# Errata to the Paper "On the Restricted Isometry of the Columnwise Khatri-Rao Product" 

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#### Abstract

In [1], Proposition 15 is incorrect. Due to this error, the statements of Theorems 2 and 3 in [1] claiming $m \geq O\left(\sqrt{k} \log ^{3 / 2} n\right)$ as sufficient for $k^{\text {th }}$ order restricted isometry property (RIP) of the columnwise Khatri-Rao product of two $m \times n$ sized random matrices containing independent subgaussian entries may not hold true. This errata corrects the claims of Theorems 2 and 3 in [1] to show that a higher sample complexity requirement, $m \geq O(k \log n)$, is the new sufficient condition. The $k$-RIP compliance of the columnwise Khatri-Rao product for $m$ scaling sublinearly with $k$ remains an open question.

The deterministic bounds for the $k^{\text {th }}$-order restricted isometric constants of a generic columnwise Khatri-Rao product presented in [1] remain unchanged.


## I. ERror in Proposition 15

Proposition 15 in [1] makes an erroneous claim that a nonnegative random variable $\mathbf{z}$ with a subgaussian tail probability $\left(\mathbb{P}(\mathbf{z}-\mathbb{E} \mathbf{z}>t) \leq \exp \left(-t^{2} / 2 \nu^{2}\right)\right)$ satisfies $\mathbb{E} \mathbf{z} \leq \sqrt{2 \pi \nu}$. As a consequence, the proofs of Lemmas 4 and 6 in [1] which rely on Proposition 15 are invalid, and the probabilistic bounds for the restricted isometry constants (RICs) of the columnwise Khatri-Rao product between random subgaussian matrices in Theorems 2 and 3 may not hold.

In Section II, we state and prove a corrected, weaker version of Theorem 2 in [1], which discusses a probabilistic bound for the $k$-RIC of the columnwise Khatri-Rao product between two independent random subgaussian matrices. In Section III, we replace Theorem 3 in [1] with its weaker version which provides a probabilistic $k$-RIC bound for the Khatri-Rao product of a random subgaussian matrix with itself. The proof of Theorem 3 is omitted due to lack of space, but it follows along similar lines as the proof of Theorem 2. The detailed proof can be found in [2]. All through this note, the notation is the same as in [1].

## II. Correction To Theorem 2

We begin with a corollary of the Hanson-Wright inequality [1, Theorem 13] about the tail probability of the weighted inner product between two subgaussian vectors.

Corollary 1. Let $\mathbf{u}=\left(\mathbf{u}_{1}, \mathbf{u}_{2}, \ldots, \mathbf{u}_{n}\right) \in \mathbb{R}^{n}$ and $\mathbf{v}=$ $\left(\mathbf{v}_{1}, \mathbf{v}_{2}, \ldots, \mathbf{v}_{n}\right) \in \mathbb{R}^{n}$ be independent random vectors with independent subgaussian components satisfying $\mathbb{E} \mathbf{u}_{i}=\mathbb{E} \mathbf{v}_{i}=$ 0 and $\left\|\mathbf{u}_{i}\right\|_{\psi_{2}} \leq K,\left\|\mathbf{v}_{i}\right\|_{\psi_{2}} \leq K$. Let $\mathbf{D}$ be an $n \times n$ matrix. Then, for every $t \geq 0$,

$$
\begin{aligned}
& \mathbb{P}\left\{\left|\mathbf{u}^{T} \mathbf{D} \mathbf{v}\right|>t\right\} \\
& \leq
\end{aligned}
$$

where $c$ is a universal positive constant.
Proof. The desired tail bound is obtained by using the HansonWright inequality [1, Theorem 13] with $\mathbf{x}=\left[\mathbf{u}^{T} \mathbf{v}^{T}\right]^{T}$ and $\mathbf{A}=\left[\mathbf{0}_{n \times n}\left|\mathbf{D} ; \mathbf{0}_{n \times n}\right| \mathbf{0}_{n \times n}\right]$.

