

# Magnitude Meets Persistence

- Magnitude
- Magnitude Homology
- Nerves, Blurring and Persistence

[Ottaviani 18] arxiv: 1807.01540

[Chen 19] arxiv: 1910.02905

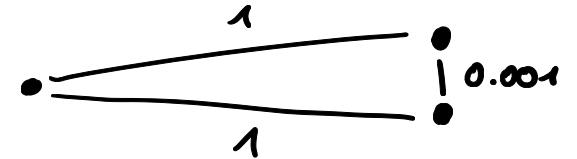
# Magnitude

$(X, d)$  finite metric space

Def. similarity matrix

$$(Z_x)_{ij} = e^{-d(x_i, x_j)}$$

[Leinster 10] arxiv: 1012.5857



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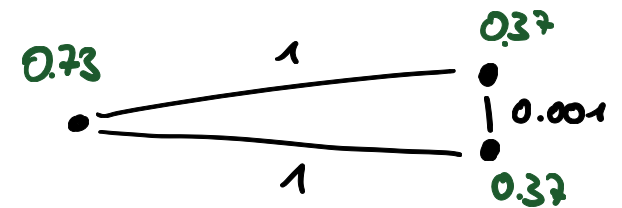
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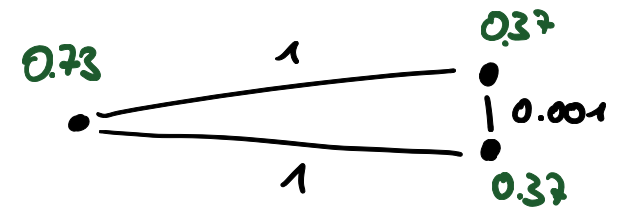
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Def. The magnitude of  $X$  is  $|X| := \sum_i w_i$

Prop. If  $Z_X$  is invertible  $|X| = \sum_{i,j} (Z^{-1})_{ij}$



$$|X| \sim 1.5$$



## Magnitude - Examples

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Magnitude is a measure for the effective number of points.

First appeared in biology (1995) to quantify biodiversity.

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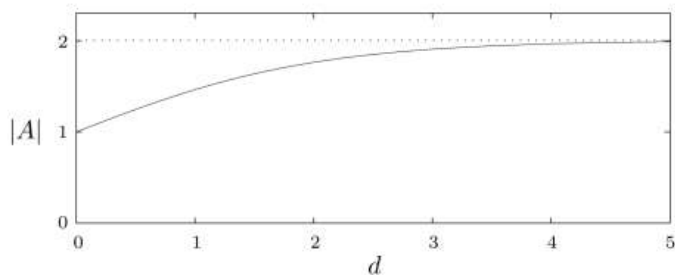
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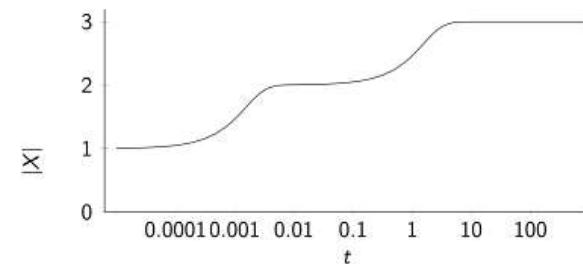
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Ex. (i)  $X = \bullet \xrightarrow{1} \bullet$ ,  $|tX| = 1 + \tanh(\frac{t}{2})$



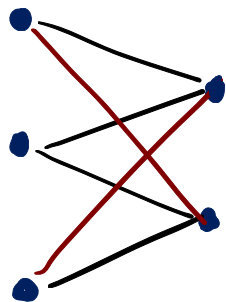
(ii)  $X = \bullet \begin{matrix} \nearrow^1 \\ \searrow_1 \end{matrix} \bullet \begin{matrix} \vdots 0.001 \\ \vdots 0 \end{matrix}$



