



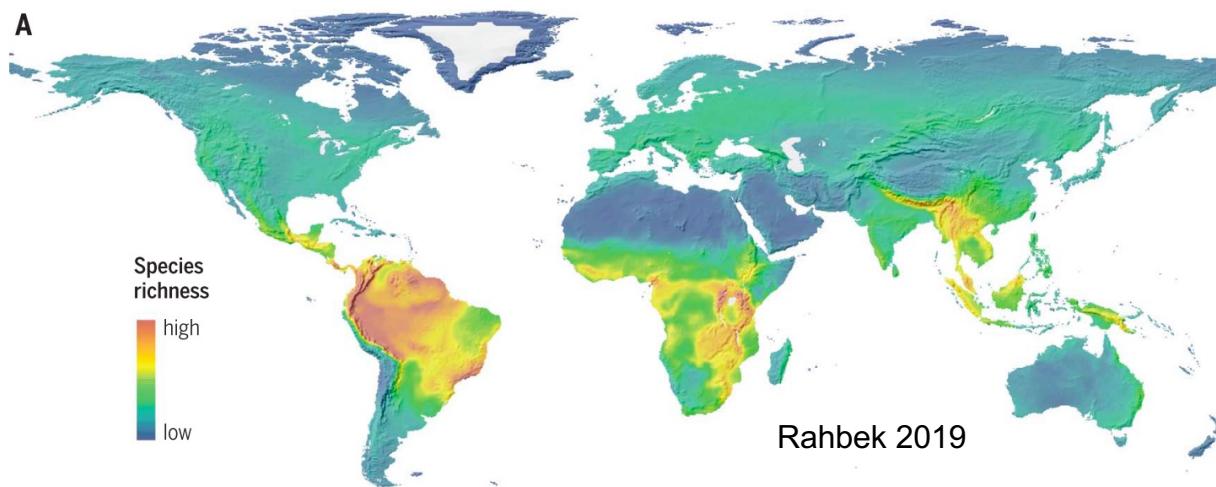
# Graph topology and habitat assortativity drive phenotypic differentiation in an eco-evolutionary model

Victor Boussange & Loïc Pellissier

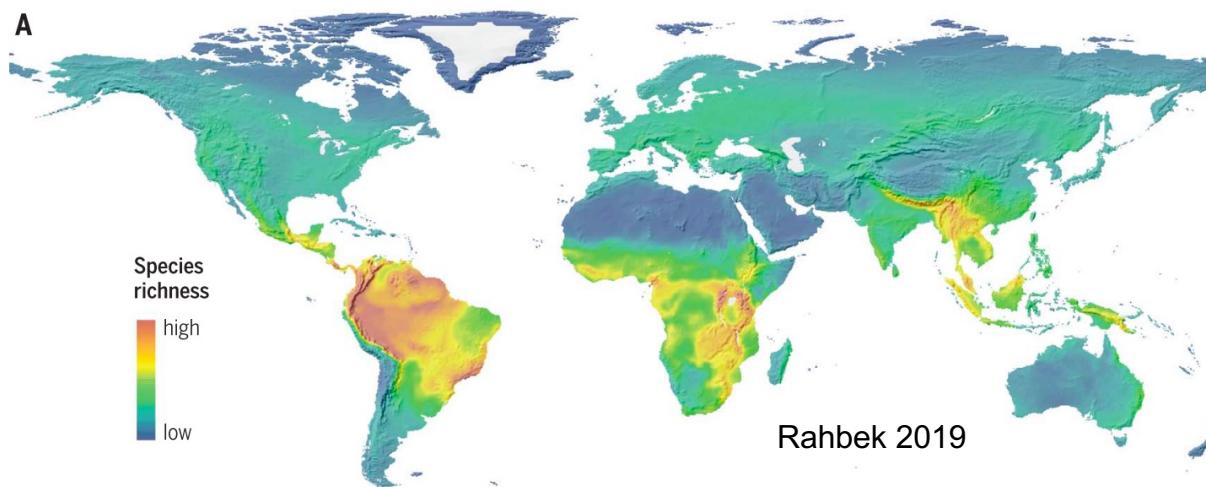
CCS2021

# Large-scale geographical patterns of species diversity

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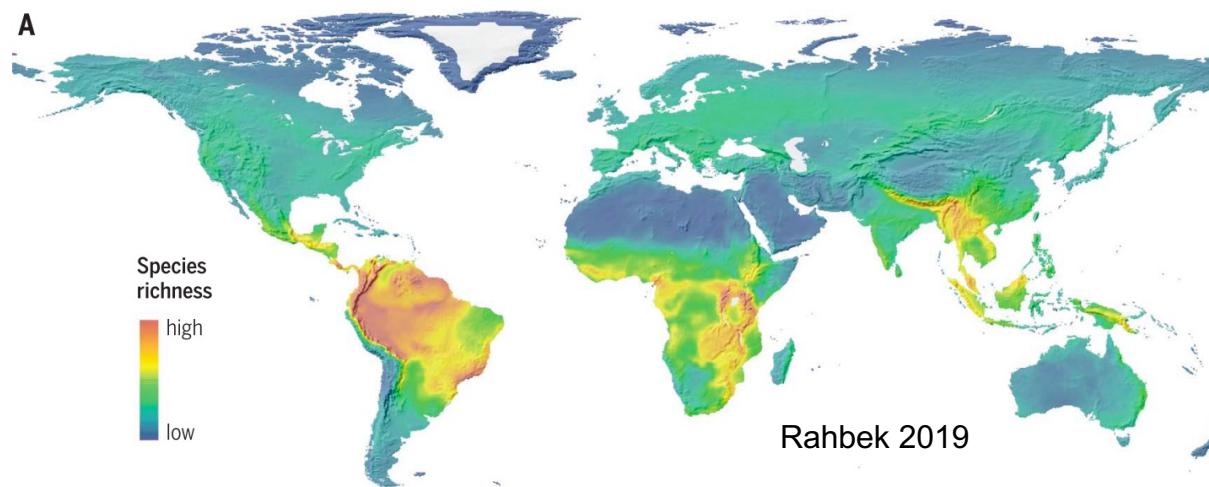


# Large-scale geographical patterns of species diversity



Mountains represent **25 % of land area**, but **85% of the world's species** of amphibians, birds and mammals, many entirely restricted to mountains (Rahbek 2019)

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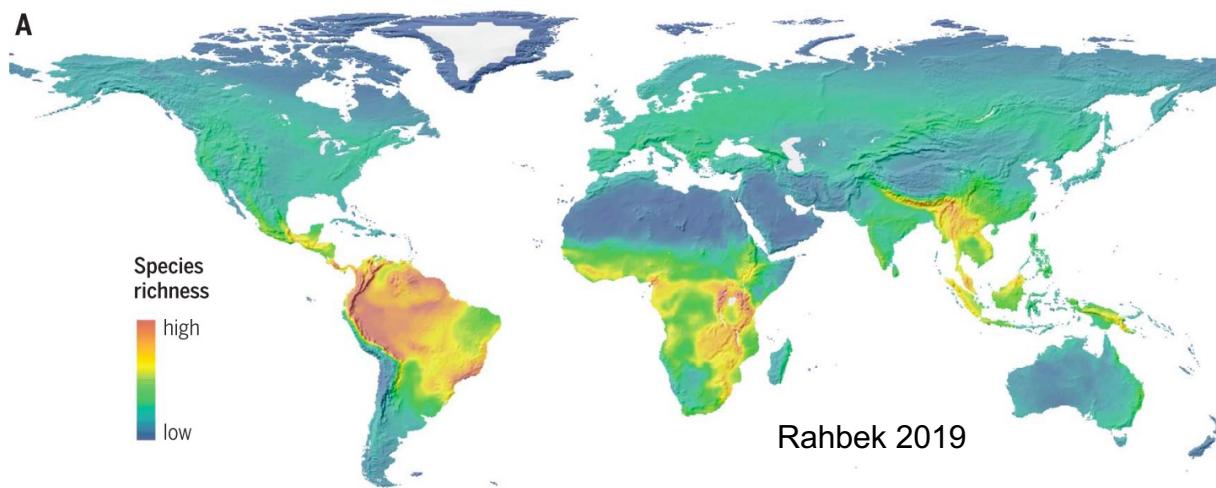


Topological constraints



Habitat heterogeneity

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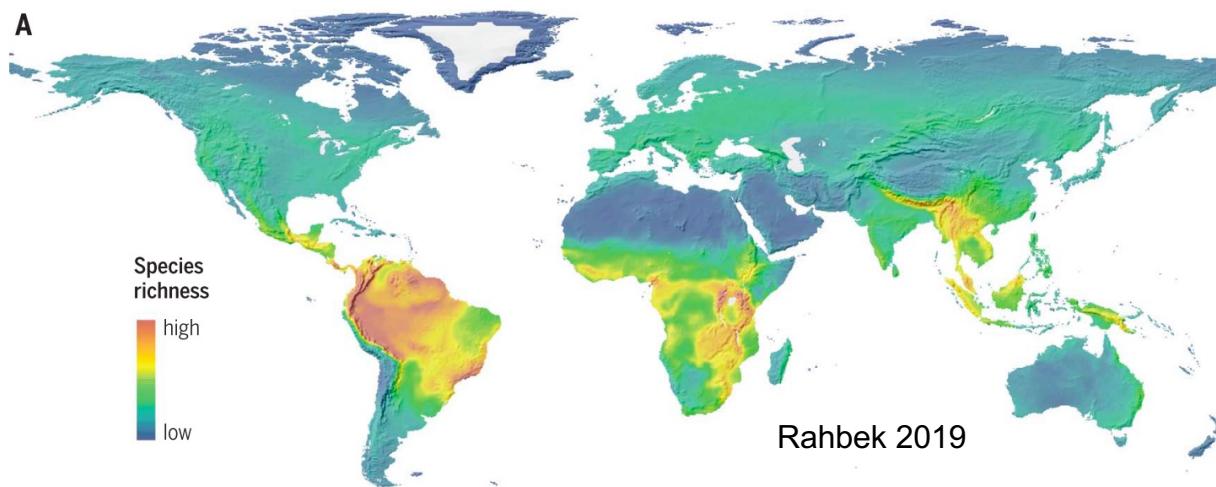


Topological constraints      Habitat heterogeneity

Underlying processes?



