

# Coexistence of many species in random ecosystems

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Lotka-Volterra population dynamics:

$$\frac{dX_i(t)}{dt} = X_i(t) \left( r_i + \sum_j A_{ij} X_j(t) \right) \quad (1)$$

- difficult with more species  $\rightarrow$  parameters fine tuning;
- we observe portions of a bigger pool (pruned by dynamics).

## Change focus

What is the probability that *all* the species in a community coexist?

$\Rightarrow$

What is the probability of finding  $k$  species when we start from a pool of  $n$  species and let the dynamic evolve?

**Goal:** finding the probability

$$\mathcal{P}(k|n)$$

of having  $k$  species...

↪ **Stably**

↪ **Cohexisting**

... when starting from  $n$  interacting populations and **random** parameters.

# Key concepts and goal

**Goal:** finding the probability

$$\mathcal{P}(k|n)$$

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↪ **Stably**



*After species pruning*



**Equilibria**

↪ **Cohexisting**

... when starting from  $n$  interacting populations and **random** parameters.

# Key concepts and goal

**Goal:** finding the probability

$$\mathcal{P}(k|n)$$

of having  $k$  species...

↪ **Stably**



*After species pruning*



**Equilibria**

↪ **Cohexisting**



possible drivers?  
Impact of structure?

... when starting from  $n$  interacting populations and **random** parameters.

$$x_i^* \left( r_i + \sum_j A_{ij} x_j^* \right) = 0 \quad \text{for } i = 1, 2, \dots, n \quad (2)$$

$$\mathbf{x}^* = -A^{-1}\mathbf{r} \quad (3)$$

$\hookrightarrow$       Equilibrium stability       $\implies$       Lyapunov diagonally stable  
interaction matrix  $A$

**Def.:** A matrix  $A$  is Lyapunov diagonally stable (LDS) if there exists a positive diagonal matrix  $D$  such that  $DA + A^\top D$  is negative definite.

$\hookrightarrow$       Assumption of  $A$   
negative definite       $\implies$        $A + A^\top$  only evl  $< 0$

$$x_i^* \left( r_i + \sum_j A_{ij} x_j^* \right) = 0 \quad \text{for } i = 1, 2, \dots, n$$

$\hookrightarrow$  Why LDS?  $\implies \exists$  **globally attractive** fixed point!

$\hookrightarrow$  Non-invasible solution (*saturated* rest point)

## Goal

Which is the **distribution** of the non-invasible fixed points?



**Def.:** A system is feasible if all abundances at equilibrium are positive.

$$x_i^* > 0$$

How are feasibility and stability related to coexistence?

- Feasibility is *necessary*
- Stability, if added, completes the hypothesis to study **coexistence**

↪ Finding an **analytical** solution for  $\mathcal{P}(k|n)$  is possible!

# Food web caricature

Starting from Lotka-Volterra system of equations (1), evolve the dynamics with:

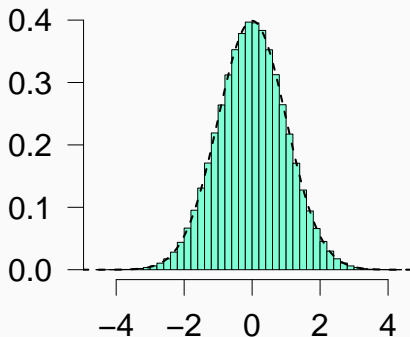
1. producers  $\rightarrow$  grow in isolation  $\rightarrow r_i > 0$
2. consumers  $\rightarrow$  grow with interactions  $\rightarrow r_i < 0$
3. **random** interactions  $A_{ij}$

$r_i$  and  $A_{ij}, j \neq i$

Symmetric distribution  
around 0

$A_{ij}$

Symmetric distribution  
around  $0 + d_i$  ( $< 0$  for  
LDS)



### Toy model: uncoupled logistic equations

- Suppose that  $A$  is diagonal (species do not interact with each other).
- For LDS  $\rightarrow A_{ii} < 0 \forall i$ . If  $p_i$  is the probability that  $r_i > 0$ , then, given that  $x_i^* = -A^{-1}r_i \dots$
- ... the probability that a **solution**  $x^*$  with  $k$  positive components is non-invasible is  $P_{NI} = \prod_{i \in \{S\}_k} p_i \prod_{i \notin \{S\}_k} (1 - p_i)$
- but if  $r_i$  distribution is symmetric, then  $p_i = \frac{1}{2}$  and  $P_{NI} = \frac{1}{2^n}$ .

