## The mathematics of diversity

#### Tom Leinster



School of Mathematics University of Edinburgh



Boyd Orr Centre for Population and Ecosystem Health University of Glasgow

#### Main reference



#### Plan



Just the left-hand half today. (Right-hand half here.)

#### Recurrent question

# What is the { unique universal canonical } such-and-such?

What is the best/canonical way to measure diversity?

Basic challenge:





- Take a community divided into species.
- Crudest diversity measure: the number of species present.
- But this is often misleading.
- Example There are 8 species of great ape on the planet...
- ... but 99.99% of ape individuals are from a single species.

## Ecologists have proposed and used many, many diversity measures...

Whittaker's index of association Percentage difference (alias Bray-Curtis) Wishart coefficient = (1-similarity ratio) D = (1 - Kulczynski)coefficient) Abundance-based Jaccard Abundance-based Sørensen Abundance-based Ochiai

Species richness  $x \equiv \sum_{i=1}^{5} p_i^0$ Shannon entropy  $x \equiv -\sum_{i=1}^{n} p_i \ln p_i$ Simpson concentration  $x \equiv \sum_{i=1}^{S} p_i^2$ Gini–Simpson index  $x \equiv 1 - \sum_{i=1}^{n} p_i^2$ HCDT entropy  $\mathbf{x} \equiv \left(1 - \sum_{i=1}^{s} p_i^q\right) / (q-1)$ Renyi entropy  $x \equiv \left(-\ln \sum_{i=1}^{s} p_i^q\right)/(q-1)$ 

## Ecologists have proposed and used many, many diversity measures...

	Whittaker	's index		<sup>1</sup> E	Sheldon 1969, Buzas McCarthy 2002, Ca	and Gibson 1969, Buzas and H margo 2008
	of assoc	iation		<sup>2</sup> E	Weiher and Keddy 199 2003, Ma 2005, Ma	99, Wilsey and Potvin 2000, Mc irtin et al. 2005, Bock et al. 200
$^{q}D_{\gamma i}$	1 / p <sub>ava</sub>	$\gamma_j = {}^q \lambda_{\gamma j}^{1/(1-q)}$	gamma	D	Camargo 2008 Alatalo 1981 Taillie 1	979 Patil and Taillie 1982 Ricc
	$n = \sqrt{\frac{N-S}{N-S}}$ $n = 1$		unit j (	D <sub>q/0</sub>	Rotenberry 1978 Alat	alo 1981 Ricotta and Avena 20
$\bar{p}_{(ij)}$ all	$\bigvee_{j=1}^{\Sigma} \sum_{i=1}^{\Sigma} \rho_{ij} \rho_{ij}^{ij}$		mean p	$l'_{11}$ or $l'_{12}$ or $1l'$	Sheldon 1969. Tramer	1969, Kricher 1972, DeBenedic
~	$g\bar{D} = \bar{g}$	1/ō "	means	/ 1/max / 1/0 /	Wills et al. 1997, Re	ex et al. 2000, Wilsey and Potvi
<u></u>	$D_{ij} = I_j$	• 7 P (ij)an	mean v		Miranda et al. 2002,	Woodd-Walker et al. 2002, Ols
			weight		et al. 2005, Kimbro	and Grosholz 2006, Wilsey and
$\alpha_{\rm d}$	$^{q}D_{x}$	α,/CU	true al <sub>l</sub>		Anticamara et al. 20	010, Castro et al. 2010, Kardol (
			sampii (measu	$H_{1-0}$	Hill 1975, Kicotta 200	1072 Deleve 1075 Smith and
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β <sub>Md</sub>	${}^{q}D_{\beta} = {}^{q}D_{\gamma}/{}^{q}D_{\alpha}$	$\gamma/\alpha_d$	true be	* TOFFIE	Vellend 2005 Ulric	h and Zalewski 2007 Jarvis et
			(measu	* <sup>2</sup> H'	Walker and Cyr 2007	
β <sub>Mt</sub>	${}^{q}D_{\gamma(\bar{\gamma})} = {}^{q}D_{\gamma}/{}^{q}\bar{D}_{\gamma}$	$\gamma/\alpha_t$	regiona	$*^{2}D \text{ or }^{1}D$	Gardezi and Gonzales	2008, Anticamara et al. 2010
$\beta_R$	${}^{q}D_{\gamma} {}^{q}D_{\omega}{}^{\prime q}D_{\gamma \omega'}$	$\gamma/\alpha_R$	two-wa	* 0	Mouillot and Wilson 2	002, Stevens and Willig 2002
$\beta_{At}$	${}^{q}D_{\gamma} - {}^{q}\tilde{D}_{\gamma}$	$\gamma-\alpha_t$	regiona (measu	*E' or Gini coefficient	Camargo 1992a, 1993 2002 Mouillot and	, Drobner et al. 1998, Mouillot Wilson 2002, Stevens and Will
$\beta_{Mt-1}$	$\gamma/\alpha_t = 1$	$(\gamma - \alpha_t)/\alpha_t$	Whitta		Ghersa 2011	
			multip	* E <sub>var</sub>	Drobner et al. 1998, V	Veiher and Keddy 1999, Mouill
			(measu		Symonds and Johns	on 2008, Bernhardt-Römerman
β <sub>Pt</sub>	$1 - \alpha_t / \gamma$	$(\gamma - \alpha_t)/\gamma$	propor as a pr	* NHC	Weiher and Keddy 19	99
H'a	H' - H'	$\log^{(1)}(B_{1,r,s}) = \log(r) - \log(r_{s})$	heta St	* E <sub>Q</sub>	Drobner et al. 1998, N	Aouillot and Wilson 2002, Ma 2
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$2\bar{\lambda}_{\gamma\gamma-\gamma}$	$2 \overline{\lambda}_{\gamma} - 2 \lambda_{\gamma}$	$(\gamma - \alpha_t)/\gamma \alpha_t$	regiona	I variance excess (measuremer	nt unit: sp <sub>E</sub> /sp <sub>E</sub> )	

