

# Magnitude, diversity, homology

A survey, with questions

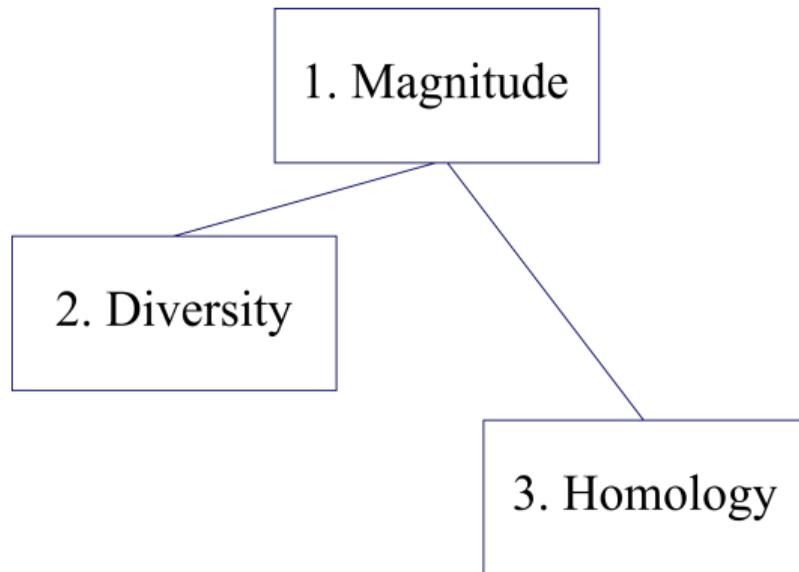
Emily Roff

University of Edinburgh

Analysis Seminar, Edinburgh

February 2023

# Plan



Part I

Magnitude

## The magnitude of a finite metric space

## The magnitude of a finite metric space

Let  $(X, d)$  be a finite metric space. The  $X \times X$  matrix  $Z_X$  defined by

$$Z_X(x, y) = e^{-d(x, y)}$$

is called the **similarity matrix** of  $X$ .

## The magnitude of a finite metric space

Let  $(X, d)$  be a finite metric space. The  $X \times X$  matrix  $Z_X$  defined by

$$Z_X(x, y) = e^{-d(x, y)}$$

is called the **similarity matrix** of  $X$ . A **weight vector** for  $X$  is  $\mathbf{v} \in \mathbb{R}^X$  such that

$$Z_X \mathbf{v}(x) = 1 \text{ for all } x \in X.$$

## The magnitude of a finite metric space

Let  $(X, d)$  be a finite metric space. The  $X \times X$  matrix  $Z_X$  defined by

$$Z_X(x, y) = e^{-d(x, y)}$$

is called the **similarity matrix** of  $X$ . A **weight vector** for  $X$  is  $\mathbf{v} \in \mathbb{R}^X$  such that

$$Z_X \mathbf{v}(x) = 1 \text{ for all } x \in X.$$

**Definition (Leinster, 2010\*)** If  $X$  possesses a weight vector, the **magnitude** of  $X$  is

$$|X| = \sum_{x \in X} \mathbf{v}(x)$$

for any weight vector  $\mathbf{v}$ . (This value is independent of the choice of  $\mathbf{v}$ .)

\*All references are to [arXiv dates](#). A reference list can be found at the end of these slides.

## The magnitude of a finite metric space

Let  $(X, d)$  be a finite metric space. The  $X \times X$  matrix  $Z_X$  defined by

$$Z_X(x, y) = e^{-d(x, y)}$$

is called the **similarity matrix** of  $X$ . A **weight vector** for  $X$  is  $\mathbf{v} \in \mathbb{R}^X$  such that

$$Z_X \mathbf{v}(x) = 1 \text{ for all } x \in X.$$

**Definition (Leinster, 2010\*)** If  $X$  possesses a weight vector, the **magnitude** of  $X$  is

$$|X| = \sum_{x \in X} \mathbf{v}(x)$$

for any weight vector  $\mathbf{v}$ . (This value is independent of the choice of  $\mathbf{v}$ .)

**Lemma** If  $Z_X$  is invertible then  $|X| = \sum_{x, y \in X} Z_X^{-1}(x, y)$ .

\*All references are to [arXiv dates](#). A reference list can be found at the end of these slides.

## The magnitude function of a finite metric space

Let  $(X, d)$  be a metric space. For each  $t \in [0, \infty)$  we denote by  $tX$  the space  $(X, td)$ .

## The magnitude function of a finite metric space

Let  $(X, d)$  be a metric space. For each  $t \in [0, \infty)$  we denote by  $tX$  the space  $(X, td)$ .

The **magnitude function** of a finite space  $X$  is

$$\begin{aligned} |\cdot - X| : [0, \infty) &\rightarrow \mathbb{R} \\ t &\mapsto |tX|. \end{aligned}$$

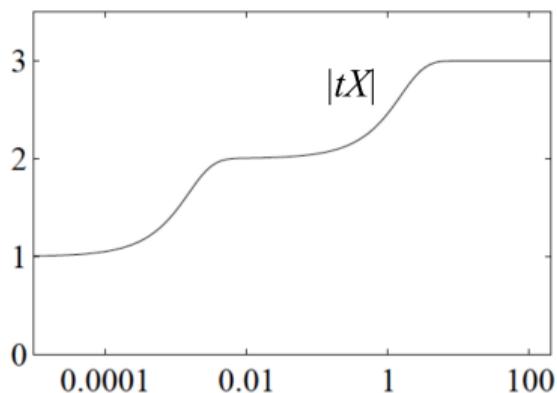
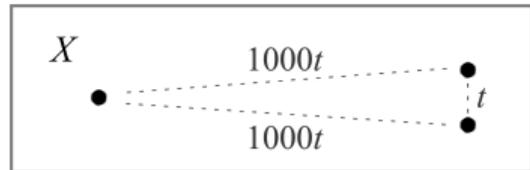
## The magnitude function of a finite metric space

Let  $(X, d)$  be a metric space. For each  $t \in [0, \infty)$  we denote by  $tX$  the space  $(X, td)$ .

The **magnitude function** of a finite space  $X$  is

$$\begin{aligned} |\cdot - X| : [0, \infty) &\rightarrow \mathbb{R} \\ t &\mapsto |tX|. \end{aligned}$$

The parameter  $t$  controls the scale of the metric in  $X$ . The magnitude function tells us the 'effective number of points' in  $X$  as the scale varies. Its growth rate tells us about the 'effective dimension' of  $X$  at different scales (Willerton, 2012).



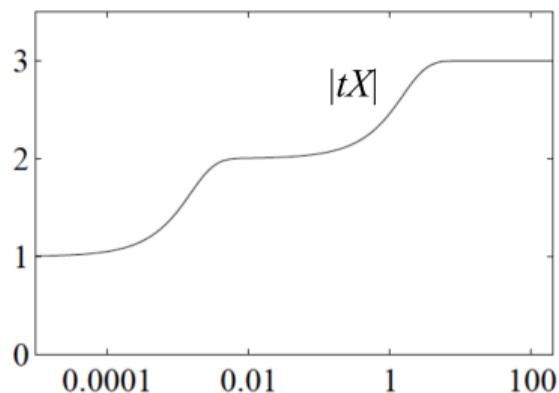
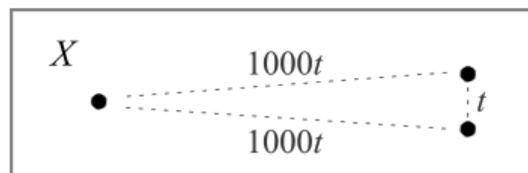
## The magnitude function of a finite metric space

Let  $(X, d)$  be a metric space. For each  $t \in [0, \infty)$  we denote by  $tX$  the space  $(X, td)$ .

The **magnitude function** of a finite space  $X$  is

$$\begin{aligned} |\cdot - X| : [0, \infty) &\rightarrow \mathbb{R} \\ t &\mapsto |tX|. \end{aligned}$$

The parameter  $t$  controls the scale of the metric in  $X$ . The magnitude function tells us the 'effective number of points' in  $X$  as the scale varies. Its growth rate tells us about the 'effective dimension' of  $X$  at different scales (Willerton, 2012).



