

# Inequalities for Non-Standard Gaussian Matrix Norms

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## Abstract

In this paper we explore upper bounds on the spectral norm for Gaussian Matrices with columns standard from Central Correlated Multivariate Normal Distributions. We utilize a lemma from [Chi17] and extend the analysis from [CD05]. These bounds find applications in the generalization of the randomized SVD given in [BT22].

## 1 Introduction

The study of the expectation of the norms of the pseudoinverse of standard normal gaussian matrices first appeared in [HMT11] when analyzing the error bounds for the Randomized SVD algorithm. The bounds developed in [HMT11] used theory developed in analyzing the condition numbers of standard normal matrices in [CD05]. In a generalization of the Randomized SVD, the need for bounds on the expectation of the spectral norm for correlated Gaussian matrices appears in [BT22].

## 2 Relevant Work in Standard Uncorrelated Matrices

In this section we will briefly discuss bounds developed for the inequalities of standard normal matrices.

**Proposition 1.** (HMT Proposition 10.2). *Draw a  $k \times (k + p)$  standard Gaussian matrix  $\mathbf{G}$  with  $k \geq 2$  and  $p \geq 2$ . Then*

$$\mathbb{E} \|\mathbf{G}^\dagger\| \leq \frac{e\sqrt{k+p}}{p} \quad (1)$$

From our search in the literature, there is no bound on equation 1 when the columns are not sampled from a multiple of the identity.

## 3 Theory

We will first introduce the necessary lemmas needed to prove our main results.

### 3.1 Necessary Lemmas

**Lemma 2.** [Jam64, Eq. (58,59)]. *If  $\lambda_1 \geq \dots \geq \lambda_m$  are the eigenvalues of  $\mathbf{W}$  s.t.  $\mathbf{W} \sim \mathcal{W}_m(n, \mathbf{C})$  s.t.  $n > m - 1$ , then the joint PDF of eigenvalues is*

$$f(\lambda_1, \dots, \lambda_m) = K_{m,n} (\det \mathbf{C})^{-n/2} \exp\left(-\frac{1}{2} \text{Tr}(\mathbf{C}^{-1}\mathbf{W})\right) \prod_{i=1}^m \lambda_i^{(n-m-1)/2} \prod_{i < j} (\lambda_i - \lambda_j) \quad (2)$$

where

$$K_{m,n} = \frac{\pi^{m^2/2}}{\Gamma_m(\frac{1}{2}m) \Gamma_m(\frac{1}{2}n)} \quad (3)$$

**Lemma 3.** [WLR08, Lemma 3.6]. Let  $m, n \in \mathbb{N}$  s.t.  $n \geq m$ . Suppose  $\mathbf{A} \in \mathbb{R}^{n \times m}$ , then if  $(\mathbf{A}^\top \mathbf{A})$  is invertible

$$\left\| (\mathbf{A}^\top \mathbf{A})^{-1} \mathbf{A}^\top \right\| = \frac{1}{\sigma_m(\mathbf{A})} \quad (4)$$

**Lemma 4.** [Chi17, Lemma 1]. Draw a  $m \times n$  matrix  $\mathbf{G}$  s.t. the columns of  $\mathbf{G}$  are sampled from  $\mathcal{N}_m(\mathbf{0}, \mathbf{C})$  where the eigenvalues of  $\mathbf{C}$  are represented as  $\sigma_1 > \sigma_2 > \dots > \sigma_m$ . Let  $\mathbf{W} \sim \mathcal{W}_m(n, \mathbf{C})$ . The eigenvalue distribution is given as

$$f(x_1, \dots, x_n) = K_{\mathbf{C}} |\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i=1}^{m-1} \prod_{j=i+1}^m (x_i - x_j) \prod_{i=1}^n x_i^{n-m} \quad (5)$$

where  $\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma}) = \{e^{-x_i/\sigma_j}\}_{i,j=1}^m = \begin{bmatrix} e^{-\frac{x_1}{\sigma_1}} & \dots & e^{-\frac{x_1}{\sigma_m}} \\ \vdots & \ddots & \vdots \\ e^{-\frac{x_m}{\sigma_1}} & \dots & e^{-\frac{x_m}{\sigma_m}} \end{bmatrix}$  and

$$K_{\mathbf{C}}^{-1} = \prod_{i=1}^{m-1} \prod_{j=i+1}^m (\sigma_i - \sigma_j) \prod_{i=1}^m \sigma_i^{n-m+1} (n-i)! \quad (6)$$

With these lemmas we will go to proving the main results.

