

Kac-Rice fixed point analysis for large complex systems

Jesper R. Ipsen
The University of Melbourne

Random Matrices, Integrability, and Complex Systems
Yad Hashmona, October 2018

Outline

What? Counting fixed points in large complex systems

Why? Stability analysis of large complex systems

How? Kac–Rice formalism + random matrix techniques

What is a complex system?

Complex systems

Discrete time dynamical systems represent a paradigm in the study of complex and chaotic systems

$$x_{n+1} = f(x_n)$$

- $f : \mathbb{R}^N \rightarrow \mathbb{R}^N$ is some “complicated” map
- $x_n \in \mathbb{R}^N$ is a point in space at time $n > 0$
- x_0 is an initial condition

Will a large complex system be stable?

The random linear model

Random linear model (version 1):

$$f(x) = \mathbf{G} \cdot x$$

- \mathbf{G} is an $N \times N$ matrix whose entries are i.i.d. centred Gaussians with variance σ^2/N .

Random linear model (version 2):

where $\mathbb{E}[f(x)] = 0$ $\mathbb{E}[f(x) \otimes (f(y))^T] = \frac{\sigma^2}{N} (x \cdot y) \mathbf{I}_N$

- $x \cdot y$ is the usual Euclidean inner product
- \mathbf{I}_N is an $N \times N$ identity matrix

The random linear model

Spectral radius

$$\rho(\sigma) = \max\{|\lambda| : \lambda \text{ is a eigenvalue of } \mathbf{G}\}$$

- If $\rho(\sigma) < 1$ then the linear model is stable
- If $\rho(\sigma) > 1$ then the linear models is unstable

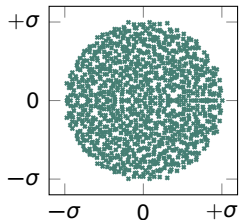
May-Wigner transition:

Spectral radius

$$\lim_{N \rightarrow \infty} \rho(\sigma) = \sigma$$

The large- N linear model is

- stable if $\sigma < 1$
- unstable if $\sigma > 1$



1 000 × 1 000 matrix

How to construct a nonlinear model?

Symmetries of the random linear model

The random linear model is defined by

$$\mathbb{E}[f(x)] = 0, \quad \mathbb{E}[f(x) \otimes (f(y))^T] = \frac{\sigma^2}{N} (x \cdot y) \mathbf{I}_N$$

where

- $x \cdot y$ is the usual Euclidean inner product
- \mathbf{I}_N is an $N \times N$ identity matrix

Symmetries:

- domain-isotropic

$$\mathbb{E}[f(Ux) \otimes (f(Uy))^T] = \mathbb{E}[f(x) \otimes (f(y))^T], \quad \forall U \in O(N)$$

- codomain-isotropic

$$\mathbb{E}[Vf(x) \otimes (Vf(y))^T] = \mathbb{E}[f(x) \otimes (f(y))^T], \quad \forall V \in O(N)$$

The nonlinear model

Let f be centred Gaussian random map with covariance

$$\mathbb{E}[f(x) \otimes f(y)^T] = \frac{1}{N} \kappa\left(\frac{\|x - y\|^2}{2}\right) \mathbf{I}_N$$

where

- $\|\bullet\|$ is the Euclidean norm
- $\kappa : \mathbb{R}_+ \rightarrow \mathbb{R}_+$ is a “nice” function

Symmetries:

- domain-isotropy
- codomain-isotropy
- homogeneity

$$\mathbb{E}[f(x + a) \otimes (f(y + a))^T] = \mathbb{E}[f(x) \otimes f(y)^T] \quad \forall a \in \mathbb{R}^N$$

**How many fixed point
does a complex system have?**

Mean number of fixed points

Theorem

Let \mathcal{N}_f be an integer valued random variable, which gives the number of fixed points for the dynamical system described earlier, then we have

$$\mathbb{E}[\mathcal{N}_f] = \mathbb{E}_{\mathbf{G}}[|\det(\sigma\mathbf{G} - \mathbf{I}_N)|]$$

where

- \mathbf{G} is an $N \times N$ matrix whose entries are i.i.d. centred Gaussian random variables with variance $1/N$
- $\mathbb{E}_{\mathbf{G}}$ is the expectation w.r.t. \mathbf{G}
- \mathbf{I}_N is the $N \times N$ identity matrix
- $\sigma = (-\kappa'(0))^{1/2} > 0$ is a constant

