

Magnitude and diversity:

How an invariant from category theory
solves a problem in mathematical ecology

Tom Leinster

Glasgow/EPSRC

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2. **Diversity** (especially biological diversity)

Magnitude and diversity:

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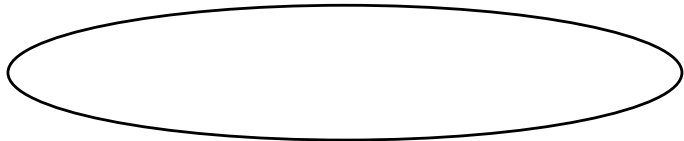
1. **Magnitude** (the invariant from category theory)
2. **Diversity** (especially biological diversity)
3. **How to maximize diversity** (the problem and its solution)

1. Magnitude

1. Enriched categories and size-like invariants

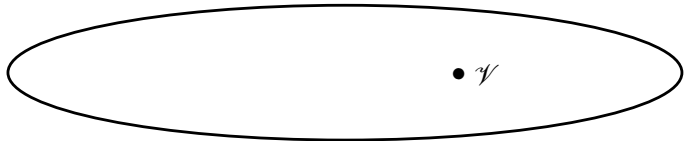
1. Enriched categories and size-like invariants

monoidal
categories



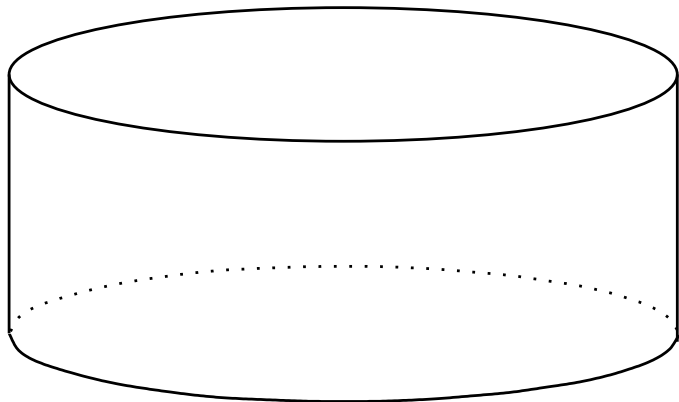
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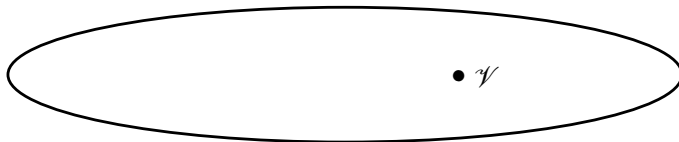


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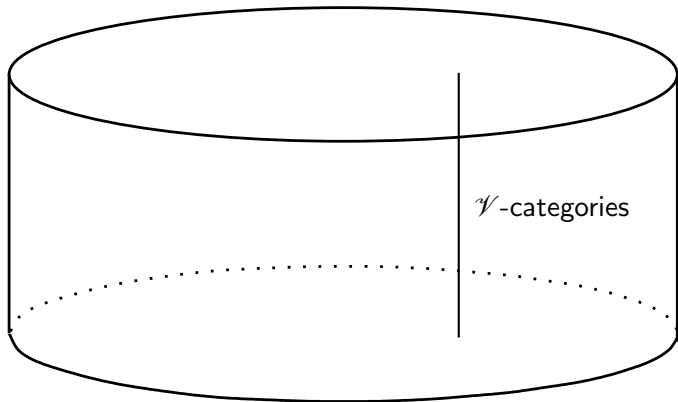


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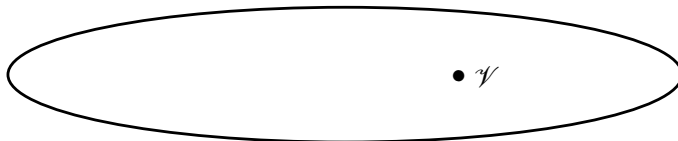


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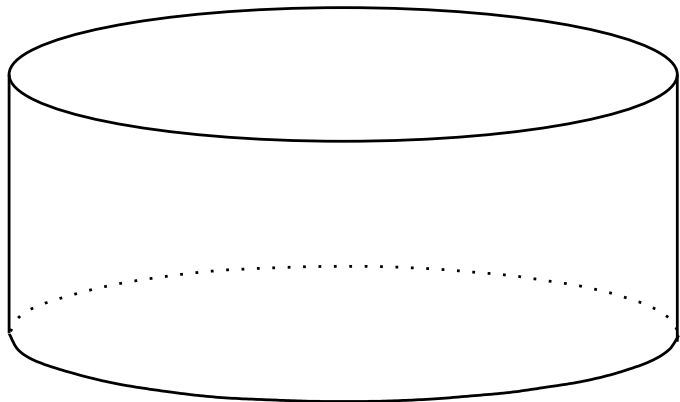