### 3.2 Main Results

**Theorem 5.** Draw a  $m \times m$  matrix  $\mathbf{G}$  s.t. the columns of  $\mathbf{G}$  are sampled from  $\mathcal{N}_m(\mathbf{0}, \mathbf{C})$  where the eigenvalues of  $\mathbf{C}$  are represented as  $\sigma_1 > \sigma_2 > \dots > \sigma_m$ . Then

$$\mathbb{E} \|\mathbf{G}^\dagger\| \approx \sqrt{\pi \sum_{k=1}^m \frac{1}{\sigma_k}} \quad (7)$$

**Proof.** We will first note

$$\|\mathbf{G}^\dagger\| \stackrel{\text{lem. 3}}{=} \frac{1}{\sigma_m(\mathbf{G})} = \frac{1}{\sqrt{\lambda_{\min}(\mathbf{G}\mathbf{G}^\top)}} \quad (8)$$

For  $\mathbf{W}$  sampled from  $\mathcal{W}_m(m, \mathbf{C})$ . We will now derive the distribution for minimum eigenvalue of  $\mathbf{W}$  similar to [NZYY08].

$$f_{\lambda_{\min}}(x_m) = \int_{x_2}^{\infty} \dots \int_{x_{m-1}}^{\infty} K_{\mathbf{C}} |\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i < j}^m (x_i - x_j) \prod_{i=1}^m x_j^{m-m} \prod_{i=1}^{m-1} dx_i \quad (9)$$

$$= K_{\mathbf{C}} \int_{x_2}^{\infty} \dots \int_{x_{m-1}}^{\infty} |\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i=1}^{m-2} \prod_{j=i+1}^{m-1} (x_i - x_j) \prod_{i=1}^{m-1} (x_i - x_m) \prod_{i=1}^{m-1} dx_i \quad (10)$$

$$\stackrel{(a)}{=} e^{-\sum_{i=1}^m \frac{x_m}{\sigma_i}} \left( \int_{y_2}^{\infty} \dots \int_{y_{m-1}}^{\infty} \sum_{i=1}^m (-1)^{i+m} K_{\mathbf{C}} |\mathbf{E}_i(\mathbf{x} - \mathbf{x}_m, \boldsymbol{\sigma})| \prod_{i=1}^{m-2} \prod_{j=i+1}^{m-1} (y_i - y_j) \prod_{i=1}^{m-1} dy_i \right) \quad (11)$$

$$\stackrel{(b)}{=} \Xi e^{-\sum_{i=1}^m \frac{x_m}{\sigma_i}} \quad (12)$$

Since the PDF must integrate to 1, we thus have,

$$f_{\lambda_{\min}}(x) = \left( \sum_{k=1}^m \frac{1}{\sigma_k} \right) e^{-x \sum_{k=1}^m \frac{1}{\sigma_k}} \quad (13)$$

The Expected Value follows from a simple integration.

$$\mathbb{E} \|\mathbf{G}^\dagger\| = \int_0^\infty \frac{1}{\sqrt{x}} e^{-x \sum_{k=1}^m \sigma_k^{-1}} dx \quad (14)$$

$$= \sqrt{\pi \sum_{k=1}^m \frac{1}{\sigma_k}} \operatorname{erf} \left( \sqrt{\pi \sum_{k=1}^m \frac{1}{\sigma_k}} \right) \lesssim \sqrt{\pi \sum_{k=1}^m \frac{1}{\sigma_k}} \quad (15)$$

The proof is complete. ■

**Theorem 6.** Draw a  $m \times n$  matrix  $\mathbf{G}$  s.t. the columns of  $\mathbf{G}$  are sampled from  $\mathcal{N}_m(\mathbf{0}, \mathbf{C})$  where the eigenvalues of  $\mathbf{C}$  are represented as  $\sigma_1 > \sigma_2 > \dots > \sigma_m$ . Let  $\mathbf{W} \sim \mathcal{W}_m(n, \mathbf{C})$ . Then,

$$\mathbb{E} \|\mathbf{G}^\dagger\| \leq \xi \quad (16)$$

**Proof.** Let  $K_{\mathbf{C}}$  and  $\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})$  be defined as in Lemma 4.

