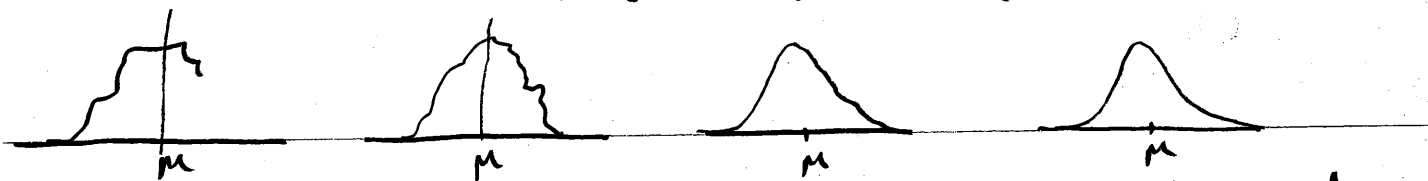


Central limit theorems.

Recall that Central limit theorems (CLTs) describe how the sum of random variables fluctuates around some quantity (eg. the mean).

The classic CLT case is to consider a sequence X_1, X_2, \dots of i.i.d. random variables with $\mathbb{E}[X_i] = \mu$ and $\text{Var}[X_i] = \sigma^2 < \infty$. Then the (Lindeberg-Lévy) CLT says if $S_n := \sum_{k=1}^n X_k$ then

$$\sqrt{n}(S_n - \mu) \xrightarrow{d} N(0, \sigma^2).$$



This lecture we will look at some equivalent statements in our random matrix setting. In particular of linear spectral statistics of the form

$$T_n = \frac{1}{p} \sum_{k=1}^p \varphi(\lambda_k) = \int \varphi(x) dF^{A_n}(x) =: F^{A_n}(\varphi).$$

of some sample matrix A_n , eg.

$$A_n = \begin{cases} \Sigma_n, & \text{sample covar matrix} \\ \mathbb{F}_n, & \text{Fisher matrix} \end{cases}$$

Some examples that we will see later in the course are:

Example 1: The generalised variance is

$$T_n = \frac{1}{p} \log |S_n| = \frac{1}{p} \sum_{k=1}^p \log(\lambda_k)$$

$$\psi(x) = \log(x).$$

Example 2: Later in the course, we shall look at testing equality of sample covariance matrices. To test the hypothesis $H_0: \Sigma = I_p$ we shall look at the log-likelihood ratio statistic

$$LRT_1 = \text{tr } S_n - \log |S_n| - p = \sum_{k=1}^p (\lambda_k - \log(\lambda_k) - 1)$$

$$\text{i.e. } \psi(x) = x - \log(x) - 1.$$

Example 3:

We shall also look at the two-sample test of the hypothesis $H_0: \Sigma_1 = \Sigma_2$ that two populations have a common covariance matrix

$$LRT_2 = -\log |I_p + \alpha_n F_n| = -\sum_{k=1}^p (1 + \alpha_n \log(\lambda_k))$$

where α_n is some constant.

$$\psi(x) = -\log(1 - \alpha_n x)$$

CLT for Linear Spectral Statistics of S_n .

We shall consider simple case

"independent vectors
without cross-correlation"

$$S_n = \frac{1}{n} \sum_{i=1}^n \mathbb{X}_i \mathbb{X}_i^*$$

In other words, the data matrix $\mathbb{X} = (\mathbb{X}_1, \mathbb{X}_2, \dots, \mathbb{X}_n) = (x_{ij})$ of size $p \times n$ has IID entries with $\mathbb{E}[x_{ij}] = 0$ $\mathbb{E}|x_{ij}|^2 = 1$.

$$S_n = \frac{1}{n} \mathbb{X} \mathbb{X}^*$$

The LSD of S_n is the Marchenko-Pastur law F_y where $y = \lim p/n$. This means, $F^{S_n}(\varphi) \rightarrow F_y(\varphi)$ for any continuous function φ .

