

# Feasibility of equilibria in large ecosystems from a random matrix theory standpoint

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## Disclaimer

A crash course on Large Random Matrices

Modelling and Understanding Ecological Networks

Hand waving

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You are going to attend a very **naive** speech on mathematical ecology by a **non-specialist**. Please, be merciful.

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- ▶ First result (1948) goes back to Nobel Laureate Eugene Wigner known as

Wigner's semi-circle law



## Example 1: Wigner Model

### Matrix model

Let  $\mathbf{X}_N = (X_{ij})$  symmetric  $N \times N$

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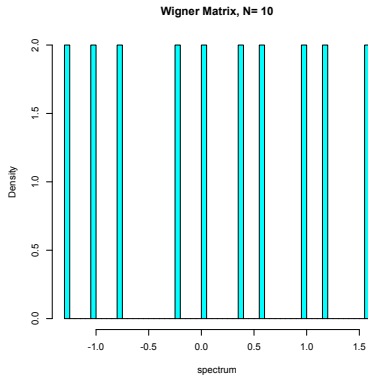


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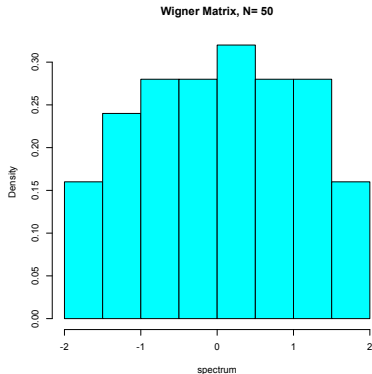


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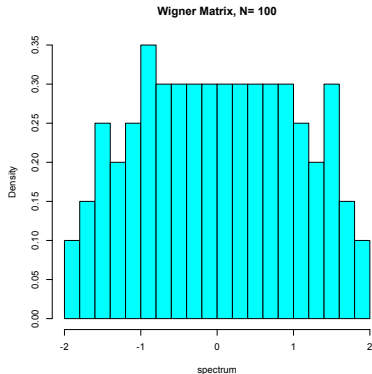


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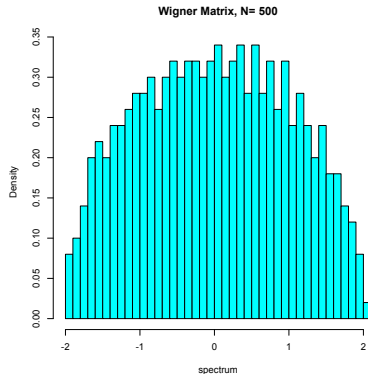
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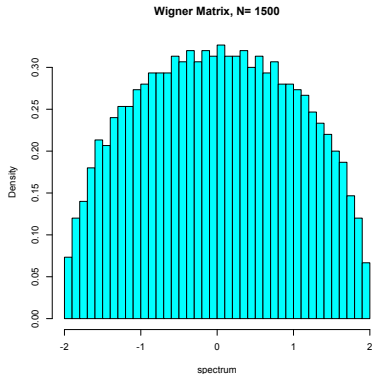


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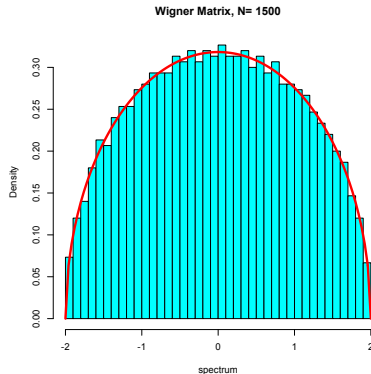


Figure: The semi-circular distribution (in red)  
with density  $x \mapsto \frac{\sqrt{4-x^2}}{2\pi}$

### Wigner's theorem (1948)

"The histogram of a Wigner matrix converges to the **semi-circular distribution**"



## Example 2: Large Covariance Matrices

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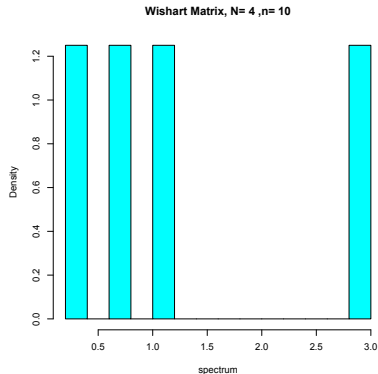


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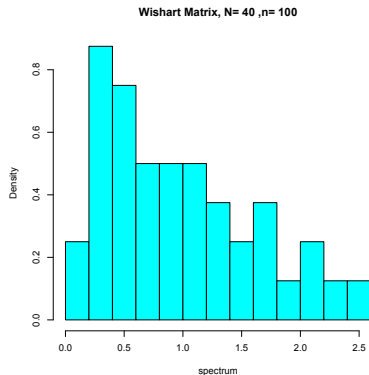


