

# State Space Structure of Random Recurrent Neuronal Networks

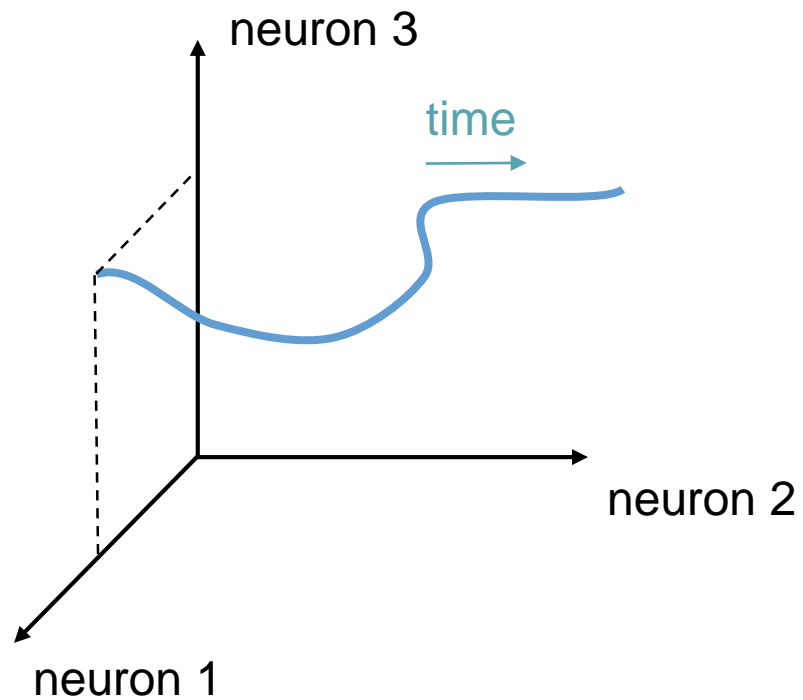
Alexander van Meegen

Current affiliation: Harvard University

Work done at: Jülich Research Centre

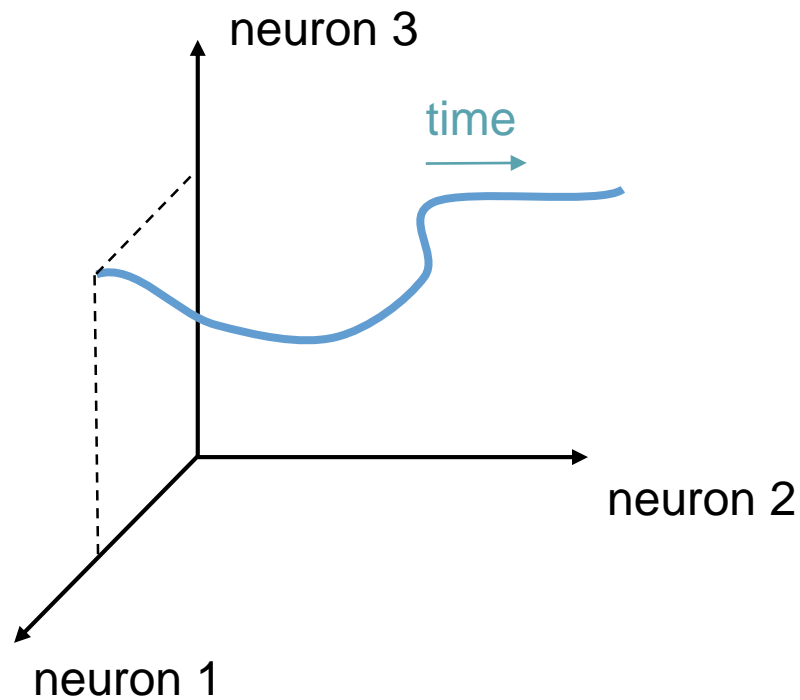