Probability of coexistence is a **Binomial distribution** with  $p = \frac{1}{2}$

$$\mathcal{P}(k|n) = \binom{n}{k} p^k (1-p)^{n-k} = \binom{n}{k} \frac{1}{2^n}$$

... Could  $\mathcal{P}(k|n)$  be a Binomial distribution also when species interacts?

# Yes, indeed!

For a *feasible* equilibrium:

$$x^* = -A^{-1}r$$

$2^n$  possible sign patterns for  $x^*$  that are equally probable (symmetry), hence it holds:

$$\mathcal{P}(n|n) = \frac{1}{2^n}$$

Let's define  $D_k = (-1)^{\delta_{ik}} \delta_{ij}$

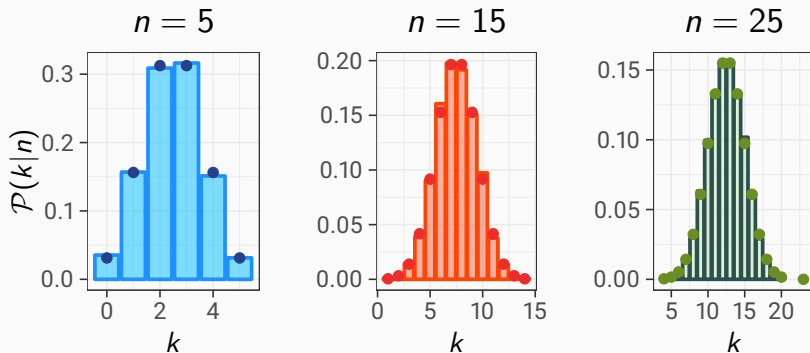
$$\implies (D_k A D_k) D_k x^* = -D_k r$$

Because of symmetry hypothesis:

- $(D_k A D_k)$  has the same distribution of  $A$
- $D_k r$  has the same distribution of  $r$

$D_k$  just flips sign of the  $k$ -th component  $\rightarrow$  applying  $D_k$  allows to obtain **any** pattern  $\implies \mathcal{P}(k|n)$  is the same as before!

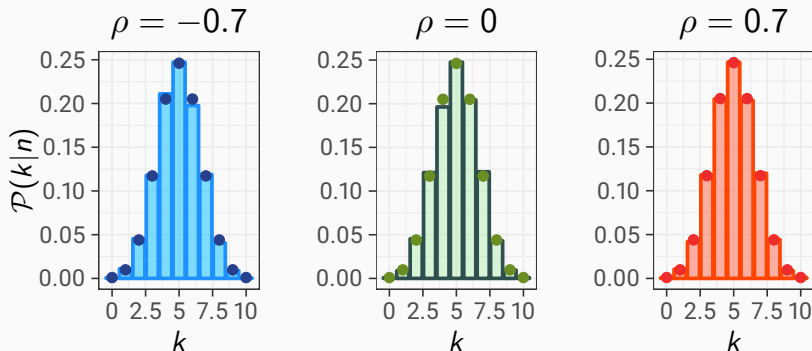
# Some simulations



**Figure 1** – Simulations of the number of coexisting species  $k$  with 50000 iterations, for systems with  $n$  starting species.

The dots are the expected values given by the Binomial distribution.

# Adding correlation



**Figure 2** – Simulations of the number of coexisting species  $k$  with 10000 iterations, for systems with  $n = 10$  starting species, for different correlations.

- $G$ : adjacency matrix of an undirected graph (structure)
- $M = G \circ A$  Hadamard (entry-wise) product
- $D(G \circ A)D = G \circ (DAD)$  for  $D$  diagonal
- Recall  $D_k = (-1)^{\delta_{ik}} \delta_{ij}$
- $(D_k A D_k)$  has the same distribution of  $A$
- $D_k r$  has the same distribution of  $r$
- the distribution of  $M$  is invariant to  $D_k M D_k$

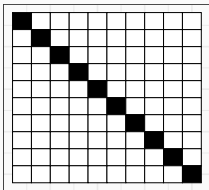
Therefore

Adding network structure does not change the probability distribution!