# Magnitude Function

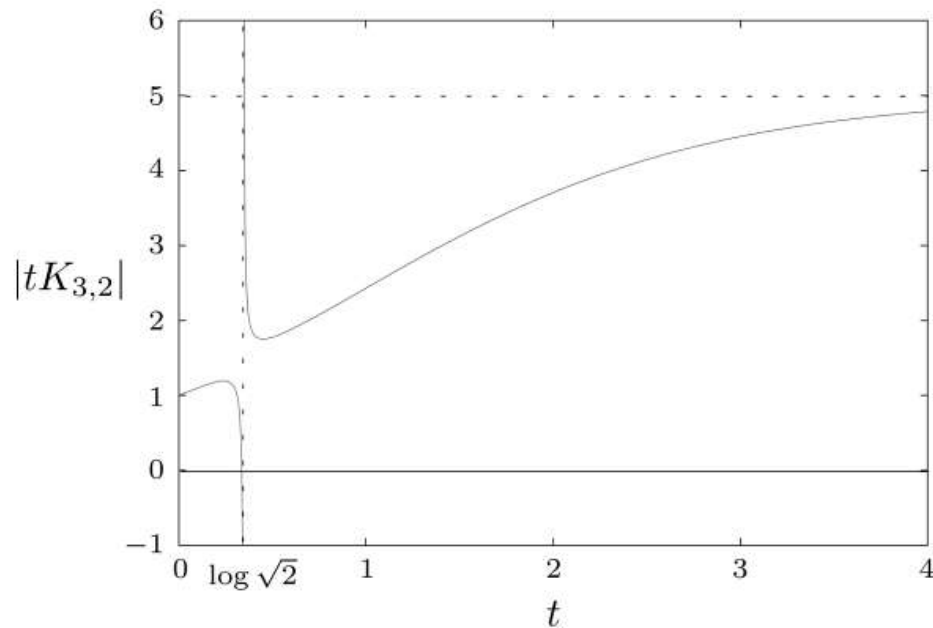
Example of bad metric space

$K_{3,2} =$



edges = distance 1  
+ shortest paths

$$|tK_{3,2}| = \frac{5 - 7e^{-t}}{(1 + e^{-t})(1 - 2e^{-2t})}$$

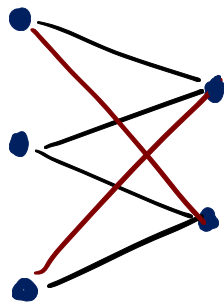




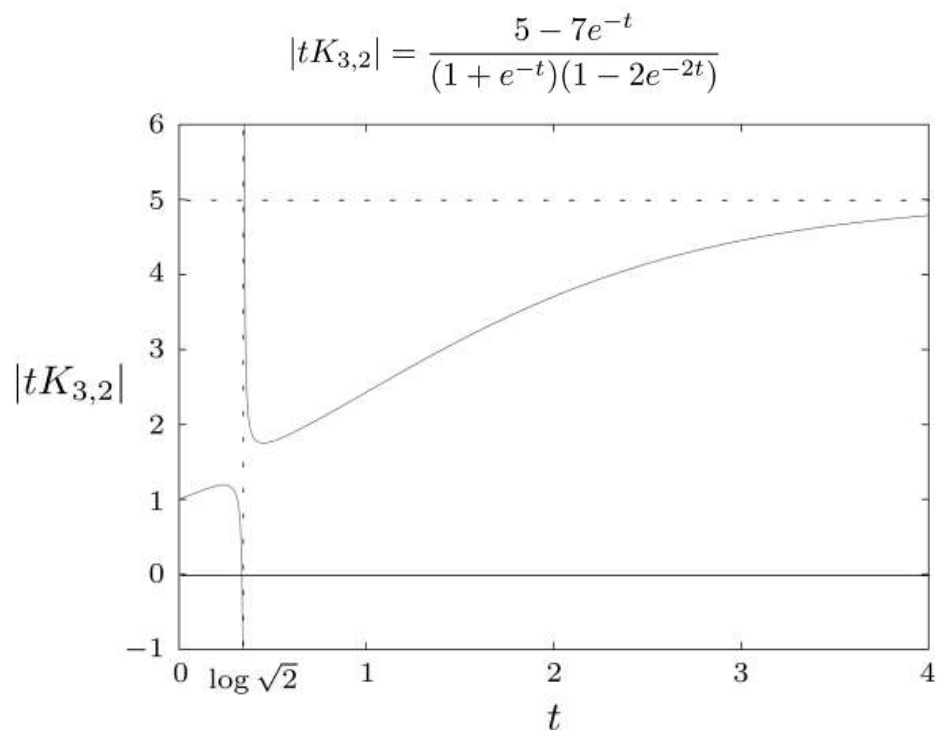
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Prop.  $X$  finite metric space