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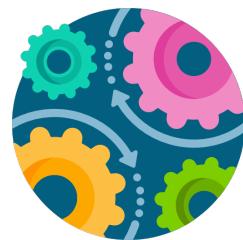


Topological constraints

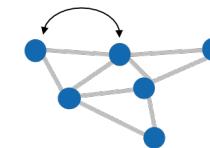


Habitat heterogeneity

Underlying processes?



First principles modelling approach



Graph representation of the landscape

$$m\partial_t v = \sum_i F_i$$

Eco-evolutionary individual based model

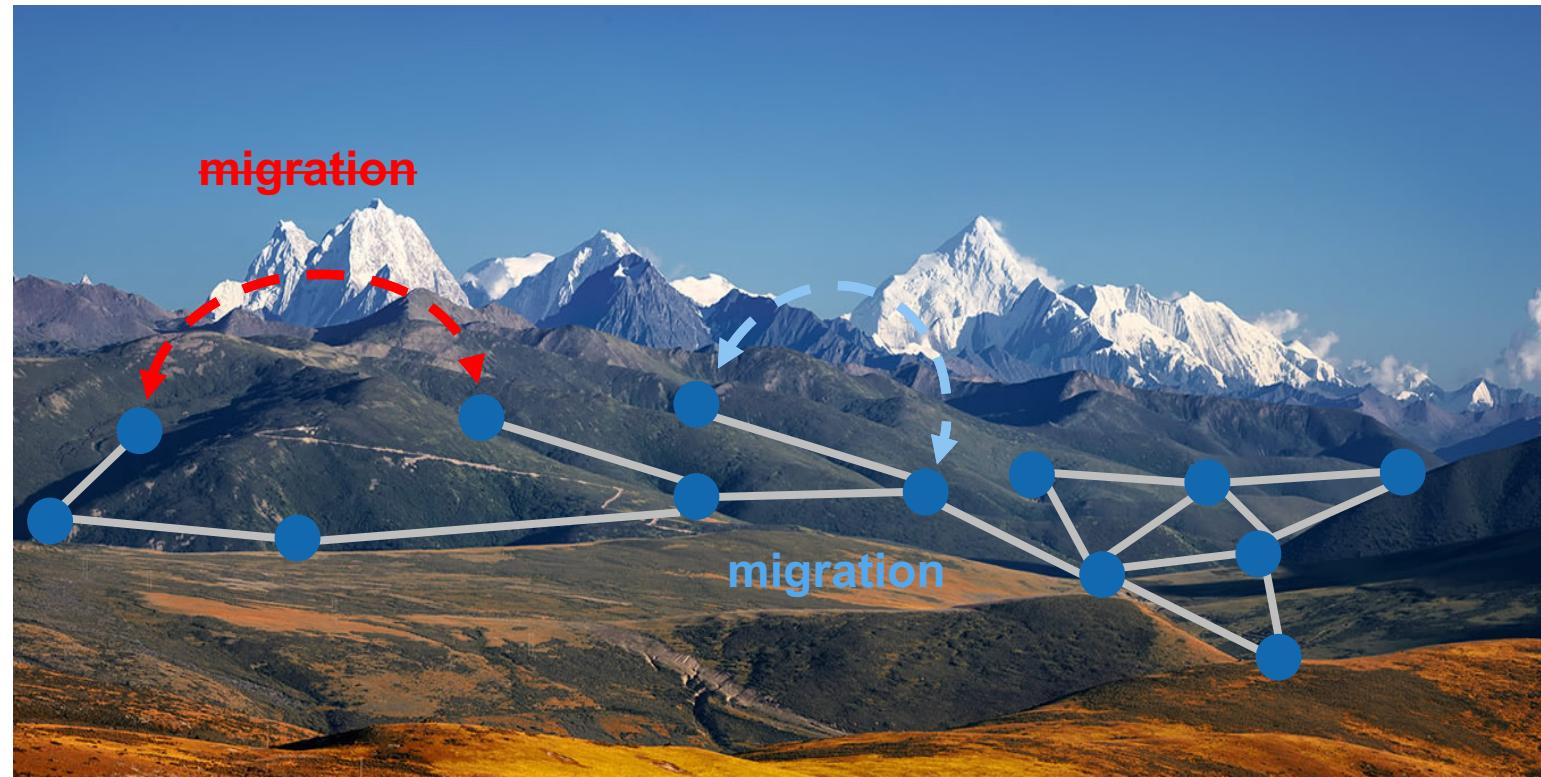
# Graphs as landscape abstraction



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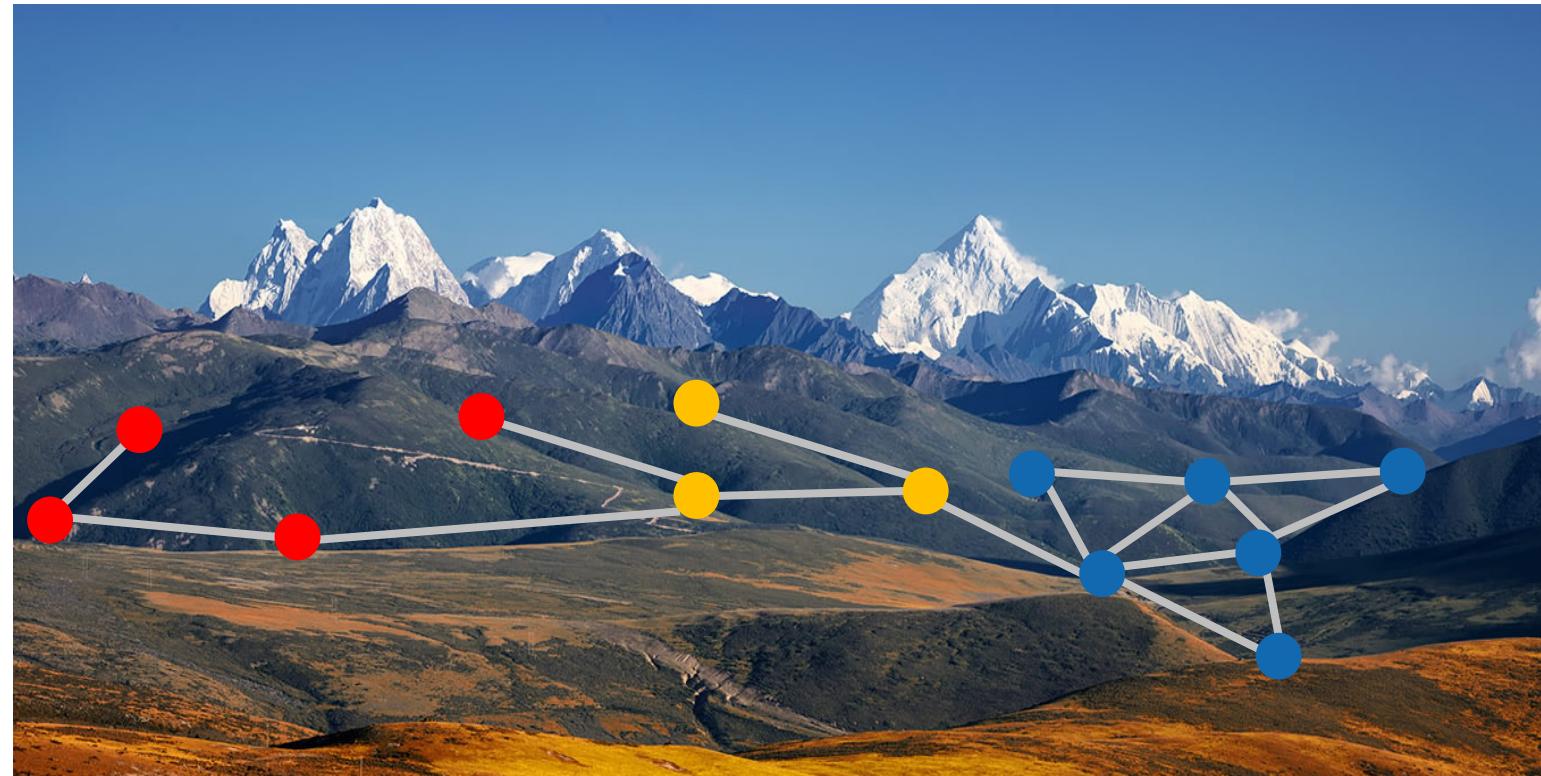


**Graphs**, to capture dispersal patterns

→ Topological constraints



# Graphs as landscape abstraction



and environmental  
heterogeneity



- Habitat 1
- Habitat 2
- Habitat 3

# Eco-evolutionary model

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Champagnat et al. 2006

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- Measure-valued point process

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- **Measure-valued point process**
  - Individuals are represented by **dirac functions**

$$\delta_{x_k^{(i)}} \quad \text{traits of individual k on vertex } V_i$$


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Champagnat et al. 2006

- **Measure-valued point process**
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  - Population on  $V_i$  is represented by a **sum** of dirac

$$\nu^{(i)} = \sum_k^{N^{(i)}} \delta_{x_k^{(i)}}$$

traits of individual k on vertex  $V_i$



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Ecology



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Population size on  $V_i$

$$\delta_{x_k^{(i)}} \quad \text{traits of individual } k \text{ on vertex } V_i$$
$$d_i(x_k) \equiv \frac{N^{(i)}}{K}$$