Making an analogy to the classic CLT we would like to understand how $F^{S_n}(\varphi)$ fluctuates around $F_y(\varphi)$, as $n \rightarrow \infty$ ($p \rightarrow \infty$).

From RMT, we know that $F^{S_n}(\varphi)$ fluctuates around its mean in such a way that $p[F^{S_n}(\varphi) - \mathbb{E}(F^{S_n}(\varphi))] \sim \text{Normal}$.

We can decompose

$$p[F^{S_n}(\varphi) - F_Y(\varphi)] = p \underbrace{[F^{S_n}(\varphi) - \mathbb{E}F^{S_n}(\varphi)]}_{\sim \text{Normal.}} + p \underbrace{[\mathbb{E}[F^{S_n}(\varphi)] - F_Y(\varphi)]}_{\text{Bias.}}$$

The "bias" term is often a function of $y_n - y = p/n - y$.

y_n is called the dimension-to-sample ratio and the difference to y can be of any order. For example, if

$$y_n - y \approx p^{-\alpha}, \quad \alpha > 0.$$

then the bias term behaves like $p^{1-\alpha}$ and the value depends on α . if α small then $p^{1-\alpha}$ can blow-up and if α large then $p^{1-\alpha}$ converges to zero or constant as $p \rightarrow \infty$.

We need more restrictions on $y_n - y$.

We also need to accurately estimate $\mathbb{E}F^{S_n}(\varphi)$. One way is to estimate $\mathbb{E}F^{S_n}(\varphi) \approx F_{y_n}(\varphi)$. "finite horizon proxy"

We saw last week that the ST \underline{S} of $\underline{F}_y := (1-y)\delta_0 + yF_y$ satisfies the equation that we found for the Generalised MP ($H = \delta_1$):

$$z = -\frac{1}{\underline{S}} + \frac{y}{1+\underline{S}}, \quad z \in \mathbb{C}.$$

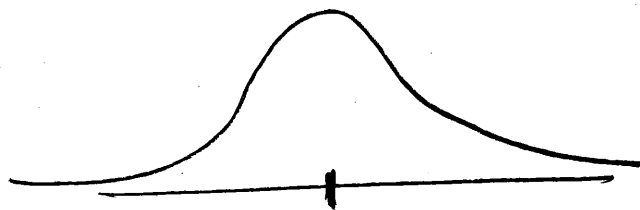
Let $\beta = E|x_{ij}|^4 - 1 - k$ $h = \sqrt{y}$

set $k=2$ if entries of X are real and $k=1$ if complex values.

If entries are Gaussian, $\beta = 0$.

The following theorem quantifies the fluctuations of

$$p(F^{\text{Sn}}(\varphi) - F_{y_n}(\varphi)).$$



Theorem: Assume $p \times n$ data matrix $X = (X_1, X_2, \dots, X_n)$ has IID entries $E x_{ij} = 0$, $E |x_{ij}|^2 = 1$, $E |x_{ij}|^4 = \beta + 1 + \kappa < \infty$

Also, $p \rightarrow \infty$, $n \rightarrow \infty$, $p/n \rightarrow y > 0$.

Let f_1, f_2, \dots, f_k be analytic functions on a open region containing support of F_Y .

The random vector $(X_n(f_1), X_n(f_2), \dots, X_n(f_k))$

where

$$X_n(f) := p(F^{S_n}(f) - F_{Y_n}(f))$$

converges weakly to a Gaussian vector

$$(X_{f_1}, \dots, X_{f_k})$$

with mean $E X_f = (\kappa - 1)I_1(f) - \beta I_2(f)$

$$\text{Cov}(X_f, X_g) = \kappa J_1(f, g) + \beta J_2(f, g).$$

where $I_1(f) = -\frac{1}{2\pi i} \oint \frac{y(z/(1+z))^3(z)f(z)}{[1-y(z/(1+z))^2]^2} dz$.

