

Continuous and discrete dynamic topology

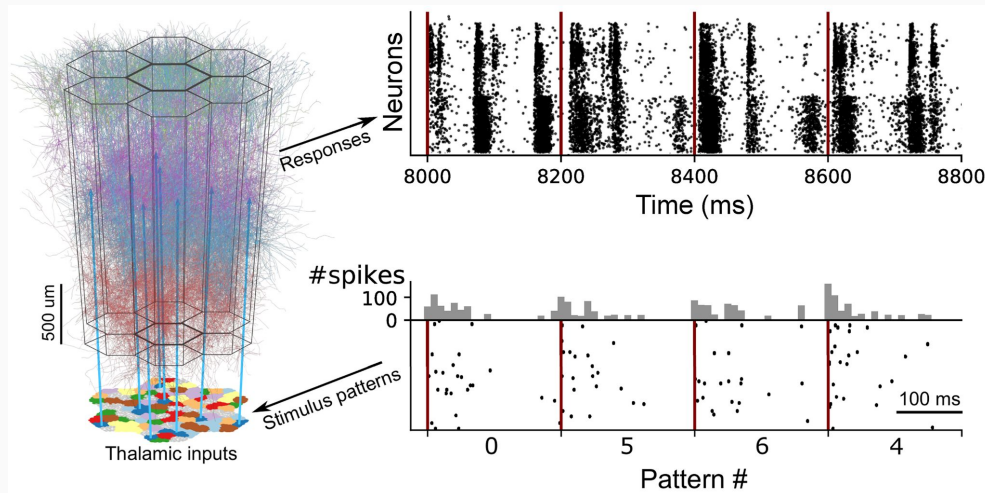
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Discrete dynamics in topology

How can topology help local binary dynamics classify global dynamics?



University of Aberdeen, Neuro-Topology group

- Ran Levi
- Jason Smith
- Henri Riihimäki
- Dejan Govc
- Pedro Rodrigues da Conceição
- Dejan Govc

EPFL, Blue Brain Project

- Kathryn Hess
- Daniela Egas Santander
- Michael Reimann
- Matteo Santoro
- Andras Ecker
- Vishal Sood
- Sirio Bolanos-Pouchet
- Nicolas Ninin
- ...

BlueBrain V5 connectome

Layer structure

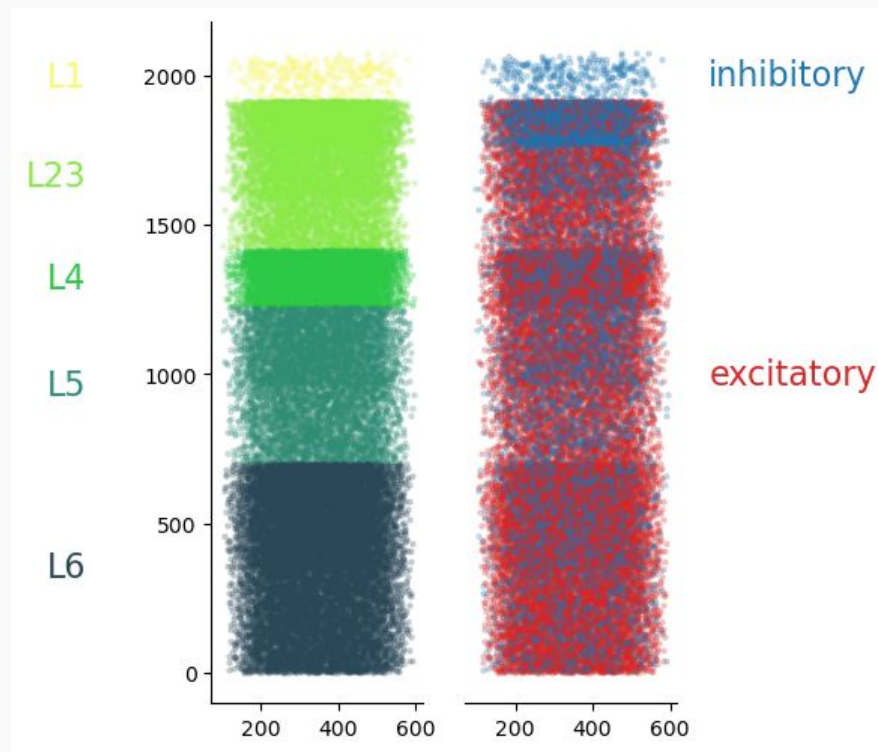
- Higher (L1) = inhibition
- Lower (L6) = information processing

