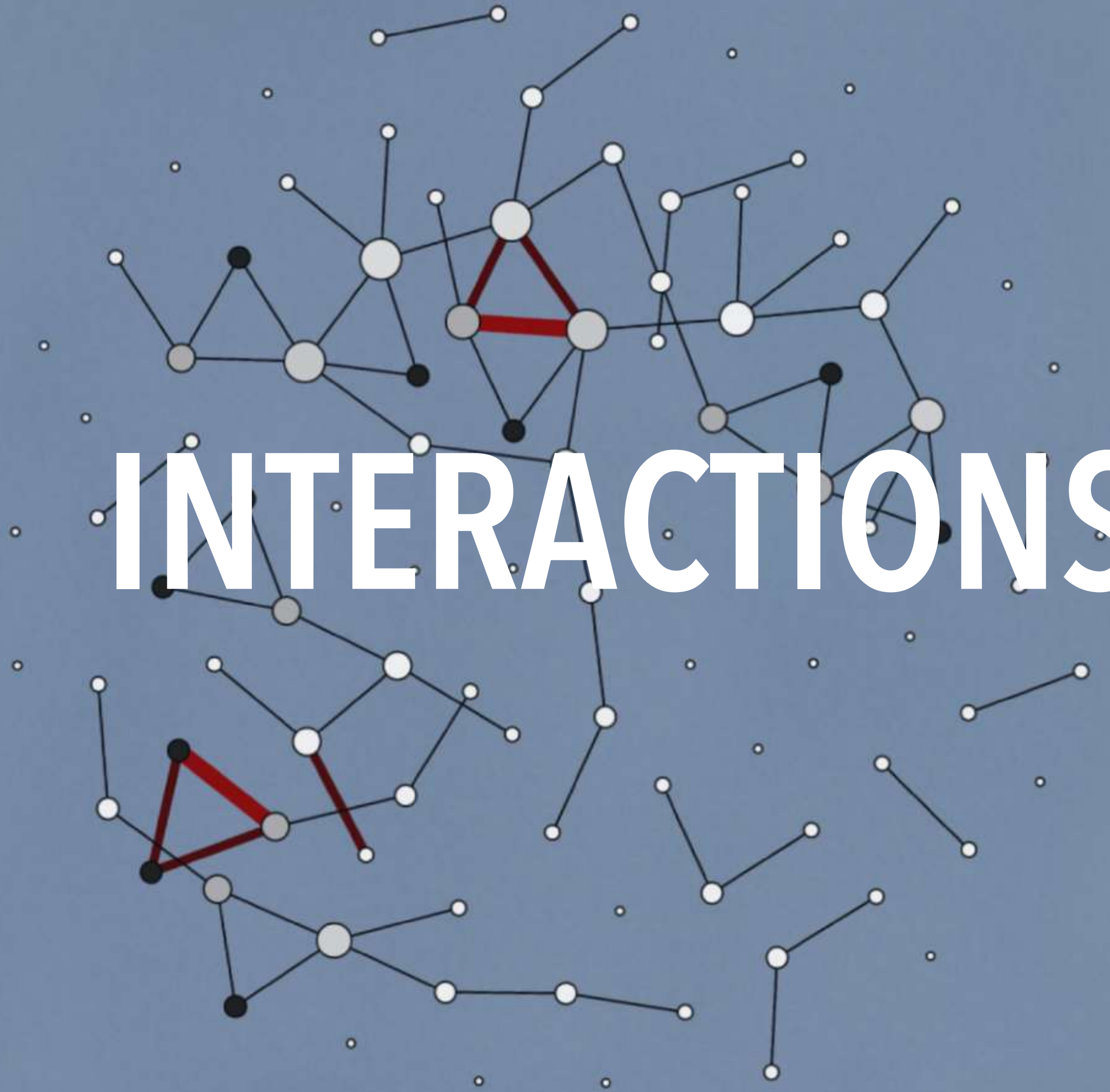
Exploring ecological and social interactions through the lens of complex systems

Violeta Calleja Solanas
PhD defense
19th July 2023



INTERACTIONS


EMERGENT BEHAVIOR

Objectives

Study emergent behavior in natural and information ecosystems

Objectives

Study emergent behavior in natural and information ecosystems

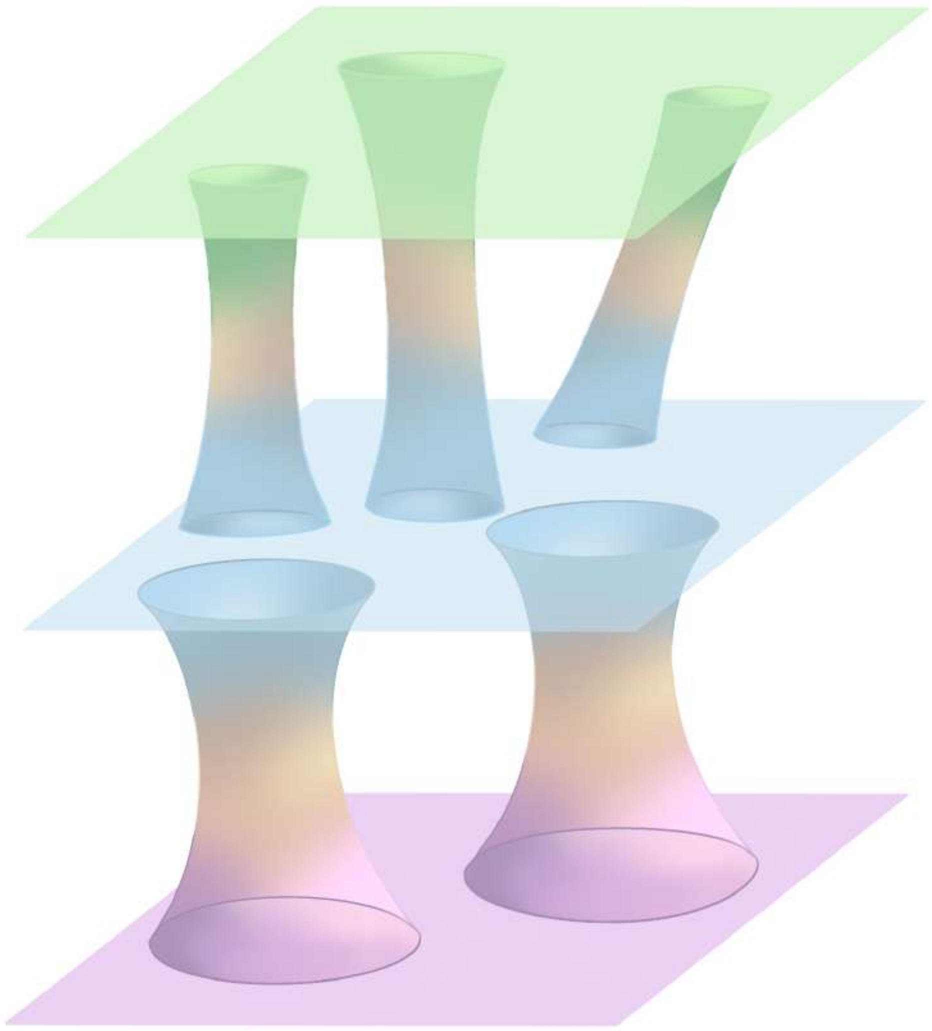
How different interactions affect the behavior of our systems

Objectives

Study emergent behavior in natural and information ecosystems

How different interactions affect the behavior of our systems

At different scales



Scales

(macro)

patterns

species

individuals

(micro)

Objectives

Study emergent behavior in natural and information ecosystems

How different interactions affect the behavior of our systems

At different scales

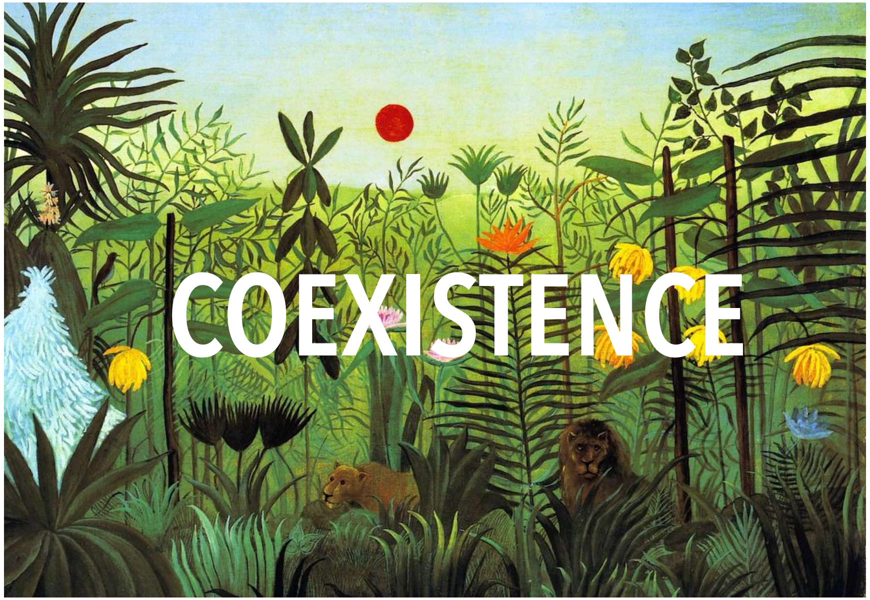
PART I

ECOLOGICAL SYSTEMS

ecology

/iˈkɒl.ə.dʒi/ noun

The science that deals with the general question of how living beings interact with each other and their environment

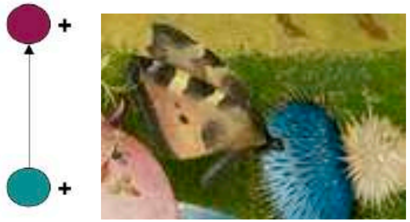


Why are there so many species living together?

Heterogeneous interactions

exploitation

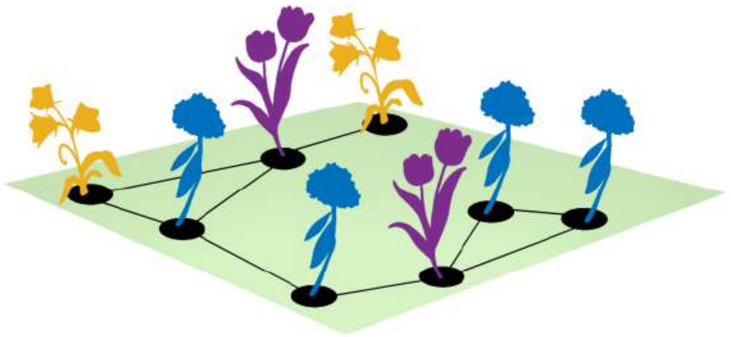
mutualism



competition

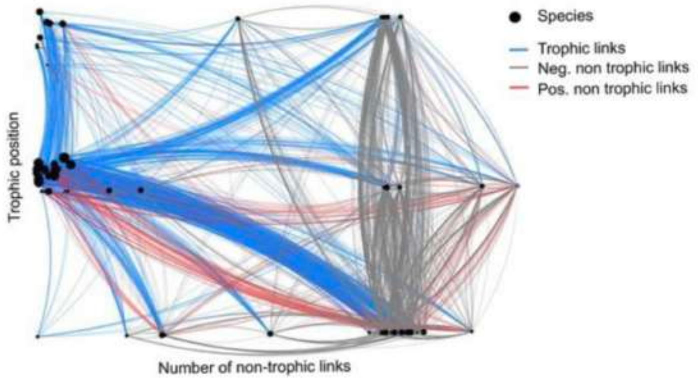
Interactions represented as **complex networks**

Space



Calleja-Solanas et al. PRE 2022

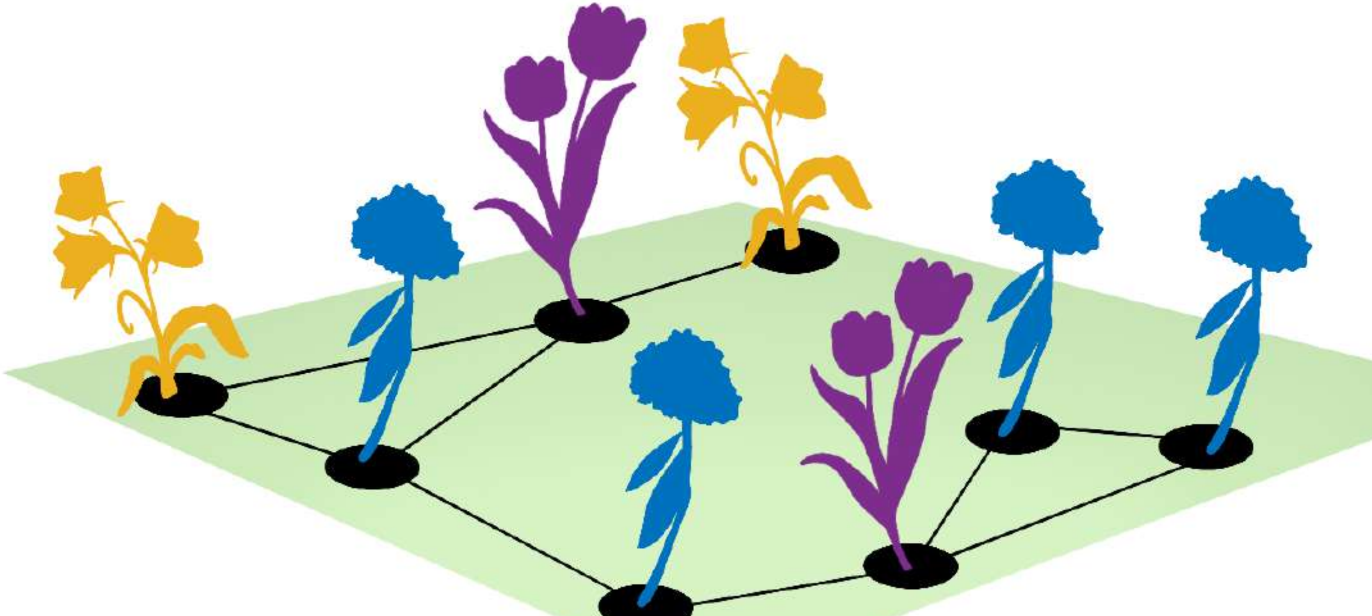
≠ types of interactions



Kefi et al. PLOS Bio 2016

Ch 3

Structured interactions & coexistence in competitive communities



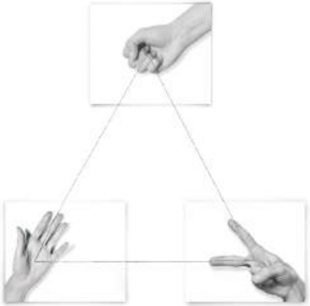
Competition

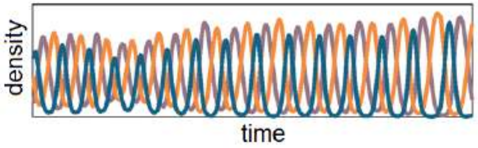
Plankton paradox

Competition

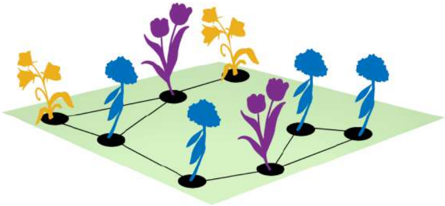
Plankton paradox

Intransitive

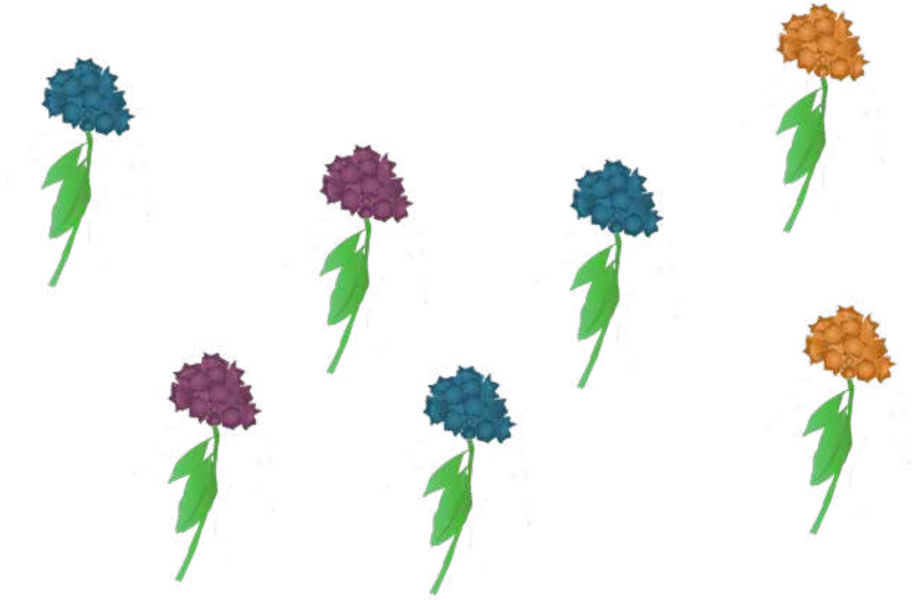




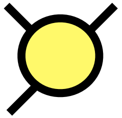
Space

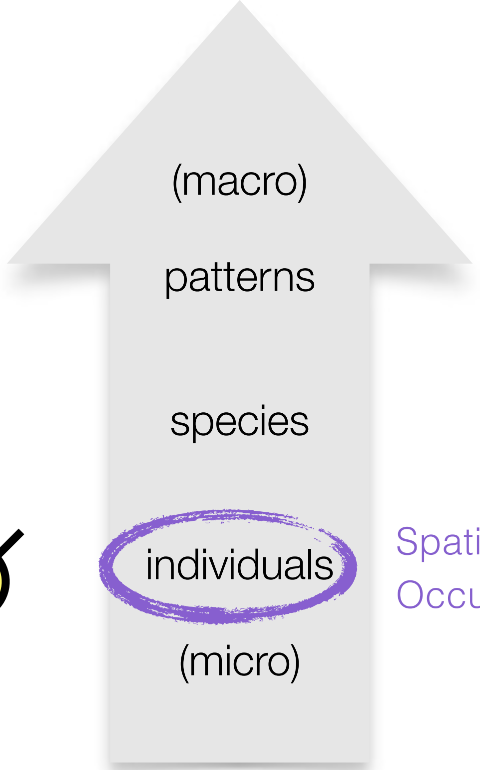


Allesina et al. Nature 2017
Kishoni et al. Nature comm 2016

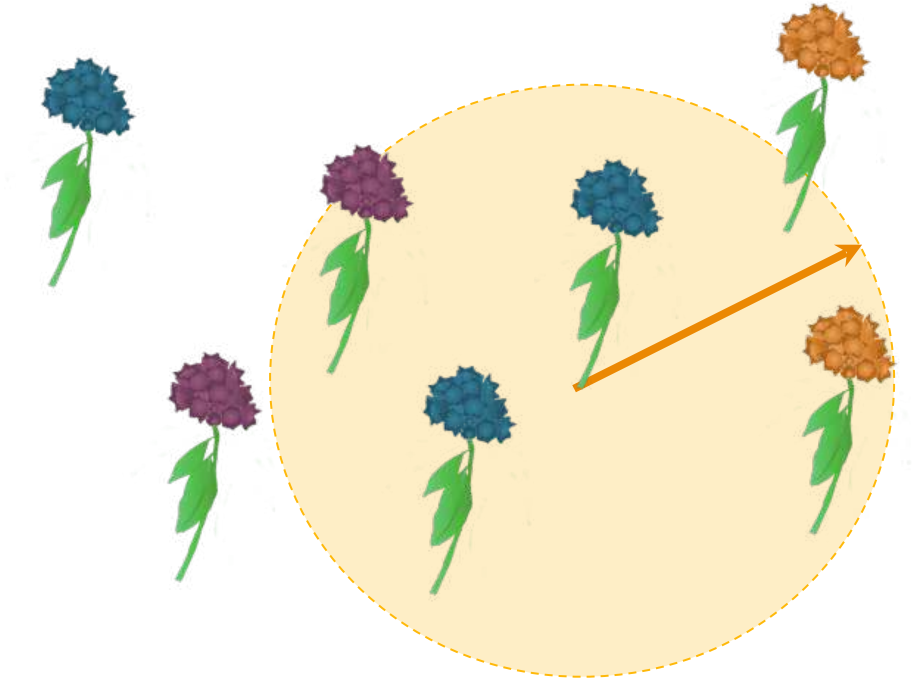


Information about **spatial** location → **Structured Interactions**

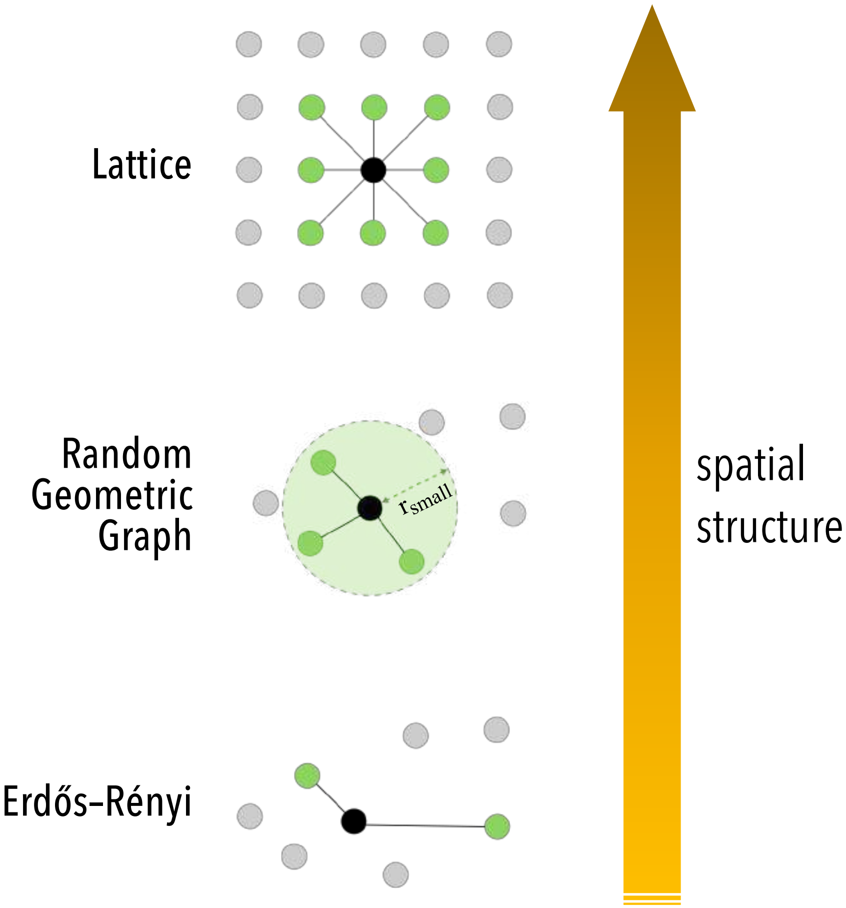


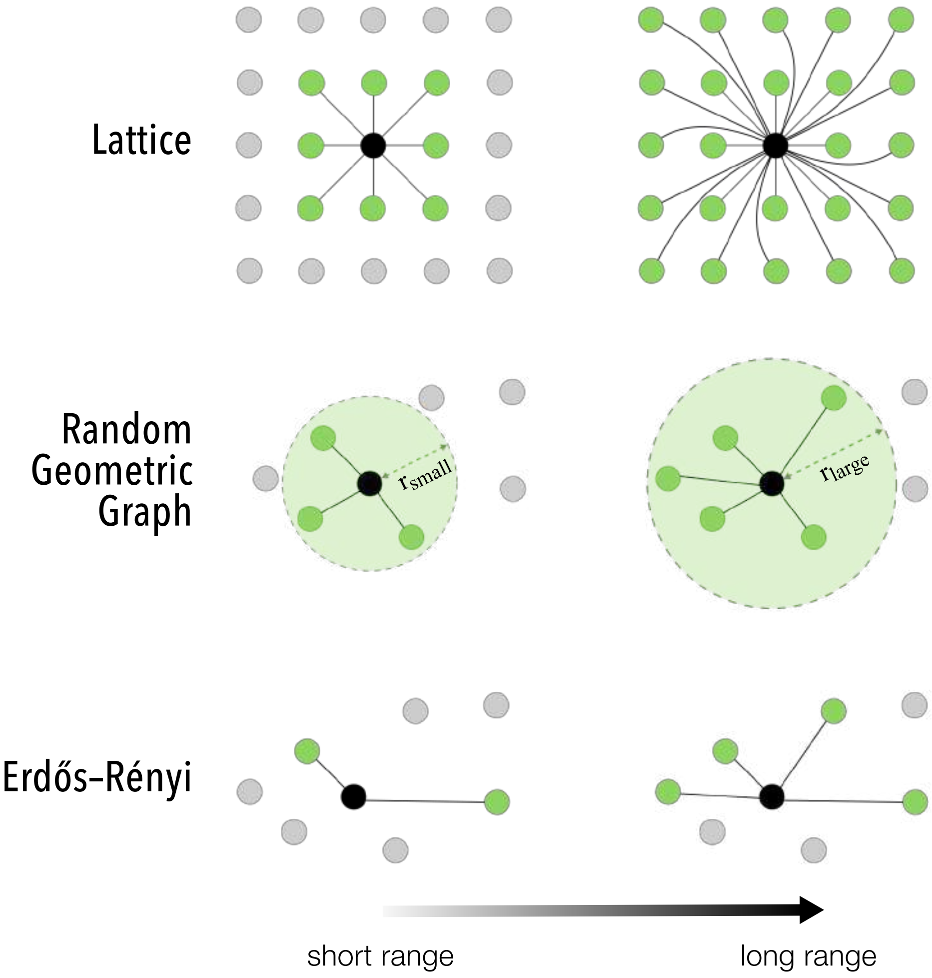


Spatial location
Occupied by 1 individual



Interaction range

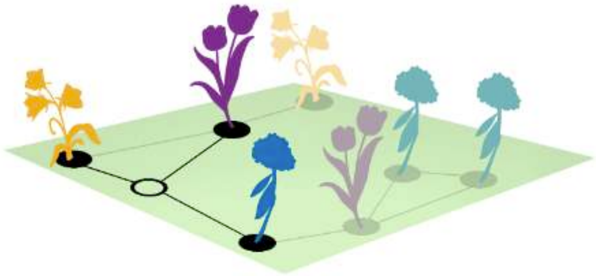

Lattice
Random
Geometric
Graph
r_{small}
Erdős–Rényi
spatial
structure



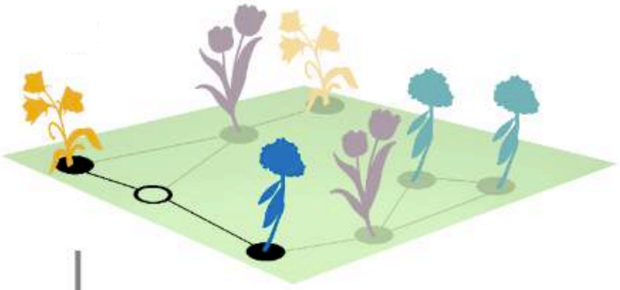
Q: How does coexistence depends on space?