Given a pair of random input matrices with i.i.d. subgaussian entries, the following corrected version of Theorem 2 in [1] provides an upper bound for the $k$-RIC of their columnwise Khatri-Rao product.
Theorem 2. Suppose $\mathbf{A}$ and $\mathbf{B}$ are $m \times n$ matrices with real i.i.d. subgaussian entries, such that $\mathbb{E} \mathbf{A}_{i j}=0, \mathbb{E} \mathbf{A}_{i j}^{2}=1$, and $\left\|\mathbf{A}_{i j}\right\|_{\psi_{2}} \leq K$, and similarly for $\mathbf{B}$. Then, for any $\delta>0$, the $k^{\text {th }}$ order restricted isometry constant $\delta_{k}$ of $\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}$ satisfies $\delta_{k} \leq \delta$ with probability at least $1-10 n^{-2(\gamma-1)}$ for any $\gamma>1$, provided that

$$
m \geq 4 c \gamma K_{o}^{4}\left(\frac{k \log n}{\delta}\right)
$$

Here, $K_{o}=\max (K, 1)$ and $c$ is a universal positive constant.
Proof. We begin with a variational definition of the $k$-RIC:
$\left.\delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right)=\sup _{\substack{\mathbf{z} \in \mathbb{R}^{n},\|\mathbf{z}\|_{2}=1,\|\mathbf{z}\|_{0} \leq k}}\left\|\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right) \mathbf{z}\right\|_{2}^{2}-1 \right\rvert\,$
In order to find a probabilistic upper bound for $\delta_{k}$, we seek to find a constant $\delta \in(0,1)$ such that $\mathbb{P}\left(\delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right) \geq \delta\right)$ is arbitrarily close to zero. We therefore consider the tail event

$$
\begin{equation*}
\mathcal{E} \triangleq\left\{\sup _{\substack{\mathbf{z} \in \mathbb{R}^{n},\|\mathbf{z}\|_{2}=1,\|\mathbf{z}\|_{0} \leq k}}\left|\left\|\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right) \mathbf{z}\right\|_{2}^{2}-1\right| \geq \delta\right\} \tag{2}
\end{equation*}
$$

and show that for $m$ sufficiently large, $\mathbb{P}(\mathcal{E})$ can be driven arbitrarily close to zero. In other words, the constant $\delta$ serves as a probabilistic upper bound for $\delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathrm{~B}}{\sqrt{m}}\right)$. Let $\mathcal{U}_{k}$ denote the set of all $k$ or less sparse unit norm vectors in $\mathbb{R}^{n}$. Then, using Proposition 12 in [1], the tail event in (2) can be rewritten as

$$
\begin{align*}
& \mathbb{P}(\mathcal{E})=\mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\mathbf{z}^{T}(\mathbf{A} \odot \mathbf{B})^{T}(\mathbf{A} \odot \mathbf{B}) \mathbf{z}-m^{2}\right| \geq \delta m^{2}\right) \\
& =\mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\mathbf{z}^{T}\left(\mathbf{A}^{T} \mathbf{A} \circ \mathbf{B}^{T} \mathbf{B}\right) \mathbf{z}-m^{2}\right| \geq \delta m^{2}\right) \\
& =\mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\sum_{i=1}^{n} \sum_{j=1}^{n} z_{i} z_{j}\left(\mathbf{a}_{i}^{T} \mathbf{a}_{j}\right)\left(\mathbf{b}_{i}^{T} \mathbf{b}_{j}\right)-m^{2}\right| \geq \delta m^{2}\right),(3) \tag{3}
\end{align*}
$$

where $\mathbf{a}_{i}$ and $\mathbf{b}_{i}$ denote the $i$ th column of $\mathbf{A}$ and $\mathbf{B}$, respectively. Further, by applying the triangle inequality and the union bound, the above tail probability splits as

$$
\begin{align*}
& \mathbb{P}(\mathcal{E}) \leq \mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\sum_{i=1}^{n} z_{i}^{2}\left\|\mathbf{a}_{i}\right\|_{2}^{2}\left\|\mathbf{b}_{i}\right\|_{2}^{2}-m^{2}\right| \geq \alpha \delta m^{2}\right) \\
& +\mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} z_{i} z_{j} \mathbf{a}_{i}^{T} \mathbf{a}_{j} \mathbf{b}_{i}^{T} \mathbf{b}_{j}\right| \geq(1-\alpha) \delta m^{2}\right) \tag{4}
\end{align*}
$$

In the above, $\alpha \in(0,1)$ is a variational union bound parameter which can be optimized at a later stage. We now proceed to find separate upper bounds for each of the two probability terms in (4).

