

# Concentration of the Measure Theory to study random matrices

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I- Concentration of the Measure Phenomenon

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# Classical study of singular values of rectangular RM

$X \in \mathcal{M}_{p,n}$ , we study  $\frac{1}{n}XX^T$

## Classial Hypothesis

- ▶  $X$  has i.i.d entries with bounded Variance
- ▶  $X = C^{\frac{1}{2}}Z$

## Classical conclusions

- ▶ Weak convergence of the spectral distribution to the Marcenko-Pastur law

**Question :** Can we find wider hypothesis and control the speed of convergence ?



# With the concentration of the measure theory (CMT)

## Hypothesis of CMT

1. For all 1-Lipschitz maps  $f : \mathcal{M}_{p,n} \rightarrow \mathbb{R}$ :

$$\forall t > 0 : \mathbb{P}(|f(X) - \mathbb{E}[f(X)]| \geq t) \leq 2e^{-t^2/2}$$

2. The column of  $X$  are i.i.d.

## Remarks

- ▶ **(Asset)** True if the columns are **Lipschitz transformation** of a Gaussian vector  $Z \sim \mathcal{N}(0, I_p)$ .  
→ dependence between the entries of a column possibly complex
- ▶ **(Drawback)** That implies that all the moments are bounded



# With the concentration of the measure theory (CMT)

## Conclusions on the spectral distribution

- ▶ Noting  $Q(z) = (\frac{1}{n}XX^T + zI_p)^{-1}$ , the resolvent of the empirical covariance,  $\frac{1}{p} \text{Tr}(Q(z))$  is the *Stieltjes transform* of its spectral distribution and:

$$\forall t > 0 : \mathbb{P} \left( \left| \text{Tr}(Q(z)) - \text{Tr}(\tilde{Q}_1) \right| \geq t \right) \leq C e^{-nt^2/c}, \quad C, c \underset{p, n \rightarrow \infty}{=} O$$

where  $\tilde{Q}_1 \in \mathcal{M}_p$  is a *deterministic equivalent* of  $Q$



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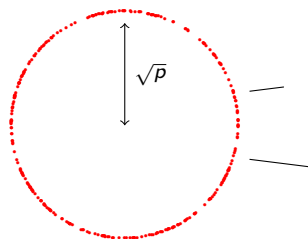
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# Concentration of the Measure Phenomenon

$$X = (X_1, \dots, X_p) \sim s_p$$

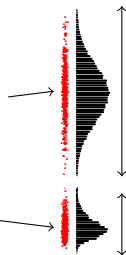


Distribution  
diameter  $\stackrel{p \rightarrow \infty}{=} O(\sqrt{p})$

Observations

$$\frac{X_1 + \dots + X_p}{\sqrt{p}}$$

$$\|X\|_\infty$$



$O(1)$

$O(1)$

Observable  
diameter  $\stackrel{p \rightarrow \infty}{=} O(1)$



## Setting

$(E, \|\cdot\|)$ , a normed vector space,  $Z \in E$ , a random vector

- ▶  $(\mathbb{R}^p, \|\cdot\|)$ , with  $\|x\| = \sqrt{\sum_{i=1}^p x_i^2}$
- ▶  $(\mathcal{M}_{p,n}, \|\cdot\|_F)$  with  $\|M\|_F = \sqrt{\text{Tr}(MM^T)} = \sqrt{\sum_{\substack{1 \leq i \leq p \\ 1 \leq j \leq n}} M_{i,j}^2}$

## Notations

- ▶ if  $\exists \alpha : \mathbb{R}^+ \rightarrow \mathbb{R}^+ \mid \forall f : E \rightarrow \mathbb{R} \text{ 1-Lipschitz} :$   
 $\boxed{\forall t > 0 : \mathbb{P}(|f(Z) - \mathbb{E}[f(Z)]| \geq t) \leq \alpha(t)},$  we note  $Z \in \alpha$
- ▶ In particular, if  $\exists \tilde{Z} \in E \mid \forall u : E \rightarrow \mathbb{R} \text{ 1-Lipschitz and linear} :$   
 $\boxed{\forall t > 0 : \mathbb{P}(|u(Z - \tilde{Z})| \geq t) \leq \alpha(t)},$  we note  $Z \in \tilde{Z} \pm \alpha$   
 $\tilde{Z} : \text{Deterministic equivalent of } Z.$   
 $(Z \in \alpha \implies Z \in \mathbb{E}[Z] \pm \alpha)$