Neuron characteristics

- 31346 in total
- 55 electro-morphological classes

Other facts

- Diameter is 4
- High dimensional simplices are over-represented
- Reciprocal connections preferentially appear in high-dimensional simplices



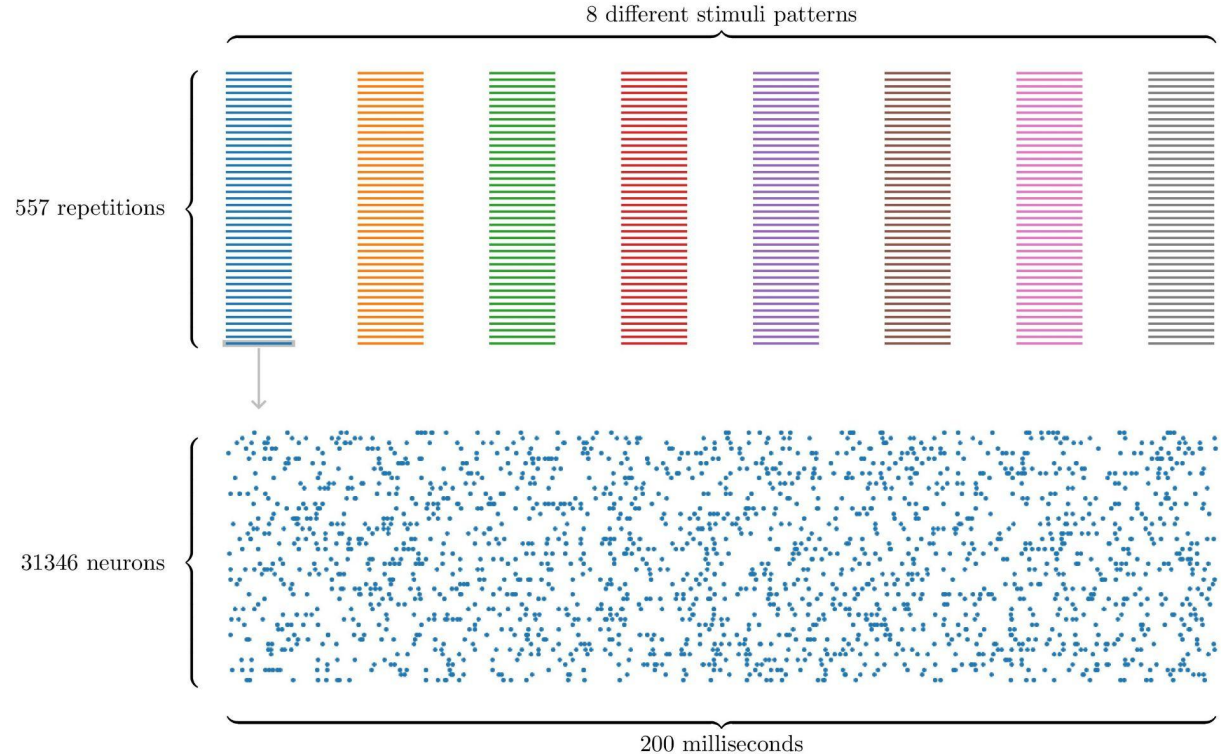
Activity

Stimulated activity

Reconstruction is stimulated from an “at rest” state.