# Neural Networks as Dynamical Systems

state space

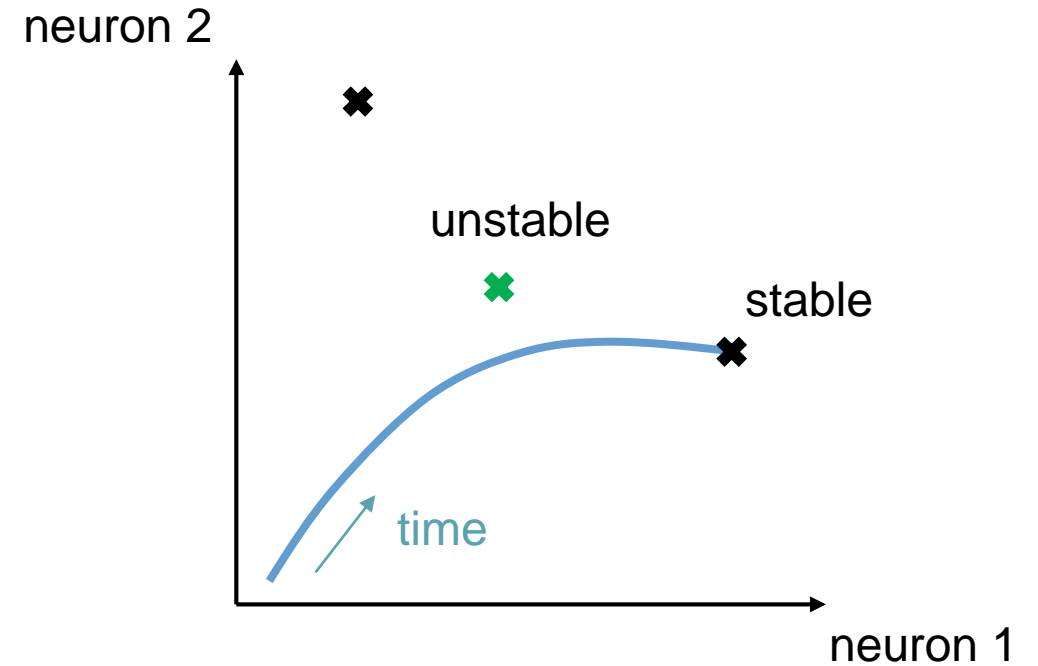


# Neural Networks as Dynamical Systems

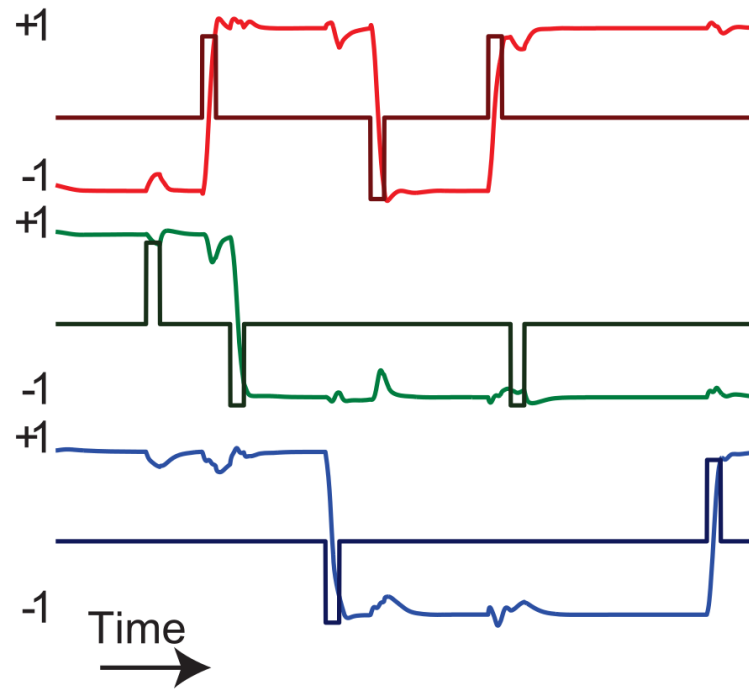
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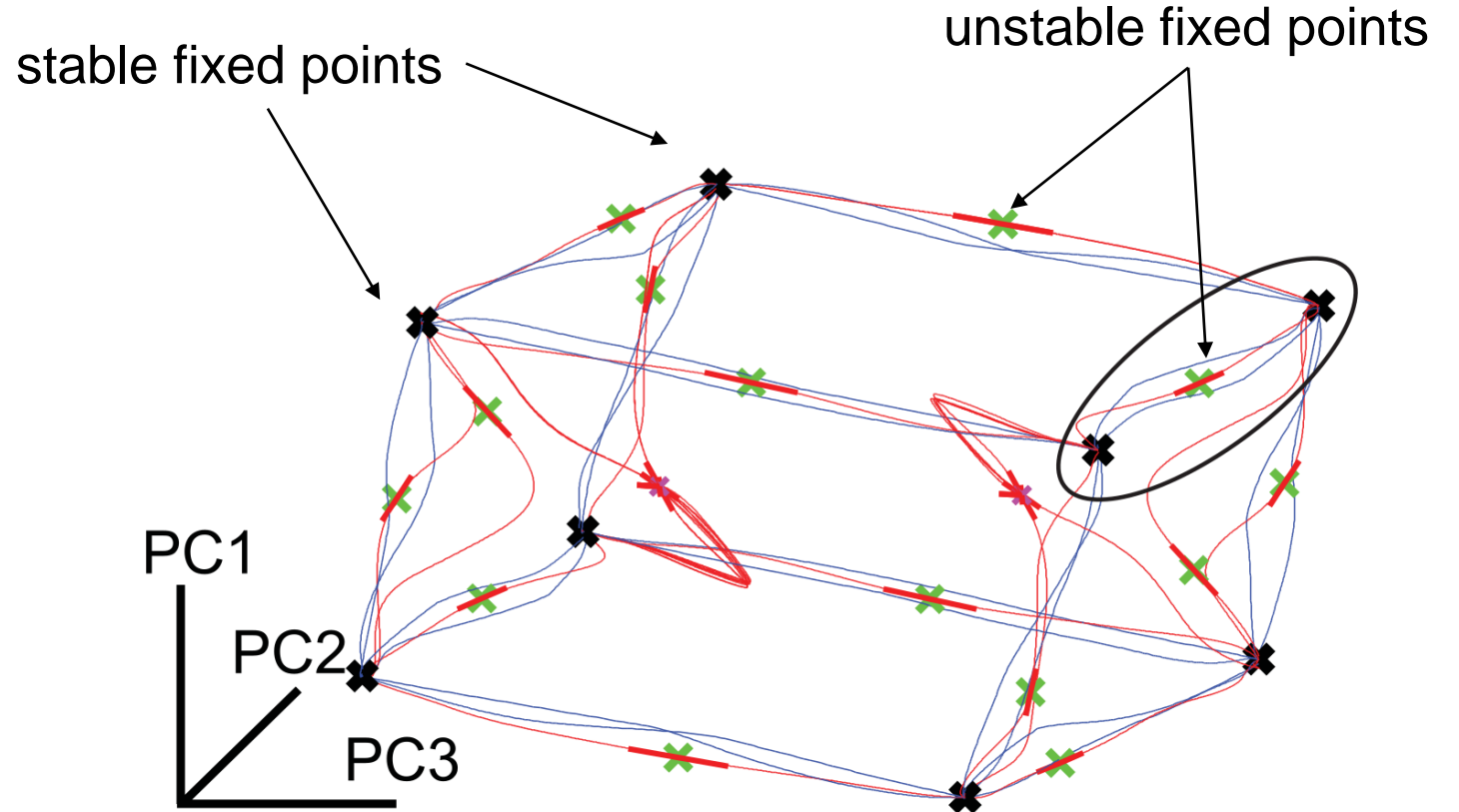
fixed points



