

The Stieltjes transform

Def: For a probability measure μ on $\mathbb{R}$ (or a random variable $X \sim \mu$), its Stieltjes transform $m: \mathbb{C} \setminus \text{supp}(\mu) \rightarrow \mathbb{C}$ is the function $m(z) = \mathbb{E}\left[\frac{1}{X-z}\right] = \int \frac{1}{x-z} d\mu(x)$.

Note: Some authors use $\mathbb{E}\left[\frac{1}{z-X}\right]$. Also sometimes called the Cauchy transform.

(Here, $\text{supp}(\mu) = \{x \in \mathbb{R} : \text{Every open nbhd } U \text{ of } x \text{ has } \mu(U) > 0\}$.

Easy to check $\text{supp}(\mu)$ is a closed subset of $\mathbb{R}$.)

Compar: For a probability measure μ on $\mathbb{R}$, its characteristic function is the function $\varphi: \mathbb{R} \rightarrow \mathbb{C}$ given by

$$\varphi(t) = \mathbb{E}[e^{itX}] = \int e^{itx} d\mu(x).$$

• If two measures μ_1, μ_2 are such that $\varphi_1(t) = \varphi_2(t)$ for all $t \in \mathbb{R}$, then $\mu_1 = \mu_2$.

• If a sequence of prob. measures $\mu_1, \mu_2, \dots$ are such that $\varphi_n(t) \rightarrow \varphi(t)$ for all $t \in \mathbb{R}$, and φ is the characteristic function of some probability measure μ on $\mathbb{R}$, then $\mu_n \rightarrow \mu$ weakly.

We'll show the same two properties for the Stieltjes transform $m(z)$.

For a random matrix with ESD μ_n ,

$$\int e^{itx} d\mu_n(x) = \frac{1}{n} \sum_{j=1}^n e^{it\lambda_j(X)} \text{ is typically hard to study,}$$

$$\text{but } \int \frac{1}{x-z} d\mu_n(x) = \frac{1}{n} \sum_{j=1}^n \frac{1}{\lambda_j(X) - z} = \frac{1}{n} \text{Tr}((X - zI)^{-1}) \text{ is tractable.}$$

Basic properties:

• Let $z = \lambda + i\eta$, where $\lambda = \text{Re } z$ and $\eta = \text{Im } z$. Then

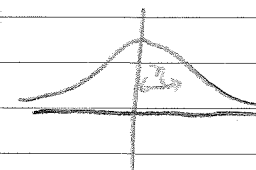
$$\begin{aligned} \text{Im } m(z) &= \int \text{Im} \frac{1}{x - \lambda - i\eta} d\mu(x) \\ &= \int \text{Im} \frac{x - \lambda + i\eta}{(x - \lambda)^2 + \eta^2} d\mu(x) \\ &= \int \frac{\eta}{(x - \lambda)^2 + \eta^2} d\mu(x). \end{aligned}$$

If $z \in \mathbb{C}^+$ so $\eta > 0$, then $m(z) \in \mathbb{C}^+$.

$$\begin{aligned} \text{Re } m(z) &= \int \text{Re} \frac{1}{x - \lambda - i\eta} d\mu(x) \\ &= \int \frac{x - \lambda}{(x - \lambda)^2 + \eta^2} d\mu(x). \end{aligned}$$

• Recall the Cauchy(0, η) distribution has density

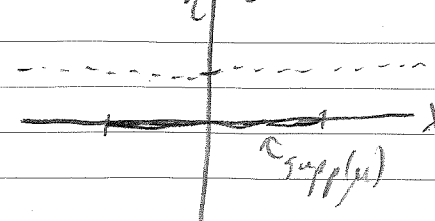
$$p(x) = \frac{1}{\pi} \cdot \frac{\eta}{x^2 + \eta^2}.$$



$$\text{Then } \frac{1}{\pi} \text{Im } m(z) = \int p(\lambda - x) d\mu(x)$$

is the density of the convolution $\mu * \text{Cauchy}(0, \eta)$.

I.e., fixing $\eta = \text{Im } z > 0$, the map $\lambda \mapsto \frac{1}{\pi} \text{Im } m(\lambda + i\eta)$ is this density.