# Standard concentration : Exponential concentration

## Fundamental example of the Theory:

$Z \in \mathbb{R}^p$ , if  $Z$  uniformly distributed on  $\sqrt{p}S^{p-1}$  or  $Z \sim \mathcal{N}(0, I_p)$ :

$\forall f : E \rightarrow \mathbb{R}$  1-Lipschitz :

$$\forall t > 0 : \mathbb{P}(|f(Z) - \mathbb{E}[f(Z')]| \geq t) \leq 2e^{-t^2/2},$$

For  $q, \sigma > 0$ , if we note  $\mathcal{E}_q(\sigma) : t \mapsto e^{-(t/\sigma)^q}$ , then :

$$Z \in 2\mathcal{E}_2(\sqrt{2}) \text{ (Independent of } p \text{ !)}.$$

Standard Hypothesis :  $Z \in \tilde{Z} \pm C\mathcal{E}_q(\sigma)$

- ▶  $\tilde{Z} \in E$  : deterministic equivalent
- ▶  $C > 0, q > 0$ : numerical constants (between  $\frac{1}{10}$  and 10)
- ▶  $\sigma > 0$  : observable diameter, gives the speed of concentration.



# How to build new concentrated random vectors ?

- ▶ If  $Z \in C\mathcal{E}_q(\sigma)$  and  $f : E \rightarrow E$   $\lambda$ -Lipschitz,  $f(Z) \in C\mathcal{E}_q(\lambda\sigma)$
- ▶ No simple way to set the concentration of  $(Z_1, \dots, Z_p)$  if  $Z_1, \dots, Z_p \in C\mathcal{E}_q(\sigma)$  **non independent**
- ▶  $Z_1, Z_2 \in C\mathcal{E}_q(\sigma)$ , **independent**  $(Z_1, Z_2) \in 2C\mathcal{E}_q(2\sigma)$
- ▶  $(Z_1, Z_2) = f(Z)$  where  $Z \in C\mathcal{E}_q(\sigma)$ , and  $f$  1-Lipschitz  $(Z_1, Z_2) \in C\mathcal{E}_q(\sigma)$



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## Same Notations:

- ▶  $\exists a \in \mathbb{R}$  such that:

$$\forall t > 0 : \mathbb{P}(|Z - a| \geq t) \leq Ce^{-(t/\sigma)^q}$$

we note  $Z \in a \pm C\mathcal{E}_q(\sigma)$ .

### Example

$X \sim \mathcal{N}(0, I_p)$ ,  $f : \mathbb{R}^p \rightarrow \mathbb{R}$ , 1-Lipschitz:

$$f(X) \in \mathbb{E}[f(X)] \pm 2\mathcal{E}_2(\sqrt{2})$$



# Characterization with the moments

$$Z \in a \pm Ce^{-(\cdot/\sigma)^q}$$

$$\Downarrow \textcircled{1}$$

$$\forall r \geq q :$$

$$\mathbb{E}[|Z - a|^r] \leq C \left(\frac{r}{q}\right)^{\frac{r}{q}} \sigma^r$$

$$\Downarrow \textcircled{2}$$

$$Z \in a \pm Ce^{-\frac{(\cdot/\sigma)^q}{e}}$$



## Proof :

①

Fubini:

$$\begin{aligned}\mathbb{E}[|Z - a|^r] &= \int_Z \left( \int_0^\infty \mathbb{1}_{t \leq |Z - a|^r} dt \right) dZ \\ &= \int_0^\infty \mathbb{P}(|Z - a|^r \geq t) dt \\ &\leq \int_0^\infty C e^{-t^{\frac{q}{r}} / \sigma^q} dt \dots \leq C \left( \frac{r}{q} \right)^{\frac{r}{q}} \sigma^r\end{aligned}$$

②

Markov inequality:

$$\mathbb{P}(|Z - a| \geq t) \leq \frac{\mathbb{E}[|Z - a|^r]}{t^r} \leq C \left( \frac{r}{q} \right)^{\frac{r}{q}} \left( \frac{\sigma}{t} \right)^r,$$

with  $r = \frac{qt^q}{e\sigma^q} \geq q : \mathbb{P}(|Z - a| \geq t) \leq C e^{-(t/\sigma)^q / e}$ .