# Opening the Black Box

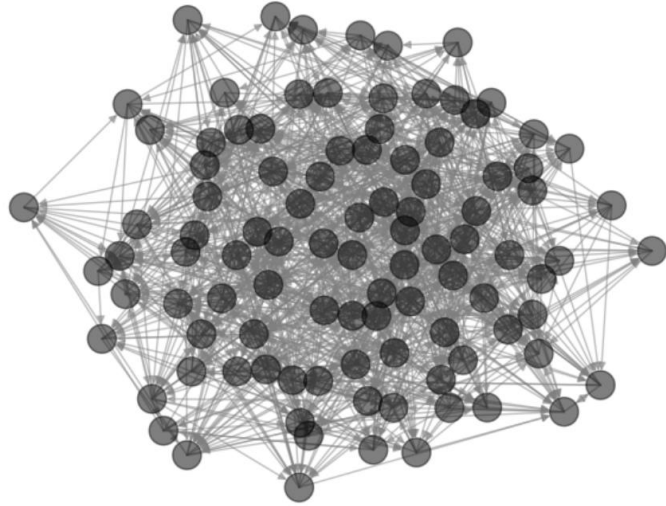


Sussillo & Barak; Neural Comput. (2013), Fig. 2



Sussillo & Barak; Neural Comput. (2013), Fig. 3

# Random Recurrent Neuronal Networks



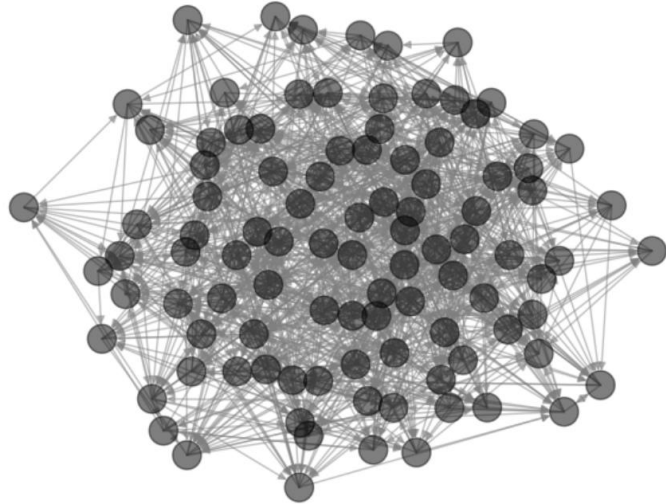
$$\dot{x}_i = -x_i$$

exponential  
relaxation

$$+ \sum_{j=1}^N J_{ij} \phi(x_j)$$

i.i.d. Gaussian coupling  
weights with strength  $g$ ,  
tanh transfer function

# Random Recurrent Neuronal Networks



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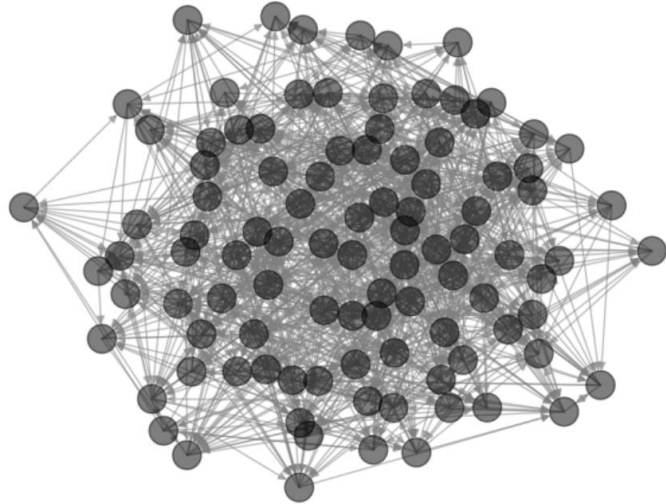
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- Dynamical Mean-Field Theory Sompolinsky, Crisanti, Sommers; Phys. Rev. Lett. (1988)
  - Activity statistics: temporal autocorrelation
  - Chaos above critical connection strength  $g_c$

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- Dynamical Mean-Field Theory
  - Activity statistics: temporal autocorrelation
  - Chaos above critical connection strength  $g_c$
- State space & fixed points:
  - Exponential number of unstable fixed points
  - *Where are the fixed points in phase space?*

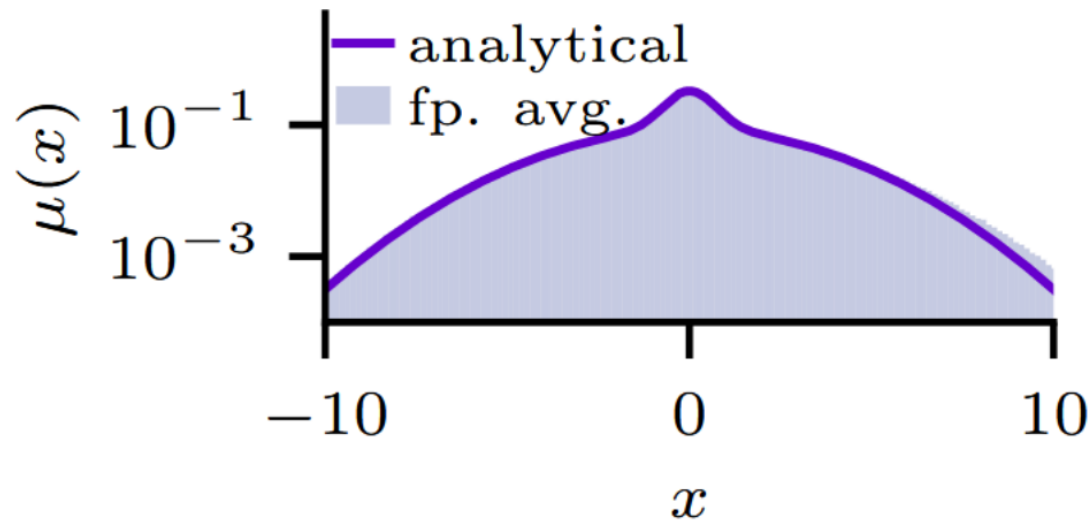
Sompolinsky, Crisanti, Sommers; Phys. Rev. Lett. (1988)

Wainrib & Touboul; Phys. Rev. Lett. (2013)

# Distribution of Fixed Points

- Random network  $\rightarrow$  *distribution* of fixed points in state space
- Approach: Kac-Rice formula  $\rightarrow$  random matrix problem

Distribution of fixed-point coordinates (of  $\sim 40,000$  fixed points for  $N = 100$ )