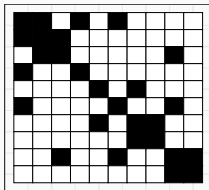
# Adding structure

## Three types of structure

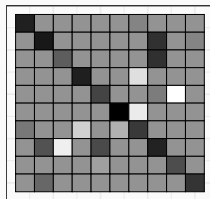
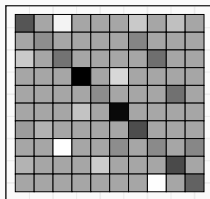
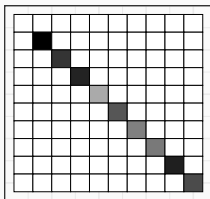
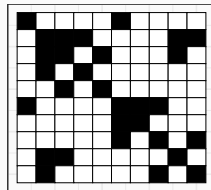
Fixed matrix



Power law



2 blocks

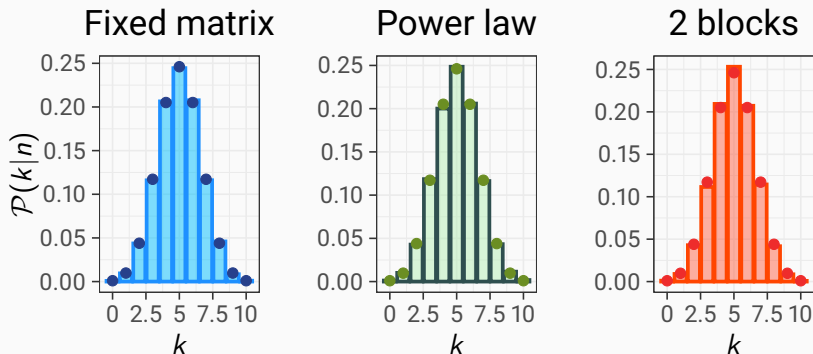


**Figure 3** – Three types of interaction matrix. Upper row: position of non-zero coefficients. Bottom row: LDS matrices, the darker the colour, the more negative is  $A_{ij}$ .



# Adding structure

## Three types of structure



**Figure 4** – Simulations of the number of coexisting species  $k$  with 10000 iterations, for systems with  $n = 10$  starting species, for different types of interaction matrix.

## Interacting competitors:

- $A_{ij} < 0, \forall i, j$
- $r_i$  sampled from gaussian distribution with mean  $\gamma \neq 0$

## **Competitive** inter-specific interactions:

$$A_{ij} = \mu = \frac{\hat{\mu}}{n} < 0$$

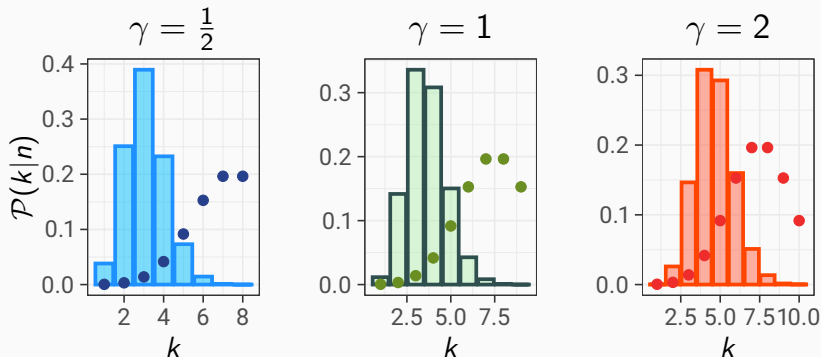
## Intra-specific interactions:

$$A_{ii} = d_i = \alpha < 0$$

To ensure LDS

$$\alpha < \mu < 0$$

In particular:  $\mu = -0.5, \alpha = -1$



**Figure 5** – Simulations of the number of coexisting species  $k$  with 10000 iterations, for systems with  $n = 15$  starting species, for different means  $\gamma$ .

## Mean $\neq 0$ How does the distribution change?

When  $r_i \sim \mathcal{N}(\gamma, 1)$ , then the equilibrium point of (3):

$$\mathbf{x}^* = -A^{-1}\mathbf{r}$$

is described by a multivariate normal distribution.

Hence,  $\mathcal{P}(k|n)$  can be written as a double integral  $\rightarrow$  computed numerically  $\rightarrow$  saddle-point approximation for  $n \gg 1$ , deriving:

$$\mathcal{P}(k|n, \alpha, \hat{\mu}, \gamma) = \frac{n(q+u)-1}{\sqrt{2\pi nq(1-q)}K(\sigma, n)} e^{nF(\sigma)+G(\sigma)} \quad (4)$$

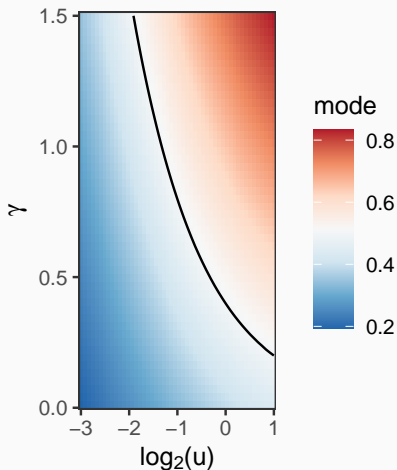
With:

- $q = \frac{k}{n}$
- $u = \frac{\alpha}{\hat{\mu}} = \frac{\alpha}{n\mu}$
- $\sigma = (q, u, v)$
- $v = \frac{\gamma(\alpha - \mu)}{\alpha - \mu + k\mu}$

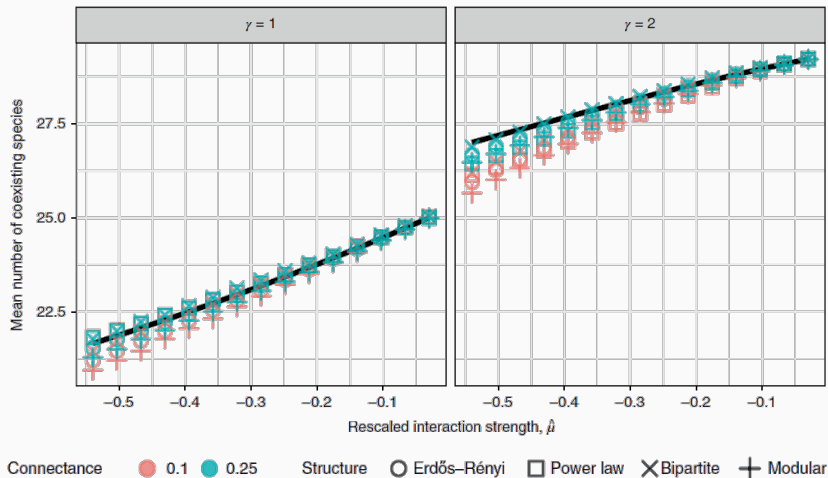
$$u = \frac{\alpha}{\hat{\mu}} = \frac{e^{-[\Phi^{-1}(1-q^*)]^2/2} - \sqrt{2\pi}q^*\Phi^{-1}(1-q^*)}{\sqrt{2\pi}[\Phi^{-1}(1-q^*) + \gamma]} \quad (5)$$

$$\frac{\alpha\gamma}{\hat{\mu}} = \frac{1}{\sqrt{2\pi}} \quad (6)$$

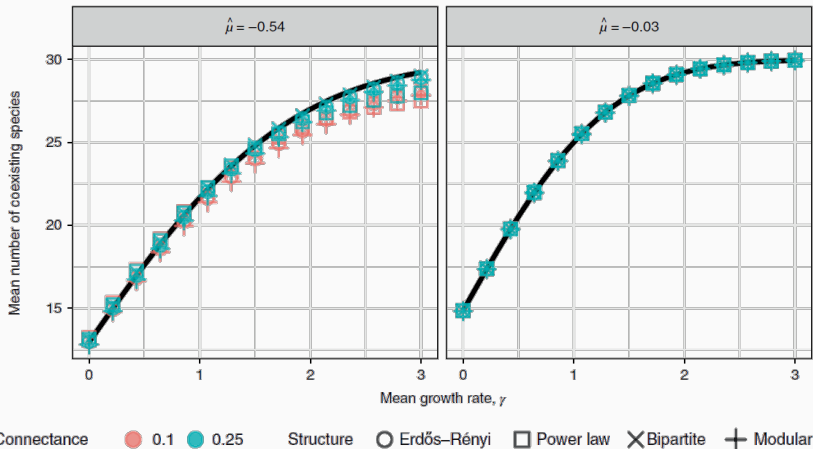
$$\frac{\alpha\gamma}{\mu} = \frac{n}{\sqrt{2\pi}} \quad (7)$$



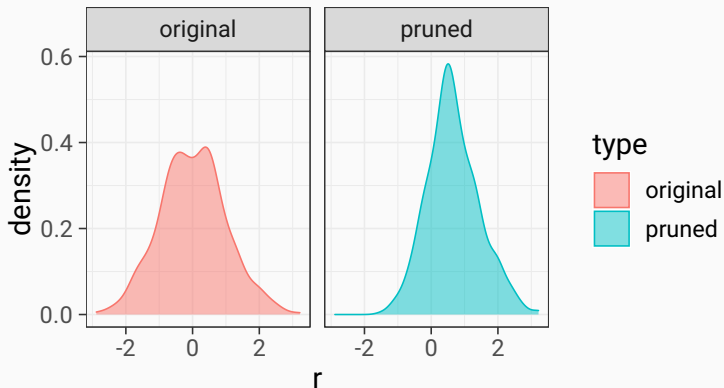
# Mean $\neq 0$ Adding structure



# Mean $\neq 0$ Adding structure



- Food web  $\rightarrow$  sampled  $A_{ij}$  and  $r_i$  independently  $\rightarrow$  some "bad" species can be generated ( $r_i < 0$ ,  $A_{ij} < 0$ )  $\rightarrow$  extinction!  $\Rightarrow$  **correlation**



**Figure 6** – Growth rates distribution before and after the dynamics has reached equilibrium, for a starting pool of  $n = 1000$  species, with  $k = 485$  species surviving.