$$I_2(f) = -\frac{1}{2\pi i} \oint \frac{y(z/(1+z))^3(z)f(z)}{[1-y(z/(1+z))^2]^2} dz.$$

and

$$J_1(f, g) = -\frac{1}{4\pi^2} \oint \oint \frac{f(z_1)g(z_2)}{(\underline{z}(z_1) - \underline{z}(z_2))^2} \underline{z}'(z_1) \underline{z}'(z_2) dz_1 dz_2.$$

$$J_2(f, g) = -\frac{y}{4\pi^2} \oint f(z_1) \frac{\partial}{\partial z_1} \left(\frac{\underline{z}}{1+\underline{z}}(z_1) \right) dz_1 \times \oint g(z_2) \frac{\partial}{\partial z_2} \left(\frac{\underline{z}}{1+\underline{z}}(z_2) \right) dz_2$$

where the integrals are over contours enclosing the support of F_Y .

Remarks:

- The asymptotic mean $E[X_f]$ is non-null and depends on fourth moment.

- This theorem is difficult to use in practice because the limiting parameters are integrals on contours that are not given explicitly.
- This theorem, from 2004, was a big breakthrough as it gave explicit formulas for the limiting mean and covariance.

A more explicit version of this theorem can be obtained:

Proposition: We have

$$I_1(f) = \lim_{r \downarrow 1} I_1(f, r)$$

$$I_2(f) = \frac{1}{2\pi i} \oint_{|\xi|=1} f(1+h\xi)^e \frac{1}{\xi^3} d\xi$$

$$J_1(f, g) = \lim_{r \downarrow 1} J_1(f, g, r).$$

$$J_2(f, g) = -\frac{1}{4\pi^2} \oint_{|\xi_1|=1} \frac{f(1+h\xi_1)^e}{\xi_1^2} d\xi_1 \oint_{|\xi_2|=1} \frac{g(1+h\xi_2)^e}{\xi_2^2} d\xi_2$$

with
$$I_1(f, r) = \frac{1}{2\pi i} \oint_{|\xi|=1} f(1+h\xi)^e \left[\frac{\xi}{\xi^2 - r^2} - \frac{1}{\xi} \right] d\xi.$$

$$I_2(f, g, r) = -\frac{1}{4\pi^2} \oint_{|\xi_1|=1} \oint_{|\xi_2|=1} \frac{f(1+h\xi_1)^e g(1+h\xi_2)^e}{(\xi_1 - r\xi_2)^2} d\xi_1 d\xi_2$$

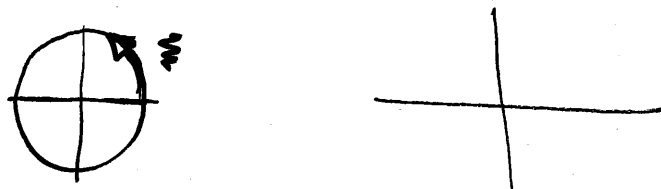
Proof: We are just going to look at the simplest case of $I_2(f)$.

The idea is to perform change of variable

$$z = 1 + hr\xi + hr^{-1}\bar{\xi} + h^2$$

with $r > 1$ but close to 1, and $|\xi| = 1$ $h = \sqrt{y}$

As ξ runs anticlockwise, z runs on contour ℓ enclosing support $[a, b] = [(1-h)^2]$.