• Letting $\bar{z} = \lambda - i\eta$,

$$m(\bar{z}) = \int \frac{1}{x - \bar{z}} d\mu(x) = \int \overline{\left(\frac{1}{x - z}\right)} d\mu(x) = \overline{m(z)}.$$

Sometimes $m(z)$ is just defined as a function $m: \mathbb{C}^+ \rightarrow \mathbb{C}^+$.

- $|m(z)| \leq \int \frac{1}{|x-z|} d\mu(x) \leq \frac{1}{\text{dist}(z, \text{supp}(\mu))}.$

In particular, if $z = \lambda + i\eta \in \mathbb{C}^+$, $|m(z)| \leq \frac{1}{\eta}.$

- Can differentiate under the integral:

$$\frac{d}{dz} m(z) = \int \frac{1}{(x-z)^2} d\mu(x).$$

Then also $|\frac{d}{dz} m(z)| \leq \int \frac{1}{|x-z|^2} d\mu(x) \leq \frac{1}{\text{dist}(z, \text{supp}(\mu))^2}.$

In particular, $m(z)$ restricted to $\{z \in \mathbb{C}^+ : \text{Im } z \geq \eta_0\}$ is $(\frac{1}{\eta_0})$ -Lipschitz.

- $m(z)$ is complex-analytic on $\mathbb{C} \setminus \text{supp}(\mu).$

(Recall: This means for any $z_0 \in \mathbb{C} \setminus \text{supp}(\mu)$, the Taylor series

$$m(z) = \sum_{k=0}^{\infty} \frac{1}{k!} \left(\frac{d^k}{dz^k} m(z_0) \right) \cdot (z - z_0)^k$$

is convergent in a neighborhood of z_0 .)

If $D \subseteq \mathbb{C}$ is a connected open set and f, g are two complex analytic functions such that $f(z_i) = g(z_i)$ for all z_i in some sequence of distinct values $z_1, z_2, z_3, \dots$ which have a limit $z \in D$, then in fact $f = g$ on all of D .)

- Suppose $\text{supp}(\mu) \subseteq [-M, M]$. Then for $z \in \mathbb{C}$ with $|z| > M$, applying $(x-z)^{-1} = -z^{-1} (1 - \frac{x}{z})^{-1} = -z^{-1} \sum_{k=0}^{\infty} (\frac{x}{z})^k$ for $|x| \leq M$,

$$m(z) = - \sum_{k=0}^{\infty} z^{-(k+1)} \int x^k d\mu(x)$$

as a convergent series. In particular, $m(z) = -\frac{1}{z} + O(\frac{1}{|z|^2})$ for large $|z|$.

One may recover μ and its density from $m(z)$:

Prop (Stieltjes inversion): For any $a < b$ where the CDF of μ is continuous,

$$\begin{aligned} \mu([a, b]) &= \lim_{\eta \rightarrow 0} \int_a^b \frac{1}{\pi} \text{Im } m(\lambda + i\eta) d\lambda \\ &= \lim_{\eta \rightarrow 0} \int_a^b \frac{1}{2\pi i} (m(\lambda + i\eta) - m(\lambda - i\eta)) d\lambda. \end{aligned}$$

If, at some $x \in \mathbb{R}$, $\lim_{z \in \mathbb{C}^+ \rightarrow x} \text{Im } m(z)$ exists, then μ has a density at x , which is $f(x) = \lim_{z \in \mathbb{C}^+ \rightarrow x} \frac{1}{\pi} \text{Im } m(z).$

Proof: Let $X \sim \mu$ and $Z_\eta \sim \text{Cauchy}(0, \eta)$ be independent. Then

$$\int_a^b \frac{1}{\pi} \text{Im } m(\lambda + i\eta) d\lambda = P[X + Z_\eta \in [a, b]].$$

Since $Z_\eta \xrightarrow{P} 0$ as $\eta \rightarrow 0$, Slutsky's Lemma implies $X + Z_\eta \rightarrow X$ in distribution.

Then $P[X + Z_\eta \in [a, b]] \rightarrow P[X \in [a, b]] = \mu([a, b]).$

For the second claim, let $F(x) = \mu((-\infty, x])$ be the CDF. Denote

$$\text{Im } m_0(x) = \lim_{z \in \mathbb{C}^+ \rightarrow x} \frac{1}{\pi} \text{Im } m(z).$$

It suffices to show

$$\lim_{\substack{x_i \rightarrow x, y_i \searrow x \\ y_i > x_i}} \frac{F(y_i) - F(x_i)}{y_i - x_i} = \frac{1}{\pi} \text{Im } m_0(x) \quad (*).$$

along any sequences $x_i \rightarrow x$ and $y_i \searrow x$ where x_i, y_i are continuity points of F .

