### Welcome to

MATH:7450 (22M:305) Topics in Topology: Scientific and Engineering Applications of Algebraic Topology

Week 1: Introduction to Topological Data Analysis via Mapper Software

Sept: Persistent Homology plus topics from student and speaker input.



### **Topological Data Analysis**

October 7-11, 2013

PROGRAM APPLICATION

#### **Organizers**

Robert Adler, Technion, Israel Gunnar Carlsson, Stanford University John Harer, Duke University

# Modern Applications of Homology and Cohomology

October 28 to November 1, 2013

PROGRAM APPLICATION

#### **Organizers**

Andrew Blumberg, University of Texas at Austin Lek-Heng Lim, University of Chicago Yuan Yao, Peking University

### **Topological Structures in Computational Biology**

December 9-13, 2013

PROGRAM APPLICATION

### **Organizers**

Gunnar Carlsson, Stanford University
Christine Heitsch, Georgia Institute of Technology
Susan Holmes, Stanford University
Konstantin Mischaikow, Rutgers, The State University of New Jersey

Are you interested in analyzing data?

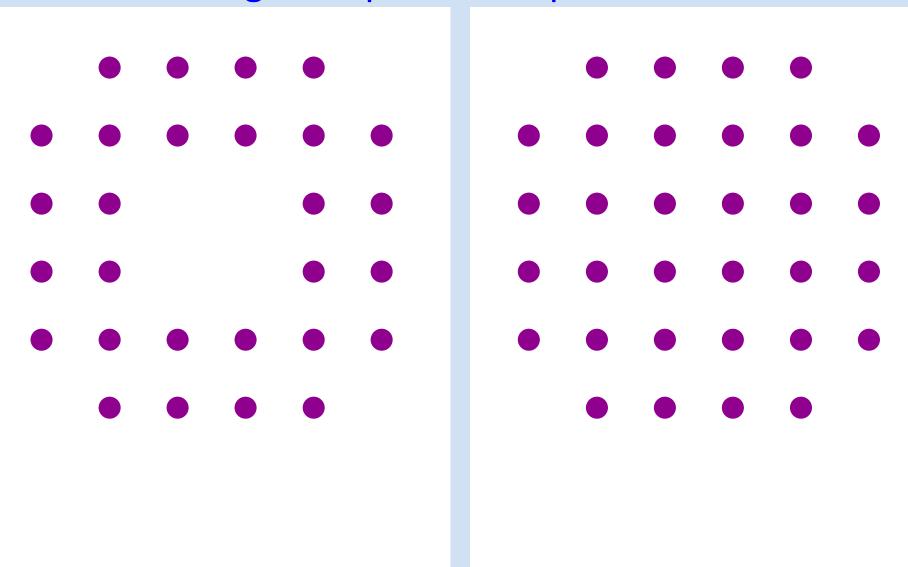
Do you have data to analyze?

Would you like collaborators?

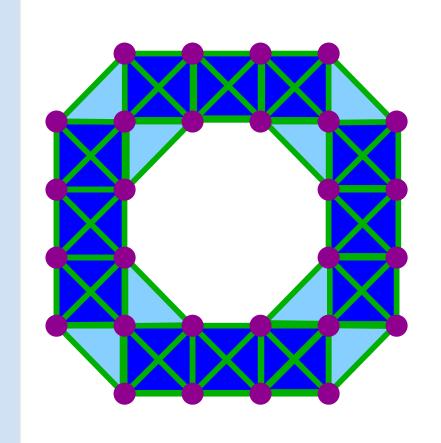
If so, let me know by mid-September.

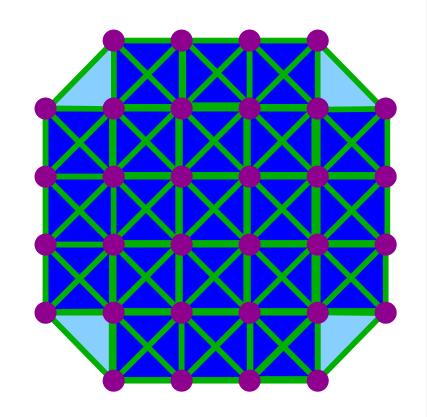
Do you have any recommendations regarding online (or offline) material?