- Interaction range
- Spatial structure

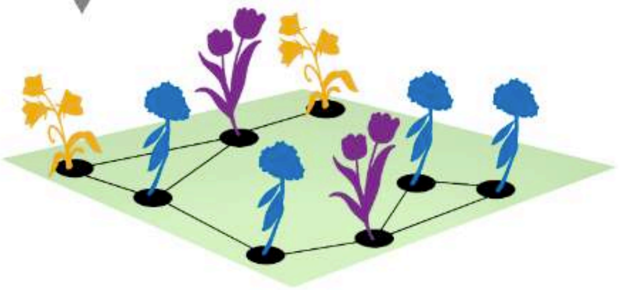
competition in neigborhood



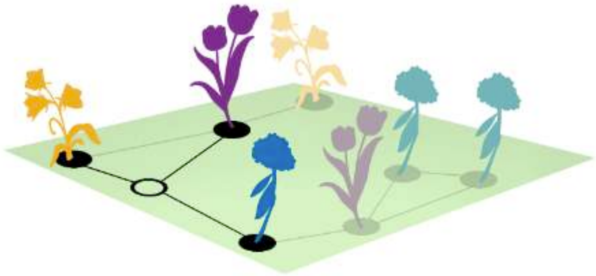
between two random neighbors



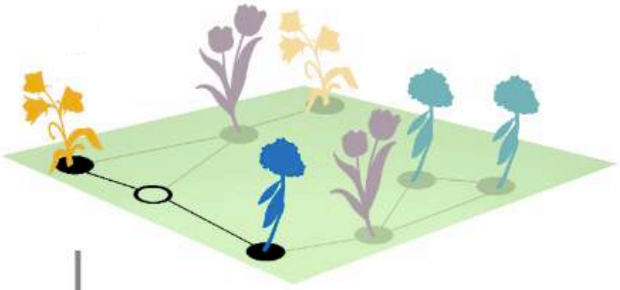
winner reproduces



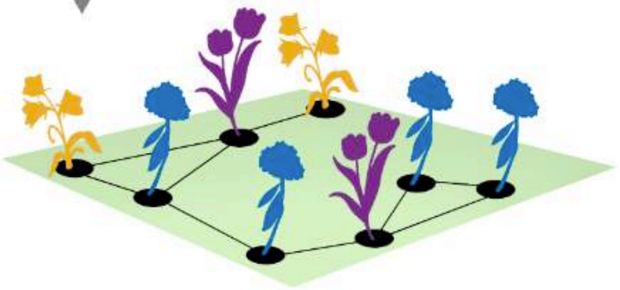
competition in neigborhood



between two random neighbors



winner reproduces



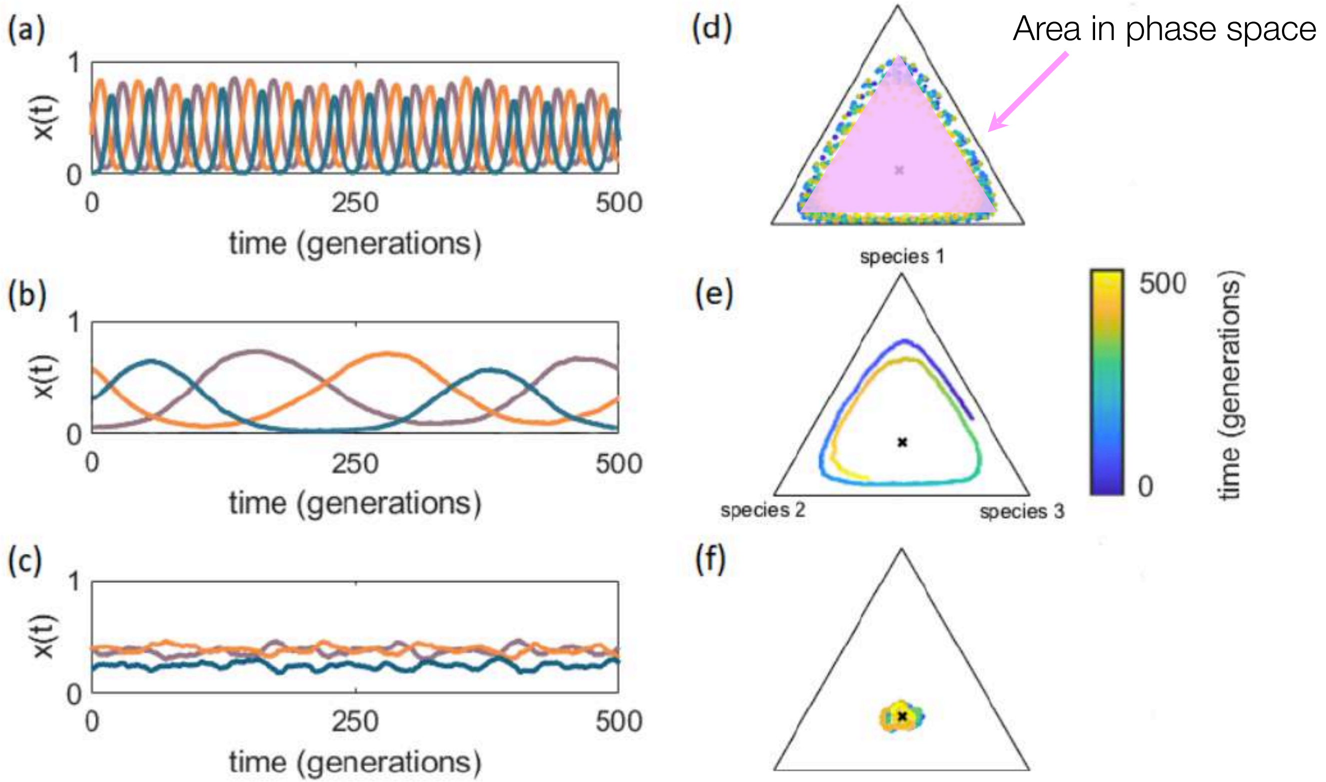
- Pairwise
- Intransitive

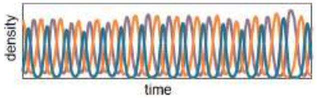
$$\begin{pmatrix} 0.5 & 0.34 & 0.75 \\ 0.66 & 0.5 & 0.25 \\ 0.25 & 0.75 & 0.5 \end{pmatrix}$$

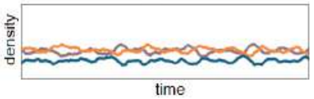
prob. species i defeats species j

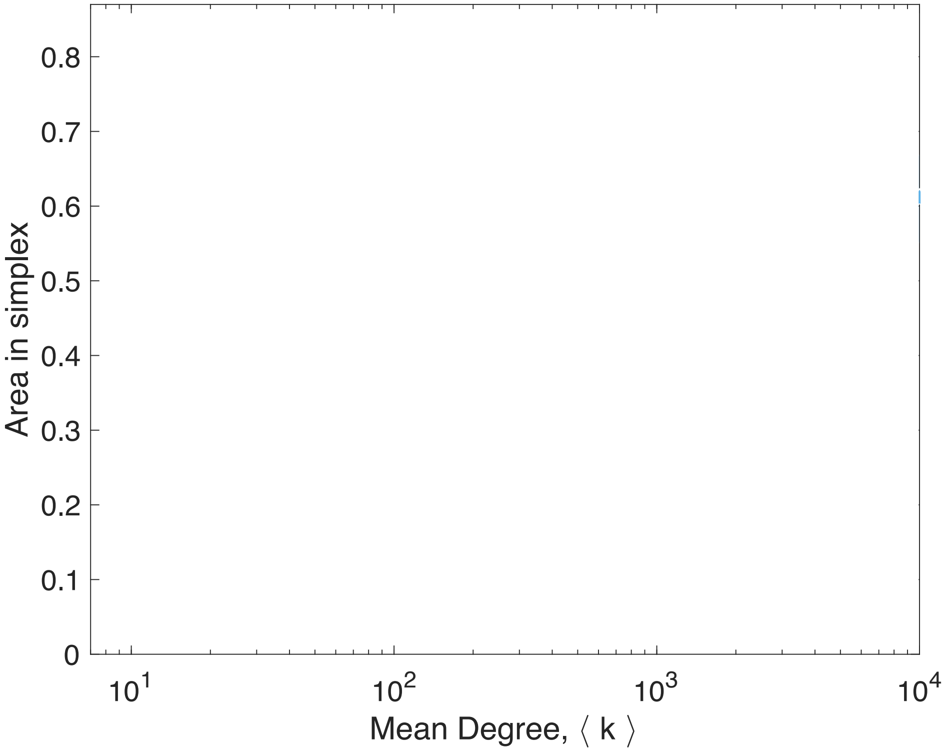
Results

Dynamics changes depending on structure



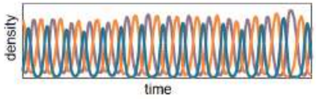


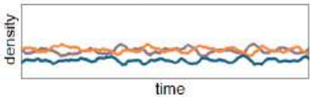


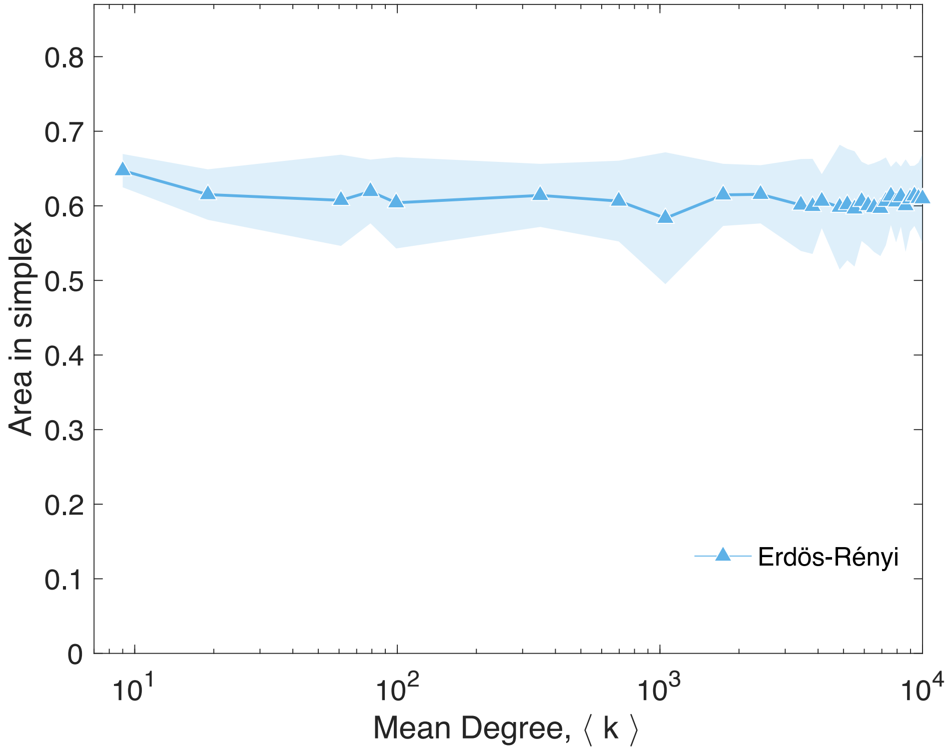


short range interactions

long range interactions

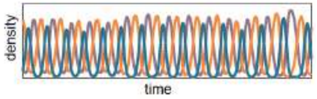


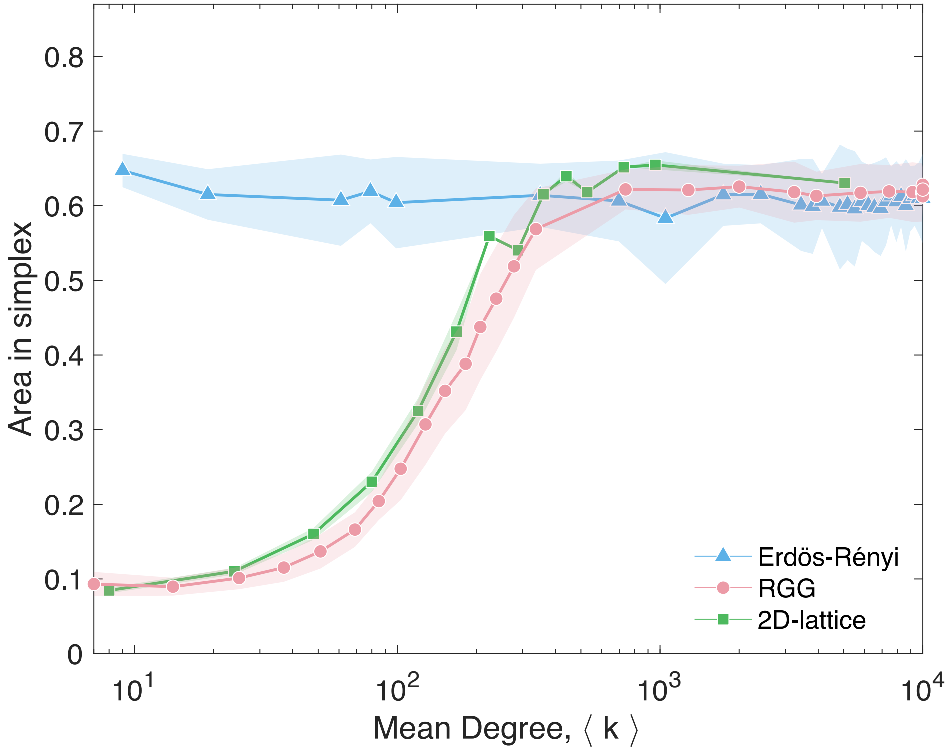


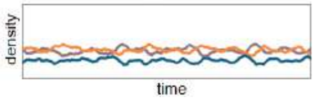


short range interactions

long range interactions

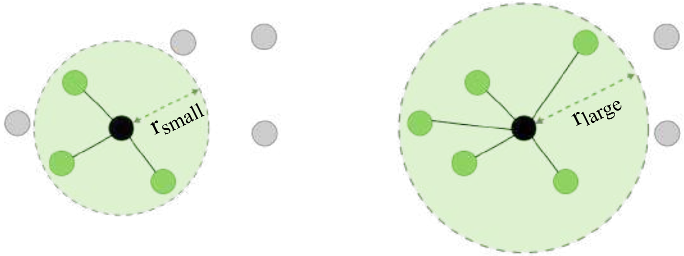






short range interactions

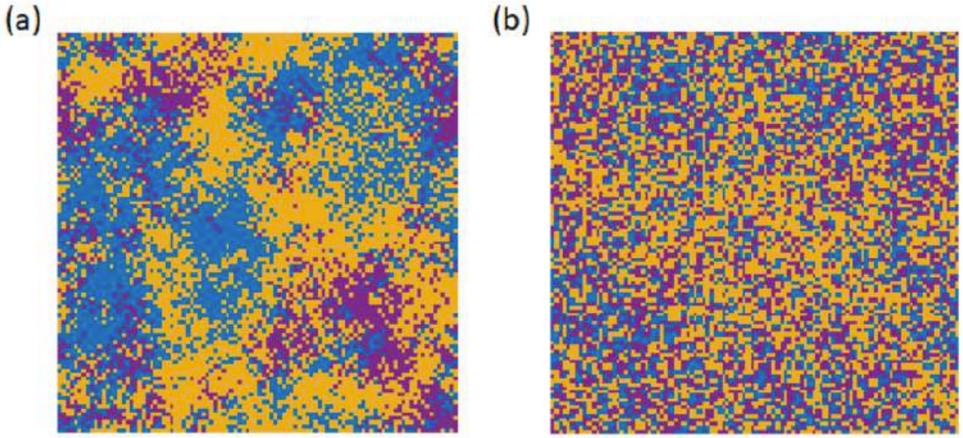
long range interactions



Dynamical behavior depends

on structured interactions

But why?

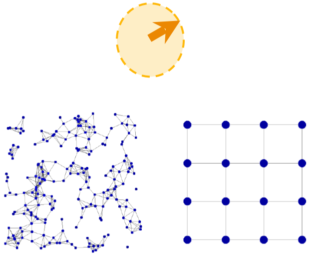


short range interactions

long range interactions

Short range interactions
create clusters that reduce competition

Conclusions

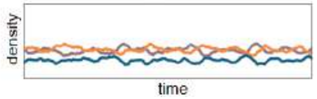


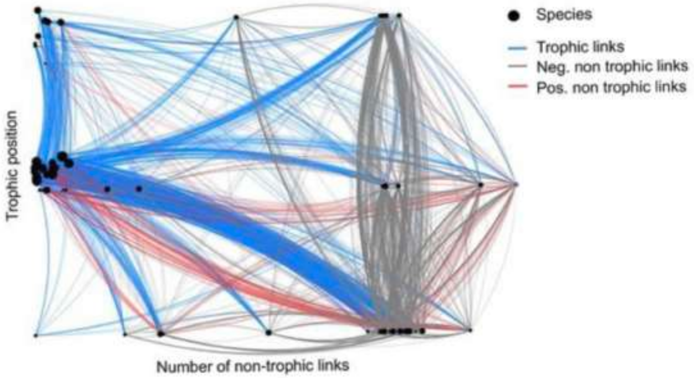
short-range interactions

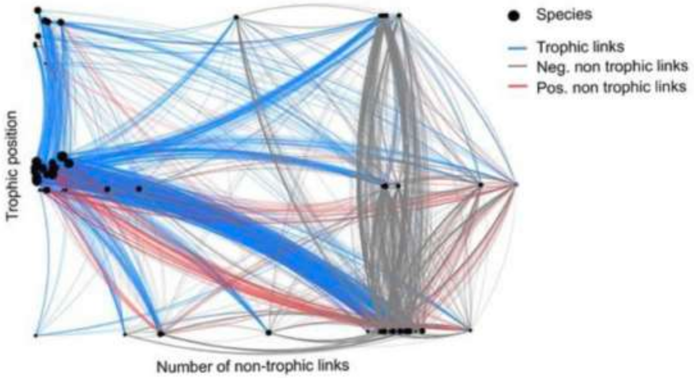
+

spatially structured network

stable coexistence




Species
Trophic links
Neg. non trophic links
Pos. non trophic links
Trophic position
Number of non-trophic links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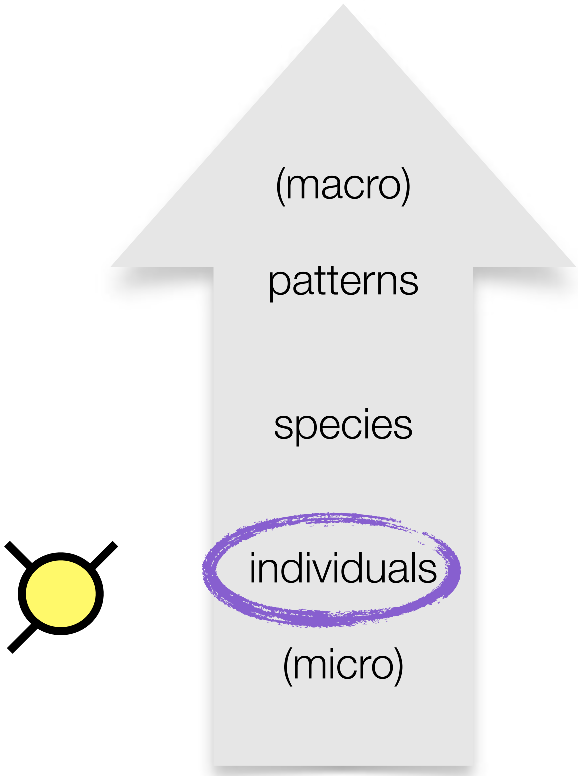
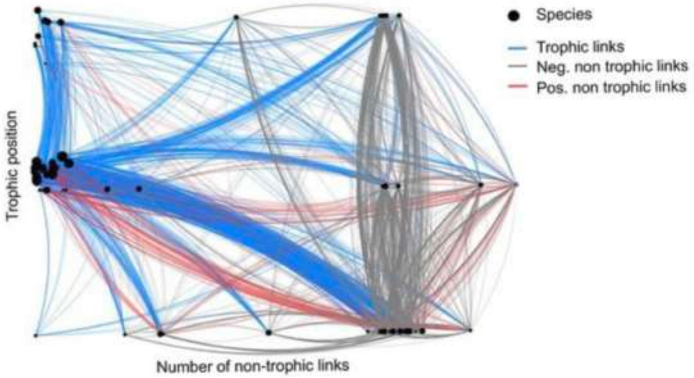
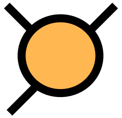
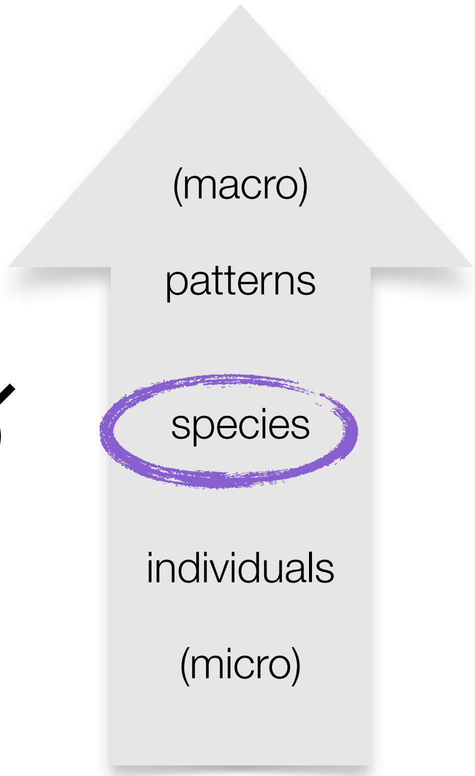

(macro)
patterns
species
individuals
(micro)


Species
Trophic links
Neg. non trophic links
Pos. non trophic links
Trophic position
Number of non-trophic links




(macro)
patterns
species
individuals
(micro)

Ch 4

Structural predictors of species survival in complex communities

Environmental changes may alter species interactions

↳ Biodiversity loss, cascades of extinctions

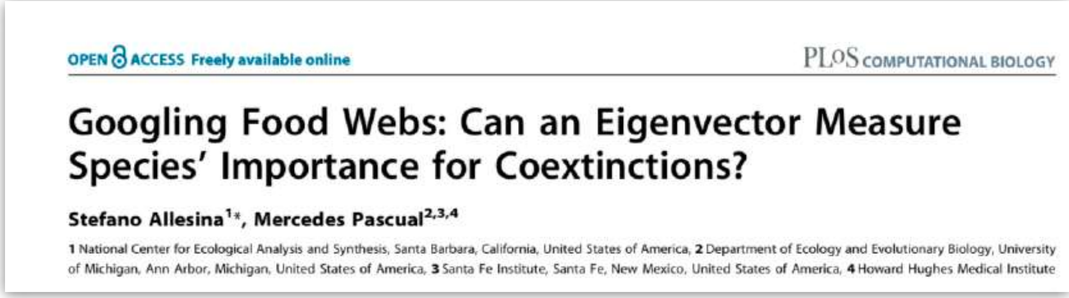
How does an ecosystem break?

