

## Sharp lower bounds on the least singular value of a random matrix without the fourth moment condition\*

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### Abstract

We obtain non-asymptotic lower bounds on the least singular value of  $\mathbf{X}_{pn}^\top/\sqrt{n}$ , where  $\mathbf{X}_{pn}$  is a  $p \times n$  random matrix whose columns are independent copies of an isotropic random vector  $X_p$  in  $\mathbb{R}^p$ . We assume that there exist  $M > 0$  and  $\alpha \in (0, 2]$  such that  $\mathbb{P}(|(X_p, v)| > t) \leq M/t^{2+\alpha}$  for all  $t > 0$  and any unit vector  $v \in \mathbb{R}^p$ . These bounds depend on  $y = p/n$ ,  $\alpha$ ,  $M$  and are asymptotically optimal up to a constant factor.

**Keywords:** Random matrices; Singular values; Heavy-tailed distributions.

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## 1 Introduction

In this paper we obtain sharp lower bounds on the least singular value of a random matrix with independent heavy-tailed rows.

For precise statements, we need to introduce some notation. Let  $X_p$  be an isotropic random vector in  $\mathbb{R}^p$ , i.e.  $\mathbb{E}X_pX_p^\top = I_p$  for a  $p \times p$  identity matrix  $I_p$ . Let also  $\mathbf{X}_{pn}$  be a  $p \times n$  random matrix whose columns  $\{X_{pk}\}_{k=1}^n$  are independent copies of  $X_p$ . Denote by  $s_p(n^{-1/2}\mathbf{X}_{pn}^\top)$  the least singular value of the matrix  $n^{-1/2}\mathbf{X}_{pn}^\top$ .

The celebrated Bai-Yin theorem states that, with probability one,

$$s_p(n^{-1/2}\mathbf{X}_{pn}^\top) = 1 - \sqrt{y} + o(1)$$

when  $n \rightarrow \infty$ ,  $p = p(n)$  satisfies  $p/n \rightarrow y \in (0, 1)$ , and the entries of  $X_p$  are independent copies of a random variable  $\xi$  with  $\mathbb{E}\xi = 0$ ,  $\mathbb{E}\xi^2 = 1$ , and  $\mathbb{E}\xi^4 < \infty$ . In [5], Tikhomirov extended this result to the case  $\mathbb{E}\xi^4 = \infty$ . Several authors have studied non-asymptotic versions of this theorem, relaxing the independence assumption, and obtained bounds of the form

$$s_p(n^{-1/2}\mathbf{X}_{pn}^\top) \geq 1 - Cy^a |\log y|^b$$

that hold with large probability for some  $C, a, b > 0$  and all small enough  $y = p/n$ . See papers [2], [3], [4], and [6]. For general isotropic random vectors  $X_p$  with dependent entries not having finite fourth moments, the optimal values of  $a$  and  $b$  are unknown. Assuming that there exist  $M > 0$  and  $\alpha \in (0, 2]$  such that

$$\mathbb{P}(|(X_p, v)| > t) \leq \frac{M}{t^{2+\alpha}} \quad \text{for all } t > 0 \text{ and any unit (in the } l^2\text{-norm) vector } v \in \mathbb{R}^p, \quad (1.1)$$

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we derive the optimal values of  $a$  and  $b$  in this paper.

The paper is organized as follows. Section 2 contains the main results of the paper. Section 3 deals with the proofs. An Appendix with proofs of auxiliary results is given in Section 4.

## 2 Main results

Our main lower bound is a corollary of Theorem 2.1 in [6]. It is given below.

**Theorem 2.1.** *Let  $C \geq 1$  and  $n > p \geq 1$ . If (1.1) holds for  $M = C^{\alpha/2}$  and some  $\alpha \in (0, 2]$ , then, with probability at least  $1 - e^{-p}$ ,*

$$s_p(n^{-1/2}\mathbf{X}_{pn}^\top) \geq 1 - 14 \begin{cases} K_\alpha(Cy)^{\alpha/(2+\alpha)}, & \alpha \in (0, 2) \\ \sqrt{Cy \log(C/y)}, & \alpha = 2 \text{ and } C/y > e \\ \sqrt{Cy}, & \alpha = 2 \text{ and } C/y \leq e \end{cases}$$

where  $y = p/n$  and  $K_\alpha = 1/(\alpha(1 - \alpha/2))^{2/(2+\alpha)}$ .

