Persistent Homology for Characterizing Stimuli Response in the Primary Visual Cortex

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The big questions

- How do we turn sensory stimuli into information?
  - Anatomy helps, but only so much,
  - Could lead to better computer models

- How is this information transmitted and represented
  - Networks in the brain
Vision is an Exemplar

- Brain is modular
  - Thresholding, linear filtering e.g. happen everywhere
  - Networking patterns, particularly dynamic rearrangement, should be common across brain regions
- We can probe it with well understood stimuli
  - 2-D pictures make great matrices!
- Computer Vision is a mature field with similar challenges
  - e.g. edge detection, object permanence
Neurons

- Neurons signal to other neurons with action potentials (spikes)

- Neurons have a receptive field that determines what stimuli cause a response

Image Credit: Wikimedia Commons
Early visual system

- It’s all just image processing!
  - (not quite)

- Mostly feed-forward

- Neurons farther from the retina select for more specific stimuli, up to individual faces
  - Jennifer Aniston neurons

Image Credit: Wikimedia Commons
Primary Visual Cortex (V1)

- Orientation Selectivity
- Edge Detection
- ?
  - Most other regions send signals back to V1
Networks in V1: Hubel Weisel Model

Circuit Building a Simple Cell from LGN Cells

Building a Complex Cell from Simple Cells

Image Credit: Callaway Lab, The Salk Institute
Identifying simple vs. complex cells

- Striate Location
- Phase invariance to a sinusoidal grating

Simple

Complex

Image Credit: Albert Lab; Loyola University Chicago
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Our Data

- 311 neurons, 330 time points, 55 repetitions

- Natural scenes or Gaussian white noise

- 30ms bins
  - Bins are interpolated as binary
Classifying Spike Trains

- In experimental settings, cells make spikes, not continuous response
- Classify cells based on the bimodal distribution of the F1/F0 response
  - F1: Response rate
  - F0: Mean Spike Rate
In experimental settings, cells make spikes, not continuous response.

Classify cells based on the bimodal distribution of the F1/F0 response:
- F1: Response rate
- F0: Mean Spike Rate
- This doesn’t easily extend to natural scenes
  - Characterization tends to be very high variance

- Conversion from intracellular voltage to neural spikes is nonlinear, so bimodality is misleading

- Could also be unimodal if peaks are low and high-gain limits of the same basic circuit
  - (Mechler and Ringach, 2002)
So now what?

- Need more methods to characterize neural response from spike train data

- Need to be able to use as much old data as possible
  - Slow (active time, approval)
  - Expensive!

- Need to be resistant to noise
  - Experimental work is messy
Persistent Homology

- Developed by Gunnar Carlsson’s Lab at Stanford
- Used for gene networks, image analysis, computer vision, and many other applications
  - Good for general purpose data analysis
  - Allows us to make comparisons across non-linearly related data
- Independent of coordinate space
  - Can we use it across animals?
- Resistant to deformation
  - Noise resistant!
Getting from Data to Topology

- Create a distance matrix from your data
  - Set a threshold
- Construct an abstract simplicial complex using a Delaunay triangulation
  - Simplice: n-D triangle
  - Simplicial complex: n-D triangulations
- We use a Witness complex for computation speed
  - javaplex package from Carlsson Lab
- Calculate homology across complex (varying $\varepsilon$), and see what rank (Betti number) persists

Image Credit: Top: Chambers 2008; Bottom: Jonathon Puckey: “Delaunay Raster” series
Calculating Persistent Homology

First-order Betti Number

Second-order Betti Number

Third-order Betti Number
Calculating Persistent Homology

First-order Betti Number

Second-order Betti Number

Third-order Betti Number

Noise
Calculating Persistent Homology

First-order Betti Number

Second-order Betti Number

Third-order Betti Number

Persistent

Noise
Connecting the Dots

Image Credit: Singh et al.
Some Pretty Pictures

<table>
<thead>
<tr>
<th>Noise</th>
<th>Cell #</th>
<th>Natural</th>
</tr>
</thead>
<tbody>
<tr>
<td>gm946_1</td>
<td>gm950_1</td>
<td>gm883_4</td>
</tr>
</tbody>
</table>

[Table of images showing different cell types and labels.]
Natural Scenes

**Histogram of Betti Numbers from Movie Stimuli**

The graph shows the distribution of first-order Betti numbers for natural stimuli and noise stimuli. The x-axis represents the first-order Betti number, ranging from 0 to 25, and the y-axis shows the number of neurons. The red bars represent natural stimuli, while the green bars represent noise stimuli. The histogram indicates a higher density of neurons in the lower Betti number ranges for natural stimuli compared to noise stimuli.
Grating responses

Sinusoidal Grating Response Ratios for V1

$F_1 / F_0 = 1$
A better look at Simple vs. Complex

Histogram of Betti Numbers from Natural Stimuli

Complex mean: 4.4
Simple mean: 7.7

Histogram of Betti Numbers from Noise Stimuli

Complex mean: 2.0
Simple mean: 6.7
Randomness yields nothing
Some Take-Aways

- Noise stimuli doesn’t probe the full feature space, as expected

- Betti numbers support the theory of high invariance for complex cells

- Dimensionality of spike trains is consistently very low
Future Directions

- Comparisons of response topology to topology of natural scenes
- Dynamic homology calculation
- Data from other areas (particularly LGN)
- Comparison to other scale-free methods such as attractor models
Acknowledgements

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Does time matter?