

Random matrix theory: lecture 17Largest eigenvalue of Wigner's matricesPreliminary: matrix norms

(complex)

Def: a norm on the space of $n \times n$ matrices is an application $\|\cdot\| : M_n \rightarrow \mathbb{R}$ such that

- $\|A\| \geq 0$, $\|A\| = 0$ iff $A = 0$, $\forall A$
- $\|cA\| = |c| \cdot \|A\|$, $\forall c \in \mathbb{C}$, $\forall A$
- $\|A+B\| \leq \|A\| + \|B\|$, $\forall A, B$

Def: $\|\cdot\|$ is called a matrix norm if moreover

$$\|AB\| \leq \|A\| \cdot \|B\|, \quad \forall A, B$$

Properties: if $\|\cdot\|$ is a matrix norm, then

- $\|A^2\| \leq \|A\|^2$; likewise, $\|A^k\| \leq \|A\|^k$
- $A^2 = A \Rightarrow \|A\| = \|A^2\| \leq \|A\|^2 \Rightarrow \|A\| \geq 1$
- in particular, $\|I\| \geq 1$
- A invertible $\Rightarrow \|I\| = \|AA^{-1}\| \leq \|A\| \cdot \|A^{-1}\|$

$$\text{so } \|A^{-1}\| \geq \frac{\|I\|}{\|A\|} \geq \frac{1}{\|A\|}$$

Examples and counter-examples (\triangle notations \triangle)

1) The ℓ^1 norm $\|A\|_1 := \sum_{j,k=1}^n |a_{jk}|$ is a matrix norm.

2) The ℓ^2 norm (or Euclidean norm or Frobenius norm)

defined as $\|A\|_2^2 := \sum_{j,k=1}^n |a_{jk}|^2$ is a matrix norm.

But note that the modified version of this norm:

$$\|A\|_2^2 := \frac{1}{n} \sum_{j,k=1}^n |a_{jk}|^2 \quad (= \|A\|_2^2 \text{ in homework 4})$$

is not a matrix norm ($\|AB\|_2 \neq \|A\|_2 \cdot \|B\|_2 \quad \forall A, B$).

NB: both $\|\cdot\|_2$ and $\|\cdot\|_2^2$ are unitarily invariant, i.e.

$$\|UAV\|_2 = \|UA\|_2 = \|AV\|_2 = \|A\|_2 \quad \forall U, V \text{ unitary}$$

3) The ℓ^∞ norm $\|A\|_\infty := \max_{1 \leq j, k \leq n} |a_{jk}|$ is not a matrix norm

but its modified version $\|A\|_\infty := n \max_{1 \leq j, k \leq n} |a_{jk}|$ is.

Induced norms

Def: let $\|\cdot\|$ be a (vector) norm on \mathbb{C}^n . We define the following induced norm on M_n :

$$\|A\| := \max_{\|x\|=1} \|Ax\| \quad (= \max_{x \neq 0} \frac{\|Ax\|}{\|x\|})$$

Proposition: Induced norms are matrix norms.

In addition, $\|Ax\| \leq \|A\| \cdot \|x\|$ and $\|I\| = 1$.

$$\forall A, x$$

Examples:

1) The maximum column sum matrix norm $\| \cdot \|_{l_1}$ defined as

$$\| A \|_{l_1} := \max_{1 \leq k \leq n} \sum_{j=1}^n |a_{jk}|$$

is induced by the ℓ^1 norm on \mathbb{C}^n , i.e.

$$\| A \|_{l_1} = \max_{\| x \|_1=1} \| Ax \|_1 \quad \text{where } \| x \|_1 = \sum_{j=1}^n |x_j|.$$

2) The spectral norm $\| \cdot \|_{l_2}$ defined as

$$\| A \|_{l_2} := \max \left\{ \sqrt{\lambda} : \lambda \text{ is an eigenvalue of } A^*A \right\}$$

is induced by the ℓ^2 norm on \mathbb{C}^n , i.e.

$$\| A \|_{l_2} = \max_{\| x \|_2=1} \| Ax \|_2 \quad (= \| A \|_{l_1} \text{ in homework 4})$$

NB: $\| \cdot \|_{l_2}$ is unitarily invariant.