The next theorem contains our main upper bound for a class of random vectors

$$X_p = \eta Z_p \quad \text{for } Z_p = (z_1, \dots, z_p) \text{ with i.i.d. entries } \{z_i\}_{i=1}^p \text{ independent of } \eta. \quad (2.1)$$

**Theorem 2.2.** *Let (2.1) hold for each  $p \geq 1$ , where  $\{z_i\}_{i=1}^\infty$  are independent copies of a random variable  $z$  with  $\mathbb{E}z = 0$ ,  $\mathbb{E}z^2 = 1$ , and  $\eta$  is a random variable with  $\mathbb{E}\eta^2 = 1$ . If there exist  $\alpha \in (0, 2]$  and  $C > 0$  such that*

$$\mathbb{P}(|\eta| > t) \geq \frac{C^{\alpha/2}}{t^{2+\alpha}} \quad \text{for all large enough } t > 0, \quad (2.2)$$

then, for each small enough  $y > 0$ ,

$$s_p(n^{-1/2}\mathbf{X}_{pn}^\top) \leq 1 + o(1) - \frac{1}{2} \begin{cases} K_\alpha(Cy)^{\alpha/(2+\alpha)}, & \alpha \in (0, 2) \\ \sqrt{Cy \log(C/y)}, & \alpha = 2 \end{cases}$$

almost surely as  $n \rightarrow \infty$ , where  $p = p(n) = yn + o(n)$  and  $K_\alpha$  is given in Theorem 2.1.

Theorem 2.2 and the next proposition show that, when  $y$  is small enough, the lower bounds in Theorem 2.1 are asymptotically optimal up to a constant factor (equal to 14).

**Proposition 2.3.** *For any given  $C > 1/4$  and  $\alpha \in (0, 2]$ , there exists a random variable  $\eta$  such that  $\mathbb{E}\eta^2 = 1$ , (2.2) holds, and*

$$\mathbb{P}(|(X_p, v)| > t) \leq \frac{(\kappa C)^{\alpha/2}}{t^{2+\alpha}} \quad \text{for all } t > 0 \text{ and any unit vector } v \in \mathbb{R}^p,$$

where  $X_p = \eta Z_p$ ,  $Z_p$  is a standard normal vector in  $\mathbb{R}^p$  that is independent of  $\eta$ , and  $\kappa > 0$  is a universal constant.

The proof of Proposition 2.3 is given at the end of the paper, before the Appendix.

## 3 Proofs

We will use below the following fact. By definition,  $s_p(n^{-1/2}\mathbf{X}_{pn}^\top)$  is the square root of  $\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top)$ , where  $\lambda_p(A)$  is the least eigenvalue of a  $p \times p$  matrix  $A$ . In addition,

$$\text{if } a \geq 1 - b \text{ for some } a, b \geq 0, \text{ then } \sqrt{a} \geq 1 - b.$$

Moreover, if  $a \leq 1 - b$  for some  $a, b \geq 0$ , then  $\sqrt{a} \leq 1 - b/2$ . Thus, to prove Theorems 2.1 and 2.2 we need to derive appropriate lower and upper bounds only for  $\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top)$ .

## Sharp lower bounds on the least singular value

*Proof of Theorem 2.1.* By Theorem 2.1 in [6], for all  $a > 0$  and  $y = p/n \in (0, 1)$ ,

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \geq c_p(a) - \frac{C_p(a)}{a} - 5ay + \frac{\sqrt{C_p(2a)}Z}{\sqrt{n}},$$

where  $Z = Z(p, n, a)$  is a random variable with  $\mathbb{E}Z = 0$  and  $\mathbb{P}(Z < -t) \leq e^{-t^2/2}$ ,  $t > 0$ ,

$$c_p(a) = \inf \mathbb{E} \min\{(X_p, v)^2, a\} \quad \text{and} \quad C_p(a) = \sup \mathbb{E}(X_p, v)^2 \min\{(X_p, v)^2, a\}$$

with inf and sup taken over all unit vectors  $v \in \mathbb{R}^p$ .

Since  $\mathbb{P}(Z < -\sqrt{2p}) \leq e^{-p}$  and  $y = p/n$ , we have, with probability at least  $1 - e^{-p}$ ,

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \geq c_p(a) - \frac{C_p(a)}{a} - 5ay - \sqrt{2yC_p(2a)}. \quad (3.1)$$

To estimate  $c_p(a)$  and  $C_p(a)$ , we will use the following lemma that is proved in the Appendix.