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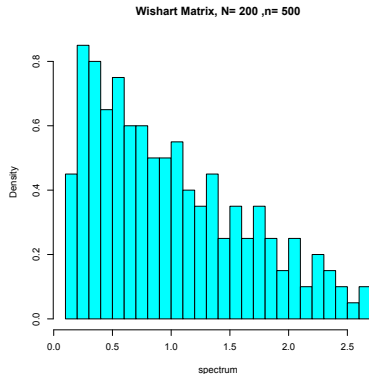


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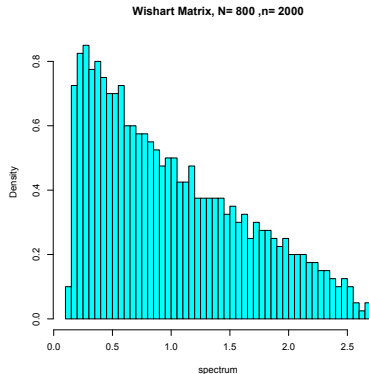


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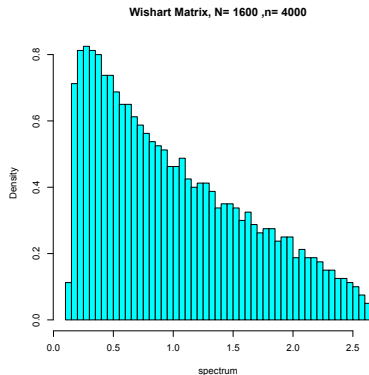


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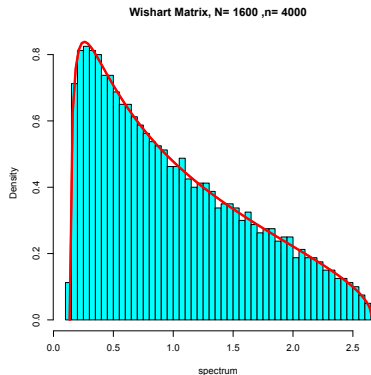


Figure: Marčenko-Pastur's distribution (in red)

### Marčenko-Pastur's theorem (1967)

"The histogram of a **Large Covariance Matrix** converges to **Marčenko-Pastur distribution** with given parameter (here **0.4**)"



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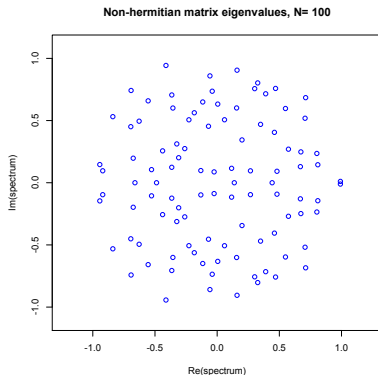


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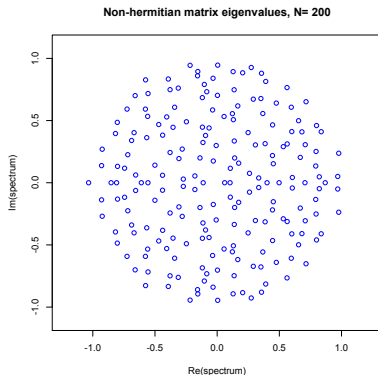


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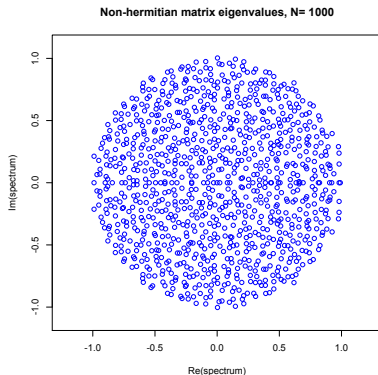


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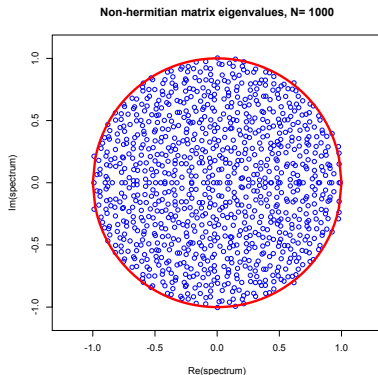


Figure: The circular law (in red)

Theorem: The Circular Law (Ginibre, Metha, Girko, Tao & Vu, etc.)