Are there predictors of species survival?

Predictors typically are...

- general measures of whole network structure
- with only one type of interaction

Ex: PageRank as predictor of importance for coextinctions in food webs



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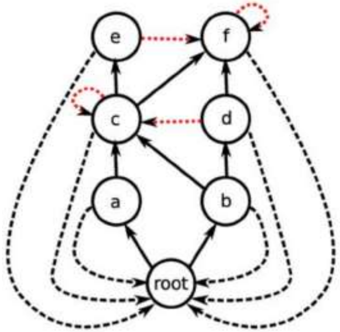
Googling Food Webs: Can an Eigenvector Measure Species' Importance for Coextinctions?

Stefano Allesina[1*], Mercedes Pascual[2,3,4]

1 National Center for Ecological Analysis and Synthesis, Santa Barbara, California, United States of America, 2 Department of Ecology and Evolutionary Biology, University of Michigan, Ann Arbor, Michigan, United States of America, 3 Santa Fe Institute, Santa Fe, New Mexico, United States of America, 4 Howard Hughes Medical Institute

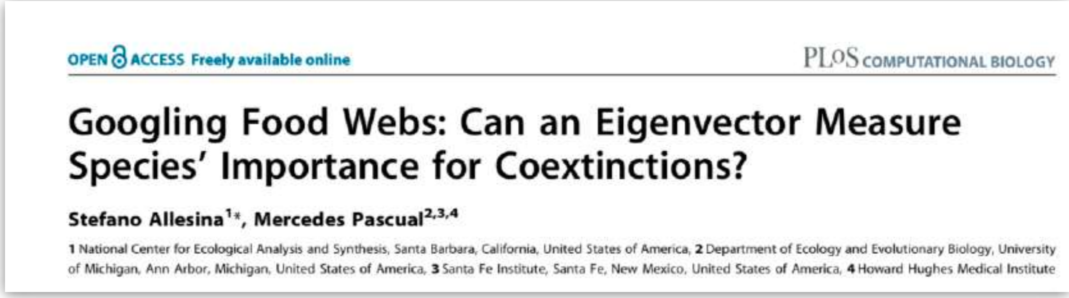


Predictors typically are...

- general measures of whole network structure
- with only one type of interaction

Q: Do predictors change if we take more interactions into account simultaneously?

Ex: PageRank as predictor of importance for coextinctions in food webs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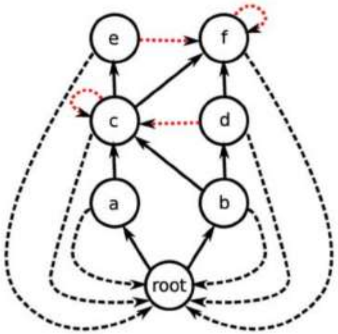


We focus on:

- properties of species ...
- … coexisting in a network with different interaction types

We focus on:

- properties of species ...
- … coexisting in a network with different interaction types

$$\dot{x}_i = x_i \left(\underbrace{\sum_i \Lambda_{ij} x_j}_{\text{local fitness}} - \underbrace{\sum_{jk} \Lambda_{jk} x_j x_k}_{\text{mean fitness}} \right)$$

Replicator equation

x_i = relative abundance

$$\Lambda_{ij} = \alpha A_{ij}$$

$$\dot{x}_i = x_i\left(\sum_i \Lambda_{ij}x_j - \sum_{jk}\Lambda_{jk}x_j x_k\right)$$

$$\Lambda_{ij} = \alpha A_{ij}$$

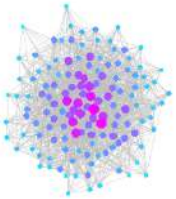
Interaction strength

Adjacency matrix

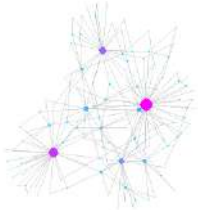
$$\left.\begin{array}{ll} \alpha > 0 & \text{mutualism} \\ \alpha < 0 & \text{competition} \end{array}\right\}$$

Environmental change
=
change in α

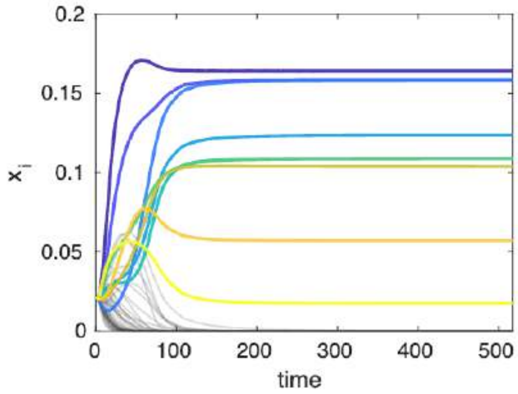
Erdős–Rényi



Scale-free
(Holme-Kim,
Barabási-Albert)

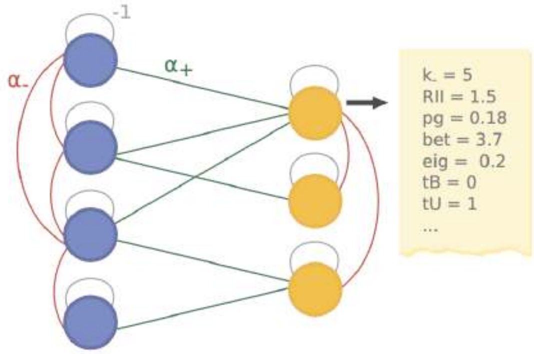


Empirical



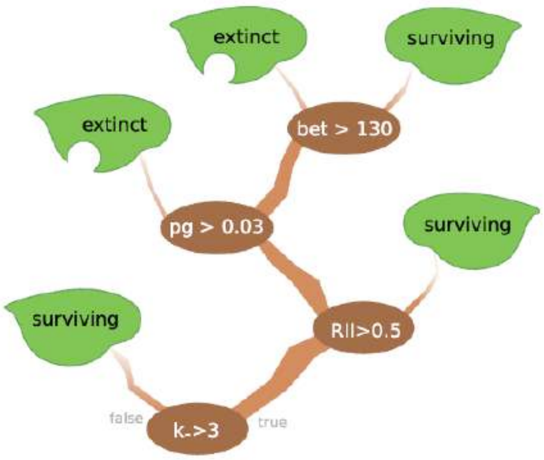
Simulate replicator dynamics:

Track survivors

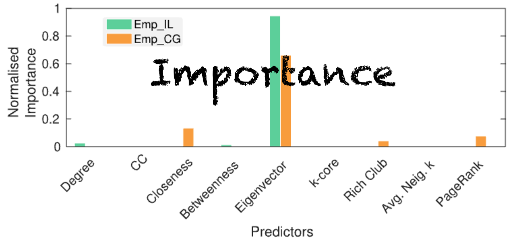


Node properties:

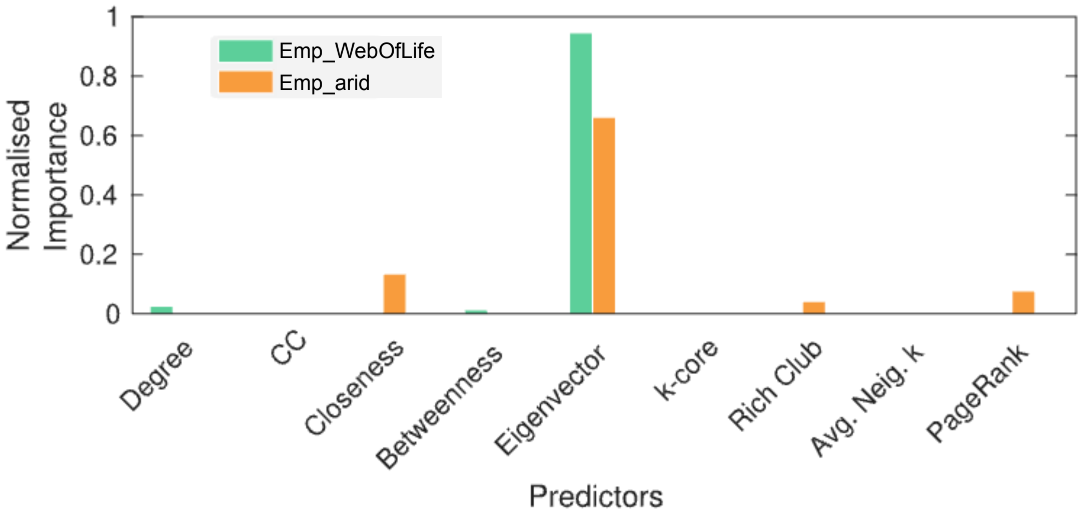
- Centrality
- Meso-scale
- Signed



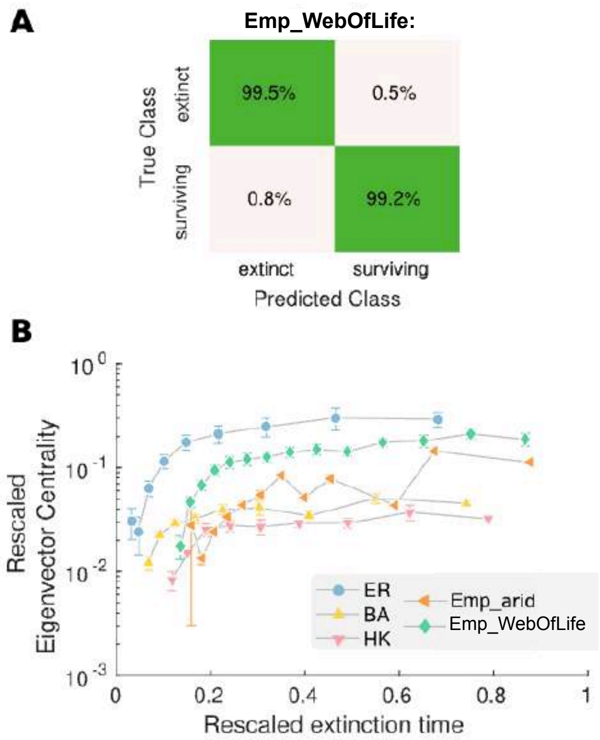
Decision tree



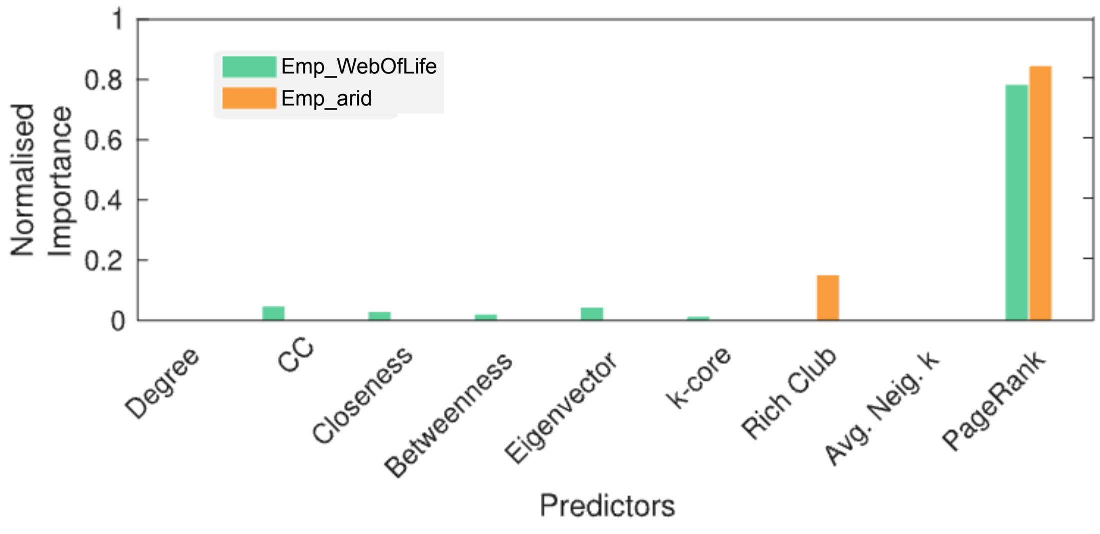
Results: Mutualism



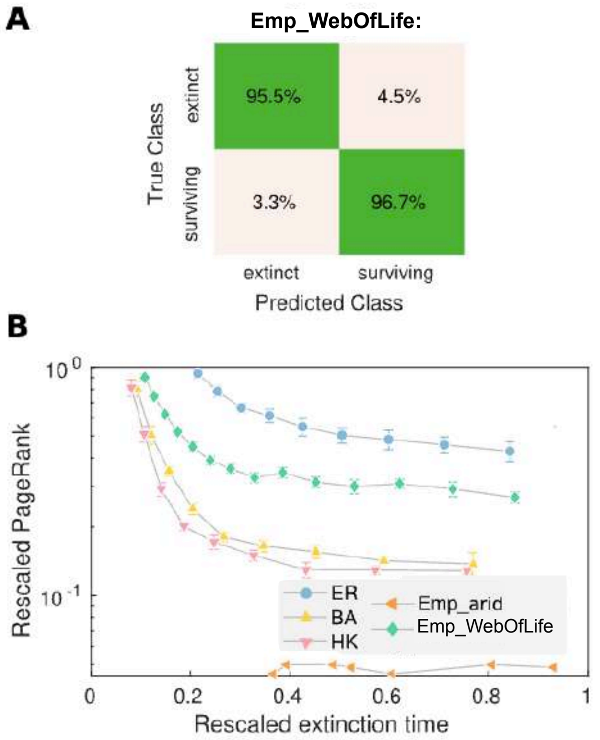
Predictor = High Eigenv. Cent. increases survival



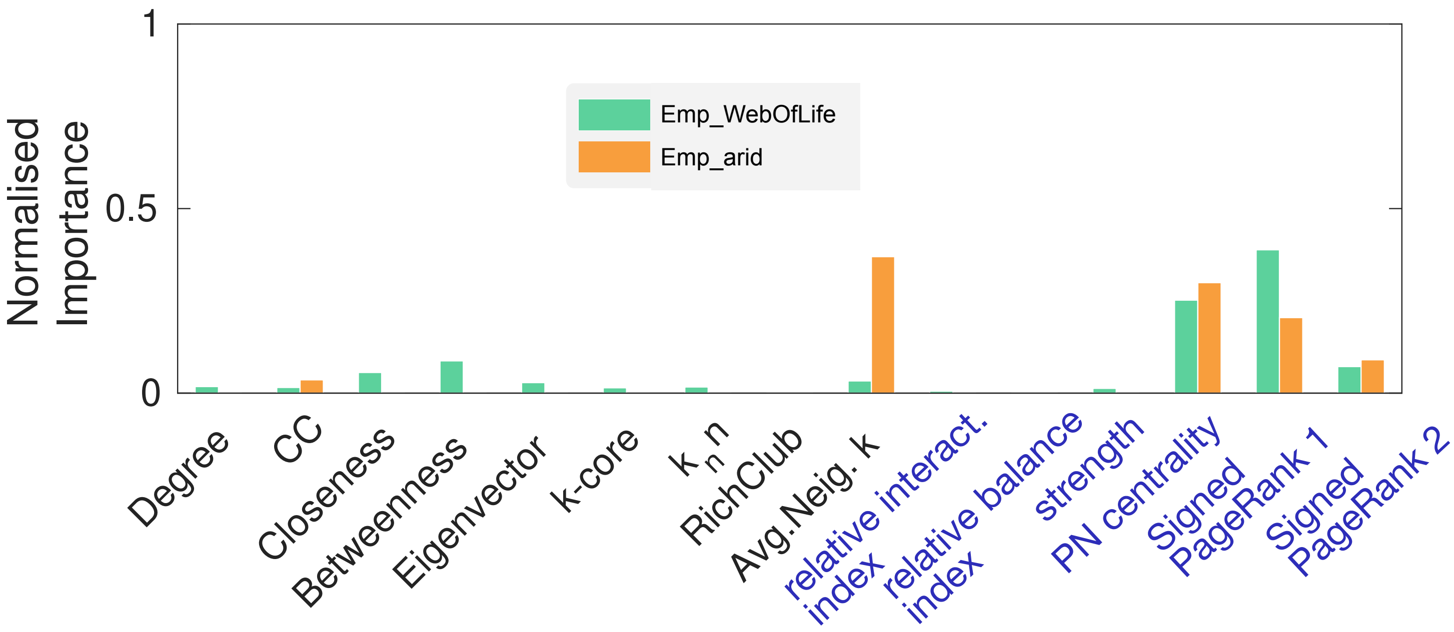
Results: Competition



Predictor = Low PR increases survival



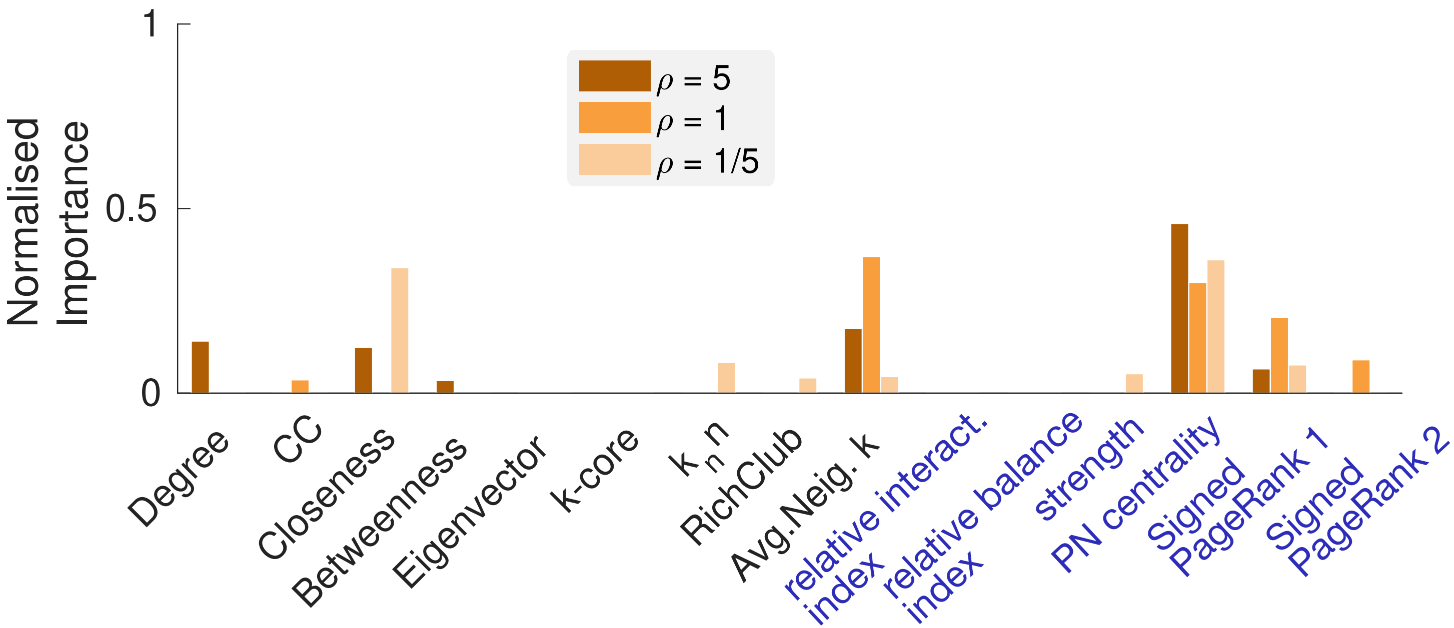
Results: Mutualism & Competition



- Network

No universal predictors…

Results: Mutualism & Competition



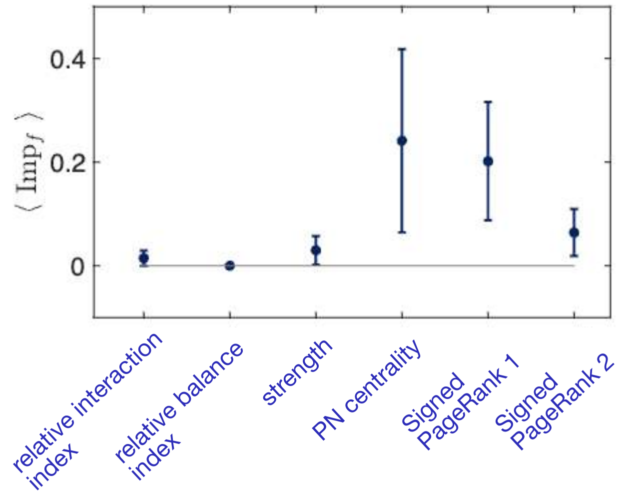
No universal predictors…

- Network
- Interaction strength

Results: Mutualism & Competition

No universal predictors…

But they usually depend on interaction strength and sign



Conclusions

Competition & Mutualism

Structural predictors are…

- Different from competition or mutualism alone
- Different for every ecosystem

Ecosystems are composed of several types of interactions…
Revisit results obtained for single interactions!

PART II

INFORMATION ECOSYSTEMS

Information ecosystems

/ˌɪn.fəˈmeɪ.ʃən ˈiː.kəʊˌsɪs.təms/

An ecological approach to computational social sciences

Spot the differences!

Natural Ecosystems

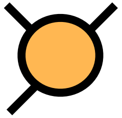
- Species
- Abundances
- Resources

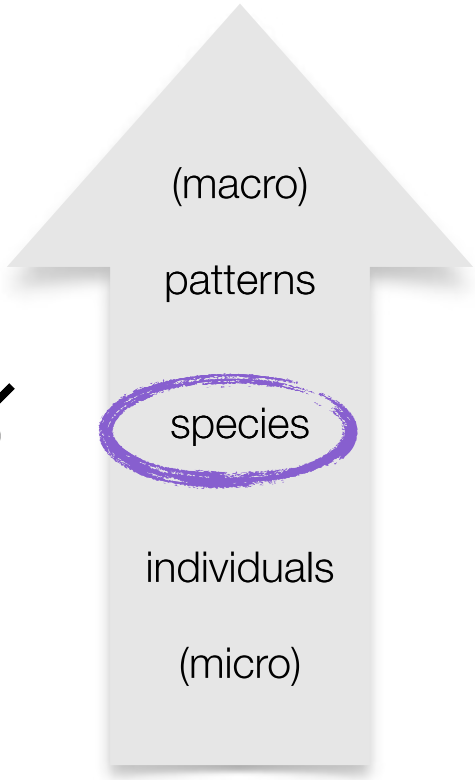
⋮

Information Ecosystems

- Memes/hashtags, users
- Popularity, visibility
- Users' attention

⋮





Natural Ecosystems

- Species
- Abundances
- Resources

⋮

Information Ecosystems

- Memes/hashtags, users
- Popularity, visibility
- Users' attention

⋮

Exploit tools and theories from Theoretical Ecology
to understand Human Behavior!!

