

# Approximate Message Passing From Theoretical Ecology to Random Matrices

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Reims - January 2024



# Presentation plan

## Introduction : A problem from theoretical ecology

Lotka-Volterra system of coupled differential equations

Elliptic matrices

## Approximate Message Passing

## Elements of proof

# Theoretical ecology

**Motivation** We want to study species coexistence within large ecosystems and try to answer the following questions:

- ▶ How many species survive in a large ecosystem ?
- ▶ What is the distribution of surviving species ?



Figure: Generated with *Midjourney AI*

# Lotka-Volterra system of coupled differential equations

**Motivation** In order to study the behavior of species coexistence within large ecosystems we will have to describe the dynamics of these interacting species and try to answer some questions:

- ▶ How many species survive at the equilibrium ?
- ▶ What are the statistical properties of these surviving species ?

**Model** A popular model used in this setting is given by a system of Lotka-Volterra equations:

$$\boxed{\frac{dx_i(t)}{dt} = x_i \left( r_i - x_i + \left( \frac{1}{\kappa} B\mathbf{x} \right)_i \right)} \quad i \in [n], \quad \mathbf{x} = (x_i).$$

Here  $(B\mathbf{x})_i = \sum_{\ell} B_{i\ell}x_{\ell}$ .

- ▶  $n$  is the **number of species** in a given food-web,
- ▶  $x_i = x_i(t)$  is the **abundance** (=population) of species  $i$  at time  $t$ ,
- ▶  $r_i$  is the **intrinsic growth rate** of species  $i$ ,
- ▶  $B = (B_{ij})$  where  $B_{ij}$  is the **interaction** between species  $j$  and species  $i$ .
- ▶  $\kappa$  an extra parameter representing the **interaction strength**.

To simplify the study we will put  $r_i = 1 \quad \forall i \in [n]$ .

## Equilibrium in Lotka-Volterra system

- **Model** We model the dynamics using Lotka-Volterra's system of differential equations.

$$\frac{dx_i}{dt} = x_i \left( 1 - x_i + \left( \frac{B}{\kappa} \mathbf{x} \right)_i \right), \quad i = 1, \dots, n$$

- **Goal** We are interested in studying the properties of the equilibrium vector of abundances  $\mathbf{x}^* \in \mathbb{R}_+^n$ , i.e. the vector  $\mathbf{x}^*$  that satisfies

$$\begin{aligned} \frac{dx}{dt} \Big|_{\mathbf{x}=\mathbf{x}^*} &= 0 \\ x_i^* \left( 1 - x_i^* + \left( \frac{B}{\kappa} \mathbf{x}^* \right)_i \right) &= 0 \end{aligned}$$

► **Questions**

1. Can we describe the statistical properties of the equilibrium ?
2. In particular, what is the proportion of surviving species at the equilibrium ?

$$\frac{\#\{i : x_i^* > 0\}}{n}$$

## Main assumption: a random model for the interaction matrix $B$

- ▶ The study of large Lotka-Volterra systems makes it **very difficult to calibrate** the model and **estimate** matrix  $B$ .
- ▶ An alternative is to consider **random matrices** [May, 1972], the statistical properties of which encode some real properties of the food-web.

- ▶  $A \sim \text{Elliptic}(n, \rho)$  if

$$\begin{pmatrix} A_{ij} \\ A_{ji} \end{pmatrix} \sim \mathcal{N}_2 \left( \mathbf{0}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix} \right)$$

and  $A_{ii} \sim \mathcal{N}(0, 1 + \rho)$ .

- ▶ Interaction matrix

$$B = \frac{1}{\sqrt{n}} A.$$

- ▶ Elliptic interaction matrices are interesting in theoretical ecology as they provide more flexibility, i.e.  $A_{ij}$  and  $A_{ji}$  are not equal but only correlated.

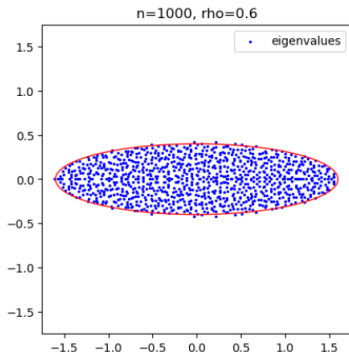


Figure: Spectrum of an elliptic matrix for  $\rho = 0.6$ .

# From Lotka-Volterra to Linear Complementarity Problem

Given that  $B = \frac{A}{\sqrt{n}}$  where  $A \sim \text{Elliptic}(n, \rho)$ .

The equilibrium writes

$$\boxed{x_i^* \left( 1 - x_i^* + \left( \frac{A}{\kappa \sqrt{n}} \mathbf{x}^* \right)_i \right) = 0} \quad i \in [n], \quad \mathbf{x}^* = (x_i^*).$$

## Stable equilibrium

$$(\text{LCP}) \quad \begin{cases} \mathbf{x}^* & \geq 0, \\ \left( I - \frac{A}{\kappa \sqrt{n}} \right) \mathbf{x}^* - \mathbf{1} & \geq 0, \\ x_i^* \left( \left[ \left( I - \frac{A}{\kappa \sqrt{n}} \right) \mathbf{x}^* \right]_i - 1 \right) & = 0. \end{cases}$$

- **Stability condition** [Takeuchi, 1996]: Lyapunov stability condition or non-invasibility condition.
- **Sufficient condition for the existence, uniqueness and stability of the equilibrium** :  $\boxed{\kappa > \sqrt{2(1 + \rho)}}$  [Clenet et al., 2022].

## Statistical properties on the equilibrium

Let  $A \sim \text{Elliptic}(n, \rho)$  matrix and consider the LV system.

$$\frac{dx_i(t)}{dt} = x_i \left( 1 - x_i + \frac{1}{\kappa} (B\mathbf{x})_i \right) \quad \text{where} \quad B = \frac{A}{\sqrt{n}}.$$

and assume that  $\kappa > \sqrt{2(1+\rho)}$ .