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$$b_i(x_k)$$

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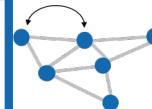
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**Ecology**



- Offsprings can migrate to neighboring vertices

**Dispersal**



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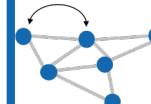
- Individuals **die**
  - competition for a finite amount of ressource
- Individuals **reproduce**

**Ecology**



- Offsprings can migrate to neighboring vertices

**Dispersal**



- Offsprings' traits slightly differ from their parents'
  - Difference follows  $\sim \mathcal{N}_{0, \sigma_\mu}$

**Evolution**



$$\delta_{x_k^{(i)}} \quad \text{traits of individual } k \text{ on vertex } V_i$$

$$\nu^{(i)} = \sum_k \delta_{x_k^{(i)}} \quad \text{Population size on } V_i$$

$$d_i(x_k) \equiv \frac{N^{(i)}}{K}$$

$$b_i(x_k)$$

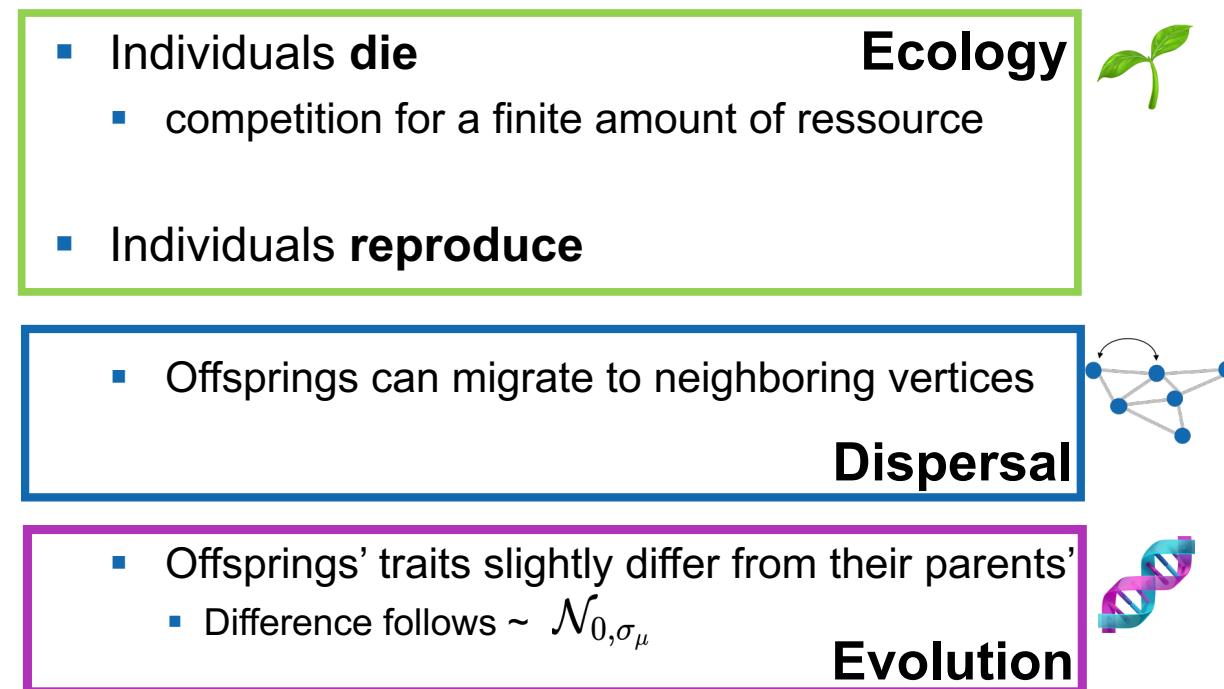
*m*

*μ*

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$$\nu^{(i)} = \sum_k \delta_{x_k^{(i)}}$$

traits of individual k on vertex  $V_i$

$d_i(x_k) \equiv \frac{N^{(i)}}{K}$

$b_i(x_k)$

$m$

$\mu$

**Rates**

Population size on  $V_i$

# Expected dynamics

- Expected time variation of the process

$$L\phi(\nu_t^{(i)}) = \partial_t \mathbb{E} \left[ \phi(\nu_t^{(i)}) \right]$$

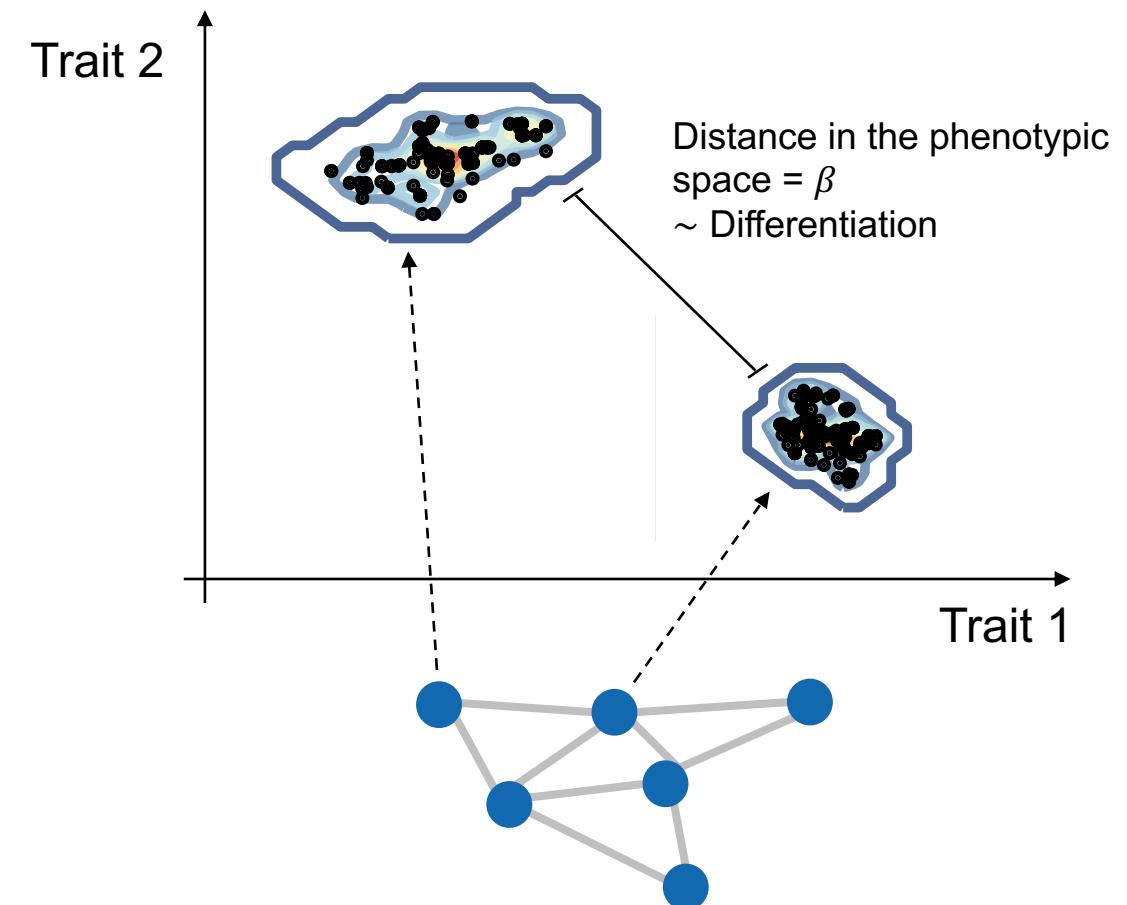
$$\begin{aligned}
 L\phi(\nu_t^{(i)}) &= \int_{\mathcal{X}} \left\{ b_i(\mathbf{x})(1-\mu)(1-m)(\phi(\nu_t^{(i)} + \delta_{\mathbf{x}}) - \phi(\nu_t^{(i)})) \right\} \nu_t^{(i)}(d\mathbf{x}) && \text{births w/o mutations, w/o migrations} \\
 &+ \int_{\mathcal{X}} \left\{ \mu(1-m) \int_{\mathcal{X}} b_i(y)(\phi(\nu_t^{(i)} + \delta_z) - \phi(\nu_t^{(i)})) \mathcal{M}(\mathbf{x}, y) dy \right\} \nu_t^{(i)}(d\mathbf{x}) && \text{births w/ mutations, w/o migrations} \\
 &+ \iint_{\mathcal{X}} \left\{ \frac{1}{K} (\phi(\nu_t^{(i)} - \delta_{\mathbf{x}}) - \phi(\nu_t^{(i)})) \nu_t^{(i)}(dy) \nu_t^{(i)}(dx) \right\} && \text{deaths} \\
 &+ \sum_{j \neq i} \frac{a_{i,j}}{d_j} \int_{\mathcal{X}} \mu m \left\{ \int_{\mathcal{X}} b_j(y)(\phi(\nu_t^{(j)} + \delta_{\mathbf{x}}) - \phi(\nu_t^{(j)})) \mathcal{M}(\mathbf{x}, y) dy \right\} \nu_t^{(j)}(d\mathbf{x}) && \text{migrations w/ mutations} \\
 &+ \sum_{j \neq i} \frac{a_{i,j}}{d_j} \int_{\mathcal{X}} \left\{ b_j(\mathbf{x})(1-\mu)m(\phi(\nu_t^{(j)} + \delta_{\mathbf{x}}) - \phi(\nu_t^{(j)})) \right\} \nu_t^{(j)}(d\mathbf{x}). && \text{migrations w/o mutations}
 \end{aligned}$$