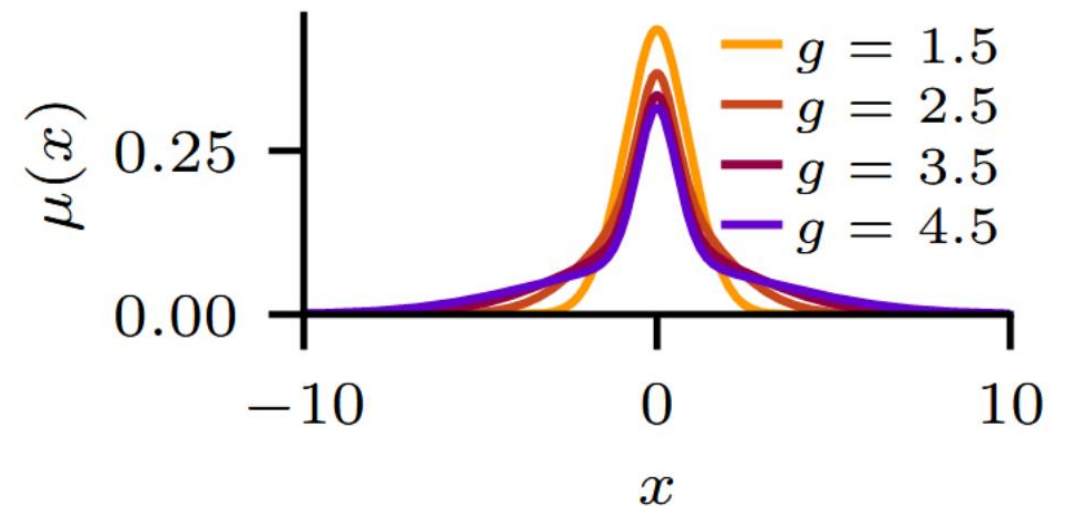
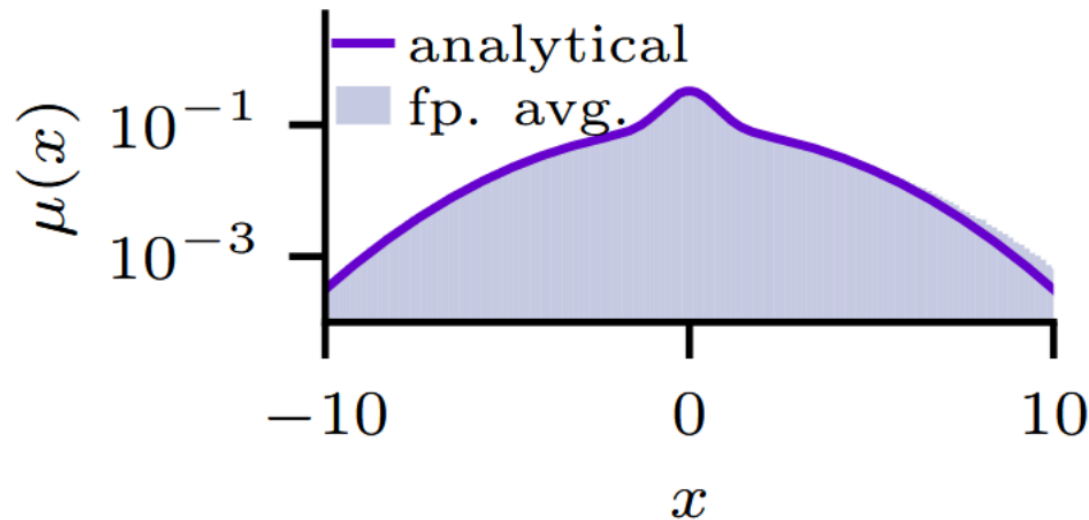




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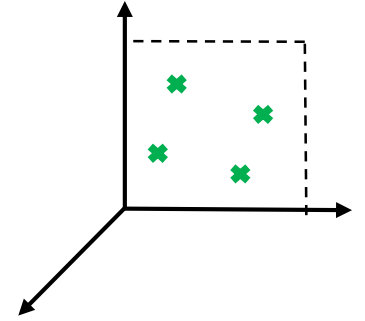
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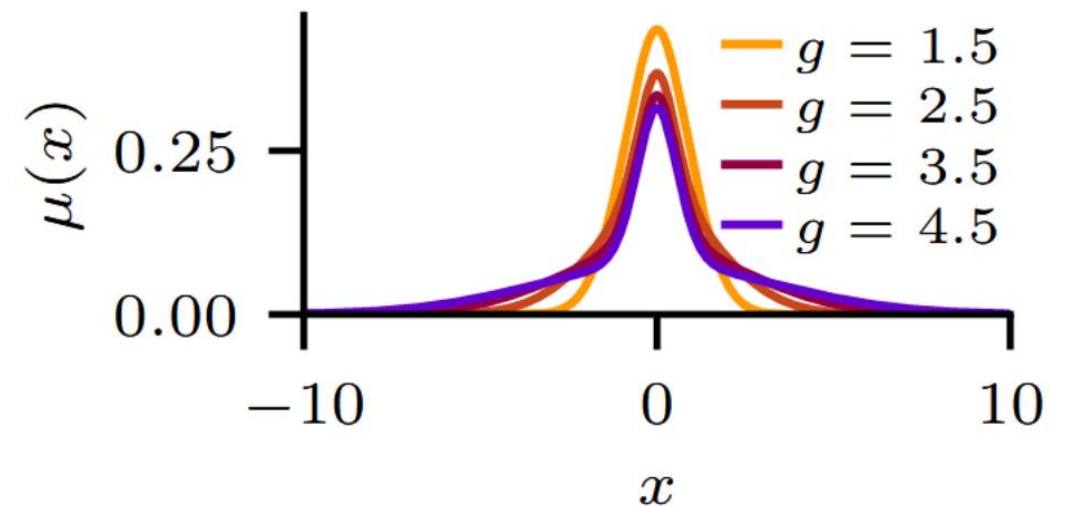
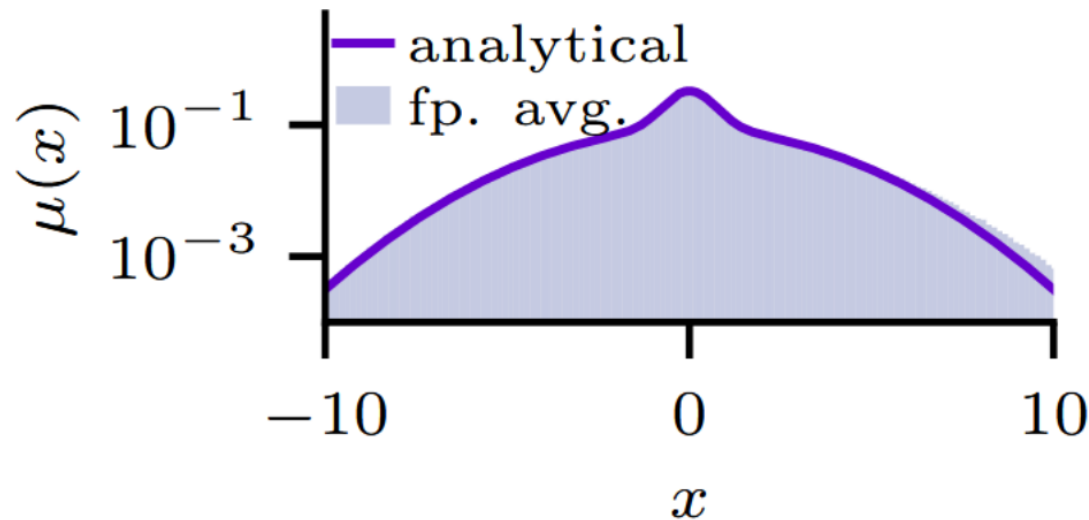
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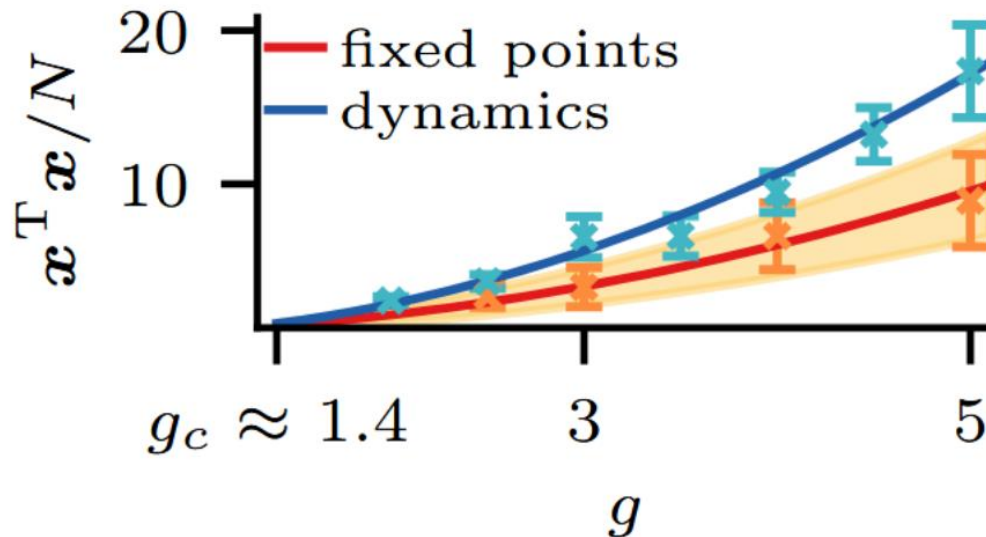
peak at zero:  
fixed points in the span  
of a subset of the axes