$$f_{\lambda_{\min}}(x_m) = \int_{x_2}^\infty \dots \int_{x_{m-1}}^\infty K_{\mathbf{C}} |\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i < j}^m (x_i - x_j) \prod_{i=1}^m x_j^{n-m} \prod_{i=1}^{m-1} dx_i \quad (17)$$

$$= K_{\mathbf{C}} x_m^{n-m} \int_{x_2}^\infty \dots \int_{x_{m-1}}^\infty |\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i < j}^{m-1} (x_i - x_j) \prod_{i=1}^{m-1} (x_i - x_m) \prod_{i=1}^m x_i^{n-m} \prod_{i=1}^{m-1} dx_i \quad (18)$$

$$\leq K_{\mathbf{C}} x_m^{n-m} \int_{x_2}^\infty \dots \int_{x_{m-1}}^\infty |\mathbf{E}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i < j}^{m-1} (x_i - x_j) \prod_{i=1}^{m-1} x_i^{n-m+1} \prod_{i=1}^{m-1} dx_i \quad (19)$$

$$\leq K_{\mathbf{C}} x_m^{n-m} \sum_{i=1}^m \left( (-1)^{i+m} e^{-\frac{x_m}{\sigma_i}} \int_{x_2}^\infty \dots \int_{x_{m-1}}^\infty |\mathbf{E}_{m,i}(\mathbf{x}, \boldsymbol{\sigma})| \cdot \prod_{i < j}^{m-1} (x_i - x_j) \prod_{i=1}^{m-1} x_i^{n-m+1} \prod_{i=1}^{m-1} dx_i \right) \quad (20)$$

$$= x_m^{n-m} K_{\mathbf{C}} \underbrace{\sum_{i=1}^m (-1)^{i+m} e^{-\frac{x_m}{\sigma_i}} K_{\mathbf{C},i}^{-1}}_{\Xi} \quad (21)$$

We will now upper bound  $\Xi$ .

$$\Xi \triangleq K_{\mathbf{C}} \sum_{i=1}^m (-1)^{i+m} e^{-\frac{x_m}{\sigma_i}} K_{\mathbf{C},i}^{-1} \quad (22)$$

$$= \sum_{k=1}^m (-1)^{k+m} \frac{\prod_{i=1}^{m-1} \prod_{j=i+1}^m \mathbb{1}_{i,j \neq k} (\sigma_i - \sigma_j) \prod_{i=1}^m \mathbb{1}_{i \neq k} \sigma_i^{n-m+1} (n-i)!}{\prod_{i=1}^{m-1} \prod_{j=i+1}^m (\sigma_i - \sigma_j) \prod_{i=1}^m \sigma_i^{n-m+1} (n-i)!} \quad (23)$$

$$= \sum_{k=1}^m (-1)^{k+m} \left( \prod_{i > k}^m (\sigma_i - \sigma_k) \prod_{i < k} (\sigma_k - \sigma_i) \cdot \sigma_k^{n-m+1} (n-k)! \right)^{-1} \quad (24)$$

■

## 4 Numerical Experiments

In Figure 1, we verify the results given in Theorem 5.

## 5 Conclusions

In this paper, we derive novel upper bounds for the spectral norm of Gaussian matrices with columns sampled from a central correlated multivariate normal distribution.

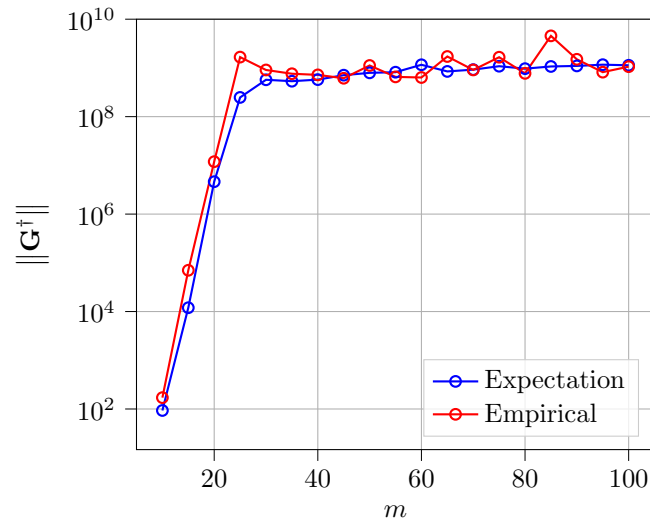


Figure 1: Comparing the expected norm upper bound on  $\|\mathbf{G}^\dagger\|$  where  $\mathbf{G} \in \mathbb{R}^{m \times m}$  and the columns of  $\mathbf{G}$  are sampled from  $\mathcal{N}_m(\mathbf{0}, \mathbf{K})$  with the average norm of  $\mathbf{G}^\dagger$  over 100 samples. The expected norm is calculated with Proposition 5.

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