Transmission is probabilistic, response can not be predicted

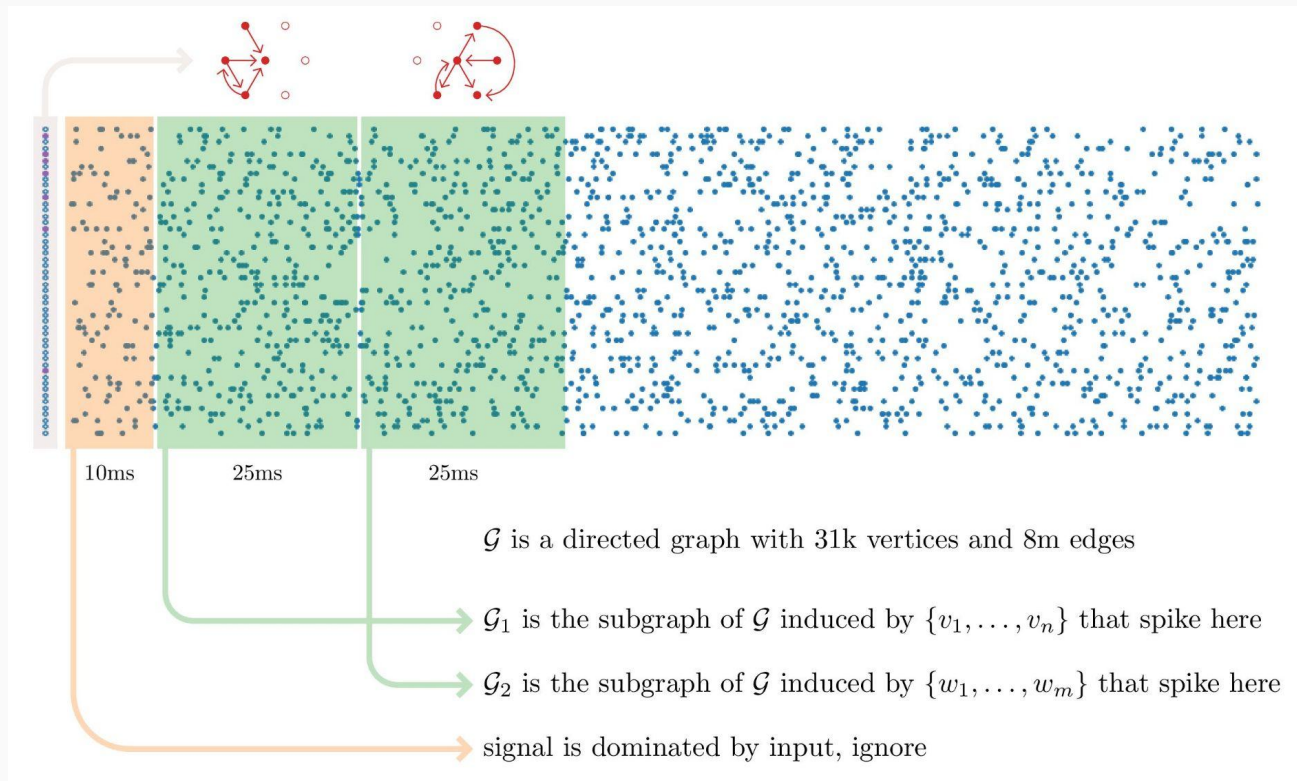
Every spike index and time is recorded



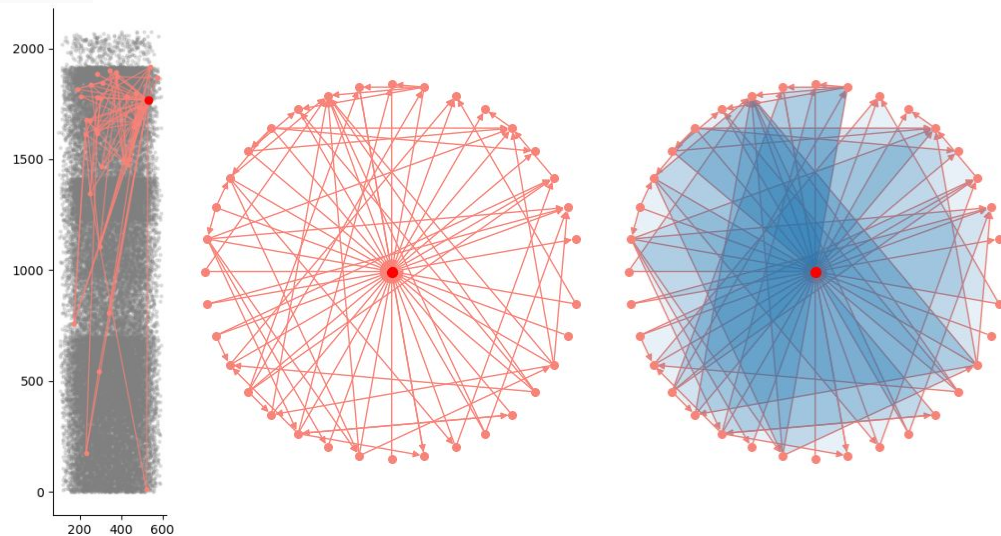
Activity extraction

Extracting features

1. Consider two “active subgraphs” of the full graph for each repetition
2. Consider two “active neighbourhoods” of N vertices in the active subgraph
3. Assign a numerical value to every active neighbourhood



Parameters



Used to:

- select $N=50$ neighbourhoods
- assign numerical values to active neighbourhoods

clustering coefficient	<i>Fagiolo (2007) generalizing Watts–Strogatz (1998) to digraphs</i>	0.043
transitive clustering coefficient	<i>ratio of all 3-cliques at v to all possible 3-cliques at v</i>	0.051
neighbourhood size	<i>size of closed neighbourhood</i>	36
number of reciprocal connections	<i>add 1 if $u \rightarrow v$ and $v \rightarrow u$ both exist</i>	1
adjacency spectral gap	<i>eigenvalues of adjacency matrix</i>	1
