



Aalto University  
School of Science  
and Technology

# On Demmel Condition Number Distributions with Applications in Telecommunications

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# Outline

## Demmel Condition Number

- Definition

- Existing results

## Derivations for DCN Distributions

- General framework

- Exact distribution

- Asymptotic distribution

## Applications in Wireless Communications

- Adaptive transmission

- Adaptive detection

# Definition

- ▶ Define a  $K \times N$  dimension matrix  $\mathbf{X}$  with independent and identically distributed (i.i.d) complex Gaussian entries, each with zero mean and unit variance.
- ▶ The  $K \times K$  Hermitian matrix  $\mathbf{R} = \mathbf{X}\mathbf{X}^\dagger$  follows a complex Wishart distribution with  $N$  degree of freedom (d.o.f).
- ▶ We denote the ordered eigenvalues of  $\mathbf{R}$  as  $\lambda_1 > \lambda_2 > \dots > \lambda_K > 0$ , and the trace of  $\mathbf{R}$  as  $T = \text{tr}\{\mathbf{R}\} = \|\mathbf{X}\|_F^2 = \sum_{i=1}^K \lambda_i$ , where  $\|\cdot\|_F$  is the Frobenius norm.

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- ▶ The Demmel Condition Number (DCN) of  $\mathbf{R}$  is defined as the ratio of its trace to its smallest eigenvalue  $\lambda_K$ ,

$$X := \frac{\sum_{i=1}^K \lambda_i}{\lambda_K} = \frac{T}{\lambda_K}, \quad (1)$$

where  $x \in [K, \infty]$ .

# Existing results

- ▶ Limited results on the DCN distribution exist in the literature.
- ▶ A. Edelman, “On the distribution of a scaled condition number,” *Math. Comp.*, vol. 58, pp. 185-190, 1992.
  - ▶ *Exact DCN distributions for the special case  $K = N$  (both real and complex cases).*
  - ▶ *Mainly based on the fact that  $\lambda_K$  has tractable expressions when  $K = N$  (e.g. exponentially distributed in complex case).*
  - ▶ *Using an equality (A. W. Davis, 1972) between Laplace transforms of PDFs of  $X$  and  $\lambda_K$ .*

# Existing results

- ▶ M. Matthaiou, M. R. McKay, P. J. Smith, and J. A. Nossek, “On the condition number distribution of complex Wishart matrices,” *IEEE Tran. Commun.*, vol. 58, no. 6, pp. 1705-1711, Jun. 2010.
  - ▶ *Exact DCN distributions for  $K = 2$  with arbitrary  $N$ .*
  - ▶ *Established through standard condition number distribution ( $\frac{\lambda_1 + \lambda_2}{\lambda_2} = 1 + \frac{\lambda_1}{\lambda_2}$ ).*
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- ▶ *Above two results are exact. No asymptotic results w.r.t. matrix dimension are available.*
- ▶ *In this work, both exact and asymptotic DCN distributions for arbitrary  $K$  and  $N$  are derived.*

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- ▶ Thus,  $\lambda_K$  equals the product of the independent r.v  $Y$  and  $T$ . Define  $f(x)$ ,  $g(x)$  and  $h(x)$  as the PDFs of  $\lambda_K$ ,  $T$  and  $Y$  respectively.

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- ▶ By this independence, it holds that

$$M_Z[f(x)] = M_Z[g(x)]M_Z[h(x)], \quad (2)$$

where  $M_Z[\cdot]$  denotes Mellin transform.

# General framework

- By Mellin inversion integral, the distribution of  $h(x)$  can be uniquely determined by

$$h(x) = \frac{1}{2\pi i} \int_{c-i\infty}^{c+i\infty} x^{-z} \frac{M_z[f(x)]}{M_z[g(x)]} dz. \quad (3)$$

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  - ▶ Mellin inversion integral (3) can be easily evaluated by the residue theorem.
- ▶ This framework provides the possibility to obtain both exact and asymptotic DCN distributions.

# Exact distribution

- ▶ C. S. Park and K. B. Lee “Statistical multimode transmit antenna selection for limited feedback MIMO systems,” *IEEE Tran. Wireless Commun.*, vol. 7, no. 11, pp. 4432-4438, Nov. 2008.

- ▶ PDF of  $\lambda_K$  represented as a weighted sum of polynomials as

$$f(x) = e^{-Kx} \sum_{n=N-K}^{(N-K)K} c_n^{(N,K)} x^n. \quad (4)$$

- ▶ Coefficients  $c_n^{(N,K)}$  is determined by the symmetry of the integral representation of  $\lambda_K$  (A. Edelman, 1989).

