

Mean Field Asymptotics in Statistical Learning.

Mar 29

Lecture 17. Random matrices and Stieltjes transforms

① Motivation.

Many quantities of interest are of form

$$\frac{1}{n} \sum_{i=1}^n \mathbb{E} f(\lambda_i(A)) = \mathbb{E} \int_{\mathbb{R}} f(\lambda) \hat{\mu}_A(d\lambda), \quad \hat{\mu}_A(d\lambda) = \frac{1}{n} \sum_{i=1}^n \delta_{\lambda_i(A)}.$$

where A is some random matrix.

Example: In double descent of linear model (Lecture 16).

$$\text{Bias: } B(\lambda) = \lambda^2 \cdot \mathbb{E} \int_{\mathbb{R}} \frac{1}{(s+\lambda)^2} \hat{\mu}_{X^T X/d}(d\lambda).$$

$$A = X^T X/d$$

$$\text{Var: } V(\lambda) = \sigma^2 \cdot \mathbb{E} \int_{\mathbb{R}} \frac{s}{(s+\lambda)^2} \hat{\mu}_{X^T X/d}(d\lambda).$$

Hope to characterize $\hat{\mu}_{X^T X/d}(d\lambda)$ for large n .

② Stieltjes transforms and Stieltjes functions.

Def: Prob. measure $\mu \in \mathcal{P}(\mathbb{R})$, the Stieltjes transform $\mathcal{S}$

$$\begin{aligned} \mathcal{S}: \mathcal{P}(\mathbb{R}) &\rightarrow \mathcal{F}(\mathbb{C}) \\ \mu &\mapsto \mathcal{S}(\mu) = m \end{aligned}$$

$m: \mathbb{C} \setminus \underbrace{\text{supp}(\mu)}_{\text{singular in support}} \rightarrow \mathbb{C}$ is the Stieltjes function associated with μ .

$$m(z) = \int \frac{1}{x-z} \mu(dx).$$

Rmk: ST is not transforming "z" to "m(z)"

ST is transforming " $\mu \in \mathcal{P}(\mathbb{R})$ " to " $m \in \mathcal{F}(\mathbb{C})$ ".

Stieltjes trans. $\leftrightarrow$ Fourier trans.

Stieltjes func.

$\leftrightarrow$ Characteristic functions

Will consider $\mu = \hat{\mu}_A \Rightarrow m(z) = \frac{1}{n} \text{tr}[(A - zI)^{-1}]$.

Properties of Stieltjes functions (fix μ , talk about property of m).

⊗ Let $z = \lambda + i\eta$, $\lambda, \eta \in \mathbb{R}$. then

$$\text{Im } m(z) = \int \text{Im} \frac{1}{x-z} \mu(dx) = \int_{\mathbb{R}} \frac{\eta}{(x-\lambda)^2 + \eta^2} \mu(dx).$$

$$\text{Re } m(z) = \int \text{Re} \frac{1}{x-z} \mu(dx) = \int_{\mathbb{R}} \frac{x-\lambda}{(x-\lambda)^2 + \eta^2} \mu(dx).$$

By Cauchy-Riemann, one almost determines the other.

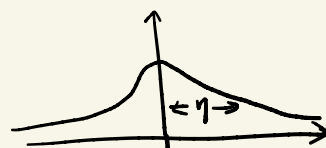
⊗ When $\eta > 0$, $\text{Im } m(z) > 0$,

So m maps $\mathbb{C}_+ \rightarrow \mathbb{C}_+$

⊗

Interpretation of $\text{Im } m(z)$

Cauchy(0, η) density: $p(x) = \frac{1}{\pi} \frac{\eta}{x^2 + \eta^2}$



$\frac{1}{\pi} \text{Im } m(z) = \int_{\mathbb{R}} p(\lambda - x) \mu(dx)$. : density of $\mu * \text{Cauchy}(0, \eta)$.

Imaginary part is the smoothed version of μ .

