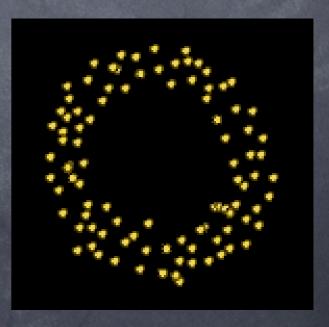
Point-cloud topology via harmonic forms

Vin de Silva, Pomona College <u>vin.desilva@pomona.edu</u>

Today's goal

Explore the use of discrete Laplacian operators...
...as applied to the topology of point-cloud data
Discuss "qualitative" vs "quantitative"
Discuss "discrete" vs "continuous"
Run one or two demos



POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23

Thanks to my former colleagues at Stanford:

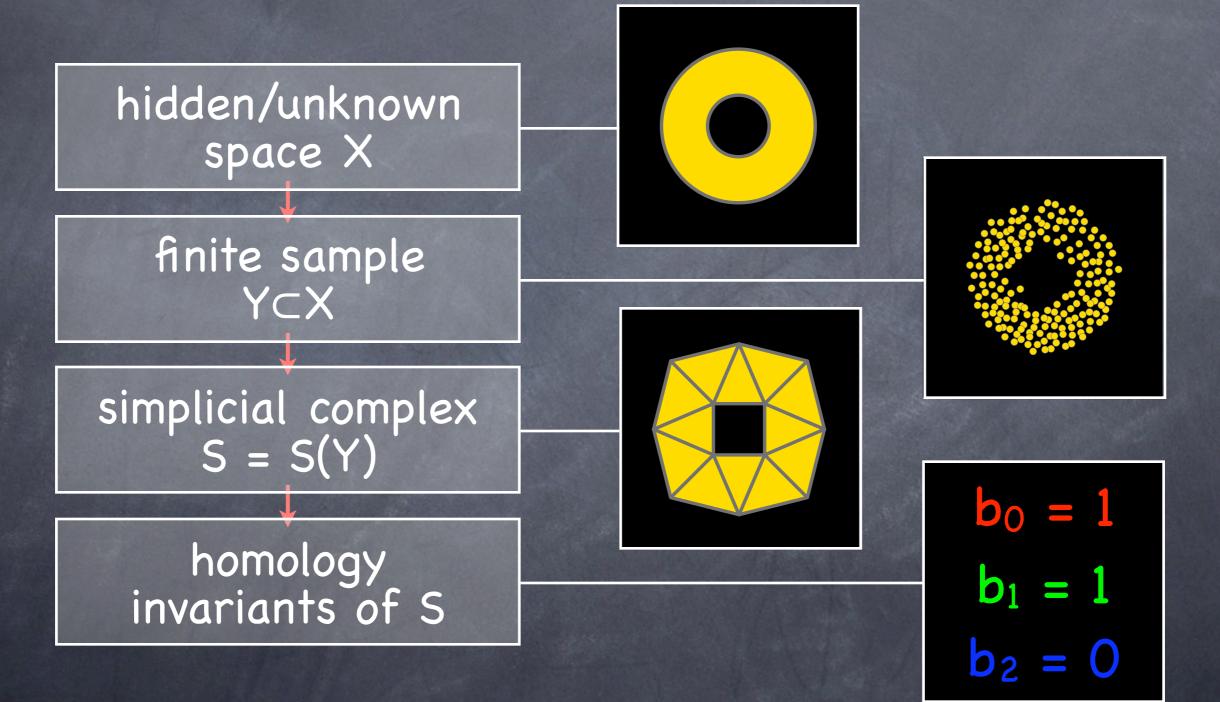
Gunnar Carlsson
Patrick Perry
Afra Zomorodian
Anne Collins
Peter Lee

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Discrete vs Continuous

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Standard Pipeline (first attempt)



WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Betti numbers ↔ features

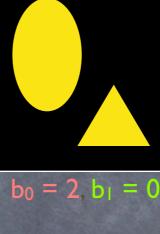
For an object in 2D space
 b₀ is the number of components
 b₁ is the number of holes