#### A very simple model of an ecological community

Take a community whose organisms are divided into *n* species.

Let  $p_i$  be the relative abundance of the *i*th species. So  $p_1 + \cdots + p_n = 1$ . Write  $p = (p_1, \dots, p_n)$ .

Mathematically: a community is a probability distribution on a finite set.

#### A spectrum of viewpoints

Species are what matter

Rare species count for as much as common ones —every species is precious *Communities* are what matter

Common species are the really important ones —they shape the community



 $\leftarrow$  This

is less diverse than

 $\leftarrow$  that

This  $\longrightarrow$ 

is more diverse than

that  $\longrightarrow$ 



#### A spectrum of viewpoints



#### How to acknowledge the spectrum of viewpoints

In 1973, the ecologist Mark Hill defined a family of diversity measures acknowledging the spectrum of viewpoints.

Let  $0 \le q \le \infty$ . The diversity or Hill number of order q of the community is

$$D_q(\mathbf{p}) = \left(\sum_i p_i^q\right)^{1/(1-q)}$$

(taking limits to get the definitions for  $q=1,\infty$ ).

The parameter q controls the relative emphasis placed on rare and common species—in other words, where on the spectrum you are.

Examples

- $D_0(\mathbf{p}) =$  number of species present.
- $D_q(1/n, \ldots, 1/n) = n$ : 'there are *n* species in perfect balance'.

#### The role of q

In the definition of diversity  $D_q(\mathbf{p})$ , there is a parameter q. What does it do?

Example Take p to be the frequencies of the eight species of great ape on the planet.

Or take  $\boldsymbol{p}$  to be the 50-50 distribution of chimpanzees and bonobos only.



Moral: You can't always say whether one distribution has higher diversity than another.

The answer may depend on q.

#### Digression: entropy

#### entropy = log(diversity)

The logarithm of the Hill number  $D_q$  is the Rényi entropy of order q:

$$H_q(\boldsymbol{p}) = \log D_q(\boldsymbol{p}).$$

- When q = 1, this is the Shannon entropy.
- For diversity, there are good reasons to use the exponential form.
- For information theory, there are good reasons to use the logarithmic form.

#### Unique characterization of the Hill numbers

Any measure of diversity should behave in a logical way that reflects biological etc. intuition.

E.g. Consider a group of islands with disjoint species.



Increasing the diversity of one island should increase the diversity of the whole.

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Theorem The only diversity measures satisfying seven sensible properties are the Hill numbers  $D_q$  ( $0 \le q \le \infty$ ).

