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# Spectra of Sample Covariance Matrices for Multiple Time Series

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## Sample Covariance Matrices of Multiple Time Series

- Covariance matrix of stationary stochastic process  $x_t = (x_t^a)$ ,  $t \in \mathbb{Z}$ ,  $1 \leq a \leq p$ :

$$C_{ij}^{ab} = \frac{1}{M} \sum_{t=1}^M x_{i+t}^a x_{j+t}^b = \frac{1}{M} (X X^T)_{ij}^{ab} .$$

Here  $X = (x_{it})$  is  $pN \times M$  matrix with entries  $x_{it} = x_{i+t}$ .

Expect finite sample fluctuation around mean

$$C_{ij}^{ab} = \langle x_i^a x_j^b \rangle \pm \mathcal{O}(1/\sqrt{M}) = \bar{C}^{ab}(i-j) \pm \mathcal{O}(1/\sqrt{M})$$

$\Rightarrow C$  is randomly perturbed block Toeplitz matrix.

- Spectrum of  $C$  as  $N \rightarrow \infty$ ,  $M \rightarrow \infty$  @ fixed  $p$  and  $\alpha = N/M$ ?  
Known result as  $\alpha \rightarrow 0$ : Szegő's Theorem

$$\rho_0(\lambda) = \frac{1}{p} \sum_{s=1}^p \int_0^{2\pi} \frac{dq}{2\pi} \delta(\lambda - \hat{C}_s(q))$$

## Compare with Wishart–Laguerre Ensemble

- Empirical covariances for  $N$  data, evaluated on the basis of  $M$  measurements for each variable. Use  $N \times M$  matrices  $X = (x_{it})$  with i.i.d. entries  $x_{it}$  to compute:

$$C_{ij} = \frac{1}{M}(X X^T)_{ij} = \frac{1}{M} \sum_{t=1}^M x_{it} x_{jt} .$$

Expect finite sample fluctuation around mean.

$$C_{ij} = \langle x_i x_j \rangle \pm \mathcal{O}(1/\sqrt{M}) = \delta_{ij} \pm \mathcal{O}(1/\sqrt{M})$$

- Spectrum of  $C$  as  $N \rightarrow \infty$ ,  $M \rightarrow \infty$  @ fixed  $\alpha = N/M$ ?  
 $\Rightarrow$  Marčenko Pastur-Law

$$\rho_\alpha(\lambda) = \frac{1}{2\pi\alpha\lambda} \sqrt{4\alpha - (\lambda - (1 + \alpha))^2}$$

## Principal Differences

- Rows of  $X$  for the multi-time series covariance problem groups of shifted sections of a **set of  $p$**  time series  $(\mathbf{x}_t)_{t \in \mathbb{Z}}$ ,  $\mathbf{x}_t \in \mathbb{R}^p$ .

$$X = \begin{pmatrix} \mathbf{x}_1 & \mathbf{x}_2 & \mathbf{x}_3 & \cdots & \mathbf{x}_M \\ \mathbf{x}_2 & \mathbf{x}_3 & \mathbf{x}_4 & \cdots & \mathbf{x}_{1+M} \\ \vdots & & & \ddots & \vdots \\ \mathbf{x}_N & \mathbf{x}_{N+1} & \mathbf{x}_{N+2} & \cdots & \mathbf{x}_{N+M} \end{pmatrix}$$

- Number of random variables in the problem is  $\mathcal{O}(N)$ , rather than  $\mathcal{O}(N^2)$  as in the Wishart Laguerre ensemble.
- Extensive body of knowledge about the Wishart-Laguerre ensemble and its variants (applications in multivariate statistics, signal-processing, finance, ...)
- Very little is known. Existence proofs (Basak, Bose, Sen 2011).  $p = 1$ -case solved only recently. (RK, P Sollich, EPL 2012)

## Spectral Density and Resolvent

- Spectral density of sample covariance matrix from resolvent

$$\rho(\lambda) = \lim_{N \rightarrow \infty} \frac{1}{\pi N_p} \text{Im} \text{Tr} \left\langle [\lambda_\varepsilon \mathbf{1} - C]^{-1} \right\rangle, \quad \lambda_\varepsilon = \lambda - i\varepsilon$$