**Lemma 3.1.** *Let  $a > 0$ ,  $X_p$  be an isotropic random vector in  $\mathbb{R}^p$ , and (1.1) hold for some  $M > 0$  and  $\alpha \in (0, 2]$ . If  $\alpha \in (0, 2)$ , then*

$$c_p(a) \geq 1 - \frac{2M}{\alpha} a^{-\alpha/2} \quad \text{and} \quad C_p(a) \leq (2/\alpha + 4/(2-\alpha))Ma^{1-\alpha/2}.$$

In addition, if  $\alpha = 2$ , then

$$c_p(a) \geq 1 - \frac{M}{a} \quad \text{and} \quad C_p(a) \leq 2M + M \log(a^2/M) I(a^2 > M).$$

First, assume that  $\alpha \in (0, 2)$ . Using (1.1) and Lemma 3.1, we get

$$c_p(a) - \frac{C_p(a)}{a} \geq 1 - \left[ \frac{4}{\alpha} + \frac{4}{2-\alpha} \right] \frac{M}{a^{\alpha/2}} = 1 - \frac{8Ma^{-\alpha/2}}{\alpha(2-\alpha)}.$$

Taking

$$a = \left[ \frac{2My^{-1}}{\alpha(2-\alpha)} \right]^{2/(2+\alpha)} = K_\alpha(M/y)^{2/(2+\alpha)},$$

we have

$$ay = \frac{2Ma^{-\alpha/2}}{\alpha(2-\alpha)} \quad \text{and} \quad c_p(a) - \frac{C_p(a)}{a} \geq 1 - 4ay.$$

In addition,

$$\frac{C_p(2a)}{2a} \leq \left[ \frac{2}{\alpha} + \frac{4}{2-\alpha} \right] M(2a)^{-\alpha/2} \leq \left[ \frac{4}{\alpha} + \frac{4}{2-\alpha} \right] Ma^{-\alpha/2} = \frac{8Ma^{-\alpha/2}}{\alpha(2-\alpha)} = 4ay$$

and

$$\sqrt{2yC_p(2a)} \leq \sqrt{2y(8a^2y)} = 4ay = 4K_\alpha(M^{2/\alpha}y)^{\alpha/(2+\alpha)}.$$

Since  $C = M^{2/\alpha}$ , we infer from (3.1) that, with probability at least  $1 - e^{-p}$ ,

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \geq 1 - 13ay = 1 - 13K_\alpha(Cy)^{\alpha/(2+\alpha)}.$$

Thus we get the desired lower bounds for  $\alpha \in (0, 2)$ .

Suppose now  $\alpha = 2$ . Then  $M = C^{\alpha/2} = C \geq 1$  and  $\log(a^2/C) \leq \log(a^2)$  for any  $a > 0$ . Lemma 3.1 implies that

$$c_p(a) - \frac{C_p(a)}{a} \geq 1 - \frac{3C + C \log(a^2) I(a^2 > C)}{a}.$$

### Sharp lower bounds on the least singular value

Consider two possibilities  $\log(C/y) > 1$  and  $\log(C/y) \leq 1$ .

Assuming that  $\log(C/y) \leq 1$  and taking  $a = \sqrt{C/y}$ , we have  $a^2 > C$ ,  $\log(a^2) \leq 1$ , and

$$\frac{3C + C \log(a^2)}{a} \leq \frac{4C}{a} = 4\sqrt{Cy}.$$

Additionally, we get  $5ay = 5\sqrt{Cy}$ ,

$$C_p(2a) \leq 2C + C \log(4a^2) \leq (3 + \log 4)C \leq 9C/2 \quad \text{and} \quad \sqrt{2yC_p(2a)} \leq 3\sqrt{Cy}.$$

As a result, we conclude from (3.1) that, with probability at least  $1 - e^{-p}$ ,

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \geq 1 - 12\sqrt{Cy}.$$

Suppose  $\log(C/y) > 1$ . Set  $a = \sqrt{(C/y)\log(C/y)}$ . Then  $a^2 > C$ ,  $\sqrt{C/y} \leq a \leq C/y$ , and

$$\frac{3C + C \log(a^2)}{a} \leq \frac{3C}{\sqrt{C/y}} + \frac{C \log(C/y)^2}{a} \leq 5\sqrt{Cy \log(C/y)}.$$

Similarly,  $C_p(2a) \leq 2C + C \log(4a^2) \leq 7C/2 + C \log(a^2) \leq (7/2 + 2)C \log(C/y)$  and

$$\sqrt{2yC_p(2a)} \leq 4\sqrt{Cy \log(C/y)}.$$

Noting that  $5ay = 5\sqrt{Cy \log(C/y)}$ , we infer that, with probability at least  $1 - e^{-p}$ ,

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \geq 1 - 14\sqrt{Cy}.$$

Thus we have proved the theorem. □

*Proof of Theorem 2.2.* We will use the following lemma (for the proof, see the Appendix).

**Lemma 3.2.** *Under the conditions of Theorem 2.2,*

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \leq \max\{0, \sup_{s>0} \lambda(s)\} + o(1) \quad \text{a.s.,} \quad n \rightarrow \infty, \quad (3.2)$$

where  $p = p(n)$ ,  $p/n \rightarrow y \in (0, 1)$ , and  $\lambda(s) = -y/s + \mathbb{E}\eta^2/(1 + s\eta^2)$ .