**Theorem (G., Hachem, Najim, 2024)**

- There exists a (random) **unique stable equilibrium**  $\mathbf{x}_n^*$ :  $\boxed{\mathbf{x}_n(t) \xrightarrow[t \rightarrow \infty]{} \mathbf{x}_n^*}$  and

$$\text{(a.s.)} \quad \boxed{\mu^{\mathbf{x}^*} \triangleq \frac{1}{n} \sum_{i \in [n]} \delta_{x_i^*} \xrightarrow[n \rightarrow \infty]{weak, L^2} \mathcal{L} \left( (1 + \rho \gamma / \delta^2) (\sigma \bar{Z} + 1)_+ \right)}$$

- where  $(\delta, \sigma, \gamma) \in (0, \infty)^3$  is the unique triple solution of **the fixed point equations**

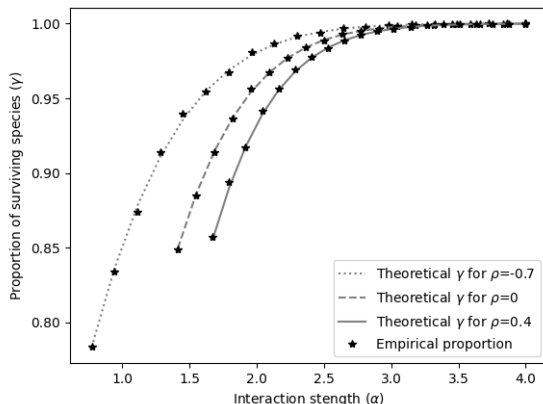
$$\begin{aligned} \kappa &= \delta + \rho \frac{\gamma}{\delta}, \\ \sigma^2 &= \frac{1}{\delta^2} \mathbb{E} (\sigma \bar{Z} + 1)_+^2, \quad \bar{Z} \sim \mathcal{N}(0, 1), \\ \gamma &= \mathbb{P} [\sigma \bar{Z} + 1 > 0]. \end{aligned}$$

- Similar results were obtained by [Bunin, 2017] and [Galla, 2018] using statistical physics methods such as “Replica trick”.



## Proportion of surviving species

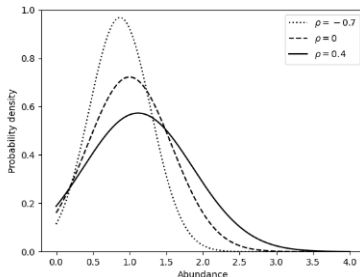
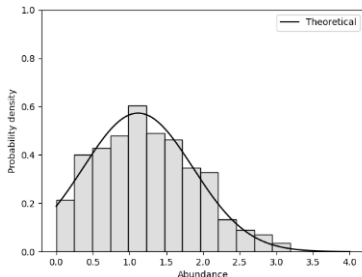
- **Theoretical values:** We solve the **fixed point equations** for  $(\delta, \sigma, \gamma)$  for different values of  $\kappa$ . We plot  $\gamma = \gamma(\kappa)$ .
- **Experimental values:** (Monte-Carlo) we solve the **Equilibrium system** associated to the Lotka-Volterra equations for 500 samples of random matrices  $A$ . (using Lemke solver in python).



# Distribution of surviving species

We fix  $\kappa = 2$ .

- **Theoretical values:** We plot the theoretical **truncated gaussian density function** for the adequate values of  $(\delta, \sigma, \gamma)$ .
- **Experimental values:** We plot the following empirical conditional distribution  $\mathcal{L}(x_i^* \mid x_i^* > 0)$ .



# Outline

Introduction : A problem from theoretical ecology

## Approximate Message Passing

Fixed point equation

Elliptic Approximate Message Passing

Elements of proof

## A fixed point equation

- We want to study the solution  $\mathbf{x}^*$  of the following system

$$\begin{cases} \mathbf{x}^* & \geq 0, \\ \left(I - \frac{A}{\kappa\sqrt{n}}\right) \mathbf{x}^* - \mathbf{1} & \geq 0, \\ x_i^* \left( \left[\left(I - \frac{A}{\kappa\sqrt{n}}\right) \mathbf{x}^*\right]_i - 1 \right) & = 0. \end{cases} \quad (1)$$

- To use an iterative scheme we need a fixed point equation. Consider the following equation of  $\mathbf{z} \in \mathbb{R}^n$ .

$$\boxed{\mathbf{z} = \frac{A}{\kappa\sqrt{n}} \mathbf{z}^+ + \mathbf{1}} \quad (2)$$

- If  $\mathbf{z}$  is a solution to (2) then  $\mathbf{z}^+$  is a solution to (1).

- Write  $\mathbf{z} = \mathbf{z}^+ - \mathbf{z}^-$ , then

$$\mathbf{z}^- = \left(I - \frac{A}{\kappa\sqrt{n}}\right) \mathbf{z}^+ - \mathbf{1}$$

- **Question:** We want an iterative algorithm  $(\mathbf{z}^k)_k$  to solve (2) while tracking

$$\boxed{\mu^{\mathbf{z}^k} \triangleq \frac{1}{n} \sum_{i=1}^n \delta_{z_i}}$$

- An obvious algorithm  $\mathbf{z}^{k+1} = \frac{A}{\kappa\sqrt{n}} (\mathbf{z}^k)^+ + \mathbf{1}$  does not have this property.

# Elliptic Approximate Message Passing

AMP was initially introduced by [Bayati and Montanari, 2011] and later generalized by [Javanmard and Montanari, 2013], [Bayati et al., 2015], [Fan, 2021].

► **Notation** Given  $f : \mathbb{R}^2 \rightarrow \mathbb{R}$  denote by  $\langle f'(\mathbf{u}, \mathbf{v}) \rangle = \frac{1}{n} \sum_{i=1}^n \frac{\partial f}{\partial u}(u_i, v_i)$ .