Less and less smooth as $\eta \rightarrow 0$

⊗

For $z \in \mathbb{C} \setminus \text{supp}(\mu)$.

$$|m(z)| \leq \int_{\mathbb{R}} \frac{1}{|x-z|} \mu(dx) \leq \frac{1}{\text{dist}(z, \text{supp}(\mu))} \leq \frac{1}{\text{Im } z} = \frac{1}{\eta}.$$

$$m'(z) = \int_{\mathbb{R}} \frac{1}{(x-z)^2} \mu(dx)$$

$$|m'(z)| \leq \int_{\mathbb{R}} \frac{1}{|x-z|^2} \mu(dx) \leq \frac{1}{\text{dist}(z, \text{supp}(\mu))^2} \leq \frac{1}{\text{Im } z^2} = \frac{1}{\eta^2}.$$

m on $\{z \in \mathbb{C}_+ : \text{Im } z \geq \eta_0\}$ is $\frac{1}{\eta_0^2}$ -Lipschitz. (no matter what is μ).

⊗

m is an analytic function on $\mathbb{C} \setminus \text{supp}(\mu)$.

Meaning: a) Its Taylor series locally converge to itself

b) If $(z_n)_{n \geq 1} \subseteq D$ open set, $z_n \rightarrow z_0 \in D$.

$$m(z_n) = \bar{m}(z_n) \implies m(z) = \bar{m}(z) \text{ on } D.$$

⊗

Suppose $\text{supp}(\mu) \subseteq [-M, M]$, then $\forall z \in \mathbb{C}$ with $|z| > M$,

$$\begin{aligned} \Rightarrow m(z) &= \int_{\mathbb{R}} \frac{1}{x-z} \mu(dx) = -z^{-1} \int_{\mathbb{R}} \left(1 - \frac{x}{z}\right)^{-1} \mu(dx) \\ &= -z^{-1} \int_{\mathbb{R}} \sum_{k=0}^{\infty} \left(\frac{x}{z}\right)^k \mu(dx) = - \sum_{k=0}^{\infty} z^{-(k+1)} \int x^k \mu(dx). \end{aligned}$$

In particular, $m(z) = -\frac{1}{z} + O\left(\frac{1}{|z|^2}\right)$ for large $|z|$.

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

is continuous, $\mu([a, b]) = \lim_{\eta \rightarrow 0} \int_a^b \frac{1}{\pi} \text{Im } m(\lambda + i\eta) d\lambda$

If for $x \in \mathbb{R}$, $\lim_{z \in \mathbb{C}^+ \rightarrow x} \text{Im } m(z)$ exists, then μ has a density at x ,

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

Intuition: $\frac{1}{\pi} \text{Im } m(\lambda + i\eta) = \mu * \text{Cauchy}(0, \eta) \rightarrow \mu$ as $\eta \rightarrow 0$.

Similar to characteristic function

"Fourier transform".

$$\hat{f}(\lambda) = \int_{\mathbb{R}} f(x) e^{-i\lambda x} dx$$

$$f(x) = \frac{1}{2\pi} \int_{\mathbb{R}} \hat{f}(\lambda) e^{i\lambda x} d\lambda.$$

Implication: If we know two distributions have the same Stieltjes function, then the two distributions are equal.

Actually, we can replace "same" by "approximately same".

"equal" by "approximate equal".

Thm: Let $(\mu_n)_{n \geq 1} \subseteq \mathcal{P}(\mathbb{R})$ with Stieltjes functions $(m_n)_{n \geq 1} \subseteq \mathcal{F}(\mathbb{C}^+)$.

If there exists $m: \mathbb{C}^+ \rightarrow \mathbb{C}^+$ s.t.

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

then $\mu_n \rightarrow \mu$ weakly.

Rmk: If our goal is to compute the limit

$$\lim_{n \rightarrow \infty} F_n = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathbb{E}[f(\lambda_i(A))], \quad \text{where } A \text{ is R.M.}$$

We can proceed with the following steps.

⊗ Figure out the limit

$$\begin{aligned} m(z) &= \lim_{n \rightarrow \infty} \mathbb{E}[m_n(z)] = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n \mathbb{E}\left[\int \frac{1}{x-z} \hat{\mu}_A(dx)\right] \\ &= \lim_{n \rightarrow \infty} \mathbb{E}[\text{tr}((A-zI)^{-1})]/n. \end{aligned}$$

show the concentration of m_n . (so that a.s. convergence).