For any $\varepsilon > 0$:

- Pick η large enough and $\delta > 0$ small enough s.t. for all $\eta < \delta$,

$$\left| \frac{1}{y_i - x_i} \int_{x_i}^{y_i} \frac{1}{\pi} \text{Im } m(\lambda + i\eta) d\lambda - \frac{1}{\pi} \text{Im } m_0(x) \right| < \frac{\varepsilon}{2}.$$

- Then pick $\eta < \delta$ small enough s.t.

$$\left| \int_{x_i}^{y_i} \frac{1}{\pi} \text{Im } m(\lambda + i\eta) d\lambda - \mu([x_i, y_i]) \right| < \frac{\varepsilon}{2} \cdot (y_i - x_i).$$

$$\begin{aligned} \text{Then } & \left| \frac{F(x_i) - F(x_i)}{y_i - x_i} - \frac{1}{\pi} \int_{x_i}^{y_i} \frac{1}{t} dm_0(t) \right| \\ & \leq \left| \frac{1}{y_i - x_i} \int_{x_i}^{y_i} \frac{1}{t} dm_0(t) - \frac{1}{\pi} \int_{x_i}^{y_i} \frac{1}{t} dm_0(t) \right| \\ & + \left| \frac{1}{y_i - x_i} (\mu((x_i, y_i]) - \int_{x_i}^{y_i} \frac{1}{t} dm_0(t)) \right| \leq \varepsilon. \end{aligned}$$

As ε is arbitrary, this shows (*).

Corollary: If μ_1, μ_2 have Stieltjes transforms m_1, m_2 s.t. $m_1(z) = m_2(z)$ for all $z \in \mathbb{C}^+$ (or for a sequence of $z \in \mathbb{C}^+$ having a limit point), then $\mu_1 = \mu_2$.

Thm: Let $\mu_1, \mu_2, \dots$ be a sequence of probability measures on $\mathbb{R}$ with Stieltjes transforms $m_1, m_2, \dots$. If there exists $m: \mathbb{C}^+ \rightarrow \mathbb{C}^+$ such that

- For each $z \in \mathbb{C}^+$, $m_n(z) \rightarrow m(z)$, and
- m is the Stieltjes transform of a probability measure μ ,

then $\mu_n \rightarrow \mu$ weakly.

Example: If $\mu_n = \frac{1}{2}\delta_0 + \frac{1}{2}\delta_n$ (discrete measures), then $m_n(z) = \frac{1}{2}(-\frac{1}{z}) + \frac{1}{2}(\frac{1}{n-z}) \rightarrow -\frac{1}{2z}$ for $z \in \mathbb{C}^+$. But $m(z) = -\frac{1}{2z}$ is not the Stieltjes transform of a probability measure μ on $\mathbb{R}$, and indeed μ_n has no weak limit. To prove the theorem:

Def: A measure μ on $\mathbb{R}$ is a sub-probability measure if $\mu(\mathbb{R}) \leq 1$.

Def: Sub-probability measures $\mu_1, \mu_2, \dots$ converge vaguely to a limit μ if, for any continuous $f: \mathbb{R} \rightarrow \mathbb{R}$ with $\lim_{x \rightarrow \pm\infty} f(x) = 0$,

$$\int f(x) d\mu_n(x) \rightarrow \int f(x) d\mu(x).$$

Equivalently, letting $F_n(x) = \mu_n((-\infty, x])$ and $F(x) = \mu((-\infty, x])$ be the "CDFs", $\mu_n(x) \rightarrow \mu(x)$ vaguely iff $F_n(x) \rightarrow F(x)$ at each continuity point x of F . (If μ is a probability measure, this is same as $\mu_n \rightarrow \mu$ weakly.)

Example: If $\mu_n = \frac{1}{2}\delta_0 + \frac{1}{2}\delta_n$, then $\mu_n \rightarrow \frac{1}{2}\delta_0$ vaguely.

Lemma: For any sequence of sub-probability measures μ_n , there exists a subsequence $\{\mu_{n_k}\}_{k=1}^\infty$ and a limit μ s.t. $\mu_{n_k} \rightarrow \mu$ vaguely.