We estimate  $\lambda = \lambda(s)$  given in Lemma 3.2 as follows. Set  $\zeta = \eta^2$ . Since  $\mathbb{E}\zeta = 1$ ,

$$\lambda(s) + \frac{y}{s} = \mathbb{E} \frac{\zeta}{1 + s\zeta} = 1 + \mathbb{E} \left( \frac{\zeta}{1 + s\zeta} - \zeta \right) = 1 - \mathbb{E} \frac{s\zeta^2}{1 + s\zeta}.$$

It follows from the inequality  $x/(1+x) \geq \min\{x, 1\}/2$ ,  $x \geq 0$ , and (4.1) that

$$\mathbb{E} \frac{s\zeta^2}{1 + s\zeta} \geq \frac{1}{2} \mathbb{E}\zeta \min\{s\zeta, 1\} = \frac{1}{2s} [\mathbb{E}(s\zeta - 1)I(s\zeta > 1) + \mathbb{E} \min\{(s\zeta)^2, 1\}].$$

As a result, for all  $s > 0$ , we get the following upper bound

$$\lambda(s) \leq 1 - \frac{y}{s} - \frac{1}{2s} [\mathbb{E}(s\zeta - 1)I(s\zeta > 1) + \mathbb{E} \min\{(s\zeta)^2, 1\}]. \quad (3.3)$$

Recall also that, by (2.2) and the definition of  $\zeta (= \eta^2)$ , there exists  $t_0 \geq 1$  such that

$$\mathbb{P}(\zeta > t) \geq \frac{C^{\alpha/2}}{t^{1+\alpha/2}} \quad \text{for all } t \geq t_0. \quad (3.4)$$

Sharp lower bounds on the least singular value

As in the proof of Lemma 3.2 (see the Appendix), we get that

$$\lambda'(s) = (y - h(s))/s^2, \quad s > 0,$$

where  $h(s) = \mathbb{E}(s\zeta)^2/(1 + s\zeta)^2$  is a continuous strictly increasing function on  $\mathbb{R}_+$  with  $h(0) = 0$  and  $h(\infty) = \mathbb{P}(\zeta > 0) > 0$ . Hence, if  $y < \mathbb{P}(\zeta > 0)$ ,  $\lambda(s)$  achieves its maximum in  $s = b$  with  $b = h^{-1}(y)$ .

Let  $\alpha \in (0, 2)$  and take  $y$  small enough to make  $b = h^{-1}(y) \leq 1/(2^{1/(1-\alpha/2)}t_0)$ . Then  $1/b > t_0$  and, by (3.4),

$$\mathbb{E}(b\zeta - 1)I(b\zeta > 1) = \int_1^\infty \mathbb{P}(b\zeta > t) dt \geq \int_1^\infty \frac{C^{\alpha/2}}{(t/b)^{1+\alpha/2}} dt = \frac{2}{\alpha} (Cb)^{\alpha/2}b.$$

Moreover,  $(1/b)^{1-\alpha/2}/2 > t_0^{1-\alpha/2}$  and, by (3.4),

$$\begin{aligned} \mathbb{E} \min\{(b\zeta)^2, 1\} &= \int_0^1 \mathbb{P}((b\zeta)^2 > t) dt = 2b^2 \int_0^{1/b} z\mathbb{P}(\zeta > z) dz \\ &\geq 2b^2 \int_{t_0}^{1/b} \frac{C^{\alpha/2}}{z^{\alpha/2}} dz = 2C^{\alpha/2}b^2 \frac{(1/b)^{1-\alpha/2} - t_0^{1-\alpha/2}}{1 - \alpha/2} \\ &\geq 2C^{\alpha/2}b^2 \frac{(1/b)^{1-\alpha/2}/2}{1 - \alpha/2} = \frac{(Cb)^{\alpha/2}b}{1 - \alpha/2}. \end{aligned}$$

By (3.3),  $\lambda(b) \leq g(b)$ , where  $g(b) = 1 - y/b - Kb^{\alpha/2}$  and

$$K = \frac{C^{\alpha/2}}{2} \left( \frac{1}{\alpha/2} + \frac{1}{1 - \alpha/2} \right) = \frac{C^{\alpha/2}}{\alpha(1 - \alpha/2)}.$$

By Young's inequality,

$$(K^{2/\alpha}y)^{\frac{\alpha}{2+\alpha}} = \left(\frac{y}{b}\right)^{\frac{\alpha}{2+\alpha}} (Kb^{\alpha/2})^{\frac{2}{2+\alpha}} \leq \frac{y/b}{(2+\alpha)/\alpha} + \frac{Kb^{\alpha/2}}{(2+\alpha)/2} \leq \frac{y}{b} + Kb^{\alpha/2}$$

and

$$\lambda(b) \leq g(b) \leq 1 - (K^{2/\alpha}y)^{\alpha/(2+\alpha)}.$$

The right-hand side of the last inequality can be made positive for small enough  $y$ . Hence, combining the above bounds with Lemma 3.2, we get the desired upper bound for  $\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top)$  when  $\alpha \in (0, 2)$  (see also the beginning of Section 3).