## Assumptions

- $(f_k)_k$  Lipschitz activation functions.  $\mathbf{a} \in \mathbb{R}^n$  is a constant parameter.
- Initialization point  $\mathbf{u}^0 \perp\!\!\!\perp A$  and  $\exists \bar{u}$  such that  $\mu^{\mathbf{u}^0} \xrightarrow{n \rightarrow \infty} \mathcal{L}(\bar{u})$ .

## Theorem (G., Hachem, Najim, 2024)

The AMP recursion for a matrix  $A \sim \text{Elliptic}(n, \rho)$  is defined as

$$\begin{cases} \mathbf{u}^1 = \frac{1}{\sqrt{n}} A f_0(\mathbf{u}^0, \mathbf{a}), \\ \mathbf{u}^{k+1} = \frac{1}{\sqrt{n}} A f_k(\mathbf{u}^k, \mathbf{a}) - \rho \langle f'_k(\mathbf{u}^k, \mathbf{a}) \rangle f_{k-1}(\mathbf{u}^{k-1}, \mathbf{a}). \end{cases}$$

Then (a.s)

$$\mu^{\mathbf{u}^k} = \frac{1}{n} \sum_{i=1}^n \delta_{u_i^k} \xrightarrow[n \rightarrow \infty]{\text{weak}, L^2} \mathcal{L}(Z_k) = \mathcal{N}(\mathbf{0}, \sigma_k^2)$$

where  $\sigma_0^2 = \mathbb{E} [f_0(\bar{u})^2]$  and  $\sigma_{k+1}^2 = \mathbb{E} [f_k(Z_k)^2]$  st  $Z_k \sim \mathcal{N}(\mathbf{0}, \sigma_k^2)$ .

**Remark:** This result is well known in the case of symmetric matrices ( $\rho = 1$ ).

*Tutorial:* [Feng et al., 2021].

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Then (a.s)

$$\mu^{\mathbf{u}^1, \dots, \mathbf{u}^k} = \frac{1}{n} \sum_{i=1}^n \delta_{(u_i^1, \dots, u_i^k)} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_1, \dots, Z_k) = \mathcal{N}_k(\mathbf{0}, \mathbf{\Gamma}^k)$$

where  $\sigma_0^2 = \mathbb{E}[f_0(\bar{u})^2]$  and  $\sigma_{k+1}^2 = \mathbb{E}[f_k(Z_k)^2]$  st  $Z_k \sim \mathcal{N}(0, \sigma_k^2)$ .

**Remark:** This result is well known in the case of symmetric matrices ( $\rho = 1$ ).

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## Design of an AMP algorithm to solve the Fixed Point equation

- ▶ We want to solve the fixed point equation  $z = \frac{A}{\kappa\sqrt{n}}z_+ + \mathbf{1}$  using AMP.
- ▶ We need to calibrate the functions  $f_k$  and the parameter  $\alpha$  ([Akjouj et al., 2023]) in the following recursion equation

$$\mathbf{u}^{k+1} = \frac{A}{\sqrt{n}}f_k(\mathbf{u}^k, \mathbf{a}) - \rho\langle f'_k(\mathbf{u}^k, \mathbf{a}) \rangle f_{k-1}(\mathbf{u}^{k-1}, \mathbf{a})$$

- ▶ Given  $\kappa$  we determine  $\delta$  and  $\gamma$  and we set  $f_k(x, a) = \frac{(x+a)_+}{\delta}$ . Parameter  $\mathbf{a}$  will be calibrated later. Then

$$\mathbf{u}^{k+1} = \frac{A}{\delta\sqrt{n}}(\mathbf{u}^k + \mathbf{a})_+ - \rho\frac{\langle \mathbf{1}_{\mathbf{u}^k + \mathbf{a} > 0} \rangle}{\delta^2}(\mathbf{u}^{k-1} + \mathbf{a})_+$$

- ▶ **Fact 1**  $\langle \mathbf{1}_{\mathbf{u}^k + \mathbf{a} > 0} \rangle \approx \gamma$  for  $k$  large.

- ▶ Set  $\xi^k = \mathbf{u}^k + \mathbf{a}$ , then we get

$$\xi^{k+1} = \frac{A}{\delta\sqrt{n}}\xi_+^k - \rho\frac{\gamma}{\delta^2}\xi_+^{k-1} + \mathbf{a} + \epsilon$$

- ▶ **Fact 2**  $\xi^{k+1} \approx \xi^k \approx \xi^{k-1}$  when  $k$  is large. Set  $\mathbf{a} = \mathbf{1} + \rho\frac{\gamma}{\delta^2} = \frac{\kappa}{\delta}$ . Then after massaging the previous equation.

$$\xi_+ - \frac{\xi_-}{1 + \rho\frac{\gamma}{\delta^2}} = \frac{A}{\kappa\sqrt{n}}\xi_+ + \mathbf{1} + \epsilon \Rightarrow \boxed{z \triangleq \xi_+ - \frac{\xi_-}{1 + \rho\frac{\gamma}{\delta^2}}} \text{ satisfies the FPE.}$$

# Outline

Introduction : A problem from theoretical ecology

Approximate Message Passing

## Elements of proof

- Background

- Why do we need the Onsager term ?

- Proof for  $k = 1$  (base case)

- Proof for  $k = 2$

- Induction step



## Background

- **Theorem** Let  $\mathbf{u}^0$  independent from  $A$  such that  $\mu^{\mathbf{u}^0} \xrightarrow{n \rightarrow \infty} \mathcal{L}(\bar{\mathbf{u}})$ . The AMP recursion for a matrix  $A \sim \text{Elliptic}(n, \rho)$  is defined as

$$\begin{cases} \mathbf{u}^1 = \frac{1}{\sqrt{n}} A f_0(\mathbf{u}^0), \\ \mathbf{u}^{k+1} = \frac{1}{\sqrt{n}} A f_k(\mathbf{u}^k) - \rho \langle f'_k(\mathbf{u}^k) \rangle f_{k-1}(\mathbf{u}^{k-1}). \end{cases}$$

Then (a.s)

$$\mu^{\mathbf{u}^k} = \frac{1}{n} \sum_{i=1}^n \delta_{u_i^k} \xrightarrow[n \rightarrow \infty]{weak, L^2} \mathcal{N}(0, \sigma_k^2)$$

where  $\sigma_{k+1}^2 = \mathbb{E} \left[ (f_k(Z_k))^2 \right]$  and  $Z_k \sim \mathcal{N}(0, \sigma_k^2)$ .