# Concentration of the sum

$$X \in a \pm C\mathcal{E}_q(\sigma), Y \in b \pm C\mathcal{E}_q(\sigma) :$$

►  $X + Y \in a + b \pm 2C\mathcal{E}_q(2\sigma)$

Proof :  $\mathbb{P}(|Z_1 + Z_2 - a_1 - a_2| \geq t)$

$$\leq \mathbb{P}\left(|Z_1 - a_1| + |Z_2 - a_2| \geq \frac{t}{2} + \frac{t}{2}\right)$$

$$\leq \mathbb{P}\left(|Z_1 - a_1| \geq \frac{t}{2}\right) + \mathbb{P}\left(|Z_2 - a_2| \geq \frac{t}{2}\right)$$

$$\leq 2Ce^{-(t/2\sigma)^q}$$



# Concentration of the product

$$X \in a \pm C\mathcal{E}_q(\sigma) \text{ and } Y \in b \pm C\mathcal{E}_q(\sigma)$$

$$\blacktriangleright XY \in ab \pm 2C\mathcal{E}_{\textcolor{red}{q}}(3\sigma \max(|a|, |b|)) + 2\mathcal{E}_{\textcolor{red}{q}}^{\frac{q}{2}}(3\sigma^2)$$

$$\text{Proof : } XY - ab = (X - a)(Y - b) + (X - a)b + (Y - b)a$$

$$\begin{aligned}\mathbb{P}(|XY - ab| \geq t) &\leq \mathbb{P}\left(|X - a| \geq \sqrt{\frac{t}{3}}\right) + \mathbb{P}\left(|Y - b| \geq \sqrt{\frac{t}{3}}\right) \\ &\quad + \mathbb{P}\left(|X - a| \geq \frac{t}{3|b|}\right) + \mathbb{P}\left(|Y - b| \geq \frac{t}{3|a|}\right) \\ &\leq Ce^{-(t/3\sigma^2)^{\frac{q}{2}}} + Ce^{-(t/3|b|\sigma)^q} + Ce^{-(t/3|a|\sigma)^q}\end{aligned}$$



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# Control of the norm

- Infinite norm :

$$\begin{aligned}\mathbb{P}\left(\|Z - \tilde{Z}\|_{\infty} \geq t\right) &= \mathbb{P}\left(\sup_{1 \leq i \leq p} e_i^T (Z - \tilde{Z}) \geq t\right) \\ &\leq p \sup_{1 \leq i \leq p} \mathbb{P}\left(e_i^T (Z - \tilde{Z}) \geq t\right) \leq p C e^{-(t/\sigma)^q},\end{aligned}$$

- For the general case, use of “ $\varepsilon$ -nets”. If  $\exists H \subset (E^*, \|\cdot\|_*)$  |

$$\forall z \in E : \|z\| = \sup_{f \in \mathcal{B}_H} f(z).$$

where  $\mathcal{B}_H = \{f \in H, \|f\|_* \leq 1\} \subset H$ , then :

$$Z \in \tilde{Z} \pm C\mathcal{E}_q(\sigma) \implies \|Z - \tilde{Z}\| \in 0 \pm 8^{\dim(H)} C\mathcal{E}_q(2\sigma)$$

on  $(\mathbb{R}^p, \|\cdot\|)$ ,  $H = \mathbb{R}^p$ , and  $\dim H = p$



# Norm degree

Degree of a subset  $H \subset E^*$  and of a norm

- ▶  $\eta_H = \log(\#H)$  if  $H$  is finite
- ▶  $\eta_H = \dim(\text{Vect}(H))$  if  $H$  is infinite

Degree of a norm

$$\eta_{\|\cdot\|} = \inf \left\{ \eta_H, H \subset E^* \mid \forall x \in E, \|x\| = \sup_{f \in H} f(x) \right\}$$

Example

- ▶  $\eta(\mathbb{R}^p, \|\cdot\|_\infty) = \log(p)$
- ▶  $\eta(\mathcal{M}_{p,n}, \|\cdot\|) = n + p$
- ▶  $\eta(\mathbb{R}^p, \|\cdot\|_r) = p$  for  $r \geq 1$
- ▶  $\eta(\mathcal{M}_{p,n}, \|\cdot\|_F) = np$ .