Distribution of fixed-point coordinates (of  $\sim 40,000$  fixed points)



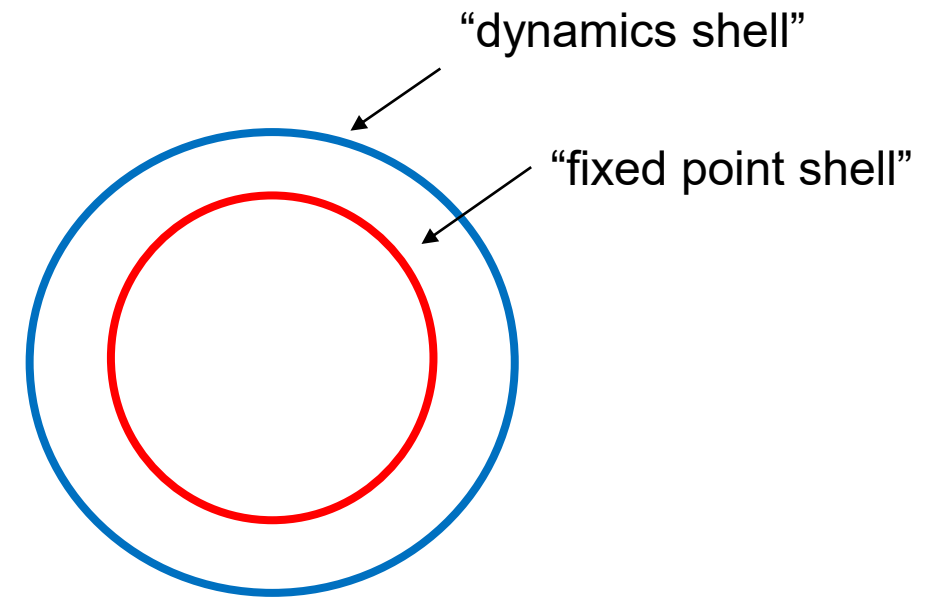
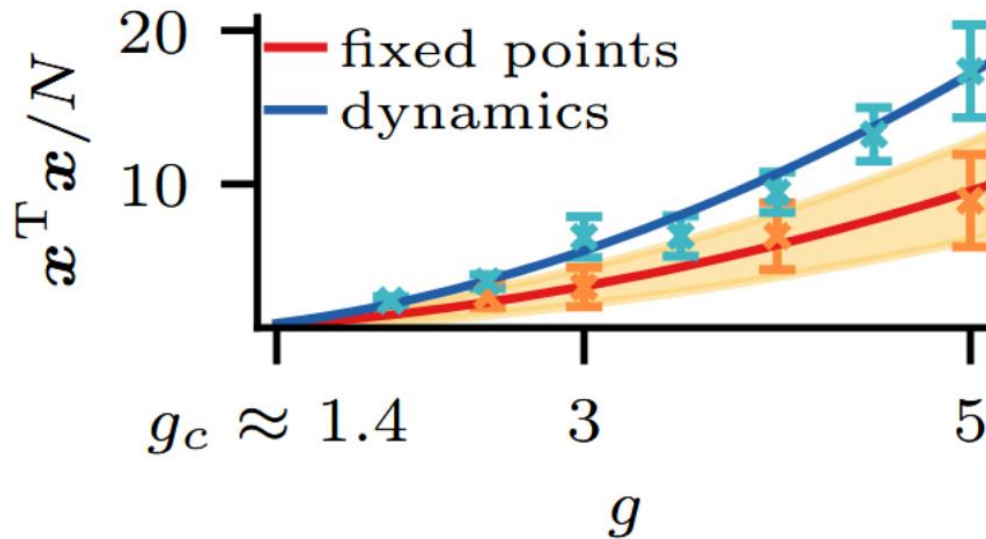
# Separation of Fixed Points and Dynamics