Sketch of derivation (part I)

Our problem of finding the number of fixed points is equivalent to the multivariate crossing problem

$$0 = f(x) - x$$

Multivariate Kac–Rice formula:

$$\mathbb{E}[\mathcal{N}_f] = \int_{\mathbb{R}^N} \mathbb{E}_{f, \nabla f} \left[\delta^N(f(x) - x) \left| \det(\partial_i f_j(x) - \delta_{i,j}) \right| \right] dx$$

where

- $\nabla f = (\partial_j f_i)_{ij}$ is a $\mathbb{R}^{N \times N}$ -valued Gaussian random map
- $\mathbb{E}_{f, \nabla f}$ is the joint expectation w.r.t. f and ∇f
- δ_{ij} is the Kronecker delta
- $\delta^N(x)$ is a Dirac delta

Sketch of derivation (part II)

We recall that we have the covariance

$$\mathbb{E}[f_i(x)f_j(y)] = \frac{1}{N}\kappa\left(\frac{\|x-y\|^2}{2}\right)\delta_{ij}$$

and consequently

$$\mathbb{E}[f_i(x)f_j(x)] = +\frac{1}{N}\kappa(0)\delta_{ij}$$

$$\mathbb{E}[\partial_k f_i(x)f_j(x)] = 0$$

$$\mathbb{E}[\partial_k f_i(x)\partial_l f_j(x)] = -\frac{1}{N}\kappa'(0)\delta_{ij}\delta_{kl}$$

- The fields $f(x)$ and $\nabla f(x)$ are uncorrelated and therefore independent
- The variance of $f(x)$ and $\nabla f(x)$ does not depend on the location x

Sketch of derivation (part III)

$$\begin{aligned}\mathbb{E}[\mathcal{N}_f] &= \int_{\mathbb{R}^N} \mathbb{E}_{f, \nabla f} \left[\delta^N(f(x) - x) \left| \det(\partial_i f_j(x) - \delta_{i,j}) \right| \right] dx \\ &= \int_{\mathbb{R}^N} \mathbb{E}_f \left[\delta^N(f(x) - x) \right] \mathbb{E}_{\nabla f} \left[\left| \det(\partial_i f_j(x) - \delta_{i,j}) \right| \right] dx \\ &= \int_{\mathbb{R}^N} \mathbb{E}_f \left[\delta^N(f(0) - x) \right] \mathbb{E}_{\nabla f} \left[\left| \det(\partial_i f_j(0) - \delta_{i,j}) \right| \right] dx \\ &= \mathbb{E}_{\mathbf{G}} \left[\left| \det(\sigma \mathbf{G} - \mathbf{I}_N) \right| \right]\end{aligned}$$

where $\mathbf{G} = (G_{ki} = \partial_k f_i(0)/\sigma)_{ki}$ is a centred Gaussian random matrix with covariance

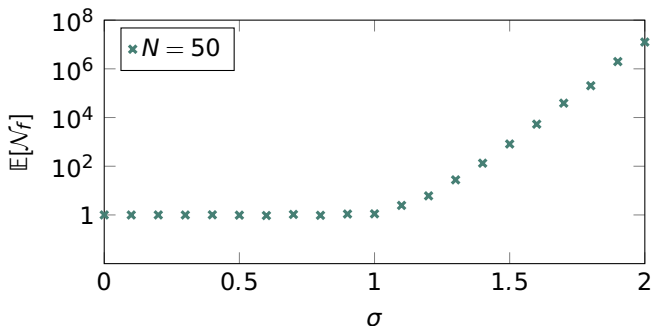
$$\mathbb{E}_{\mathbf{G}}[G_{ki}G_{lj}] = \frac{1}{N} \delta_{ij} \delta_{kl}$$

How many fixed points does complex system have?

We recall that

$$\mathbb{E}[\mathcal{N}_f] = \mathbb{E}_{\mathbf{G}}[|\det(\sigma \mathbf{G} - \mathbf{I}_N)|]$$

where right-hand side is easy to estimate numerically



Multi-layered systems

Multilayered systems

Let f_1, \dots, f_D be independent Gaussian maps as described earlier, i.e.

- domain-isotropic
- codomain-isotropic
- homogeneous

Consider a dynamical system $x_{n+1} = f(x_n)$. If

$$f(x) = f_D \circ \dots \circ f_2 \circ f_1(x),$$

then we say that the system is multilayered with depth D .