## Applications

- Application to local communities composed of subsets of the same pool of species (**metacommunities**): model the distribution of the number of species found in local patches
- Application to microbial communities (**assembly**)

## Future work

- Consider stronger form of networks, in which also the non-zero coefficient have a pattern
- Relaxing LDS: very challenging
- Understanding the process of assembly in which communities are built

In conclusion:

- Large communities *can* stably coexist thanks to the selection imposed by the dynamical pruning of a large species pool.
- Successfully tested many different structures, no particular impact from network once stability is reached

### Mean = 0

- $\mathcal{P}(k|n) = \text{Bin}(n, \frac{1}{2})$
- No effect due to network

### Mean $\neq 0$

- $\mathcal{P}(k|n)$  not binomial but with strong central tendency and known mode
- Little effect due to network

# Backup slides

- $r_i \sim \mathcal{N}(\gamma, 1) \implies P(\mathbf{r}) = \frac{1}{\sqrt{(2\pi)^n}} \exp\left(-\sum_{i=1}^n \frac{(r_i - \gamma)^2}{2}\right) = \frac{1}{\sqrt{(2\pi)^n}} \exp\left(-\frac{1}{2} \|\mathbf{r}^{(s)} - \gamma \mathbf{1}_k\|^2 - \frac{1}{2} \|\mathbf{r}^{(n)} - \gamma \mathbf{1}_{n-k}\|^2\right)$
- **Def:**  $\mathbf{z} = \mathbf{r}^{(n)} + A^{(ns)}\mathbf{x}$  for  $n - k$  non-surviving species,  $A^{(s)}\mathbf{x} = -\mathbf{r}^{(s)}$  for  $k$  surviving ones.
- Combining them, joint pdf is  $f(\mathbf{x}, \mathbf{z} | A) = \frac{|\det \Lambda|}{(2\pi)^{n/2}} \exp\left(-\frac{1}{2} \|A^{(s)}\mathbf{x} + \gamma \mathbf{1}_k\|^2 - \frac{1}{2} \|\mathbf{z} - A^{(ns)}\mathbf{x} - \gamma \mathbf{1}_{n-k}\|^2\right)$
- with  $\Lambda$  = Jacobian matrix of change of base  $\mathbf{r} \rightarrow (\mathbf{x}, \mathbf{z})$ . Note that  $|\det \Lambda| = |\det A^{(s)}|$
- Change of variables:  $\|A^{(s)}\mathbf{x} + \gamma \mathbf{1}_k\|^2 = (\mathbf{x} - \boldsymbol{\xi})^T G (\mathbf{x} - \boldsymbol{\xi})$ , with  $\boldsymbol{\xi} = -\gamma (A^{(s)})^{-1} \mathbf{1}_k$  and  $G = (A^{(s)})^T A^{(s)}$
- set that  $\mathbf{x} > 0$  and  $\mathbf{z} < 0$  (feasibility)

$$\mathcal{P}(\{S\}_k | A) \equiv \int d^k \mathbf{x} \left( \prod_{i=1}^k \Theta(x_i) \right) \int d^{n-k} \mathbf{z} \left( \prod_{j=k+1}^n \Theta(-z_j) \right) f(\mathbf{x}, \mathbf{z} | A)$$

(8)

- $A = (\alpha - \mu)I_n + \mathbf{1}_n \mathbf{1}_n^T$
- $\xi = -\gamma (A^{(s)})^{-1} \mathbf{1}_k = \xi^{(k)} \mathbf{1}_k = -\frac{\gamma}{\alpha + (k-1)\mu} \mathbf{1}_k$
- $G = (A^{(s)})^T A^{(s)} = (\alpha - \mu)^2 I_k + [k\mu^2 + 2\mu(\alpha - \mu)] \mathbf{1}_k \mathbf{1}_k^T$
- change of variables  $x'_i = x_i - \xi^{(k)}$  in (8)

$$\begin{aligned} \mathcal{P}(\{S\}_k | n) &= \frac{|\det A^{(s)}|}{(2\pi)^{n/2}} \int d^k \mathbf{x} \prod_{i=1}^k \Theta(x_i + \xi^{(k)}) e^{-\frac{1}{2} \mathbf{x}^T G \mathbf{x}} \times \\ &\times \int d^{n-k} \mathbf{z} \prod_{j=k+1}^n \Theta(-z_j) e^{-\frac{1}{2} \|\mathbf{z} - [\gamma + k\mu \xi^{(k)} + \mu(\mathbf{1}_k^T \mathbf{x})] \mathbf{1}_{n-k}\|^2} \quad (9) \end{aligned}$$