Chung Laplacian spectral gap	<i>of largest strongly connected component</i>	0.5
transition probability spectral gap	<i>eigenvalues of transition probability matrix</i>	0.707
Euler characteristic	<i>alternating sum of Betti numbers</i>	1
normalized Betti coefficient	<i>weighted sum of Betti numbers, weighted by dimension d and number of d-simplices</i>	0.027
density coefficients	<i>ratio of $(d+1)$-cliques to d-cliques, normalised to be 1 on complete graphs</i>	{0.028, 0.02, 0, 0}

Overview: the “pipeline”

1. **Select neighbourhoods:**

Compute graph / topological parameters for all neighbourhoods, select top $N=50$ by parameter P_1 value

2. **Measure active neighbourhoods:**

For each selected neighbourhood, compute parameter P_2 value on each of $B=2$ active subgraphs

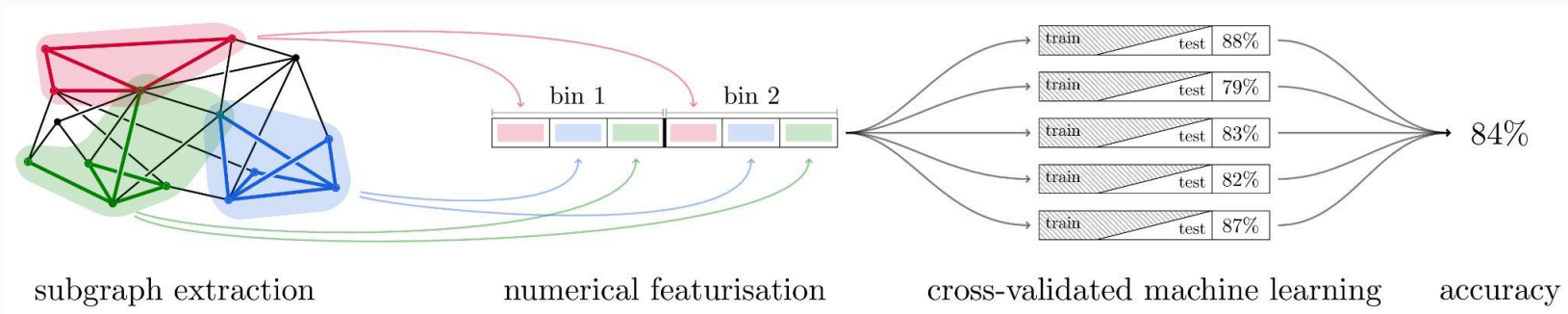
3. **Classify with measurements as feature vectors**

Length of feature vector is $N \cdot B$, number of feature vectors is $(8 \text{ signals}) \cdot (557 \text{ repetitions})$