# Concentration of the norm

If  $Z \in \tilde{Z} \pm C\mathcal{E}_q(\sigma)$ :

$$\|Z - \tilde{Z}\| \in 0 \pm C'\mathcal{E}_q(c'\sigma\eta_{\|\cdot\|}^{1/q}) \quad \text{and} \quad \mathbb{E}\|Z - \tilde{Z}\| \leq C'\sigma\eta_{\|\cdot\|}^{1/q}$$

Example  $Z \in \mathbb{R}^p$ ,  $X \in \mathcal{X}_{p,n}$

- ▶ if  $Z \in \tilde{Z} \pm 2\mathcal{E}_2(\sqrt{2})$  :  $\mathbb{E}\|Z\| \leq \|\tilde{Z}\| + C\sqrt{p}$
- ▶ if  $X \in \tilde{X} \pm 2\mathcal{E}_2(\sqrt{2})$  :  $\mathbb{E}\|X\| \leq \|\tilde{X}\| + C\sqrt{p+n}$ ,
- ▶ if  $X \in \tilde{X} \pm 2\mathcal{E}_2(\sqrt{2})$  :  $\mathbb{E}\|X\| \leq \|\tilde{X}\| + C\sqrt{pn}$ .



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# Concentration of the sum and the product

If  $(X, Y) \in \mathcal{CE}_q(\sigma)$ :

- ▶  $X + Y \in \mathcal{CE}_q(\sigma)$
- ▶  $(X - \tilde{X})(Y - \tilde{Y})$

$$\in C' \mathcal{E}_{\frac{q}{2}}(c\sigma^2) + C' \mathcal{E}_q\left(c\sigma^2 \eta_{\|\cdot\|'}^{\frac{1}{q}}\right) \quad \text{in } (\mathcal{A}, \|\cdot\|)$$

where  $\forall x, y \in \mathcal{A} \quad \|xy\| \leq \|x\|' \|y\|$  (usually  $\|x\|' \leq \|x\|$ ).

Example  $Z \in \mathbb{R}^p$ ,  $X \in \mathcal{M}_{p,n}$ ,  $Z, X \in 2\mathcal{E}_2(\sqrt{2})$

- ▶  $\frac{XX^T}{\sqrt{n+p}} \in \mathcal{CE}_2(\textcolor{red}{c}) + \mathcal{CE}_1\left(\frac{c}{\sqrt{p+n}}\right) \quad \text{in } (\mathcal{M}_{p,n}, \|\cdot\|_F)$
- ▶  $\frac{XX^T}{\sqrt{\log(np)}} \in \mathcal{CE}_2(\textcolor{red}{c}) + \mathcal{CE}_1\left(\frac{c}{\sqrt{\log(pn)}}\right) \quad \text{in } (\mathcal{M}_{p,n}, \|\cdot\|_\infty),$
- ▶  $\frac{Z^{\odot 2}}{\sqrt{\log p}} = \frac{Z \odot Z}{\sqrt{\log p}} \in \mathcal{CE}_2(\textcolor{red}{c}) + \mathcal{CE}_1\left(\frac{c}{\sqrt{\log p}}\right) \quad \text{in } (\mathbb{R}^p, \|\cdot\|)$





# Hanson Wright Theorem

## Classical Theorem

If  $Z_1, \dots, Z_p \in C\mathcal{E}_2(\sigma)$  **independent**:

$$\mathbb{P}\left(\left|Z^T A Z - \mathbb{E} Z^T A Z\right| \geq t\right) \leq C \exp\left(-c \min\left(\left(\frac{t}{\sigma^2 \|A\|_F}\right)^2, \frac{t}{\sigma^2 \|A\|}\right)\right)$$

With the Concentration of the measure phenomenon

If  $Z = (Z_1, \dots, Z_p) \in C\mathcal{E}_2(\sigma)$ :

$$\begin{aligned}\mathbb{P}\left(\left|Z^T A Z - \mathbb{E} Z^T A Z\right| \geq t\right) \\ \leq C \exp\left(-c \min\left(\left(\frac{t}{\sigma \mathbb{E} \|Z\| \|A\|}\right)^2, \frac{t}{\sigma^2 \|A\|}\right)\right)\end{aligned}$$

→ about the same result since  $\mathbb{E}[\|Z\|] \approx \sigma\sqrt{p}$  and  $\|A\|_F \approx \sqrt{p} \|A\|$