- change of variables:  $z'_j = z_j - \gamma - k\mu\xi^{(k)}$
- $|\det A^{(s)}| = |\alpha - \mu|^{k-1} |\alpha + (k-1)\mu|$
- call all the exponent  $g(\mathbf{x}, \mathbf{z})$

$$\begin{aligned} \mathcal{P}(\{S\}_k | n) &= \frac{|\alpha - \mu|^{k-1} |\alpha + (k-1)\mu|}{(2\pi)^{n/2}} \int d^k \mathbf{x} \prod_{i=1}^k \Theta(x_i + \xi^{(k)}) \times \\ &\quad \times \int d^{n-k} \mathbf{z} \prod_{j=k+1}^n \Theta(-z_j - \gamma - k\mu\xi^{(k)}) e^{g(\mathbf{x}, \mathbf{z})} \quad (10) \end{aligned}$$

- apply **Hubbard-Stratonovich** transformation on  $g$

$$e^{-bd^2/c^2 \pm de/c} = \frac{c}{2\pi} \int_{-\infty}^{\infty} dy \int_{-\infty}^{\infty} e^{-(by^2 + ey + idw \pm icwy)} dw$$

$$\begin{aligned} \mathcal{P}(\{S\}_k | n) &= \frac{|\alpha - \mu|^{k-1} |\alpha + (k-1)\mu|}{(2\pi)^{n/2+1} |\mu|} \int_{-\infty}^{\infty} dy \times \\ &\times \int_{-\infty}^{\infty} e^{-\frac{1}{2}[n+2(\frac{\alpha}{\mu}-1)]y^2 + i\frac{yw}{\mu\mu}} dw \int d^k \mathbf{x} \prod_{i=1}^k \Theta(x_i + \xi^{(k)}) \times \\ &\times \int d^{n-k} \mathbf{z} \prod_{j=k+1}^n \Theta(-z_j - \gamma - k\mu\xi^{(k)}) e^{-\frac{1}{2}(\alpha-\mu)^2 \mathbf{x}^T \mathbf{x} - i(\mathbf{1}_k^T \mathbf{x})w} e^{-\frac{1}{2} \mathbf{z}^T \mathbf{z} - (\mathbf{1}_{n-k}^T \mathbf{z})y} \end{aligned} \quad (11)$$

- complete the squares + cumulative distribution function of  $\mathcal{N}(0, 1)$

$$\Phi(x) = \frac{1}{2} \left[ 1 + \operatorname{erf} \left( \frac{x}{\sqrt{2}} \right) \right]$$

$$\begin{aligned} \mathcal{P}(\{S\}_k | n) &= \frac{1}{2\pi} \left| k + \frac{\alpha}{\mu} - 1 \right| \int_{-\infty}^{\infty} dy \times \\ &\times \int_{-\infty}^{\infty} e^{-\frac{1}{2}[k+2(\frac{\alpha}{\mu}-1)]y^2 + i|\frac{\alpha}{\mu}-1|yw - \frac{1}{2}kw^2} dw \times \\ &\times \left[ 1 - \Phi \left( iw - |\alpha - \mu|\xi^{(k)} \right) \right]^k \left[ \Phi \left( y - \gamma - k\mu\xi^{(k)} \right) \right]^{n-k} \end{aligned} \quad (12)$$

- Note that  $\gamma + k\mu\xi^{(k)} = \gamma \left(1 - \frac{k\mu}{\alpha + (k-1)\mu}\right) = \frac{\gamma(\alpha - \mu)}{\alpha + (k-1)\mu}$
- Define  $s := \frac{\alpha}{\mu} - 1$  ( $s > 0$  for LDS) and  $v := \frac{\gamma(\alpha - \mu)}{\alpha - \mu + k\mu} = \frac{\gamma s}{k + s}$
- Then, given that  $\alpha < \mu$ , it holds that  $|\alpha - \mu|\xi^{(k)} = -\frac{\gamma|\alpha - \mu|}{\alpha + (k-1)\mu} = v$

$$\mathcal{P}(\{S\}_k | n) = \frac{k + s}{2\pi} \int_{-\infty}^{\infty} dy \int_{-\infty}^{\infty} e^{-\frac{1}{2}(k+2s)y^2 + isyw - \frac{1}{2}kw^2} \times \\ \times [1 - \Phi(iw - v)]^k [\Phi(y - v)]^{n-k} dw \quad (13)$$