- $\mu_n \xrightarrow{n \rightarrow \infty} \mu$  if  $\int \varphi d\mu_n \xrightarrow{n \rightarrow \infty} \int \varphi d\mu$  for all  $\varphi$ .
- Let  $\mathbf{X} \in \mathbb{R}^n$  be a random vector and  $\bar{x} \in \mathbb{R}$  a random variable. We say  $\mu^{\mathbf{X}} = \frac{1}{n} \sum_{i \in [n]} \delta_{X_i} \xrightarrow{n \rightarrow \infty} \mathcal{L}(\bar{x})$  if

$$\forall \varphi \quad \frac{1}{n} \sum_{i \in [n]} \varphi(X_i) \xrightarrow[n \rightarrow \infty]{c} \mathbb{E}[\varphi(\bar{x})].$$

- Consider two random variables  $X$  and  $Y$ , we write  $X \stackrel{\mathcal{L}}{=}_{|\mathcal{F}} Y$  if

$$\forall \varphi \quad \mathbb{E}[\varphi(X) \mid \mathcal{F}] = \mathbb{E}[\varphi(Y) \mid \mathcal{F}] \quad (\text{a.s.})$$

## Why the Onsager term ?

Recall the AMP recursion

$$\begin{cases} \mathbf{u}^1 = A f(\mathbf{u}^0, \mathbf{a}), \\ \mathbf{u}^{k+1} = A f(\mathbf{u}^k, \mathbf{a}) - \rho \langle f'(\mathbf{u}^k, \mathbf{a}) \rangle f(\mathbf{u}^{k-1}, \mathbf{a}). \end{cases}$$

- **Goal** We want to describe the statistical behavior of  $\mathbf{u}$  in the high dimensional regime  $n \rightarrow \infty$ , where  $\mathbf{u}$  satisfies the fixed point equation,

$$\mathbf{u} = A f(\mathbf{u}) \quad \text{and } A \text{ is random}$$

- **Idea** Iterative approximation,  $\mathbf{u}^k \xrightarrow{n \rightarrow \infty} \mathbf{u}$  while tracking the  $\mu^{\mathbf{u}^k}$ .
- **Step 1** Initialize with  $\mathbf{u}^0$  independent of  $A$  where  $\mu^{\mathbf{u}^0}$  is known and construct

$$\mathbf{u}^1 = A f(\mathbf{u}^0)$$

$A$  and  $\mathbf{u}^0$  are independent so  $\mu^{\mathbf{u}^1}$  is easy to determine. 😊

- **Step 2** Construct  $\mathbf{u}^2$  such that

$$\mathbf{u}^2 = A f(\mathbf{u}^1)$$

$\mathbf{u}^1$  and  $A$  are now correlated so studying  $\mu^{\mathbf{u}^2}$  is not simple. 😞

- **Correction term** [Bayati and Montanari, 2011] subtract a correction term

$$\boxed{\mathbf{u}^2 = A f(\mathbf{u}^1) - \text{onsager term}} \quad \left( \Leftrightarrow \mathbf{u}^2 = \tilde{A} f(\mathbf{u}^1) \text{ and } \tilde{A} \perp\!\!\!\perp \mathbf{u}^1 \right)$$

## Base case

- For  $k = 1$ , recall that  $\mathbf{u}^1 = \frac{1}{\sqrt{n}} A \mathbf{q}^0$  where  $\mathbf{q}^0 = f_0(\mathbf{u}^0)$  and  $\mathbf{u}^0 \perp\!\!\!\perp A$ . We want

$$\mu^{\mathbf{u}^1} = \frac{1}{n} \sum_{i \in [n]} \delta_{u_i^1} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_1) \text{ where } Z_1 \sim \mathcal{N}(0, \sigma_1^2) \text{ and } \sigma_1^2 = \mathbb{E} \left[ \left( f_0(\bar{u})^2 \right) \right].$$

### Lemma

If  $A \sim \text{Elliptic}(n, \rho)$  and  $\mathbf{q} \in \mathbb{R}^n$  normalized, then  $A\mathbf{q} \sim \mathcal{N}(0, I + \rho \mathbf{q} \mathbf{q}^\top)$ .

Or  $A\mathbf{q} \stackrel{\mathcal{L}}{=} \boldsymbol{\xi} + (\sqrt{1+\rho} - 1) \mathbf{q} \mathbf{q}^\top \boldsymbol{\xi}$  where  $\boldsymbol{\xi} \sim \mathcal{N}_n(0, I_n)$ .

- Using this lemma,

$$\begin{aligned} \mathbf{u}^1 &= \frac{1}{\sqrt{n}} A \mathbf{q}^0 \\ &\stackrel{\mathcal{L}}{=} \left[ \| \mathbf{q}^0 \| \boldsymbol{\xi} + c \frac{\mathbf{q}^0 \mathbf{q}^{0\top}}{\sqrt{n} \| \mathbf{q}^0 \|} \boldsymbol{\xi} \right] \text{ where } \boldsymbol{\xi} \sim \mathcal{N}_n(0, I_n). \end{aligned}$$

## Proof of the previous Lemma

### Lemma

If  $A \sim \text{Elliptic}(n, \rho)$  and  $\mathbf{q} \in \mathbb{R}^n$  normalized, then  $A\mathbf{q} \sim \mathcal{N}(0, I + \rho\mathbf{q}\mathbf{q}^\top)$ .

Or  $A\mathbf{q} \stackrel{\mathcal{L}}{=} \boldsymbol{\xi} + (\sqrt{1+\rho} - 1)\mathbf{q}\mathbf{q}^\top\boldsymbol{\xi}$  where  $\boldsymbol{\xi} \sim \mathcal{N}_n(0, I_n)$ .