Proof: Billingsley Probability and Measure, Chapter 28.

Proof of Thm: Suppose $m_n(z) \rightarrow m(z)$ for each $z \in \mathbb{C}^+$, but $\mu_n \not\rightarrow \mu$ weakly.

Then exists a subsequence where $d(\mu_{n_k}, \mu) > \varepsilon$ along this subsequence, for some $\varepsilon > 0$. Take a further subsequence n_k where $\mu_{n_k} \rightarrow \nu$ vaguely for some sub-probability limit ν . Since $x \mapsto \frac{1}{x-z}$ is continuous and satisfies $\lim_{x \rightarrow \pm\infty} \frac{1}{x-z} = 0$, by definition of vague convergence

$$m_{n_k}(z) = \int \frac{1}{x-z} d\mu_{n_k}(x) \rightarrow \int \frac{1}{x-z} d\nu(x).$$

Then $m(z)$ is the Stieltjes transform of ν . This implies $\nu = \mu$. But then $\mu_{n_k} \rightarrow \mu$ weakly, contradicting $d(\mu_{n_k}, \mu) > \varepsilon$ for all k .

Prop: If μ_n are prob. measures s.t. $m_n(z) \rightarrow m(z)$, then $m(z)$ is the Stieltjes transform of a probability measure μ iff

$$\lim_{y \rightarrow \infty} y \cdot m(iy) = -1.$$

Proof: Previous argument shows $m(z)$ is the Stieltjes transform of a sub-probability measure μ . For $z = iy$, by Dominated Convergence,

$$\lim_{n \rightarrow \infty} z \cdot m(z) = \lim_{n \rightarrow \infty} \int \frac{z}{x-z} d\mu(x) = \int (-1) d\mu(x) = -\mu(\mathbb{R}).$$

So μ is a probability measure iff this limit is -1 .

Semicircle law via Stieltjes transform

Heuristic: Fix $z \in \mathbb{C}^+$. Let X be a Wigner matrix with ESD μ_n .

$$\text{Let } m_n(z) = \int \frac{1}{x-z} d\mu_n(x) = \frac{1}{n} \sum_{i=1}^n \frac{1}{\lambda_i(X)-z} = \frac{1}{n} \text{Tr}(X-zI)^{-1}.$$

Recall the Schur complement formula for block inversion:

$$\begin{pmatrix} A & B \\ C & D \end{pmatrix}^{-1} = \begin{pmatrix} (A-BD^{-1}C)^{-1} & * \\ * & * \end{pmatrix}.$$

Applying with A being the (i,i) coordinate,

$$[(X-zI)^{-1}]_{ii} = \frac{1}{x_{ii}-z - x_i^T (X^{(i)}-zI)^{-1} x_i}$$

where x_i is column i of X with entry i removed ($\in \mathbb{R}^{n-1}$).

$X^{(i)}$ is the minor of X with row/column i removed ($\in \mathbb{R}^{(n-1) \times (n-1)}$).

Note: x_i is independent of $X^{(i)}$. For any fixed A ,

$$\mathbb{E}[x_i^T A x_i] = \mathbb{E}\left[\sum_{j,k} x_{ij} x_{ik} A_{jk}\right] = \frac{1}{n} \sum_j A_{jj} = \frac{1}{n} \text{Tr} A.$$

We will show $x_i^T (X^{(i)}-zI)^{-1} x_i$ concentrates around $\frac{1}{n} \text{Tr}(X^{(i)}-zI)^{-1}$.

Make the approximations:

$$\bullet x_{ii} \approx 0$$

$$\bullet x_i^T (X^{(i)}-zI)^{-1} x_i \approx \frac{1}{n} \text{Tr}(X^{(i)}-zI)^{-1}$$

$$\bullet \frac{1}{n} \text{Tr}(X^{(i)}-zI)^{-1} \approx \frac{1}{n} \text{Tr}(X-zI)^{-1} = m_n(z).$$

$$\text{Then } m_n(z) = \frac{1}{n} \sum_{i=1}^n \frac{1}{x_{ii}-z - x_i^T (X^{(i)}-zI)^{-1} x_i} \approx \frac{1}{-z - m_n(z)}.$$