**Question** Can a magnitude function be defined for larger metric spaces?

## Positive definite spaces

**Definition (Meckes, 2010)** A metric space  $X$  is **positive definite** if, for all finite subspaces  $Y \subseteq X$ , the matrix  $Z_Y$  is positive definite.

**Examples** Spheres with geodesic metric, hyperbolic space, subsets of Euclidean space.

## Positive definite spaces

**Definition (Meckes, 2010)** A metric space  $X$  is **positive definite** if, for all finite subspaces  $Y \subseteq X$ , the matrix  $Z_Y$  is positive definite.

**Examples** Spheres with geodesic metric, hyperbolic space, subsets of Euclidean space.

**Proposition (Leinster, 2010)** Let  $X$  be a finite positive definite space. Then

$$|X| = \sup \frac{(\sum_{x \in X} \mathbf{v}(x))^2}{\mathbf{v}^T Z_X \mathbf{v}}$$

where the supremum is over  $\mathbf{v} \neq \mathbf{0}$  in  $\mathbb{R}^X$ . (**Proof** Cauchy–Schwarz inequality.  $\square$ )

## Positive definite spaces

**Definition (Meckes, 2010)** A metric space  $X$  is **positive definite** if, for all finite subspaces  $Y \subseteq X$ , the matrix  $Z_Y$  is positive definite.

**Examples** Spheres with geodesic metric, hyperbolic space, subsets of Euclidean space.

**Proposition (Leinster, 2010)** Let  $X$  be a finite positive definite space. Then

$$|X| = \sup \frac{(\sum_{x \in X} \mathbf{v}(x))^2}{\mathbf{v}^T Z_X \mathbf{v}}$$

where the supremum is over  $\mathbf{v} \neq \mathbf{0}$  in  $\mathbb{R}^X$ . (**Proof** Cauchy–Schwarz inequality.  $\square$ )

**Corollary** For any finite positive definite space  $X$  we have  $|X| = \sup\{|Y| \mid Y \subseteq X\}$ .

**Idea** Let this formulation *define* the magnitude of larger metric spaces.

# The magnitude of a compact metric space

Proposition (Leinster & Meckes, 2016)

The quantity  $S(X) = \sup\{|Y| \mid \text{finite } Y \subseteq X\}$  is lower semicontinuous as a function on the class of positive definite metric spaces with the Gromov–Hausdorff topology.

# The magnitude of a compact metric space

Proposition (Leinster & Meckes, 2016)

The quantity  $S(X) = \sup\{|Y| \mid \text{finite } Y \subseteq X\}$  is lower semicontinuous as a function on the class of positive definite metric spaces with the Gromov–Hausdorff topology.

So there is a **canonical** way to extend magnitude to compact positive definite spaces:

Definition (Leinster & Meckes, 2016)

Let  $X$  be a compact positive definite metric space. The **magnitude** of  $X$  is

$$|X| = \sup\{|Y| \mid \text{finite } Y \subseteq X\}.$$

The **magnitude function** of  $X$  is the the function  $t \mapsto |tX|$ .

## Magnitude via weight measures

Given a compact metric space  $X$ , let  $M(X) = \{\text{finite Borel measures on } X\}$ .

For  $t \geq 0$ , define  $\mathcal{Z}_X(t) : M(X) \rightarrow C(X)$  by

$$\mathcal{Z}_X(t)(\mu)(x) = \frac{1}{t} \int_X e^{-td(x,y)} d\mu(y).$$

## Magnitude via weight measures

Given a compact metric space  $X$ , let  $M(X) = \{\text{finite Borel measures on } X\}$ .

For  $t \geq 0$ , define  $\mathcal{Z}_X(t) : M(X) \rightarrow C(X)$  by

$$\mathcal{Z}_X(t)(\mu)(x) = \frac{1}{t} \int_X e^{-td(x,y)} d\mu(y).$$

Definition (Willerton, 2010)

A **weight measure** for  $tX$  is a solution  $\mu_t$  to the equation  $t\mathcal{Z}_X(t)(\mu_t) = 1$ .

Proposition (Meckes, 2010)

If  $tX$  is positive definite and admits a weight measure, then  $|tX| = \mu_t(X)$ .

## The magnitude function carries geometric information

Theorem (Barceló & Carbery, 2015)

Let  $X \subset \mathbb{R}^n$  be a nonempty compact set. Then  $|tX| \rightarrow 1$  as  $t \rightarrow 0$  and

$$\frac{|tX|}{t^n} \rightarrow \frac{\text{Vol}(X)}{n! \omega_n} \text{ as } t \rightarrow +\infty.$$

## The magnitude function carries geometric information

### Theorem (Barceló & Carbery, 2015)

Let  $X \subset \mathbb{R}^n$  be a nonempty compact set. Then  $|tX| \rightarrow 1$  as  $t \rightarrow 0$  and

$$\frac{|tX|}{t^n} \rightarrow \frac{\text{Vol}(X)}{n!\omega_n} \text{ as } t \rightarrow +\infty.$$

### Theorem (Gimperlein & Goffeng, 2017)

Let  $X \subset \mathbb{R}^n$  be a compact, smooth domain, with  $n$  odd. Then

$$|tX| \sim \frac{1}{n!\omega_n} \sum_{j=0}^{\infty} c_j t^{n-j} \text{ as } t \rightarrow +\infty$$

where  $c_0$ ,  $c_1$  and  $c_2$  record the volume, surface area, and total mean curvature of  $X$ .

## Magnitude via weight distributions

Gimperlein, Goffeng & Louca show that when  $X \subset \mathbb{R}^n$  is a compact domain,  $\mathcal{Z}_X(t)$  is a pseudodifferential operator which extends to a certain space  $H$  of distributions on  $X$ .\*

\*Specifically, the Sobolev space  $\dot{H}^{-\frac{n+1}{2}}(X)$ .

## Magnitude via weight distributions

Gimperlein, Goffeng & Louca show that when  $X \subset \mathbb{R}^n$  is a compact domain,  $\mathcal{Z}_X(t)$  is a pseudodifferential operator which extends to a certain space  $H$  of distributions on  $X$ .\*

Proposition (Gimperlein, Goffeng & Louca, 2022, via Meckes, 2015)

Let  $X \subseteq \mathbb{R}^n$  be a compact domain. Then

$$|tX| = \langle u_t, 1 \rangle_X$$

where  $u_t \in H$  is the unique distributional solution to  $t\mathcal{Z}_X(t)(u_t) = 1$  on  $X$ .

\*Specifically, the Sobolev space  $\dot{H}^{-\frac{n+1}{2}}(X)$ .

## Magnitude via weight distributions

Gimperlein, Goffeng & Louca show that when  $X \subset \mathbb{R}^n$  is a compact domain,  $\mathcal{Z}_X(t)$  is a pseudodifferential operator which extends to a certain space  $H$  of distributions on  $X$ .\*

Proposition (Gimperlein, Goffeng & Louca, 2022, via Meckes, 2015)

Let  $X \subseteq \mathbb{R}^n$  be a compact domain. Then

$$|tX| = \langle u_t, 1 \rangle_X$$

where  $u_t \in H$  is the unique distributional solution to  $t\mathcal{Z}_X(t)(u_t) = 1$  on  $X$ .

They construct an approximate inverse to  $\mathcal{Z}_X(t)$  and thus can compute magnitude as

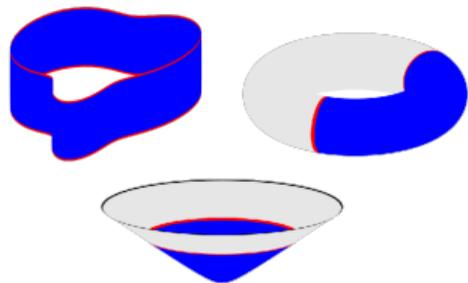
$$|tX| = \frac{1}{t} \langle \mathcal{Z}_X(t)^{-1}(1), 1 \rangle_X.$$

\*Specifically, the Sobolev space  $\dot{H}^{-\frac{n+1}{2}}(X)$ .