3) The maximum row sum norm $\| \cdot \|_{l_\infty}$ defined as

$$\| A \|_{l_\infty} := \max_{1 \leq j \leq n} \sum_{k=1}^n |a_{jk}|$$

is induced by the ℓ^∞ norm on \mathbb{C}^n , i.e.

$$\| A \|_{l_\infty} = \max_{\| x \|_\infty=1} \| Ax \|_\infty \quad \text{where } \| x \|_\infty = \max_{1 \leq j \leq n} |x_j|$$

(Pfs: first show that $\| Ax \| \leq \| A \| \cdot \| x \| \quad \forall x \in \mathbb{C}^n$)
 Then find a x such that there is equality

Spectral radius

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$$\rho(A) := \max \{ |\lambda| : \lambda \text{ is an eigenvalue of } A \}$$

Proposition

If A is normal, then $\rho(A) = \max_{\|x\|_2=1} |x^* A x|$

(proof goes along the same lines as the proof of $\|A\|_2 = \max_{\|x\|_2=1} \|Ax\|$)

Note that $\rho(\cdot)$ is not a norm, but the following holds:

Proposition

For any matrix norm $\|\cdot\|$, $\rho(A) \leq \|A\|$.

Proof

$\exists \lambda, x \text{ st } Ax = \lambda x \text{ and } |\lambda| = \rho(A)$.

Let X be the matrix whose columns are all equal to x .

Then $AX = \lambda X$ and for any matrix norm $\|\cdot\|$, we have

$$|\lambda| \cdot \|X\| = \|\lambda X\| = \|AX\| \leq \|A\| \cdot \|X\|$$

so $\rho(A) = |\lambda| \leq \|A\|$, since $\|X\| \neq 0$. \blacksquare

Proposition (whose proof is more involved)

For any matrix norm $\|\cdot\|$, $\rho(A) = \lim_{e \rightarrow \infty} \|A^e\|^{1/e}$.

[ref: Horn-Johnson p.299]

Back to Wigner's matrices

Let H^0 be a $n \times n$ real symmetric random matrix s.t.

- (i) $\{h_{jk}^0, j \leq k\}$ are iid random variables ($\& h_{kj}^0 = h_{jk}^0$)
- (ii) $|h_{1j}^0(\omega)| \leq C \quad \forall \omega$ (bdd random variable)
- (iii) $\mathbb{E}(h_{nn}^0) = 0, \quad \mathbb{E}(h_{nn}^0)^2 = 1$

and $H^{(0,n)} := \frac{1}{\sqrt{n}} H^0, \lambda_1^{(0,n)}, \dots, \lambda_n^{(0,n)}$:= eigenvalues of $H^{(0,n)}$

We already know that

$$F_n(t) := \frac{1}{n} \# \{ j : \lambda_j^{(0,n)} \leq t \} \xrightarrow[n \rightarrow \infty]{\text{a.s.}} \int_{-\infty}^t p_m(x) dx$$

where p_m is the semi-circle distribution:

$$p_m(x) = \frac{1}{2\pi} \sqrt{4-x^2} \cdot \mathbf{1}_{|x| \leq 2}$$

First remark

The same result holds if we replace assumption (iii)

by the weaker assumption (iii)': $\mathbb{E}(h_{nn}) = a \in \mathbb{R}, \text{Var}(h_{nn}) = 1$

Proof

- x • Notice that $H = a \mathbf{1} + H^0$, where $\mathbf{1}$ is the all-ones matrix and H^0 satisfies assumptions (i)-(iii).

Therefore, $\text{rank}(H - H^0) = 1$.