- Distance from origin in state space
  - Dynamics: Zero-lag autocorrelation from Dynamical Mean-Field Theory
  - Fixed points: From distribution of fixed points



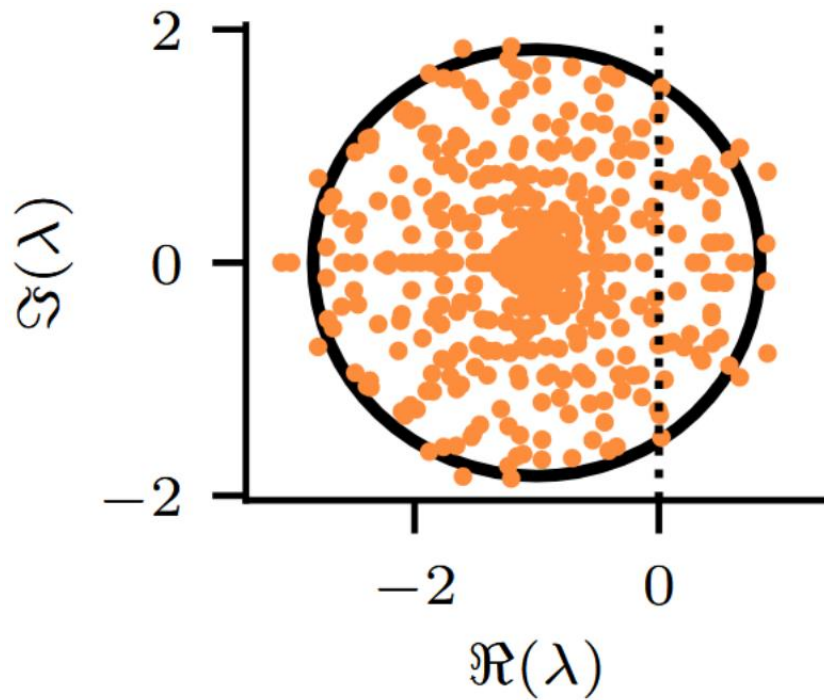
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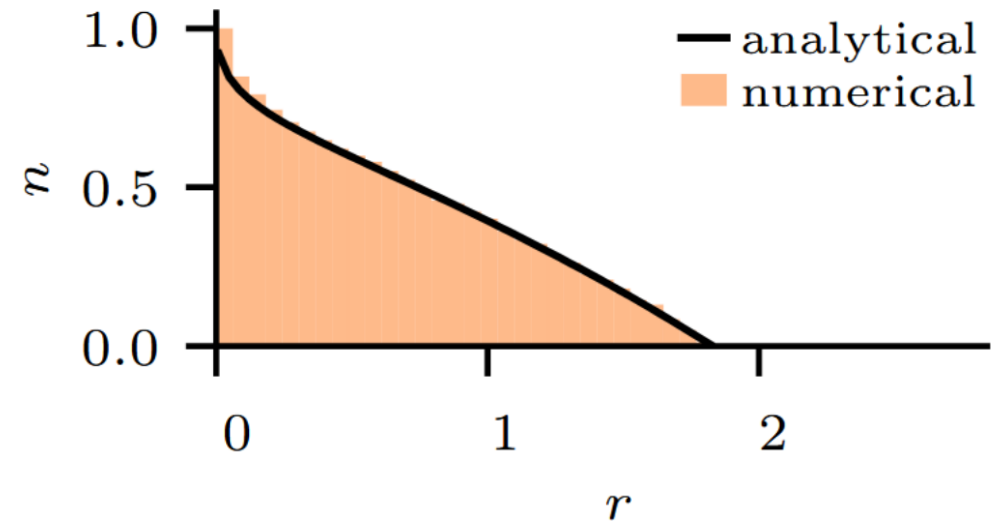


# Linearized Dynamics

Jacobian spectrum at fixed points



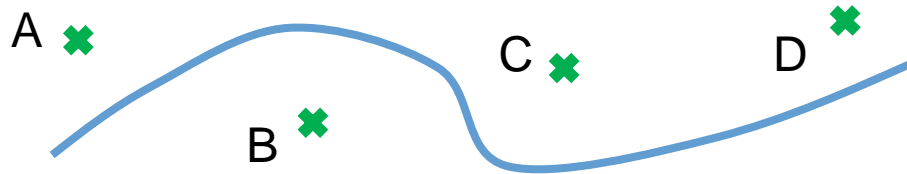
Radial eigenvalue distribution



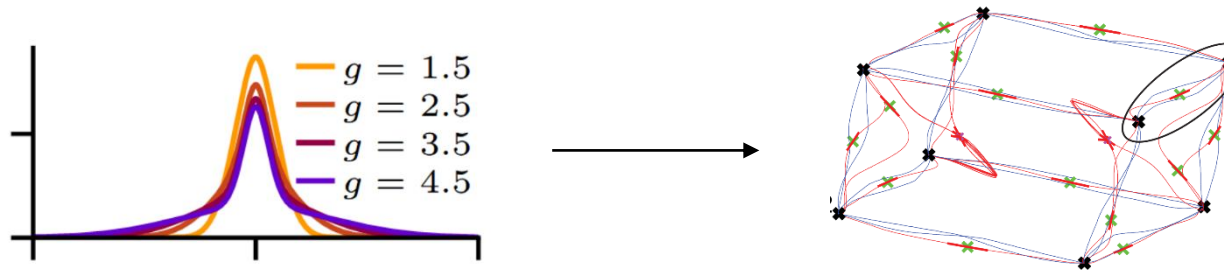
# Summary & Outlook

- Analytical calculation of fixed point distribution for random recurrent network
  - Located in the span of a subset of axes; radial separation in state space
  - Linearized dynamics (Jacobian)
- Structural backbone for sequence processing

Rabinovich, Huerta, Laurent; Science (2008)



- How does training shape the state space structure of the network?