Let now  $\alpha = 2$  and take  $y$  small enough to make  $b = h^{-1}(y) \leq 1/t_0^2$ . Since  $t_0 \geq 1$ , we have  $1/b \geq t_0^2 \geq t_0$  and, hence, the same arguments as above yield

$$\mathbb{E}(b\zeta - 1)I(b\zeta > 1) = \int_1^\infty \mathbb{P}(b\zeta > t) dt \geq \int_1^\infty \frac{C}{(t/b)^2} dt = Cb^2,$$

$$\mathbb{E} \min\{(b\zeta)^2, 1\} \geq 2b^2 \int_{t_0}^{1/b} \frac{C}{z} dz = 2Cb^2 \log \frac{1}{bt_0} \geq 2Cb^2 \log \frac{1}{\sqrt{b}} = Cb^2 \log(1/b).$$

Therefore, it follows from (3.3) that  $\lambda(b) \leq g(b)$ , where

$$g(s) = 1 - \frac{y}{s} - \frac{Cs}{2}(\log(1/s) + 1), \quad s > 0.$$

Differentiating  $g$  yields

$$g'(s) = \frac{y}{s^2} - \frac{C}{2}(\log(1/s) + 1) + \frac{Cs}{2} \frac{1}{s} = \frac{2y - Cs^2 \log(1/s)}{2s^2}.$$

If  $2y/C$  is small enough, then  $g = g(s)$  has a unique local maximum in  $s_1$  and a unique local minimum in  $s_2$ , where  $s_1 < s_2$ , and  $s_1, s_2$  are solutions to the equation  $f(s) = 2y/C$  with  $f(s) = s^2 \log(1/s)$ .

The function  $f = f(s)$  is increasing on  $[0, 1/\sqrt{e}]$ , decreasing on  $[1/\sqrt{e}, \infty]$  and has  $f(0) = f(1) = 0$ . Hence,  $s_2 > 1/2$  and  $b = h^{-1}(y) < 1/2$  when  $y$  is small enough. Thus,

$$\lambda(b) \leq g(b) \leq 1 - \frac{y}{s_1} - \frac{Cs_1}{2}(\log(1/s_1) + 1) \leq 1 - \frac{y}{s_1} - \frac{Cs_1^2 \log(1/s_1)}{2s_1} = 1 - \frac{2y}{s_1}.$$

Let us bound  $s_1$  from above. Take  $s_0 = \sqrt{(4y/C)/\log(C/y)}$ . If  $y$  is small enough, then  $s_0 < 1/\sqrt{e}$  as well as

$$s_0^2 \log(1/s_0) = \frac{4y/C}{\log(C/y)} \left[ \frac{1}{2} \log(C/y) + \frac{1}{2} \log\left(\frac{1}{4} \log(C/y)\right) \right] = \frac{2y}{C} + \frac{2y \log \log \sqrt[4]{C/y}}{C \log(C/y)} > \frac{2y}{C}.$$

Therefore,  $s_1 < s_0$  and

$$\lambda(b) \leq 1 - \frac{2y}{s_1} \leq 1 - \frac{2y}{s_0} = 1 - \sqrt{Cy \log(C/y)}.$$

The right-hand side of the last inequality can be made positive for small enough  $y$ . Hence, combining the above bounds with Lemma 3.2, we get the desired upper bound for  $\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top)$  in the case with  $\alpha = 2$  (see also the beginning of Section 3).  $\square$

*Proof of Proposition 2.3.* Let  $t_0 = (1 + 2/\alpha)^{-1}$  and  $q = C/t_0^{1+2/\alpha}$ . If  $\alpha \in (0, 2]$ , then

$$q \geq C \inf_{\alpha \in (0, 2]} (1 + 2/\alpha)^{1+2/\alpha} = 4C > 1.$$

Let  $\eta = \sqrt{\xi\zeta}$ , where  $\xi$  and  $\zeta$  are independent random variables,

$$\mathbb{P}(\xi = q) = q^{-1} \quad \text{and} \quad \mathbb{P}(\xi = 0) = 1 - q^{-1},$$