# Differentiation

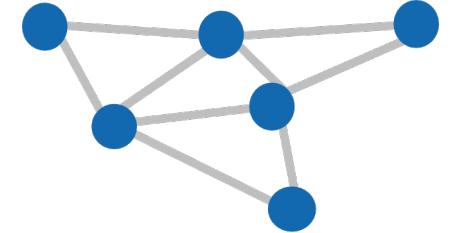
Variance of the mean trait  $\bar{x}^{(i)}$  across nodes

$$\beta = \frac{1}{2M} \sum_i \sum_j (\bar{x}^{(i)} - \bar{x}^{(j)})^2$$

number of vertices

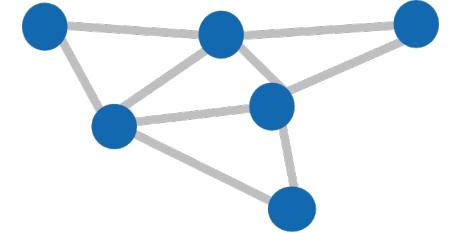


# Setting #1 – Effect of topology on differentiation



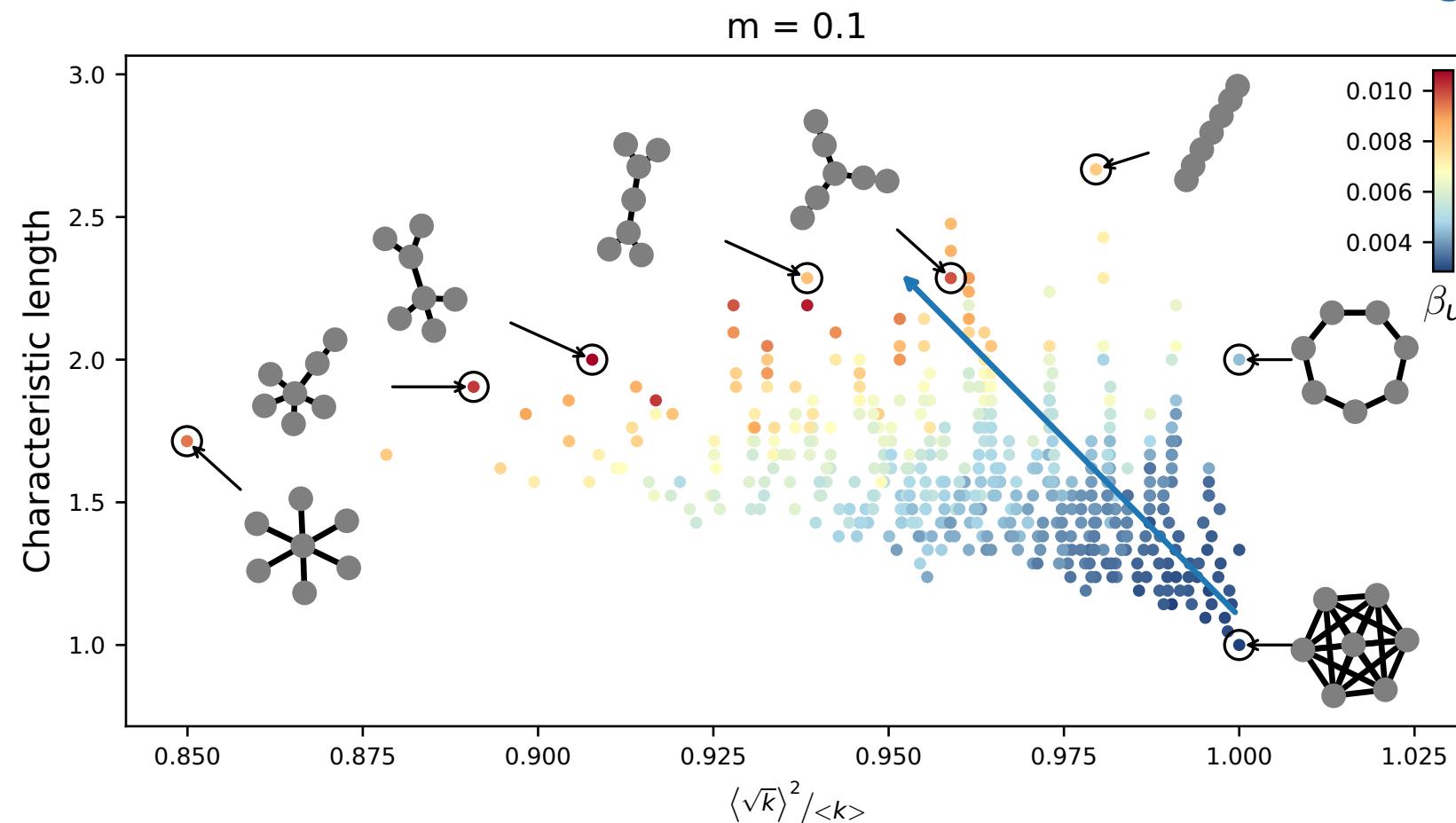
# Setting #1 – Effect of topology on differentiation