#### A major shortcoming

Intuitively, diversity should reflect how *different* the species (etc.) are, not just their frequencies.

'Biological diversity' means the variability among living organisms

—UN Environment Programme definition (quoted in Magurran, *Measuring Biological Diversity*, p.6).

... associated with the idea of diversity is the concept of '*distance*', i.e. some measure of the dissimilarity of the resources in question

-OECD Handbook of Biodiversity Valuation: A Guide for Policy Makers.

#### A slightly less simple model of an ecological community



Tom Leinster and Christina Cobbold, Measuring diversity: the importance of species similarity, *Ecology* 93 (2012), 477–89.

Assume we also have a measure of the similarity between the ith and jth species,

$$0 \leq Z_{ij} \leq 1.$$

Here  $Z_{ij} = 0$  means total dissimilarity, and  $Z_{ij} = 1$  means identical species. This defines an  $n \times n$  matrix  $Z = (Z_{ij})$ .

The similarities  $Z_{ij}$  can be determined genetically, phylogenetically, functionally, morphologically, taxonomically, .... You choose!

- E.g. The naive model Z = I: different species have nothing in common.
- E.g. Given a metric d on  $\{1, \ldots, n\}$ , put  $Z_{ij} = e^{-d(i,j)}$ .

Roughly: a community is a probability distribution on a finite metric space.

#### Similarity-sensitive diversity

How typical is the *i*th species? Multiply the similarity matrix Z by the abundance vector p:

$$(Z\mathbf{p})_i = \sum_j Z_{ij}p_j.$$

So the *atypicality* of the *i*th species can be quantified as

 $1/(Zp)_{i}$ .

Diversity is defined as the average atypicality of an individual.

Here 'average' could be the ordinary arithmetic mean

$$\sum_i p_i \cdot \frac{1}{(Z\boldsymbol{p})_i},$$

but it's useful to consider *all* power means. So for  $0 \le q \le \infty$ , define

$$\boldsymbol{D}_{q}^{Z}(\boldsymbol{p}) = \left(\sum_{i} p_{i} \left(\frac{1}{(Z\boldsymbol{p})_{i}}\right)^{1-q}\right)^{1/(1-q)}$$

(taking limits at  $q = 1, \infty$ ).

Features of the similarity-sensitive diversity measures

- This definition unifies many of the diversity measures used by ecologists (and elsewhere in the life sciences).
- When Z = I (naive model), we recover the Hill numbers:  $D'_q = D_q$ .
- They have been applied at all ecological scales, from microbial to large predators.
- Mathematically: taking logs, we get a notion of the entropy of a probability distribution on a metric space.

#### Digression: social applications

#### From the Scottish Index of Multiple Deprivation. Red: high deprivation. Blue: low deprivation.



How would you quantify the concentration/spread of deprivation? Can you measure how separated the poor and rich areas are?

A group of Edinburgh undergraduates is working on it. . .

Maximizing diversity



Tom Leinster and Mark Meckes, Maximizing diversity in biology and beyond, *Entropy* 18 (2016), article 18.

Fix a similarity matrix Z, i.e. a list of species with known similarities.

Or if you prefer: fix a finite metric space.

Allow the relative abundance distribution p to vary.

Which p achieves the maximum possible diversity? What *is* that maximum?

#### Example: frogs and newts

Take a three-species system with these similarities:



Which distribution maximizes diversity?

- Not (1/3, 1/3, 1/3), because then we'd have 2/3 frog and 1/3 newt.
- Not (1/4, 1/4, 1/2), because the frog species aren't quite identical.
- It should be somewhere in between.

In particular, the maximizing distribution should not be uniform.

#### The maximum diversity theorem

- Fix a similarity matrix Z, i.e. a list of species with known similarities.
- Or if you prefer: fix a finite metric space.
- Allow the relative abundance distribution  $\boldsymbol{p}$  to vary.
- Which p achieves the maximum possible diversity? What *is* that maximum? In principle, both answers depend on q.
- Theorem (with Mark Meckes)
- Both answers are independent of q. That is:
  - there is a probability measure p maximizing  $D_q^Z(p)$  for all  $q \in [0,\infty]$  simultaneously
  - $\sup_{\boldsymbol{p}} D_q^Z(\boldsymbol{p})$  is independent of q.
- If  $\boldsymbol{p}$  maximizes  $D_q^Z(\boldsymbol{p})$  for all q, we call  $\boldsymbol{p}$  a maximizing measure.
- It is usually unique, making it a *canonical probability measure on a finite metric space*.