PHYSICAL REVIEW RESEARCH 3, 013070 (2021)

Neutral theory for competing attention in social networks

Carlos A. Plata,[1,2] Emanuele Pigani,[1] Sandro Azaele,[1] Violeta Calleja-Solanas,[3] María J. Palazzi,[4] Albert Solé-Ribalta,[4,5] Javier Borge-Holthoefer,[4] Sandro Meloni,[3] and Samir Suweis[1,6,7]

nature COMMUNICATIONS

ARTICLE

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https://doi.org/10.1038/s41467-021-22184-2 OPEN

An ecological approach to structural flexibility in online communication systems

María J. Palazzi[1], Albert Solé-Ribalta[1,2], Violeta Calleja-Solanas[3], Sandro Meloni[3], Carlos A. Plata[4,5], Samir Suweis[4] & Javier Borge-Holthoefer[1]✉

nature COMMUNICATIONS

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https://doi.org/10.1038/s41467-019-09311-w OPEN

Accelerating dynamics of collective attention

Philipp Lorenz-Spreen[1,2], Bjarke Mørch Mønsted[3], Philipp Hövel[1,4] & Sune Lehmann[3,5]


nature COMMUNICATIONS

ARTICLE

https://doi.org/10.1038/s41467-021-22184-2 OPEN

An ecological approach to structural flexibility in online communication systems

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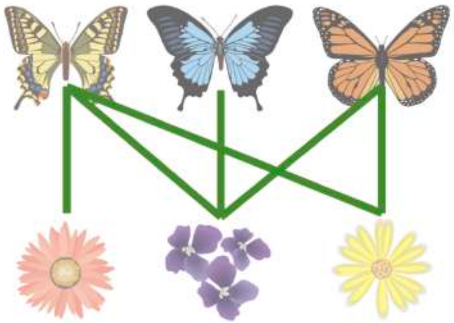
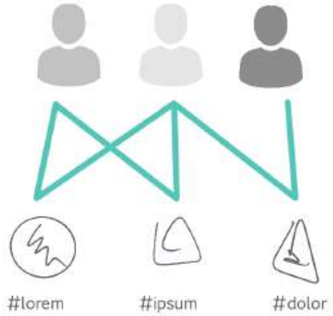
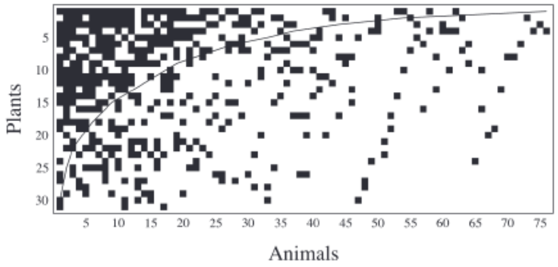
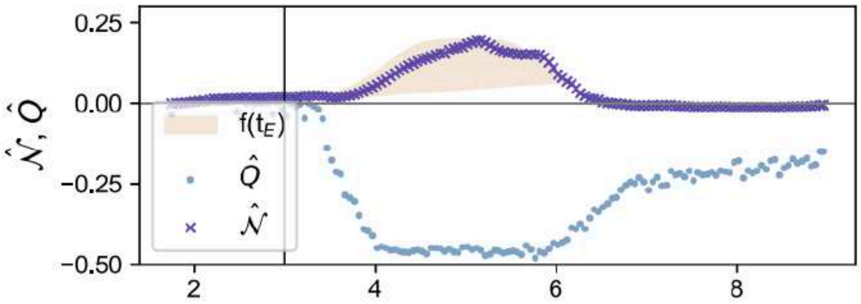


Rohr et al. *Science 345 (2014)*



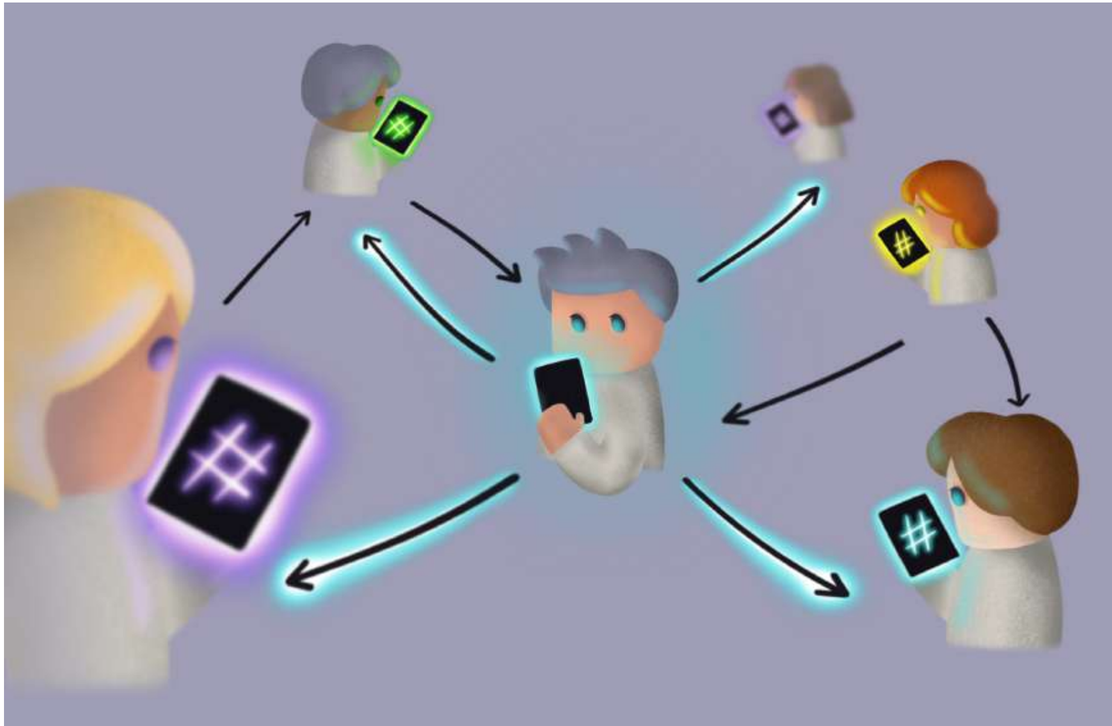


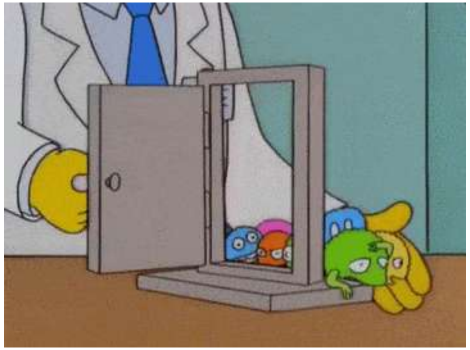
Bascompte et al. PNAS 100 (2003)



Ch 5

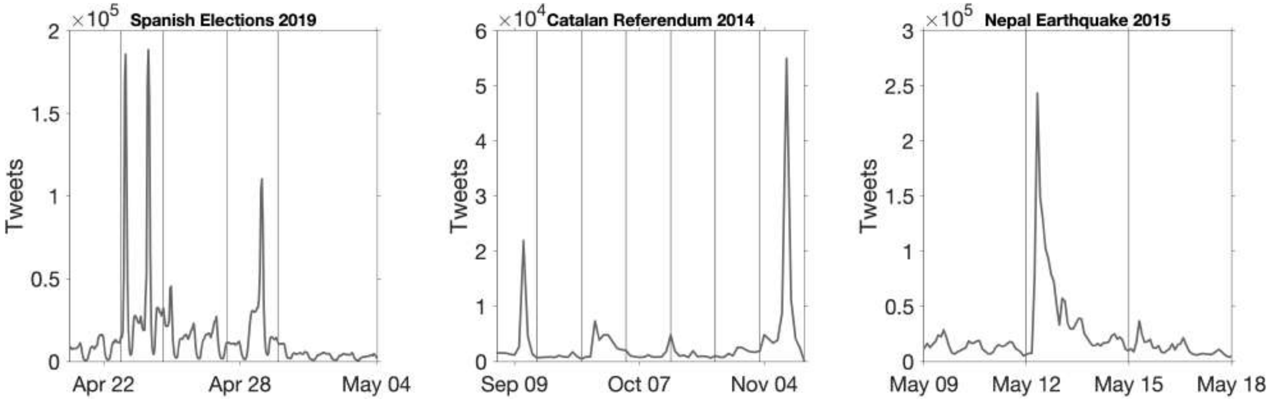
Quantifying the drivers behind collective attention

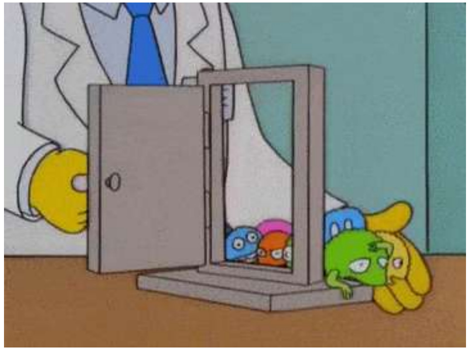




- Cognitive bottleneck
- Attention is the new currency
- Competition for attention

Collective attention during *events*





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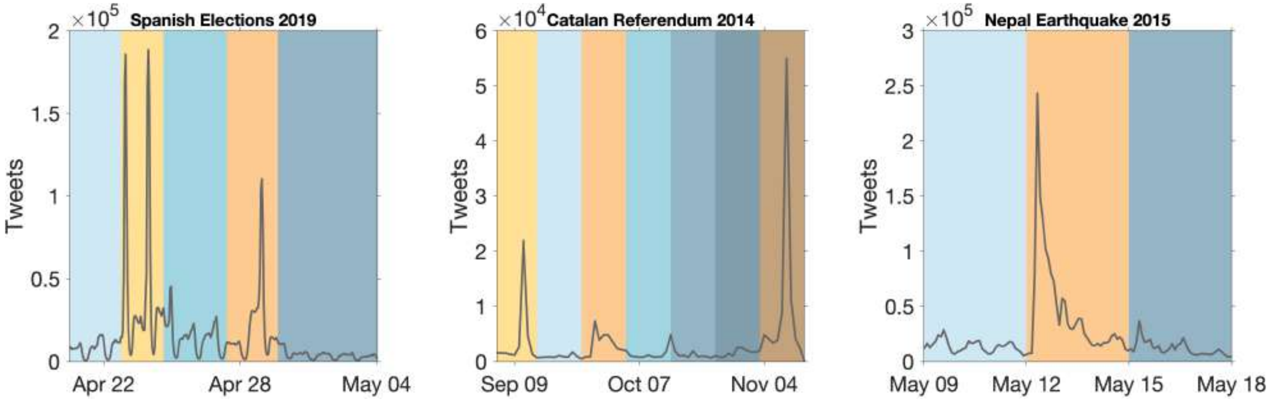

Q1: How can we quantitatively characterize competition?

Method based on:

- Generalized Lotka-Volterra equations
- Niche theory

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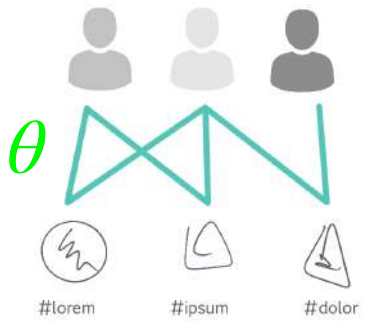
Method based on:

- Generalized Lotka-Volterra equations
- Niche theory

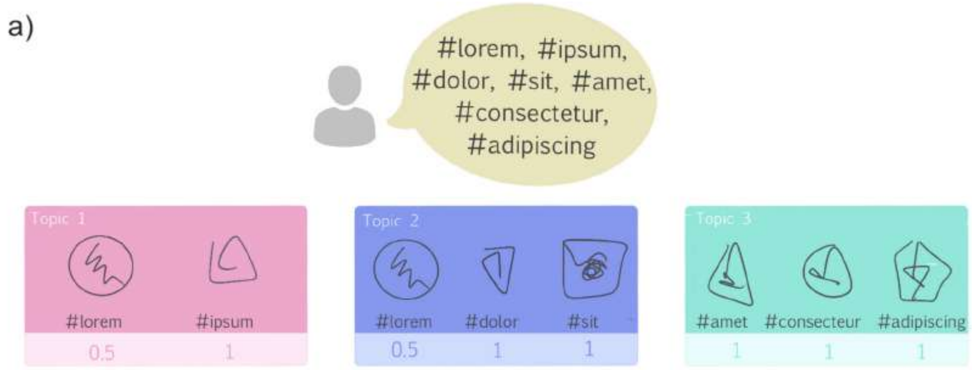
competition mutualism

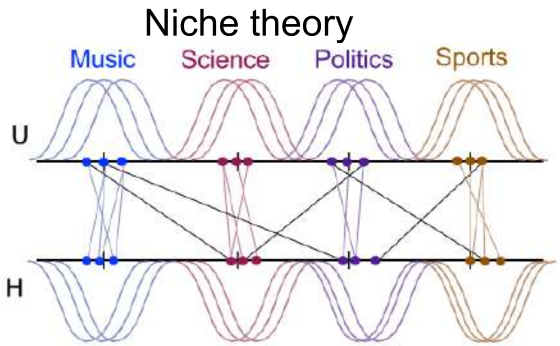
$$\frac{dn_i^U}{dt} = n_i^U\left(\rho_i^U - \sum_j \beta_{ij}^{UU} n_j^U + \frac{\sum_k \gamma_{ik}^{UH} n_k^H}{1 + h\sum_l \theta_{il} n_l^H}\right)$$

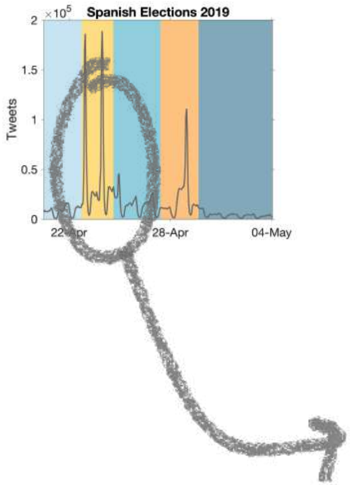
$$\frac{dn_k^H}{dt} = n_k^H\left(\rho_k^H - \sum_l \beta_{kl}^{HH} n_l^H + \frac{\sum_i \gamma_{ki}^{HU} n_i^U}{1 + h\sum_j \theta_{kj} n_j^U}\right)$$



Quantifying competition & mutualism

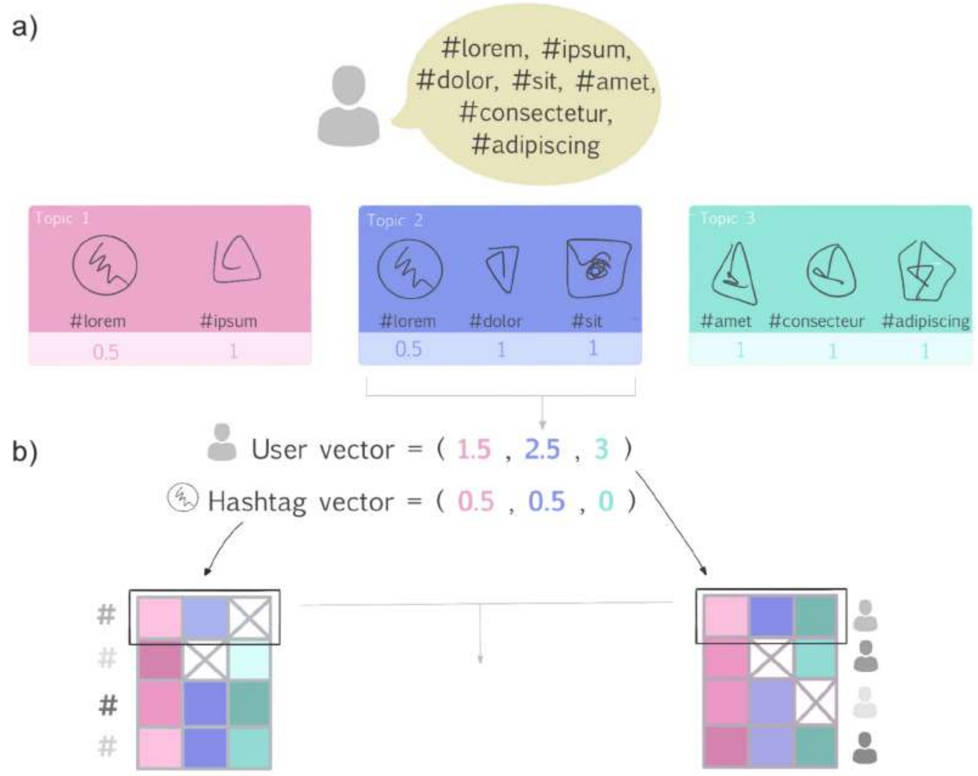




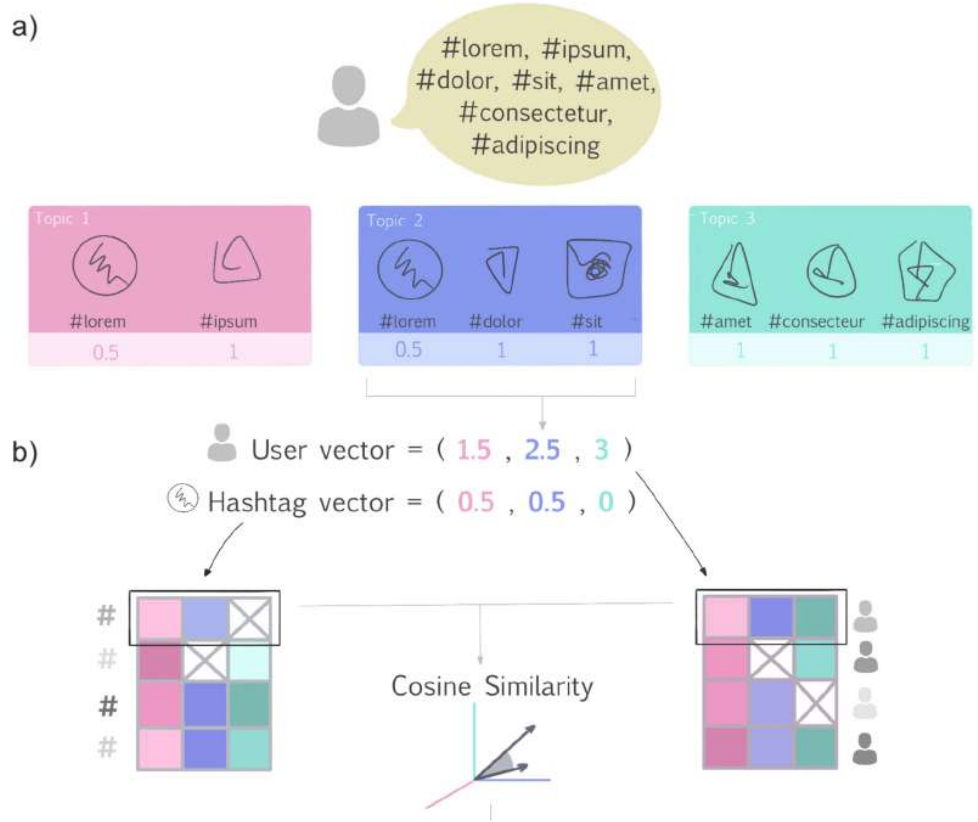


Some topics and their #

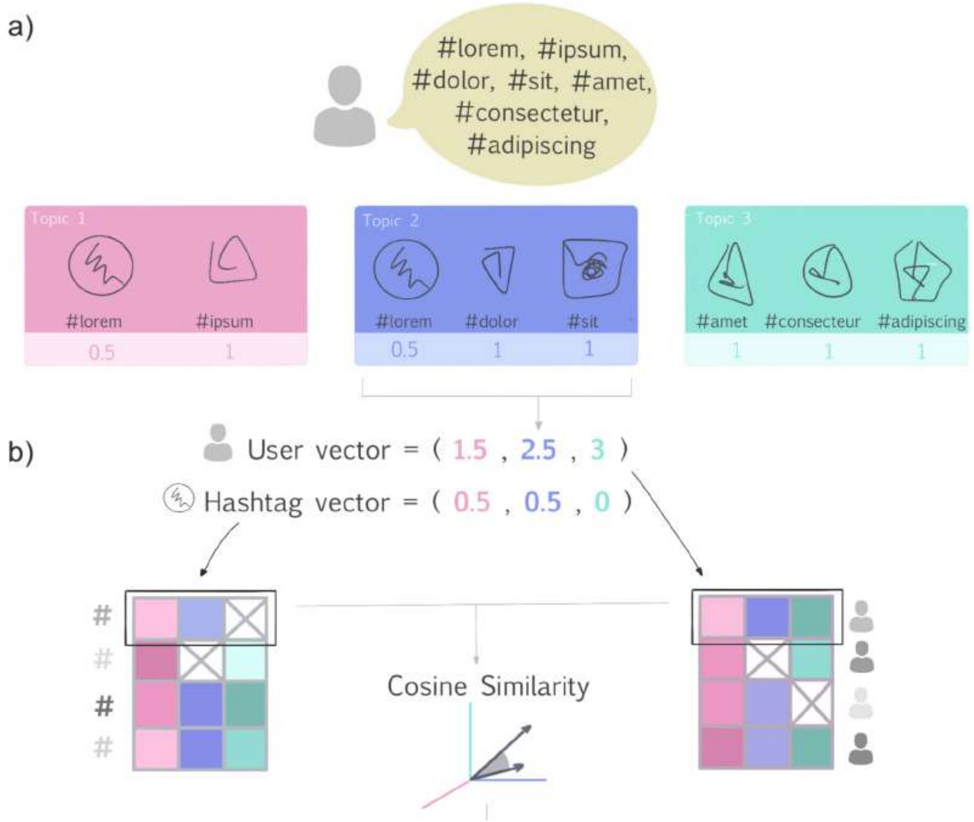
Quantifying competition & mutualism

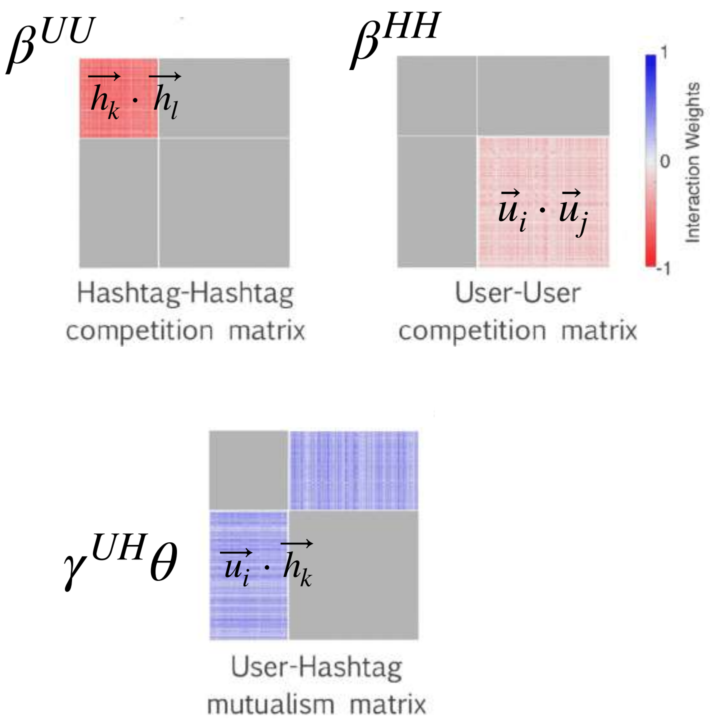


Quantifying competition & mutualism

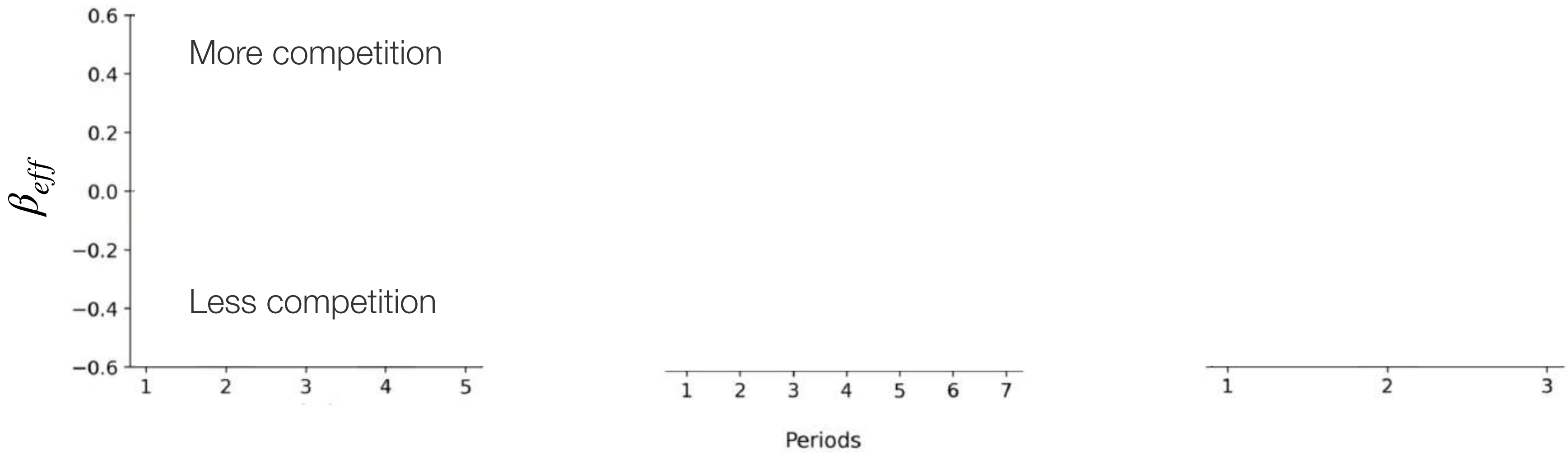


Quantifying competition & mutualism





Results



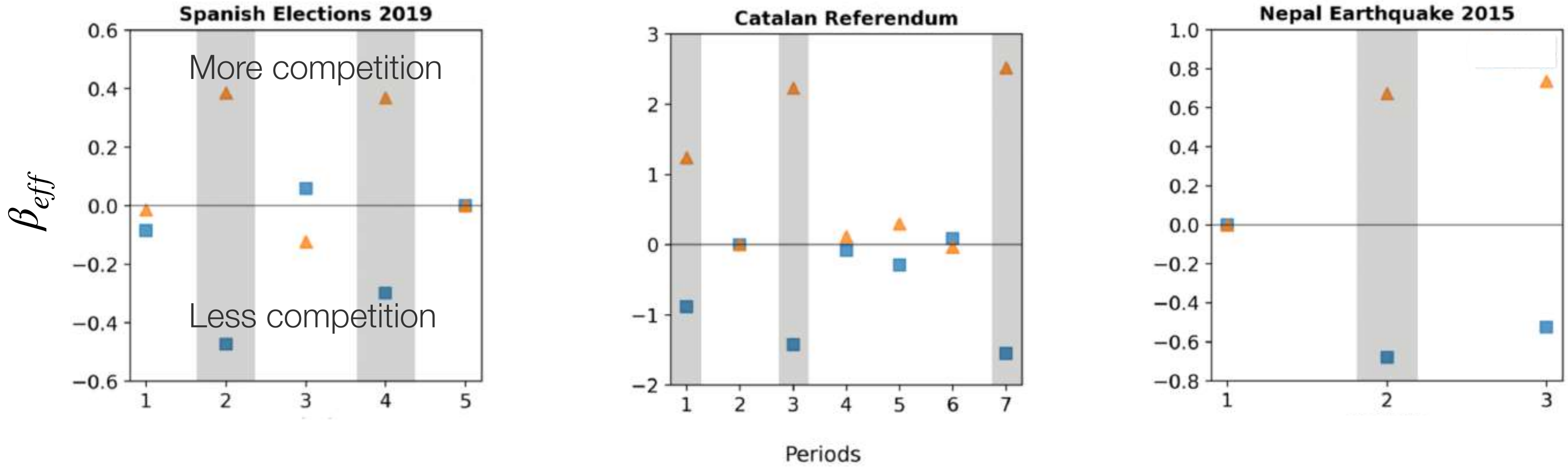
What weights more?