⊗ Express F_n as a function of m_n . i.e. $\mathcal{F}: \mathcal{P}(\mathbb{R}) \rightarrow \mathbb{R}$.

$$F_n = \mathcal{F}(m_n) = \lim_{\eta \rightarrow 0} \int f(\lambda) \frac{1}{\pi} \text{Im } m_n(\lambda + i\eta) d\lambda$$

Sometimes has a simpler form.

$$\text{e.g. } B_n(\lambda) = \lambda^2 \cdot m'_n(-\lambda).$$

⊗ Show continuity property of $\mathcal{F}$,

$$\text{so that } \lim_{n \rightarrow \infty} F_n = \mathcal{F}(m).$$

③ Limiting Stieltjes transform for GOE matrix.

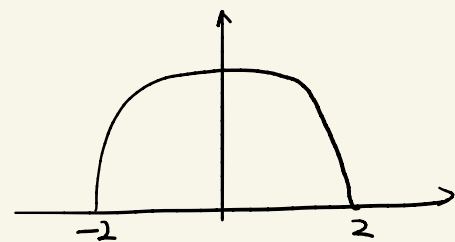
$$W \sim \text{GOE}(n), \quad W_{ij} \sim N(0, \frac{1}{n}) \quad 1 \leq i < j \leq n$$

$$W_{ii} \sim N(0, \frac{2}{n}) \quad 1 \leq i \leq n.$$

$$W_{ji} = W_{ij}$$

Semicircle law:

$$\mu = \frac{1}{2\pi} \sqrt{4-x^2} \mathbb{1}_{\{x \in [-2, 2]\}}.$$



Thm: Let $W \sim \text{GOE}(n)$. Then almost surely as $n \rightarrow \infty$,

$\mu_n = \frac{1}{n} \sum_{i=1}^n \delta_{\lambda_i(W)}$ converges weakly to the semicircle law μ .

Rmk: Generalizable to Wigner matrix:

symmetric matrix having independent entries (lower-left triangle part)
with matching first and second moment with $W \sim \text{GOE}(n)$.
(and other Higher moment conditions).

Idea: Show the convergence of $m_n(z)$ to $m(z)$ ← Stieltjes function of Semi-circle law.

$$m(z) = \frac{\sqrt{z^2 - 4} - z}{2} \quad (\text{satisfy } m^2 + zm + 1 = 0).$$

Heuristics:

$$\otimes \quad m_n(z) = \frac{1}{n} \text{tr}((W - zI)^{-1})$$

$\otimes$ Block matrix inversion formula.

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

$$W_i \triangleq (W_{si})_{s \neq i} \in \mathbb{R}^{n-1}, \quad W^{(i)} = (W_{st})_{s, t \neq i} \in \mathbb{R}^{(n-1) \times (n-1)}$$

$$A = W_{ii} - z, \quad B^T = C = w_i, \quad D = W^{(i)} - zI.$$

$$(W - zI)^{-1}_{ii} = W_{ii} - z - w_i^T (W^{(i)} - zI)^{-1} w_i$$

$$\otimes \quad m_n(z) = \frac{1}{n} \sum_{i=1}^n (W - zI)^{-1}_{ii} = \frac{1}{n} \sum_{i=1}^n \frac{1}{W_{ii} - z - w_i^T (W^{(i)} - zI)^{-1} w_i}.$$

Note: W_{ii} , w_i , $W^{(i)}$ are mutually independent,

$$z = O(1), \quad W_{ii} = O(\frac{1}{n}) = o(1).$$

$$\mathbb{E}[w_i^T (W^{(i)} - zI)^{-1} w_i | W^{(i)}] = \text{tr}[(W^{(i)} - zI)^{-1}] / n$$

$$\text{Concentration: } w_i^T (W^{(i)} - zI)^{-1} w_i / n$$

$$\approx \text{tr}[(W^{(i)} - zI)^{-1}] / n \approx m_n(z).$$

⊗ Self consistent equation

$$m_n(z) \approx \frac{1}{-z - m_n(z)} \Rightarrow m_n(z)^2 + z \cdot m_n(z) + 1 \approx 0.$$

$$m_n(z) \rightarrow m(z), \quad m(z)^2 + z \cdot m(z) + 1 = 0.$$

Proof of thm:

⊗ Lemma 1: We have a.s. convergence.

$$\lim_{n \rightarrow \infty} \sup_{i \in [n]} |\langle w_i, (W^{(i)} - zI)^{-1} w_i \rangle - \text{tr}((W^{(i)} - zI)^{-1})/n| = 0$$

Proof:

Lemma (Hanson - Wright inequality).