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# Position of the problem

Data matrix  $X = (x_1, \dots, x_n) \in \mathcal{M}_{p,n}$ ,

Hypothesis:

- ▶  $p = O(n)$  and  $n = O(p)$
- ▶  $X \in \mathcal{CE}_2(c)$
- ▶  $\|\mathbb{E}[X]\| = O(\sqrt{n})$

Goal:

Show the concentration of the resolvent:

$$Q = Q(z) = \left( \frac{1}{n} X X^T + z I_p \right)^{-1}$$

and find a computable *deterministic equivalent*  $\tilde{Q}_1$  depending on the population covariance :  $\Sigma = \frac{1}{n} \mathbb{E}[X X^T]$



# Basic results on the resolvent $Q = \left(\frac{1}{n}XX^T + zI_p\right)^{-1}$

- ▶ The resolvent is **bounded**:

$$\|Q(z)\| \leq \frac{1}{z}, \left\|Q(z)\frac{XX^T}{n}\right\| \leq 1 \text{ and } \left\|Q(z)\frac{X}{\sqrt{n}}\right\| \leq \frac{1}{z^{1/2}}$$

- ▶  $X \mapsto Q(z)$  is  $\frac{1}{\sqrt{nz^{3/2}}}$ -**Lipschitz**:

If we note  $Q(z)^H = \left(\frac{1}{n}(X+H)(X+H)^T + zI_p\right)^{-1}$  :

$$\begin{aligned}\|Q(z)^H - Q(z)\|_F &= \left\|\frac{1}{n}Q(z)^H(XX^T - (X+H)(X+H)^T)Q(z)\right\|_F \\ &= \left\|-\frac{1}{n}Q(z)^H HX^T + (X+H)H^T Q(z)\right\|_F \\ &\leq \frac{1}{\sqrt{n}} \left( \|Q(z)^H\| \left\|\frac{1}{\sqrt{n}}X^T Q\right\| + \left\|\frac{1}{\sqrt{n}}Q^H(X+H)\right\| \|Q(z)\| \right) \|H\|_F\end{aligned}$$



- $Q(z) \in \mathbb{E}[Q(z)] \pm C\mathcal{E}_2\left(\frac{c}{\sqrt{n}}\right)$  (we suppose that  $\frac{1}{z} = O(1)$ )

## Question

How to estimate  $\mathbb{E}\left[\left(\frac{1}{n}XX^T + zI_p\right)^{-1}\right]$  ?

## Design of a Deterministic equivalent

Let  $\tilde{\Sigma} \in \mathcal{M}_p$  to be chosen precisely later and we set:

$$\tilde{Q}_1 = (\tilde{\Sigma} + zI_p)^{-1}$$



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With identity  $A^{-1} - B^{-1} = A^{-1}(B - A)B^{-1}$ :

$$\mathbb{E}[\tilde{Q}_1 - Q] = \mathbb{E} \left[ Q \left( \frac{1}{n} X X^T - \tilde{\Sigma} \right) \tilde{Q}_1 \right] = \sum_{i=1}^n \frac{1}{n} \mathbb{E} \left[ Q(x_i x_i^T - \tilde{\Sigma}) \tilde{Q}_1 \right].$$

## Schur formulas

We set  $X_{-i} = (x_1, \dots, x_{i-1}, 0, x_{i+1}, \dots, x_n) \in \mathcal{M}_{p,n}$   
and  $Q_{-i} = (\frac{1}{n} X_{-i} X_{-i}^T + z I_p)^{-1}$ :

$$Q = Q_{-i} - \frac{1}{n} \frac{Q_{-i} x_i x_i^T Q_{-i}}{1 + \frac{1}{n} x_i^T Q_{-i} x_i} \quad \text{and} \quad Q x_i = \frac{Q_{-i} x_i}{1 + \frac{1}{n} x_i^T Q_{-i} x_i}.$$

Then:

$$\begin{aligned} \tilde{Q}_1 - \mathbb{E}Q &= \sum_{i=1}^n \frac{1}{n} \mathbb{E} \left[ Q_{-i} \left( \frac{x_i x_i^T}{1 + \frac{1}{n} x_i^T Q_{-i} x_i} - \tilde{\Sigma} \right) \tilde{Q}_1 \right] \\ &\quad - \frac{1}{n^2} \sum_{i=1}^n \mathbb{E} \left[ Q_{-i} x_i x_i^T Q \tilde{\Sigma} \tilde{Q}_1 \right]. \end{aligned}$$