(i)  $t \in X$  has magnitude for all but finitely many  $t_i \in [0, \infty)$ .

(ii) the magnitude function of  $X$  is analytic at all  $t \notin \{t_i\}$

(iii) For  $t \gg 0$  the magnitude function of  $X$  is increasing

(iv)  $|tX| \rightarrow \#X$  as  $t \rightarrow \infty$

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Fact If  $X \hookrightarrow \mathbb{R}^n$  isometrically, the magnitude function does not have singularities

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How do these singularities arise?  $|tX| = \frac{a_1 q^n + \dots + a_m q^{n+m}}{b_1 q^r + \dots + b_s q^{r+s}}, \quad q = e^{-t}$

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$$(z_x - 1)(x, x) = 0$$

$$(z_x - 1)^n(x_0, x_n) = \sum_{x_i \neq x_j} z_x(x_0, x_1) \dots z_x(x_{n-1}, x_n)$$

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$$z_{tX}(x_i, x_j) = e^{-t d(x_i, x_j)} = q^{d(x_i, x_j)}$$

# Magnitude Function

In summary

$$|X| = \sum_{i,j} z_X^{-1}(x_i, x_j) = \sum_{n=1}^{\infty} \sum_{\ell \in \{0, \dots\}} (-1)^n a_{n,\ell} q^{\ell}$$

# Magnitude Function Homology

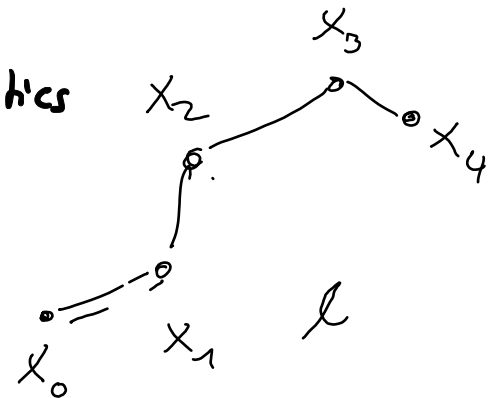
[Leinster-Shulman 17] arxiv:1711.00802

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Does there exist a homology theory whose Euler characteristics gives the magnitude of  $X$  when evaluated at  $q = e^{-1}$ ?

↳ Magnitude Homology





# Magnitude Homology

Def. Magnitude Complex

$$MC_{n,\ell}(X) = \mathbb{Z} \left[ \left\{ \langle x_0, \dots, x_n \rangle \mid \ell = \sum_{i=0}^{n-1} d(x_i, x_{i+1}), x_i \neq x_{i+1} \right\} \right]$$

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$$d_n^i(\langle x_0, \dots, x_n \rangle) = \begin{cases} \langle x_0, \dots, x_{i-1}, \hat{x}_i, x_{i+1}, \dots, x_n \rangle & \text{if } d(x_{i-1}, x_i) + d(x_i, x_{i+1}) = d(x_{i-1}, x_{i+1}) \\ 0 & \text{otherwise} \end{cases}$$



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Thm [LS 17]  $|tX| = \text{Poin}(MH_{*,*}(X))(t=-1, q) = \sum_{n,\ell} \text{rk } MH_{n,\ell}(X) t^n q^\ell \Big|_{t=-1}$