(NB: $a \mathbf{1}$ has 1 eigenvalue equal to na and $n-1$ zero eigenvalues)

- We will need Weyl's inequalities: if A, B are two real symmetric matrices with respective eigenvalues $\lambda_1^A \geq \dots \geq \lambda_n^A$ and $\lambda_1^B \geq \dots \geq \lambda_n^B$, then

$$\lambda_{j+k-1}^{A+B} \leq \lambda_j^A + \lambda_k^B \quad \forall j, k \geq 1 \text{ s.t. } j+k-1 \leq n$$

- Let $F_n(t) := \frac{1}{n} \# \{j : \lambda_j^{(n)} \leq t\}$ with $\lambda_j^{(n)}$ = e.v. of $H^{(n)} = \frac{1}{\sqrt{n}} H$.

$$\text{Then } \sup_{t \in \mathbb{R}} |F_n(t) - F_n^o(t)| \leq \frac{\text{rank}(H - H^o)}{n} = \frac{1}{n} \quad (*)$$

Therefore, F_n and F_n^o converge to the same limit as $n \rightarrow \infty$. #

- Proof of $(*)$ using Weyl's inequalities:

Let $A = \frac{1}{\sqrt{n}} a \mathbf{1}^\top$: since A is rank one, $\lambda_2^A = \dots = \lambda_n^A = 0$

Let $B = H^{(0,n)}$; i.e. $A+B = \frac{1}{\sqrt{n}} (a \mathbf{1}^\top + H^o) = H^{(n)}$

Weyl's inequalities therefore imply that

$$\lambda_{k+1}^{(n)} \leq \lambda_k^{(0,n)} \quad \forall k \leq n-1 \quad (\text{take } j=2)$$

Likewise, one can show that $\lambda_{k+1}^{(0,n)} \leq \lambda_k^{(n)}$.

$$\text{So } |F_n(t) - F_n^o(t)| = \frac{1}{n} |\#\{j : \lambda_j^{(n)} \leq t\} - \#\{j : \lambda_j^{(0,n)} \leq t\}| \leq \frac{1}{n} \#$$

Conclusion: The global regime (that of the semi-circle distribution) does not "see" the non-zero mean of the entries. The situation is quite different for local properties (such as the position of the largest eigenvalue).

Second remark

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Wigner's result implies a law of large numbers on the largest eigenvalue of Wigner's matrices: for any $\varepsilon > 0$,

$$\frac{1}{n} \mathbb{E}(\#\{j : \lambda_j^{(n)} \in [2-\varepsilon, 2]\}) \xrightarrow[n \rightarrow \infty]{} \int_{2-\varepsilon}^2 p_n(x) dx = c_\varepsilon > 0$$

i.e. the number of eigenvalues lying between $2-\varepsilon$ & 2 is equal to $n c_\varepsilon$ in expectation. Therefore, there is in expectation at least one eigenvalue larger than $2-\varepsilon$,

$$\text{i.e. } \lim_{n \rightarrow \infty} \mathbb{E}(\lambda_{\max}(H^{(n)})) \geq 2 - \varepsilon \quad \forall \varepsilon > 0, \text{ i.e. } \geq 2.$$

Third remark

On the other hand, the largest eigenvalue of $H^{(n)}$ might be much greater than 2!

Example :

Consider $P(h_{ii}=2) = P(h_{ii}=0) = \frac{1}{2}$. Then $\mathbb{E}(h_{ii})=1$, $\text{Var}(h_{ii})=1$.

It can easily be shown that

(satisfying hyp. (iii)')

$$\sqrt{n} \leq \mathbb{E}(\lambda_{\max}(H^{(n)})) \leq \sqrt{2n}$$

(\rightarrow homework)

Finally: let us show that in the case where

$$\mathbb{P}(h_{ii} = +1) = \mathbb{P}(h_{ii} = -1) = \frac{1}{2},$$

we have $\mathbb{E}(\lambda_{\max}(H^{(n)})) \leq 2, \forall n$.

Proof:

- We will actually show that $\mathbb{E}(e(H^{(n)})) \leq 2, \forall n$.

Implying that both the largest and lowest eigenvalues of $H^{(n)}$ lie in the interval $[-2, 2]$ in expectation.