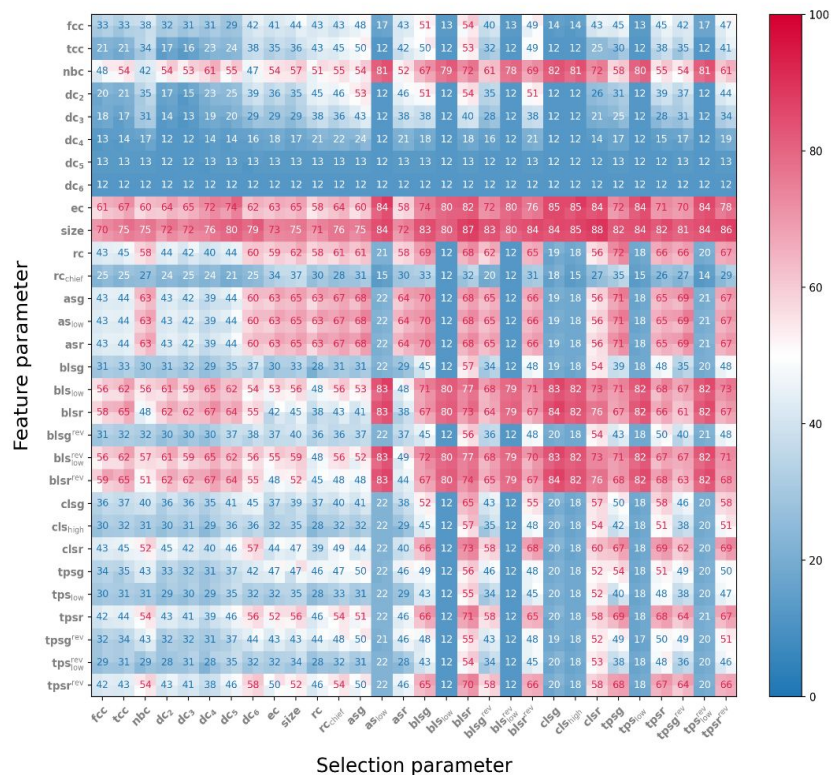
Classify with support vector machines (SVM) with 60/40 train/test five different ways

4. **Validate with baseline results**

Random measurements, random neighbourhood choices, random ambient graph



Results and extensions



Classification accuracy of ~88% when:

- selecting by a **spectral** parameter
- featurising by neighbourhood **size**

Observations:

- Active neighbourhood size is firing rate
- Euler characteristic is a good classifier
- Density coefficients not useful

Development:

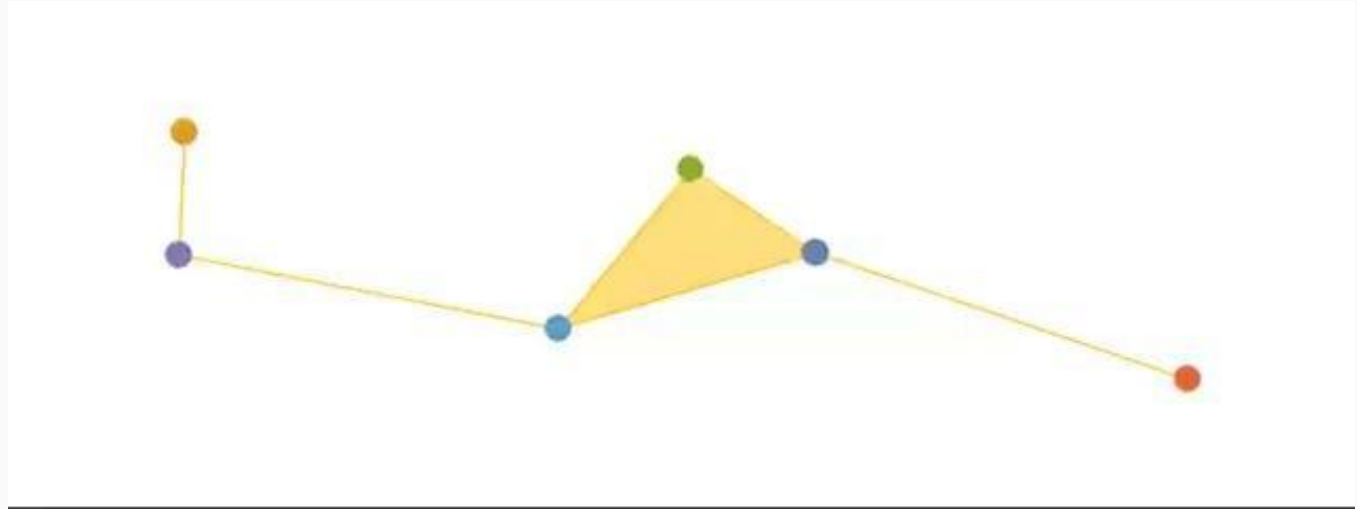
- github repo for easy parameter measurement
- Double selection for better results