- (13) is a complex path integral, move integration on  $\Gamma = \{w' \in \mathbb{C} | w' = iw + x_0\}$  with  $x_0 \rightarrow 0$

$$\mathcal{P}(\{S\}_k | n) = \frac{k + s}{2\pi i} \int_{-\infty}^{\infty} dy \int_{\Gamma} e^{-\frac{1}{2}(k+2s)y^2 + syw - \frac{1}{2}kw^2} \times \\ \times [1 - \Phi(w - v)]^k [\Phi(y - v)]^{n-k} dw \quad (14)$$

- double integral of (13), (14) can be estimated numerically with FFT



- Probability of coexistence is  $\mathcal{P}(k|n) = \binom{n}{k} \mathcal{P}(\{S\}_k | n)$ , for  $n \rightarrow \infty$  can be approximated with **saddle point** technique
- Defining  $q = k/n$ , grouping the  $y, w, q$  dependent terms in  $\hat{h}(y, w; q) = \frac{q}{2} (y^2 - w^2) - q \log[1 - \Phi(w - v)] - (1 - q) \log \Phi(y - v)$ , equation (14) becomes:

$$\mathcal{P}(\{S\}_k | n) = \frac{k + s}{2\pi i} \int_{-\infty}^{\infty} dy \int_{\Gamma} e^{-sy^2 + syw} e^{-n\hat{h}(y, w; q, v)} dw \quad (15)$$

- set  $\mu = \hat{\mu}/n$  to have scaling in  $n$
- set  $s = n\alpha/\hat{\mu} - 1 = nu - 1$
- call  $\sigma = (q, u, v)$  and  $h(y, w; \sigma) = \hat{h}(y, w; q) + uy^2 - uyw$

$$\mathcal{P}(\{S\}_k | n) = \frac{k + nu - 1}{2\pi i} \int_{-\infty}^{\infty} dy \int_{\Gamma} e^{y^2 - yw} e^{-nh(y, w; \sigma)} dw \quad (16)$$

- $e^{-nh(y,w;\sigma)}$  is very peaked around global minimum of the real part of  $h(y, w; \sigma) \implies$  approximate the exponent up to second order
- find critical point by setting  $dh/dy = 0, dh/dw = 0$
- compute discriminant of second derivative matrix, we find it is indeed a saddle point  $\implies$  approximate  $\mathcal{P}(k|n)$
- add also **Stirling** approximation for binomial coefficient:

$$\binom{n}{k} = \binom{n}{qn} \approx \frac{\exp(-n[q \log q + (1-q) \log(1-q)])}{\sqrt{2\pi nq(1-q)}}$$

$$P(k | n) = \frac{n(q + u) - 1}{\sqrt{2\pi nq(1 - q)}K(\sigma, n)} e^{nF(\sigma) + G(\sigma)} \quad (17)$$

With:

$$\begin{aligned} K(\sigma, n) := & (nu - 1)^2 + n^2 \left[ -q + (uy^* + qw^*) \left( v + \frac{uy^*}{q} \right) \right] \\ & \times \left[ \frac{2}{n} - 2u - q - (2uy^* + qy^* - uw^*) \left( -v + \frac{y^* - u(w^* - 2y^*)}{1 - q} \right) \right] \end{aligned} \quad (18)$$

$$\begin{aligned} F(\sigma) := & \frac{q}{2} (w^{*2} - y^{*2}) + (1 - q) \log [\Phi(y^* - v)] + q \log [1 - \Phi(w^* - v)] \\ & - uy^{*2} + uy^* w^* - q \log q - (1 - q) \log(1 - q) \end{aligned} \quad (19)$$

$$G(\sigma) := y^* (y^* - w^*) \quad (20)$$

# Mode of $\mathcal{P}(k|n)$ Mean $\neq 0 - 1$

$$v = \frac{\gamma(\alpha - \mu)}{\alpha - \mu + k\mu} \cdot \frac{\mu}{\mu} = \frac{\gamma(nu - 1)}{k + nu - 1} \cdot \frac{n}{n} \xrightarrow{n \gg 1} \frac{\gamma u}{q + u}$$

$$\begin{aligned} \frac{\partial F}{\partial q} = & \frac{1}{2} (w^{*2} - y^{*2}) + q (w^* w^{*'} - y^* y^{*'}) - \log \Phi(y^* - v) + \\ & + \log(1 - \Phi(w^* - v)) + (w^* - 2y^*) u y^{*'} + \\ & + u y^* w^{*'} + (1 - q) (y^{*'} - v') \frac{\Phi'(y^* - v)}{\Phi(y^* - v)} - \\ & - q (w^{*'} - v') \frac{\Phi'(w^* - v)}{1 - \Phi(w^* - v)} + \log \frac{1 - q}{q} \stackrel{!}{=} 0 \quad (21) \end{aligned}$$