# From Preparatory Lecture 6 Creating a simplicial complex from data



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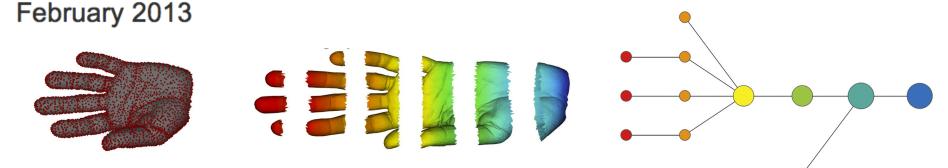
# Extracting insights from the shape of complex data using topology

P. Y. Lum, G. Singh, A. Lehman, T. Ishkanov, M. Vejdemo-Johansson, M. Alagappan, J. Carlsson & G. Carlsson

Affiliations | Contributions | Corresponding authors

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Received 13 September 2012 | Accepted 06 December 2012 | Published 07



http://www.nature.com/srep/2013/130207/srep01236/full/srep01236.html

## A Original Point Cloud

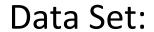


A) Data Set

Example: Point cloud data

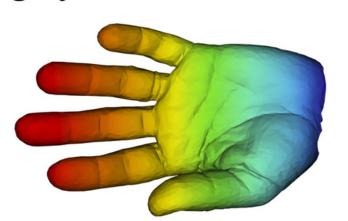
representing a hand.

### A Original Point Cloud



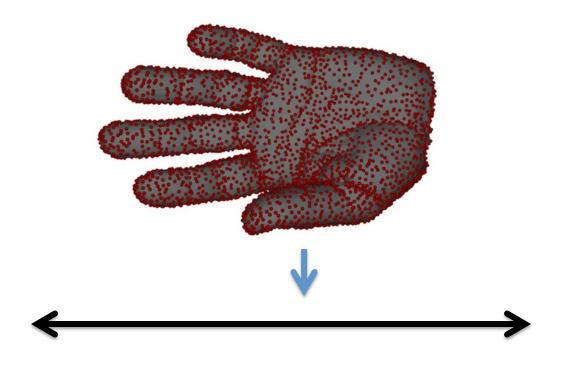


B Coloring by filter value



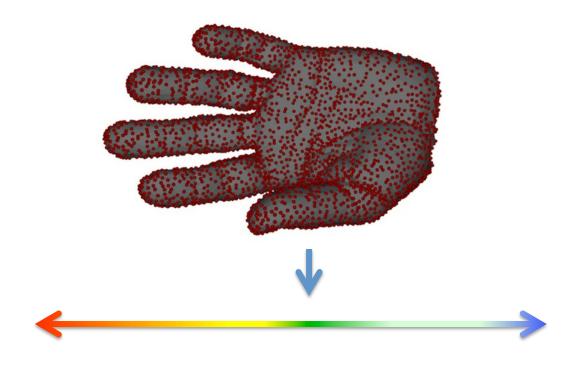
Function f: Data Set  $\rightarrow \mathbf{R}$ 

Example: x-coordinate



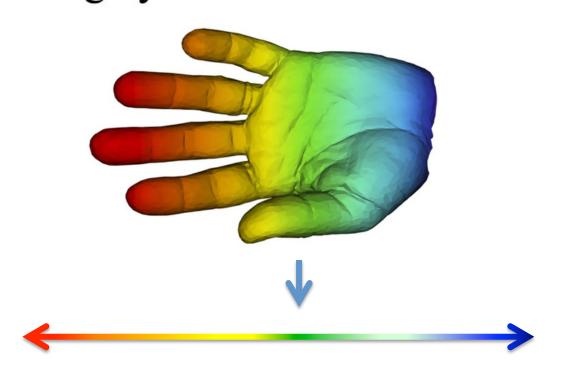
Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate



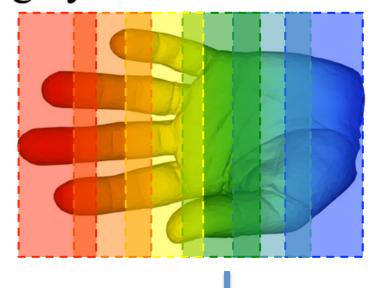
Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate



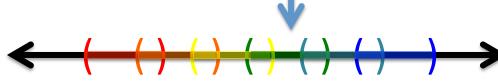
Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate



Put data into overlapping bins.

Example:  $f^{-1}(a_i, b_i)$ 



Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate

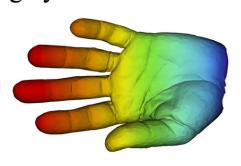
### A Original Point Cloud



### Data Set

Example: Point cloud data representing a hand.