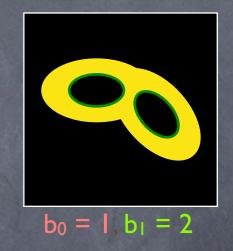
For an object in 3D space

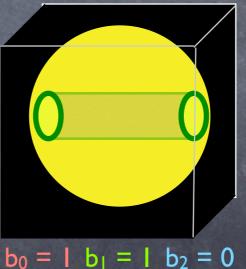
- b₀ is the number of components
- b1 is the number of tunnels or handles
- O **b**₂ is the number of voids

(and so on, in higher dimensions)

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research







 $b_0 = | b_1 = 0 b_2 = |$

Reconstruction theorems

Various constructions for S(Y)

- Cech complex (folklore)
- Rips-Vietoris complex (folklore)
- α-shape complex (Edelsbrunner, Mücke)
- strong/weak witness complexes (Carlsson, dS)

Desire theorems of the form:

If Y is well-sampled from X then S(Y) ≈ X

e.g. Niyogi-Smale-Weinberger (2004), Cech complex

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Discrete vs continuous

Betti numbers are discrete

Topological spaces

topological spaces are continuous

the space of topological spaces is discrete

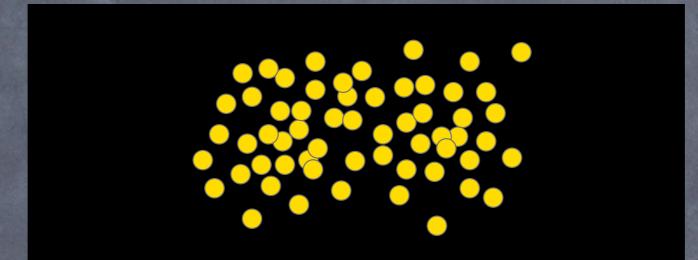
Finite point-clouds

ø point-clouds are discrete

the space of point-clouds is continuous

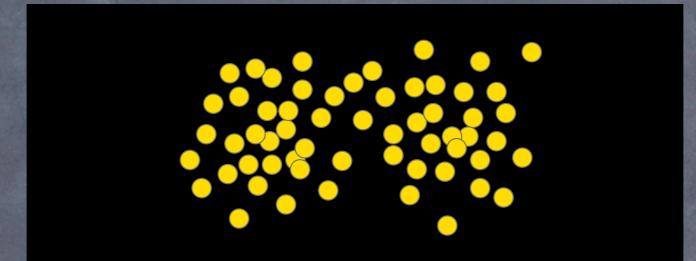
Therefore, raw Betti numbers are
 very handy for topological spaces
 a bit dangerous for point-clouds

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



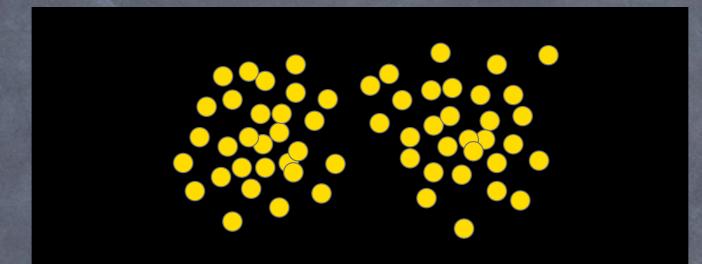
At which parameter value does the number of components change?

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23



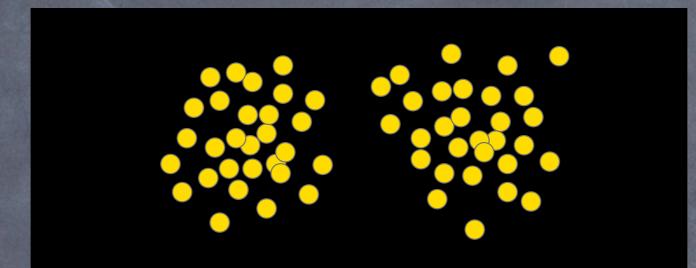
At which parameter value does the number of components change?