- $\mathbb{E}(e(H^{(n)})) = \mathbb{E}\left(\lim_{\ell \rightarrow \infty} \|H^{(n)}\|^{\ell/2}\right)$ for any matrix norm $\|\cdot\|$ (cf. preceding proposition page 5)

Let us choose $\|A\|^2 := \sum_{j,k=1}^n |a_{jk}|^2 = \text{Tr}(A^* A)$:

$$\begin{aligned} \mathbb{E}(e(H^{(n)})) &= \mathbb{E}\left(\lim_{\ell \rightarrow \infty} \text{Tr}((H^{(n)})^{2\ell})^{1/2\ell}\right) \quad ((H^{(n)})^* = H^{(n)}) \\ &= \lim_{\ell \rightarrow \infty} \mathbb{E}\left(\text{Tr}((H^{(n)})^{2\ell})^{1/2\ell}\right) \leq \lim_{\ell \rightarrow \infty} \mathbb{E}(\text{Tr}((H^{(n)})^{2\ell}))^{1/2\ell} \\ &\quad \text{Oct} \qquad \qquad \qquad \text{Jensen} \end{aligned}$$

- We have already computed $\mathbb{E}(\text{Tr}((H^{(n)})^{2\ell}))$: (see lec. 13)

$$= \frac{1}{n^{\ell}} \sum_{j_1 \dots j_{2\ell}=1}^n \mathbb{E}(h_{j_1 j_2} \dots h_{j_{2\ell} j_{2\ell}})$$

$$= \frac{1}{n^{\ell}} \sum_{g_{2\ell}} \sum_{j_{2\ell} \in g_{2\ell}} \mathbb{E}(h(g_{2\ell}))$$

$$= \frac{1}{n^{\ell}} \sum_{\substack{g_{2\ell} \text{ even} \\ |\nu(g_{2\ell})| \leq 1+\ell}} n(n-1) \dots (n-|\nu(g_{2\ell})|+1) \cdot \underbrace{Q(g_{2\ell})}_{\equiv 1 \text{ here, since } h_{j_{2\ell}}^{2m} \equiv 1}$$

$\equiv 1$ here, since $h_{j_{2\ell}}^{2m} \equiv 1$

Note that allowing for "repetitions" of vertices, each graph with strictly less than $1+e$ vertices may be seen as a graph with $1+e$ vertices, allowing some of the vertices to be identical; and there are less than $\overset{(*)}{n^{1+e}}$ such graphs, so

(*) since we are overcounting some graphs here

$$\mathbb{E}(\text{Tr}((H^{(n)})^{2e})) \leq \frac{1}{ne} \sum_{\substack{\text{g}_{2e} \text{ even} \\ |\mathcal{V}(g_{2e})| = 1+e}} n^{1+e}$$

(catalan numbers
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$$= n \cdot \#\{g_{2e} \text{ even}: |\mathcal{V}(g_{2e})| = 1+e\} = n t_e$$

Therefore,

$$\mathbb{E}(\rho(H^{(n)})) \leq \lim_{e \rightarrow \infty} (nt_e)^{1/2e} = \lim_{e \rightarrow \infty} t_e^{1/2e} = 2, \quad \text{by}$$

↑
computed before (lect. 13)

Remarks:

$$(\text{NB: } t_e = \int_{-2}^2 x^{2e} p_{t_e}(x) dx)$$

- The inequality $\rho(A) \leq \|A\|_1$ with the same choice of matrix norm $\|A\|_1^2 = \text{Tr}(A^*A)$ does not suffice here:

$$\mathbb{E}(\rho(H^{(n)})) \leq \mathbb{E}(\sqrt{\text{Tr}((H^{(n)})^2)}) \leq \sqrt{\frac{1}{n} \sum_{j,k=1}^n \mathbb{E}(h_{jk}^2)} = \sqrt{n}$$

and recall that $\|A\|_1^2 = \frac{1}{n} \text{Tr}(A^*A)$ is not a matrix norm.

- Similarly, one can get bounds on $P(\rho(H^{(n)}) \geq n^\varepsilon)$ using Chebyshev's inequality, but a more careful analysis is required for tighter bounds. [ref: Soshnikov].