Since $z = -\frac{1}{\underline{s}} + \frac{y}{1+\underline{s}}$, $z \in \mathbb{C}^+$. We have

$$\underline{s} = -\frac{1}{1+h r \xi} \text{ and } dz = h(r - r^{-1} \xi^{-2}) d\xi$$

Applying this to $I_2(f)$ in Thm:

$$\begin{aligned} I_2(f) &= \lim_{r \downarrow 1} \frac{1}{2\pi i} \oint_{|\xi|=1} f(z) \frac{1}{\xi^3} \frac{r\xi^2 - r^{-1}}{r(r^2\xi^2 - 1)} d\xi \\ &= \frac{1}{2\pi i} \oint_{|\xi|=1} f(|1+h\xi|^2) \frac{1}{\xi^3} d\xi. \end{aligned}$$

$$\begin{aligned} \text{as } |1+h\xi|^2 &= (1+h\xi)(\overline{1+h\xi}) \\ &= (1+h\xi)(1+h\bar{\xi}) \\ &= 1+h\xi+h\bar{\xi}+h^2|\xi| \\ &= 1+h\xi+h\bar{\xi}+h^2. \end{aligned}$$

An example application of CLT

Proposition: Consider two linear spectral statistics

$$\sum_{i=1}^P \log(\lambda_i), \quad \sum_{i=1}^P \lambda_i$$

where (λ_i) are eigenvalues of sample covariance S_n .

Then, under assumptions of Theorem, the vector

$$\begin{pmatrix} \sum_{i=1}^P \log(\lambda_i) - p F_n(\log x) \\ \sum_{i=1}^P \lambda_i - p F_n(x) \end{pmatrix} \xrightarrow{d} N(\mu_1, Q_1)$$

$$\mu_1 = \begin{pmatrix} \frac{k-1}{2} \log(1-y) - \frac{1}{2} \beta y \\ 0 \end{pmatrix}$$

$$Q_1 = \begin{pmatrix} -k \log(1-y) + \beta y & (\beta+k)y \\ (\beta+k)y & (\beta+k)y \end{pmatrix}$$

$$F_n(x) = 1 \quad F_n(\log x) = \frac{y_n - 1}{y_n} \log(1) - y_n - 1.$$

Proof: In the Theorem, take $k=2$ with

$$f(x) = \log(x) \quad g(x) = x, \quad x > 0.$$

and we are going to consider the vector (X_f, X_g) .

$$\mathbb{E}[X_f] = (k-1)I_1(f) + \beta I_2(f) \quad \mathbb{E}[X_g] = (k-1)I_1(g) + \beta I_2(g)$$

etc.

We shall use the proposition to calculate

$$I_1(f, r) = \frac{1}{2\pi i} \oint_{|\xi|=1} f(1+h\xi) \left[\frac{\xi}{\xi^2 - r^2} - \frac{1}{\xi} \right] d\xi.$$

$$= \frac{1}{2\pi i} \int_{|\xi|=1} \log(1+h\xi) \left[\frac{\xi}{\xi^2 - r^2} - \frac{1}{\xi} \right] d\xi.$$

recall $|1+h\xi|^2 = (1+h\xi)(1+h\bar{\xi})$ $|\xi|=1 \Rightarrow \bar{\xi} = e^{-i\theta} = \frac{1}{\xi}$

$$= (1+h\xi)(1+h/\xi)$$

$$= \frac{1}{2\pi i} \oint_{|\xi|=1} [\log(1+h\xi) + \log(1+h/\xi)] \left[\frac{\xi}{\xi^2 - r^2} - \frac{1}{\xi} \right] d\xi$$

$$= \frac{1}{2\pi i} \left[\oint_{|\xi|=1} \log(1+h\xi) \frac{\xi}{\xi^2 - r^2} d\xi - \oint_{|\xi|=1} \log(1+h\xi) \frac{1}{\xi} d\xi \right.$$

$$\left. + \oint_{|\xi|=1} \log(1+h\xi^{-1}) \frac{\xi}{\xi^2 - r^2} d\xi - \oint_{|\xi|=1} \log(1+h\xi^{-1}) \frac{1}{\xi} d\xi \right]$$