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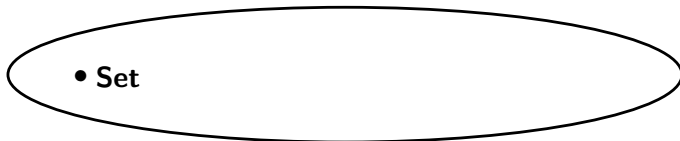


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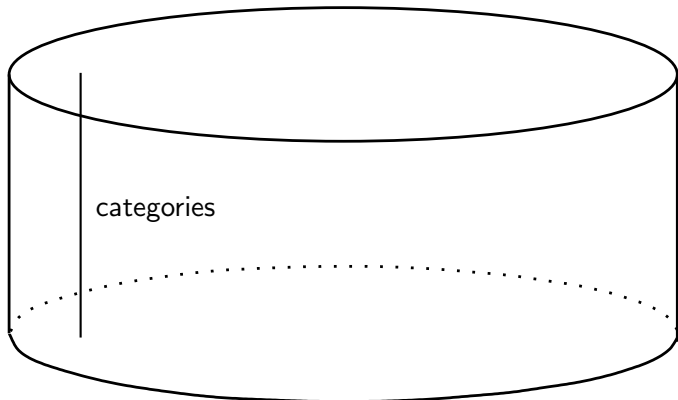


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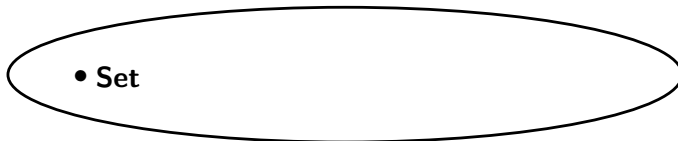


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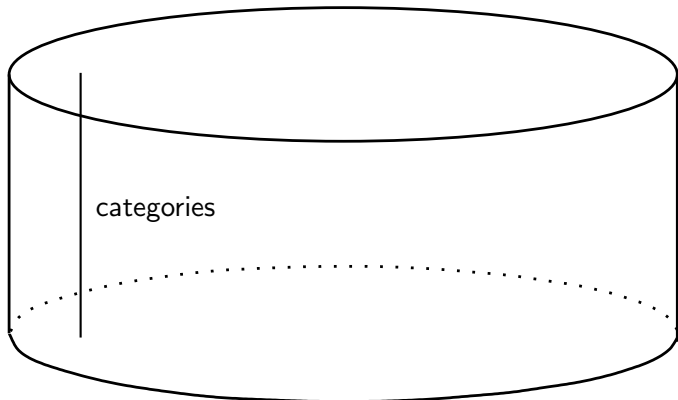


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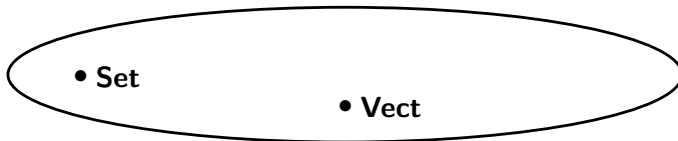