Users *effective* competition

Hashtags *effective* competition

$$\beta_{eff} = (\beta - \beta_{calm}) - (\gamma - \gamma_{calm})$$

Results



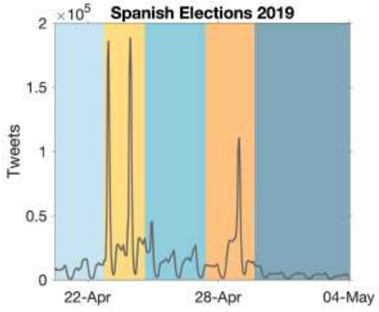
What weights more?

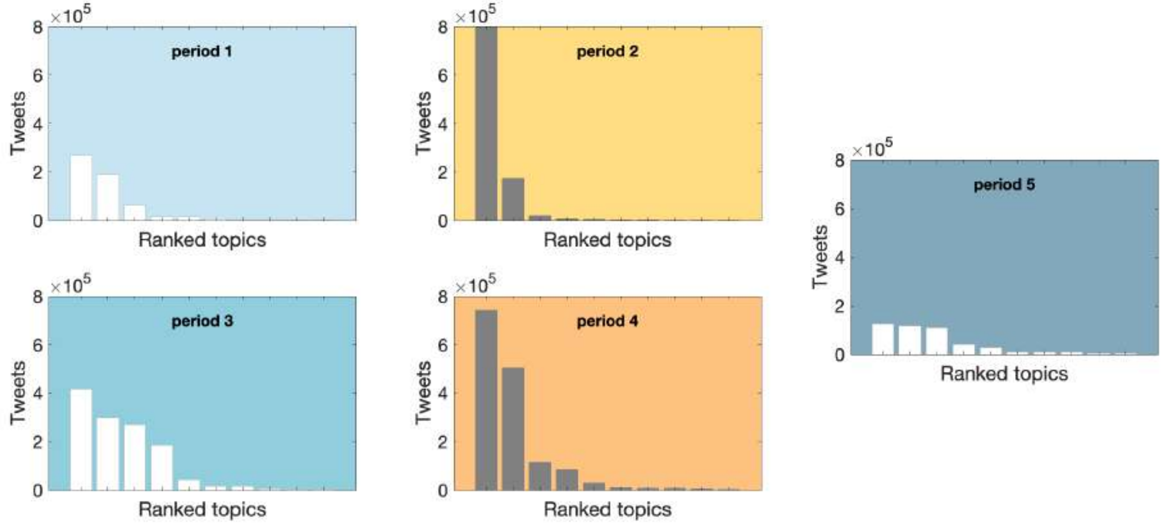
Users *effective* competition ↓ during **peaks**

Hashtags *effective* competition ↑ during **peaks**

$$\beta_{eff} = (\beta - \beta_{calm}) - (\gamma - \gamma_{calm})$$

Topic evolution:



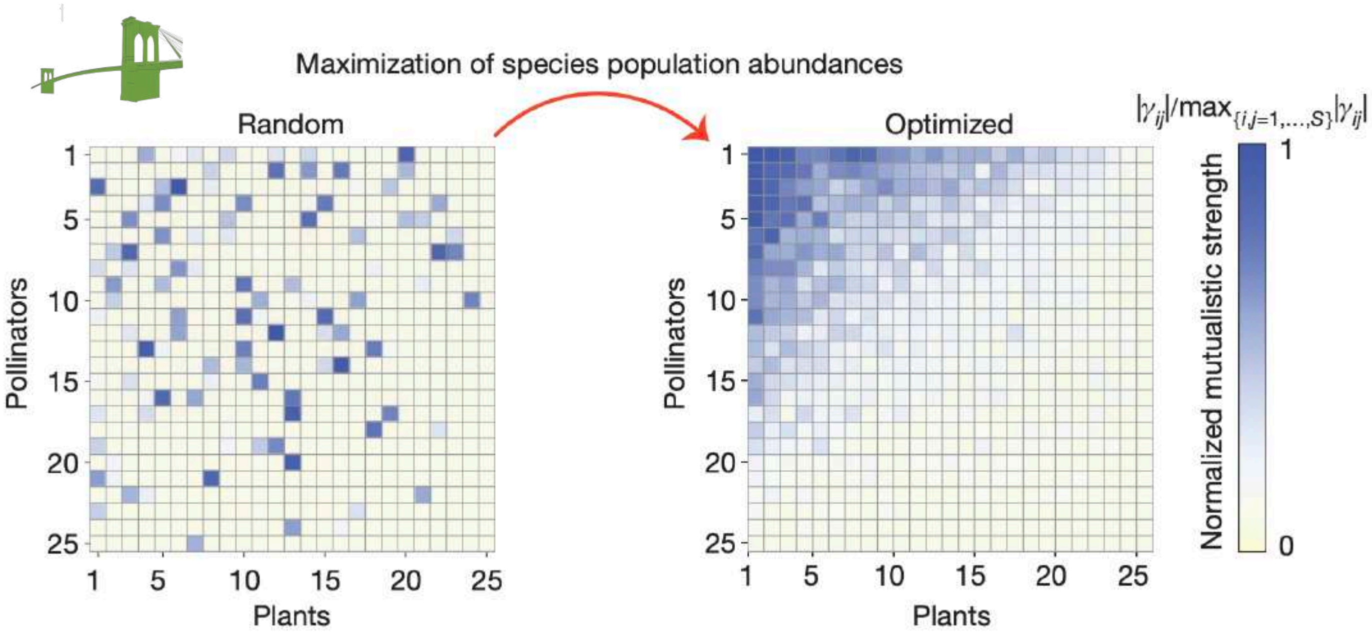


During peaks:

one or two topics generate almost the 90% of the tweets

Q2: What are the drivers behind collective attention?

Assumption: users maximize their visibility



Suweis et al. Nature 500 (2013)

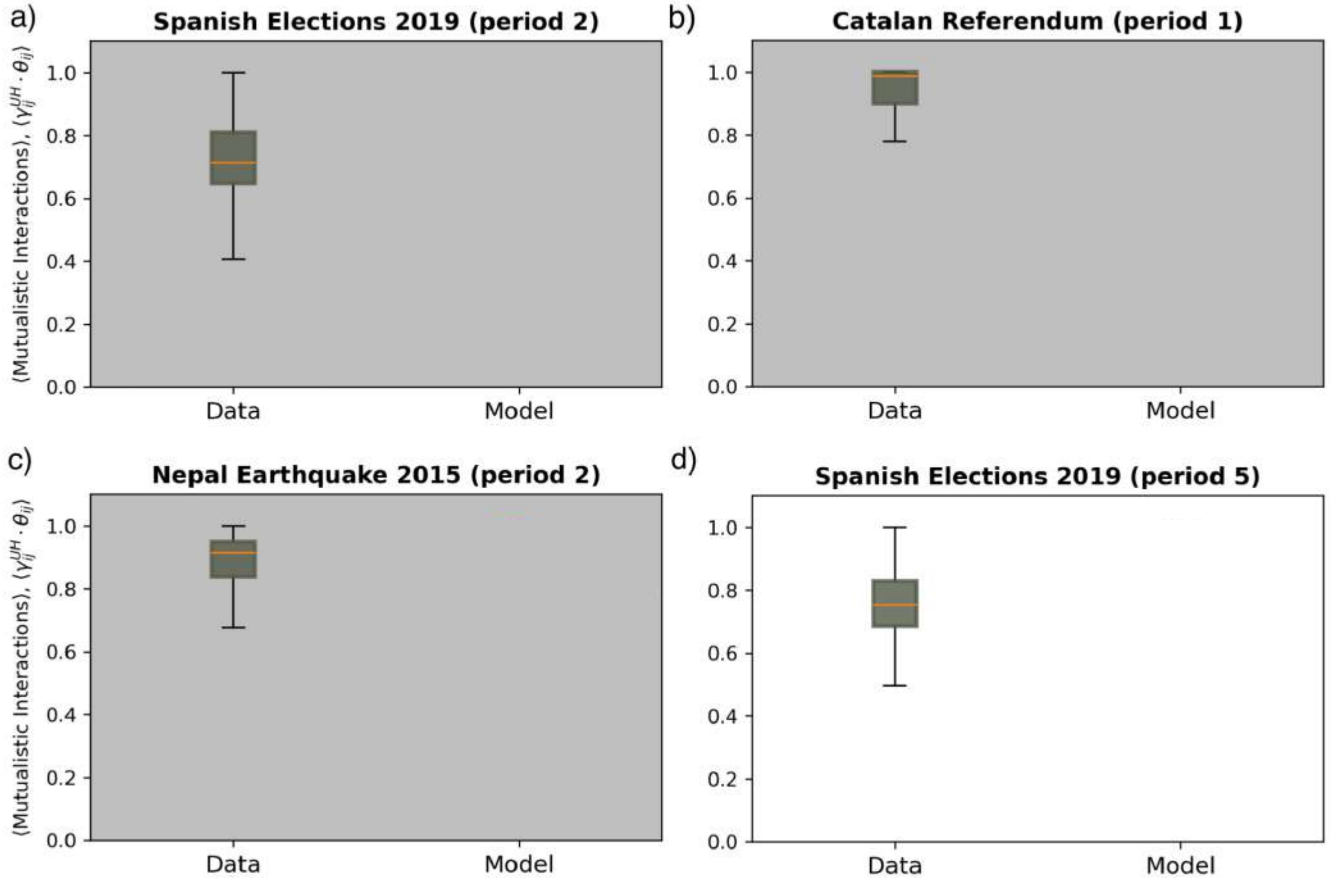
Cai et al. Nature Communications 11, (2020)

Q2: What are the drivers behind collective attention?

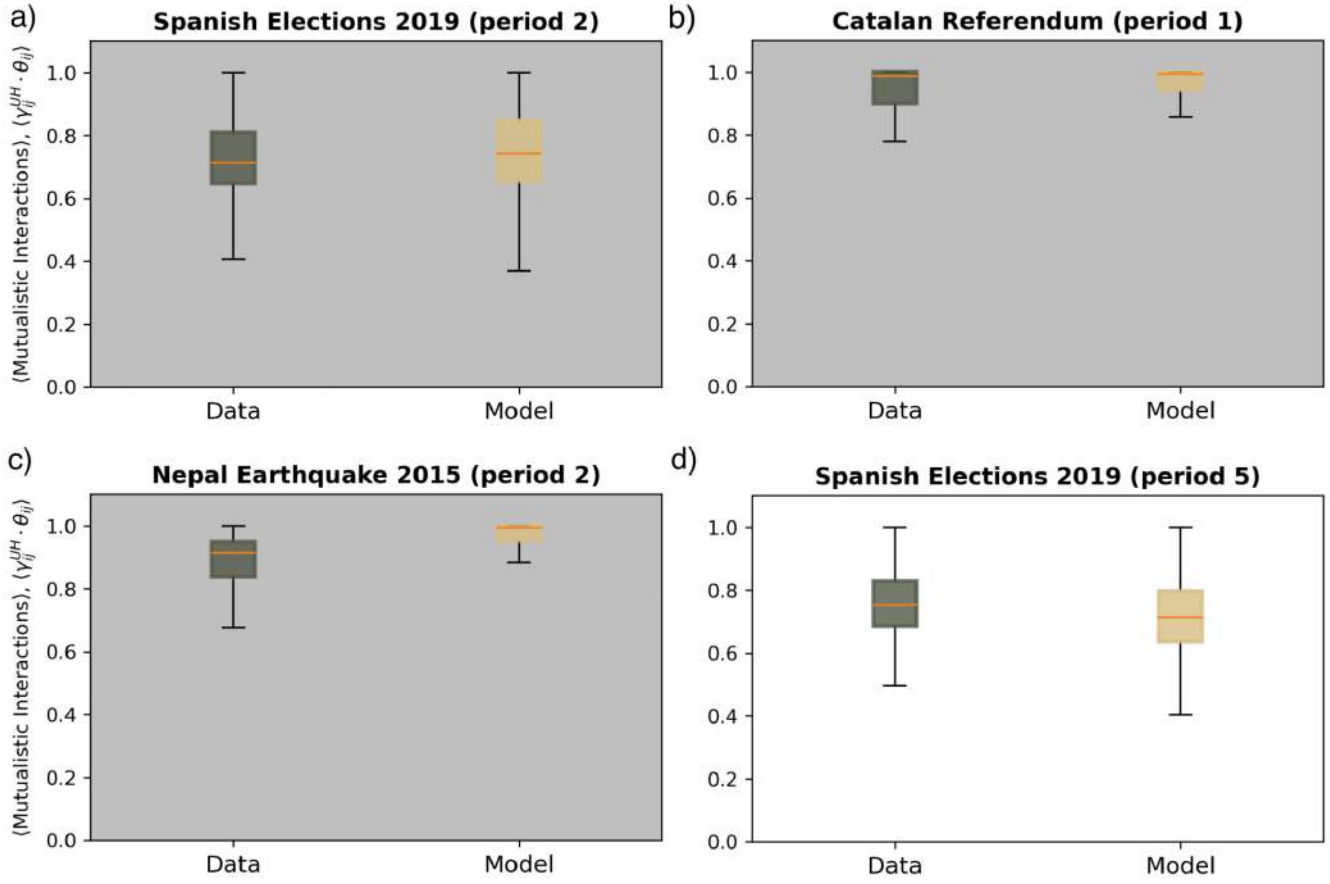
Assumption: users maximize their visibility

Results

Comparison empirical interactions with optimization model



Comparison empirical interactions with optimization model



It's a match!

Conclusions

An analogy between natural and information ecosystems can quantify the competition for attention experienced by agents during events

- Users effectively reduce net competition
- Hashtags experience stronger competition
- The driver is visibility optimization

Ch 6

Finding macroecological patterns in information ecosystems

Universal statistical laws across ecosystems

- Abundance
- Distribution
- Diversity

Important for:

- Finding mechanisms
- Modeling
- Health and prediction

Universal statistical laws across ecosystems

- Abundance
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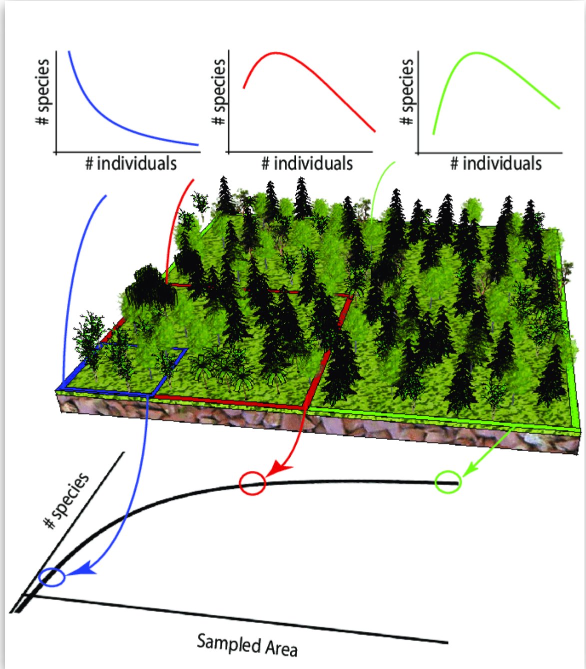


S. Azaele, et al. Rev. Mod. Phys. **88**, 035003 (2016)

Universal statistical laws across ecosystems

- Abundance
- Distribution
- Diversity

- Species = Hashtags
- Abundance = Popularity
- Sampling

Important for:

- Finding mechanisms
- Modeling
- Health and prediction

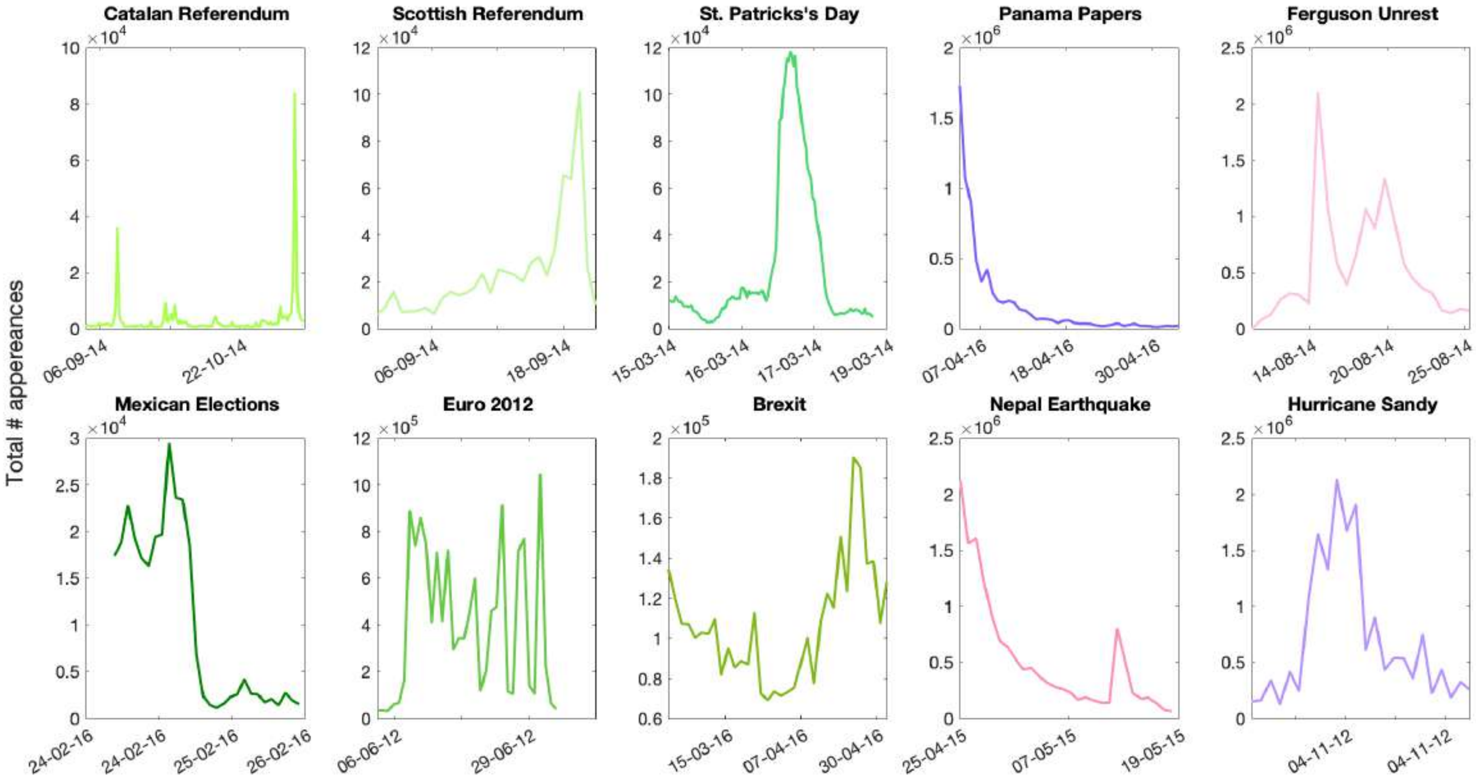
Q: How do these laws apply to Information Ecosystems?

10 “Events” datasets + 1 “Random” sample of Twitter Activity

Dataset	Type	Posts	Hashtags	Days
Mexican Elections	E	191788	158	1
Scottish Referendum	E	429901	313	23
Catalan Referendum	E	222783	375	69
St. Patrick’s Day	E	2882010	1591	3
Brexit	E	182629	1689	69
UK random sample	R	1649482	1833	9
Ferguson Unrest	U	8782071	2811	17
Panama Papers	U	5044378	3696	23
Euro 2012	E	8992157	4361	34
Nepal Earthquake	U	12004187	5032	23
Hurricane Sandy	U	5658525	5353	6

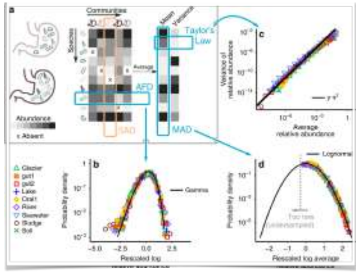
10 “Events” datasets + 1 “Random” sample of Twitter Activity

HETEROGENEOUS!

