

Circular law for matrices with iid entries

Corollary 4.10

For all $z \in \mathbb{C}$ there exists a prob. measure ν_z depending only on z such that a.s.

$$\nu_{n^{-1}X - zI} \xrightarrow{w} \nu_z \text{ as } n \rightarrow \infty$$

$$\uparrow$$

$$\mathbb{E} \nu_{n^{-1}X - zI}$$

Step 1

Lemma 4.18 (Concentr. of measure for sing. val. emp. measure)

If M is an $n \times n$ complex random matrix with independent rows then for any $f: \mathbb{R} \rightarrow \mathbb{R}$ going to 0 at $\pm\infty$ with $\|f\|_{TV} \leq 1$ and every $t \geq 0$

$$\mathbb{P}(|\int f d\nu_M - \mathbb{E} \int f d\nu_M| \geq t) \leq 2e^{-2nt^2}$$

Proof

$$A, B \in M_n(\mathbb{C}) \quad \text{rank}(A - B) \leq k$$

$$S_{i-k}(A) \geq S_i(B) \geq S_{i+k}(A)$$

$$F_A(t) = \nu_A([-\infty, t])$$

$$F_B(t) = \nu_B([-\infty, t])$$

$$\|F_A - F_B\|_{\infty} \leq \frac{\text{rank}(A - B)}{n}$$

For a smooth $f: \mathbb{R} \rightarrow \mathbb{R}$

$$|\int f d\nu_A - \int f d\nu_B| = \left| \int f'(t) (F_A(t) - F_B(t)) dt \right| \leq$$

$$\leq \frac{\text{rank}(A - B)}{n} \int |f'(t)| dt$$

$$\|f\|_{TV}$$

It follows that if f is measurable with $\|f\|_{TV} \leq 1$

$$\text{then } |\int f d\nu_A - \int f d\nu_B| \leq \frac{\text{rank}(A - B)}{n}$$

Fix f as above. For every x_1, \dots, x_n in \mathbb{C}^n denote by $A(x_1, \dots, x_n)$ the $n \times n$ matrix with rows x_1, \dots, x_n define $F: (\mathbb{C}^n)^n \rightarrow \mathbb{R}$ by

$$F(x_1, \dots, x_n) = \int f dV_{A(x_1, \dots, x_n)}^n$$

For any $i \in \{1, \dots, n\}$ $x_i' \in \mathbb{C}^n$, we have

$$\text{rank}(A(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n) - A(x_1, \dots, x_{i-1}, x_i', x_{i+1}, \dots, x_n)) \leq 1$$

thus

$$|F(x_1, \dots, x_{i-1}, x_i, x_{i+1}, \dots, x_n) - F(x_1, \dots, x_{i-1}, x_i', x_{i+1}, \dots, x_n)| \leq \frac{1}{n}$$

If X_1, \dots, X_n are indep. r.v.'s in $\mathcal{X}_1, \dots, \mathcal{X}_n$ and $f: \mathcal{X}_1 \times \dots \times \mathcal{X}_n \rightarrow \mathbb{R}$ is a measurable function then

$$\mathbb{P}(|f(X_1, \dots, X_n) - \mathbb{E}f(X_1, \dots, X_n)| \geq \epsilon) \leq 2 \exp\left(-\frac{2\epsilon^2}{c_1^2 + \dots + c_n^2}\right)$$

for any $\epsilon \geq 0$

$$c_k = \sup_{x, x' \in D_k} |f(x) - f(x')| \quad \text{on } D_k = \{(x, x') : x_i = x_i' \text{ if } i \neq k\}$$

It is enough to look at $\mathbb{E} V_{n^{-1} X - z}$

Step 2

Hoffman-Wielandt inequality

$$\sum_{i=1}^n (s_i(A) - s_i(B))^2 \leq \|A - B\|_2^2 = \sum_{1 \leq i, j \leq n} |(A - B)_{ij}|^2$$

Define

$$Y_{i,j} = X_{i,j} \mathbb{I}_{\{|X_{i,j}| \leq K\}}$$

$$K = K_n$$

$$K_n \rightarrow \infty$$

$$Y = (Y_{i,j})_{1 \leq i, j \leq n}$$

$$\frac{1}{n} \sum_{k=1}^n |s_k(n^{-1} Y - z I) - s_k(n^{-1} X - z I)|^2 \leq$$

$$\leq \frac{1}{n} \sum_{1 \leq i, j \leq n} \frac{1}{n} |X_{i,j}|^2 \mathbb{I}_{|X_{i,j}| > K_n} = \left(\frac{1}{n^2} \sum_{1 \leq i, j \leq n} \frac{|X_{i,j}|^2}{|X_{i,j}| > K_n} \right)$$

By our assumptions $\mathbb{E}|X_{i,j}|^2 \mathbb{I}_{|X_{i,j}| > K_n} \xrightarrow{n \rightarrow \infty} 0$

(W2)

Wasserstein distance between $V_{n^{-1} Y - z I}$ and $V_{n^{-1} X - z I}$

Convergence in W_2 implies weak convergence so it is enough to look at $\mathbb{E} \sum_{i,j} Y_{ij}^2 - \mathbb{E} Y_{ij}^2$