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23



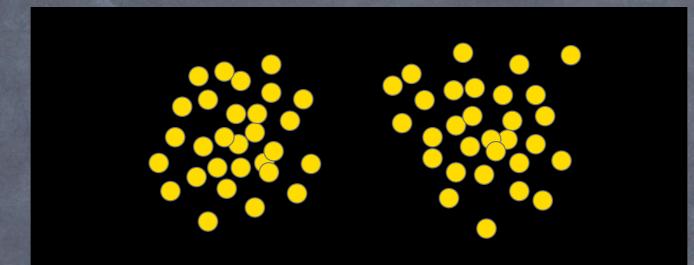
At which parameter value does the number of components change?

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23



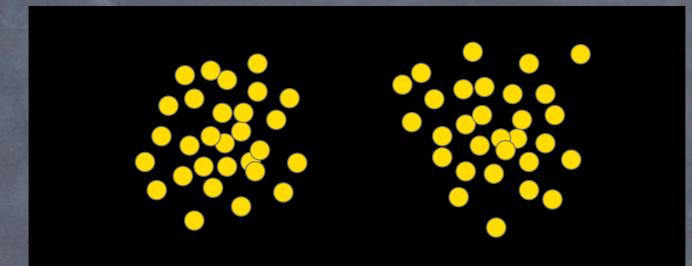
At which parameter value does the number of components change?

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23



At which parameter value does the number of components change?

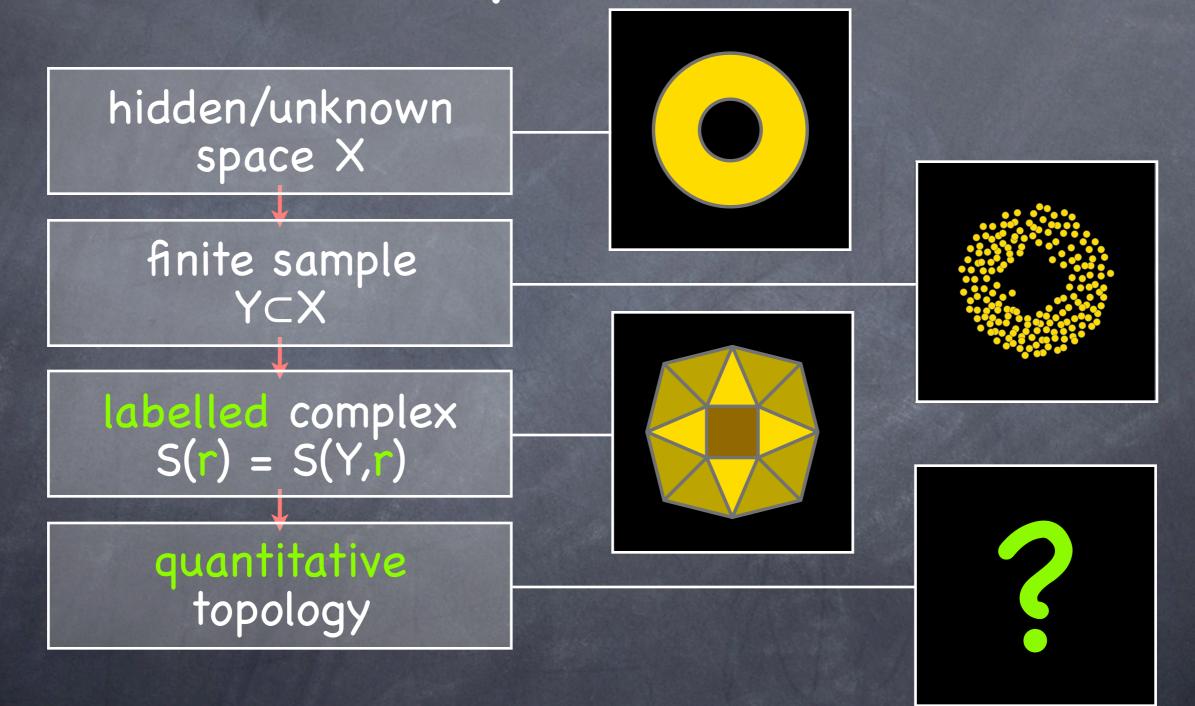
WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23



At which parameter value does the number of components change?