$\zeta$  has the Pareto distribution

$$\mathbb{P}(\zeta > t) = \begin{cases} (t_0/t)^{1+\alpha/2}, & t \geq t_0, \\ 1, & t < t_0. \end{cases}$$

It is easy to see that  $\mathbb{E}\xi = 1$ . Moreover,  $\mathbb{P}(\zeta > t) \leq (t_0/t)^{1+\alpha/2}$  for all  $t > 0$  and

$$\mathbb{E}\zeta = \int_0^\infty \mathbb{P}(\zeta > t) dt = t_0 + \int_{t_0}^\infty (t_0/t)^{1+\alpha/2} dt = t_0 + \frac{2t_0}{\alpha} = 1.$$

Hence,  $\mathbb{E}\eta^2 = \mathbb{E}\xi \mathbb{E}\zeta = 1$ . In addition, (2.2) holds since, for all large enough  $t > 0$ ,

$$\mathbb{P}(|\eta| > t) = q^{-1} \mathbb{P}(\zeta > t^2/q) = q^{-1} (qt_0/t^2)^{1+\alpha/2} = \frac{q^{\alpha/2} t_0^{1+\alpha/2}}{t^{2+\alpha}} = \frac{C^{\alpha/2}}{t^{2+\alpha}}.$$

We also have

$$|(X_p, v)| = \sqrt{\xi\zeta} |(Z_p, v)| \stackrel{d}{=} \sqrt{\xi\zeta} |Z| \quad \text{for all unit vectors } v \in \mathbb{R}^p,$$

where  $Z \sim \mathcal{N}(0, 1)$  is independent of  $(\xi, \zeta)$ ,  $\stackrel{d}{=}$  means equality in law. Hence, if  $t > 0$ ,

$$\begin{aligned} \mathbb{P}(\sqrt{\xi\zeta} |Z| > t) &= \mathbb{E} \mathbb{P}(s\zeta > t^2) |_{s=\xi Z^2} \leq \mathbb{E} (st_0/t^2)^{1+\alpha/2} I(s > 0) |_{s=\xi Z^2} \leq \\ &\leq \frac{\mathbb{E}(t_0 \xi Z^2)^{1+\alpha/2}}{t^{2+\alpha}} = \frac{t_0^{1+\alpha/2} q^{\alpha/2} \mathbb{E}|Z|^{2+\alpha}}{t^{2+\alpha}} = \frac{C^{\alpha/2} \mathbb{E}|Z|^{2+\alpha}}{t^{2+\alpha}} \leq \frac{(\kappa C)^{\alpha/2}}{t^{2+\alpha}}, \end{aligned}$$

where

$$\kappa = \sup_{\alpha \in (0,2]} (\mathbb{E}|Z|^{2+\alpha})^{2/\alpha}.$$

Let us show that  $\kappa < \infty$ . If  $Z \sim \mathcal{N}(0,1)$ , then

$$f(\alpha) = \mathbb{E}|Z|^{2+\alpha} = \frac{2^{\frac{2+\alpha}{2}} \Gamma\left(\frac{3+\alpha}{2}\right)}{\sqrt{\pi}}$$

is a smooth function on  $[0, 2]$  with  $f(0) = 1$  and, in particular,  $f'(0)$  exists and is finite. The function  $g(\alpha) = f(\alpha)^{2/\alpha}$  is continuous on  $(0, 2]$  and

$$g(\alpha) = (1 + f'(0)\alpha + o(\alpha))^{2/\alpha} \rightarrow \exp\{2f'(0)\}, \quad \alpha \rightarrow 0+.$$

As a result,  $\kappa = \sup\{g(\alpha) : \alpha \in (0, 2]\}$  is finite. This finishes the proof of the proposition.  $\square$

#### 4 Appendix

*Proof of Lemma 3.1.* If  $U$  is a non-negative random variable with  $\mathbb{E}U = 1$ , then

$$\mathbb{E} \min\{U, a\} = \int_0^a \mathbb{P}(U > t) dt = \mathbb{E}U - \int_a^\infty \mathbb{P}(U > t) dt \geq 1 - \int_a^\infty \frac{M}{t^{1+\alpha/2}} dt = 1 - \frac{2M}{\alpha a^{\alpha/2}},$$

where  $M = \sup\{t^{1+\alpha/2}\mathbb{P}(U > t) : t > 0\}$ . Putting  $U = (X_p, v)^2$  for a given unit vector  $v \in \mathbb{R}^p$  and taking the infimum over such  $v$ , we obtain the desired lower bound for  $c_p(a)$ .