Let $A \in \mathbb{C}^{n \times n}$ be deterministic,

$$\Rightarrow \mathbb{P}_{g \sim N(0, I_n)} (|\langle g, Ag \rangle - \text{tr}(A)| \geq t) \leq 2 \exp \left[-c \cdot \min \left(\frac{t^2}{\|A\|_F^2}, \frac{t}{\|A\|_{\text{op}}} \right) \right].$$

$$A = (W^{(i)} - zI)^{-1}, \quad g = \sqrt{n} w_i$$

$$\|A\|_{\text{op}} \leq \max_{j \in [n-1]} |(\lambda_j(W^{(i)}) - z)^{-1}| \leq \frac{1}{\text{Im } z} = \frac{1}{\eta}.$$

$$\|A\|_F \leq \sqrt{n} \|A\|_{\text{op}} \leq \frac{\sqrt{n}}{\eta}.$$

$$\Rightarrow \mathbb{P}(|\langle w_i, (W^{(i)} - zI)^{-1} w_i \rangle - \text{tr}((W^{(i)} - zI)^{-1})/n| \geq \frac{s}{\sqrt{n}})$$

$$\leq 2 \exp \left\{ -C \cdot n \cdot \min(\eta^2 s^2, \eta s) \right\}.$$

$$\Rightarrow \mathbb{P}(\forall i \in [n], |\langle w_i, (W^{(i)} - zI)^{-1} w_i \rangle - \text{tr}((W^{(i)} - zI)^{-1})/n| \geq \frac{s}{\sqrt{n}})$$

$$\leq 2n \cdot \exp \left\{ -C \cdot n \cdot \min(\eta^2 s^2, \eta s) \right\}. \quad \square$$

⊗ Lemma 2: For any deterministic symmetric $W \in \mathbb{R}^{n \times n}$ and minor matrix $W^{(i)} \in \mathbb{R}^{(n-1) \times (n-1)}$, we have

$$\left| \frac{1}{n} \text{tr}(W - zI) - \frac{1}{n} \text{tr}(W^{(i)} - zI) \right| \leq \frac{1}{n} \left(\frac{2\|W\|_{\text{op}}}{(\text{Im } z)^2} + \frac{1}{|\text{Im } z|} \right).$$

When $W \sim \text{GOE}(n)$, this $\rightarrow 0$ a.s.

To prove this, we use eigenvalue interpolating property.

Lemma: If $W \in \mathbb{R}^{n \times n}$ symmetric and $W^{(i)} \in \mathbb{R}^{(n-1) \times (n-1)}$ is the minor matrix

Let $\lambda_1(W) \geq \lambda_2(W) \geq \dots \geq \lambda_n(W)$ be eigs of W

$\lambda_1(W^{(i)}) \geq \lambda_2(W^{(i)}) \geq \dots \geq \lambda_{n-1}(W^{(i)})$ be the eigs of $W^{(i)}$

Then $\lambda_1(W) \geq \lambda_1(W^{(i)}) \geq \lambda_2(W) \geq \dots \geq \lambda_{n-1}(W) \geq \lambda_{n-1}(W^{(i)}) \geq \lambda_n(W)$.

—○—○—○—○— eig of W

—×—×—×— eig of $W^{(1)}$

Proof use Courant-Fischer min-max formula (variational formula for eig).

$$\textcircled{*} \text{ This gives } m_n(z) = \frac{1}{n} \sum_{i=1}^n \frac{1}{W_{ii} - z - \langle w_i, (W^{(1)} - z)^{-1} w_i \rangle}$$

$$= \frac{1}{-z - m_n(z) - r_n(z)}$$

where $r_n(z) \rightarrow 0$ a.s. (for fixed $z \in \mathbb{C}^+$)

$$m_n(z) = \frac{-(z + r_n(z)) \pm \sqrt{(z + r_n(z))^2 - 4}}{2}$$

When $r_n(z)$ small, choose "+" for $m_n(z) \in \mathbb{C}_+$.

$$\Rightarrow \lim_{n \rightarrow \infty} m_n(z) = \frac{-z + \sqrt{z^2 - 4}}{2} \quad \text{a.s.} \quad \square$$