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research POINT-CLOUD TOPOLOGY VIA HARMONIC FORMS Vin de Silva 2006-june-23

Standard Pipeline (second attempt)



WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Example: Persistence

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

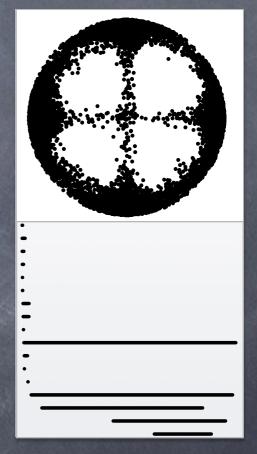
Persistent homology

Edelsbrunner, Letscher, Zomorodian (2000)
 effective algorithm for persistence in 3-space

Carlsson, Zomorodian (2005)
 general theory of persistent homology

Cells of S(Y) labelled by "time of birth"

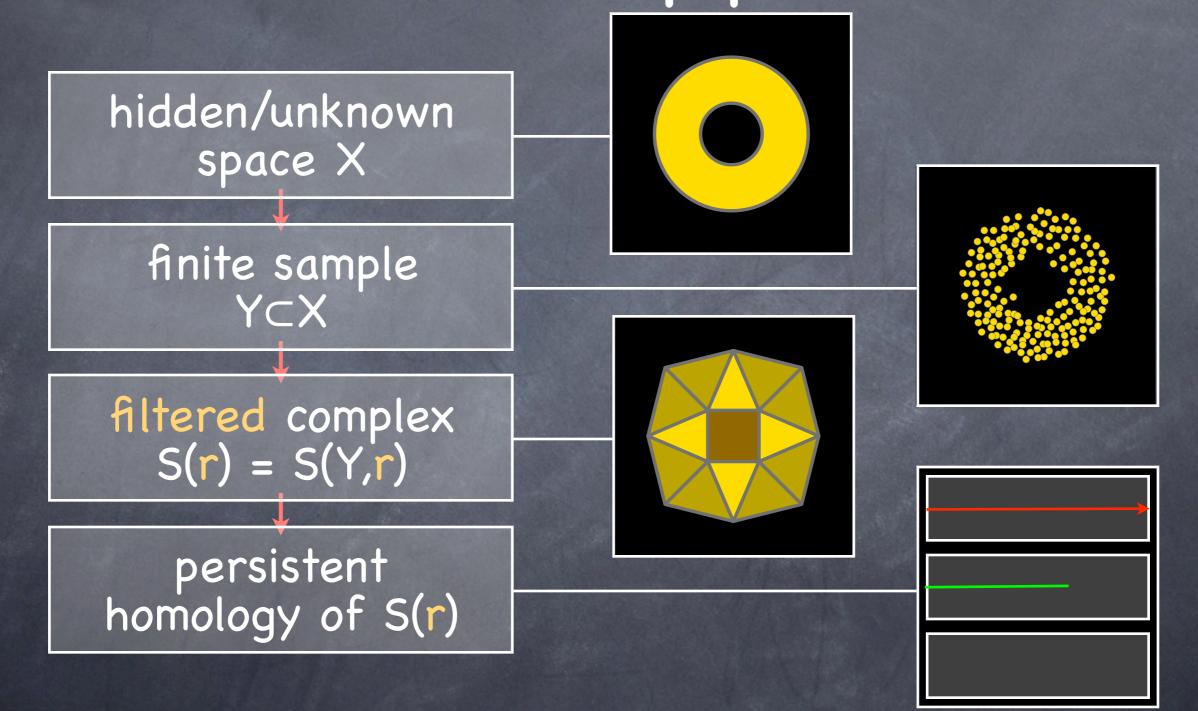
Bar-codes indicate feature lifetimes



Continuous measurements (interval length) coupled to discrete information (number of intervals)