Similarly, we have

$$\begin{aligned} \mathbb{E}U \min\{U, a\} &= a\mathbb{E}(U - a)I(U > a) + a^2\mathbb{P}(U > a) + \mathbb{E}U^2I(U \leq a) \\ &= a\mathbb{E}(U - a)I(U > a) + \mathbb{E} \min\{U^2, a^2\} \\ &= I_1 + I_2, \end{aligned} \tag{4.1}$$

where

$$I_1 = a \int_a^\infty \mathbb{P}(U > t) dt \leq a \int_a^\infty \frac{M}{t^{1+\alpha/2}} dt = \frac{2M}{\alpha} a^{1-\alpha/2}, \quad I_2 = \int_0^{a^2} \mathbb{P}(U^2 > t) dt.$$

If  $\alpha \in (0, 2)$ , then  $I_2$  can be bounded as follows

$$I_2 \leq \int_0^{a^2} \frac{M dt}{t^{1/2+\alpha/4}} = \frac{Ma^{1-\alpha/2}}{1/2 - \alpha/4}.$$

Similarly, if  $\alpha = 2$ , then

$$I_2 \leq M + I(a^2 > M) \int_M^{a^2} \frac{M dt}{t} = M + M \log(a^2/M)I(a^2 > M).$$

Thus, we have proved that

$$\mathbb{E}U \min\{U, a\} \leq M \cdot \begin{cases} (2/\alpha + 4/(2 - \alpha))a^{1-\alpha/2}, & \alpha \in (0, 2), \\ 2 + \log(a^2/M)I(a^2 > M), & \alpha = 2. \end{cases}$$

Putting  $U = (X_p, v)^2$  for a given unit vector  $v \in \mathbb{R}^p$  and taking the supremum over such  $v$ , we get the desired upper bound for  $C_p(a)$ .  $\square$

## Sharp lower bounds on the least singular value

*Proof of Lemma 3.2.* We have  $n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top = n^{-1}\mathbf{Z}_{pn}\mathbf{T}_n\mathbf{Z}_{pn}^\top$ , where  $\mathbf{Z}_{pn}$  is a  $p \times n$  matrix with i.i.d. entries,  $\mathbf{T}_n$  is a  $n \times n$  diagonal matrix whose diagonal entries are independent copies of  $\zeta = \eta^2$ , and  $\mathbf{Z}_{pn}$  is independent of  $\mathbf{T}_n$ .

By the Glivenko-Cantelli theorem, the empirical spectral distribution of  $\mathbf{T}_n$  converges a.s. to the distribution of  $\zeta$ . By Theorem 4.3 in [1], there is a non-decreasing càdlàg function  $F = F(\lambda)$ ,  $\lambda \in \mathbb{R}$ , such that  $F(\lambda) = 0$  for  $\lambda < 0$ ,  $F(\infty) \leq 1$ , and

$$\mathbb{P}\left(\lim_{n \rightarrow \infty} \frac{1}{p} \sum_{k=1}^p I(\lambda_{kn} \leq \lambda) = F(\lambda)\right) = 1 \quad \text{for all continuity points } \lambda \text{ of } F, \quad (4.2)$$

where  $p = p(n) = yn + o(n)$  and  $\{\lambda_{kn}\}_{k=1}^p$  is the set of eigenvalues of  $p^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top$ . The Stieltjes transform

$$f(z) = \int_{\mathbb{R}} \frac{F(d\lambda)}{\lambda - z}, \quad z \in \mathbb{C}^+ = \{w \in \mathbb{C} : \Im z > 0\}, \quad (4.3)$$

of  $F$  can be defined explicitly as a unique solution in  $\mathbb{C}^+$  to the equation

$$f(z) = -\left(z - \frac{1}{y} \mathbb{E} \frac{\zeta}{1 + f(z)\zeta}\right)^{-1} \quad \text{or, equivalently, } z = -\frac{1}{f(z)} + \frac{1}{y} \mathbb{E} \frac{\zeta}{1 + f(z)\zeta}. \quad (4.4)$$

Define

$$\mathcal{S}_G = \{\lambda \geq 0 : G(\lambda + \varepsilon) > G(\lambda - \varepsilon) \text{ for any small enough } \varepsilon > 0\}$$

for a non-decreasing càdlàg function  $G = G(\lambda)$ ,  $\lambda \in \mathbb{R}$ . In other words,  $\mathcal{S}_G$  is the set of points of increase of  $G$ . Obviously,  $\mathcal{S}_G$  is a closed set. Using (4.2) and setting  $G = F$  as well as

$$a = \inf\{\lambda \geq 0 : \lambda \in \mathcal{S}_F\},$$

we conclude that  $a \in \mathcal{S}_F$  and

$$\lambda_p(n^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) = \frac{p}{n} \lambda_p(p^{-1}\mathbf{X}_{pn}\mathbf{X}_{pn}^\top) \leq ay + o(1) \quad \text{a.s.} \quad (4.5)$$

when  $n \rightarrow \infty$ .