We expect $m_n(z) \rightarrow m_0(z)$ where $m_0(z)$ is the root of

$$m_0(z) = \frac{1}{-z - m_0(z)}$$

in $\mathbb{C}^+$. Solving this quadratic equation,

$$m_0(z) = \frac{-z + \sqrt{z^2 - 4}}{2} = \frac{-\lambda - i\eta + \sqrt{\lambda^2 - \eta^2 - 4 + 2i\lambda\eta}}{2} \quad z = \lambda + i\eta$$

$$\lim_{\eta \rightarrow 0} m_0(z) = \begin{cases} \frac{-\lambda + \sqrt{\lambda^2 - 4}}{2} & \lambda > 2 \\ \frac{-\lambda - \sqrt{\lambda^2 - 4}}{2} & \lambda < -2 \\ \frac{-\lambda + i\sqrt{4 - \lambda^2}}{2} & \lambda \in [-2, 2] \end{cases}$$

So $\lim_{\eta \rightarrow 0} \frac{1}{n} \text{Im } m_0(z) = \frac{1}{2\pi} \sqrt{4 - \lambda^2} \mathbb{1}_{\{\lambda \in [-2, 2]\}}$, the semicircle density.

Lemma 1: Let $A \in \mathbb{C}^{n \times n}$ be deterministic. Let $x = \frac{1}{\sqrt{n}} z \in \mathbb{R}^n$

where z_i are independent, $\mathbb{E}[z_i] = 0$, $\text{Var}[z_i] = 1$, and z_i satisfy

LSI with constant $c > 0$. Then there exist constants $C, \delta > 0$ s.t.

$$\mathbb{P}\left[\left|x^T A x - \frac{1}{n} \text{Tr} A\right| \geq \frac{t}{\sqrt{n}}\right] \leq 2e^{-c t^2 / \|A\|^2} + e^{-\delta n} \text{ for all } t \geq C.$$

Note: There is a sharper result called the Hanson-Wright inequality. If

$z_1, \dots, z_n$ are sub-Gaussian

$$\mathbb{P}\left[\left|x^T A x - \frac{1}{n} \text{Tr} A\right| \geq \frac{t}{\sqrt{n}}\right] \leq 2 \exp\left(-c \min\left(\frac{t^2 n}{\|A\|_F^2}, \frac{t \sqrt{n}}{\|A\|}\right)\right).$$

See Rudelson, Vershynin '13 "Hanson-Wright ineq. and sub-Gaussian concentration".

Lemma 2: For any deterministic, symmetric $X \in \mathbb{R}^{n \times n}$ and minor $X' \in \mathbb{R}^{(n-1) \times (n-1)}$,

$$\left|\frac{1}{n} \text{Tr}(X'-zI)^{-1} - \frac{1}{n} \text{Tr}(X-zI)^{-1}\right| \leq \frac{1}{n} \left(\frac{2\|X\|}{(\text{Im } z)^2} + \frac{1}{|\text{Im } z|}\right).$$

Prop (Lipschitz extension): Let $G \subseteq \mathbb{R}^n$ and let $f: G \rightarrow \mathbb{R}$ be L -Lipschitz: For all $x, y \in G$, $|f(x) - f(y)| \leq L\|x - y\|$. Then there exists an L -Lipschitz function $F: \mathbb{R}^n \rightarrow \mathbb{R}$ s.t. $F(x) = f(x)$ for all $x \in G$.

Note: If G is convex and f differentiable, suffices to check $\|\nabla f(x)\| \leq L$ for all $x \in G$. In general need to check $|f(x) - f(y)| \leq L\|x - y\|$ when G not convex.

Proof: Let $F(x) = \inf_{y \in G} f(y) + L\|x - y\|$. For any $x, y \in G$,

$$f(x) \leq f(y) + L\|x - y\|, \text{ so } F(x) = f(x) \text{ when } x \in G.$$

For any $x, x' \in \mathbb{R}^n$, $\varepsilon > 0$, there is $y' \in G$ where

$$F(x') \geq f(y') + L\|x' - y'\| - \varepsilon. \text{ For this } y', F(x) \leq f(y') + L\|x - y'\|.$$

$$\text{Then } F(x) - F(x') \leq L\|x - y'\| - L\|x' - y'\| + \varepsilon \leq L\|x - x'\| + \varepsilon.$$

$$\text{Take } \varepsilon > 0: F(x) - F(x') \leq L\|x - x'\|. \text{ Similarly } F(x') - F(x) \leq L\|x - x'\|.$$

Proof of Lemma 1: Assume WLOG $\|A\| = 1$.