For the first integral, the poles are $\pm \frac{1}{r}$

$$\begin{aligned} \frac{1}{2\pi i} \oint_{|\xi|=1} \log(1+h\xi) \frac{\xi}{\xi^2 - r^2} d\xi &= \frac{\log(1+h\xi) \xi}{\xi - r^{-1}} \bigg|_{\xi = -r^{-1}} \\ &\quad + \frac{\log(1+h\xi) \xi}{\xi + r^{-1}} \bigg|_{\xi = r^{-1}} \\ &= \frac{1}{2} \log\left(1 - \frac{h^2}{r^2}\right). \end{aligned}$$

For second integral, singularity at $\xi = 0$.

$$\frac{1}{2\pi i} \oint_{|\xi|=1} \log(1+h\xi) \frac{1}{\xi} d\xi = \log(1+h\xi) \bigg|_{\xi=0} = 0.$$

For third integral, we perform a change of variable $z = \frac{1}{\xi}$
so $d\xi = -z^{-2} dz$

$$\begin{aligned} \frac{1}{2\pi i} \oint_{|\xi|=1} \log(1+h\xi^{-1}) \frac{\xi}{\xi^2 - r^2} d\xi &= -\frac{1}{2\pi i} \oint_{|z|=1} \log(1+h z) \frac{z^{-1}}{z^{-2} - r^2} \cdot \frac{-1}{z^2} dz \\ &= \frac{1}{2\pi i} \oint_{|z|=1} \frac{\log(1+h z) r^2}{z(z+r)(z-r)} dz = \frac{\log(1+h z) r^2}{(z+r)(z-r)} \bigg|_{z=0} = 0. \end{aligned}$$

Fourth integral:

$$z = \xi^{-1} \quad d\xi = -z^{-2} dz.$$

13

$$\begin{aligned} \frac{1}{2\pi i} \oint_{|\xi|=1} \log(1+h\xi^{-1}) \frac{1}{\xi} d\xi &= -\frac{1}{2\pi i} \oint_{|z|=1} \log(1+hz) \frac{-z}{z^2} dz \\ &= \log(1+hz) \Big|_{z=0} = 0. \end{aligned}$$

Collecting all terms gives $I_1(f, r) = \frac{1}{2} \log(1 - h^2/r^2)$

$$\begin{aligned} I_1(g, r) &= \frac{1}{2\pi i} \oint_{|\xi|=1} g(1+h\xi^{-1}) \cdot \left[\frac{\xi}{\xi^2 - r^{-2}} - \frac{1}{\xi} \right] d\xi \\ &= \frac{1}{2\pi i} \oint_{|\xi|=1} |1+h\xi|^{-2} \left[\frac{\xi}{\xi^2 - r^{-2}} - \frac{1}{\xi} \right] d\xi \end{aligned}$$

$$\begin{aligned} \text{and } |1+h\xi|^{-2} &= (1+h\xi)(1+h\bar{\xi}) = 1+h\xi^{-1}+h\xi+h^2 \\ &= \frac{\xi+h+h\xi^2+h^2\xi}{\xi} \end{aligned}$$

$$\begin{aligned} \text{so } &= \frac{1}{2\pi i} \oint_{|\xi|=1} \frac{(\xi+h+h\xi^2+h^2\xi)}{\xi} \times \frac{\xi}{\xi^2 - r^{-2}} d\xi \\ &+ \frac{1}{2\pi i} \oint_{|\xi|=1} \frac{\xi+h+h\xi^2+h^2\xi}{\xi} \frac{1}{\xi} d\xi \end{aligned}$$

The first integral

14

$$\frac{1}{2\pi i} \oint_{|\xi|=1} \frac{\xi + h + h\xi^2 + h^2\xi}{(\xi - r)(\xi + r)} d\xi = \frac{\xi + h + h\xi^2 + h^2\xi}{\xi - r} \Big|_{\xi = -r^{-1}} + \frac{\xi + h + h\xi^2 + h^2\xi}{\xi + r} \Big|_{\xi = r^{-1}} = 1 + h^2$$

and second integral

$$\frac{1}{2\pi i} \oint_{|\xi|=1} \frac{\xi + h + h\xi^2 + h^2\xi}{\xi^2} d\xi = \frac{\partial}{\partial \xi} (\xi + h + h\xi^2 + h^2\xi) \Big|_{\xi=0} = 1 + h^2$$