- Express as (S F Edwards & R C Jones, JPA, 1976)

$$\begin{aligned} \rho_\alpha(\lambda) &= \lim_{N \rightarrow \infty} \frac{1}{\pi N_p} \text{Im} \frac{\partial}{\partial \lambda} \text{Tr} \left\langle \ln [\lambda_\varepsilon \mathbf{1} - C] \right\rangle \\ &= \lim_{N \rightarrow \infty} -\frac{2}{\pi N_p} \text{Im} \frac{\partial}{\partial \lambda} \left\langle \ln Z_{N_p} \right\rangle, \end{aligned}$$

where  $N_p = Np$  and  $Z_{N_p}$  is a Gaussian integral:

$$Z_{N_p} = \int \prod_{k,a} \frac{du_{ka}}{\sqrt{2\pi/i}} \exp \left\{ -\frac{i}{2} \sum_{ka,lb} u_{ka} (\lambda_\varepsilon \delta_{ab} \delta_{kl} - C_{kl}^{ab}) u_{lb} \right\}.$$

## Performing the Average

- Standard Approach – Replica Method

$$\langle \ln Z_{N_p} \rangle = \lim_{n \rightarrow 0} \frac{1}{n} \ln \langle Z_{N_p}^n \rangle$$

- For integer  $n$ ,  $Z_{N_p}^n$  is partition function of  $n$  identical copies of the system ( $n$ -th power of Gaussian integral)
- Experience: final result has structure of replica-symmetric high-temperature solution  $\Leftrightarrow$  annealed calculation ( $n = 1$ ).  
 $\langle \ln Z_{N_p} \rangle \simeq \ln \langle Z_{N_p} \rangle \Rightarrow$  Do annealed calculation from the start

$$\langle Z_{N_p} \rangle = \left\langle \int \prod_{k,a} \frac{du_{ka}}{\sqrt{2\pi/i}} \exp \left\{ -\frac{i}{2} \sum_{ka,lb} u_{ka} (\lambda \varepsilon \delta_{ab} \delta_{kl} - C_{kl}^{ab}) u_{lb} \right\} \right\rangle$$

## Performing the Average (contd.)

- Insert definition of  $C$ , and  $\alpha_p = \alpha p$ ,

$$\langle Z_{N_p} \rangle = \left\langle \int \prod_{ka} \frac{du_{ka}}{\sqrt{2\pi/i}} \exp \left\{ -\frac{i}{2} \lambda_\varepsilon \sum_{ka} u_{ka}^2 + \frac{i}{2} \alpha_p \sum_{i=1}^M z_i^2 \right\} \right\rangle$$

- with disorder dependence of  $Z_{N_p}$  only through the  $M$  variables

$$z_i = \frac{1}{\sqrt{N_p}} \sum_{ka} x_{k+i}^a u_{ka} , \quad 1 \leq i \leq M .$$

- By CLT (for weakly dependent rv's) normally distributed for large  $M$  with

$$\langle z_i \rangle = 0 , \quad \langle z_i z_j \rangle = \frac{1}{N_p} \sum_{ka, lb} \langle x_{k+i}^a x_{l+j}^b \rangle u_{ka} u_{lb} \equiv Q_{ij}$$

and  $Q$  given in terms of true process auto-covariance

$$Q_{ij} = \langle z_i z_j \rangle = \frac{1}{N_p} \sum_{ka, lb} \bar{C}^{ab}(i-j+k-l) u_{ka} u_{lb}$$

## Exploiting Szegő's Theorem for Spectral Sums

- $\{z_i\}$  average is Gaussian; with  $\alpha_p = \alpha p$ :

$$\langle Z_{N_p} \rangle = \int \prod_{ka} \frac{du_{ka}}{\sqrt{2\pi/i}} \exp \left\{ -\frac{i}{2} \lambda_\varepsilon \sum_{ka} u_{ka}^2 - \frac{1}{2} \ln \det(\mathbb{1} - i\alpha_p Q) \right\}$$

- $Q$  is a Toeplitz matrix.  $\Rightarrow$  evaluate  $\ln \det(\mathbb{1} - i\alpha_p Q)$  using **Szegő's theorem**:

$$\ln \det(\mathbb{1} - i\alpha_p Q) \sim \sum_{\mu=-(M-1)/2}^{(M-1)/2} \ln \left( 1 - i\alpha_p Q_\mu \right)$$

where

$$Q_\mu = \frac{1}{N_p} \sum_{ka, lb} \hat{C}^{ab}(q_\mu) e^{-iq_\mu(k-l)} u_{ka} u_{lb} = \frac{1}{p} \sum_{ab} \hat{C}^{ab}(q_\mu) \hat{u}_a^*(q_\mu) u_b(q_\mu)$$

with  $\hat{u}_a(q_\mu) = \frac{1}{\sqrt{N}} \sum_{k=1}^N e^{iq_\mu k} u_{ka}$  and  $q_\mu = \frac{2\pi}{M} \mu$ .