If $D = 1$, then we say that the system is single-layered.

Mean number of fixed points

Theorem

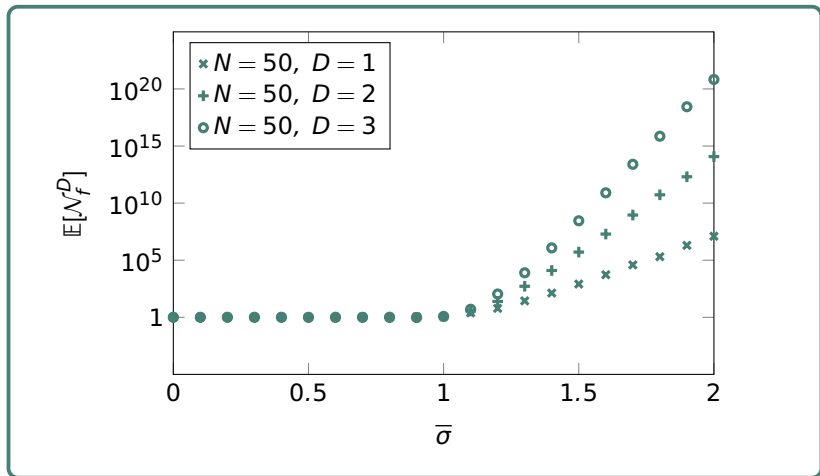
Let \mathcal{N}_f^D be an integer valued random variable, which gives the number of fixed points for the dynamical system described earlier, then we have

$$\mathbb{E}[\mathcal{N}_f^D] = \mathbb{E}_{\mathbf{G}_1, \dots, \mathbf{G}_D} [|\det(\bar{\sigma}^D \mathbf{G}_1 \cdots \mathbf{G}_D - \mathbf{I}_N)|]$$

where

- $\mathbf{G}_1, \dots, \mathbf{G}_D$ are independent $N \times N$ matrices whose entries are i.i.d. centred Gaussian random variables with variance $1/N$
- $\mathbb{E}_{\mathbf{G}_1, \dots, \mathbf{G}_D}$ is the joint expectation w.r.t. $\mathbf{G}_1, \dots, \mathbf{G}_D$
- $\bar{\sigma} = (\sigma_1 \cdots \sigma_D)^{1/D}$ is the geometric mean
- $\sigma_d = (-\kappa'_d(0))^{1/2} > 0$ is a constant

Number of fixed points for a multilayered system



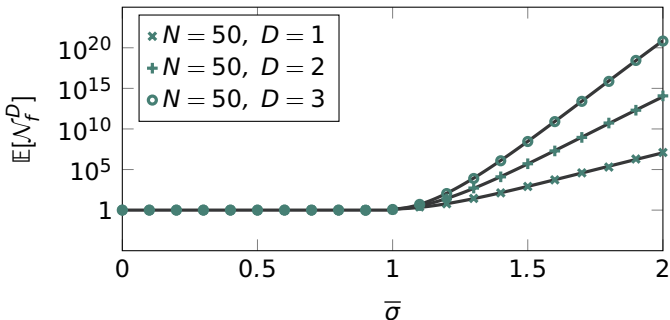
Asymptotic results for large systems

The high dimensional case

We have

$$\mathbb{E}[\mathcal{N}_f^D] \sim \begin{cases} \sqrt{2} e^{ND(\log \bar{\sigma} + \frac{1}{2}(\frac{1}{\bar{\sigma}^2} - 1))}, & \bar{\sigma} > 1 \\ 1, & \bar{\sigma} < 1 \end{cases}$$

for large N .

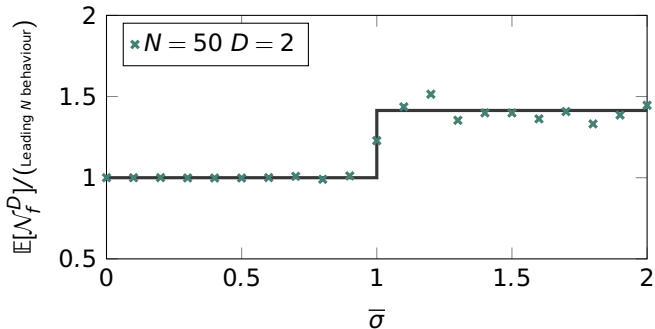


The high dimensional case

We have

$$\mathbb{E}[\mathcal{N}_f^D] \sim \begin{cases} \sqrt{2} e^{ND(\log \bar{\sigma} + \frac{1}{2}(\frac{1}{\bar{\sigma}^2} - 1))}, & \bar{\sigma} > 1 \\ 1, & \bar{\sigma} < 1 \end{cases}$$

for large N .