$$b_i(x_k) \equiv b \in \mathbb{R}$$

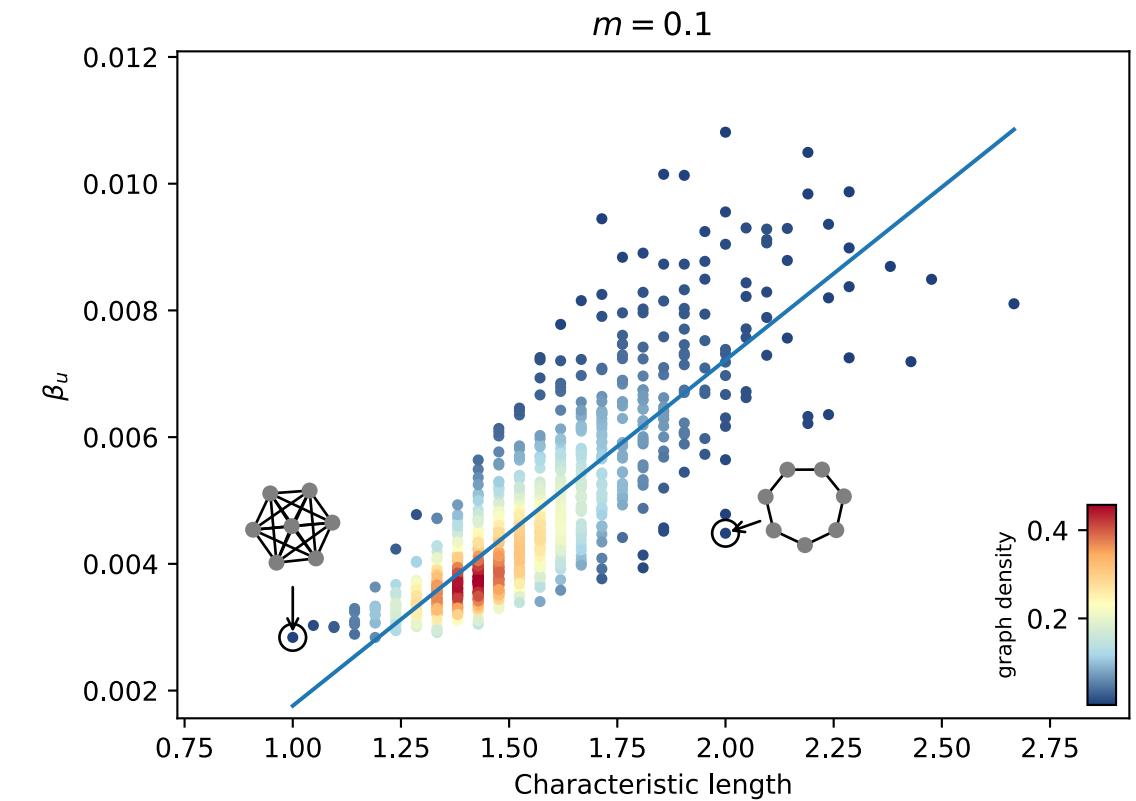


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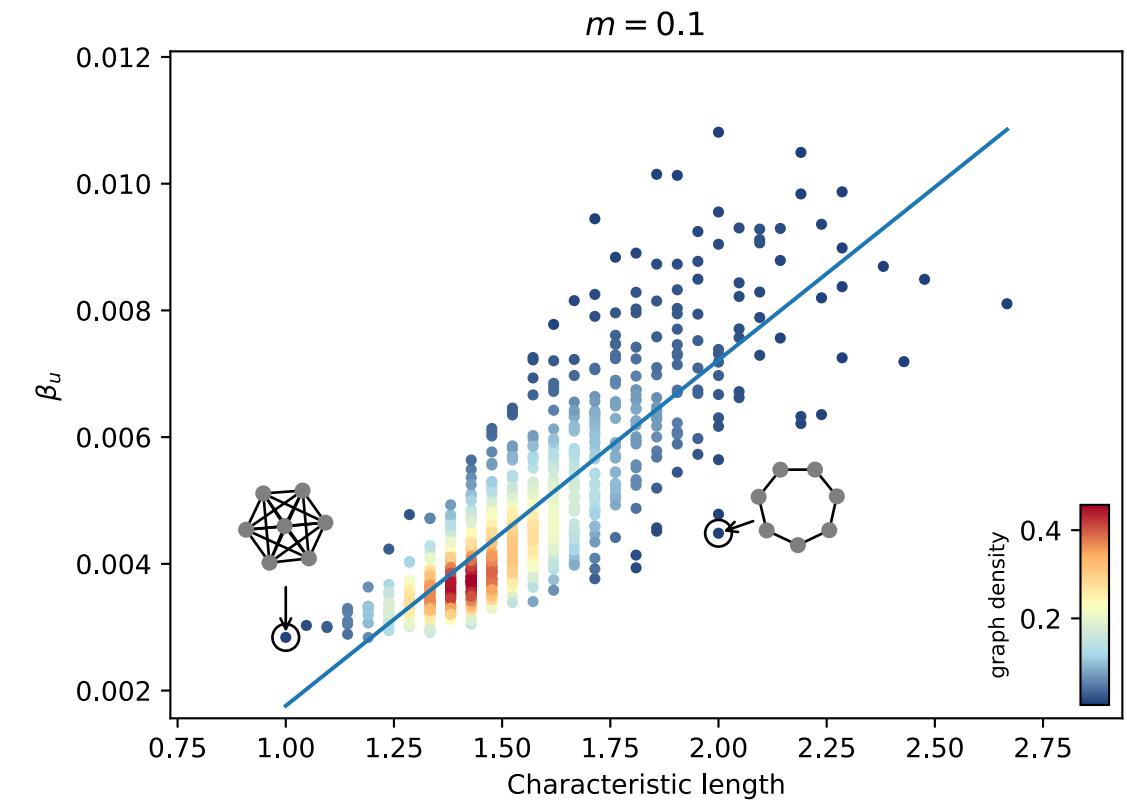
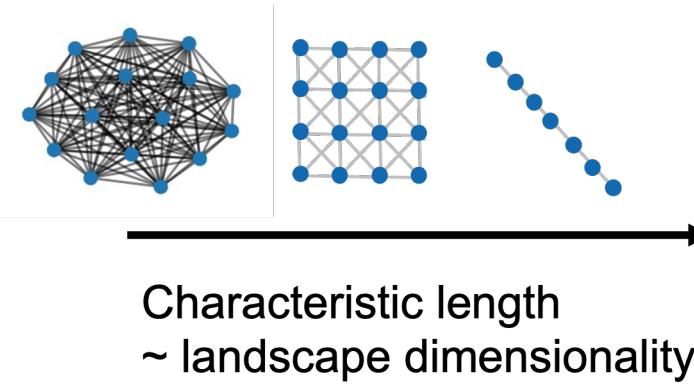
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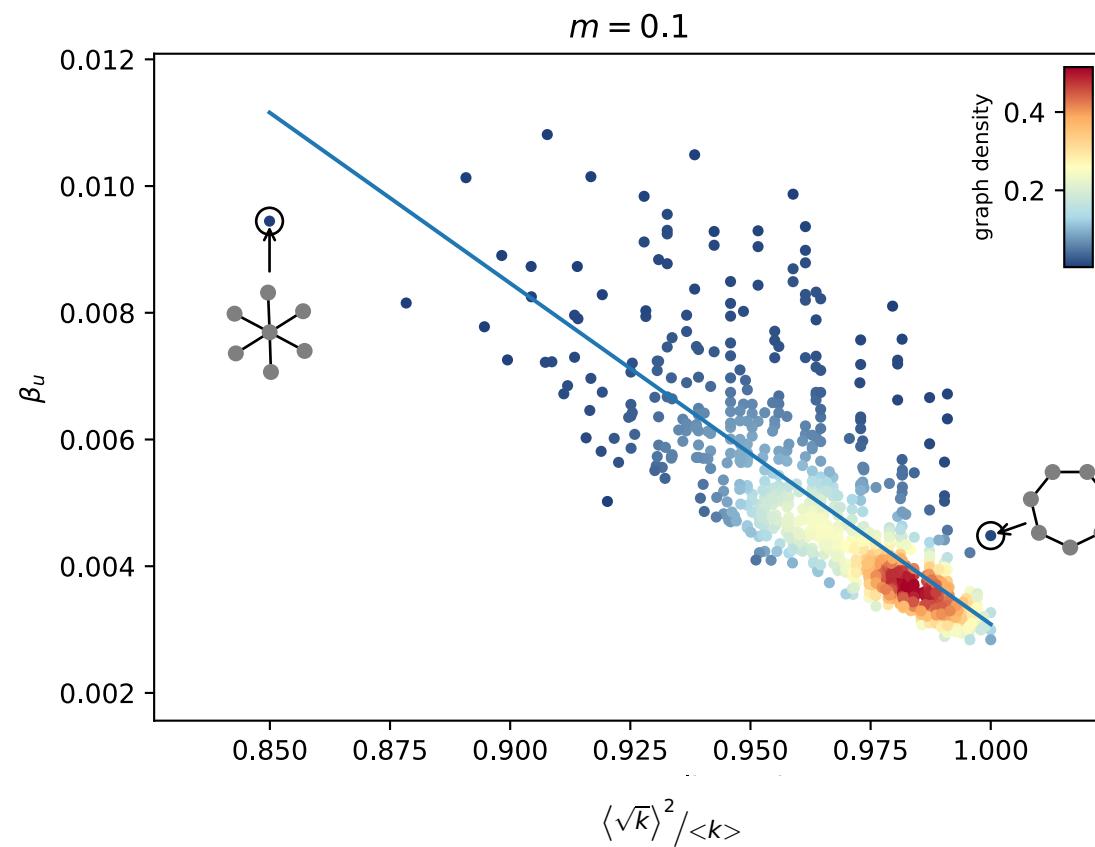
# Setting #1 – Effect of characteristic length on differentiation



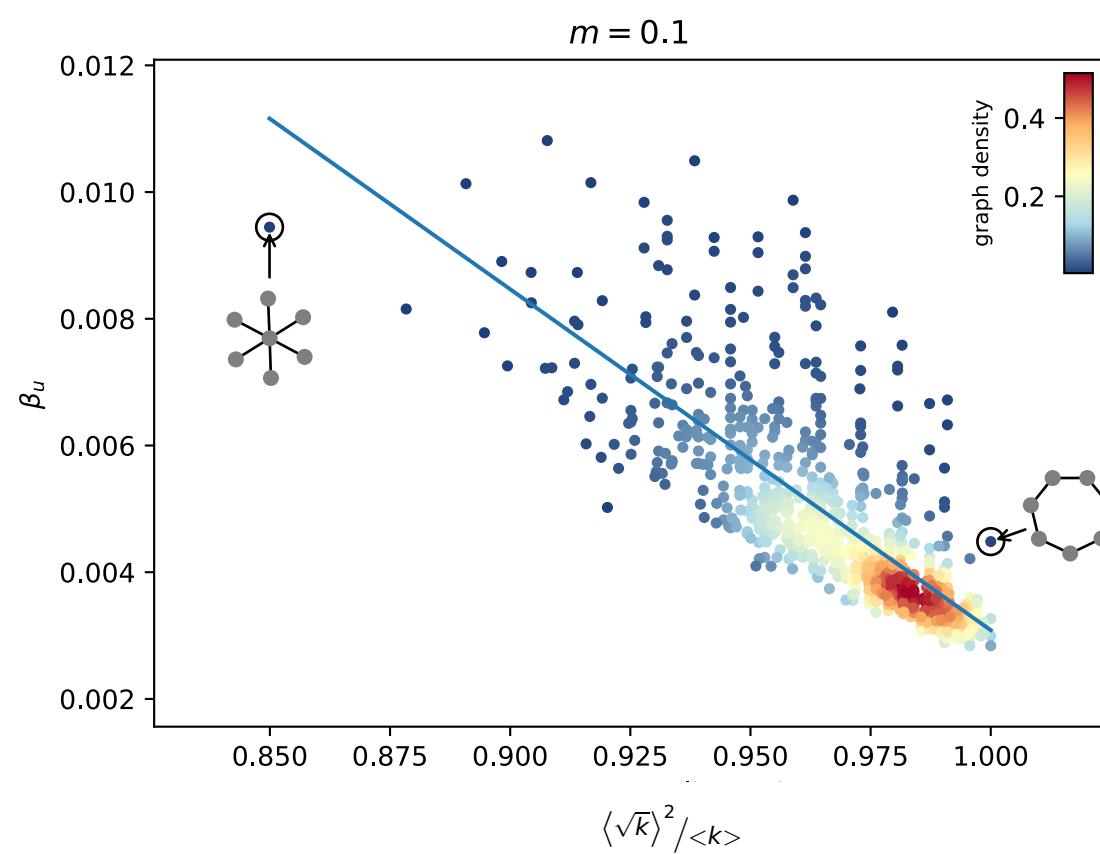
# Setting #1 – Effect of characteristic length on differentiation



# Setting #1 – Effect of heterogeneity in degree on differentiation



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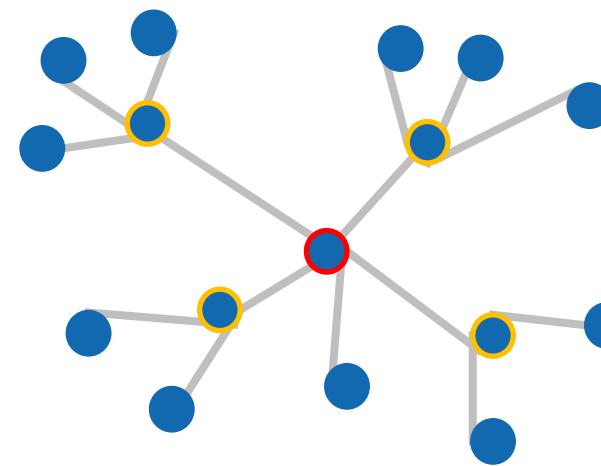
$$\begin{aligned}\partial_t N_t^{(i)} = & N_t^{(i)} \left[ b(1-m) - \frac{N_t^{(i)}}{K} \right] \\ & + mb \sum_{j \neq i} \frac{a_{i,j}}{d_j} N_t^{(j)}\end{aligned}$$