## Closed Form Approximation & Scaling

- Get closed form expression of  $\langle Z_{N_p} \rangle = \prod_{\nu \geq 0} I_\nu$  with

$$I_\nu = \frac{i^p}{\prod_s \hat{C}_s(p_\nu)} \int_0^\infty \prod_{s=1}^p dx_s \frac{e^{-i \sum_s x_s \lambda_\varepsilon / \hat{C}_s(p_\nu)}}{\left(1 - i \frac{\alpha}{2} \sum_s x_s\right)^{2/\alpha}}$$

where  $\hat{C}_s(p_\nu)$ ,  $s = 1, \dots, p$  are eigenvalues of  $\hat{C}(p_\nu) = (\hat{C}^{ab}(p_\nu))$

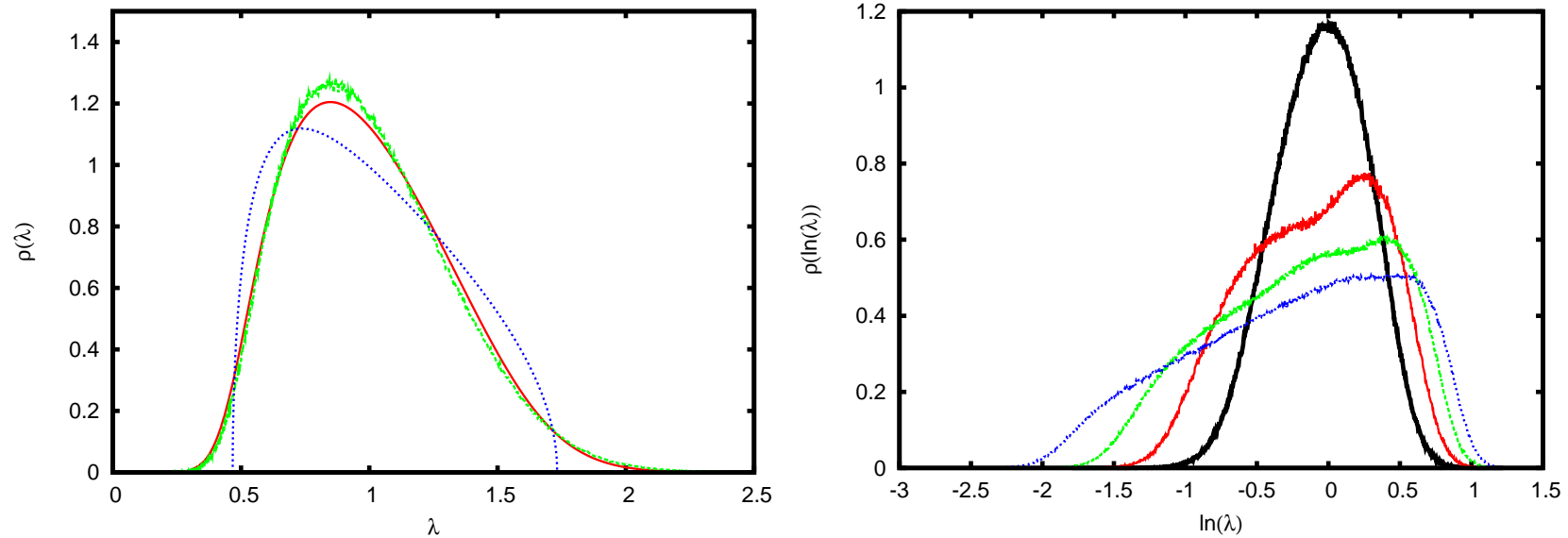
- Gives

$$\rho_\alpha(\lambda) = \frac{1}{p} \int_0^\pi \frac{dq}{\pi} \sum_{s=1}^p \frac{1}{\hat{C}_s(q)} \rho_s \left( \left\{ \frac{\lambda}{\hat{C}_s(q)} \right\} \right)$$

- For uncorrelated data  $\hat{C}_s(q) \equiv 1$ , and  $\rho_s$  is independent of  $s \Rightarrow$  identify  $\rho_s$  with the spectral density for covariance matrices of  $p$  time series of i.i.d. (uncorrelated) data.