# Determining the coefficients $c_n^{(N,K)}$

- Define

$$I_n(m) := \sum_{k=0}^n \binom{n}{k} (m+n-k)! x^k. \quad (5)$$

- $K = 2$ , PDF of  $\lambda_K$  is

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- $K = 4$ , PDF of  $\lambda_K$  is

$$c_4 e^{-4x} x^{N-4} [I_{N-4}(6)I_{N-4}(4)I_{N-4}(2) - I_{N-4}(6)(I_{N-4}(3))^2 \quad (8) \\ + 2I_{N-4}(5)I_{N-4}(4)I_{N-4}(3) - (I_{N-4}(5))^2 I_{N-4}(2) - (I_{N-4}(4))^2].$$

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- ▶ Note:
  - ▶ After some basic manipulations, the expressions for coefficients of  $x$  can be obtained.
  - ▶ Although tedious, coefficients for arbitrary  $K$  can be similarly calculated.

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- ▶ We first calculate,

$$M_z[f(x)] = \sum_{n=N-K}^{(N-K)K} c_n^{(N,K)} \frac{\Gamma(z+n)}{K^{z+n}},$$

$$M_z[g(x)] = \frac{1}{\Gamma(m/2)} \Gamma\left(z + \frac{m}{2} - 1\right), \quad (m = 2KN).$$

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- ▶ Using the residue theorem,  $h(x)$  is uniquely determined to be

$$h(x) = \frac{\Gamma(m/2)}{(1 - Kx)^{2-m/2}} \sum_{n=N-K}^{(N-K)K} \frac{c_n^{(N,K)}}{\Gamma(m/2 - n - 1)} \left(\frac{x}{1 - Kx}\right)^n. \quad (9)$$

# Exact distribution

- By a simple transform, PDF of DCN is obtained as,

$$d(x) = \frac{\Gamma(m/2)x^{-m/2}}{(x-K)^{2-m/2}} \sum_{n=N-K}^{(N-K)K} \frac{c_n^{(N,K)}}{\Gamma(m/2-n-1)} (x-K)^{-n}. \quad (10)$$



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- Then CDF of DCN is calculated to be,

$$D(y) = \Gamma\left(\frac{m}{2}\right) \sum_{n=N-K}^{(N-K)K} \frac{K^{-n-1} c_n^{(N,K)}}{\Gamma(m/2 - n - 1)} (B(a, b) - B_{\frac{K}{y}}(a, b)) \quad (11)$$

$B_x(a, b)$  and  $B(a, b)$  are incomplete and complete Beta function respectively and  $a = n + 1$ ,  $b = \frac{m}{2} - n - 1$ .

# Special cases

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- ▶  $K = N$  (A. Edelman, 1992)
  - ▶ The only coefficient left is  $c_0^{(K,K)} = K$ .
  - ▶ Inserting this coefficient into the derived PDF,  $d(x)$  simplifies to

$$d(x) = K(K^2 - 1)x^{-K^2}(x - K)^{K^2-2}. \quad (12)$$

- ▶ Agrees with the known result.

# Special cases

- ▶  $K = 2$ , with arbitrary  $N$  (M. Matthaiou, 2010)

- ▶ The coefficient in this case is

$$c_n^{(N,2)} = \frac{\Gamma(2N - n - 1)}{\Gamma(N)\Gamma(n - N + 3)\Gamma(2N - n - 3)}. \quad (13)$$

- ▶ Inserting  $c_n^{(N,2)}$  into the derived PDF,  $d(x)$  simplifies to

$$d(x) = \frac{\Gamma(2N)}{\Gamma(N)\Gamma(N-1)}(x-2)^2x^{-2N}(x-1)^{N-2}. \quad (14)$$

- ▶ In agreement with the known result.

# One numerical example

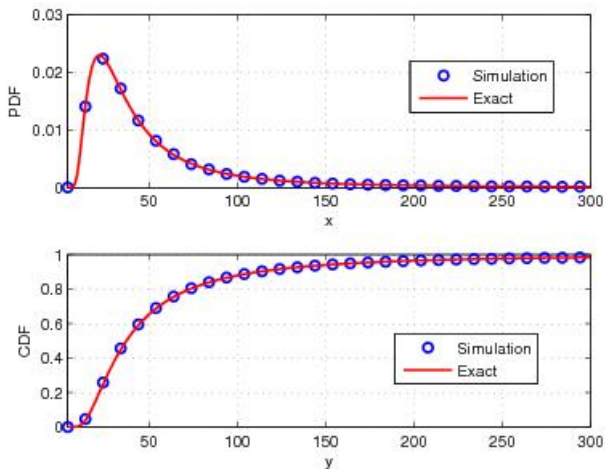
- ▶  $K = 4, N = 5$ .
- ▶  $d(x)$  is calculated to be

$$3420(x - 4)^{14}(x^3 + 5x^2 - 20x + 4)x^{-20}. \quad (15)$$

- ▶  $D(y)$  is calculated to be

$$\begin{aligned} &1 - 213.75B_{\frac{4}{y}}(2, 18) - 908.438B_{\frac{4}{y}}(3, 17) \\ &- 908.438B_{\frac{4}{y}}(4, 16) - 227.109B_{\frac{4}{y}}(5, 15). \end{aligned} \quad (16)$$

# One numerical example: $K = 4, N = 5$



# Asymptotic distribution

- ▶ Motivation:
  - ▶ Determining the coefficients may appear a problem for large dimensional matrices.
  - ▶ We would like to gain insight into the behavior of DCN distribution when the dimension  $K$ ,  $N$  are large.