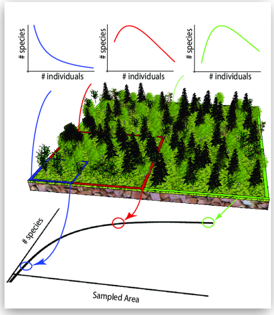


Patterns

- Taylor's Law
- Mean Abundance Distribution *MAD*
- Abundance Fluctuations Distribution *AFD*
- Relative Species Abundance *RSA*
- Species-Area Curve *SAC*
- Short-Term Abundance Change *STAC*



J. Grilli. Nature Communications ***11****, 4743 (2020)*



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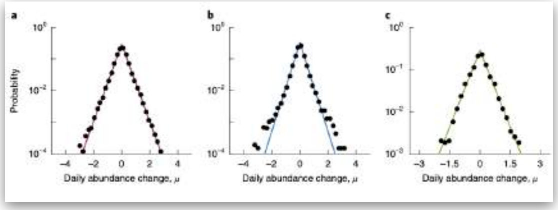


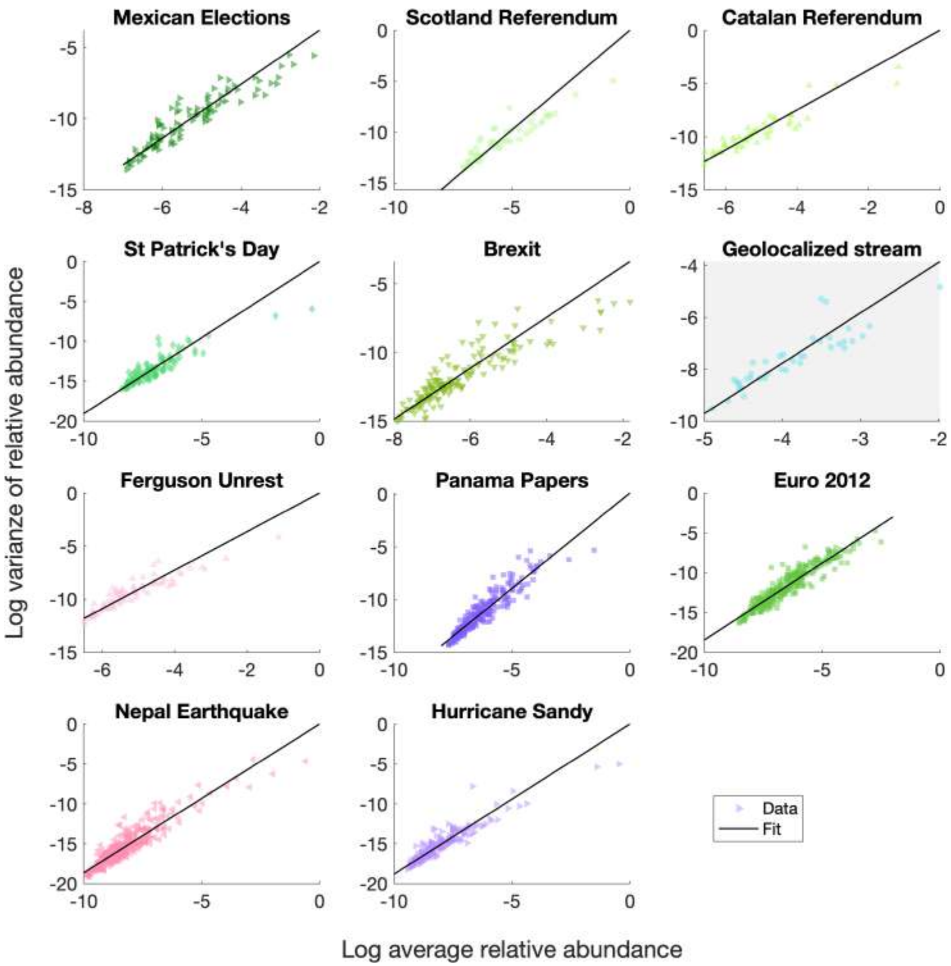
Ji, et al. Nature Microbiology ***5****, 768–775 (2020)*

Taylor's Law

Connects mean abundance of a hashtag

with its variance

$$\sigma_h^2 \sim \bar{x}_i^2$$



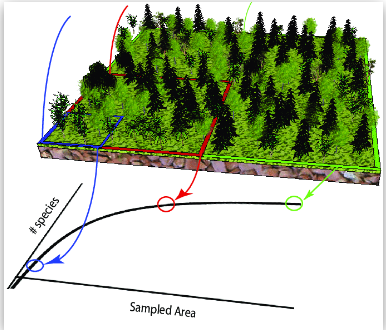
Species-Area Curve - SAC

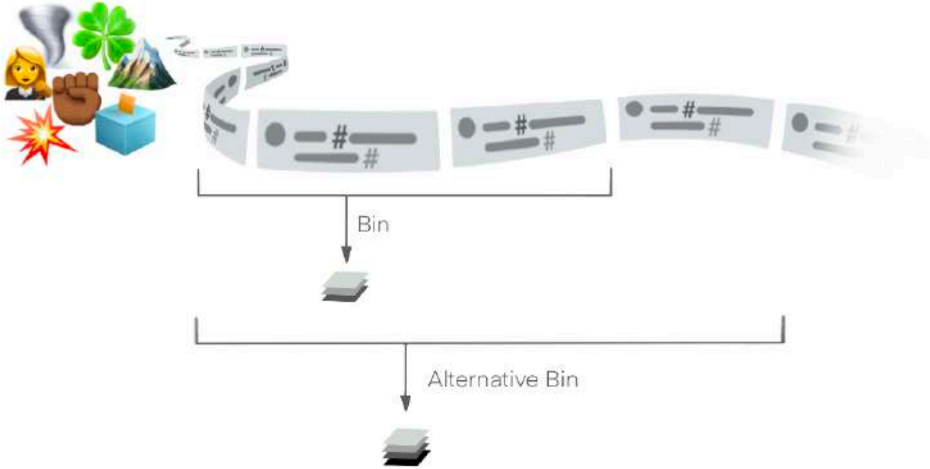
How diversity scales with sampling size

$$\langle s(N)\rangle = s_{tot}\left(1-\int d\eta \frac{\exp\frac{-(\eta-\mu)^2}{2\sigma^2}}{\sqrt{2\pi\sigma^2}}\left(\frac{\beta}{\beta+e^{\eta}N}\right)^{\beta}\right)$$

J. Grilli. Nature Communications ***11****, 4743 (2020)*

S. Azaele, et al. Rev. Mod. Phys. ***88****, 035003 (2016)*





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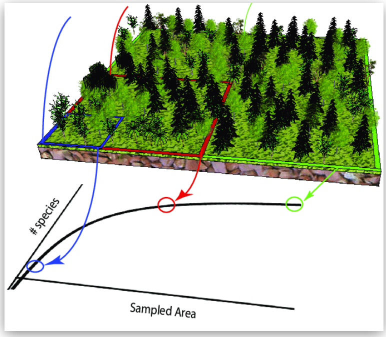
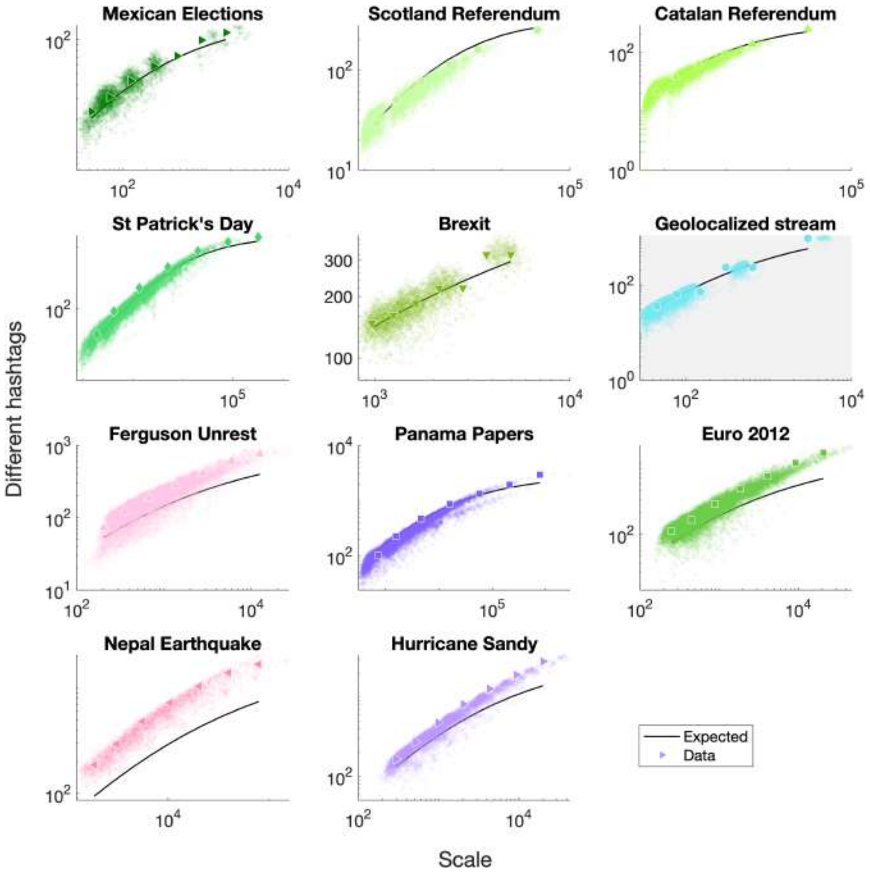




Short-Term Abundance Change - STAC

Distribution of ratio between

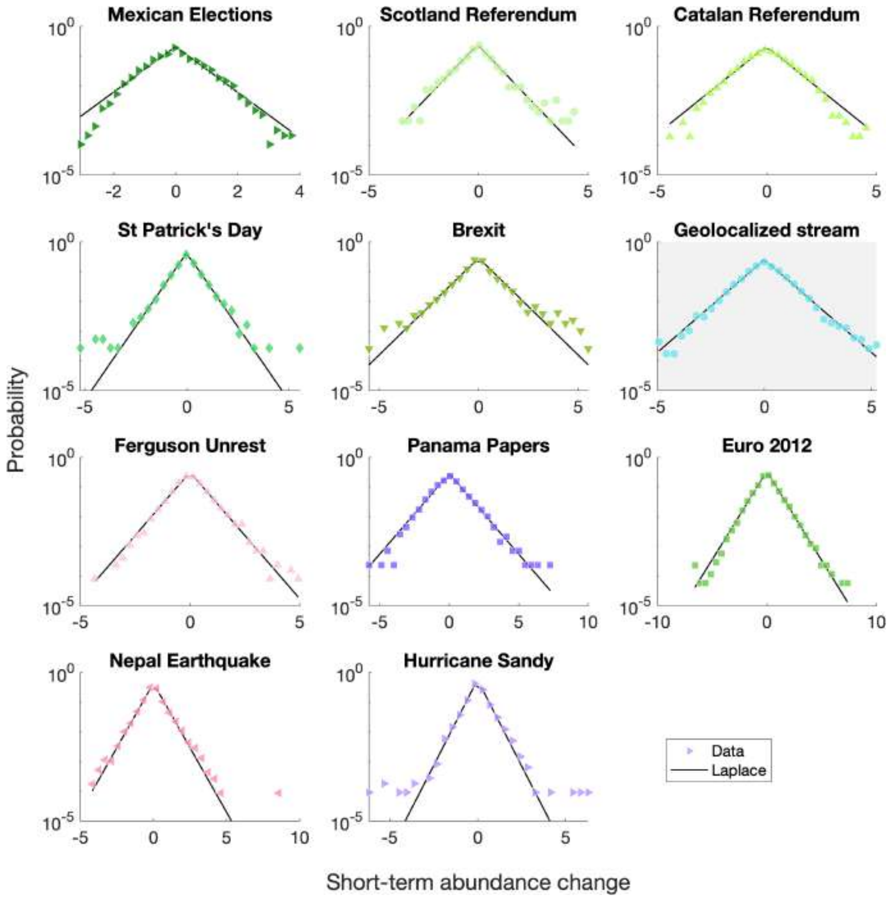
abundances at consecutive times

$$\lambda_{hb} = \log\left(\frac{x_{hb+1}}{x_{hb}}\right)$$

Laplace distribution

$$p(\lambda) = \frac{1}{2\gamma}\exp\left(\frac{-|\lambda - u|}{\gamma}\right)$$

Ji, et al. Nature Microbiology **5**, *768–775 (2020)*



Conclusions

Q: How do these laws apply to Information Ecosystems?

- Same patterns as in ecology!
- Patterns are universal

General conclusions

★ Reinforce the crucial role of interactions

- Taking **structured interactions / multiple interaction types** into account change ecological behavior

★ Take advantage of developments of one domain to understand another

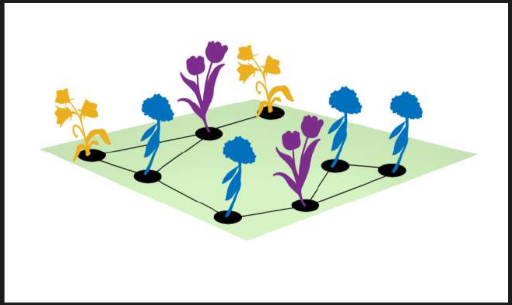
- Mapping ecological interactions on social networks to understand human behavior

Outlook

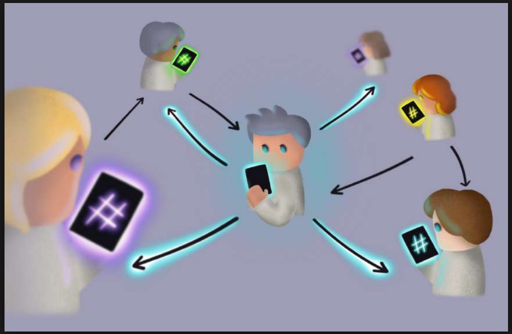
★ How higher-order interactions change the competition game

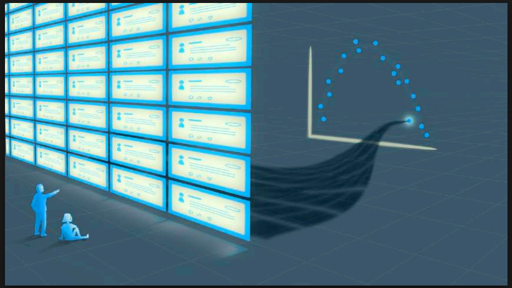
★ What are the underlying mechanisms of information ecosystems' patterns

★ How patterns change during events

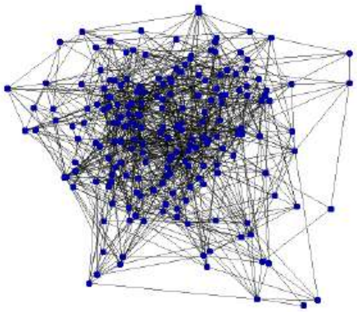


QUESTIONS?

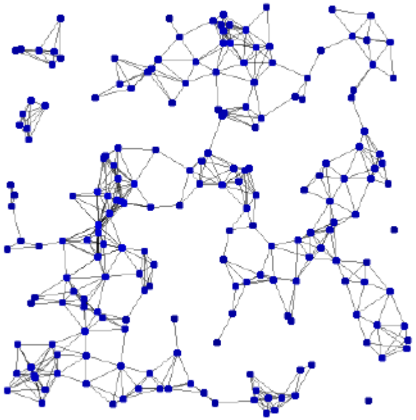




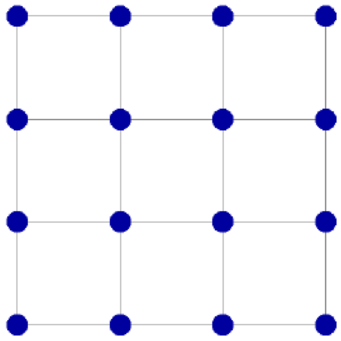
Erdős Rényi



Random Geometric Graph
(RGG)

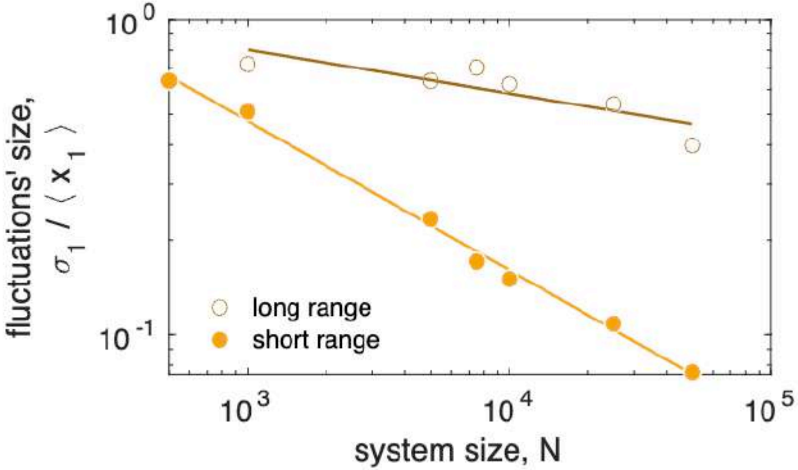


Lattice



Spatial structure

✔ Small fluctuations are noise



✓ Stability after a perturbation

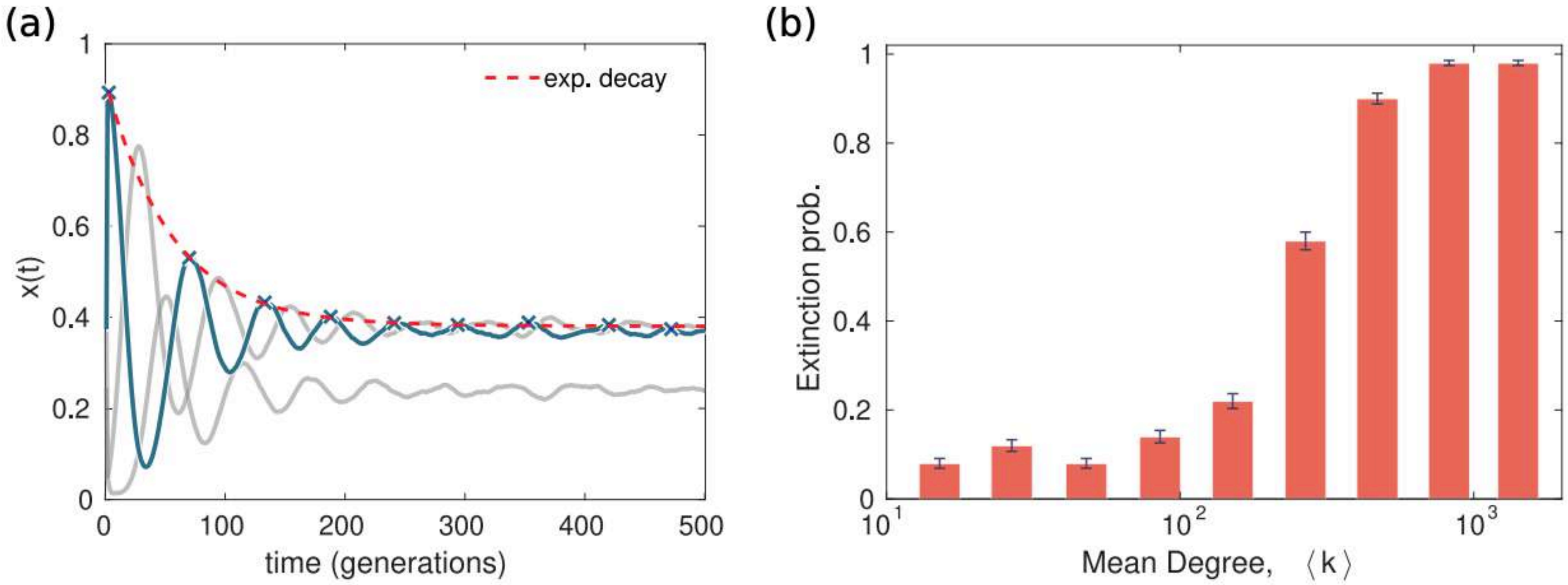
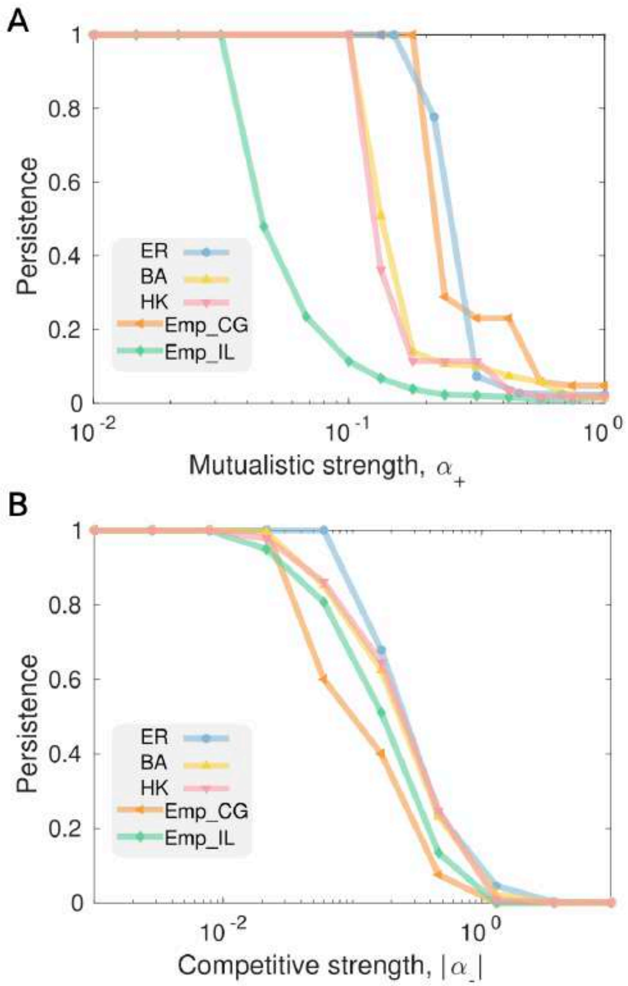
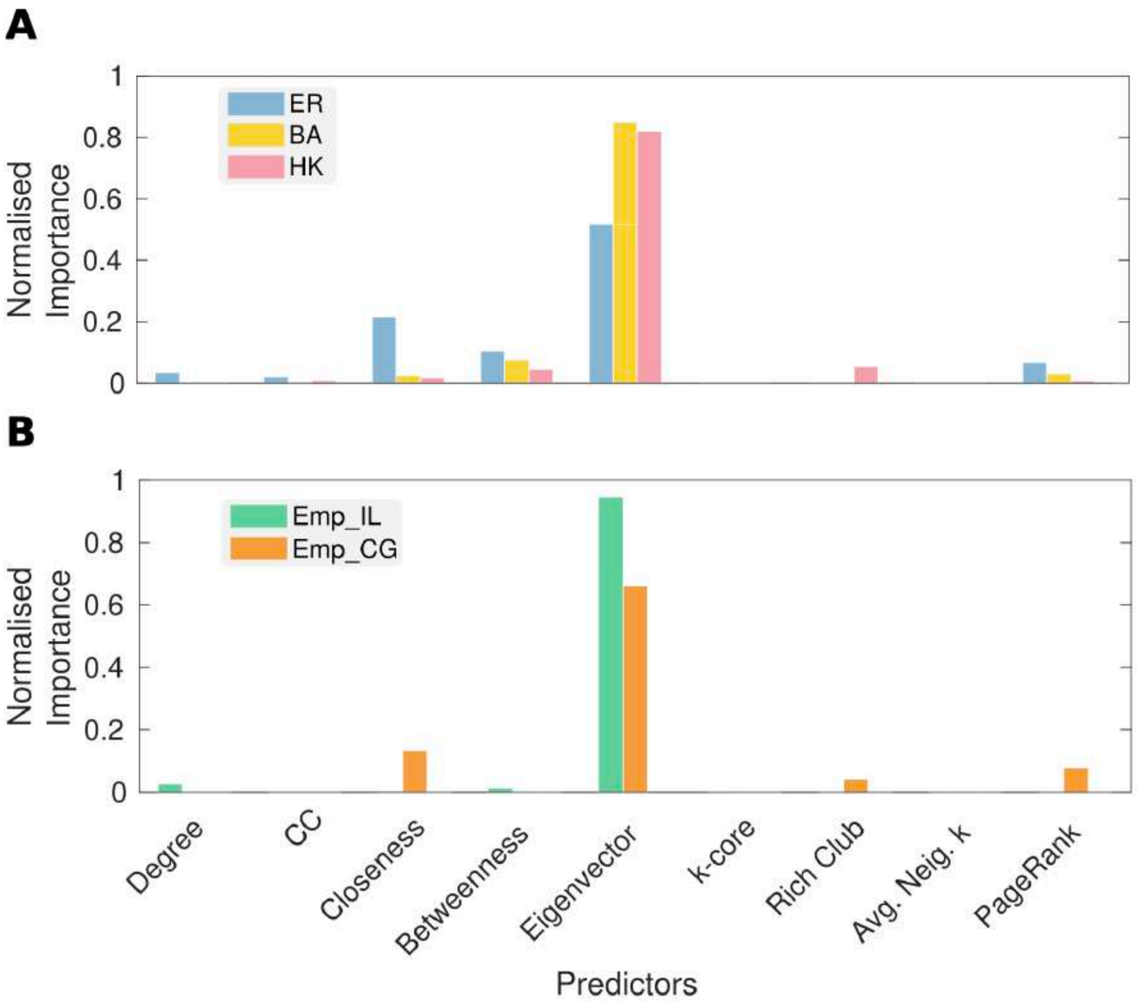


FIG. 5. (a) Time evolution of the recovery from a 90% pulse perturbation in a 3-species community for the dominance matrix H of Eq. (1). The relative abundance of one species (blue) is artificially modified from its equilibrium value to be the 90% of the whole population, whereas other species' relative abundances (in gray) are proportionally decreased. The simulation is performed in a RGG of 10^4 individuals and $R_{\mathrm{RGG}} = 0.03$. The red line represents the fit of the local maxima of the relative abundance (blue crosses) to the function $ae^{-\alpha} + b$ with $\alpha = 0.018$, $a = 0.53$ and $b = 0.38$. (b) For the same setting than in (a), we have varied the interaction range to obtain how the extinction probability varies with the average degree. Each bar corresponds to the mean over 50 different networks with 95% confidence intervals shown as error bars.