## Numerical Tests

- Spectral density for  $x_n \sim \mathcal{N}(0, 1)$  i.i.d. @  $\alpha = 0.1$



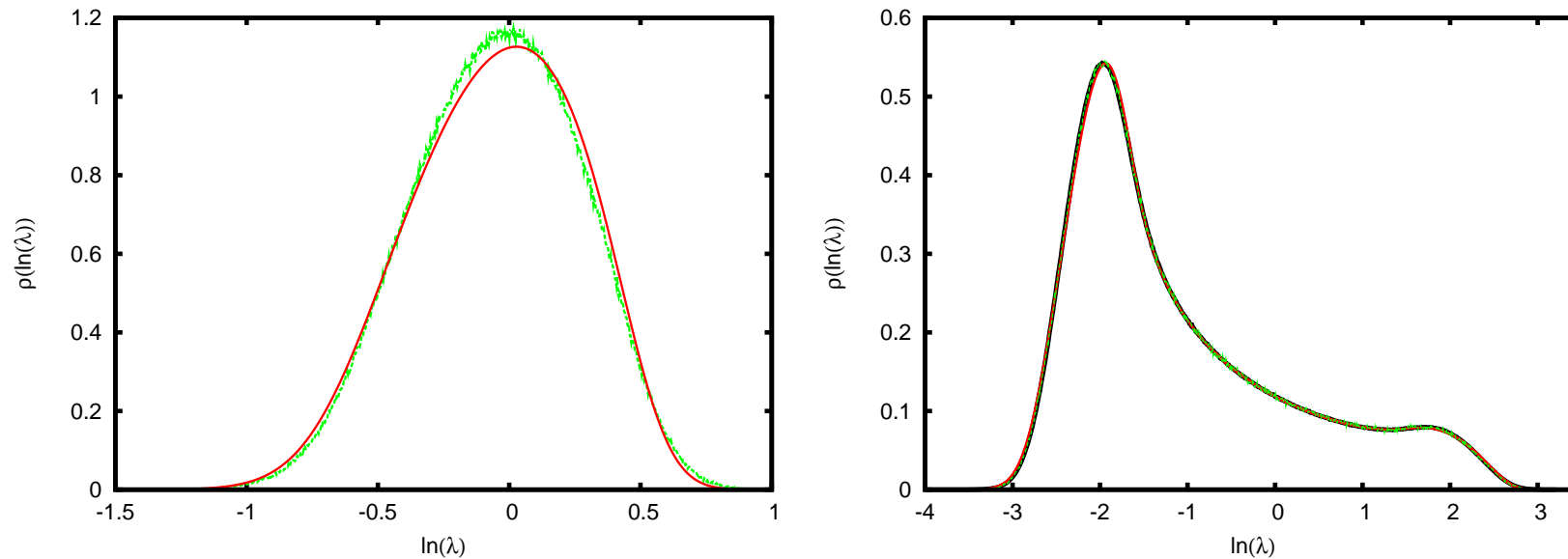
**(Left)**  $p = 1$ : simulation results (green); analytic approximation for  $\rho_\alpha^{(0)}(\lambda)$  (red), Marčenko-Pastur law (blue-dashed) (. From RK, P Sollich, EPL 2012.)