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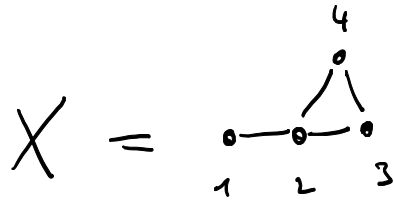
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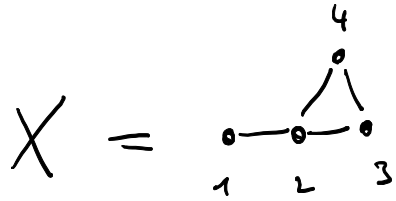
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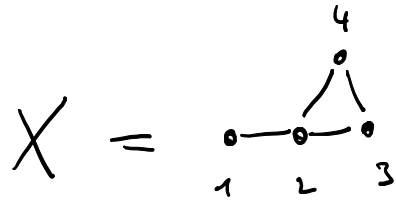
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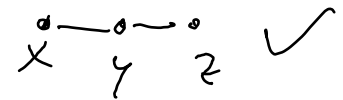
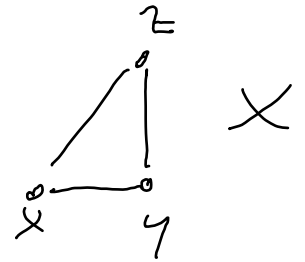
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Say  $y$  is between  $x$  and  $z$ , if  $d(x,y) + d(y,z) = d(x,z)$ .

If there is no  $y$  between  $x$  and  $z$  then they are adjacent.

$$MH_{1,l} = \begin{cases} \mathbb{Z}[\langle x_i, x_j \rangle] & l = d(x_i, x_j) \text{ and } x_i, x_j \text{ adjacent} \\ 0 & \end{cases}$$

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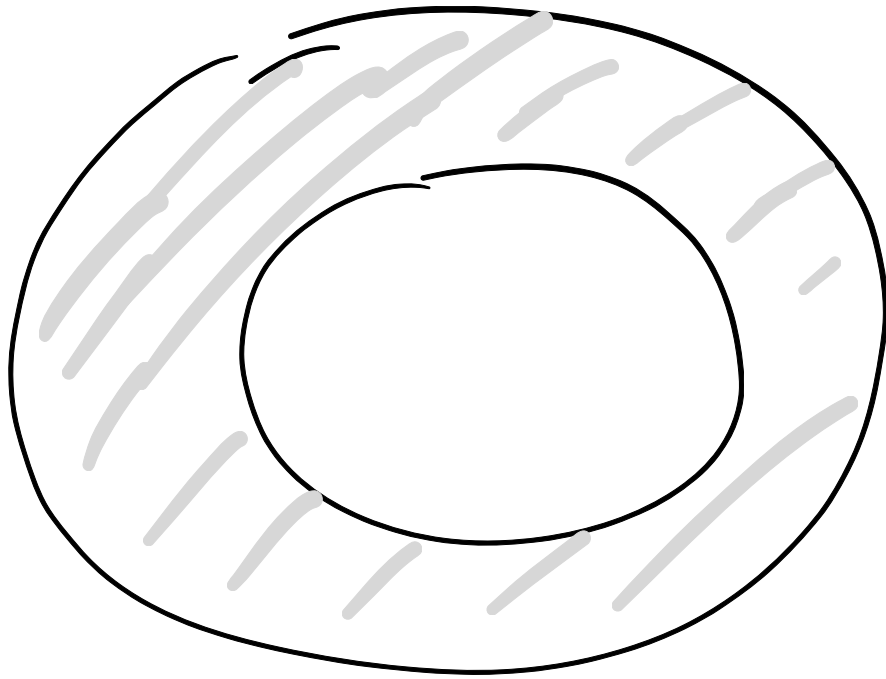
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Corollary If  $X \subset \mathbb{R}^n$  is a closed convex subset (not necessarily finite)  
then  $MH_{1,\ell}(X) = 0$ .