### Proof.

Let  $\rho = 1$ , we have  $A \sim \text{GOE}(n)$ , let  $Q = [\mathbf{q}, *] \in \mathbb{R}^{n \times n}$  be an orthogonal matrix, using **orthogonal invariance** of GOE matrices

$$\begin{aligned} A\mathbf{q} &\stackrel{\mathcal{L}}{=} Q A Q^\top \mathbf{q} \\ &= Q A \mathbf{e}_1 \sim \mathcal{N}_n\left(0, Q \left(I_n + \mathbf{e}_1 \mathbf{e}_1^\top\right) Q^\top\right) \\ &\stackrel{\mathcal{L}}{=} \mathcal{N}_n\left(0, I + \mathbf{q}\mathbf{q}^\top\right). \end{aligned}$$

For a general  $\rho \in [-1, 1]$  we use the following decomposition of  $A$

$$A \stackrel{\mathcal{L}}{=} \sqrt{\frac{1+\rho}{2}} G + \sqrt{\frac{1-\rho}{2}} \tilde{G}$$

where  $G \sim \text{GOE}(n)$  and  $\tilde{G}$  (antisymmetric) are independent. □

## Base case

- We have  $\mathbf{u}^1 \stackrel{\mathcal{L}}{=} \frac{1}{\sqrt{n}} \|\mathbf{q}^0\| \boldsymbol{\xi} + c \frac{\mathbf{q}^0 \mathbf{q}^{0\top}}{\sqrt{n} \|\mathbf{q}^0\|} \boldsymbol{\xi}$  where  $\boldsymbol{\xi} \sim \mathcal{N}_n(0, I_n)$  is independent of  $\mathbf{u}^0$ .
- Using the assumption  $\mu^{\mathbf{u}^0} \xrightarrow{n \rightarrow \infty} \mathcal{L}(\bar{\mathbf{u}})$  we can see that

$$\frac{1}{n} \|\mathbf{q}^0\|^2 = \frac{1}{n} \sum_{i \in [n]} (f_0(u_i^0))^2 \xrightarrow{n \rightarrow \infty} \mathbb{E} \left[ (f_0(\bar{\mathbf{u}}))^2 \right] \triangleq \sigma_1^2$$

- The term  $\frac{\mathbf{q}^0 \mathbf{q}^{0\top}}{\sqrt{n} \|\mathbf{q}^0\|} \boldsymbol{\xi}$  can be handled by writing

$$\begin{aligned} \frac{\mathbf{q}^0 \mathbf{q}^{0\top}}{\|\mathbf{q}^0\|^2} \boldsymbol{\xi} &= (\text{rank 1 projection matrix}) \times \mathcal{N}_n(0, I_n) \\ &\Rightarrow \frac{1}{\sqrt{n}} \left\| \frac{\mathbf{q}^0 \mathbf{q}^{0\top}}{\|\mathbf{q}^0\|^2} \boldsymbol{\xi} \right\| \xrightarrow{n \rightarrow \infty} 0 \end{aligned}$$

- Write

$$\mathbf{u}^1 \stackrel{\mathcal{L}}{=} \sigma_1 \boldsymbol{\xi} + \Delta^1$$

where  $\Delta^1 = \left( \frac{1}{\sqrt{n}} \|\mathbf{q}^0\| - \sigma_1 \right) \boldsymbol{\xi} + c \frac{\mathbf{q}^0 \mathbf{q}^{0\top}}{\sqrt{n} \|\mathbf{q}^0\|} \boldsymbol{\xi}$  such that  $\Delta^1 \approx 0$

Finally

$$\boxed{\mu^{\mathbf{u}^1} \approx \mu^{\sigma_1 \boldsymbol{\xi}} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_1), \quad Z_1 \sim \mathcal{N}(0, \sigma_1^2) \quad \text{where } \sigma_1^2 = \mathbb{E} \left[ f_0(\bar{\mathbf{u}})^2 \right]}$$

## Proof for $k = 2$

- We have  $\mu^{\mathbf{u}^1} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_1)$  where  $Z_1 \sim \mathcal{N}(0, \sigma_1^2)$  and  $\sigma_1^2 = \mathbb{E} \left[ f_0(\bar{u})^2 \right]$ .
- We want  $\mu^{\mathbf{u}^2} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_2)$  where  $Z_2 \sim \mathcal{N}(0, \sigma_2^2)$  and  $\sigma_2^2 = \mathbb{E} \left[ f_1(Z_1)^2 \right]$ .
- Recall the expression of  $\mathbf{u}^2$

$$\mathbf{u}^2 = \frac{A}{\sqrt{n}} f_1(\mathbf{u}^1) - \overbrace{\rho \langle f_1'(\mathbf{u}^1) \rangle f_0(\mathbf{u}^0)}^{\text{Onsager term}} = \boxed{\frac{A}{\sqrt{n}} \mathbf{q}^1 - \rho d_n \mathbf{q}^0}$$

- Notations

$$\mathbf{q}^1 = f_1(\mathbf{u}^1) \quad \text{and} \quad d_n = \frac{1}{n} \sum_{i \in [n]} f_1'(\mathbf{u}_i^1)$$

$$P_0 = \mathbf{q}^0 \mathbf{q}^{0\top} / \|\mathbf{q}^0\|^2 \quad \text{and} \quad P_0^\perp = I_n - P_0$$

- Structural decomposition

$$\begin{aligned} \mathbf{u}^2 &= A_n P_0 \mathbf{q}^1 + A_n P_0^\perp \mathbf{q}^1 - \rho d_n \mathbf{q}^0 \\ &= A_n P_0 \mathbf{q}^1 + \rho (A_n P_0)^\top P_0^\perp \mathbf{q}^1 - \rho d_n \mathbf{q}^0 + \left( A_n - \rho P_0 A_n^\top \right) P_0^\perp \mathbf{q}^1 \\ &= \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} \mathbf{u}^1 + \rho (A_n P_0)^\top \mathbf{q}^1 - \rho (A_n P_0)^\top P_0 \mathbf{q}^1 - \rho d_n \mathbf{q}^0 + \mathcal{I}(A) \\ &= \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} \mathbf{u}^1 + \rho \left( \langle \mathbf{u}^1, \mathbf{q}^1 \rangle - d_n \|\mathbf{q}^0\|^2 - \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} \langle \mathbf{u}^1, \mathbf{q}^0 \rangle \right) \frac{\mathbf{q}^0}{\|\mathbf{q}^0\|^2} + \mathcal{I}(A) \end{aligned}$$