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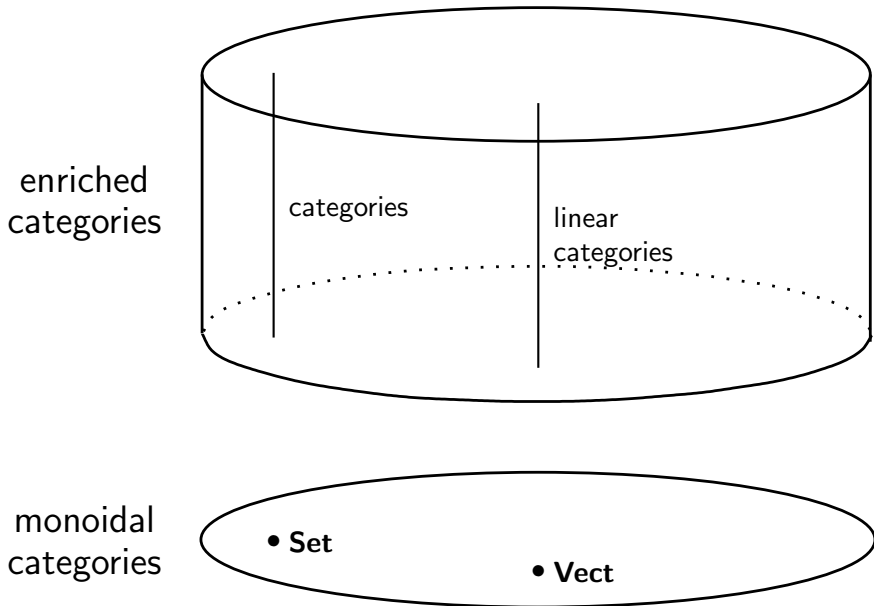
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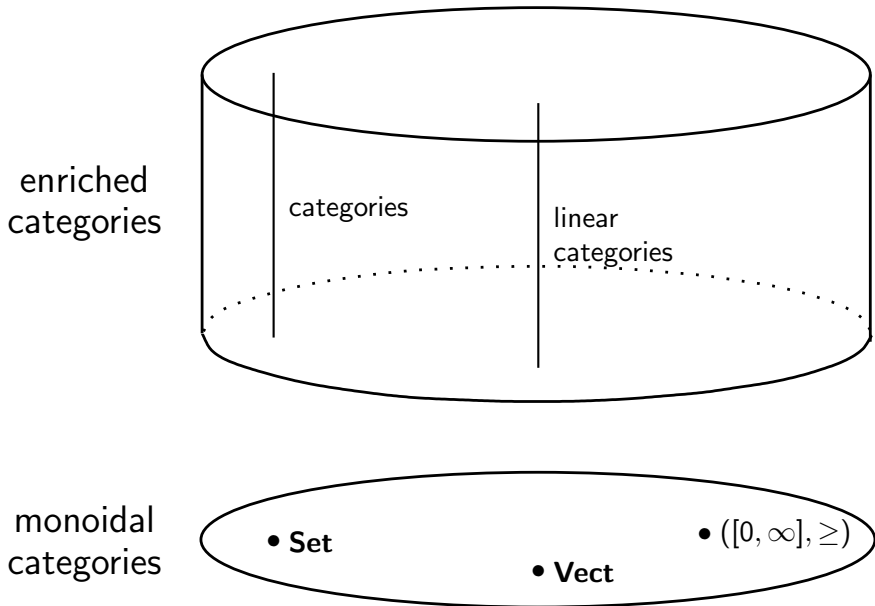
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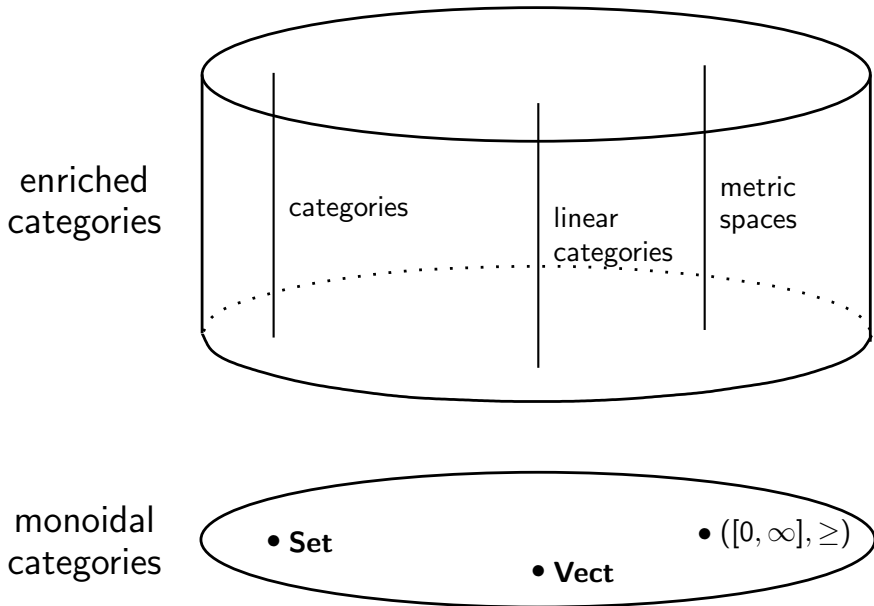
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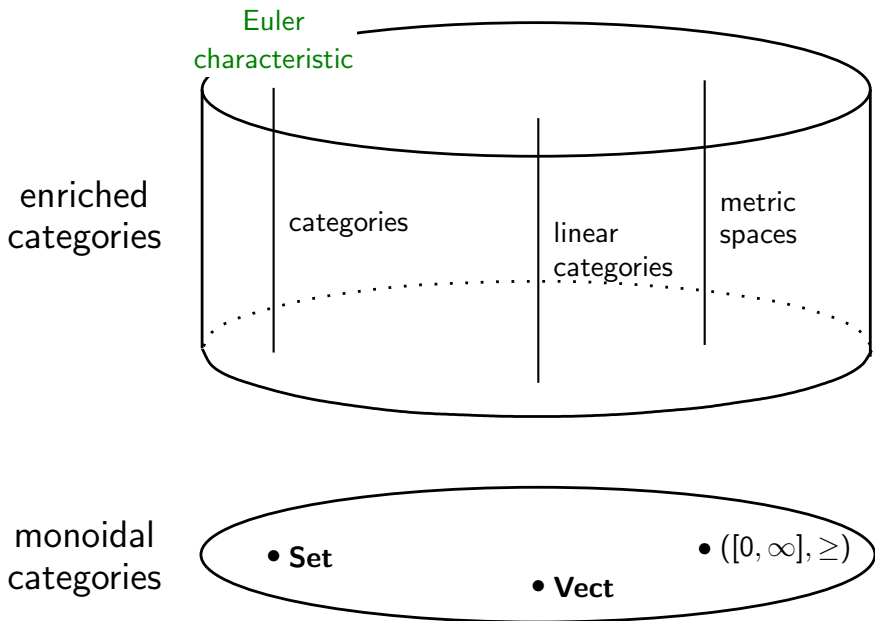