Persistence decreases with high interaction strength in absolute value

Results: Mutualism



F.1 Persistence not equal to 50%

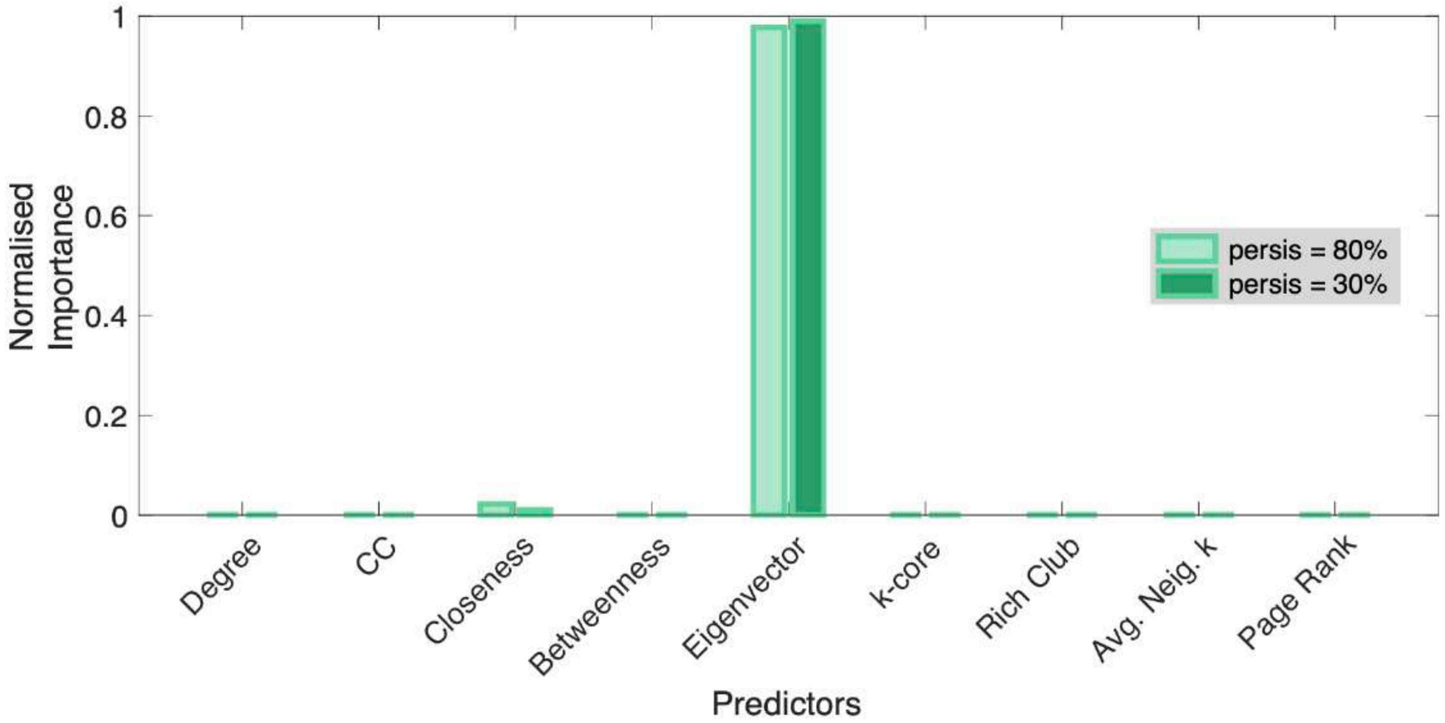
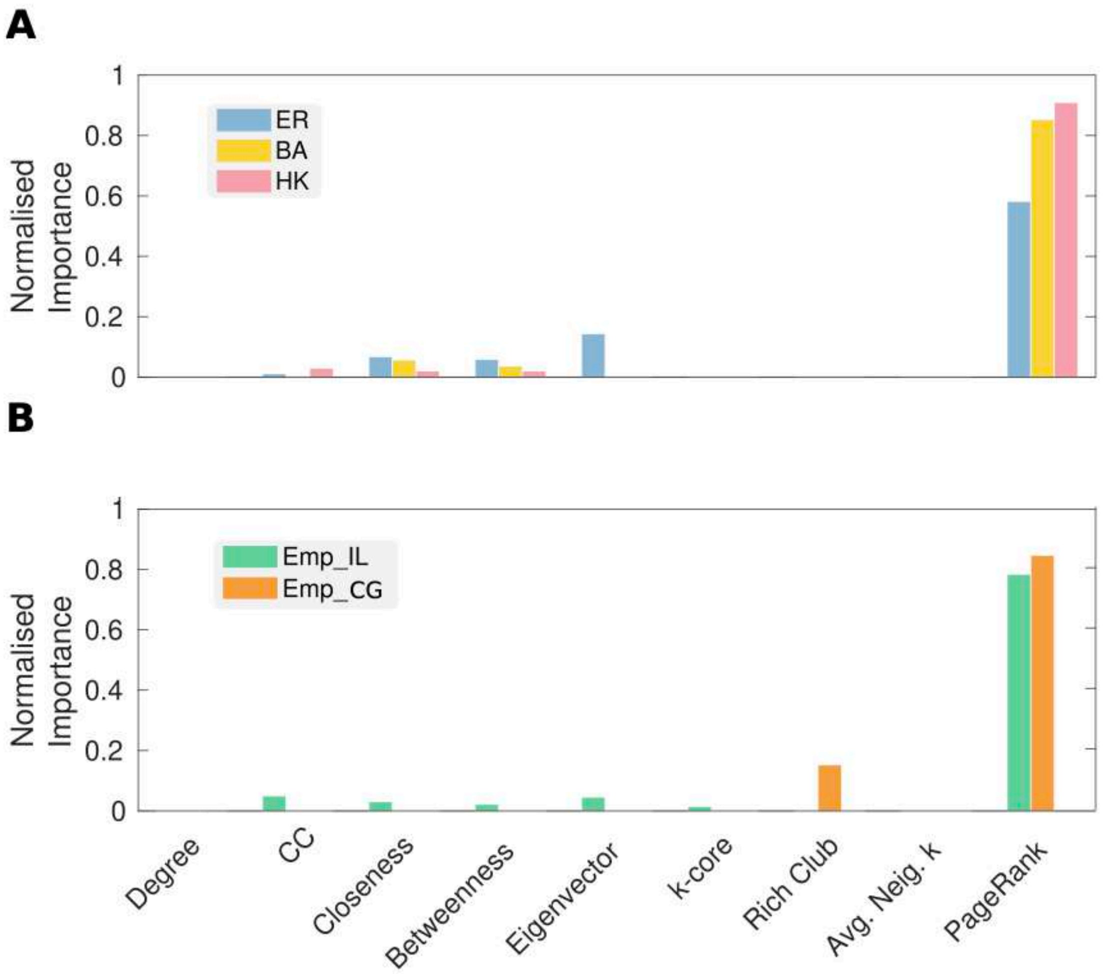
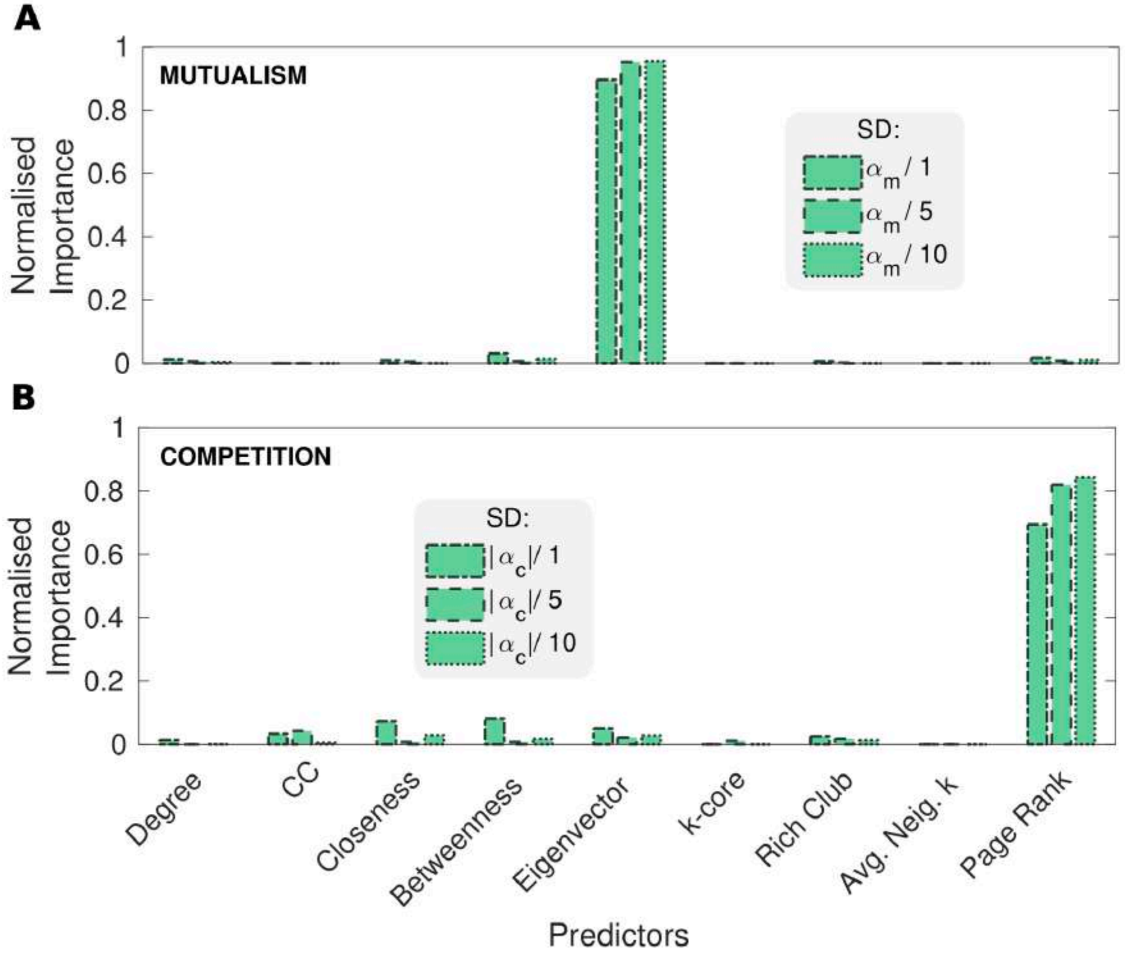


Figure F.1.1: Normalized importance for empirical network `Emp_IL` ($N = 1500$) with only mutualistic interactions when persistence is 30% ($\alpha_+ = 0.05$) and 80% ($\alpha_+ = 0.03$).

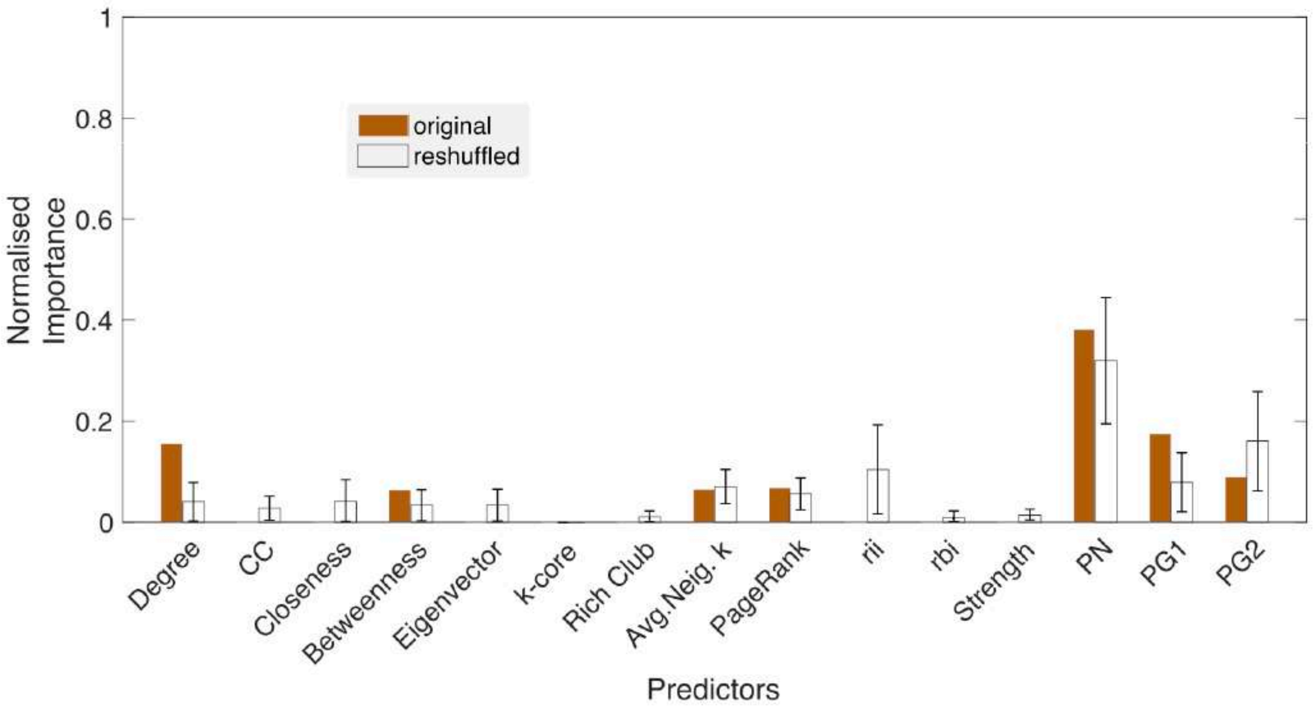
Results: Competition



The importance is not modified when we add Gaussian noise to α



Results: Mutualism & Competition



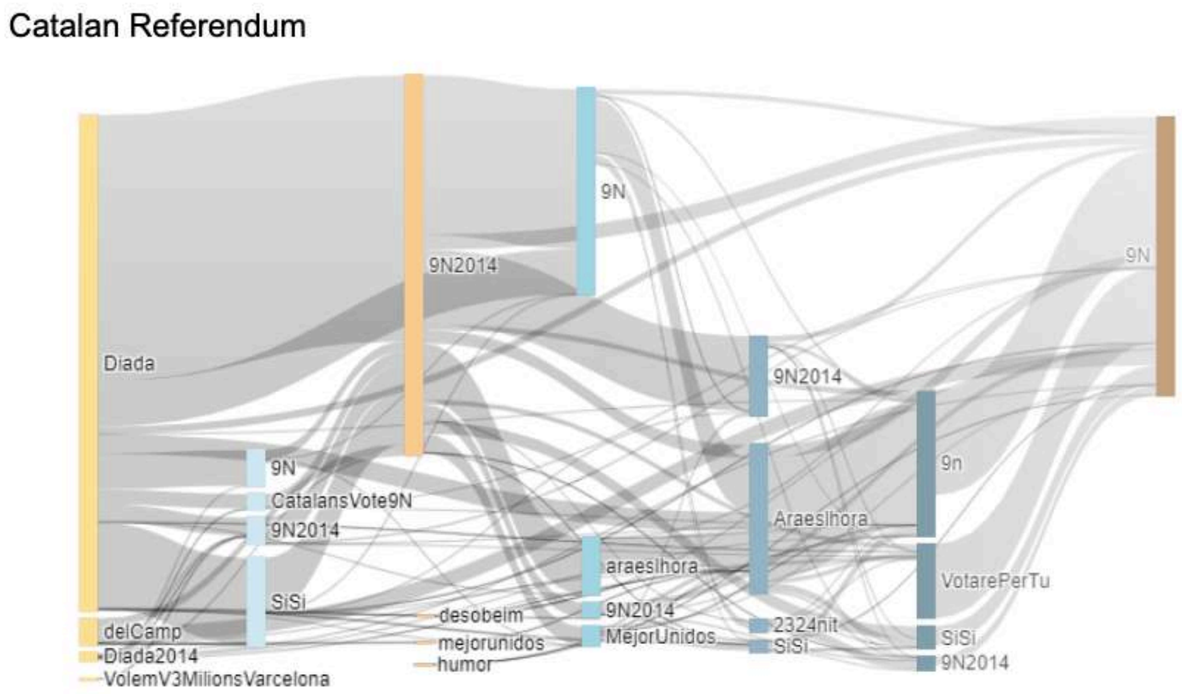


Figure 5.2.3: Topics' development for the Catalan referendum dataset is illustrated with an alluvial diagram. Boxes represent topics (communities in the co-occurrence network). Their colors encode the different periods, and their sizes are proportional to the number of tweets that belong to each topic. To ensure readability visibility, only the four largest topics are shown for each period. Flows represent the volume of tweets moving from one topic in a certain period to another topic in successive periods.

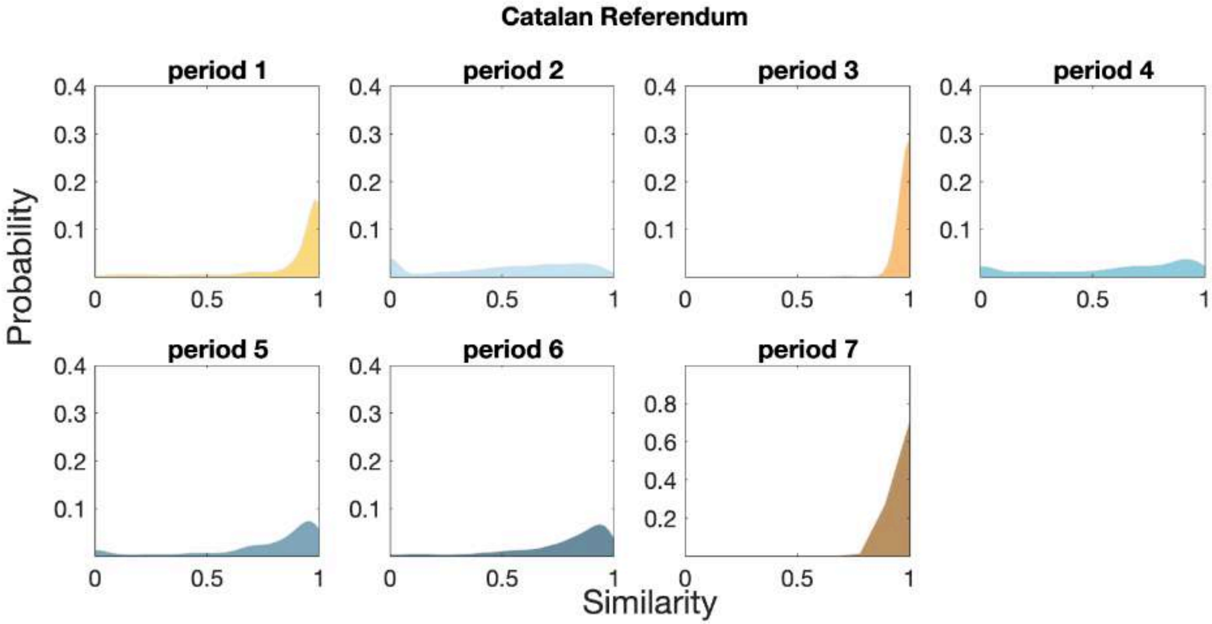


Figure 5.2.4: Cosine similarity distribution of user-topic vectors for the most active users of the Catalan referendum dataset. The cosine similarity has been calculated following Eq. 5.1. The most active users are the ones that have taken part in the discussion for at least 90% of the time and posted a minimum of 10 tweets within the whole period, which comprise around 400 accounts.

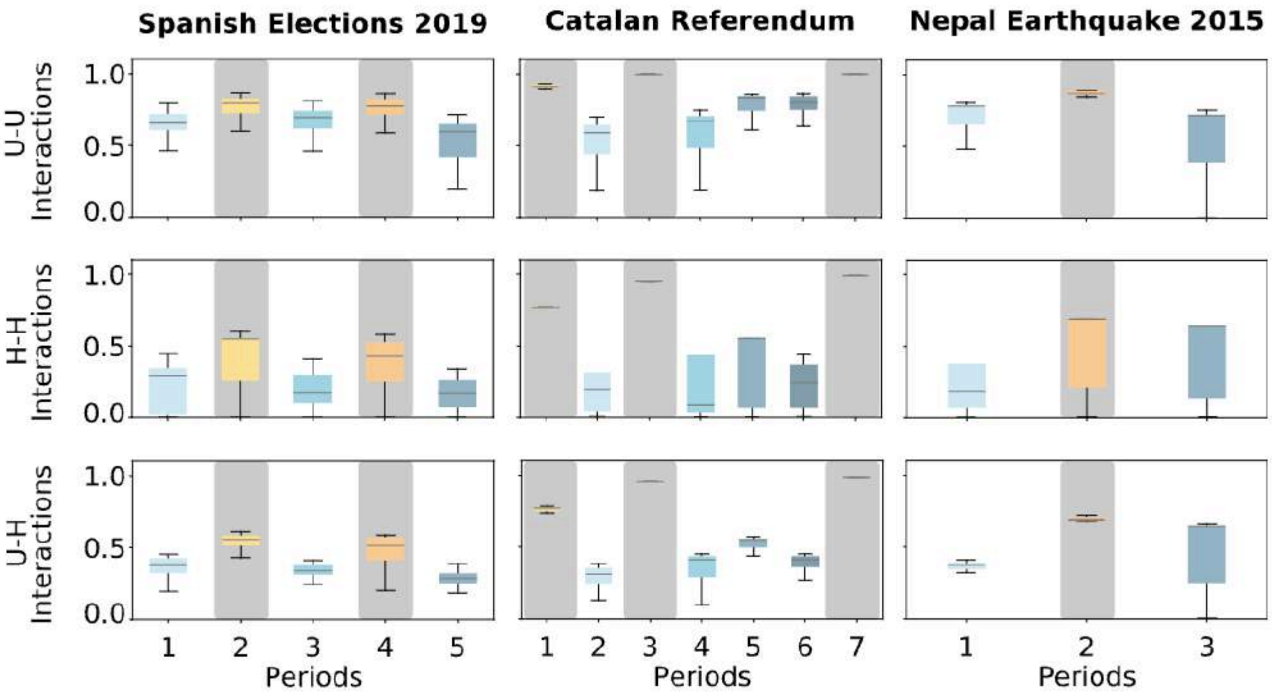


Figure 5.2.5: Strength estimations for hashtag-hashtag and user-user competitive interactions (first and second row), and user-hashtag mutualism (third row) for the 400 most active users and the hashtags they wrote. The interaction strength is the average value of the elements of the matrices β^{HH}, β^{UU}, and γ^{UH}.