## Proof for $k = 2$

$$\mathbf{u}^2 = \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} \mathbf{u}^1 + \rho \left( \langle \mathbf{u}^1, \mathbf{q}^1 \rangle - d_n \|\mathbf{q}^0\|^2 - \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} \langle \mathbf{u}^1, \mathbf{q}^0 \rangle \right) \frac{\mathbf{q}^0}{\|\mathbf{q}^0\|^2} + \mathcal{I}(A)$$

Recall that  $\mu^{\mathbf{u}^1} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_1)$  and  $\mu^{\mathbf{u}^0} \xrightarrow{n \rightarrow \infty} \mathcal{L}(\bar{u})$  such that  $Z_1 \sim \mathcal{N}(0, \sigma_1^2)$  and  $\bar{u}$  are independent random variables where  $\sigma_1^2 = \mathbb{E}[(f_0(\bar{u}))^2]$

- ▶  $\|\mathbf{q}^0\|^2/n = \frac{1}{n} \sum_{i \in [n]} f_0(u_i^0)^2 \xrightarrow{n \rightarrow \infty} \sigma_1^2.$
- ▶  $\langle \mathbf{q}^1, \mathbf{q}^0 \rangle / \|\mathbf{q}^0\|^2 = \frac{1}{\|\mathbf{q}^0\|^2} \frac{1}{n} \sum_{i \in [n]} f_1(u_i^1) f_0(u_i^0) \xrightarrow{n \rightarrow \infty} \underbrace{\frac{1}{\sigma_1^2} \mathbb{E}[f_1(Z_1) f_0(\bar{u})]}_{\triangleq \alpha_1}.$
- ▶  $d_n = \frac{1}{n} \sum_{i \in [n]} f_1'(u_i^1) \xrightarrow{n \rightarrow \infty} \mathbb{E}[f_1'(Z_1)].$
- ▶  $\frac{1}{n} \langle \mathbf{u}^1, \mathbf{q}^1 \rangle = \frac{1}{n} \sum_{i \in [n]} u_i^1 f_1(u_i^1) \xrightarrow{n \rightarrow \infty} \mathbb{E}[Z_1 f_1(Z_1)] \stackrel{\text{Stein}}{=} \sigma_1^2 \mathbb{E}[f_1'(Z_1)].$
- ▶  $\frac{1}{n} \langle \mathbf{u}^1, \mathbf{q}^0 \rangle = \frac{1}{n} \sum_{i \in [n]} u_i^1 f_0(u_i^0) \xrightarrow{n \rightarrow \infty} \mathbb{E}[Z_1 f_0(\bar{u})] = 0.$

Thus we can decompose  $\mathbf{u}^2$  in the following way

$$\boxed{\mathbf{u}^2 = \alpha_1 \mathbf{u}^1 + \mathcal{I}(A) + \Delta}$$

where  $\Delta = \rho \left( \langle \mathbf{u}^1, \mathbf{q}^1 \rangle - d_n \|\mathbf{q}^0\|^2 - \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} \langle \mathbf{u}^1, \mathbf{q}^0 \rangle \right) \frac{\mathbf{q}^0}{\|\mathbf{q}^0\|^2} + \left( \frac{\langle \mathbf{q}^1, \mathbf{q}^0 \rangle}{\|\mathbf{q}^0\|^2} - \alpha_1 \right)$

and  $\Delta \approx 0$

## Proof for $k = 2$

$$\mathbf{u}^2 = \underbrace{\alpha_1 \mathbf{u}^1 + \Delta}_{\mathcal{F}_1\text{-measurable}} + \mathcal{I}(\mathbf{A}) \quad \text{where} \quad \mathcal{F}_1 = \sigma(\{\mathbf{u}^0, \mathbf{u}^1\}) \quad \text{and} \quad \Delta \approx 0.$$

► **Question** What about the term  $\mathcal{I}(\mathbf{A}) = (\mathbf{A}_n - \rho P_0 \mathbf{A}_n^\top) P_0^\perp \mathbf{q}^1$  ?

### Lemma

Let  $\mathbf{A} \sim \text{Elliptic}(n, \rho)$ . Let  $\mathbf{v} \in \mathbb{R}^n$  be a unit-norm deterministic vector, and let  $P$  be a deterministic orthogonal projection matrix on a subspace of  $\mathbb{R}^n$  such that  $P\mathbf{v} = 0$ . Then,

$$(\mathbf{A} - \rho P \mathbf{A}^\top) \mathbf{v} \sim \mathcal{N}(0, I - \rho^2 P + \rho \mathbf{v} \mathbf{v}^\top).$$

$$(\mathbf{A} - \rho P \mathbf{A}^\top) \mathbf{v} \stackrel{\mathcal{L}}{=} \boldsymbol{\xi} + o(1) \quad \text{where} \quad \boldsymbol{\xi} \sim \mathcal{N}_n(0, I_n).$$

### Proposition (G., Hachem, Najim, 2024)

There exists a  $n \times n$  matrix  $\tilde{\mathbf{A}}$  such that  $\tilde{\mathbf{A}} \sim \text{Elliptic}(n, \rho)$ ,  $\tilde{\mathbf{A}} \perp \mathcal{F}_1$  and

$$(\mathbf{A} - \rho P_0 \mathbf{A}^\top) P_0^\perp \mathbf{q}^1 \stackrel{\mathcal{L}}{=}_{|\mathcal{F}_1} (\tilde{\mathbf{A}} - \rho P_0 \tilde{\mathbf{A}}^\top) P_0^\perp \mathbf{q}^1.$$