## Recent geometric results

### Theorem (Gimperlein & Goffeng, 2021)

For a smooth, compact domain  $X$  in odd dimensions, the asymptotics of  $|tX|$  determine the **Willmore energy** of the boundary  $\partial X$ .



### Theorems (Gimperlein, Goffeng & Louca, 2022)

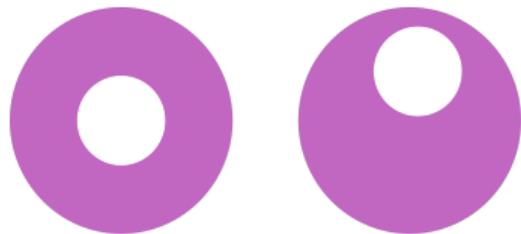
- For nice enough domains, magnitude satisfies an asymptotic **inclusion-exclusion principle**.
- You can 'magnitude the shape of a ball'!
- When  $n = 2$  or  $n$  is odd, magnitude **characterizes domains with constant mean curvature**.

...and lots more exciting stuff!

## Open questions

What is the geometric content of the magnitude function?

In general,  $|tX|$  does not determine  $X$  up to isometry. Meckes has showed that these two spaces have the same magnitude function  $\rightarrow$



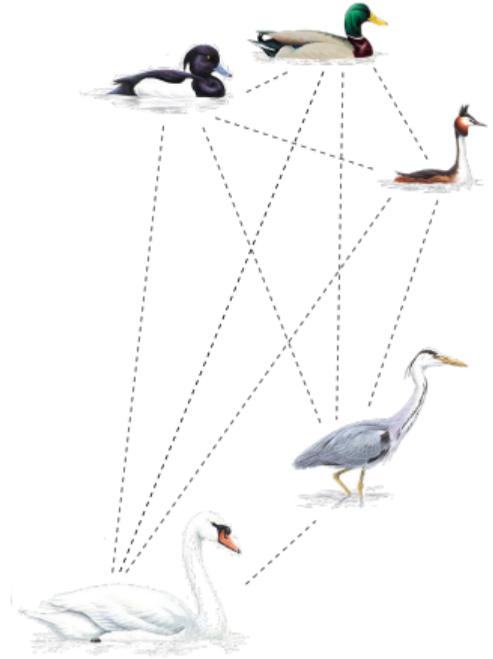
- If  $X$  and  $Y$  are such that  $|tX|$  and  $|tY|$  coincide, what can we say about them?
- Can you **magnitude the shape of convex drums**? Star-shaped drums?
- Can one **compute the magnitude function exactly** for interesting domains?
- The magnitude function extends to a meromorphic function on the complex plane. Do the **poles** of this function carry geometric information?
- What can be said about the **small- $t$  asymptotics** of  $|tX|$ ?

Part II

Diversity

# Ecological connections

Let  $X$  be a (finite) set of biological species and  $d$  a metric on  $X$  recording differences among species.

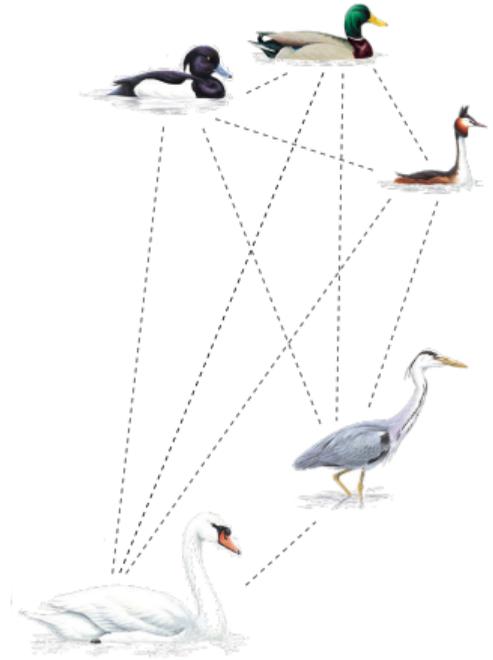
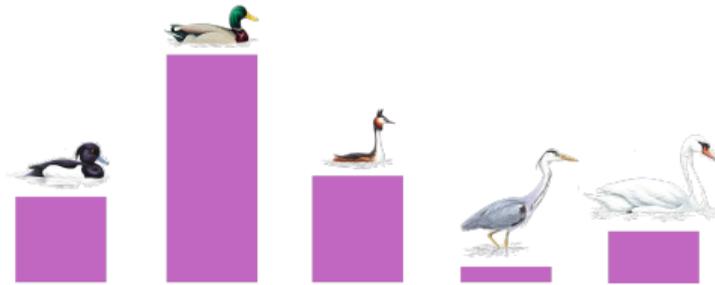


Bird illustrations from the RSPB.

# Ecological connections

Let  $X$  be a (finite) set of biological species and  $d$  a metric on  $X$  recording differences among species.

An **ecological community** comprising members of species in  $X$  can be modelled by a **probability distribution  $\mathbf{p}$**  on  $X$ , where  $\mathbf{p}(x)$  is the **relative abundance** of species  $x$  in the community.



Bird illustrations from the RSPB.

## Typicality and diversity

The matrix  $Z_X$  records the **similarity** between each pair of species in  $X$ . So

$$(Z_X \mathbf{p})(x) = \sum_{y \in X} e^{-d(x,y)} \mathbf{p}(y)$$

tells us the **expected similarity** between a member of species  $x$  and an individual chosen at random from  $\mathbf{p}$ . Call this the **typicality** of members of species  $x$  in  $\mathbf{p}$ .

## Typicality and diversity

The matrix  $Z_X$  records the **similarity** between each pair of species in  $X$ . So

$$(Z_X \mathbf{p})(x) = \sum_{y \in X} e^{-d(x,y)} \mathbf{p}(y)$$

tells us the **expected similarity** between a member of species  $x$  and an individual chosen at random from  $\mathbf{p}$ . Call this the **typicality** of members of species  $x$  in  $\mathbf{p}$ .

**Idea** A community in which the **average member** is highly **typical** is **homogenous**.

## Typicality and diversity

The matrix  $Z_X$  records the **similarity** between each pair of species in  $X$ . So

$$(Z_X \mathbf{p})(x) = \sum_{y \in X} e^{-d(x,y)} \mathbf{p}(y)$$

tells us the **expected similarity** between a member of species  $x$  and an individual chosen at random from  $\mathbf{p}$ . Call this the **typicality** of members of species  $x$  in  $\mathbf{p}$ .

**Idea** The **less homogenous** a community is, the **more diverse** we should consider it.

## Typicality and diversity

The matrix  $Z_X$  records the **similarity** between each pair of species in  $X$ . So

$$(Z_X \mathbf{p})(x) = \sum_{y \in X} e^{-d(x,y)} \mathbf{p}(y)$$

tells us the **expected similarity** between a member of species  $x$  and an individual chosen at random from  $\mathbf{p}$ . Call this the **typicality** of members of species  $x$  in  $\mathbf{p}$ .

**Idea** The **less homogenous** a community is, the **more diverse** we should consider it.

**Definition (temporary!)** The **diversity** of a probability distribution  $\mathbf{p}$  on  $X$  is

$$\frac{1}{\sum_{x \in X} (Z_X \mathbf{p})(x) \mathbf{p}(x)}.$$

The denominator is the **mean typicality** of members of the community modelled by  $\mathbf{p}$ .

## Maximizing diversity

**Question** How diverse is the most diverse community a given space  $X$  can support?

## Maximizing diversity

**Question** How diverse is the most diverse community a given space  $X$  can support?

Since

$$\frac{1}{\sum_{x \in X} (Z_X \mathbf{p})(x) \mathbf{p}(x)} = \frac{1}{\mathbf{p}^T Z_X \mathbf{p}}$$

we're looking for

$$\text{MaxDiv}(X) = \sup \frac{1}{\mathbf{p}^T Z_X \mathbf{p}}$$

where the sup is over probability distributions  $\mathbf{p}$ .