↖ 2nd-order pole at $\xi=0$.

hence $I_1(g, r) = 0$.

$$I_2(f) = \frac{1}{2\pi i} \oint_{|\xi|=1} \log(1 + h\xi^2) \frac{1}{\xi^3} d\xi$$

$$= \frac{1}{2\pi i} \left[\oint_{|\xi|=1} \frac{\log(1 + h\xi)}{\xi^3} d\xi + \oint_{|\xi|=1} \frac{\log(1 + h\xi^{-1})}{\xi^3} d\xi \right]$$

First integral:

$$\frac{1}{2\pi i} \oint_{|\xi|=1} \frac{\log(1 + h\xi)}{\xi^3} d\xi = \frac{1}{2} \frac{\partial^2}{\partial \xi^2} \log(1 + h\xi) \Big|_{\xi=0} = -\frac{1}{2} h^2$$

↖ 3rd order pole

Second integral:

$$z = \xi^{-1} \quad d\xi = -z^{-2} dz.$$

15

$$\begin{aligned} \frac{1}{2\pi i} \oint_{|\xi|=1} \frac{\log(1+h\xi^{-1})}{\xi^3} d\xi &= -\frac{1}{2\pi i} \oint_{|z|=1} \frac{\log(1+hz)}{z^{-3}} \cdot \frac{-1}{z^2} dz \\ &= \log(1+hz) \Big|_{z=0} = 0. \end{aligned}$$

Now for the covariance terms.

$$\begin{aligned} J_1(f, g, r) &= -\frac{1}{4\pi^2} \oint_{|\xi_1|=1} \oint_{|\xi_2|=1} \frac{\log(1+h|\xi_1|^2) |1+h\xi_2|^2}{(\xi_1 - r\xi_2)^2} d\xi_1 d\xi_2 \\ &= \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\log(1+h|\xi_1|^2)}{(\xi_1 - r\xi_2)^2} d\xi_1 \cdot \frac{1}{2\pi i} \oint_{|\xi_2|=1} |1+h\xi_2|^2 d\xi_2. \end{aligned}$$

First integral,

$$\begin{aligned} \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\log(1+h|\xi_1|^2)}{(\xi_1 - r\xi_2)^2} d\xi_1 &= \frac{1}{2\pi i} \left[\oint_{|\xi_1|=1} \frac{\log(1+h\xi)}{(\xi_1 - r\xi_2)^2} d\xi_1 \right. \\ &\quad \left. + \oint_{|\xi_1|=1} \frac{\log(1+h\xi^{-1})}{(\xi_1 - r\xi_2)^2} d\xi_1 \right] \\ &= \frac{1}{2\pi i} [A + B]. \end{aligned}$$

Notice for A, for $|\xi_2|=1$ fixed, $|r\xi_2| > 1$ so $r\xi_2$ not a pole.

$$A = 0.$$

$$B = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\log(1+h\xi_1^{-1})}{(\xi_1 - r\xi_2)^2} d\xi_1$$

$$z = \frac{1}{\xi_1} \quad d\xi_1 = -z^{-2} dz$$

$$= \frac{-1}{2\pi i} \oint_{|z|=1} \frac{\log(1+hz)}{(z^{-1} - r\xi_2)^2} \frac{-1}{z^2} dz = \frac{1}{2\pi i} \oint_{|z|=1} \frac{\log(1+hz)}{(z - \frac{1}{r\xi_2})^2} dz$$