From [1, (32)], the first tail probability term in (4) is bounded as

$$
\begin{gather*}
\mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\sum_{i=1}^{n} z_{i}^{2}\left\|\mathbf{a}_{i}\right\|_{2}^{2}\left\|\mathbf{b}_{i}\right\|_{2}^{2}-m^{2}\right| \geq \alpha \delta m^{2}\right) \\
\leq 8 n e^{-c m \frac{\alpha^{2} \delta^{2}}{4 K_{o}^{4}(1-\alpha \delta / 4)^{2}}} \\
=8 n^{-\left(\frac{c m \alpha^{2} \delta^{2}(1-\alpha \delta / 4)^{2}}{4 K_{o}^{4} \log n}-1\right)} \tag{5}
\end{gather*}
$$

In order to bound the second tail probability term in (4), we note that

$$
\begin{align*}
& \sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} z_{i} z_{j} \mathbf{a}_{i}^{T} \mathbf{a}_{j} \mathbf{b}_{i}^{T} \mathbf{b}_{j}\right| \\
& \quad \leq \sup _{\mathbf{z} \in \mathcal{U}_{k}} \sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n}\left|z_{i} z_{j}\right|\left|\mathbf{a}_{i}^{T} \mathbf{a}_{j}\right|\left|\mathbf{b}_{i}^{T} \mathbf{b}_{j}\right| \\
& \quad \leq \sup _{\mathbf{z} \in \mathcal{U}_{k}}\left(\sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n}\left|z_{i} z_{j}\right|\right)\left(\max _{\substack{i, j \in \operatorname{supp}(\mathbf{u}), i \neq j}}\left|\mathbf{a}_{i}^{T} \mathbf{a}_{j}\right|\left|\mathbf{b}_{i}^{T} \mathbf{b}_{j}\right|\right) \\
& \quad \leq k\left(\max _{\substack{i, j \in[n], i \neq j}}\left|\mathbf{a}_{i}^{T} \mathbf{a}_{j}\right|\left|\mathbf{b}_{i}^{T} \mathbf{b}_{j}\right|\right) \tag{6}
\end{align*}
$$

where the second step is an application of Hölders inequality. The last step follows from $\|\mathbf{z}\|_{1} \leq \sqrt{k}$ for $\mathbf{z} \in \mathcal{U}_{k}$. Using (6), and by applying the union bound over $\binom{n}{2}$ possible distinct $(i, j)$ pairs, the second probability term in (4) can be bounded as

$$
\begin{align*}
& \mathbb{P}\left(\sup _{\mathbf{z} \in \mathcal{U}_{k}}\left|\sum_{i=1}^{n} \sum_{j=1, j \neq i}^{n} z_{i} z_{j} \mathbf{a}_{i}^{T} \mathbf{a}_{j} \mathbf{b}_{i}^{T} \mathbf{b}_{j}\right| \geq(1-\alpha) \delta m^{2}\right) \\
& \quad \leq \frac{n^{2}}{2} \mathbb{P}\left(\left|\mathbf{a}_{1}^{T} \mathbf{a}_{2}\right|\left|\mathbf{b}_{1}^{T} \mathbf{b}_{2}\right| \geq \frac{(1-\alpha) \delta m^{2}}{k}\right) \\
& \quad \leq n^{2} \mathbb{P}\left(\left|\mathbf{a}_{1}^{T} \mathbf{a}_{2}\right| \geq \frac{\sqrt{(1-\alpha) \delta} m}{\sqrt{k}}\right) \\
& \quad \leq 2 n^{2} e^{-\frac{c(1-\alpha) \delta m}{K_{o}^{4} k}}=2 n^{-\left(\frac{c(1-\alpha) \delta m}{K_{o}^{4} k \log n}-2\right)} \tag{7}
\end{align*}
$$

The last inequality in the above is obtained by using the tail bound for $\left|\mathbf{a}_{1}^{T} \mathbf{a}_{2}\right|$ from Corollary 1. Finally, by combining
(4), (5) and (7), and setting $\alpha=1 / 2$, we obtain the following simplified tail bound,

$$
\begin{equation*}
\mathbb{P}(\mathcal{E}) \leq 8 n^{-\left(\frac{c m \delta^{2}(1-\delta / 8)^{2}}{16 K_{o}^{4} \log n}-1\right)}+2 n^{-\left(\frac{c \delta m}{2 K_{o}^{4} k \log n}-2\right)} \tag{8}
\end{equation*}
$$