## Maximizing diversity

**Question** How diverse is the most diverse community a given space  $X$  can support?

Since

$$\frac{1}{\sum_{x \in X} (Z_X \mathbf{p})(x) \mathbf{p}(x)} = \frac{1}{\mathbf{p}^T Z_X \mathbf{p}}$$

we're looking for

$$\text{MaxDiv}(X) = \sup \frac{1}{\mathbf{p}^T Z_X \mathbf{p}}$$

where the sup is over probability distributions  $\mathbf{p}$ .

### Recall

For a positive definite space  $X$ ,

$$|X| = \sup \frac{(\sum_{x \in X} \mathbf{v}(x))^2}{\mathbf{v}^T Z_X \mathbf{v}}$$

where the sup is over  $\mathbf{v} \in \mathbb{R}^X$ .

## Maximizing diversity

**Question** How diverse is the **most diverse community** a given space  $X$  can support?

Since

$$\frac{1}{\sum_{x \in X} (Z_X \mathbf{p})(x) \mathbf{p}(x)} = \frac{1}{\mathbf{p}^T Z_X \mathbf{p}}$$

we're looking for

$$\text{MaxDiv}(X) = \sup \frac{(\sum_{x \in X} \mathbf{p}(x))^2}{\mathbf{p}^T Z_X \mathbf{p}}$$

where the sup is over probability distributions  $\mathbf{p}$ .

Recall

For a positive definite space  $X$ ,

$$|X| = \sup \frac{(\sum_{x \in X} \mathbf{v}(x))^2}{\mathbf{v}^T Z_X \mathbf{v}}$$

where the sup is over  $\mathbf{v} \in \mathbb{R}^X$ .

## Maximizing diversity

**Question** How diverse is the most diverse community a given space  $X$  can support?

Since

$$\frac{1}{\sum_{x \in X} (Z_X \mathbf{p})(x) \mathbf{p}(x)} = \frac{1}{\mathbf{p}^T Z_X \mathbf{p}}$$

we're looking for

$$\text{MaxDiv}(X) = \sup \frac{(\sum_{x \in X} \mathbf{p}(x))^2}{\mathbf{p}^T Z_X \mathbf{p}}$$

where the sup is over probability distributions  $\mathbf{p}$ .

### Recall

For a positive definite space  $X$ ,

$$|X| = \sup \frac{(\sum_{x \in X} \mathbf{v}(x))^2}{\mathbf{v}^T Z_X \mathbf{v}}$$

where the sup is over  $\mathbf{v} \in \mathbb{R}^X$ .

**Theorem** Let  $X$  be a finite positive definite space admitting a non-negative weight vector  $\mathbf{v}$ . Then  $\mathbf{p} = \mathbf{v}/|X|$  maximizes diversity on  $X$ , and  $\text{MaxDiv}(X) = |X|$ .

## An uncountable family of diversity indices

Leinster & Cobbold observe that the **weighted arithmetic mean** of atypicality is not the only way to quantify diversity. We should consider **weighted power means** of all orders! Their approach **unifies** many diversity indices used in practice by ecologists.

## An uncountable family of diversity indices

Leinster & Cobbold observe that the **weighted arithmetic mean** of atypicality is not the only way to quantify diversity. We should consider **weighted power means** of all orders! Their approach **unifies** many diversity indices used in practice by ecologists.

**Definition** (Leinster & Roff, 2019, following Leinster & Cobbold, 2012)

Let  $X$  be a compact metric space and  $\mu$  a probability measure on  $X$ . For  $q \in [0, \infty)$  not equal to 1, the **diversity of order  $q$**  of  $\mu$  is

$$D_q(\mu) = \left( \int \left( \int e^{-d(x,y)} d\mu(x) \right)^{q-1} d\mu(y) \right)^{1/(1-q)}.$$

At  $q = 1, \infty$  this expression takes its limiting values.

## An uncountable family of diversity indices

Leinster & Cobbold observe that the **weighted arithmetic mean** of atypicality is not the only way to quantify diversity. We should consider **weighted power means** of all orders! Their approach **unifies** many diversity indices used in practice by ecologists.

**Definition** (Leinster & Roff, 2019, following Leinster & Cobbold, 2012)

Let  $X$  be a compact metric space and  $\mu$  a probability measure on  $X$ . For  $q \in [0, \infty)$  not equal to 1, the **diversity of order  $q$**  of  $\mu$  is

$$D_q(\mu) = \left( \int \left( \int e^{-d(x,y)} d\mu(x) \right)^{q-1} d\mu(y) \right)^{1/(1-q)}.$$

At  $q = 1, \infty$  this expression takes its limiting values.

**Examples**  $D_2(\mu)$  is  $1/(\text{the expected proximity of a } \mu\text{-random pair of points})$ .

## An uncountable family of diversity indices

Leinster & Cobbold observe that the **weighted arithmetic mean** of atypicality is not the only way to quantify diversity. We should consider **weighted power means** of all orders! Their approach **unifies** many diversity indices used in practice by ecologists.

**Definition** (Leinster & Roff, 2019, following Leinster & Cobbold, 2012)

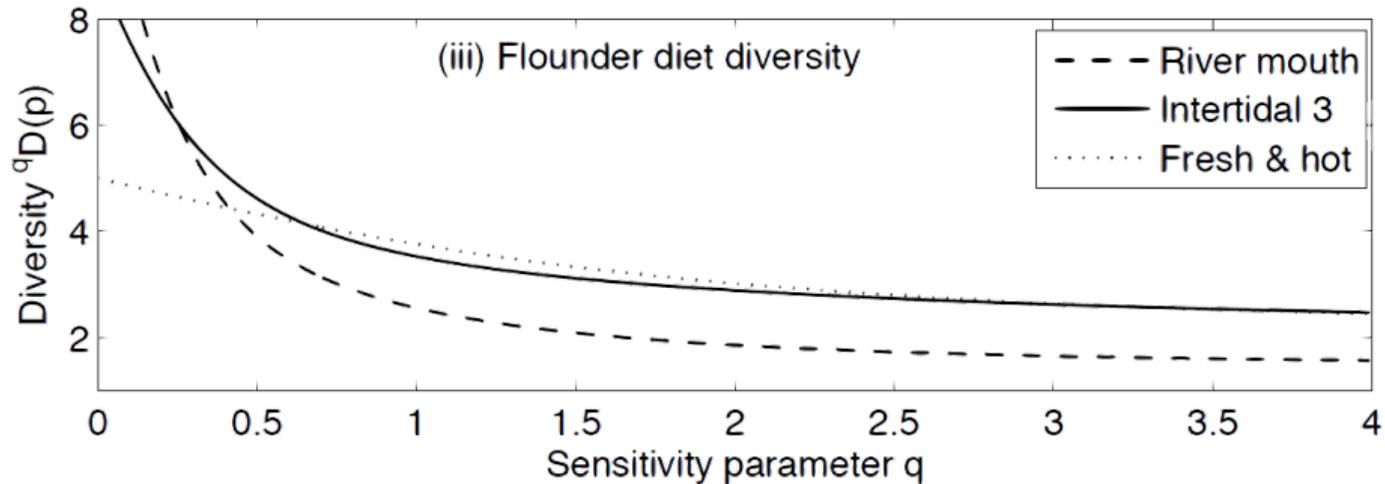
Let  $X$  be a compact metric space and  $\mu$  a probability measure on  $X$ . For  $q \in [0, \infty)$  not equal to 1, the **diversity of order  $q$**  of  $\mu$  is

$$D_q(\mu) = \left( \int \left( \int e^{-d(x,y)} d\mu(x) \right)^{q-1} d\mu(y) \right)^{1/(1-q)}.$$

At  $q = 1, \infty$  this expression takes its limiting values.

**Examples**  $D_\infty(\mu)$  is  $1/(\text{the ess.sup. of the 'typicality function' of } \mu \text{ on } X)$ .

## The parameter $q$ matters!



Leinster & Cobbold, *Measuring Diversity...*, Ecology 93 (2012)

## A maximization theorem

Theorem (Leinster & Roff, 2019)

Let  $X$  be a non-empty compact metric space.

