_{m,n})}{m}\Big\}^{1/4},$$

where

$$KD\Big(T_{m,n}^G, T_{m,n}^{JK}\Big) = \sup_{t\geq 0}\Big|\mathbb{P}_{\boldsymbol{e}}\Big(\|W_m^{eX} + \delta_{m,n}W_n^{eY}\|_\infty \leq t\Big) - \mathbb{P}\Big(\|T_m^{G_1} + \delta_{m,n}T_n^{G_2}\|_\infty \leq t\Big)\Big|.$$

The claim of the theorem follows from the triangle inequality and (e'), since

$$KD(T_{m,n}, T_{m,n}^{JK}) \leq KD(T_{m,n}, T_{m,n}^G) + KD(T_{m,n}^G, T_{m,n}^{JK}).$$

Proof of Corollary 4.1. The proof is an immediate consequence of Theorem 4.1 with the definition of $c_B(\alpha)$.

Proof of Theorem 5.1. In the proof below, C and c^* are positive and large enough universal constants, not depending on m, n, d, whose values keep changing depending on the context. We shall approximate the power function of the test with its bootstrap counterpart and prove the consistency of the proposed test. Recall $\mathcal{D} := \Sigma_1 - \Sigma_2$. Under H_{alt},

$$\mathbb{P}\Big(\Big\|\frac{\sqrt{m}(U_m^X - U_n^Y)}{2}\Big\|_\infty \geq c_B(\alpha)\Big) \geq \mathbb{P}_{e^*}\Big(\Big\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\Big\|_\infty \leq \Big\|\frac{\sqrt{m}\mathrm{vec}(\mathcal{D})}{2}\Big\|_\infty - c_B(\alpha)\Big)$$
$$- \sup_{t\geq 0}\Big|\mathbb{P}\Big(\Big\|\frac{\sqrt{m}(U_m^X - U_n^Y) - \sqrt{m}\mathrm{vec}(\mathcal{D})}{2}\Big\|_\infty \leq t\Big) - \mathbb{P}_{e^*}\Big(\Big\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\Big\|_\infty \leq t\Big)\Big|.$$

By arguing as in Theorem 4.1, we obtain that with probability tending to one, under H_{alt},

$$\sup_{t\geq 0}\Big|\mathbb{P}\Big(\Big\|\frac{\sqrt{m}(U_m^X - U_n^Y) - \sqrt{m}\mathrm{vec}(\mathcal{D})}{2}\Big\|_\infty \leq t\Big) - \mathbb{P}_{e^*}\Big(\Big\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\Big\|_\infty \leq t\Big)\Big| \lesssim \Big\{B_{m,n}^2 \log^7(dm)/m\Big\}^{1/6}. \quad (10.14)$$

Next, we shall prove the consistency of the proposed test. Let $\eta_a, a = 1, 2, \cdots, d$ denote unit basis vectors in $\mathbb{R}^d$. Then, for any $t > 0$,

$$\mathbb{P}_{e^*}\Big(\Big\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\Big\|_\infty \geq t\Big) \leq \sum_{a=1}^{d}\mathbb{P}_{e^*}\Big(\Big|T_{ma}^{e^*X} - \sqrt{\frac{m}{n}}T_{na}^{e^*Y}\Big| \geq t\Big) \leq 2d\exp\Big[-\frac{t^2}{2\max_{1\leq a\leq d}\{\eta_a^T(\tilde{\Gamma}_m^{JK} + \frac{m}{n}\tilde{\Gamma}_n^{JK})\eta_a\}}\Big].$$

The last bound follows from Hoeffding's inequality for Gaussian variables. Now setting the above bound equal to α by plugging in $t = c_B(\alpha)$, for large enough m, we obtain that

$$c_B(\alpha) \leq \Big[2\log(2d/\alpha)\max_{1\leq a\leq d}\Big\{\eta_a^T(\tilde{\Gamma}_m^{JK} + \frac{m}{n}\tilde{\Gamma}_n^{JK})\eta_a\Big\}\Big]^{1/2} \leq \Big[4\log(dn)\max_{1\leq a\leq d}\Big\{\eta_a^T(\tilde{\Gamma}_m^{JK} + \frac{m}{n}\tilde{\Gamma}_n^{JK})\eta_a\Big\}\Big].$$