# The Team



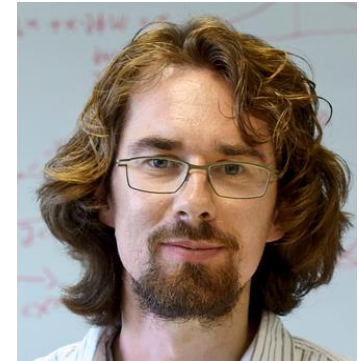
**Jakob Stubenrauch**



Christian Keup



Anno Kurth



Moritz Helias

Details: Stubenrauch, Keup, Kurth, Helias, van Meegen; arXiv 2210.07877 (2022)

# Kac-Rice Formula

$$\dot{\boldsymbol{x}} = \boldsymbol{y}(\boldsymbol{x})$$

$$\boldsymbol{y}(\boldsymbol{x}) = -\boldsymbol{x} + \mathbf{J}\phi(\boldsymbol{x}) + \boldsymbol{\eta}$$

Counting fixed points

$$N_{\text{fp}}(V) = \int_V d\boldsymbol{x} \, \delta[\boldsymbol{y}(\boldsymbol{x})] |\det \boldsymbol{y}'(\boldsymbol{x})|$$

Kac-Rice formula

$$\rho(\boldsymbol{x}) = \langle \delta[\boldsymbol{y}(\boldsymbol{x})] |\det \boldsymbol{y}'(\boldsymbol{x})| \rangle_{\mathbf{J}, \boldsymbol{\eta}}$$

$$\rho(\boldsymbol{x}) = \int d\boldsymbol{y}' \, p_{\boldsymbol{x}}(\boldsymbol{y} = 0, \boldsymbol{y}') |\det \boldsymbol{y}'|$$



# Velocity & Jacobian Statistics

$$\mathbf{y}(\mathbf{x}) = -\mathbf{x} + \mathbf{J}\phi(\mathbf{x}) + \boldsymbol{\eta}$$

$$\mathbf{y}'(\mathbf{x}) = -\mathbb{1} + \mathbf{J} \operatorname{diag} [\phi'(\mathbf{x})]$$

$$\langle y_i(\mathbf{x}) \rangle = -x_i \equiv \mu_i(\mathbf{x}), \quad \langle [\mathbf{y}'(\mathbf{x})]_{ik} \rangle = -\delta_{ik} \equiv [\boldsymbol{\mu}_i(\mathbf{x})]_k$$

$$\langle \langle y_i(\mathbf{x}) y_j(\mathbf{x}) \rangle \rangle = \delta_{ij} \left[ \frac{g^2}{N} \sum_k \phi(x_k)^2 + D \right] \equiv \delta_{ij} [\kappa(\mathbf{x}) + D]$$

$$\langle \langle y_i(\mathbf{x}) [\mathbf{y}'(\mathbf{x})]_{jk} \rangle \rangle = \frac{g^2}{N} \delta_{ij} \phi(x_k) \phi'(x_k) \equiv \delta_{ij} [\mathbf{k}(\mathbf{x})]_k,$$

$$\langle \langle [\mathbf{y}'(\mathbf{x})]_{ik} [\mathbf{y}'(\mathbf{x})]_{jl} \rangle \rangle = \delta_{ij} \delta_{kl} \frac{g^2}{N} \phi'(x_k)^2 \equiv \delta_{ij} [\mathbf{K}(\mathbf{x})]_{kl}.$$

# Random Matrix Problem

Kac-Rice formula  $\rho(\boldsymbol{x}) = \int d\boldsymbol{y}' p_{\boldsymbol{x}}(\boldsymbol{y} = 0, \boldsymbol{y}') |\det \boldsymbol{y}'|$

$$\rho(\boldsymbol{x}) = p_{\text{L}}(\boldsymbol{x}) \langle |\det \boldsymbol{y}'| \rangle_{\boldsymbol{y}' \sim p_{\boldsymbol{x}}(\boldsymbol{y}' | \boldsymbol{y}=0)}$$

$$\rho(\boldsymbol{x}) = p_{\text{L}}(\boldsymbol{x}) \langle |\det [\mathbf{M}(\boldsymbol{x}) + \mathbf{X} \boldsymbol{\Sigma}(\boldsymbol{x})]| \rangle_{X_{ij} \stackrel{\text{i.i.d.}}{\sim} \mathcal{N}(0, 1/N)}$$

# Fixed Point Distribution

$$\rho(\boldsymbol{x}) \doteq \exp \left( - N S(\boldsymbol{x}) \right)$$

$$S(\boldsymbol{x}) = \frac{q(\boldsymbol{x})}{2[\kappa(\boldsymbol{x}) + D]} + \frac{1}{2} \ln \{ 2\pi [\kappa(\boldsymbol{x}) + D] \} - \zeta(\boldsymbol{x})$$

$$q(\boldsymbol{x}) = \frac{1}{N} \sum_{i=1}^N x_i^2$$

$$\kappa(\boldsymbol{x}) = \frac{g^2}{N} \sum_{i=1}^N \phi(x_i)^2$$

$$\zeta(\boldsymbol{x}) = -\frac{1}{2} z_* + \frac{1}{2N} \sum_{i=1}^N \ln[1 + z_* g^2 \phi'(x_i)^2]$$

$$1 = \frac{1}{N} \sum_{i=1}^N \frac{g^2 \phi'(x_i)^2}{1 + z_* g^2 \phi'(x_i)^2}$$