2nd order
at $z = \frac{1}{r\xi_2}$

$$= \frac{1}{(r\xi_2)^2} \frac{\partial}{\partial z} (\log(1+hz)) \Big|_{z=\frac{1}{r\xi_2}} = \frac{h}{r\xi_2(r\xi_2+h)}$$

$$\text{Now, } J_1(f, g, r) = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\log(1+h\xi_1^{-1})}{(\xi_1 - r\xi_2)^2} d\xi_1 \cdot \frac{1}{2\pi i} \oint_{|\xi_2|=1} |1+h\xi_2|^2 d\xi_2$$

$$= \frac{h}{2\pi i r^2} \oint_{|\xi_2|=1} \frac{(1+h\xi_2)(1+h\bar{\xi}_2)}{\xi_2(\xi_2+hr^{-1})} d\xi_2$$

$$= \frac{h}{2\pi i r^2} \oint_{|\xi_2|=1} \frac{\xi_2 + h\xi_2^2 + h + h^2\bar{\xi}_2}{\xi_2^2(\xi_2+hr^{-1})} d\xi_2$$

$$= \frac{h}{2\pi i r^2} \left[\underbrace{\oint_{|\xi_2|=1} \frac{1+h^2}{\xi_2(\xi_2+hr^{-1})} d\xi_2}_0 + \underbrace{\oint_{|\xi_2|=1} \frac{h}{(\xi_2+hr^{-1})} d\xi_2}_{2\pi i h} + \underbrace{\oint_{|\xi_2|=1} \frac{h}{\xi_2^2(\xi_2+hr^{-1})} d\xi_2}_0 \right]$$

$$= \frac{h^2}{r^2}$$

$$J_1(f, f, r) = \frac{1}{2\pi i} \oint_{|\xi_2|=1} f(1+h\xi_2|^2) \cdot \underbrace{\frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{f(1+h\xi_2|^2)}{(\xi_1 - r\xi_2)^2} d\xi_1 d\xi_2}_{\text{DONE BEFORE.}}$$

$$= \frac{1}{2\pi i} \oint_{|\xi_2|=1} f(1+h\xi_2|^2) \frac{h}{r\xi_2(r\xi_2+h)} d\xi_2.$$

$$= \underbrace{\frac{h}{2\pi i r^2} \oint_{|\xi_2|=1} \frac{\log(1+h\xi_2)}{\xi_2(\frac{h}{r} + \xi_2)} d\xi_2}_A + \underbrace{\frac{h}{2\pi i r^2} \oint_{|\xi_2|=1} \frac{\log(1+h\xi_2^{-1})}{\xi_2(\frac{h}{r} + \xi_2)} d\xi_2}_B.$$

$$A = \frac{h}{r^2} \left[\frac{\log(1+h\xi_2)}{\frac{h}{r} + \xi_2} \Big|_{\xi_2=0} + \frac{\log(1+h\xi_2)}{\xi_2} \Big|_{\xi_2=-\frac{h}{r}} \right]$$

$$= -\frac{1}{r^2} \log\left(1 - \frac{h^2}{r}\right).$$

$$B = \frac{-h}{2\pi i r^2} \oint_{|z|=1} \frac{\log(1+h z)}{z^{-1}(\frac{h}{r} + z^{-1})} \cdot \frac{-1}{z^2} dz = \frac{1}{2\pi i r} \oint_{|z|=1} \frac{\log(1+h z)}{z + \frac{h}{r}} dz = 0$$

↑ NOT a pole
since $|\frac{h}{r}| > 1$.

hence, $J_1(f, f, r) = -\frac{1}{r} \log\left(1 - \frac{h^2}{r}\right)$

$$J_1(g, g, r) = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{1}{|1+h\xi_1|^2} \cdot \frac{1}{2\pi i} \oint_{|\xi_2|=1} \frac{|1+h\xi_2|^2}{(\xi_1 - r\xi_2)^2} d\xi_1 d\xi_2.$$

$$\text{and } \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{|1+h\xi_1|^2}{(\xi_1 - r\xi_2)^2} d\xi_1 = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\xi_1 + h\xi_1^2 + h + h^2\xi_1}{\xi_1(\xi_1 - r\xi_2)^2} d\xi_1$$