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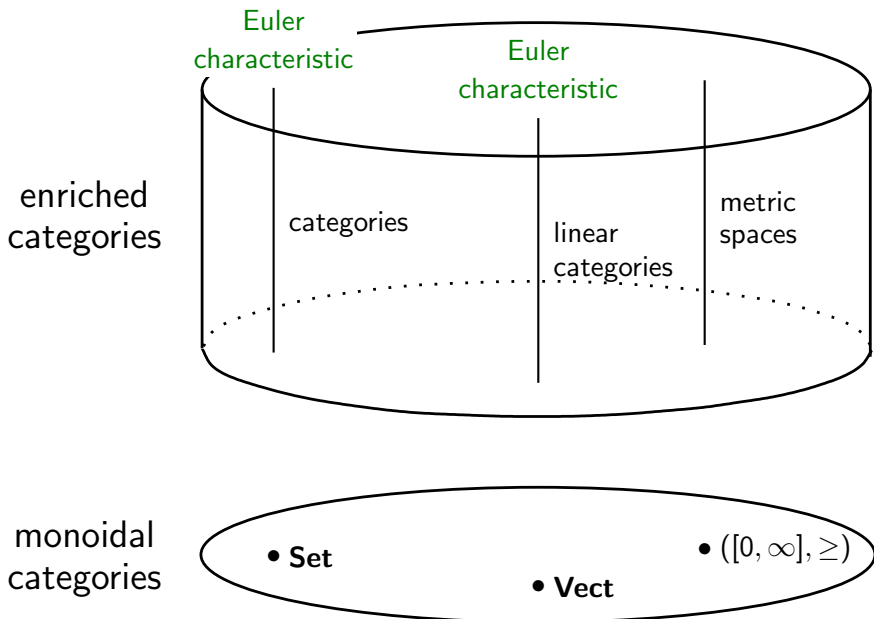
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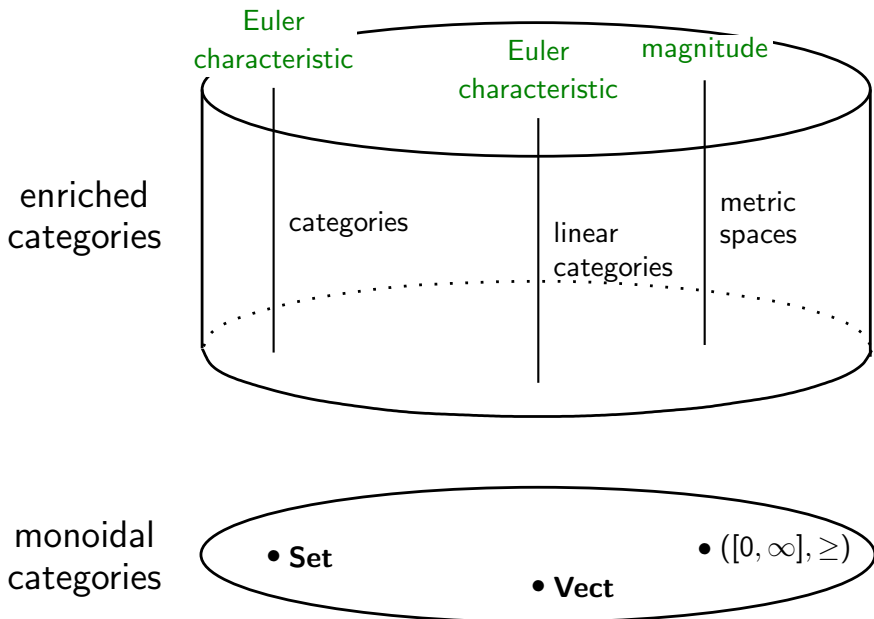
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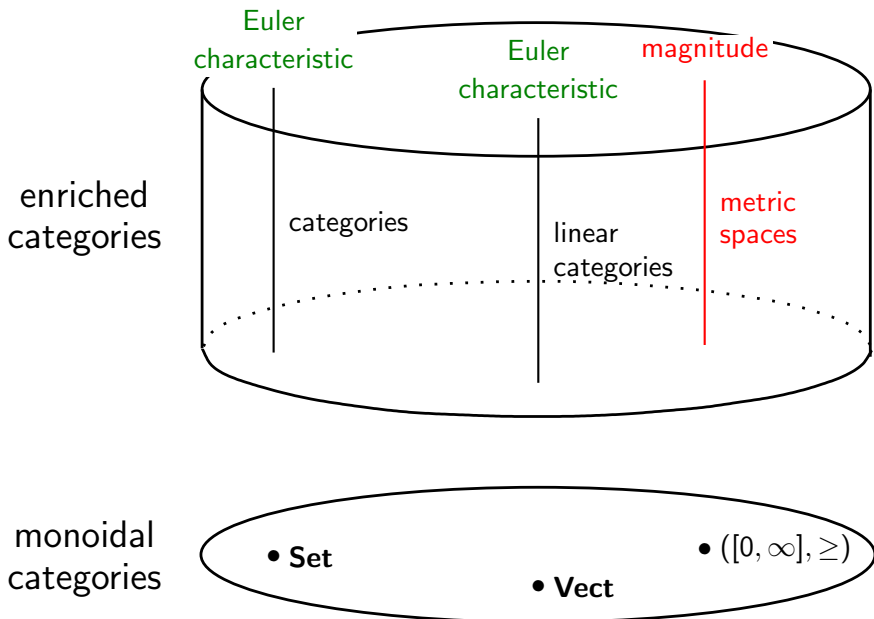
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The magnitude of a matrix