## A first deterministic equivalent

$$\begin{aligned}\left\|\tilde{Q}_1 - \mathbb{E}Q\right\| &= \sup_{\|u\|, \|v\| \leq 1} u^T \left(\tilde{Q}_1 - \mathbb{E}Q\right) v \\ &= \sup_{\|u\|, \|v\| \leq 1} \frac{1}{n} \sum_{i=1}^n \Delta_i + \varepsilon_i\end{aligned}$$

with:

- ▶  $\Delta_i = \mathbb{E} \left[ u^T Q_{-i} \left( \frac{x_i x_i^T}{1 + \frac{1}{n} x_i^T Q_{-i} x_i} - \tilde{\Sigma} \right) \tilde{Q}_1 v \right]$
- ▶  $\varepsilon_i = \frac{1}{n} \mathbb{E} \left[ u^T Q_{-i} x_i x_i^T Q \tilde{\Sigma} \tilde{Q}_1 v \right]$

→ we note  $\delta_1 = \frac{1}{n} \text{Tr}(\Sigma \mathbb{E}[Q])$  and we chose  $\tilde{\Sigma} = \frac{\Sigma}{1 + \delta_1}$

Let us show that with this choice:  $\Delta_i, \varepsilon_i = O\left(\frac{1}{\sqrt{n}}\right)$



# Preliminary lemmas

- ▶  $u^T Q x_i = \frac{1}{\sqrt{n}}(\sqrt{n} u^T Q) x_i \in C\mathcal{E}_2(c) + C\mathcal{E}_1\left(\frac{c}{\sqrt{p}}\right)$
- ▶ 
$$\begin{aligned}\mathbb{E}[u^T Q x_i] &\leq \sqrt{\mathbb{E}[u^T Q x_i x_i^T Q u]} = \sqrt{\frac{1}{n} \mathbb{E}[u^T Q X X^T Q u]} \\ &\leq \mathbb{E}[u^T Q u] = O(1)\end{aligned}$$
- ▶ The same way:  
 $u^T Q_{-i} x_i, u^T \tilde{Q}_1 x_i \in O(1) \pm C\mathcal{E}_2(c) + C\mathcal{E}_1\left(\frac{c}{\sqrt{p}}\right)$



# Preliminary lemmas

- ▶  $\frac{1}{n} \mathbf{x}_i^T \mathbf{Q}_{-i} \mathbf{x}_i \in C\mathcal{E}_2(c) + C\mathcal{E}_1\left(\frac{c}{\sqrt{n}}\right)$
- ▶  $\mathbb{E} \left[ \frac{1}{n} \mathbf{x}_i^T \mathbf{Q}_{-i} \mathbf{x}_i \right] = \frac{1}{n} \text{Tr}(\Sigma \mathbb{E}[\mathbf{Q}_{-i}]) \leq \frac{1}{n} \text{Tr}(\Sigma) \mathbb{E}[\|\mathbf{Q}_{-i}\|] = O(1)$
- ▶  $\|\mathbb{E} \mathbf{Q}_{-i} - \mathbb{E} \mathbf{Q}\| = \sup_{\|u\|, \|v\| \leq 1} u^T (\mathbb{E} \mathbf{Q}_{-i} - \mathbb{E} \mathbf{Q}) v$   
$$= \sup_{\|u\|, \|v\| \leq 1} \mathbb{E} \left[ \frac{1}{n} u^T \mathbf{Q}_{-i} \mathbf{x}_i \mathbf{x}_i^T \mathbf{Q} v \right] = O\left(\frac{1}{n}\right)$$
- ▶  $\frac{1}{n} \mathbf{x}_i^T \mathbf{Q}_{-i} \mathbf{x}_i \in \delta_1 \pm C\mathcal{E}_2(c) + C\mathcal{E}_1\left(\frac{c}{\sqrt{n}}\right)$  (recall that  $\delta_1 = \frac{1}{n} \text{Tr}(\Sigma \mathbb{E}[\mathbf{Q}])$ )



End of the proof of the estimation with the first

deterministic equivalent  $\tilde{Q}_1 = \left( \frac{\Sigma}{1+\delta_1} + zI_p \right)^{-1}$