① Bound $\mathbb{P}[\|x\| > 1 + t]$, $t > 0$.

The map $x \mapsto \|x\|$ is 1-Lipschitz in x , so $\frac{1}{\sqrt{n}}$ -Lipschitz in z .

$$\text{Then } \mathbb{P}[\|x\| - \mathbb{E}[\|x\|] > t] \leq e^{-c't^2/n}. \quad \mathbb{E}[\|x\|] \leq \sqrt{\mathbb{E}\|x\|^2} = 1.$$

$$\text{So } \mathbb{P}[\|x\| > 1 + t] \leq \mathbb{P}[\|x\| - \mathbb{E}\|x\| > t] \leq e^{-c't^2/n}.$$

② Note $\|\nabla_x (x^T A x)\| = \|(A + A^T)x\| \leq 2\|A\| \cdot \|x\| \leq 2$ for $\|x\| \leq 2$.

Thus $x \mapsto x^T A x$ is 2-Lipschitz (in x) over $B = \{x: \|x\| \leq 2\}$.

Let $F(x)$ be the 2-Lipschitz extension to B^c .

$$\text{Then } \mathbb{P}[|F(x) - \mathbb{E}F(x)| > t] \leq 2e^{-c't^2/n}.$$

$$\text{So } \mathbb{P}[|x^T A x - \mathbb{E}F(x)| > t] \leq 2e^{-c't^2/n} + \mathbb{P}[\|x\| > 2] \\ \leq 2e^{-c't^2/n} + e^{-c'n}.$$

$$\text{We have } |\mathbb{E}F(x) - \mathbb{E}x^T A x| \leq \mathbb{E}[|F(x) - x^T A x|]$$

$$= \mathbb{E}[|F(x) - x^T A x| \cdot \mathbb{I}\{\|x\| > 2\}]$$

$$\leq \mathbb{E}[(L+1)\|x\|^2 \cdot \mathbb{I}\{\|x\| > 2\}]$$

since $|F(x)| = |F(x) - F(0)| \leq L\|x\|$, and $|x^T A x| \leq \|x\|^2$.

By same argument as last lecture, $|\mathbb{E}F(x) - \mathbb{E}x^T A x| \leq Ce^{-cn}$.

Set $t = \frac{s}{\sqrt{n}}$ where $s > C'$, C' large enough s.t. $Ce^{-cn} \leq \frac{C'}{2\sqrt{n}}$.

$$\text{Then } \mathbb{P}[|x^T A x - \mathbb{E}x^T A x| > \frac{s}{\sqrt{n}}]$$

$$\leq \mathbb{P}[|x^T A x - \mathbb{E}F(x)| > \frac{s}{2\sqrt{n}}] \leq 2e^{-c's^2/n} + e^{-cn}$$

Prop (eigenvalue interlacing): If $X \in \mathbb{R}^{n \times n}$ is symmetric, with eigenvalues $\lambda_1(X) \geq \dots \geq \lambda_n(X)$, and X' is a minor with one row and column removed, with eigenvalues $\lambda_1(X') \geq \dots \geq \lambda_{n-1}(X')$, then

$$\lambda_1(X) \geq \lambda_1(X') \geq \lambda_2(X) \geq \dots \geq \lambda_{n-1}(X') \geq \lambda_{n-1}(X) \geq \lambda_n(X).$$

$$\begin{array}{ccccccc} & 0 & 0 & 0 & \dots & 0 & \\ x & x & x & \dots & x & x & \end{array} \quad \begin{array}{l} \text{Eigs of } X \\ \text{Eigs of } X'. \end{array}$$

Proof: Recall the Courant-Fischer min-max principle:

$$\lambda_k(X) = \max_{U \subseteq \mathbb{R}^n, \dim U = k} \min_{v \in U, \|v\|=1} v^T X v \\ = \min_{U \subseteq \mathbb{R}^n, \dim U = n-k+1} \max_{v \in U, \|v\|=1} v^T X v$$

(Proof: Let $X = \sum \lambda_i v_i v_i^T$. Take $U = \text{span}(v_1, \dots, v_k)$. Then $\min_{v \in U: \|v\|=1} v^T X v = v_k^T X v_k = \lambda_k$. So $\lambda_k \leq \max_U \min_v v^T X v$.