Let \mathbf{Z} be a matrix.

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A **weighting** on \mathbf{Z} is a column vector \mathbf{w} such that

$$\mathbf{Z}\mathbf{w} = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix}.$$

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for any weighting \mathbf{w} .

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It is also equal to $\sum_j v_j$ for any coweighting \mathbf{v} .

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Let $A = \{a_1, \dots, a_n\}$ be a finite metric space.

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It is a real number.

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Example: Let $A = \{a_1, \dots, a_n\}$ with $d(a_i, a_j) = \infty$ for all $i \neq j$.
Then $|A| = n$.

2. Diversity

joint with Christina Cobbold (Glasgow)

A spectrum of viewpoints on biodiversity

A spectrum of viewpoints on biodiversity

Conserving *species*
is what matters

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Rare species
count for as much
as common ones

A spectrum of viewpoints on biodiversity

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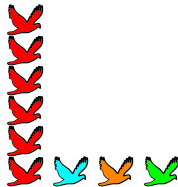
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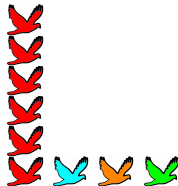
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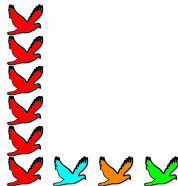


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This →



is more diverse than

that →



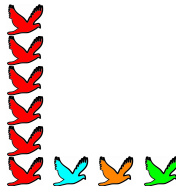
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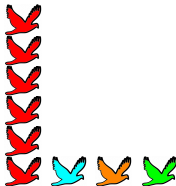