1. There exists a probability measure  $\mu$  on  $X$  that maximizes  $D_q$  for all  $q$  at once.
2. The **maximum diversity**  $D_{\max}(X) = \sup_{\mu} D_q(\mu)$  is independent of  $q \in [0, \infty]$ .

## A maximization theorem

### Theorem (Leinster & Roff, 2019)

Let  $X$  be a non-empty compact metric space.

1. There exists a probability measure  $\mu$  on  $X$  that maximizes  $D_q$  for all  $q$  at once.
2. The **maximum diversity**  $D_{\max}(X) = \sup_{\mu} D_q(\mu)$  is independent of  $q \in [0, \infty]$ .

### Theorem (Leinster & Roff, 2019)

Let  $X$  be a non-empty positive definite compact metric space admitting a positive weight measure  $\mu$ . Then  $D_{\max}(X) = |X|$ .

These results extend those proved for finite spaces by Leinster & Meckes in 2015.

## Open questions

What do diversity-maximizing measures look like?

What do weight distributions look like?

Even in the finite setting, **diversity-maximizing measures** are typically **not uniform**.

Weight measures and diversity-maximizing measures on finite spaces have been used in **boundary-detection** algorithms (e.g. **Bunch *et al*, 2021**).

But in the compact setting, even on very familiar spaces, we know little about them!

Part III

Homology

## Combinatorial connections

Let  $(A, \leq)$  be a finite poset.

The **incidence algebra**  $\mathbb{I}(A)$  is the algebra of functions  $A \times A \xrightarrow{f} \mathbb{Q}$  satisfying  $f(a, b) = 0$  unless  $a \leq b$ . Multiplication in  $\mathbb{I}(A)$  is by convolution.

## Combinatorial connections

Let  $(A, \leq)$  be a finite poset.

The **incidence algebra**  $\mathbb{I}(A)$  is the algebra of functions  $A \times A \xrightarrow{f} \mathbb{Q}$  satisfying  $f(a, b) = 0$  unless  $a \leq b$ . Multiplication in  $\mathbb{I}(A)$  is by convolution.

The **zeta function** of  $A$  is  $\zeta \in \mathbb{I}(A)$  defined by

$$\zeta(a, b) = \begin{cases} 1 & a \leq b \\ 0 & \text{otherwise.} \end{cases}$$

If  $\zeta$  is invertible,  $\zeta^{-1}$  is the **Möbius function** of  $A$ .

## Combinatorial connections

Let  $(A, \leq)$  be a finite poset.

The **incidence algebra**  $\mathbb{I}(A)$  is the algebra of functions  $A \times A \xrightarrow{f} \mathbb{Q}$  satisfying  $f(a, b) = 0$  unless  $a \leq b$ . Multiplication in  $\mathbb{I}(A)$  is by convolution.

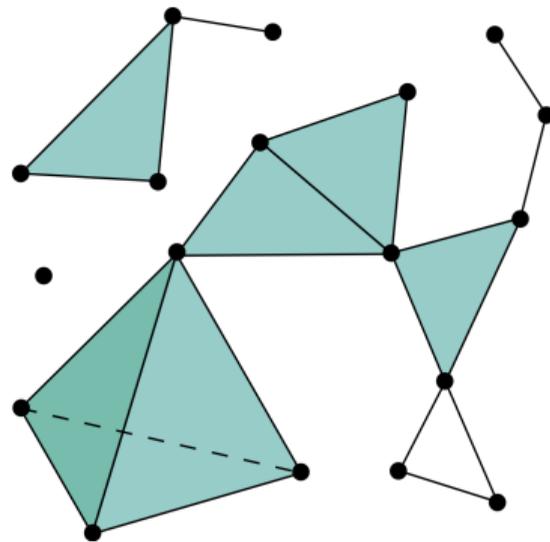
The **zeta function** of  $A$  is  $\zeta \in \mathbb{I}(A)$  defined by

$$\zeta(a, b) = \begin{cases} 1 & a \leq b \\ 0 & \text{otherwise.} \end{cases}$$

If  $\zeta$  is invertible,  $\zeta^{-1}$  is the **Möbius function** of  $A$ .

**Theorem** Let  $A$  be the poset of simplices in a finite simplicial complex  $S$ . Then

$$\sum_{a, b \in A} \zeta^{-1}(a, b) = \chi(S).$$



Graphic from Wikipedia.

## The Euler characteristic of a category

More generally, let  $\mathbf{C}$  be a finite category. Write  $\text{ob}(\mathbf{C})$  for its set of objects.

The **zeta matrix** of  $\mathbf{C}$  is the  $\text{ob}(\mathbf{C}) \times \text{ob}(\mathbf{C})$  matrix  $Z_{\mathbf{C}}$  defined by

$$Z_{\mathbf{C}}(a, b) = \#\{\text{arrows } a \rightarrow b \text{ in } \mathbf{C}\}.$$

If  $Z_{\mathbf{C}}$  is invertible over  $\mathbb{Q}$ , call  $Z_{\mathbf{C}}^{-1}$  the **Möbius matrix** of  $\mathbf{C}$ .

# The Euler characteristic of a category

More generally, let  $\mathbf{C}$  be a finite category. Write  $\text{ob}(\mathbf{C})$  for its set of objects.

The **zeta matrix** of  $\mathbf{C}$  is the  $\text{ob}(\mathbf{C}) \times \text{ob}(\mathbf{C})$  matrix  $Z_{\mathbf{C}}$  defined by

$$Z_{\mathbf{C}}(a, b) = \#\{\text{arrows } a \rightarrow b \text{ in } \mathbf{C}\}.$$

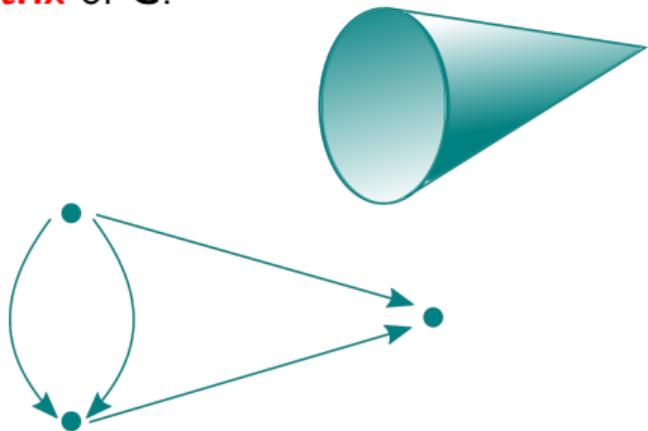
If  $Z_{\mathbf{C}}$  is invertible over  $\mathbb{Q}$ , call  $Z_{\mathbf{C}}^{-1}$  the **Möbius matrix** of  $\mathbf{C}$ .

**Theorem (Leinster, 2006)**

If  $Z_{\mathbf{C}}$  is invertible, then

$$\sum_{a, b \in \text{ob}(\mathbf{C})} Z^{-1}(a, b) = \chi(\mathbb{B}\mathbf{C})$$

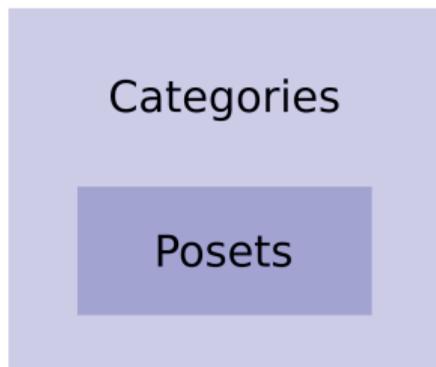
where  $\mathbb{B}\mathbf{C}$  is the **classifying space** of  $\mathbf{C}$ .