B Coloring by filter value

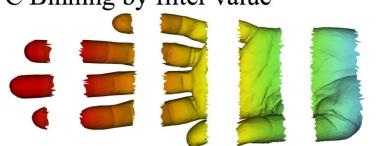


Function  $f: Data Set \rightarrow \mathbf{R}$ 

Example: x-coordinate

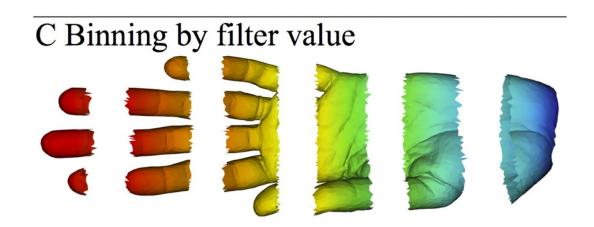
 $f:(x, y, z) \rightarrow x$ 

C Binning by filter value

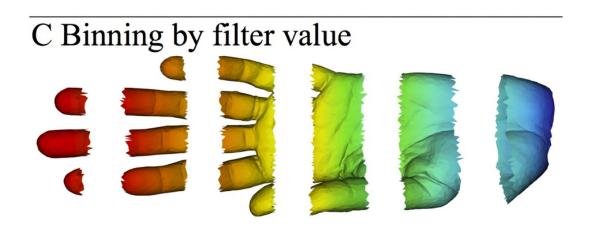


Put data into overlapping bins.

Example:  $f^{-1}(a_i, b_i)$ 



### D) Cluster each bin



D) Cluster each bin

& create network.

Vertex = a cluster of a bin.

Edge = nonempty intersection between clusters

A Original Point Cloud



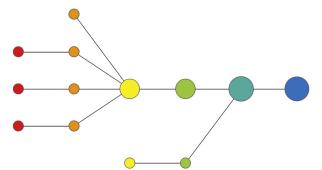
B Coloring by filter value



C Binning by filter value



D Clustering and network construction



### A) Data Set

Example: Point cloud data representing a hand.

B) Function f: Data Set  $\rightarrow$  R

Example: x-coordinate

 $f:(x, y, z) \rightarrow x$ 

C) Put data into overlapping bins.

Example:  $f^{-1}(a_i, b_i)$ 

D) Cluster each bin & create network.

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# Note: we made many, many choices

It helps to know what you are doing when you make choices, so collaborating with others is highly recommended.

## A Original Point Cloud

We chose how to model the data set

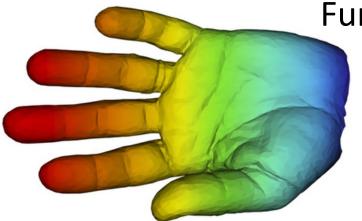


A) Data Set

Example: Point cloud data

representing a hand.

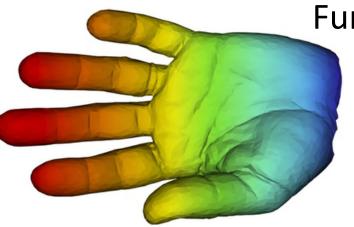
Chose filter function



Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate

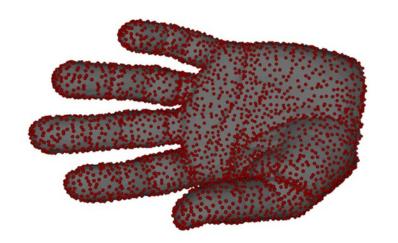
Chose filter function



Function  $f: Data Set \rightarrow \mathbf{R}$ 

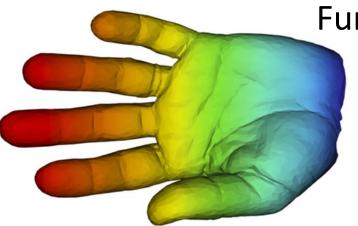
Ex 1: x-coordinate

 $f:(x, y, z) \rightarrow x$ 



Ex 2: y-coordinate

Chose filter function



Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate

 $f:(x, y, z) \rightarrow x$ 

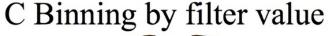
### Possible filter functions:

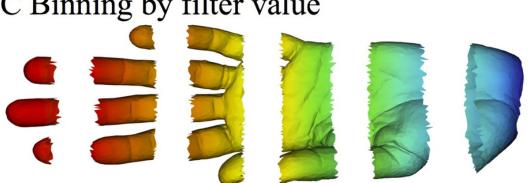
Principle component analysis

L-infinity centrality:

 $f(x) = max\{d(x, p) : p in data set\}$ 

Norm: f(x) = ||x|| = length of x





### Chose bins

Put data into overlapping bins.