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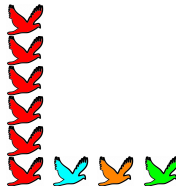
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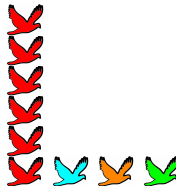
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← This

is more diverse than

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that →



← that

A spectrum of viewpoints on biodiversity

*Rare species are
important*

*Rare species are
unimportant*

This →

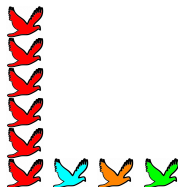
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Quantifying diversity

Quantifying diversity

model of
community



Quantifying diversity

model of
community



formula

Quantifying diversity

model of
community



measure of
diversity

Quantifying diversity



model of
community

Quantifying diversity

similarity matrix \mathbf{Z}

model of
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Quantifying diversity

similarity matrix **Z**

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Quantifying diversity

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Quantifying diversity

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Quantifying diversity


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Quantifying diversity


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$$0 \leq Z_{ij} \leq 1, Z_{ii} = 1$$

totally
dissimilar

identical

Example: a crude model would take $Z = \begin{pmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \ddots & \vdots \\ \vdots & \ddots & \ddots & 0 \\ 0 & \dots & 0 & 1 \end{pmatrix}$.

This model assumes that distinct species are totally dissimilar.

Quantifying diversity

similarity matrix **Z**

Quantifying diversity

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model of
community

Quantifying diversity

similarity matrix **Z**

frequency distribution **p**

model of
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Quantifying diversity

similarity matrix Z

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Quantifying diversity

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p_i = relative frequency,
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$$p_i \geq 0 \text{ and } \sum p_i = 1$$