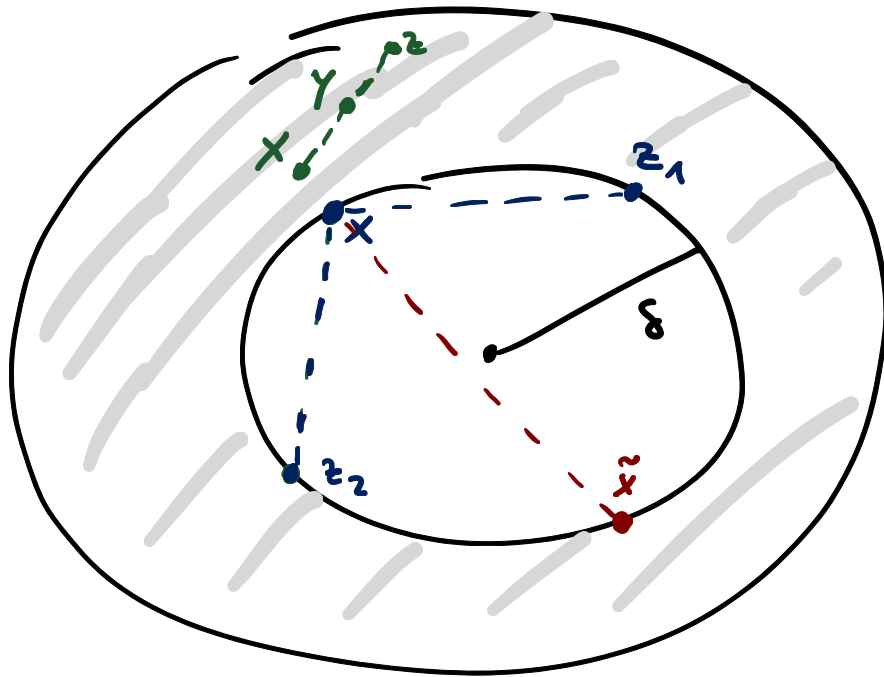
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$$MH_{1,2} = \begin{cases} \mathbb{Z}[s^{1,2}] & 0 < l < \delta \\ \mathbb{Z}[s^1] & l = \delta \\ 0 & \text{else} \end{cases}$$

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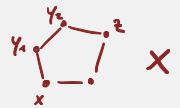
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$$d(y_1, y_2) + d(y_2, z) = d(y_1, z)$$

$$\Rightarrow d(x, z) = d(x, y_1) + d(y_1, y_2) + d(y_2, z)$$



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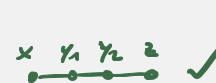
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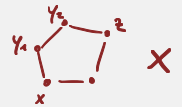
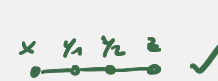
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or  $X$  is geodesic  $\approx d(x, y) = \text{shortest path length}$

Then  $MH_{2,\bullet}(X) = 0$ .

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- and

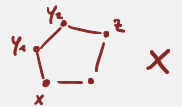
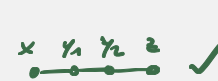
either  $X$  is Menger convex  $\approx$  any 2 pts are non-adjacent

roughly  
equivalent  
for diff.  
situations

and has no 4-cuts

$$\begin{aligned}d(x, y_1) + d(y_1, y_2) &= d(x, y_2) \\d(y_1, y_2) + d(y_2, z) &= d(y_1, z)\end{aligned}$$

$$\Rightarrow d(x, z) = d(x, y_1) + d(y_1, y_2) + d(y_2, z)$$



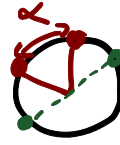
or  $X$  is geodesic  $\approx d(x, y) = \text{shortest path length}$

Then  $MH_{2,\bullet}(X) = 0$ .