# Distribution of Coordinates

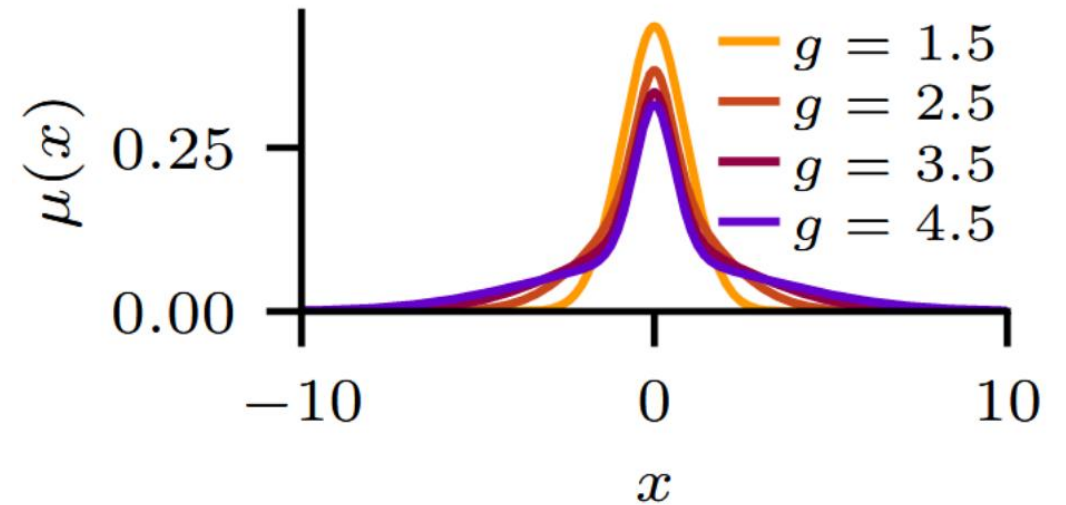
$$\mu_{\mathbf{x}}(y) = \frac{1}{N} \sum_{i=1}^N \delta(y - x_i)$$

$$\mu_{\star}(y) \propto \sqrt{1 + \alpha \phi'(y)^2} e^{-\frac{y^2}{2\beta} + \gamma \phi(y)^2}$$

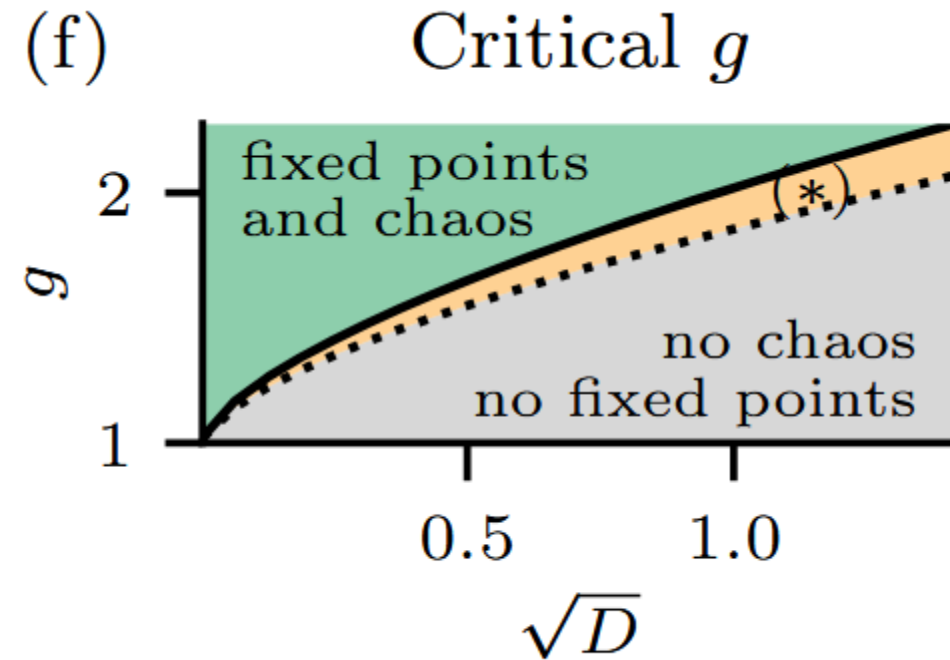
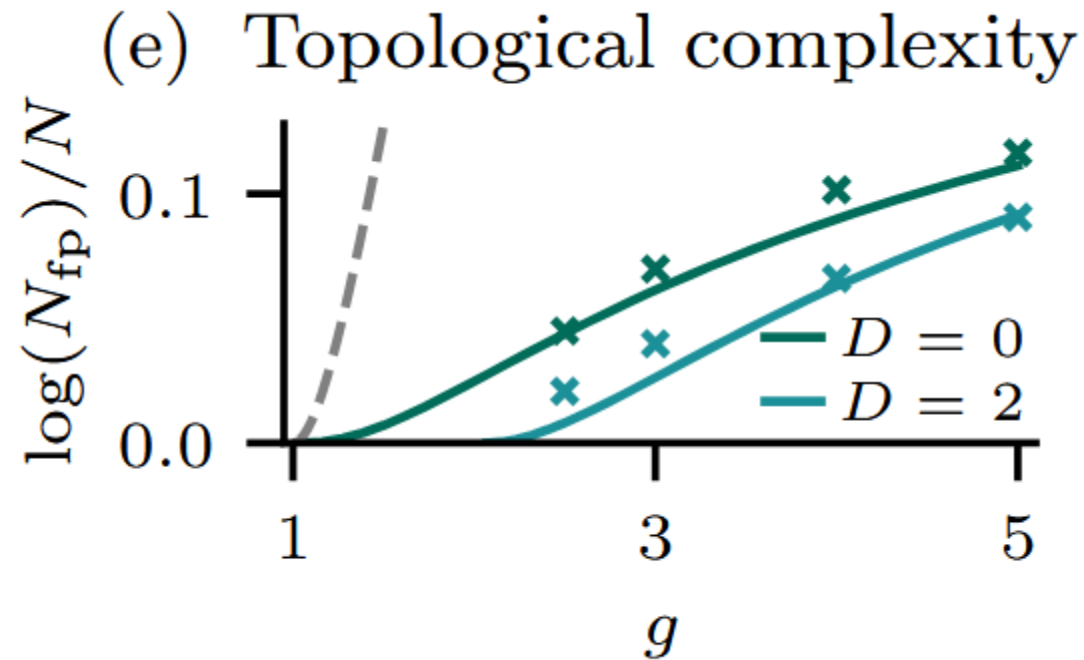
$$1 = g^2 \left\langle \left( \phi'(y)^{-2} + \alpha \right)^{-1} \right\rangle_{\mu_{\star}}$$

$$\beta = \langle \phi(y)^2 \rangle_{\mu_{\star}} + D$$

$$\gamma = \frac{g^2}{2\beta} \left( \beta^{-1} \langle y^2 \rangle_{\mu_{\star}} - 1 \right)$$



# Number of Fixed Points



# Lorenz Attractor