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Persistence pipeline



WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Discrete Laplacians

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



C_k = { real-valued functions on k-simplices of S(Y) }
 a floating point rather than exact arithmetic

Ø Define discrete Laplacian operators Δ_k : C_k → C_k

• Consider the harmonic spaces $H_k = Ker(\Delta_k)$ • H_k is isomorphic to standard homology of X

Consider eigenspaces { f : Δ_kf = λf } for λ small
 "almost homology" or "ε-homology"

Information derived from the ranks of these spaces (Betti numbers) and the eigenfunctions themselves

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Constructing Δ_k

Given a chain complex over the real numbers...

$$\cdots C_{k-1} \xleftarrow{\partial_k} C_k \xleftarrow{\partial_{k+1}} C_{k+1} \cdots \xrightarrow{\text{homology is defined}} \text{using a chain complex}$$

...and an inner product on each C_k , we can form the dual cochain complex:

$$\cdots C_{k-1} \xrightarrow{\partial_k^*} C_k \xrightarrow{\partial_{k+1}} C_{k+1} \cdots$$
 cohomology is defined using a cochain complex

The discrete Laplacian is defined...

$$\Delta_k = \partial_k^* \partial_k + \partial_{k+1} \partial_{k+1}^*$$

...and one can easily prove (in the finite dimensional case):

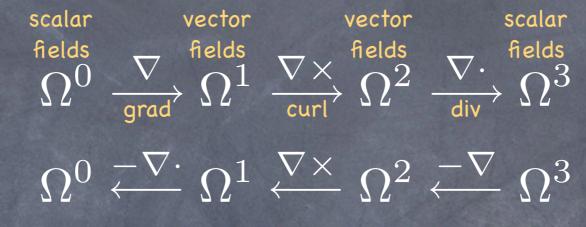
$$\mathcal{H}_{k} := \operatorname{Ker}(\Delta_{k}) \cong \frac{\operatorname{Ker}(\partial_{k})}{\operatorname{Im}(\partial_{k+1})} =: H_{k} \text{homology}$$

harmonic space

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Aside: Hodge theory

For a 3-dimensional domain:



For example:

$\Delta_0 f$:=	$- abla \cdot (abla f)$	=	$-\sum_{i=1}^{3}$	$\frac{\partial^2 f}{\partial x_i^2}$
$\Delta_1 \vec{f}$:=	$\begin{aligned} -\nabla \cdot (\nabla f) \\ \nabla \times (\nabla \times \vec{f}) - \nabla (\nabla \cdot \vec{f}) \end{aligned}$	=	$-\sum_{i=1}^{3}$	$\frac{\partial^2 \vec{f}}{\partial x_i^2}$

Proof that $Ker(\Delta_k) = H_k$ is much more difficult.