$\leadsto MH_{2,\bullet}$  obstructs any (or both) of these properties

# Magnitude Homology - Geometric Interpretation

Examples •  $X = S^1$  w/ arc-distance.



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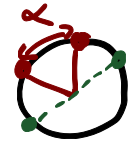
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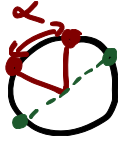
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•  $X = \text{circle with shaded interior}$  is geodesic and does not have 4-cuts.



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•  $X = \text{disk}$  is geodesic and does not have 4-cuts.

But it is not Menger convex:

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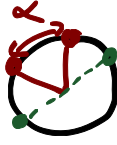
•  $X = \text{triangle}$  is geodetic and does not have 4-cuts.

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$$MH_{2,\ell}(X) = \mathbb{Z} \left[ \left\{ \langle x, y, z \rangle \mid \overset{\text{adjacent}}{d(x,y)} + \overset{\text{adjacent}}{d(y,z)} = \ell + \overset{\text{i.e. } y \text{ not betw. } x,z.}{d(x,z)} \right\} \right]$$

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measures failure of  
"simultaneous convexity"  
of triangle's edges

$$MH_{2,\ell}(X) = \mathbb{Z} \left[ \left\{ \langle x, y, z \rangle \mid d(x, y) + d(y, z) = \ell + d(x, z) \right\} \right]$$

↔ adjacent      ↖ i.e.  $y$  not betw.  $x, z$ .

## Nerves, Blurring and Persistence

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[Choi 19] arxiv: 1910.02905

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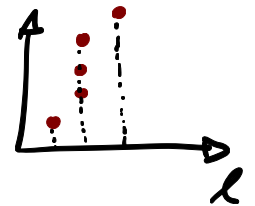
1. Chain complexes in persistent homology (usually) are Nerves

$\leadsto$  Nerve construction of magnitude complex

2. Magnitude Homology only contains "ephemeral" interval modules

$\leadsto$  MH is "fully localized" at  $\ell$ ,

we are looking for "blurred" magnitude homology that has "observable" bars to make contact w/ persistence.



These two steps are easiest described in categorical language

# Nerves, Blurring and Persistence - Lawvere metric spaces

Recall the following generalizations of metric spaces

- Pseudo-metric drops separation:  $d(x,y) = 0 \not\Rightarrow x = y$
- Quasi-metric drops symmetry:  $d(x,y) \neq d(y,x)$
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$$X(x,y) \times X(y,z) \rightarrow X(x,z)$$

$$\uparrow \mathbb{A}$$

$$d(x,y) + d(y,z) \geq d(x,z)$$

Thm [Lawvere 74]

A  $([0, \infty], +, 0)$ -enriched category  $X$  is an extended pseudo-quasi-metric space.

## Nerves, Blurring and Persistence - $\ell^p$ -Nerves

Note: We could also use  $a \dot{+}_p b := (a^p + b^p)^{1/p}$  as composition in  $(V, \oplus, 0)$   
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## Nerves, Blurring and Persistence - Blurring and Localizing

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Def 
$$\text{Loc}_{\mathcal{J}}(\tilde{MC}_{\bullet, \bullet})(r) = \tilde{MC}_{\bullet, r} / \bigcup_{s \in \mathcal{J}_r} \text{im}(\tilde{MC}_{\bullet, s} \rightarrow \tilde{MC}_{\bullet, r})$$

## Nerves, Blurring and Persistence - Blurring and Localizing

Choosing the maximal non-trivial sieve  $\mathcal{I}_{\max}$ , i.e.

$$\mathcal{I}_r = \{ s \in [0, \infty) \mid s < r \}$$

leads to

Thm [Cho 15]

Maximally localized blurred magnitude homology is magnitude homology

$$\mathrm{Loc}_{\mathcal{I}_{\max}}(\tilde{MC}_{\bullet,\bullet}) = MC_{\bullet,\bullet}$$

# Nerves, Blurring and Persistence - Summary