$$= \frac{1}{2\pi i} \left[\oint_{|\xi_1|=1} \frac{1+h^2}{(\xi_1 - r\xi_2)^2} d\xi_1 + \oint_{|\xi_1|=1} \frac{h\xi_1}{(\xi_1 - r\xi_2)^2} d\xi_1 + \oint_{|\xi_1|=1} \frac{h}{\xi_1(\xi_1 - r\xi_2)^2} d\xi_1 \right]$$

$$= \frac{h}{r^2 \xi_2^2} \cdot 2\pi i \frac{h}{(\xi_1 - r\xi_2)^2} \Big|_{\xi_1=0} = \frac{2\pi i h}{r^2 \xi_2^2}$$

Therefore

$$J_1(g, g, r) = \frac{h}{2\pi i r^2} \oint_{|\xi_2|=1} \frac{\xi_2 + h\xi_2^2 + h + h^2\xi_2}{\xi_2^3} d\xi_2.$$

$$= \frac{h}{2\pi i r^2} \left[\oint_{|\xi_2|=1} \frac{1+h^2}{\xi_2^2} d\xi_2 + \oint_{|\xi_2|=1} \frac{h}{\xi_2} d\xi_2 + \oint_{|\xi_2|=1} \frac{h}{\xi_2^3} d\xi_2 \right]$$

$$= \frac{h^2}{r^2}.$$

Now we have to calculate all the J_2 terms:

$$J_2(f, g), J_2(f, f), J_2(g, g).$$

19

$$J_2(F, a) = -\frac{1}{4\pi^2} \oint_{|\xi_1|=1} \frac{F(1+h\xi_1|^2)}{\xi_1^2} d\xi_1 \oint_{|\xi_2|=1} \frac{a(1+h\xi_2|^2)}{\xi_2^2} d\xi_2.$$

First notice that.

$$\begin{aligned} \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\log(1+h\xi_1|^2)}{\xi_1^2} d\xi_1 &= \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{\log(1+h\xi_1) + \log(1+h\xi_1^{-1})}{\xi_1^2} d\xi_1 \\ &= \frac{1}{2\pi i} \left[2\pi i \underbrace{\left[\frac{\partial}{\partial \xi_1} \log(1+h\xi_1) \right]}_h \Big|_{\xi_1=0} - \oint_{|z|=1} \frac{\log(1+hz)}{z^{-2}} \frac{-1}{z^2} dz \right] \\ &= h. \end{aligned}$$

And we have.

$$\frac{1}{2\pi i} \oint_{|\xi_2|=1} \frac{g(1+h\xi_2|^2)}{\xi_2^2} d\xi_2 = \frac{1}{2\pi i} \oint_{|\xi_2|=1} \frac{\xi_2 + h\xi_2^2 + h + h^2\xi_2}{\xi_2^3} d\xi_2 = h$$

$$J_2(f, g) = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{f(1+h\xi_1|^2)}{\xi_1^2} d\xi_1 \cdot \frac{1}{2\pi i} \oint_{|\xi_2|=1} \frac{g(1+h\xi_2|^2)}{\xi_2^2} d\xi_2 = h^2$$

$$J_2(f, f) = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{f(1+h\xi_1|^2)}{\xi_1^2} d\xi_1 \cdot \frac{1}{2\pi i} \oint_{|\xi_2|=1} \frac{f(1+h\xi_2|^2)}{\xi_2^2} d\xi_2 = h^2$$

$$J_2(g, g) = \frac{1}{2\pi i} \oint_{|\xi_1|=1} \frac{g(1+h\xi_1|^2)}{\xi_1^2} d\xi_1 \cdot \frac{1}{2\pi i} \oint_{|\xi_2|=1} \frac{g(1+h\xi_2|^2)}{\xi_2^2} d\xi_2 = h^2 \quad \blacksquare$$