But,

$$\max_{1\leq a\leq d}\Big\{\eta_a^T(\tilde{\Gamma}_m^{JK} + \frac{m}{n}\tilde{\Gamma}_n^{JK})\eta_a\Big\} = \Big\|\tilde{\Gamma}_m^{JK} + \frac{m}{n}\tilde{\Gamma}_n^{JK}\Big\|_\infty \leq \Big\|\tilde{\Gamma}_m^{JK} - \Gamma^X + \frac{m}{n}(\tilde{\Gamma}_n^{JK} - \Gamma^Y)\Big\|_\infty + \Big\|\Gamma^X + \frac{m}{n}\Gamma^Y\Big\|_\infty.$$

From the bounds of $\hat{\Delta}_{m,n}$ in Theorem 3.2 with $\delta_{m,n} = \sqrt{m/n}$ and $\gamma_{m,n} = 1/(dm)$, it follows with probability tending to one that

$$\Big\|\tilde{\Gamma}_m^{JK} - \Gamma^X + \frac{m}{n}(\tilde{\Gamma}_n^{JK} - \Gamma^Y)\Big\|_\infty \lesssim \sqrt{\frac{B_{m,n}^2\log^3(md)}{m}}.$$

For the term, $\|\Gamma^X + \frac{m}{n}\Gamma^Y\|_\infty$, we note that, $m/n \leq c^*$ by the condition (a') and using Holder's inequality and (c), it follows that

$$\Big\|\Gamma^X + \frac{m}{n}\Gamma^Y\Big\|_\infty \leq C\Big[\max_{1\leq a_1\leq d}\Big\{\mathbb{E}(\mathrm{vec}(h(X_1, X_2))_{a_1})^2\Big\}^{1/2}\max_{1\leq a_2\leq d}\Big\{\mathbb{E}(\mathrm{vec}(h(X_1, X_3)_{a_2})^2\Big\}^{1/2}$$
$$+ c^*\max_{1\leq a_1\leq d}\Big\{\mathbb{E}(\mathrm{vec}(h(Y_1, Y_2)_{a_1})^2\Big\}^{1/2}\max_{1\leq a_2\leq d}\Big\{\mathbb{E}(\mathrm{vec}(h(Y_1, Y_3)_{a_2})^2\Big\}^{1/2}\Big]$$
$$\leq B_{m,n}^{2/3} \leq B_{m,n}.$$

Therefore, with probability tending to one, we obtain that,

$$c_B(\alpha) \leq 4\log(dn)\max_{1\leq a\leq d}\Big\{\eta_a^T(\tilde{\Gamma}_m^{JK} + \frac{m}{n}\tilde{\Gamma}_n^{JK})\eta_a\Big\} \leq \Big(8CB_{m,n}\log(dn)\Big)^{1/2}.$$

Upon choosing the constant C in (f′) to be $K = \sqrt{8C}$, we obtain that

$$\Big\|\sqrt{m}\mathrm{vec}(\mathcal{D})/2\Big\|_\infty - c_B(\alpha) \geq \Big\{8CB_{m,n}\log(dm)\Big\}^{1/2}.$$

Therefore, we conclude that as $m \wedge n \to \infty$ and $d \to \infty$, with probability tending to one,

$$\begin{aligned}
\mathbb{P}_{e^*}\Big(\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y} + \frac{\sqrt{m}\mathrm{vec}(\mathcal{D})}{2}\|_\infty \geq c_B(\alpha)\Big) &\geq \mathbb{P}_{e^*}\Big(\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\|_\infty \leq \|\frac{\sqrt{m}\mathrm{vec}(\mathcal{D})}{2}\|_\infty - c_B(\alpha)\Big) \\
&\geq \mathbb{P}_{e^*}\Big(\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\|_\infty \leq \{8CB_{m,n}\log(dm)\}^{1/2}\Big) \\
&= 1 - \mathbb{P}_{e^*}\Big(\|W_m^{e^*X} - \sqrt{\frac{m}{n}}W_n^{e^*Y}\|_\infty \geq \{8CB_{m,n}\log(dm)\}^{1/2}\Big) \\
&\geq 1 - 2d\exp\Big(-4CB_{m,n}\log(dm)/B_{m,n}\Big) \geq 1 - \frac{2}{m} \to 1.
\end{aligned}$$

This bound together with (10.14) completes the proof.

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