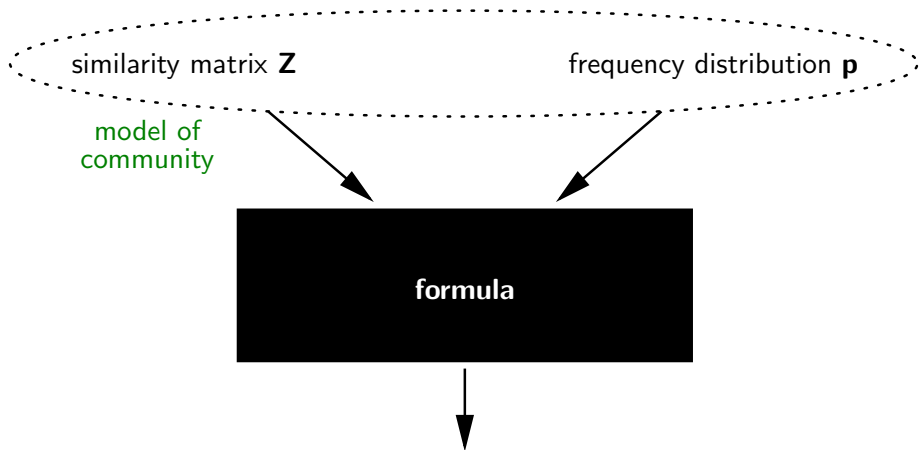
Quantifying diversity

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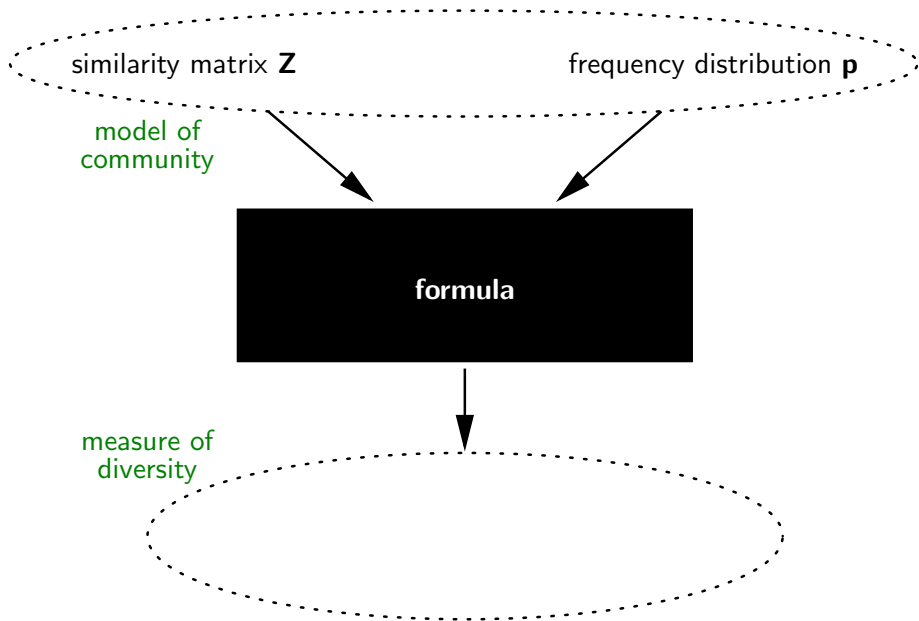
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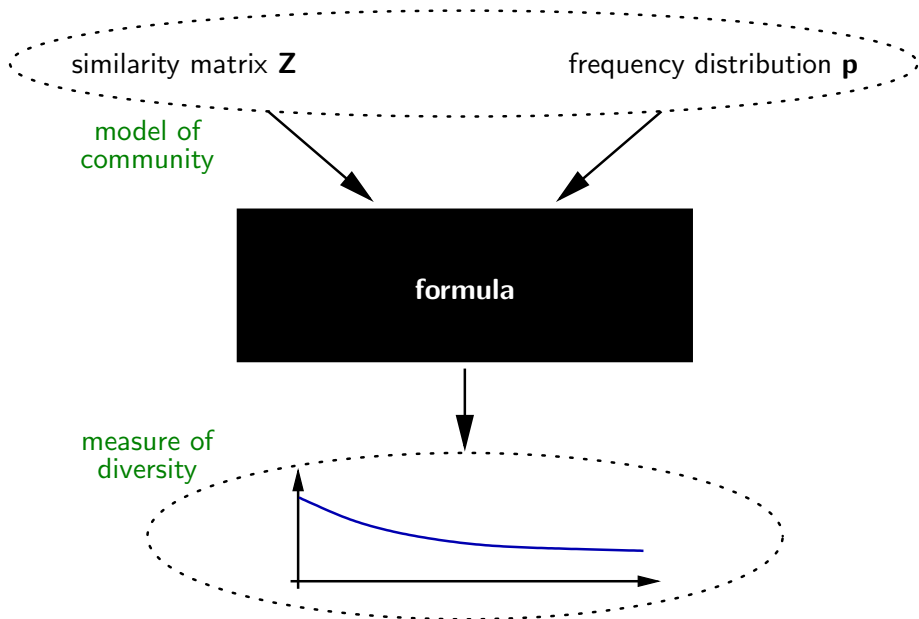
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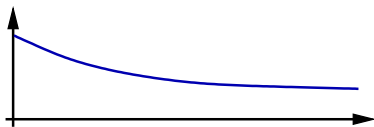
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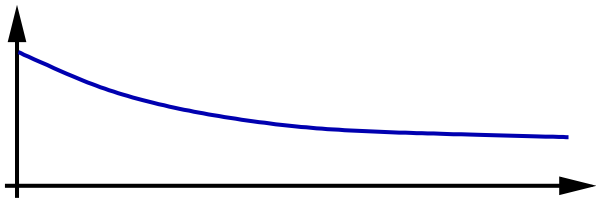
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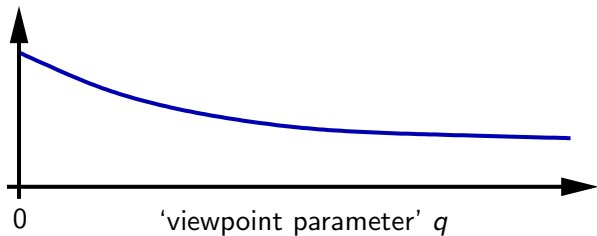
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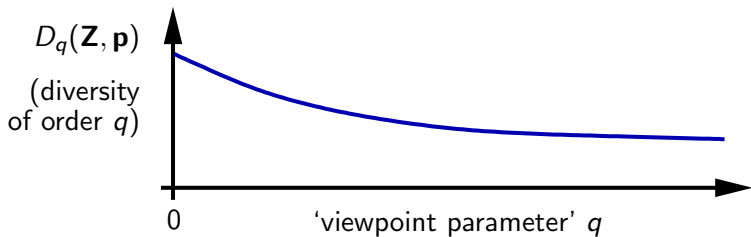
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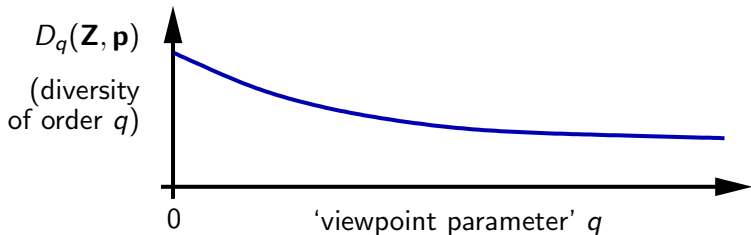