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

E-Betti numbers

Structure theorem for homology and ϵ -homology

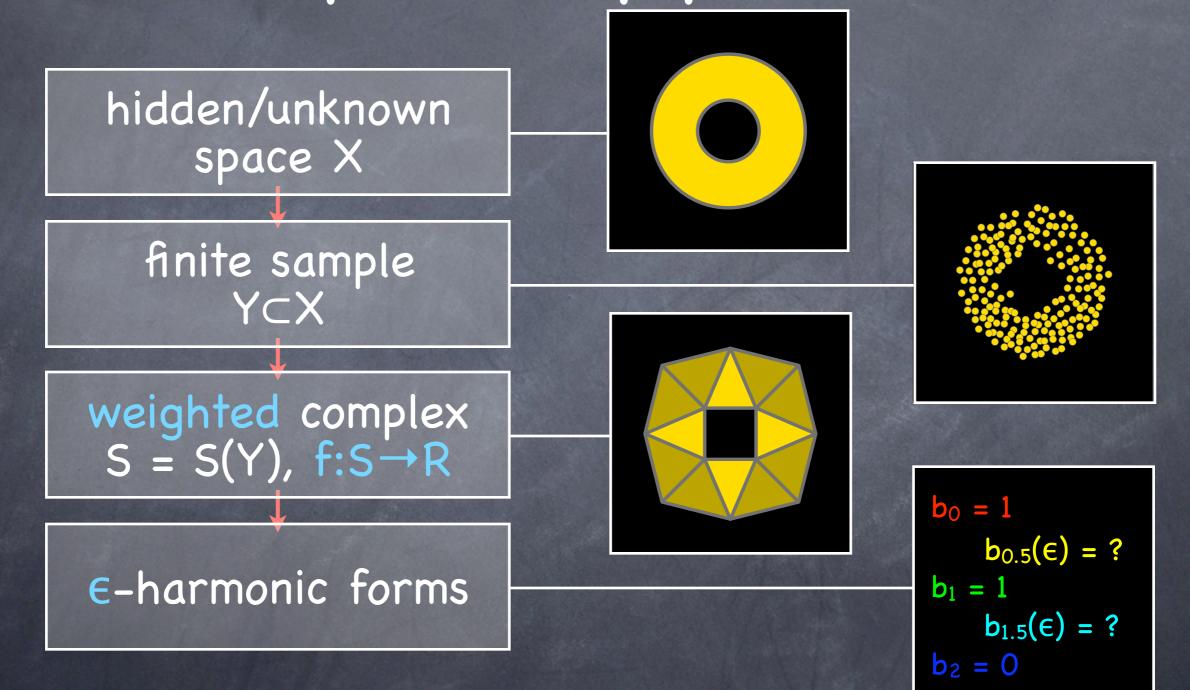
For every nonnegative integer k, and $\epsilon > 0$: Integers b_k "Betti numbers" Integers $b_{k+\frac{1}{2}}(\epsilon)$ " ϵ -Betti numbers"

such that: $dim(Ker(\Delta_k)) = b_k$ $dim(Eig(\Delta_{k},\epsilon)) = b_{k-\frac{1}{2}}(\epsilon) + b_k + b_{k+\frac{1}{2}}(\epsilon)$

space spanned by eigenfunctions with eigenvalue less than $\boldsymbol{\varepsilon}$

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Laplacian pipeline



WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Pros and cons

- Several ways to incorporate continuous parameters
 meaning of "λ is close to zero" how close?
 simplices can be weighted prior to construction of Δ_k
- Harmonic cycles have global optimality properties
 localising features/minimal cycle problem
- Non-zero eigenfunctions encode subtle relationships between cells of adjacent dimensions
- More expensive than persistent homology
- Theory somewhat underdeveloped
 (except graph Laplacians, see "Spectral Graph Theory" by Chung)

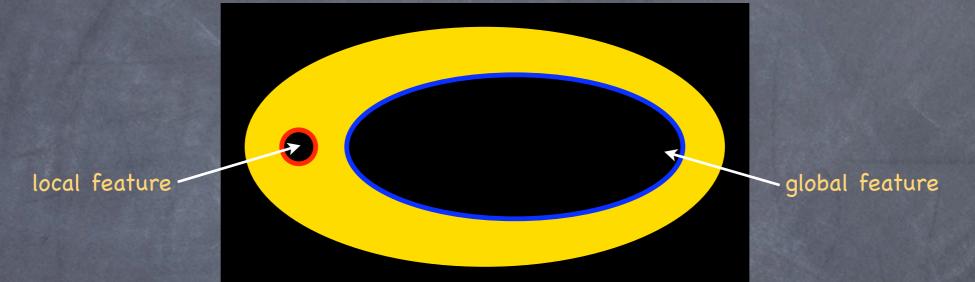
WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Entropy

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Local vs global features

Homological features can be local or global to varying degrees:



This example has a 2-dimensional space of harmonic 1-forms. Can we pick out 1-forms representing the two features?