## A common generalization

Posets

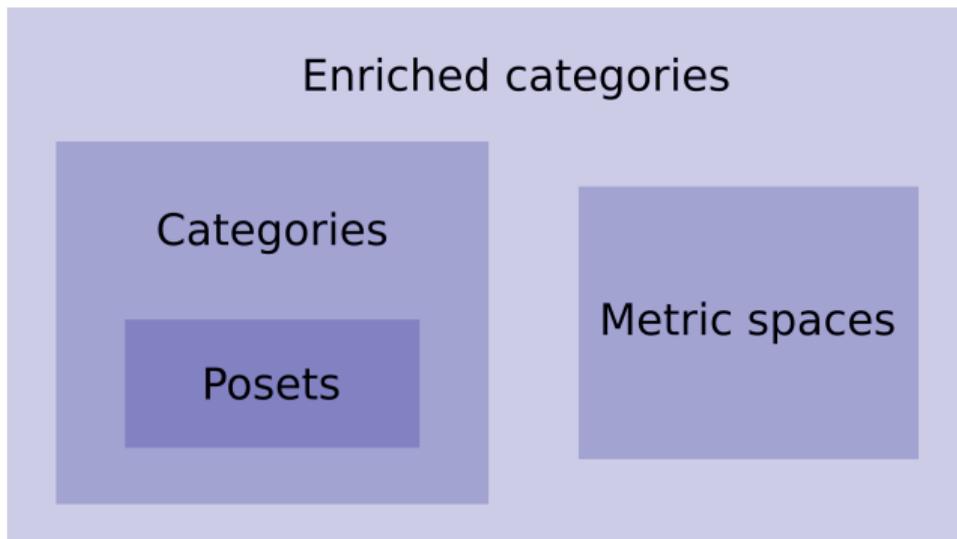
## A common generalization



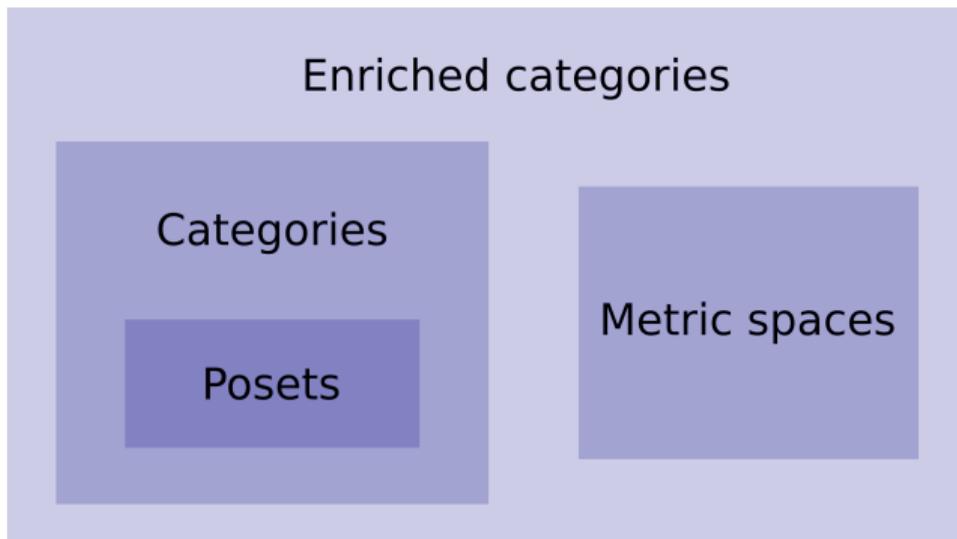
## A common generalization



## A common generalization

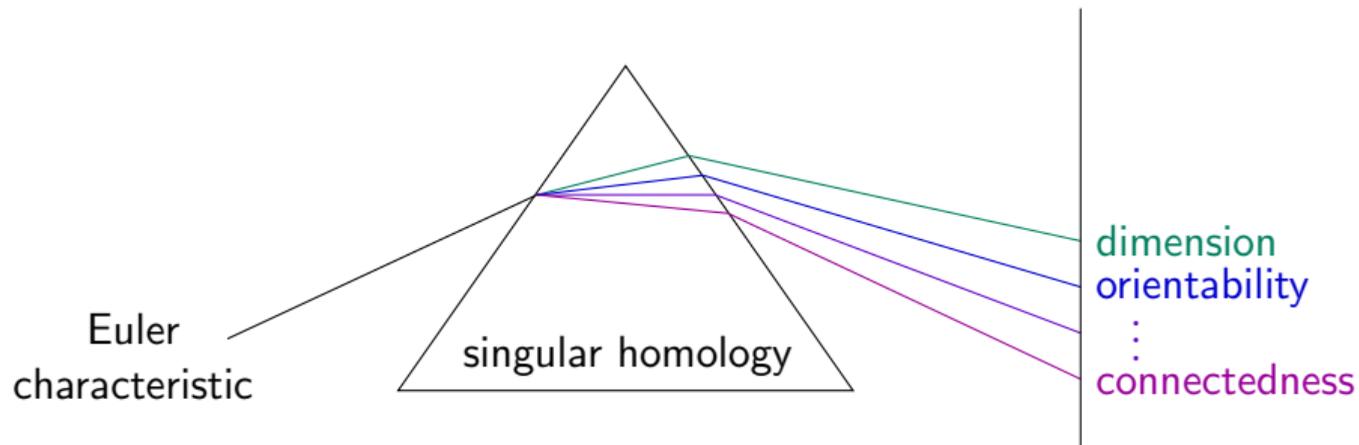


## A common generalization

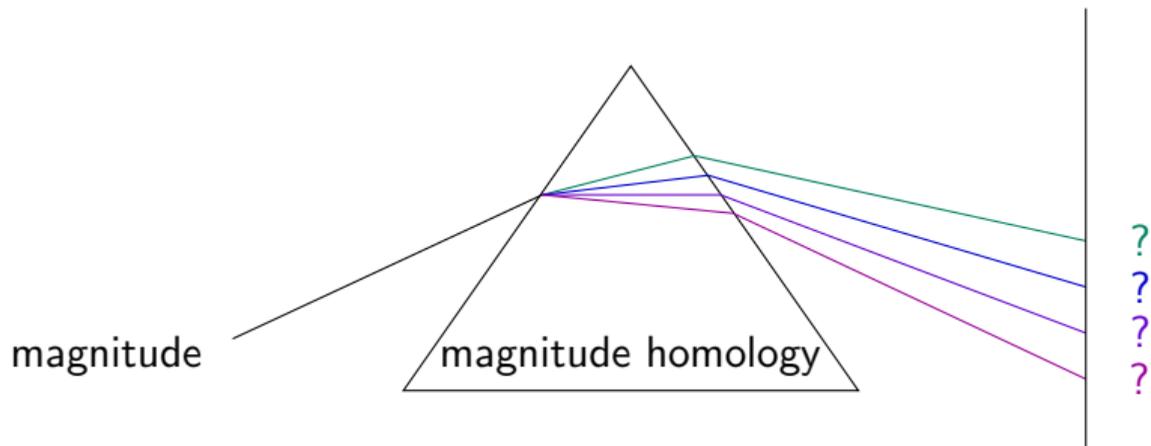


You can define **magnitude** for enriched categories. It specializes to **Euler characteristic** for ordinary categories and to **the magnitude function** for finite metric spaces.

# Categorifying magnitude



# Categorifying magnitude



## Novikov series

Let  $\mathbb{Z}[q^{\mathbb{R}_+}] = \{a_0 q^{\ell_0} + \cdots + a_n q^{\ell_n} \mid a_i \in \mathbb{Z}, \ell_i \in [0, \infty)\}$ . This ring carries a valuation—

$v(p)$  = the minimal exponent with non-zero coefficient in  $p$

—and thus a metric:  $d(p, r) = e^{-v(p-r)}$ . It's also an integral domain.

## Novikov series

Let  $\mathbb{Z}[q^{\mathbb{R}_+}] = \{a_0 q^{\ell_0} + \dots + a_n q^{\ell_n} \mid a_i \in \mathbb{Z}, \ell_i \in [0, \infty)\}$ . This ring carries a valuation—

$v(p)$  = the minimal exponent with non-zero coefficient in  $p$

—and thus a metric:  $d(p, r) = e^{-v(p-r)}$ . It's also an integral domain.