# Asymptotic distribution

- ▶ Motivation:
  - ▶ Determining the coefficients may appear a problem for large dimensional matrices.
  - ▶ We would like to gain insight into the behavior of DCN distribution when the dimension  $K$ ,  $N$  are large.
- ▶ We derive a closed-form asymptotic DCN distribution, which circumvents the need to calculate the coefficients.
- ▶ The asymptotic result falls in the developed Mellin transform framework as well.



# An asymptotic result on $\lambda_k$ distribution

- ▶ For  $\lambda_k$ , there exists sequences  $a(K, N)$  and  $b(K, N)$  such that the distribution of the random variable

$$\Lambda_K = \frac{\lambda_K - a(K, N)}{b(K, N)} \quad (17)$$

converges to the Tracy-Widom distribution of order two (O. N. Feldheim, 2010), denoted as  $F_{\text{TW}2}$ .

- ▶ This result provides an approximation to  $\lambda_k$  for large  $K$  and  $N$ ,

$$F(x) \approx F_{\text{TW}2} \left( \frac{x - a(K, N)}{b(K, N)} \right). \quad (18)$$

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- ▶ Numerical burden to calculate  $F_{\text{TW}2}(\cdot)$ , simpler closed-form approximation is more desirable.

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- ▶ It was stated in (A. Edelman, 2005) that  $\lambda_k$  can be well approximated by a Gamma distribution.
- ▶ Motivated by this, we propose a Gamma approximation by calculating the first two asymptotic moments via Tracy-Widom distribution.
  - ▶  $E[\lambda_K] = a(K, N) + b(K, N)E[\Lambda_K]$ .
  - ▶  $V[\lambda_K] = (b(K, N))^2 V[\Lambda_K]$ .
- ▶ Convergence in distribution implies

$$E[\Lambda_K] \rightarrow E[x_{\text{TW2}}] = -1.7711, \quad (19)$$

$$V[\Lambda_K] \rightarrow V[x_{\text{TW2}}] = 0.8132. \quad (20)$$

# Gamma approximation to $\lambda_k$ distribution

- For a Gamma distribution with parameters  $\theta$  and  $k$ , by matching the two moments of  $\lambda_k$ ,  $\theta$  and  $k$  is obtained as

$$k = \frac{(a(K, N) + b(K, N)E[x_{TW2}])^2}{(b(K, N))^2 V[x_{TW2}]}, \quad (21)$$

$$\theta = \frac{(b(K, N))^2 V[x_{TW2}]}{a(K, N) + b(K, N)E[x_{TW2}]}. \quad (22)$$

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$$M_z[f(x)] = \frac{\theta^{z-1}}{\Gamma(k)} \Gamma(z + k - 1). \quad (23)$$

- ▶ By the residue theorem and a variable transform, the PDF of asymptotic DCN is calculated as

$$d(x) = c_1 x^{-m/2} (\theta x - 1)^{m/2-k-1}. \quad (24)$$

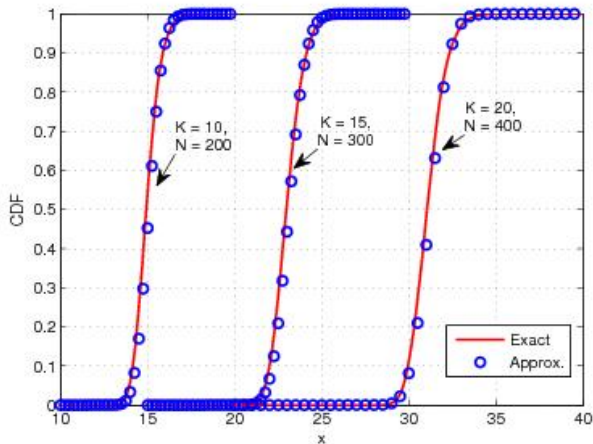
- ▶ Then, CDF of asymptotic DCN is calculated as

$$D(y) = c_2 (C(K) - C(y)), \quad (25)$$

$$C(x) = {}_2F_1(k, 1 + k - \frac{m}{2}; k + 1; \frac{1}{\theta x}) x^{-k}.$$



# Numerical results



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- ▶ Performance analysis and design of MIMO techniques relies on the statistical properties of the random MIMO channels.
- ▶ DCN reflects the eigenvalue spread of the random MIMO channel – indicates multipath richness for a given channel realization.
- ▶ Using this fact, several MIMO transmit and receive schemes can be proposed.

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# Thank you!