**Mean field approach:** all vertices having the same degree are equivalent

$$\bar{N} = bK \frac{\langle \sqrt{k} \rangle^2}{\langle k \rangle}$$

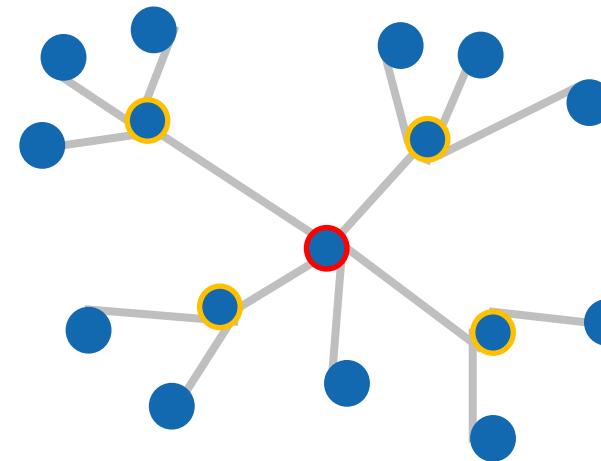
Average degree of the graph

# Setting #1 – Effect of heterogeneity in degree on differentiation



# Setting #1 – Effect of heterogeneity in degree on differentiation

Nodes with relatively  
high degree

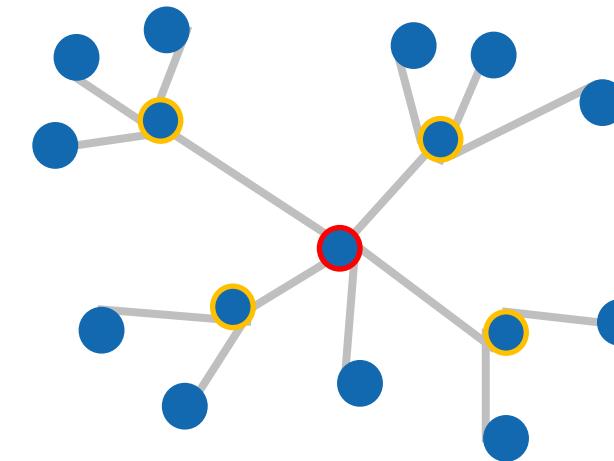


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Nodes with relatively  
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High influx of migrants



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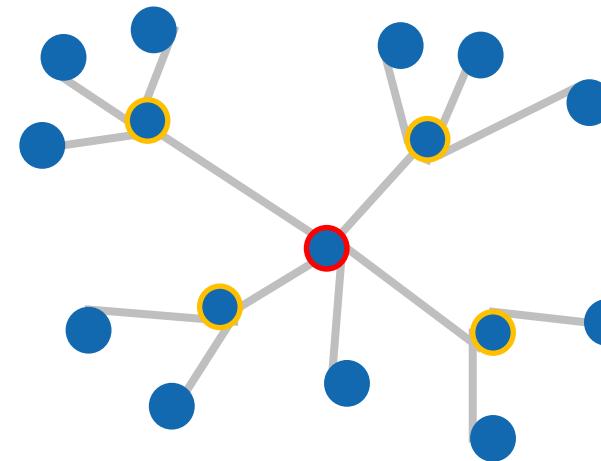
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Increased competition



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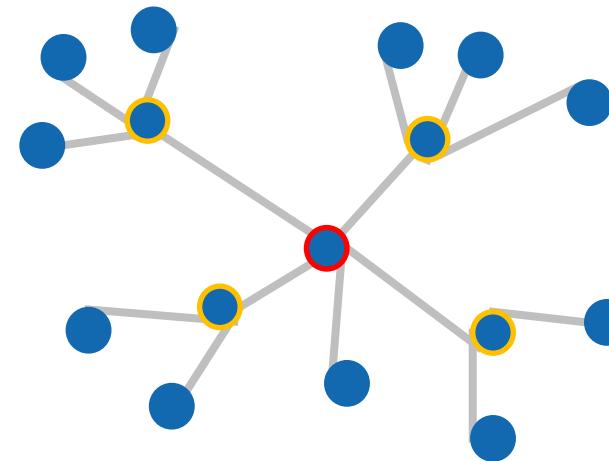
High influx of migrants



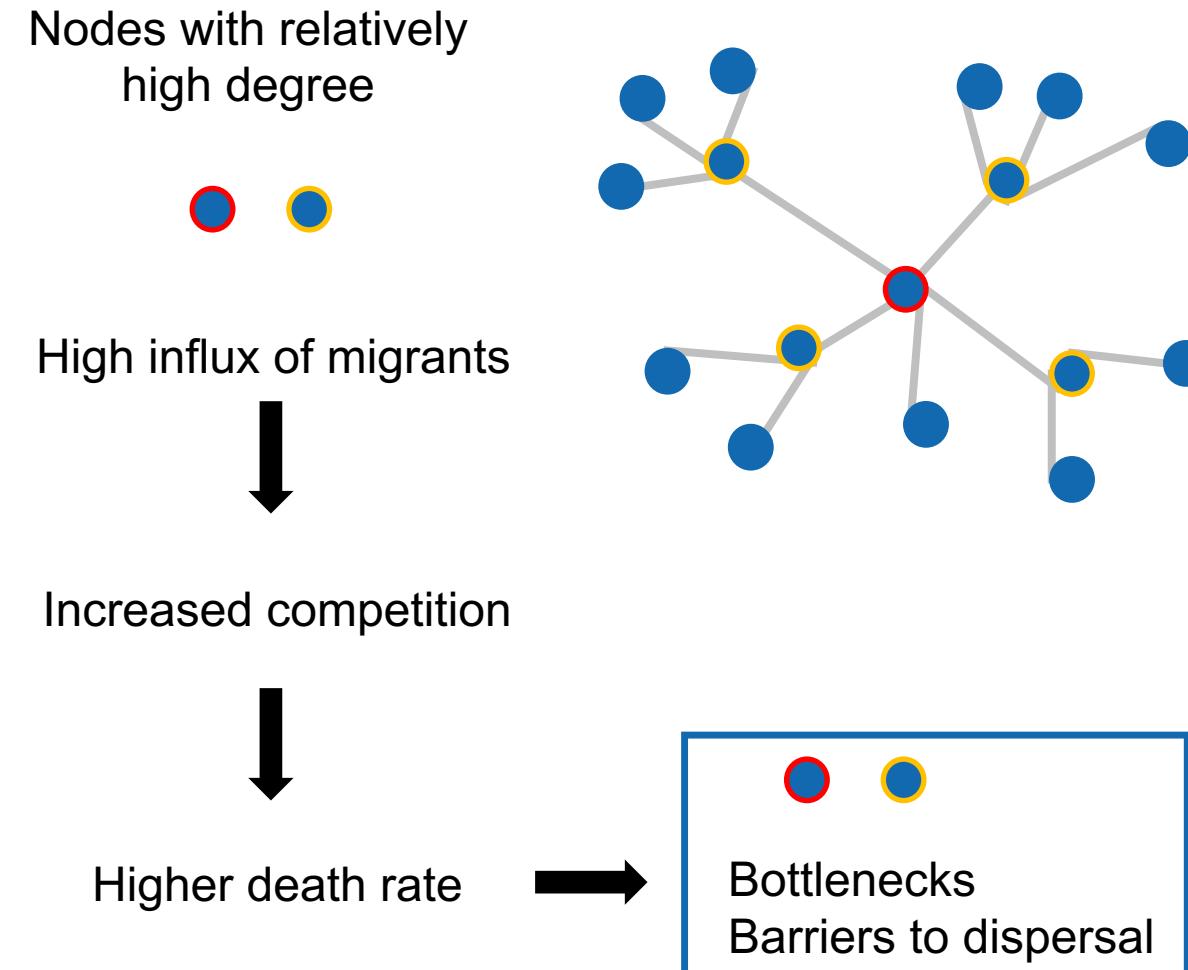
Increased competition



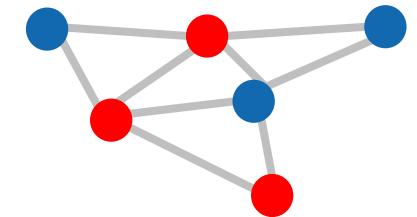
Higher death rate



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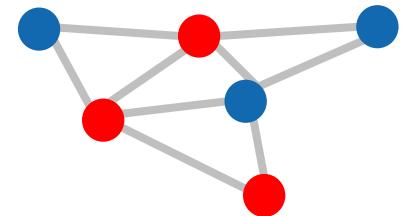
## Setting #2 – Effect of topology & habitat heterogeneity on differentiation