Sketch of derivation of asymptotic result (Part I)

We are interested in the quantity

$$\mathbb{E}_{\mathbf{X}}[|\det(\mathbf{X} - \lambda \mathbf{I}_N)|]$$

where \mathbf{X} is an asymmetric random matrix.

Assume \mathbf{X} has n real and $2m$ complex eigenvalues

- $\lambda_1, \dots, \lambda_n$: real eigenvalues
- $z_1, z_1^*, \dots, z_m, z_m^*$: complex eigenvalues

and the JPDF for the eigenvalues is

$$P_{N,n}(\lambda_1, \dots, \lambda_n, z_1, \dots, z_m) = \frac{1}{n!m!} \frac{1}{Z_N} \prod_{k=1}^n w_{\mathbb{R}}(\lambda_k) \prod_{l=1}^m w_{\mathbb{C}}(z_l) \times |\Delta(\lambda_1, \dots, \lambda_n, z_1, z_1^*, \dots, z_m, z_m^*)|$$

Sketch of derivation of asymptotic result (Part II)

We are interested in the quantity

$$\mathbb{E}_{\mathbf{X}}[|\det(\mathbf{X} - \lambda \mathbf{I}_N)|]$$

where \mathbf{X} is an asymmetric random matrix.

Lemma

$$\mathbb{E}_{\mathbf{X}}[|\det(\mathbf{X} - \lambda \mathbf{I}_N)|] = \frac{1}{w_{\mathbb{R}}(\lambda)} \frac{Z_{N+1}}{Z_N} \rho_{\mathbb{R}, N+1}(\lambda)$$

where $\rho_{\mathbb{R}, N}(\lambda)$ is the mean spectral density of the real eigenvalues of $N \times N$ matrix

The proof the lemma is based on the trivial identity

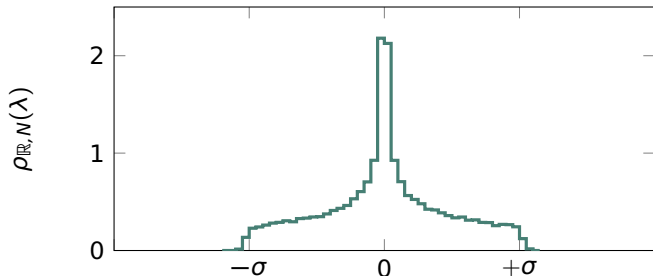
$$\Delta(x_0, x_1, \dots, x_N) = \Delta(x_1, \dots, x_N) \prod_{k=1}^N (x_k - x_0).$$

Sketch of derivation of asymptotic result (Part III)

We are interested in the quantity

$$\mathbb{E}_{\mathbf{X}}[|\det(\mathbf{X} - \lambda \mathbf{I}_n)|] = \frac{1}{w_{\mathbb{R}}(\lambda)} \frac{Z_{N+1}}{Z_N} \rho_{\mathbb{R}, N+1}(\lambda)$$

where \mathbf{X} is an asymmetric random matrix.



Summary

Summary

Similarly to May's random linear model, our non-linear model has a **phase transition** at the critical point $\bar{\sigma}_c = 1$.

- If $\bar{\sigma} < 1$ our non-linear system has a single fixed point
- If $\bar{\sigma} > 1$ then the number of fixed points grows exponentially fast with N

The expected number of fixed points is **universal** in the sense that does not depend on the full structure of the covariance functions

$$\kappa_1, \dots, \kappa_D : \mathbb{R}_+ \rightarrow \mathbb{R}_+$$

but only on local quantity

$$\bar{\sigma} = ((-\kappa'_1(0)) \cdots (-\kappa'_D(0)))^{1/D}$$

References

- Ipsen & Forrester, arXiv:1807.05790
- Ipsen & Kieburg, PRE 89 (2014) 032106
- Forrester & Ipsen, LAA 510 (2016) 259
- May, Nature 238 (1972) 413
- Fyodorov & Khoruzhenko, PNAS 113 (2016) 6827
- Simm, ECP 22 (2017) 11

Thanks for your attention!