> persistent homology can do this very easily

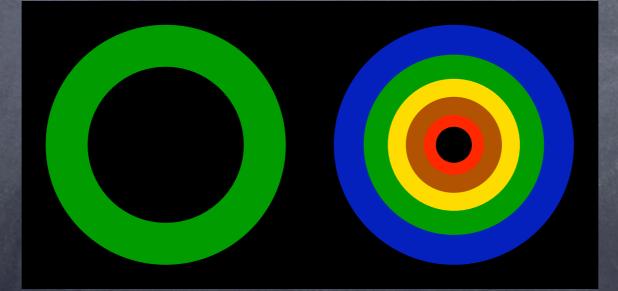


WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Concentration

Heuristic arguments suggest that harmonic cycles concentrate energy...

...weakly along global features
...strongly along local features



Entropy & L^p comparison

How to detect whether a cycle is highly concentrated in some region?

Simple estimate: compare L¹ and L² norms
 E[f] := ||f||₁ / ||f||₂
 E[f] large ↔ global feature
 E[f] small ↔ local feature

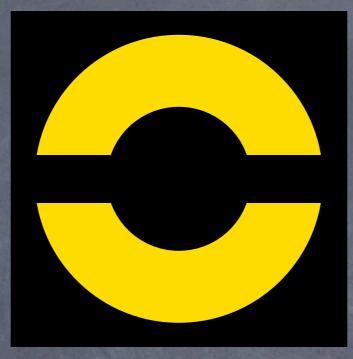


WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Betti numbers: examples

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

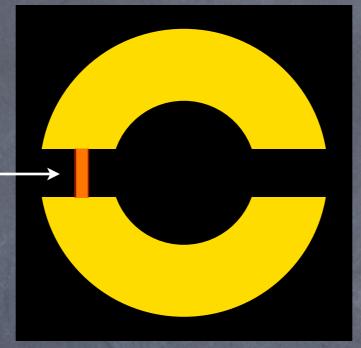




bo	b _{0.5} (€)	b ₁	b₁.5(€)	b ₂
2	0	0	0	0

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



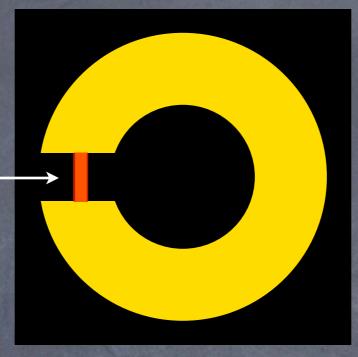


hot spot for 1-chain j, where $\Delta_1 j = \lambda j$

bo	<mark>b</mark> 0.5 (ε)	b ₁	b _{1.5} (ε)	b ₂
1		0	0	0

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research





hot spot for 1-cycle j, where $\Delta_1 j = 0$

bo	b _{0.5} (ε)	b ₁	b₁.5(€)	b ₂
1	0		0	0

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

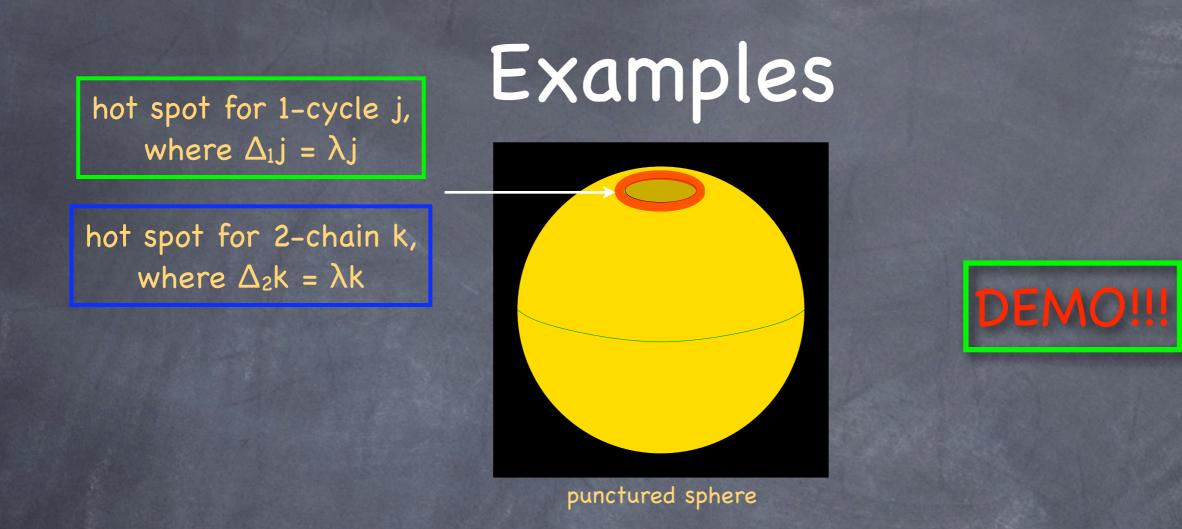




annulus