Example:  $f^{-1}(a_i, b_i)$ 

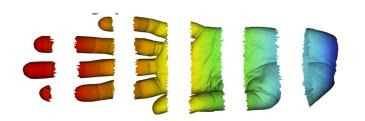
If equal length intervals:

Choose length.

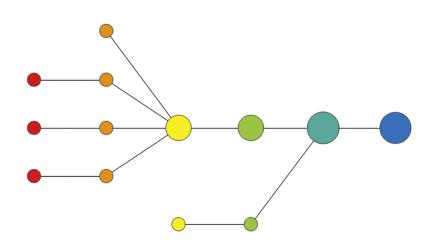
Choose % overlap.

# Chose how to cluster.

Normally need a definition of distance between data points



D Clustering and network construction



Cluster each bin & create network.

Vertex = a cluster of a bin.

Edge = nonempty intersection between clusters

# Note: we made many, many choices

It helps to know what you are doing when you make choices, so collaborating with others is highly recommended.

### Note: we made many, many choices

"It is useful to think of it as a camera, with lens adjustments and other settings. A different filter function may generate a network with a different shape, thus allowing one to explore the data from a different mathematical perspective."

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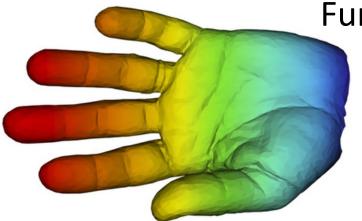
False positives???

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"It is useful to think of it as a camera, with lens adjustments and other settings. A different filter function may generate a network with a different shape, thus allowing one to explore the data from a different mathematical perspective."

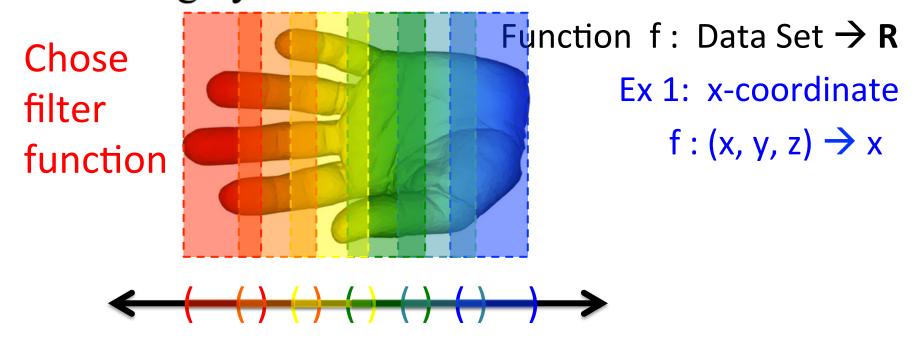
# False positives vs Persistence

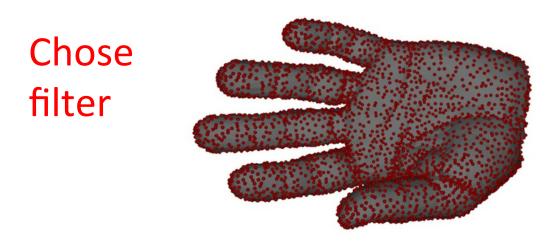
Chose filter function



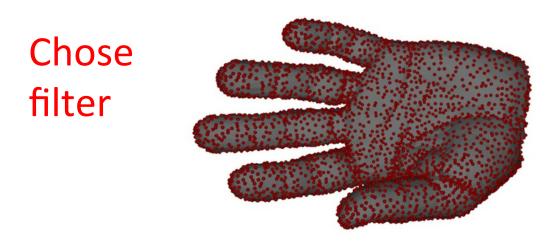
Function  $f: Data Set \rightarrow \mathbf{R}$ 

Ex 1: x-coordinate

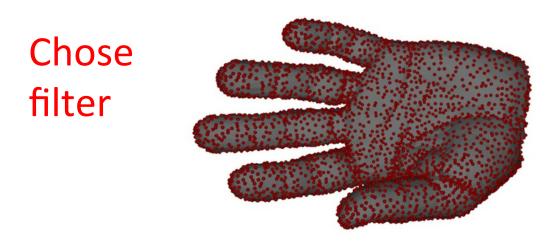




Only need to cover the data points.