Cauchy completing and taking the field of fractions yields a square

$$\begin{array}{ccc} \mathbb{Z}[q^{\mathbb{R}_+}] & \xleftarrow{c_1} & \mathbb{Z}[[q^{\mathbb{R}_+}]] \\ f_1 \downarrow & & \downarrow f_2 \\ \mathbb{Q}(q^{\mathbb{R}}) & \xleftarrow{c_2} & \mathbb{Q}((q^{\mathbb{R}})) \end{array}$$

The field  $\mathbb{Q}((q^{\mathbb{R}}))$  is the field of **Novikov series**: generalized formal Laurent series.

## Formal magnitude for finite spaces

Let  $X$  be a finite metric space. Its **formal similarity matrix** is defined by

$$Z(x, y) = q^{d(x, y)}.$$

**Lemma** Every formal similarity matrix is invertible over  $\mathbb{Q}((q^{\mathbb{R}}))$ .

**Proof.**

All diagonal entries in  $Z$  are 1 and off-diagonal entries are  $q^\ell$  for some  $\ell > 0$ . So  $\det(Z)$  is a generalized polynomial with constant term 1 and thus a unit in  $\mathbb{Z}[[q^{\mathbb{R}}]]$ .  $\square$

## Formal magnitude for finite spaces

Let  $X$  be a finite metric space. Its **formal similarity matrix** is defined by

$$Z(x, y) = q^{d(x, y)}.$$

**Lemma** Every formal similarity matrix is invertible over  $\mathbb{Q}((q^{\mathbb{R}}))$ .

**Proof.**

All diagonal entries in  $Z$  are 1 and off-diagonal entries are  $q^\ell$  for some  $\ell > 0$ . So  $\det(Z)$  is a generalized polynomial with constant term 1 and thus a unit in  $\mathbb{Z}[[q^{\mathbb{R}}]]$ .  $\square$

The **formal magnitude** of  $X$  is the Novikov series  $\text{Mag}(X) = \sum_{x, y \in X} Z^{-1}(x, y)$ .

**Theorem**

For every finite metric space  $X$  and all  $t \in [0, \infty)$  we have  $|tX| = \text{Mag}(X)|_{q=e^{-t}}$ .  $\square$

## A combinatorial formula for the coefficients

Theorem (Leinster, 2014\*)

Let  $X$  be a finite metric space. Then  $\text{Mag}(X) = \sum_{\ell \in [0, \infty)} a_\ell q^\ell$  where

$$a_\ell = \sum_{k=0}^{\infty} (-1)^k \#\{(x_0, \dots, x_k) \mid x_i \in X, x_i \neq x_{i+1} \text{ and } d(x_0, x_1) + \dots + d(x_{k-1}, x_k) = \ell\}.$$

\* In fact it's proved here for graphs, but the statement holds for general finite metric spaces.

## A combinatorial formula for the coefficients

Theorem (Leinster, 2014\*)

Let  $X$  be a finite metric space. Then  $\text{Mag}(X) = \sum_{\ell \in [0, \infty)} a_\ell q^\ell$  where

$$a_\ell = \sum_{k=0}^{\infty} (-1)^k \#\{(x_0, \dots, x_k) \mid x_i \in X, x_i \neq x_{i+1} \text{ and } d(x_0, x_1) + \dots + d(x_{k-1}, x_k) = \ell\}.$$

Idea (Hepworth & Willerton, 2015)

Each coefficient in  $\text{Mag}(X)$  is the Euler characteristic of a chain complex.

\* In fact it's proved here for graphs, but the statement holds for general finite metric spaces.

# Magnitude homology

Definition (Leinster & Shulman, 2017, following Hepworth & Willerton, 2015)

The **magnitude chain complex** of a metric space  $X$  is a real-graded chain complex of vector spaces. In grading  $\ell \in [0, \infty)$  and degree  $k \in \mathbb{N}$  it's given by

$$MC_k^\ell(X) = \mathbb{Z} \cdot \{(x_0, \dots, x_k) \mid x_i \neq x_{i+1} \text{ and } d(x_0, x_1) + \dots + d(x_{k-1}, x_k) = \ell\}.$$

The **magnitude homology** of  $X$  is defined by  $MH_k^\ell(X) = H_k(MC_\bullet^\ell(X))$ .

# Magnitude homology

Definition (Leinster & Shulman, 2017, following Hepworth & Willerton, 2015)

The **magnitude chain complex** of a metric space  $X$  is a real-graded chain complex of vector spaces. In grading  $\ell \in [0, \infty)$  and degree  $k \in \mathbb{N}$  it's given by

$$MC_k^\ell(X) = \mathbb{Z} \cdot \{(x_0, \dots, x_k) \mid x_i \neq x_{i+1} \text{ and } d(x_0, x_1) + \dots + d(x_{k-1}, x_k) = \ell\}.$$

The **magnitude homology** of  $X$  is defined by  $MH_k^\ell(X) = H_k(MC_\bullet^\ell(X))$ .

Theorem (Leinster & Shulman, 2017)

For finite metric spaces, magnitude homology recovers formal magnitude:

$$\chi(MH_\bullet^*(X)) := \sum_{i \geq 0} (-1)^i \text{rk}(MH_i^*(X)) = \text{Mag}(X).$$

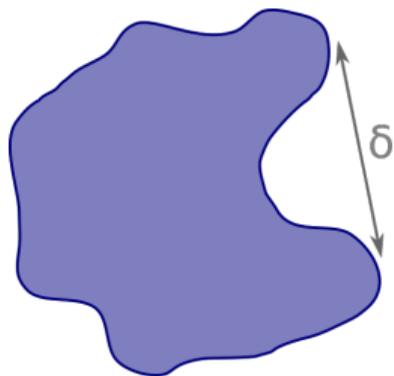
## Geometric content of magnitude homology

Applied to metric spaces,  $MH_{\bullet}^*$  carries **geometric**, rather than **topological** information.

## Geometric content of magnitude homology

Applied to metric spaces,  $MH_{\bullet}^*$  carries **geometric, rather than topological** information.

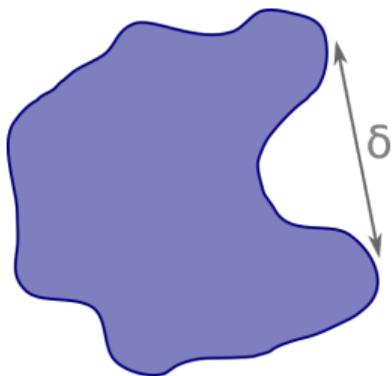
**Theorem (Leinster & Shulman, 2017)** Let  $X$  be a closed subset of Euclidean space. Then  $MH_1^*(X)$  vanishes if and only if  $X$  is **convex**.



## Geometric content of magnitude homology

Applied to metric spaces,  $MH_{\bullet}^*$  carries **geometric**, rather than **topological** information.

**Theorem (Leinster & Shulman, 2017)** Let  $X$  be a closed subset of Euclidean space. Then  $MH_1^*(X)$  vanishes if and only if  $X$  is **convex**.



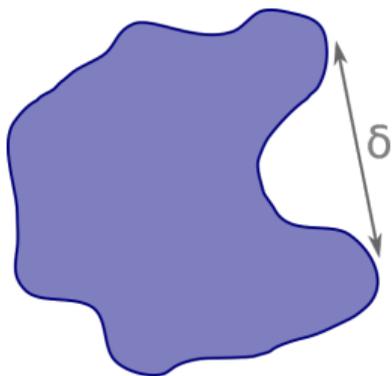
**Theorem (Kaneta & Yoshinaga, 2018)**

Let  $X$  be a closed subset of Euclidean space which is *not* convex. Then  $MH_1^*(X)$  records the 'diameter' of the **largest 'dent'** in  $X$ .

## Geometric content of magnitude homology

Applied to metric spaces,  $MH_{\bullet}^*$  carries **geometric, rather than topological** information.

**Theorem (Leinster & Shulman, 2017)** Let  $X$  be a closed subset of Euclidean space. Then  $MH_1^*(X)$  vanishes if and only if  $X$  is **convex**.