(A) From  $dh/dy = 0$  it holds  $\frac{\Phi'(y^* - v)}{\Phi(y^* - v)} = \frac{q y^* + 2u y^* - u w^*}{1 - q} = \frac{e^{-(y^* - v)^2/2}}{\sqrt{2\pi} \Phi(y^* - v)}$

(B) From  $dh/dw = 0$  it holds  $\frac{\Phi'(w^* - v)}{1 - \Phi(w^* - v)} = \frac{u y^* + q w^*}{q} = \frac{e^{-(w^* - v)^2/2}}{\sqrt{2\pi} [1 - \Phi(w^* - v)]}$

## Mode of $\mathcal{P}(k|n)$ Mean $\neq 0 - 2$

Simplifying (21):

$$\begin{aligned}\frac{\partial F}{\partial q} = \frac{1}{2} (w^{*2} - y^{*2}) - v (w^* - y^*) - \log \Phi (y^* - v) + \\ + \log (1 - \Phi (w^* - v)) + \log \frac{1 - q}{q} \stackrel{!}{=} 0\end{aligned}$$

From which we derive:

$$(1 - q^*) e^{w^{*2}/2 - vw^*} [1 - \Phi (w^* - v)] = q^* e^{y^{*2}/2 - vy^*} \Phi (y^* - v), \quad (22)$$

where the functions  $y^*(\sigma)$ ,  $w^*(\sigma)$  and  $v(q)$  are evaluated at  $q = q^*$ . On the other hand, given (A) and (B):

$$\begin{aligned}(1 - q)e^{-(y^* - v)^2/2} &= \sqrt{2\pi} \Phi (y^* - v) (qy^* + 2uy^* - uw^*), \\ qe^{-(w^* - v)^2/2} &= \sqrt{2\pi} [1 - \Phi (w^* - v)] (uy^* + qw^*)\end{aligned}$$

Substituting these expressions into equation (22) yields, after some algebra, this simple condition for the mode of the distribution,  $q^*$  :

$$y^* (q^*, u, v (q^*)) = w^* (q^*, u, v (q^*)). \quad (23)$$

Meaning that (22) reduces to:

$$\log \frac{1 - \Phi(y^* - v)}{\Phi(y^* - v)} = \log \frac{q^*}{1 - q^*} \implies \Phi(y^* - v) = 1 - q^* \quad (24)$$

Inverting (24) and putting it into (A) we obtain

$$\sqrt{2}\gamma u + 2(q^* + u) \operatorname{erf}^{-1}(1 - 2q^*) = \frac{e^{-[\operatorname{erf}^{-1}(1 - 2q^*)]^2}}{\sqrt{\pi}}$$

which is a transcendental equation that determines the mode of the distribution  $q^* = \frac{k^*}{n}$  as a function of interaction strengths and growth rates.

Equivalently, with  $\Phi^{-1}(q) = \sqrt{2} \operatorname{erf}^{-1}(2q - 1)$ , the transcendental condition for the mode can be expressed as

$$\frac{\alpha}{\hat{\mu}} = \frac{e^{-[\Phi^{-1}(1 - q^*)]^2/2} - \sqrt{2\pi} q^* \Phi^{-1}(1 - q^*)}{\sqrt{2\pi} [\Phi^{-1}(1 - q^*) + \gamma]}$$

By choosing  $q^* = \frac{1}{2}$ , we get:

$$\frac{\alpha\gamma}{\hat{\mu}} = \frac{1}{\sqrt{2\pi}} \implies \frac{\alpha\gamma}{\mu} = \frac{n}{\sqrt{2\pi}} \quad (25)$$

In the limit of small interaction strengths ( $\hat{\mu} \ll \alpha$ ) of the mean zero case ( $\gamma = 0$ ), (25) reproduces the expected (binomial) behaviour:

$$\frac{k^*}{n} \approx \frac{1}{2} - \frac{1}{2\pi} \frac{\hat{\mu}}{\alpha} + \frac{1}{4\pi} \left( \frac{\hat{\mu}}{\alpha} \right)^2,$$