► Finally, we can write

$$\mathbf{u}^2 \stackrel{\mathcal{L}}{=}_{|\mathcal{F}_1} \alpha_1 \mathbf{u}^1 + \mathcal{I}(\tilde{\mathbf{A}}) + \Delta \quad \text{where} \quad \tilde{\mathbf{A}} \perp \mathcal{F}_1$$

$$\stackrel{\mathcal{L}}{=}_{|\mathcal{F}_1} \alpha_1 \mathbf{u}^1 + \|\mathbf{P}_0^\perp \mathbf{q}^1\| \boldsymbol{\xi} + \Delta$$



## Proof for $k = 2$

$$\mathbf{u}^2 \stackrel{\mathcal{L}}{=}_{|\mathcal{F}_1} \alpha_1 \mathbf{u}^1 + \|P_0^\perp \mathbf{q}^1\| \boldsymbol{\xi} + \Delta \quad \text{where} \quad \boldsymbol{\xi} \sim \mathcal{N}_n(0, I_n) \quad \text{and} \quad \Delta \approx 0$$

$$\text{and } \alpha_1 = \lim_{n \rightarrow \infty} |\langle \mathbf{q}^0, \mathbf{q}^1 \rangle| / \|\mathbf{q}^0\|^2$$

- Recall that by the induction hypothesis

$$\mu^{\mathbf{u}^1} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_1) \quad \text{where} \quad Z_1 \sim \mathcal{N}(0, \sigma_1^2)$$

$$\text{► } \frac{1}{n} \|P_0^\perp \mathbf{q}^1\|^2 = \frac{1}{n} \|\mathbf{q}^1\|^2 - \frac{1}{n} |\langle \mathbf{q}^0, \mathbf{q}^1 \rangle|^2 / \|\mathbf{q}^0\|^2 \xrightarrow{n \rightarrow \infty} \underbrace{\mathbb{E} \left[ f_1(Z_1)^2 \right]}_{\triangleq \sigma_2^2} - \alpha_1^2 \sigma_1^2$$

- Then

$$\mathbf{u}^2 \stackrel{\mathcal{L}}{=}_{|\mathcal{F}_1} \alpha_1 \mathbf{u}^1 + \sqrt{\sigma_2^2 - \alpha_1^2 \sigma_1^2} \boldsymbol{\xi} + \Delta \Rightarrow \mu^{\mathbf{u}^2} \xrightarrow{n \rightarrow \infty} \mathcal{L} \left( \alpha_1 Z_1 + \sqrt{\sigma_2^2 - \alpha_1^2 \sigma_1^2} \xi \right)$$

$$Z_1 \sim \mathcal{N}(0, \sigma_1^2) \perp \xi \sim \mathcal{N}(0, 1) \Rightarrow \alpha_1 Z_1 + \sqrt{\sigma_2^2 - \alpha_1^2 \sigma_1^2} \xi \sim \mathcal{N}(0, \sigma_2^2)$$

- Finally

$$\boxed{\mu^{\mathbf{u}^2} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_2)}$$

$$\text{where } Z_2 \sim \mathcal{N}(0, \sigma_2^2) \text{ and } \sigma_2^2 = \mathbb{E} \left[ f_1(Z_1)^2 \right]$$

## General case (Induction step)

- We prove the theorem by induction, we suppose that for certain  $k$  we have

$$\mu^{\mathbf{u}^k} = \frac{1}{n} \sum_{i \in [n]} \delta_{\mathbf{u}_i^k} \xrightarrow{n \rightarrow \infty} \mathcal{L}(Z_k) \quad \text{where } Z_k \sim \mathcal{N}(0, \sigma_k^2)$$

$(\sigma_k^2)_{k \in \mathbb{N}}$  is recursively defined by  $\sigma_k^2 = \mathbb{E}[f_{k-1}(Z_{k-1})^2]$  and  $Z_0 = \bar{u}$ .

- **Step 1** Decompose  $\mathbf{u}^{k+1}$  as follows

$$\mathbf{u}^{k+1} = \sum_{\ell=1}^k \alpha_{\ell} \mathbf{u}^{\ell} + \left( A - \rho P_k A^{\top} \right) P_k^{\perp} \mathbf{q}^k + o_{n \rightarrow \infty}(1),$$

where  $\mathbf{q}^k = f_k(\mathbf{u}^k)$  and  $P_k$  is the  $n \times n$  projection matrix on the space  $\text{Span}(\mathbf{q}^1, \dots, \mathbf{q}^k)$ . And  $P_k^{\perp} = I - P_k$ .

- **Step 2** Replace with an independent matrix  $\tilde{A}$

$$\left( A - \rho P_k A^{\top} \right) P_k^{\perp} \stackrel{\mathcal{L}}{=} \Big|_{\mathbf{u}^1, \dots, \mathbf{u}^k} \left( \tilde{A} - \rho P_k \tilde{A}^{\top} \right) P_k^{\perp},$$

Where  $\tilde{A} \stackrel{\mathcal{L}}{=} A$  and  $\tilde{A}$  is independent of the past  $\{\mathbf{u}^1, \dots, \mathbf{u}^k\}$ .