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$$x_k = (u_k, s_k)$$

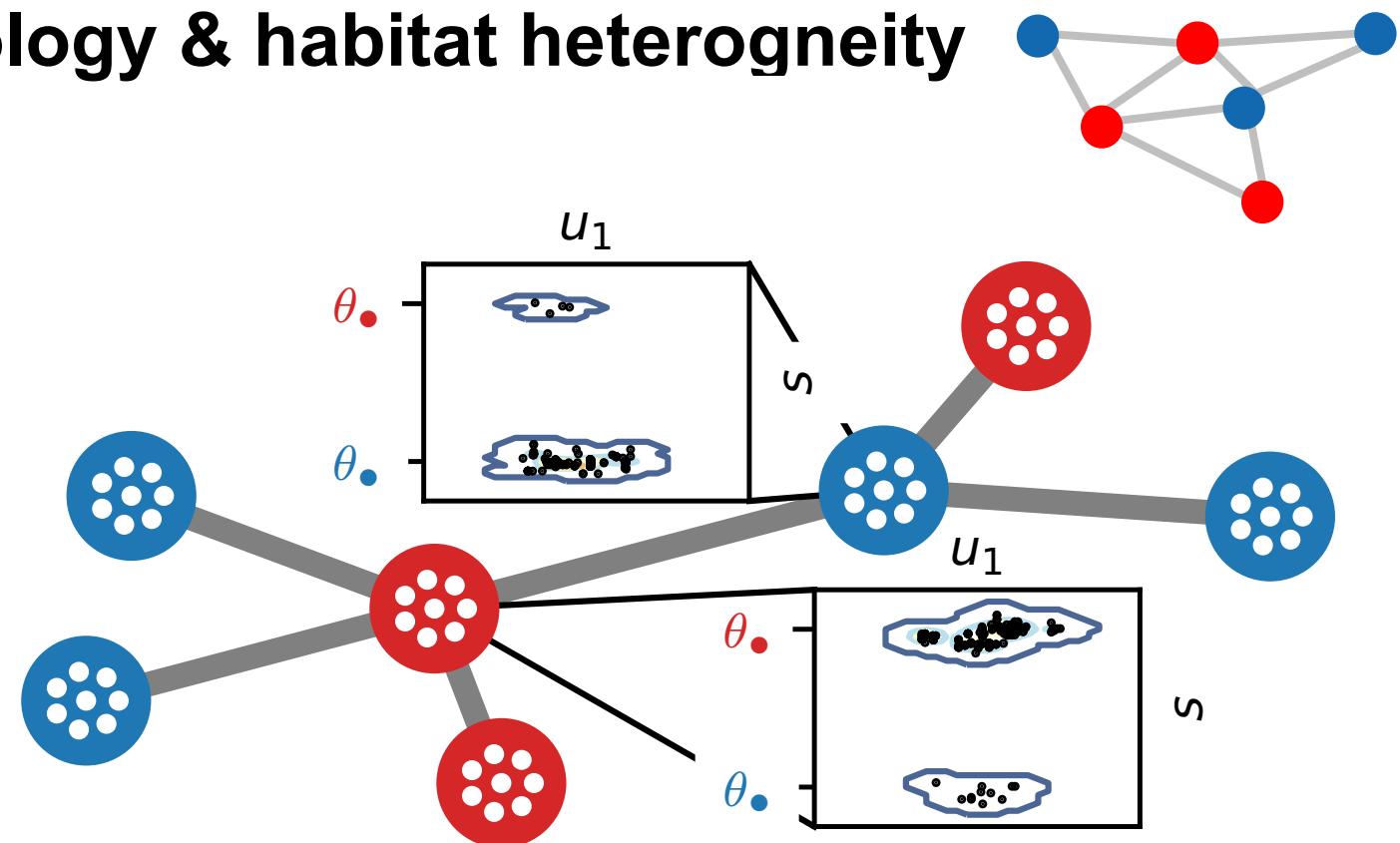
$$b_i(x_k) \equiv b(1 - p(s_k - \theta_i)^2).$$



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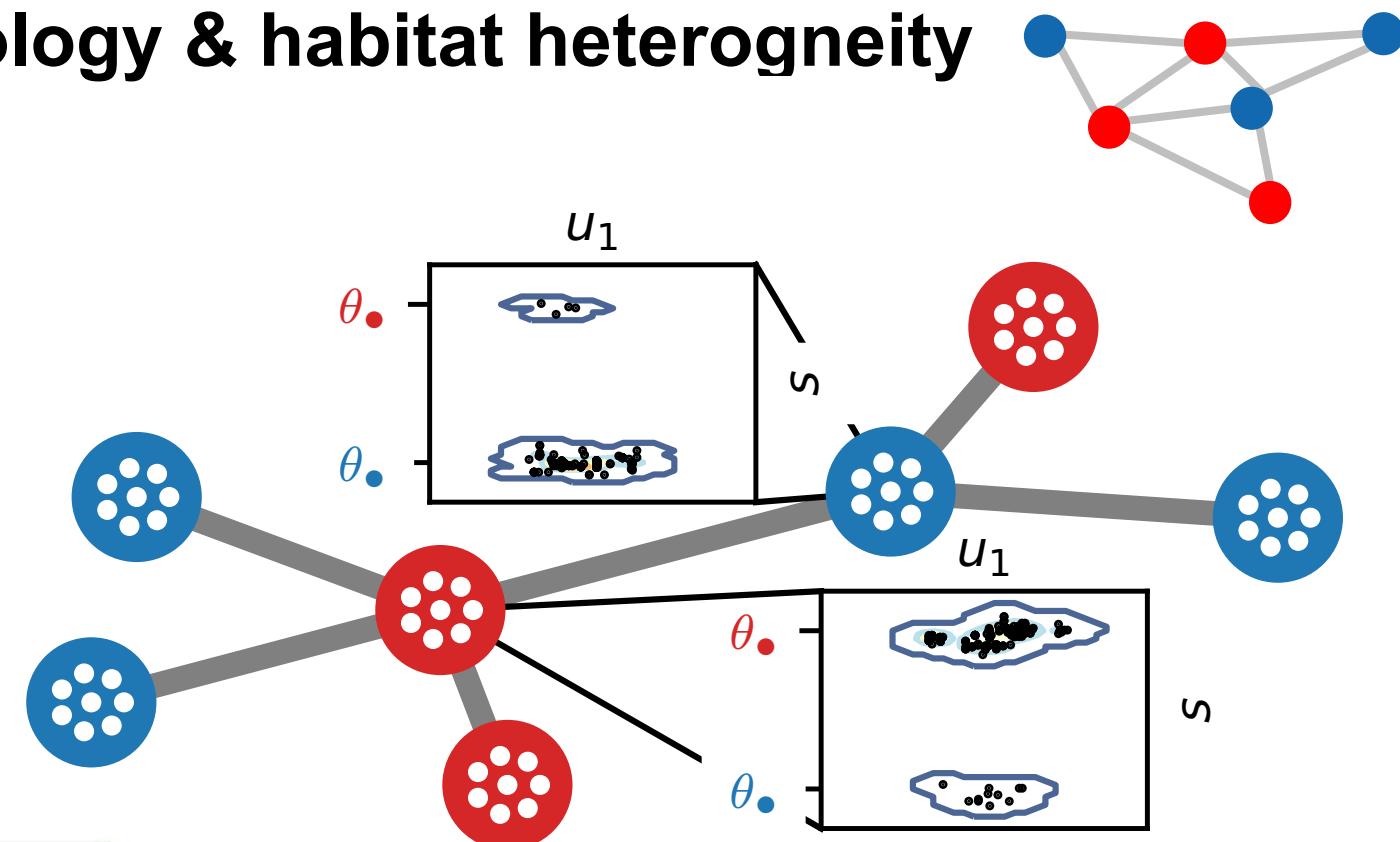
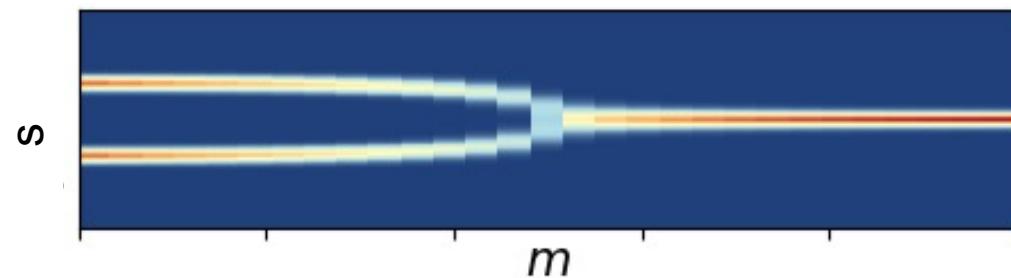
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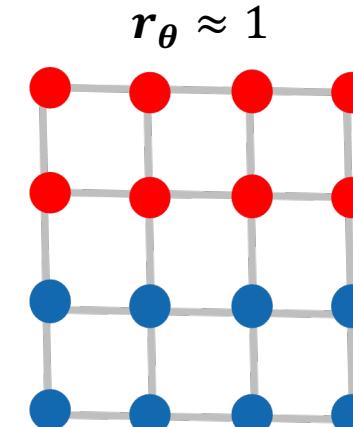
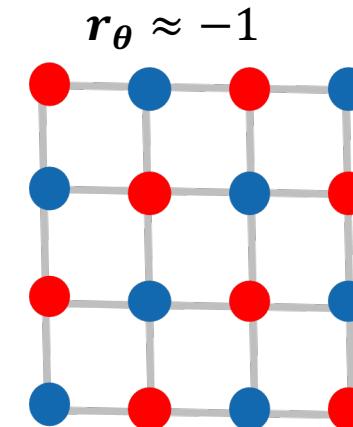
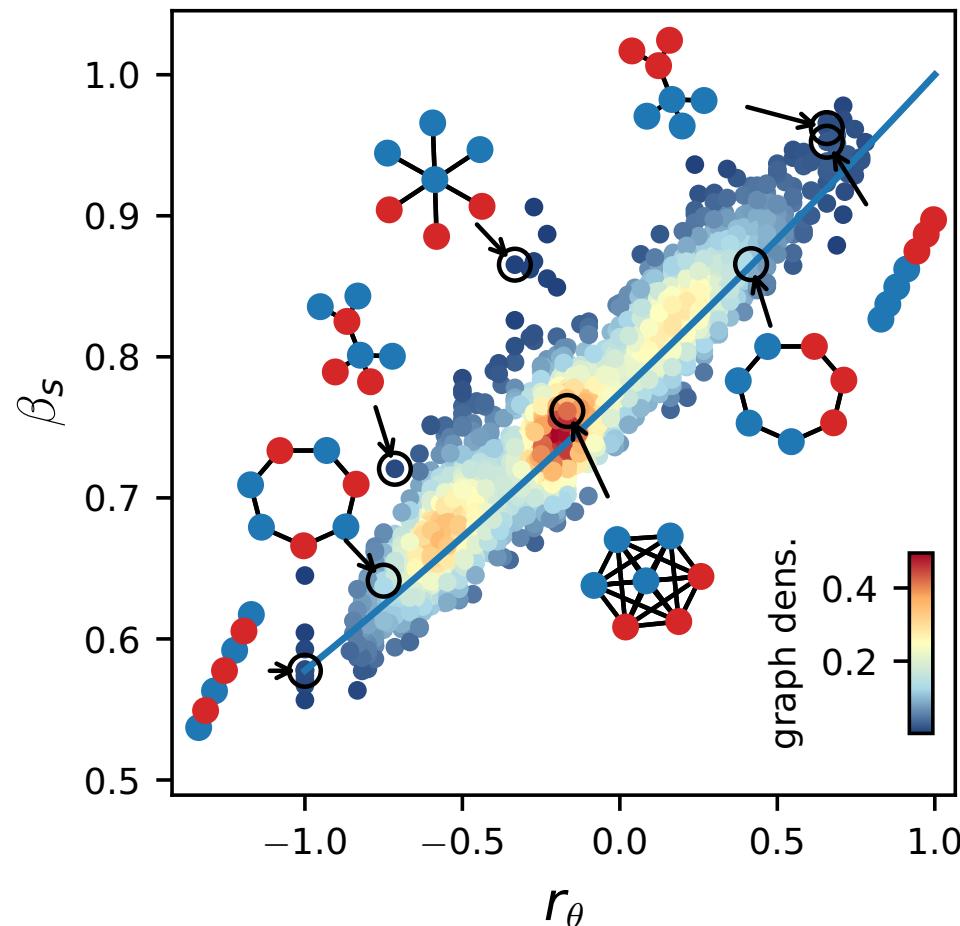
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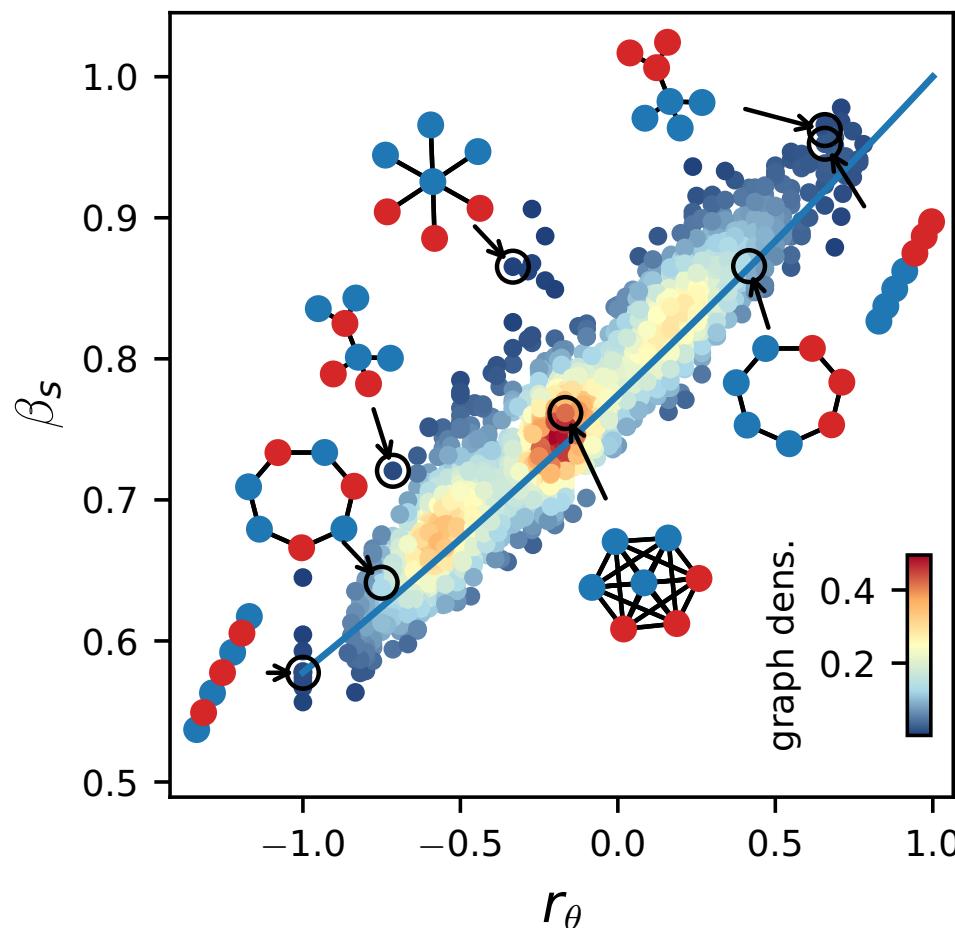
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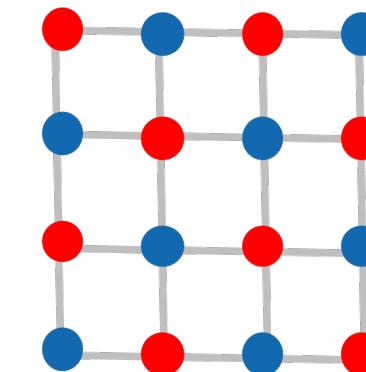
# Setting #2 – Environmental assortativity $r_\theta$ drives differentiation through Isolation by Environment