Consider the function

$$z(s) = -\frac{1}{s} + \frac{1}{y} \mathbb{E} \frac{\zeta}{1 + s\zeta}$$

defined for  $s \in D$ , where  $D$  consists of all  $s \in \mathbb{R} \setminus \{0\}$  with  $-s^{-1} \notin \mathcal{S}_G$  for  $G(\lambda) = \mathbb{P}(\zeta \leq \lambda)$ ,  $\lambda \in \mathbb{R}$ . This function differs from  $\lambda = \lambda(s)$  given in Lemma 3.2 by the factor  $y$ , i.e.  $\lambda(s) = yz(s)$  for all  $s > 0$ . Therefore, to finish the proof, we only need to show that

$$a = \max\{0, \sup_{s>0} z(s)\}.$$

Let us show that  $a = 0$  when  $z(s) \leq 0$  for all  $s > 0$ . The latter can be reformulated as follows: if  $a > 0$ , then there is  $s > 0$  satisfying  $z(s) > 0$ . Suppose  $a > 0$ . Then  $a/2 \in \mathbb{R} \setminus \mathcal{S}_F$  and  $F(a/2) = 0$ . Hence,

$$f(a/2) = \int_{\mathbb{R}} \frac{F(d\lambda)}{\lambda - a/2} > 0 \quad \text{and} \quad \lim_{\varepsilon \rightarrow 0^+} f(a/2 + i\varepsilon) = f(a/2) > 0.$$

Taking  $z = a/2 + i\varepsilon$  in (4.4) and tending  $\varepsilon$  to zero, we get  $a/2 = z(s) > 0$  for  $s = f(a/2)$ .

Assume further that there is  $s > 0$  satisfying  $z(s) > 0$  or, equivalently,

$$g(s) = \mathbb{E} \frac{s\zeta}{1 + s\zeta} > y.$$

## Sharp lower bounds on the least singular value

The function  $g = g(s)$  is continuous and strictly increasing on  $\mathbb{R}_+$ . It changes from zero to  $\mathbb{P}(\zeta > 0)$  when  $s$  changes from zero to infinity. The same can be said about

$$h(s) = \mathbb{E} \frac{(s\zeta)^2}{(1 + s\zeta)^2}.$$

Hence,  $y < \mathbb{P}(\zeta > 0)$  and there is  $b = b(y) > 0$  that solves  $h(b) = y$ . By the Lebesgue dominated convergence theorem,

$$z'(s) = \frac{1}{s^2} - \frac{1}{y} \mathbb{E} \frac{\zeta^2}{(1 + s\zeta)^2} = \frac{y - h(s)}{ys^2} \quad \text{for any } s > 0.$$

Therefore,  $b$  is a strict global maximum point of  $z = z(s)$  on  $\{s : s > 0\}$ .

The rest of the proof is based on Lemma 6.1 in [1] which states that  $z'(s) > 0$  and  $s \in D$  if  $s = f(\lambda)$  for some  $\lambda \in \mathbb{R} \setminus \mathcal{S}_F$ . Moreover,  $\{z(s) : s \in D, z'(s) > 0\} \subseteq \mathbb{R} \setminus \mathcal{S}_F$ .

We will now prove that  $a \leq z(b)$ . Suppose the contrary, i.e.  $a > z(b)$ . By definition,  $F(\lambda) = 0$  for all  $\lambda < a$ . Set  $z_0 = z(b)$ . Then  $z_0 \in \mathbb{R} \setminus \mathcal{S}_F$ ,

$$s_0 = f(z_0) = \int_{\mathbb{R}} \frac{F(d\lambda)}{\lambda - z_0} > 0,$$

and, by the above lemma,  $z'(s_0) > 0$ . Taking  $z = z_0 + i\varepsilon$  in (4.4) and tending  $\varepsilon$  to zero, we arrive at  $z(b) = z_0 = z(f(z_0)) = z(s_0)$ . Since  $z'(s_0) > 0$  and  $s_0 > 0$ , we get the contradiction to the fact that  $b$  is a strict global maximum point of  $z = z(s)$  on  $\{s : s > 0\}$ .

Let us finally prove that  $a \geq z(b)$ . The function  $z = z(s)$  is continuous and strictly increasing on the set  $(0, b)$  with  $z(0+) = -\infty$  and  $z(b-) = z(b)$ . By the above lemma,

$$z((0, b)) = (-\infty, z(b)) \subseteq \mathbb{R} \setminus \mathcal{S}_F.$$

Thus,  $z(b) \leq a$ . This finishes the proof.  $\square$

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