On the other hand, for any U of dim. k , it has non-empty intersection w/ $\text{span}(v_k, \dots, v_n)$. Let v be a unit vector in this intersection. Then $v^T X v \leq v_k^T X v_k = \lambda_k$.

So $\lambda_k \geq \min_{v \in U: \|v\|=1} v^T X v$ for any U of dim. k . Then $\lambda_k \geq \max_U \min_v v^T X v$. The second statement is similar.)

Let X' remove the last row & column of X .

Derive $\mathbb{R}^{n-1} = \{v \in \mathbb{R}^n: v_n = 0\}$. For each $k \in \{1, \dots, n-1\}$,

$$\begin{aligned} \lambda_k(X) &= \max \left(\min_{v \in U: \|v\|=1} v^T X v : U \subseteq \mathbb{R}^n, \dim(U) = k \right) \\ &\geq \max \left(\min_{v \in U: \|v\|=1} v^T X v : U \subseteq \mathbb{R}^{n-1}, \dim(U) = k \right) \\ &= \max \left(\min_{v \in U: \|v\|=1} v^T X' v : U \subseteq \mathbb{R}^{n-1}, \dim(U) = k \right) = \lambda_k(X'). \end{aligned}$$

For each $k \in \{2, \dots, n\}$:

$$\begin{aligned} \lambda_k(X) &= \min \left(\max_{v \in U: \|v\|=1} v^T X v : U \subseteq \mathbb{R}^n, \dim(U) = n-k+1 \right) \\ &\leq \min \left(\max_{v \in U: \|v\|=1} v^T X v : U \subseteq \mathbb{R}^{n-1}, \dim(U) = n-k+1 \right) \\ &= \min \left(\max_{v \in U: \|v\|=1} v^T X' v : U \subseteq \mathbb{R}^{n-1}, \dim(U) = n-k+1 \right) = \lambda_{k-1}(X'). \end{aligned}$$

Proof of Lemma 2: Let $\lambda_1, \dots, \lambda_n$ be eigs of X , $\lambda'_1, \dots, \lambda'_{n-1}$ those of X' .

$$\begin{aligned} &\left| \frac{1}{n} \text{Tr}(X - zI)^{-1} - \frac{1}{n} \text{Tr}(X' - zI)^{-1} \right| \\ &= \left| \frac{1}{n} \left(\frac{1}{\lambda_1 - z} - \frac{1}{\lambda'_1 - z} + \frac{1}{\lambda_2 - z} - \frac{1}{\lambda'_2 - z} + \dots + \frac{1}{\lambda_{n-1} - z} - \frac{1}{\lambda'_{n-1} - z} - \frac{1}{\lambda_n - z} \right) \right| \end{aligned}$$

$$\begin{aligned} &\leq \frac{1}{n} \sum_{i=1}^{n-1} \left| \frac{1}{\lambda_i - z} - \frac{1}{\lambda'_i - z} \right| + \frac{1}{n} \cdot \frac{1}{|\lambda_n - z|} \\ &= \frac{1}{n} \sum_{i=1}^{n-1} \frac{|\lambda'_i - \lambda_i|}{|\lambda_i - z| |\lambda'_i - z|} + \frac{1}{n} \cdot \frac{1}{|\lambda_n - z|} \end{aligned}$$

Apply $|\lambda_i - z| \geq |\text{Im}(\lambda_i - z)| = |\text{Im } z|$, and by interlacing

$$\sum_{i=1}^{n-1} |\lambda'_i - \lambda_i| \leq \lambda_1 - \lambda_n \leq 2\|X\|. \text{ Get LHS} \leq \frac{1}{n} \left(\frac{2\|X\|}{(\text{Im } z)^2} + \frac{1}{|\text{Im } z|} \right)$$

Proof #2 of semicircle law (when X_{ij} satisfy LSI).

$$\text{Recall } m_n(z) = \frac{1}{n} \sum_{i=1}^n \frac{1}{\lambda_i - z - x_i^T (X^{(i)} - zI)^{-1} x_i}.$$

On an event of probability $\leq C e^{-\sqrt{n}}$:

- Applying Lemma 1 conditional on $X^{(i)}$, $\left| x_i^T (X^{(i)} - zI)^{-1} x_i - \frac{1}{n} \text{Tr}(X^{(i)} - zI)^{-1} \right| \leq \frac{\|X^{(i)} - zI\|^{-1}}{n^{1/4}}$.