Centralization

$$Z_{ij} = Y_{ij} - \mathbb{E} Y_{ij} = Y_{ij} - \mathbb{E} X_{ij} \mathbb{1}_{\{|X_{ij}| \leq K_n\}}$$

By Lidskii inequality

$$\max_{t \geq 0} | \sum_{i,j} Y_{ij}^2 - \sum_{i,j} \mathbb{E} Y_{ij}^2 | \leq \frac{\text{rank}(\gamma - z)}{n} \leq \frac{1}{n}$$

It is enough to prove that $\mathbb{E} \sum_{i,j} Y_{ij}^2 \xrightarrow{w} \sum_{i,j} \mathbb{E} Y_{ij}^2$

In the following we allow the law of $X_{i,j}$ depend on n but we assume

$$\mathbb{E} X_{i,j} = 0 \quad \text{and} \quad \mathbb{P}(|X_{i,j}| \geq K_n) = 0$$

$$\mathbb{E} |X_{i,j}|^2 = \sigma_n^2 \quad \text{and} \quad K_n = o(\sqrt{n})$$

$$\sigma_n \rightarrow 1 \quad \text{as } n \rightarrow \infty$$

Step 3 Linearization

$$X \in M_n(\mathbb{C}) \quad s_1(X), \dots, s_n(X)$$

$$\begin{pmatrix} 0 & X \\ X^* & 0 \end{pmatrix} \text{ - eigenvalues are } \pm s_1(X), \dots, \pm s_n(X)$$

By \tilde{V} denote symmetrization of V

$$\tilde{V}(A) = (V(A) + V(-A)) / 2$$

$$m_V(z) = \int \frac{1}{x-z} dV(x)$$

We have

$$\rightarrow m_{\sum_{i,j} Y_{ij}^2 - \sum_{i,j} \mathbb{E} Y_{ij}^2}(\eta) = \frac{1}{n} \text{Tr} \left(H(z) - \eta \mathbb{I} \right)^{-1}$$

$$\text{where } H(z) = \begin{pmatrix} 0 & n^{-\frac{1}{2}} X - z \\ (n^{-\frac{1}{2}} X - z)^* & 0 \end{pmatrix}$$

Though working with perm. matrix $H(z)$ is eq. with the matrix

$$B(z) = B - \varrho(z, 0) \otimes \mathbb{I}_n$$

$$\varrho(z, \eta) = \begin{pmatrix} z & z \\ z & \eta \end{pmatrix}$$

$$n \quad 1 \quad 0 \quad X_{i,j}$$

$$B_{ij} = \frac{1}{n} \begin{pmatrix} 0 & X_{ij} \\ \overline{X_{ji}} & 0 \end{pmatrix}$$

$$B = \begin{pmatrix} 0 & 0 & \overline{n^{-1}X_{11}-z} & n^{-1}X_{12} \\ 0 & 0 & n^{-1}X_{21} & n^{-1}X_{22}-z \\ \overline{n^{-1}X_{11}-z} & n^{-1}\overline{X_{21}} & 0 & 0 \\ n^{-1}\overline{X_{12}} & n^{-1}\overline{X_{22}-z} & 0 & 0 \end{pmatrix}$$

$$B_{\text{def}} = \begin{pmatrix} 0 & \overline{n^{-1}X_{11}-z} & 0 & n^{-1}X_{12} \\ \overline{n^{-1}X_{11}-z} & 0 & n^{-1}X_{21} & 0 \\ 0 & n^{-1}X_{21} & 0 & n^{-1}X_{22}-z \\ n^{-1}X_{12} & 0 & n^{-1}X_{22}-z & 0 \end{pmatrix}$$

$$R(z) = (B(z) - \eta I_{2n})^{-1} = (B - z(z, \eta) \otimes I_n)^{-1}$$

$$m_{\overline{V_{n^{-1}X_{11}-z}}}(\eta) = \frac{1}{2n} \text{Tr}(R(z))$$

We set $R(z)_{kk} = \begin{pmatrix} a_k(z) & b_k(z) \\ c_k(z) & d_k(z) \end{pmatrix}$

It is easy to check that

$$a(z) = \frac{1}{n} \sum_{k=1}^n a_k(z) = \frac{1}{n} \sum_{k=1}^n d_k(z)$$

$$b(z) = \frac{1}{n} \sum_{k=1}^n b_k(z) = \frac{1}{n} \sum_{k=1}^n \overline{c_k(z)}$$

$$\begin{aligned} R(z) &= (B(z) - \eta I_{2n})^{-1} \\ &= -\frac{1}{\eta} \left(I - \frac{B(z)}{\eta} \right)^{-1} \\ &= -\frac{1}{\eta} \sum_{k=0}^{\infty} \left(\frac{B(z)}{\eta} \right)^k \end{aligned}$$

Similar property holds for every power of $B(z)$

$$m_{\overline{V_{n^{-1}X_{11}-z}}}(\eta) = a(z)$$

Want: $\{a(z)\}_k$ converges