bo	b _{0.5} (ε)	b ₁	b₁.5(€)	b ₂
1	0		0	0

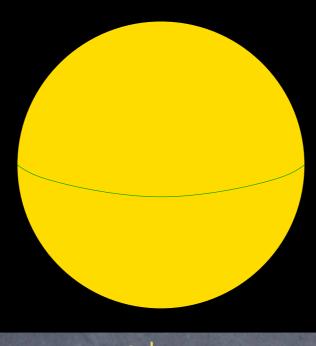
WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



bo	b _{0.5} (ε)	b ₁	b₁.5(€)	b 2
1	0	0		0

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research





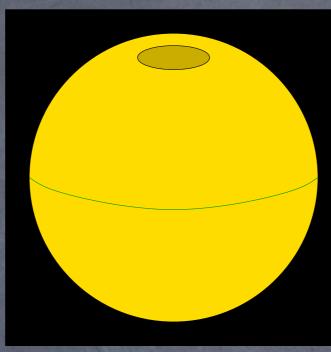
sphere

bo	<mark>b</mark> 0.5 (€)	b ₁	b₁.5(€)	b 2
1	0	0	0	1

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

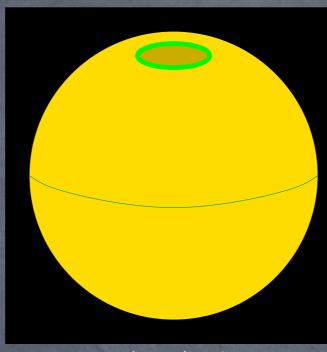
Take-home message

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



punctured sphere

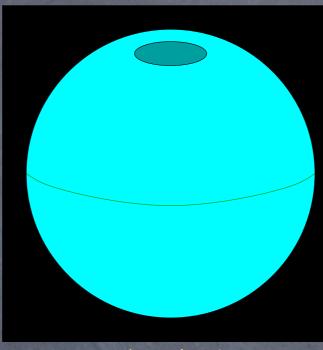
WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



punctured sphere

A 1-D cycle which is a boundary (but only just)

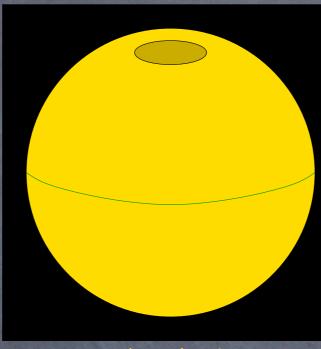
WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



punctured sphere

A 1-D cycle which is a boundary (but only just) A 2-D chain which is almost (but not quite) closed

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research



punctured sphere

A 1-D cycle which is a boundary (but only just) A 2-D chain which is almost (but not quite) closed

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research

Thank you

WORKSHOP ON MODERN MASSIVE DATA SETS Stanford University & Yahoo! Research