Quantifying diversity

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frequency distribution \mathbf{p}

$q = 0$:
rare species are
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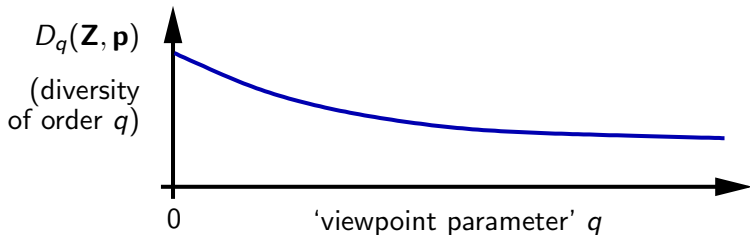
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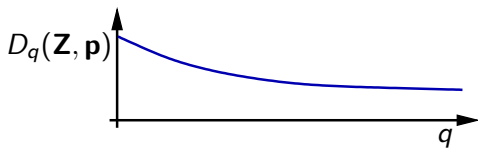
$q = \infty$:
rare species are
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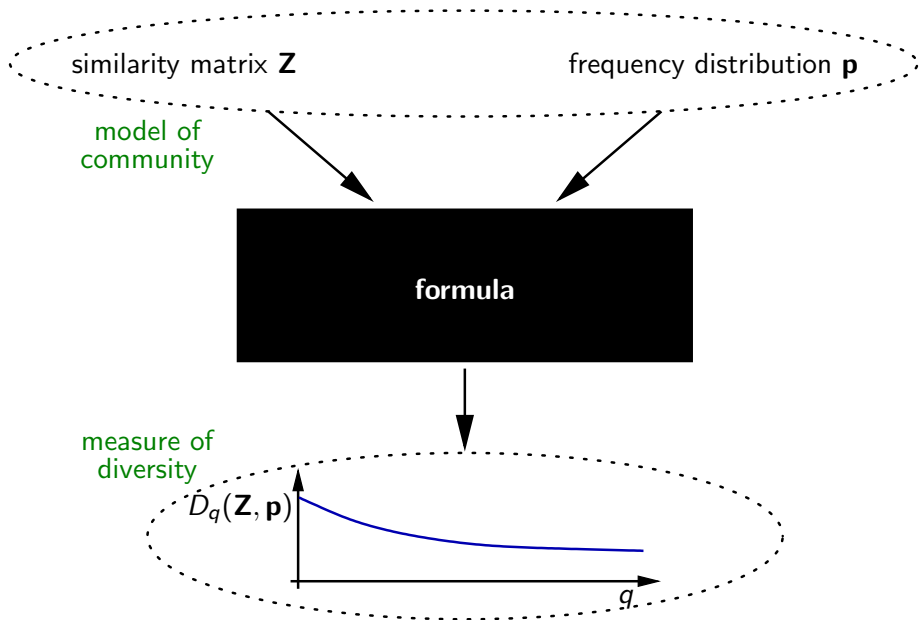
Quantifying diversity

similarity matrix \mathbf{Z}

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Quantifying diversity



Quantifying diversity

similarity matrix \mathbf{Z}

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model of
community

The diversity of order $q \in [0, \infty]$ is

$$D_q(\mathbf{Z}, \mathbf{p}) = \left(\sum_{i: p_i > 0} p_i (\mathbf{Zp})_i^{q-1} \right)^{\frac{1}{1-q}}$$

measure of
diversity

$D_q(\mathbf{Z}, \mathbf{p})$

q

3. How to maximize diversity

The maximum diversity problem

Fix a list of n species, with similarity matrix \mathbf{Z} .

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Let $0 \leq q \leq \infty$.

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I.e., what is

$$\sup\{D_q(\mathbf{Z}, \mathbf{p}) : \text{frequency distributions } \mathbf{p}\},$$

and which \mathbf{p} attain this supremum?

A guess

A guess

The maximum diversity is the magnitude $|\mathbf{Z}|$.

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The distributions that maximize diversity are the weightings on \mathbf{Z}

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The maximum diversity is the magnitude $|\mathbf{Z}|$.

The distributions that maximize diversity are the weightings on \mathbf{Z} , normalized to sum to 1.

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After all, different values of q represent different viewpoints on what diversity is.

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Corollary

There is a frequency distribution that maximizes diversity of order q for all q simultaneously.

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'There is a best of all possible worlds.'