#### From finite to infinite spaces



Tom Leinster and Emily Roff, The maximum entropy of a metric space, *Quarterly Journal of Mathematics*, to appear.

All this can be done for a general *compact* metric space, not necessarily finite.

For a probability measure  $\mathbb{P}$  on a compact metric space X, put

$$\mathbb{ZP}(x) = \int e^{-d(x,y)} d\mathbb{P}(y)$$

and

$$D_q^{\mathsf{X}}(\mathbb{P}) = \left(\int \left(\frac{1}{Z\mathbb{P}(x)}\right)^{1-q} d\mathbb{P}(x)\right)^{1/(1-q)}$$

The maximum diversity theorem holds for all compact metric spaces.

#### Example: real interval

Take a real interval [0, L] of length L with its usual metric. Which probability measure on [0, L] maximizes diversity?

- One guess:  $\frac{1}{2}(\delta_0 + \delta_L)$  (push all the mass to the ends).
- Another guess: the uniform distribution, i.e. the normalization of Lebesgue measure λ<sub>[0,L]</sub>.
- In fact, it's a linear combination of these. It's the normalization of

$$\delta_0 + \lambda_{[0,L]} + \delta_L.$$



#### What is the uniform distribution?

Given a space X, which probability measure on X deserves to be called the 'uniform distribution' on X?

The answer is obvious for certain classes of space X. E.g.:

- finite spaces •••
- suitably symmetric spaces



: the unique symmetric measure

• subsets of  $\mathbb{R}^n$  with  $0 < Vol(X) < \infty$ : normalized Lebesgue measure.

And clearly there's no sensible uniform distribution for some X, e.g.  $\mathbb{R}$  or  $\mathbb{Z}$ . Is there a good general answer?

## What is the uniform distribution on a compact metric space?

• Old idea from statistics: the canonical choice of probability distribution is the one with the maximum entropy.

Should we refer to the maximizing measure as the 'uniform distribution'?

No! It's scale-dependent, and that's bad.

It also gives the wrong answer in examples (e.g. the interval).

• But if we take the large-scale limit, it works...

#### The uniform measure

Let X be a compact metric space.

For t > 0, write tX for X with the metric scaled up by a factor of t.

Assume that for  $t \gg 0$ , there is only one maximizing measure  $\mathbb{P}_t$  on tX.

Definition The uniform measure on X is

$$\mathbb{U}_{\boldsymbol{X}} = \lim_{t \to \infty} \mathbb{P}_t,$$

if this limit exists (in the weak\* topology).

This is scale-independent:  $\mathbb{U}_{tX} = \mathbb{U}_X$  for all t > 0.

The uniform measure is a canonical scale-independent measure on a compact metric space.

#### Easy examples

- Finite spaces: The uniform measure on a finite space is the uniform measure in the usual sense.
- Symmetric spaces: Let X be a compact metric space such that for all x, y ∈ X, some self-isometry of X maps x to y. The Haar measure theorem implies that there is a unique isometry-invariant probability measure on X. And that's what the uniform measure on X is.

#### Slightly less easy example: the interval

- Consider the real interval [0, L].
- We saw that the maximizing measure on [0,L] is the normalization of  $\delta_0+\lambda_{[0,L]}+\delta_L.$
- When we scale up by a large factor t, the point masses at the endpoints become negligible.
- So the uniform measure on [0,L] is the normalization of Lebesgue measure,  $\lambda_{[0,L]}/L.$
- That is, it's the uniform distribution in the usual sense.

#### Much harder case: subsets of $\mathbb{R}^n$

- Let X be a compact subset of  $\mathbb{R}^n$ .
- Problem Unlike for the interval, we have no description of the maximizing measure on X even when X is a 2-dimensional disc!
- So unlike for the interval, we can't find the uniform measure on X by finding the maximizing measure on tX for each finite t, then letting  $t \to \infty$ .
- Nevertheless, assuming that X has nonzero measure...
- Theorem The uniform measure  $\mathbb{U}_X$  is normalized Lebesgue measure on X. Proof Lots of analysis (paper with Emily Roff).



### Thanks