**(Right)** logarithmic spectral density; simulation results for  $p = 1, \dots, 4$ . In all cases @  $\alpha = 0.1$

## AR-1 Process @ $\alpha = 0.1, p = 1$

$$x_n = a_1 x_{n-1} + \sqrt{1 - a_1^2} \xi_n$$

- (Logarithmic) Spectral density for AR-1 process @  $\alpha = 0.1$



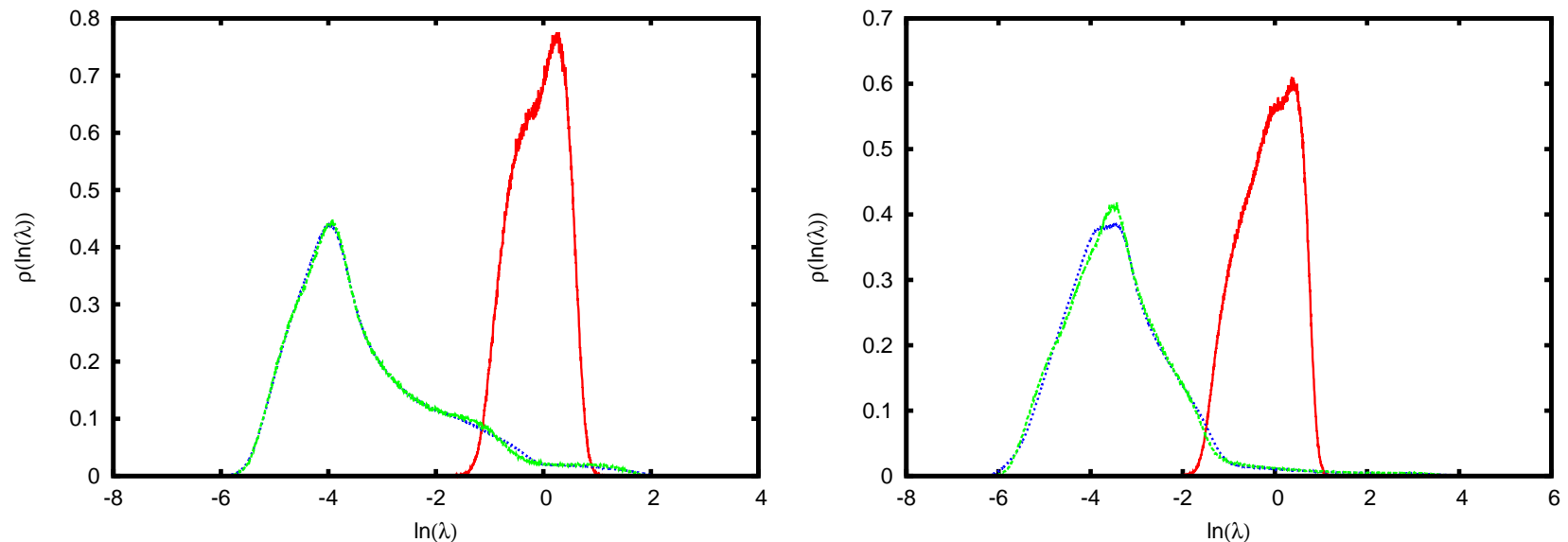
**Left:** i.i.d. data, simulation (green) and analytic result (red).

**Right**  $a_1 = 0.8$ . Comparing scaling based on the empirical scaling function (black) with that based on the analytic result (red) and simulations (green).

## AR-1 Process @ $\alpha = 0.1$ , $p = 2$ and $p = 3$

- (Logarithmic) Spectral density for AR-1 process @  $\alpha = 0.1$

$$\mathbf{x}_n = A \mathbf{x}_{n-1} + \sigma \xi_n$$



**(Left)** Spectra for  $p = 2$ , uncorrelated data and  $A = \begin{bmatrix} 0.8 & 0.1 \\ 0.1 & 0.8 \end{bmatrix}$ , **(Right)**  $p = 3$ , uncorrelated data and  $A = \begin{bmatrix} 0.8 & 0.2 & 0.1 \\ 0.2 & 0.6 & 0.1 \\ 0.1 & 0.1 & 0.5 \end{bmatrix}$ . In both cases  $\sigma = 0.2$ , and simulation results are compared with scaling using an approximate evaluation of scaling integrals.

## Summary

- Computed DOS of sample covariance matrices for multiple time-series using annealed calculation.
- Key ingredient: Szegő's theorem for (block) Toeplitz matrices
- Rectangular window and decorrelation approximation  $\Rightarrow$  Closed form approximation.
- Use of Szegős theorem suggests a scaling form for DOS.
  - scaling is requires knowledge of a function on  $\mathbb{R}^p$ ! **DOS for i.i.d. data is insufficient.**
  - currently working on effective methods to evaluate scaling function for  $p > 1$ .
- **Lots of possible applications.**