- **Step 3** Condition on the past and apply induction hypothesis

$$\mathbf{u}^{k+1} \stackrel{\mathcal{L}}{=} \Big|_{\mathbf{u}^1, \dots, \mathbf{u}^k} \sum_{i=1}^k \alpha_i \mathbf{u}^i + \left( \tilde{A} - \rho P_k \tilde{A}^{\top} \right) P_k^{\perp} \mathbf{q}^k + o_{n \rightarrow \infty}(1).$$

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## Existence of a stable equilibrium

### Theorem (Takeuchi and Adachi (1980))

*If there exists a positive diagonal matrix  $\Delta$  such that  $\Delta M + M^\top \Delta$  is positive definite, then there exists a **unique** and **stable** equilibrium of the Lotka-Volterra system.*

### Lemma

*Let  $A$  an elliptic matrix with coefficient  $\rho$  and  $\alpha > \sqrt{2(1+\rho)}$ , then*

*$\left(I - \frac{A}{\alpha\sqrt{n}}\right) + \left(I - \frac{A}{\alpha\sqrt{n}}\right)^\top$  is a.s. positive definite.*

### Proof.

Let  $\Delta = I$ ,

$$\left(I - \frac{A}{\alpha\sqrt{n}}\right) + \left(I - \frac{A}{\alpha\sqrt{n}}\right)^\top = 2I - \frac{A + A^\top}{\alpha\sqrt{n}}$$



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$A$  is  $\rho$ -elliptic  $\Rightarrow A_{ij} + A_{ji} \sim \mathcal{N}(0, 2(1+\rho))$

□

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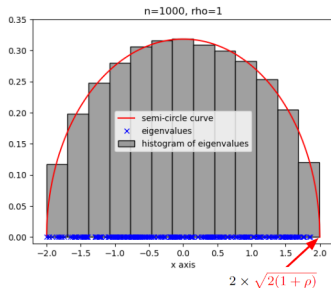
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Let  $\Delta = I$ ,

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$$\lambda_{\max}\left(\frac{A + A^\top}{\sqrt{n}}\right) \xrightarrow{n \rightarrow \infty} 2 \times \sqrt{2(1+\rho)}$$



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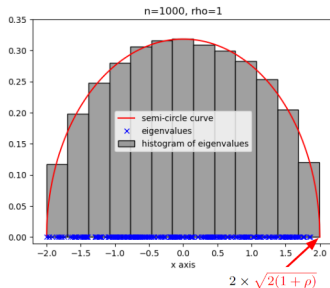
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$\left(I - \frac{A}{\alpha\sqrt{n}}\right) + \left(I - \frac{A}{\alpha\sqrt{n}}\right)^\top$  is a.s. positive definite.

## Proof.

Let  $\Delta = I$ ,

$$\begin{aligned} 2I - \frac{A + A^\top}{\alpha\sqrt{n}} \\ \lambda_{\max} \left( \frac{A + A^\top}{\sqrt{n}} \right) &\xrightarrow{n \rightarrow \infty} 2 \times \sqrt{2(1+\rho)} \\ \lambda_{\min} \left( 2I - \frac{A + A^\top}{\alpha\sqrt{n}} \right) &= 2 - \frac{1}{\alpha} \lambda_{\max} \left( \frac{A + A^\top}{\sqrt{n}} \right) \\ &\approx 2 - \frac{2\sqrt{2(1+\rho)}}{\alpha} \end{aligned}$$



□



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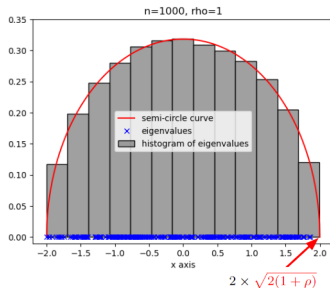
$\left(I - \frac{A}{\alpha\sqrt{n}}\right) + \left(I - \frac{A}{\alpha\sqrt{n}}\right)^\top$  is a.s. positive definite.

## Proof.

Let  $\Delta = I$ ,

$$\lambda_{\min} \left( 2I - \frac{A + A^\top}{\alpha\sqrt{n}} \right) \approx 2 - \frac{2\sqrt{2(1+\rho)}}{\alpha} > 0$$

$\alpha > \sqrt{2(1+\rho)}$



## Proportion of surviving species

Given  $\alpha > \sqrt{2(1+\rho)}$ , we have  $\mu^{x_n^*} \xrightarrow{n \rightarrow \infty} \pi := \mathcal{L} \left( (1 + \rho\gamma/\delta^2) (\sigma\bar{Z} + \bar{r})_+ \right)$  i.e.

$$\forall \varphi \in \mathcal{C}_b \quad \frac{1}{n} \sum_{i=1}^n \varphi(x_i^*) \xrightarrow{n \rightarrow \infty} \mathbb{E} \left[ \varphi \left( (1 + \rho\gamma/\delta^2) (\sigma\bar{Z} + \bar{r})_+ \right) \right]$$

In particular, the proportion of surviving species can be accessed via  $\varphi(x) = \mathbf{1}_{x>0}$ .

$$\frac{\#\{i : x_i^* > 0\}}{n} \xrightarrow{n \rightarrow \infty} \mathbb{P} [\sigma\bar{Z} + r > 0] = \gamma.$$

# Elliptic Approximate Message Passing

## Theorem (G., Hachem, Najim, 2023)

The AMP recursion for a  $\rho$ -**elliptic matrix**  $A$  is defined as

$$\mathbf{u}^{k+1} = \frac{A}{\sqrt{n}} f_k(\mathbf{u}^k, \mathbf{a}) - \rho \langle f'_k(\mathbf{u}^k, \mathbf{a}) \rangle f_{k-1}(\mathbf{u}^{k-1}, \mathbf{a})$$

Then

$$(a.s) \quad \mu^{\mathbf{u}^1, \dots, \mathbf{u}^k} = \frac{1}{n} \sum_{i=1}^n \delta_{(u_i^1, \dots, u_i^k)} \xrightarrow[N \rightarrow \infty]{weak, L^2} (Z_1, \dots, Z_k) \sim \mathcal{N}_k(\mathbf{0}, \Gamma^k)$$

where  $\Gamma^k$  is defined recursively (**State Evolution Equations**).

## State Evolution Equations

The  $k \times k$  covariance matrices  $\Gamma^k$  are recursively defined as follows

$$\Gamma_{ij}^k = \mathbb{E}[f_{i-1}(Z_{i-1}) f_{j-1}(Z_{j-1})] \text{ where } (Z_1, \dots, Z_k) \sim \mathcal{N}_{k-1}(\mathbf{0}, \Gamma^{k-1}).$$

In particular

$$\mathbb{E}[Z_{k+1}^2] = \mathbb{E}[(f_k(Z_k))^2]$$