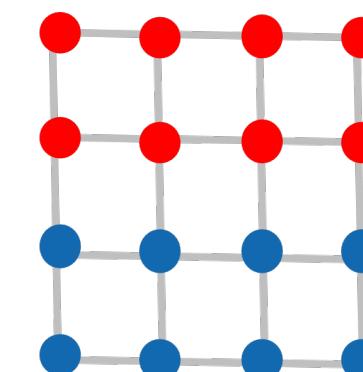
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$r_\theta \approx -1$



$r_\theta \approx 1$



**Mean field approach:** all vertices with a similar habitat are equivalent

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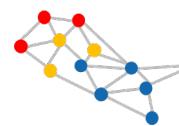
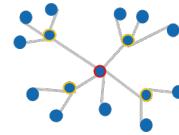
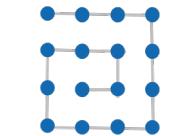
# Summary

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- How do complex landscapes drive differentiation patterns?

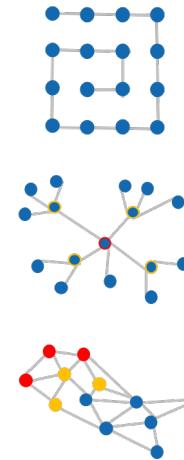
# Summary

- How do complex landscapes drive differentiation patterns?
- Numerical and analytical results show that **three important graph properties control the level of differentiation**
  - Characteristic length
  - Heterogeneity in degree
  - Environmental assortativity  $r_\theta$



# Summary

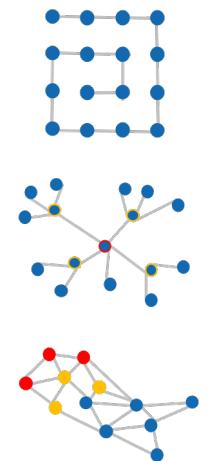
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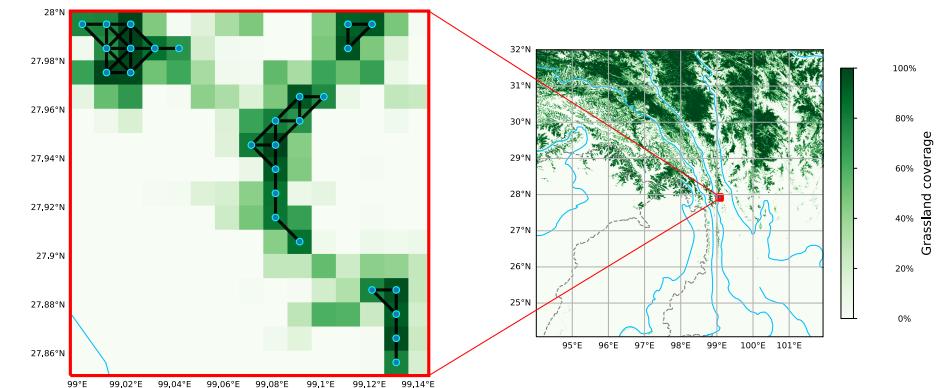
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<https://doi.org/10.1101/2021.07.06.451404>

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- Numerical and analytical results show that **three important graph properties control the level of differentiation**
  - Characteristic length
  - Heterogeneity in degree
  - Environmental assortativity  $r_\theta$
- **Theory validation:** using graph-based metrics for realistic landscapes



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# Acknowledgements

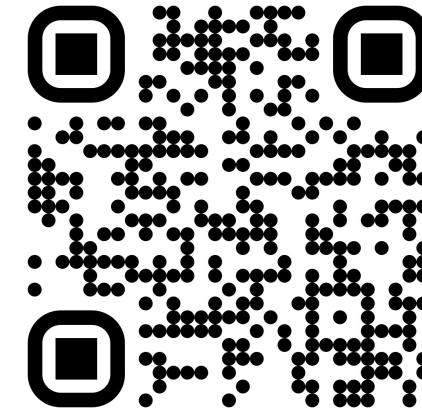


## Acknowledgements



**Thanks!  
(looking for a postdoc  
next year ☺)**

Check out my personal website



to discover more  
about my research