► Since  $\left\| \tilde{\Sigma} \tilde{Q}_1 \right\| = O(1)$ ,  $\varepsilon_i = \frac{1}{n} \mathbb{E} \left[ u^T Q_{-i} x_i x_i^T Q \tilde{\Sigma} \tilde{Q}_1 v \right] = O\left(\frac{1}{n}\right)$

►  $\Delta_i = \mathbb{E} \left[ u^T Q_{-i} \left( \frac{x_i x_i^T}{1 + \frac{1}{n} x_i^T Q_{-i} x_i} - \frac{\Sigma}{1 + \delta_1} \right) \tilde{Q}_1 v \right]$

$$= \mathbb{E} \left[ \frac{u^T Q_{-i} x_i x_i^T \tilde{Q}_1 v (\delta_1 - \frac{1}{n} x_i^T Q_{-i} x_i)}{(1 + \frac{1}{n} x_i^T Q_{-i} x_i) (1 + \delta_1)} \right]$$

$$+ \mathbb{E} \left[ u^T Q_{-i} \left( \frac{x_i x_i^T - \Sigma}{1 + \delta_1} \right) \tilde{Q}_1 v \right]$$

$$= O\left(\frac{1}{\sqrt{n}}\right)$$

$$\Rightarrow \left\| \mathbb{E}[Q] - \tilde{Q}_1 \right\| = O\left(\frac{1}{\sqrt{n}}\right)$$



# Sommaire

## Introduction

### I- Concentration of the Measure Phenomenon

- A - Description of the phenomenon
- B - Concentration of random variables
- C - Concentration of the norm of a random vector
- D - Concentration of the sum and the product of random vectors

### II - Spectral Distribution of Empirical Covariance matrices

- A - Position of the problem
- B - A first Deterministic equivalent
- C - Second Deterministic equivalent



## Second deterministic equivalent

$$\begin{aligned}\text{Note that } \delta_1 &= \frac{1}{n} \text{Tr}(\Sigma \mathbb{E}[Q]) = \frac{1}{n} \text{Tr}(\Sigma \tilde{Q}_1) + O\left(\frac{1}{\sqrt{n}}\right) \\ &= \frac{1}{n} \text{Tr}\left(\Sigma \left(\frac{\Sigma}{1 + \delta_1} + z l_p\right)^{-1}\right) + O\left(\frac{1}{\sqrt{n}}\right)\end{aligned}$$

The function

$$\begin{aligned}\mathbb{R}^+ &\longrightarrow \mathbb{R}^+ \\ \delta &\longmapsto \frac{1}{n} \text{Tr}\left(\Sigma \left(\frac{\Sigma}{1 + \delta} + z l_p\right)^{-1}\right)\end{aligned}$$

is contracting for the semimetric:  $d_s(\delta, \delta') = \frac{|\delta - \delta'|}{\sqrt{\delta \delta'}}$

$\implies$  It admits a unique fixed point:

$$\delta_2 = \frac{1}{n} \text{Tr}\left(\Sigma \left(\frac{\Sigma}{1 + \delta_2} + z l_p\right)^{-1}\right)$$



# End of the proof

It can be showed that  $\delta_1 - \delta_2 = O\left(\frac{1}{\sqrt{n}}\right)$  thus if we set

$$\tilde{Q}_2 = \left( \frac{\Sigma}{1+\delta_2} + z l_p \right)^{-1} :$$

$$\begin{aligned} \left\| \mathbb{E}[Q] - \tilde{Q}_2 \right\| &\leq \left\| \mathbb{E}[Q] - \tilde{Q}_1 \right\| + \left\| \tilde{Q}_1 - \tilde{Q}_2 \right\| \\ &\leq \left\| \tilde{Q}_1 \frac{\Sigma(\delta_2 - \delta_1)}{(1 + \delta_2)(1 + \delta_1)} \tilde{Q}_2 \right\| + O\left(\frac{1}{\sqrt{n}}\right) = O\left(\frac{1}{\sqrt{n}}\right) \end{aligned}$$

$$\Rightarrow \forall t > 0 : \mathbb{P} \left( \left| \frac{1}{p} \text{Tr}(Q) - \frac{1}{p} \text{Tr}(\tilde{Q}_2) \right| \geq t \right) \leq C e^{-cnt^2}$$