From (8), for $m>\max \left(\frac{4 \gamma K_{o}^{4} k \log n}{c \delta}, \frac{32 \gamma K_{o}^{4} \log n}{c \delta^{2}(1-\delta / 8)^{2}}\right)$ and any $\gamma>1$, we have $\mathbb{P}(\mathcal{E})<10 n^{-2(\gamma-1)}$. Note that, in terms of $k$ and $n$, the first term in the inequality for $m$ scales as $k \log n$; it dominates the second term, which scales as $\log n$. This ends our proof.

## III. Correction To Theorem 3

Theorem 3. Let $\mathbf{A}$ be an $m \times n$ matrix with real i.i.d. subgaussian entries, such that $\mathbb{E} \mathbf{A}_{i j}=0, \mathbb{E} \mathbf{A}_{i j}^{2}=1$, and $\left\|\mathbf{A}_{i j}\right\|_{\psi_{2}} \leq K$. Then, for any $\delta>0$ the $k^{\text {th }}$ order restricted isometry constant $\delta_{k}$ of the column-normalized self Khatri-Rao product $\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{A}}{\sqrt{m}}$ satisfies $\delta_{k} \leq \delta$ with probability at least $1-5 n^{-2(\gamma-1)}$ for any $\gamma \geq 1$, provided

$$
m \geq 4 c^{\prime} \gamma K_{o}^{4}\left(\frac{k \log n}{\delta}\right)
$$

Here, $K_{o}=\max (K, 1)$ and $c^{\prime}>0$ is a universal constant.
Proof. A detailed proof is given in [2].

## IV. Remarks

Remark 1: According to Theorem 2, for fixed $k$ and $n$, $\delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right) \leq O\left(\frac{1}{m}\right)$ with high probability, which is an improvement over $O\left(\frac{1}{\sqrt{m}}\right)$ decay rate [3] for individual $k$-RICs of the input subgaussian matrices $\frac{\mathrm{A}}{\sqrt{m}}$ and $\frac{\mathrm{B}}{\sqrt{m}}$. Therefore, we conclude that the Khatri-Rao product exhibits stronger restricted isometry property, with smaller $k$-RICs compared to the $k$-RICs for the input matrices.

Remark 2: For $\mathbf{A}, \mathbf{B}$ as constructed in Theorem 2, a straightforward application of [4, Lemma 2] and the eigenvalue interlacing theorem [5] gives the following relation.

$$
\begin{equation*}
\delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right) \leq \delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \otimes \frac{\mathbf{B}}{\sqrt{m}}\right) \leq O\left(\frac{1}{\sqrt{m}}\right) \tag{9}
\end{equation*}
$$

for $n, k$ fixed. In comparison, Theorem 2 suggests a tighter upper bound $\delta_{k}\left(\frac{\mathbf{A}}{\sqrt{m}} \odot \frac{\mathbf{B}}{\sqrt{m}}\right) \leq O\left(\frac{1}{m}\right)$. We conjecture that an even faster $O\left(\frac{1}{m^{2}}\right)$ decay rate prevails, but it appears that a different approach would be required to establish this result.

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## References

[1] S. Khanna and C. R. Murthy, "On the restricted isometry of the columnwise Khatri-Rao product," vol. 66, no. 5, pp. 1170-1183, March 2018.
[2] -_, "On the restricted isometry of the columnwise Khatri-Rao product," CoRR, vol. abs/1709.05789, 2017. [Online]. Available: http://arxiv.org/abs/1709.05789
[3] S. Foucart and H. Rauhut, A Mathematical Introduction to Compressive Sensing. Birkhäuser Basel, 2013.
[4] M. F. Duarte and R. G. Baraniuk, "Kronecker compressive sensing," IEEE Trans. Image Process., vol. 21, no. 2, pp. 494-504, Feb. 2012.
[5] R. A. Horn and C. R. Johnson, Eds., Matrix Analysis. Cambridge University Press, 1986.