Note $\|(X^{(i)} - zI)^{-1}\| = \max_j \frac{1}{|\lambda_j^{(i)} - z|} \leq \frac{1}{\text{Im } z}$.

- Applying Lemma 2 and $\|X\| \leq C$, $\left| \frac{1}{n} \text{Tr}(X^{(i)} - zI)^{-1} - m_n(z) \right| \leq \frac{C}{n} \left(\frac{1}{(\text{Im } z)^2} + \frac{1}{\text{Im } z} \right)$.

- $|x_{ii}| = \frac{1}{\sqrt{n}} |z_{ii}| \leq \frac{C}{n^{1/4}}$.

So on this event, $m_n(z) = \frac{1}{-z - m_n(z) + r_n}$

where $|r_n| \leq C n^{-1/4}$. (C depends on $\text{Im } z$.) Solving this equation,

$$m_n(z) \in \frac{-(z + r_n) \pm \sqrt{(z + r_n)^2 - 4}}{2}. \text{ Then } |m_n(z) - \tilde{m}(z)| \leq C \cdot n^{-1/4},$$

For $\tilde{m}(z) \in \left\{ \frac{-z + \sqrt{z^2 - 4}}{2}, \frac{-z - \sqrt{z^2 - 4}}{2} \right\}$. Let $m(z)$ be the root

wt positive imaginary part. Since $\bar{m}_n(z)$ also has positive imaginary part, for large enough n we must have

$$|m_n(z) - m(z)| \leq Cn^{-1/4}, \text{ on this event.}$$

By Borel-Cantelli, $m_n(z) \rightarrow m(z)$ a.s. This holds for each fixed $z \in \mathbb{C}^+$, so $\mu_n \rightarrow \mu$ weakly where μ has Stieltjes transform $m(z)$, i.e. μ is the semi-circle law.

Problem 2. For each $z \in \mathbb{C}^+$, let $m(z)$ be the Stieltjes transform of the semi-circle law, i.e. the root of

$$m^2 + zm + 1 = 0 \quad (*)$$

with positive imaginary part.

(a) Let $z = \lambda + i\eta$, where $\eta > 0$, $\lambda \in [-3, 3]$. Set $K = \min(|\lambda - 2|, |\lambda + 2|)$.

Show there are universal constants $C, c > 0$ such that for any such

z ,

$$c < |m(z)| < C$$

$$\text{If } \lambda \in [-2, 2], \text{ then } c\sqrt{\eta+K} < \text{Im } m(z) < C\sqrt{\eta+K}.$$

$$\text{If } \lambda \in [-3, -2] \cup [2, 3] \text{ then } \frac{c\eta}{\sqrt{\eta+K}} < \text{Im } m(z) < \frac{C\eta}{\sqrt{\eta+K}}.$$

(b) Fix any $\varepsilon \in (0, \frac{1}{4})$ and set

$$D_n = \{z = \lambda + i\eta \in \mathbb{C}^+ : \lambda \in [-3, 3], \eta \in [n^{-1/4+\varepsilon}, 1]\}.$$

Using Lemmas 1 and 2 of today's class, show a.s. as $n \rightarrow \infty$,

$$\sup_{z \in D_n} |m_n(z) - m(z)| \rightarrow 0.$$

(Two things to be careful about:

(i) How close is $m_n(z)$ to some root of $(*)$, if $z = z_n$ is s.t. $|z_n - z| \rightarrow 0$?

(ii) How close are the imaginary parts of the two roots of $(*)$ to 0?)

(c) If you restrict to the domain

$$D_n^{\text{in}} = \{z = \lambda + i\eta \in \mathbb{C}^+ : \lambda \in [-2+\varepsilon, 2-\varepsilon], \eta \in [n^{-\alpha+\varepsilon}, 1]\},$$

for what α can you prove a similar statement?

What about the domain

$$D_n^{\text{out}} = \{z = \lambda + i\eta \in \mathbb{C}^+ : \lambda \in [-3, -2-\varepsilon] \cup [2+\varepsilon, 3], \eta \in [n^{-\alpha+\varepsilon}, 1]\}?$$