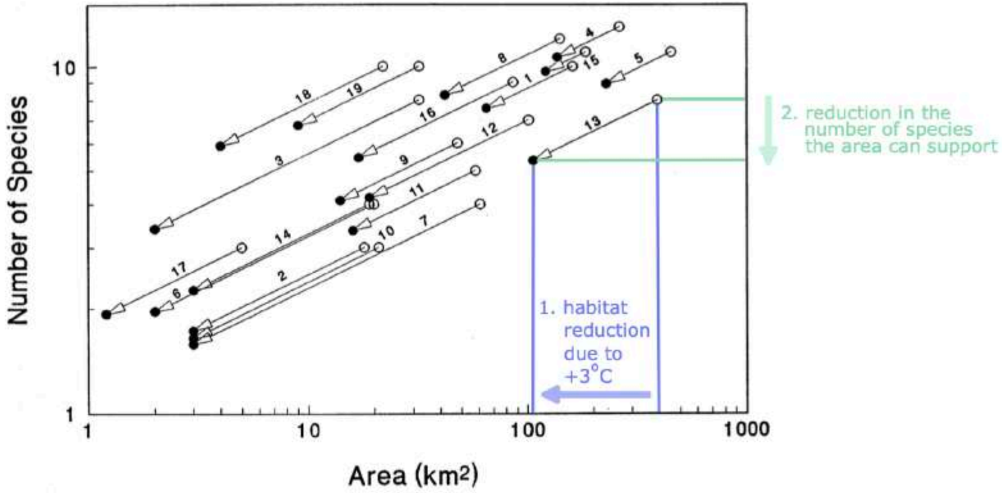
Universal statistical laws across ecosystems

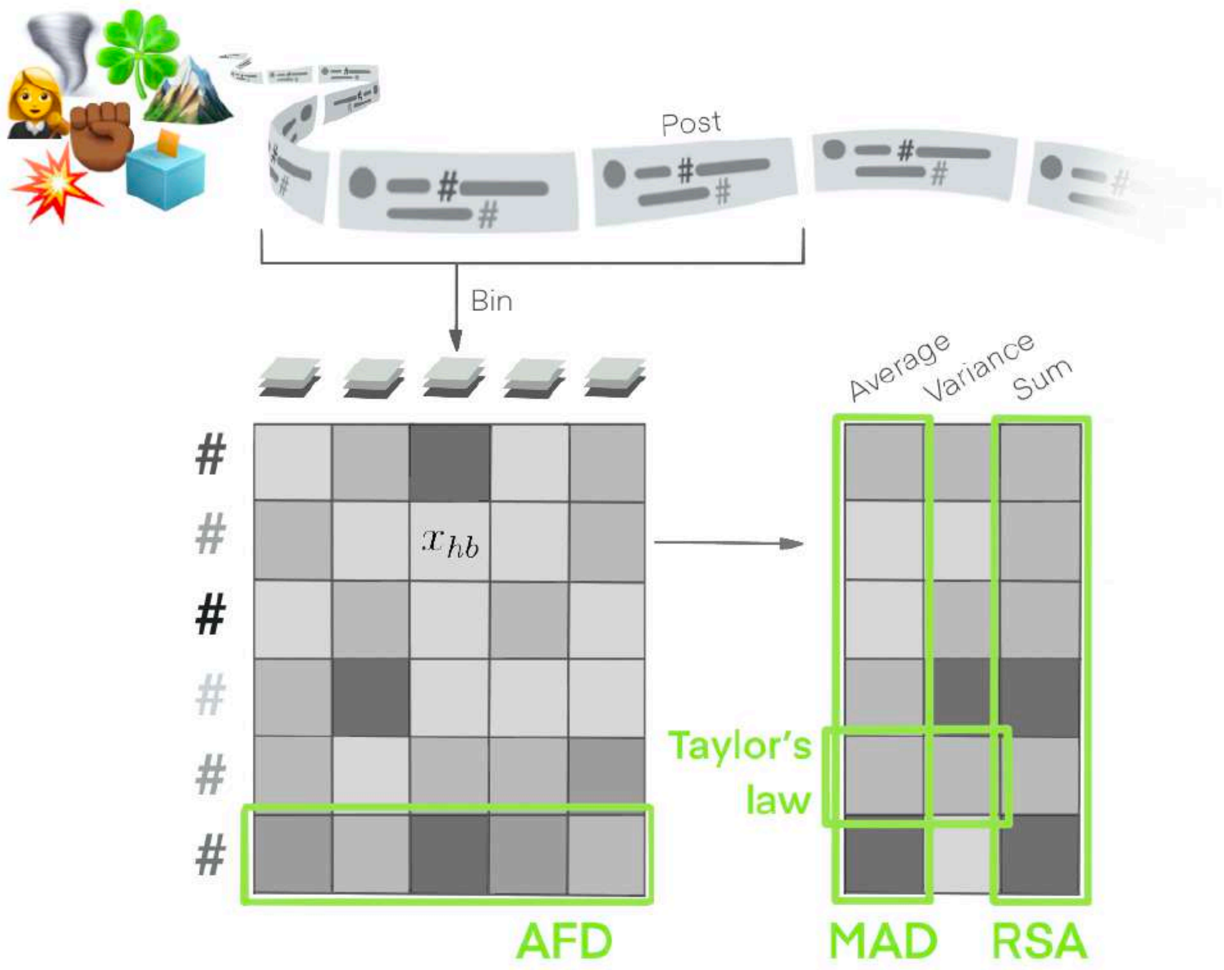
- Abundance
- Distribution
- Diversity

Important for:

- Finding mechanisms
- Modeling
- Health and prediction

- Species = Hashtags
- Abundance = Popularity
- Sampling





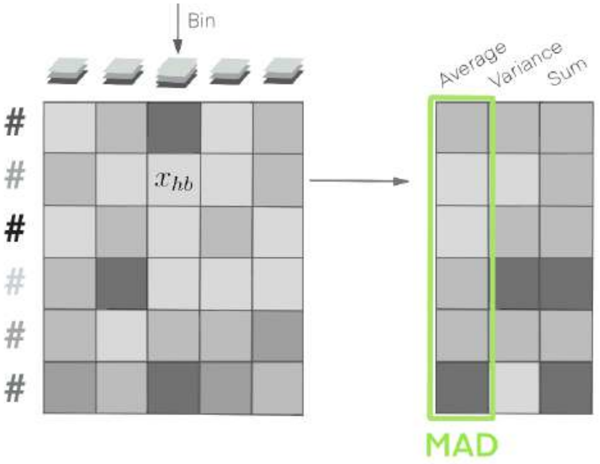
Post
Bin
Average
Variance
Sum
x_{hb}
Taylor's law
AFD
MAD
RSA

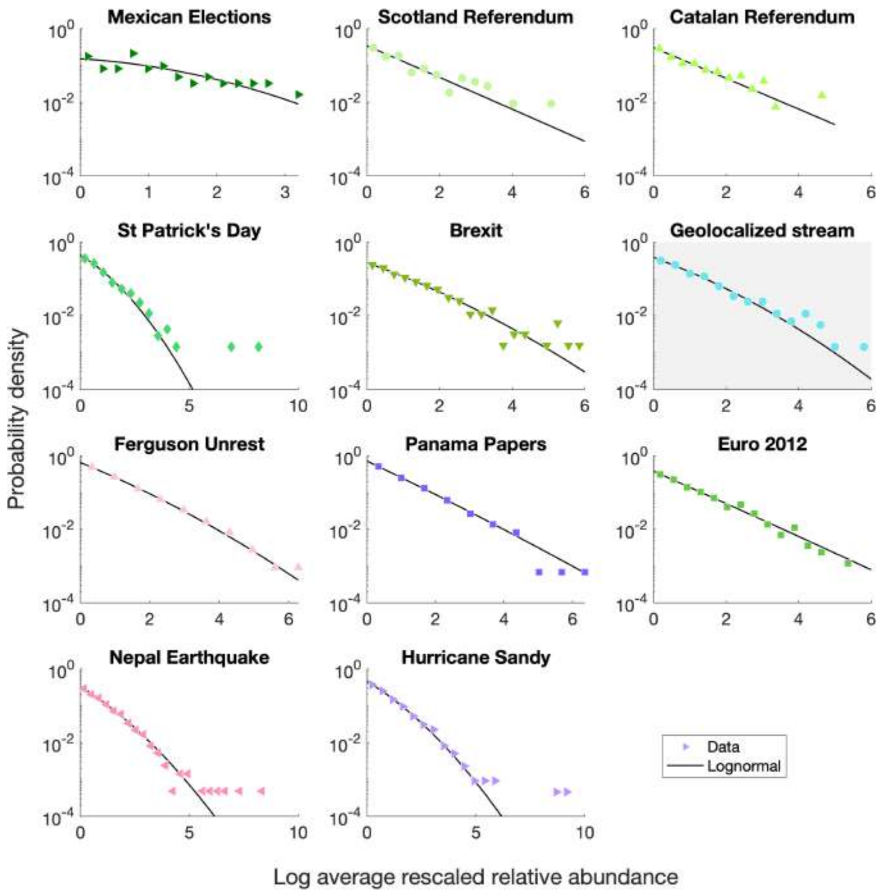
Mean Abundance Distribution - MAD

Lognormal distribution

J. Grilli. Nature Communications ***11****, 4743 (2020)*

$$p(\bar{x}) = \frac{1}{\sqrt{2\pi\sigma^2\bar{x}}}\exp\left(-\frac{(\log\bar{x} - \mu)^2}{2\sigma^2}\right)$$



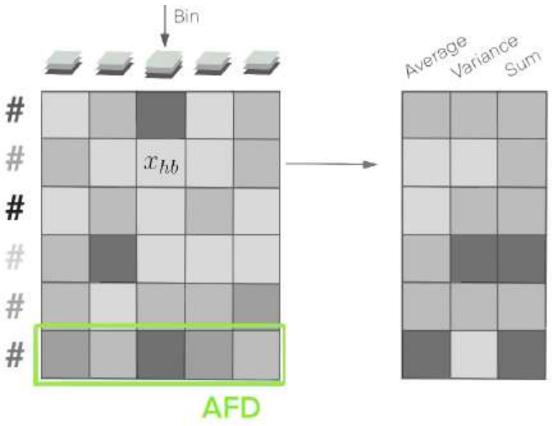


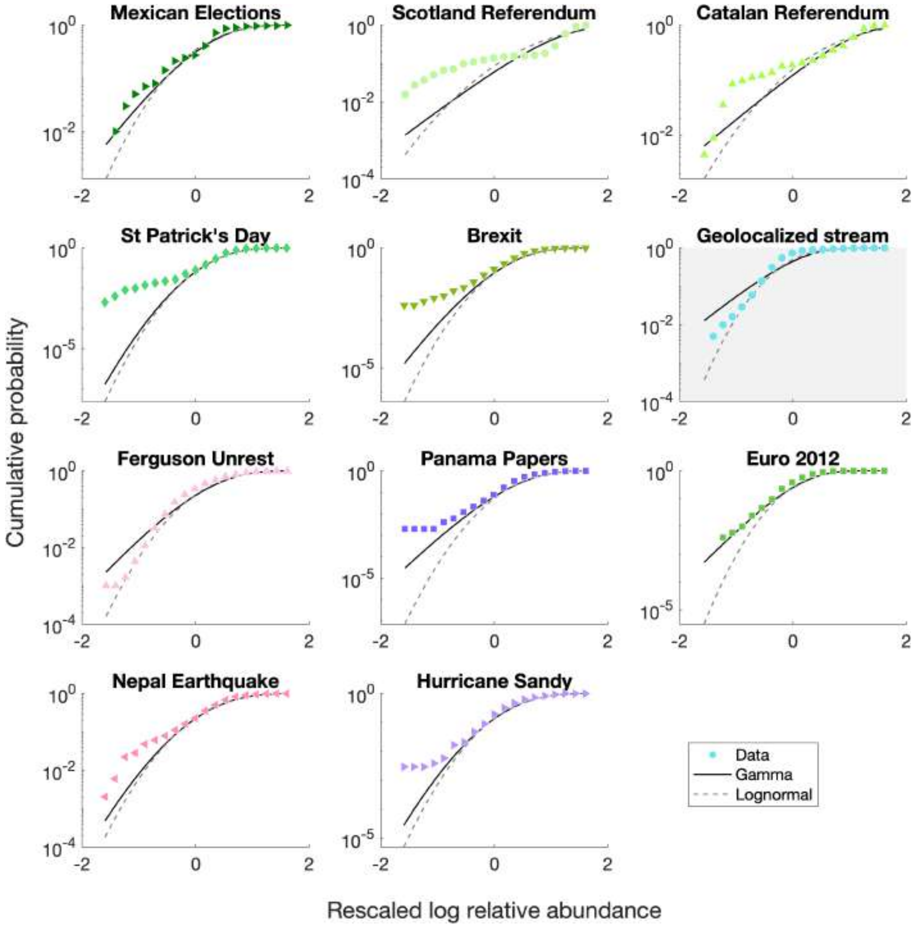
Abundance Fluctuations Distribution - AFD

Gamma distribution

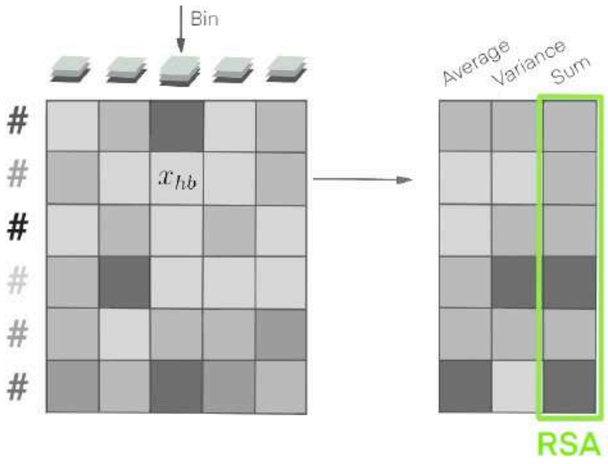
J. Grilli. Nature Communications ***11****, 4743 (2020)*

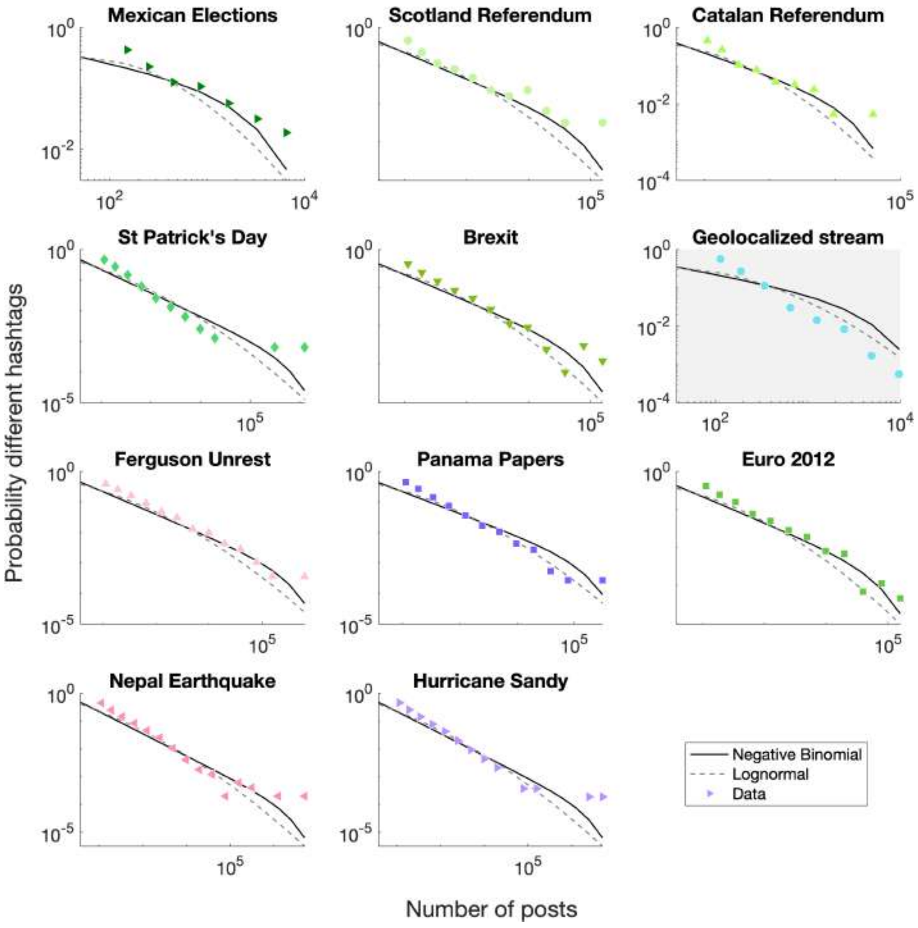
$$\rho_h(x) = \frac{1}{\Gamma(\beta_h)} \left(\frac{\beta_h}{\bar{x}_h}\right)^{\beta_h} \bar{x}^{\beta_h - 1} \exp\left(-\beta_h \frac{x}{\bar{x}_h}\right)$$



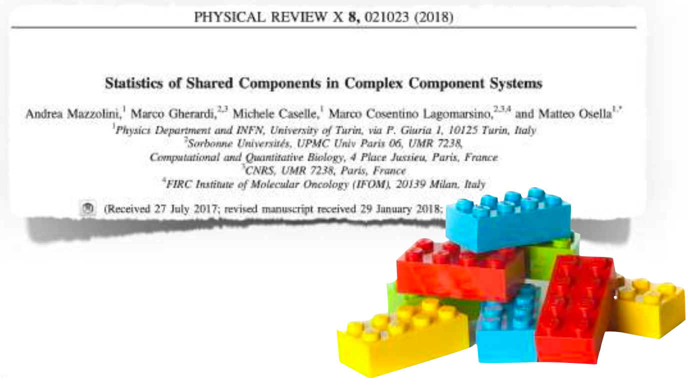


Relative Species Abundance - RSA



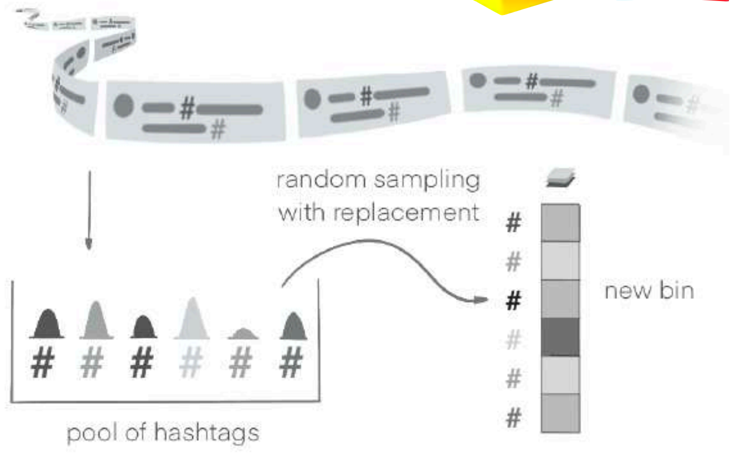


MODEL FOR HASHTAG SAMPLING

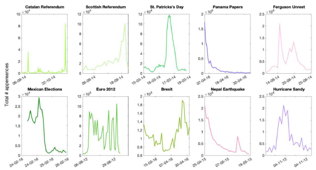


SUP: given a set of # frequencies,
multinomial random sampling

$$P(n_1, \ldots, n_H, N_b) = \frac{N_b!}{\prod n_h!} \prod f_h^{n_h}$$



MODEL FOR HASHTAG SAMPLING



Taylor's Law	✓	✗
Mean Abundance Distribution ***MAD***	✓	–
Abundance Fluctuations Distribution ***AFD***	✓	–
Relative Species Abundances. ***RSA***	✓	✓
Species-Area Curve ***SAC***	✓	✓
Daily Abundance Change ***STAC***	✓	–

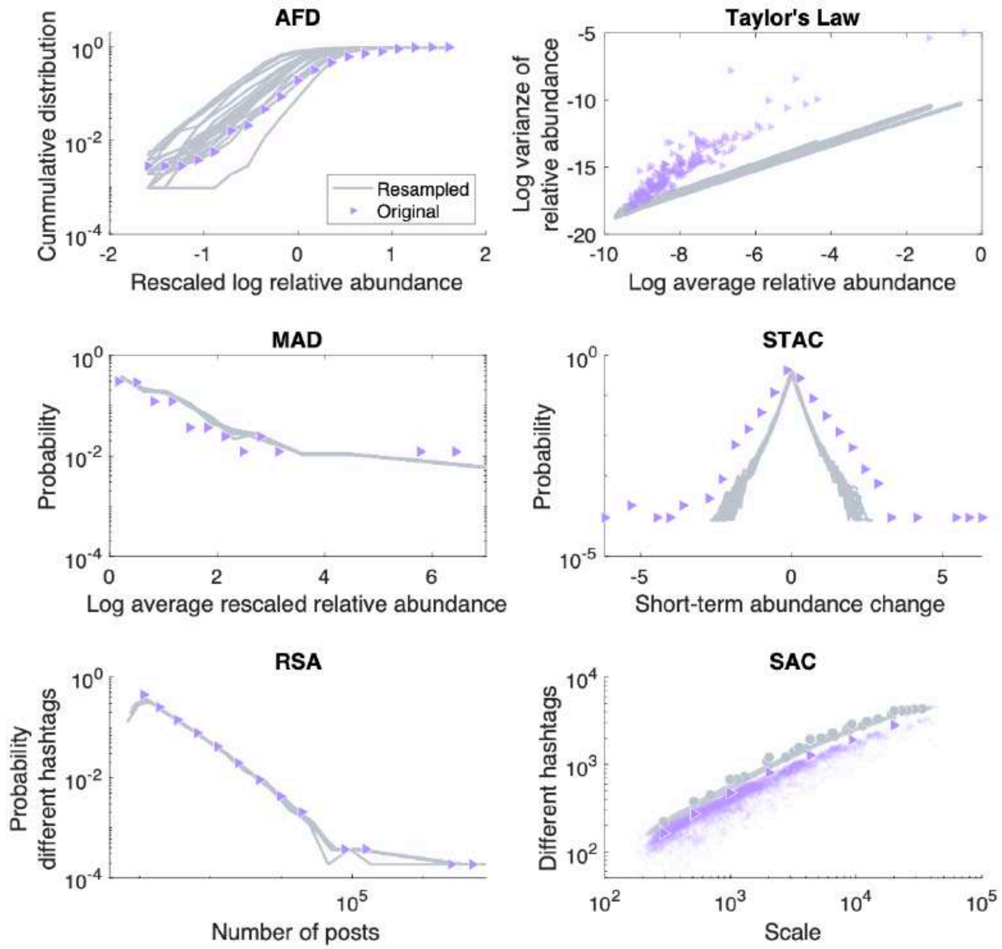


Figure 6.5.2: Macropatterns obtained by the multinomial random sampling model for the largest dataset (Hurricane Sandy) confronted with the original patterns, in colored dots. Each gray line corresponds to a resampling of the entire dataset.

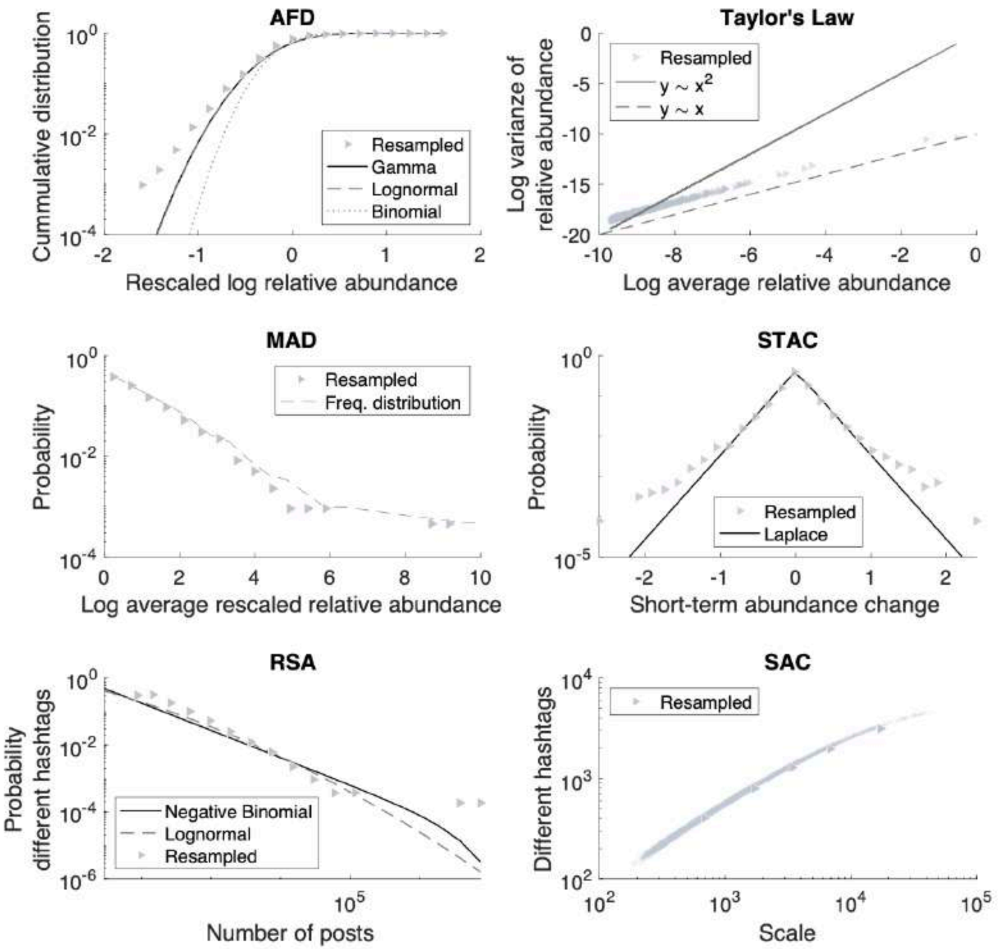


Figure H.3.1: Macropatterns (gray dots) obtained by multinomial random sampling of the largest dataset (Hurricane Sandy) and their fits to theoretical predictions. The dots correspond to one of the gray lines of Figure 6.5.2.