The spectrum of  $\mathbf{Y}_N$  converges to **the uniform probability on the disc**

## To go beyond: Many more results ..

- ▶ Matrices with a variance profile

$$Y_N = \frac{1}{\sqrt{N}} (a_{ij} X_{ij}) \quad \text{where} \quad (a_{ij}) \text{ are deterministic}$$



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- ▶ Spiked models, etc.

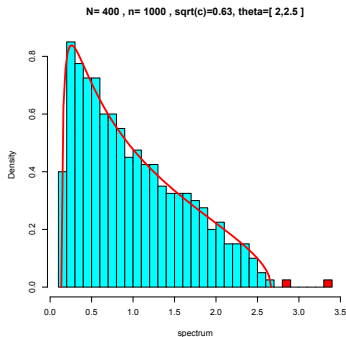


Figure: Spiked model: the largest eigenvalues separate from the others

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## The Lotka-Volterra model

For foodwebs, the dynamics of interacting species may be described by the Lotka-Volterra equations:

$$\frac{da_i(t)}{dt} = a_i \left( r_i - \theta a_i + \sum_{j=1}^N \frac{Z_{ij}}{N^\delta} a_j \right)$$

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- ▶  $\delta$  is a parameter controlling the interaction  $j \rightarrow i$  strength.

Interaction	Value of $\delta$	Comment
strong	$\delta \in (0, 1/2)$	-
moderate	$\delta = 1/2$	RMT regime
weak	$\delta \in (1/2, 1)$	Perturbation theory

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## Equilibrium

- ▶ The equilibrium  $\mathbf{a}^*$  is given by

$$\frac{da_i(t)}{dt} = 0 \quad \Rightarrow \quad \boxed{\mathbf{a}^* = \left( \theta I_N - \frac{Z}{N^\delta} \right)^{-1} \mathbf{r}}$$

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- ▶ Given the jacobian  $\mathcal{J}(\mathbf{a}^*)$ , which is explicit for Lotka-Volterra systems

$$\boxed{\mathcal{J}(\mathbf{a}^*) = \text{diag}(\mathbf{a}^*) \left( -\theta I_N + \frac{Z}{N^\delta} \right)}$$

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### Conclusion

Static analysis (equilibrium and stability) of the Lotka-Volterra model can be addressed by means of RMT for large  $N$

# An intriguing argument for moderate interactions

## Theorem (Dougoud et al.)

For moderate interactions,

- ▶ all the components  $a_i^*$ 's of the equilibrium vector

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As a consequence ..

$$\mathbb{P}\{a_i^* < 0 \text{ for some } i \in [n]\} \xrightarrow{N \rightarrow \infty} 1 \quad \Longleftrightarrow$$

<b>No feasible equilibrium with proba 1!</b>
--

## Reference

- ▶ "The feasibility of equilibria in large ecosystems: A primary but neglected concept in the complexity-stability debate",  
*Dougoud, Vikenbosch, Rohr, Bersier, Mazza, PLoS Comput. Biology, 2018*



## Feasibility and the strenght of interactions

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- Consider the equilibrium vector

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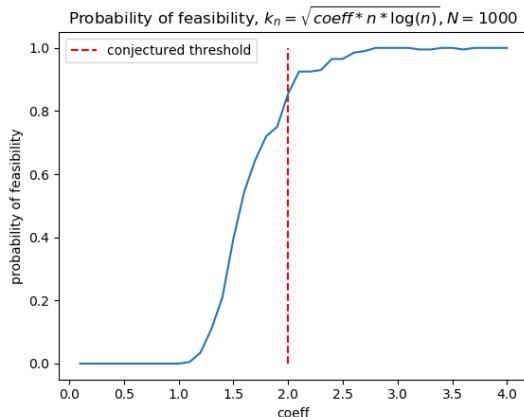
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- For weak interactions,

$$\kappa_N \gg \kappa_N^* \quad (\text{Ex: } \kappa_N = N) \implies$$

**All the equilibriums are feasible with probability 1**

# Simulations



**Figure:** We plot the probability of feasibility as a function of the normalization parameter  $\kappa_N = \sqrt{\text{coeff} \times n \log(n)}$ . As expected, we get an approximate threshold phenomenon around the critical value  $\text{coeff} = 2$ . We use uniform random variables, centered and normalized for the interaction matrix,  $N = 1000$ . We compute the frequency over 200 simulations.

Disclaimer

A crash course on Large Random Matrices

Modelling and Understanding Ecological Networks

**Hand waving**



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Many interesting questions in RMT arise from ecological models.

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random	$Z_{ij}$ i.i.d. and $\mathbb{E}Z_{ij} = 0$	Circular law
structured	$Z_{ij} = 0$ for $(i, j) \in \mathcal{S}$	Sparse variance profiles / open
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For those of you interested in RMT

- GDR **MEGA** (**M**atrices **E**t **G**raphes **A**léatoires)