**Theorem (Kaneta & Yoshinaga, 2018)**

Let  $X$  be a closed subset of Euclidean space which is *not* convex. Then  $MH_1^*(X)$  records the 'diameter' of the **largest 'dent'** in  $X$ .

**Theorem (Asao, 2022)**

The magnitude homology of a **graph** is closely related to its **path homology**.

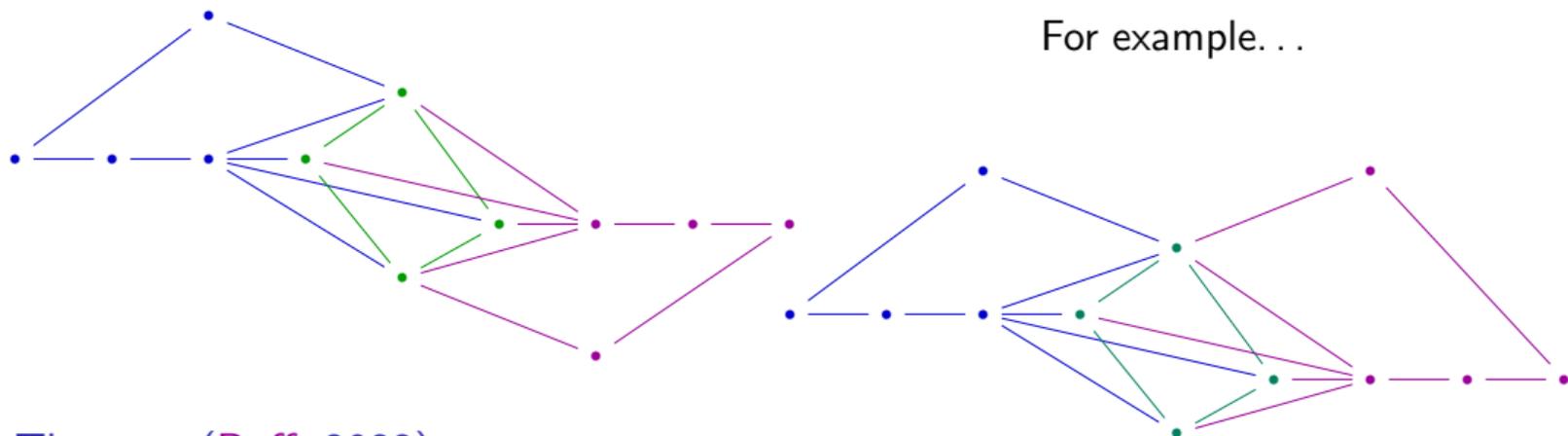
## Magnitude via magnitude homology

We are beginning to prove **new results about magnitude** using magnitude homology.

For example. . .

## Magnitude via magnitude homology

We are beginning to prove **new results about magnitude** using magnitude homology.



Theorem (Roff, 2022)

Let  $X$  and  $Y$  be graphs which differ by a **sycamore twist**. Then  $\text{Mag}(X) = \text{Mag}(Y)$ .

**The Proof** is homological—related to, but independent from, an excision theorem.

## Open question

Can we categorify the magnitude function for compact metric spaces?

The magnitude homology of a compact space does not recover its magnitude function.

Problem is: we don't know how to extend **formal magnitude** to compact spaces.

## Open question

Can we categorify the magnitude function for compact metric spaces?

The magnitude homology of a compact space does not recover its magnitude function.

Problem is: we don't know how to extend **formal magnitude** to compact spaces.

Things that don't work:

- **Taking suprema:**  $\mathbb{Q}((q^{\mathbb{R}}))$  is an ordered field, but not Dedekind complete!
- **Taking limits:**  $\text{Mag}(-)$  is not continuous with respect to the valuation metric!

## Open question

Can we categorify the magnitude function for compact metric spaces?

The magnitude homology of a compact space does not recover its magnitude function.

Problem is: we don't know how to extend **formal magnitude** to compact spaces.

Things that might work:

- Treat  $\mathbb{Q}((q^{\mathbb{R}}))$  as a space of **distributions** (**Hepworth**).
- Treat  $\mathbb{Q}((q^{\mathbb{R}}))$  as the **stalk at zero** of a certain sheaf of functions (**me**).
- Mimic Meckes's '**weighting space**' approach over  $\mathbb{Q}((q^{\mathbb{R}}))$  (**me**).

# Summary

- What is the **geometric content** of the magnitude function?
  - If  $X$  and  $Y$  are such that  $|tX| \sim |tY|$ , what can we say about them?
  - Can you magnitude the shape of a convex drum?
  - Do the poles of the magnitude function carry interesting information?
  - What can be said about the small- $t$  asymptotics of  $|tX|$ ?
- What do **diversity-maximizing measures** and **weight distributions** look like?
- How should the **formal magnitude** of a compact space be defined?

Thank you.

## References

- **Asao**. Magnitude homology and path homology. arXiv:2201.08047, 2022; *Bulletin of the LMS* (to appear).
- **Barceló and Carbery**. On the magnitudes of compact sets in Euclidean spaces. arXiv:1507.02502, 2015; *American Journal of Mathematics* 140, 2018.
- **Bunch et al.** Weighting vectors for machine learning: numerical harmonic analysis applied to boundary detection. arXiv:2106.00827, 2021.
- **Gimperlein and Goffeng**. On the magnitude function of domains in Euclidean space. arXiv:1706.06839, 2017; *American Journal of Mathematics* 143, 2021.
- **Gimperlein and Goffeng**. The Willmore energy and the magnitude of Euclidean domains. arXiv:2109.10097, 2021; to appear in *Proceedings of the AMS*.
- **Gimperlein, Goffeng and Louca**. The magnitude and spectral geometry. arXiv:2201.11363, 2022.

## References

- **Hepworth and Willerton.** Categorifying the magnitude of a graph. arXiv:1505.04125, 2015; *Homology, Homotopy and Applications* 19, 2017.
- **Kaneta and Yoshinaga.** Magnitude homology of metric spaces and order complexes. arXiv:1803.04247, 2018; *Bulletin of the LMS* 53(3), 2021.
- **Leinster.** The Euler characteristic of a category. arXiv:math.CT/0610260, 2006; *Documenta Mathematica* 13, 2008.
- **Leinster.** The magnitude of metric spaces. arXiv:1012.5857, 2010; *Documenta Mathematica* 18, 2013.
- **Leinster.** The magnitude of a graph. arXiv:1401.4623, 2014; *Mathematical Proceedings of the Cambridge Philosophical Society* 166, 2019.
- **Leinster and Cobbold** Measuring diversity: the importance of species similarity. *Ecology* 93, 2012.

## References

- **Leinster and Meckes** Maximizing diversity in biology and beyond. arXiv:1512.06314, 2015; *Entropy* 18, 2016.
- **Leinster and Meckes** The magnitude of a metric space: from category theory to geometric measure theory. arXiv:1606.00095, 2016; in Nicola Gigli (ed.), *Measure Theory in Non-Smooth Spaces*, de Gruyter Open, 2017.
- **Leinster and Roff**. The maximum entropy of a metric space. arXiv:1908.11184, 2019; *The Quarterly Journal of Mathematics* 72(4), 2021.
- **Leinster and Shulman**. Magnitude homology of enriched categories and metric spaces. arXiv:1711.00802, 2017; *Algebraic and Geometric Topology* 21 (2021).
- **Meckes**. Positive definite metric spaces. arXiv:1012.5863, 2010; *Positivity* 17, 2013.

## References

- **Meckes**. Magnitude, diversity, capacities, and dimensions of metric spaces. arXiv:1308.5407, 2013; *Potential Analysis* 42, 2015.
- **Roff**. Magnitude, homology, and the Whitney twist. arXiv:2211.02520, 2022.
- **Willerton**. On the magnitude of spheres, surfaces and other homogeneous spaces. arXiv:1005.4041, 2010; *Geometriae Dedicata* 168, 2014.
- **Willerton**. Spread: a measure of the size of metric spaces. arXiv:1209.2300, 2012; *International Journal of Computational Geometry and Applications* 25, 2015.