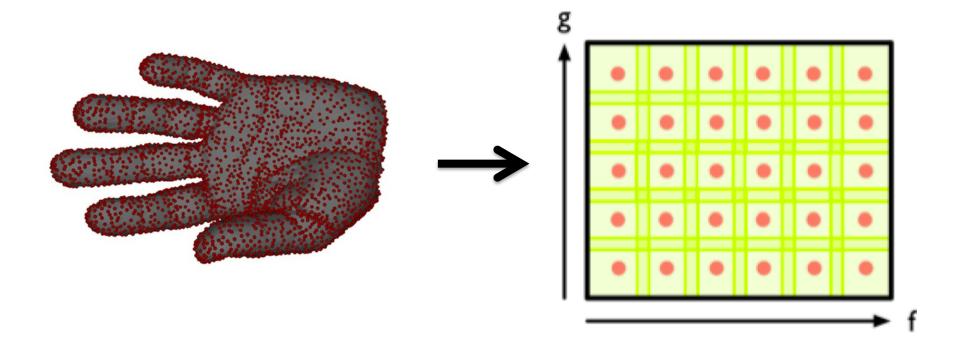


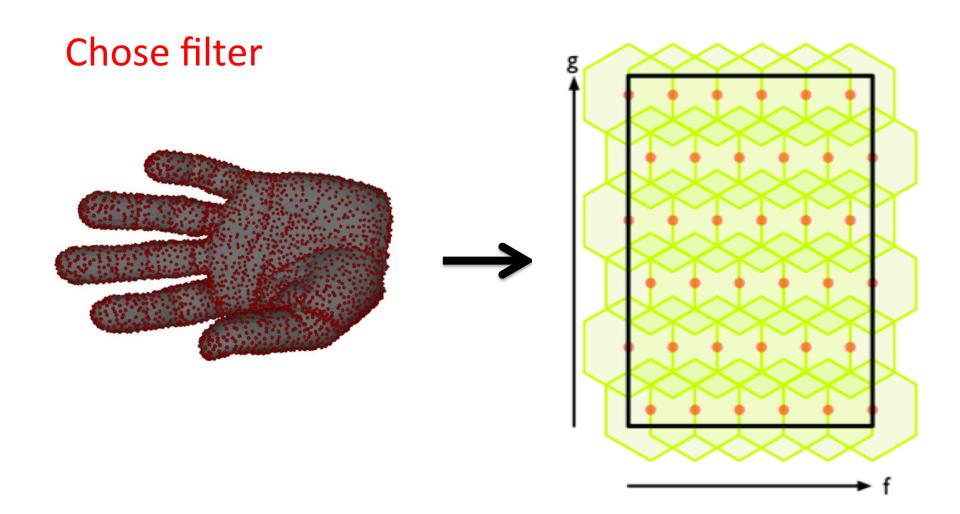
Only need to cover the data points.



Only need to cover the data points.

### Chose filter





Topological Data Analysis (TDA): Three key ideas of topology that make extracting of patterns via shape possible.

### 1.) coordinate free.

- No dependence on the coordinate system chosen.
- Can compare data derived from different platforms
- vital when one is studying data collected with different technologies, or from different labs when the methodologies cannot be standardized.

Topological Data Analysis (TDA): Three key ideas of topology that make extracting of patterns via shape possible.

### 2.) invariant under "small" deformations.

less sensitive to noise

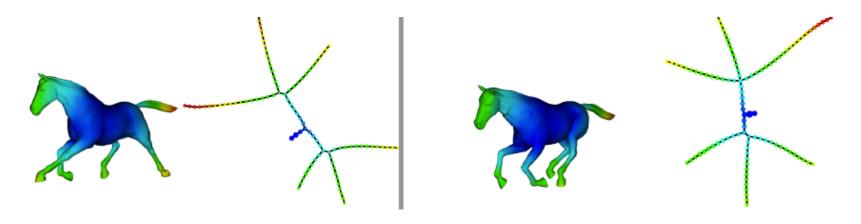


Figure from http://comptop.stanford.edu/u/preprints/mapperPBG.pdf http://www.nature.com/srep/2013/130207/srep01236/full/srep01236.html

Topological Methods for the Analysis of High Dimensional Data Sets and 3D Object Recognition, Singh, Mémoli, Carlsson Topological Data Analysis (TDA): Three key ideas of topology that make extracting of patterns via shape possible.

- 3.) compressed representations of shapes.
- Input: dataset with thousands of points
- Output: network with
   13 vertices and 12 edges.

A Original Point Cloud



B Coloring by filter value



C Binning by filter value

D Clustering and network construction