Continuous dynamics in topology

How can spatial change be quantified as topological change?

Assumptions:

- Euclidean space
- Linear paths
- Unique locations
- Times with pairwise equal distance are measure zero



Barbara Giunti, *TU Graz*

David Millman, *Montana State University*

Zigzags of simplicial maps

Movement as algebra

- Fix a radius
- Every pair of points defines a quadratic distance function

Entering a parabola (left):

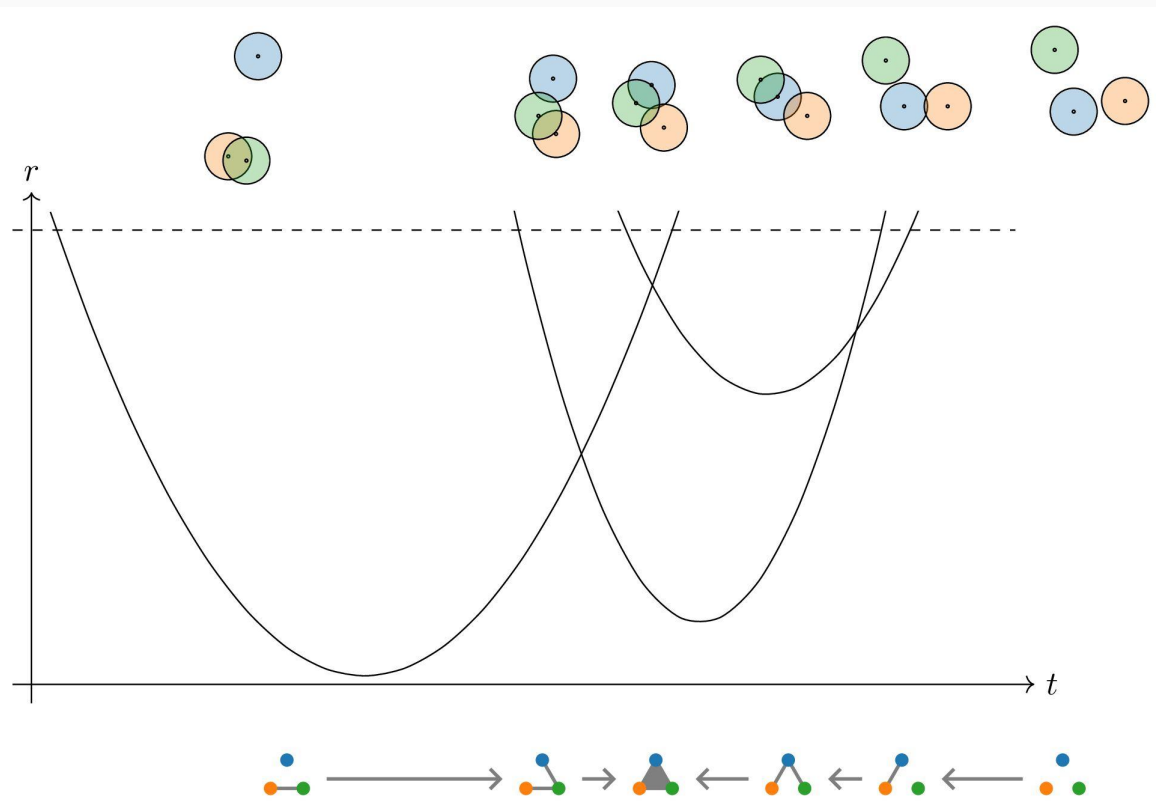
- adds an edge

Exiting a parabola (right):

- removes an edge

Motivation

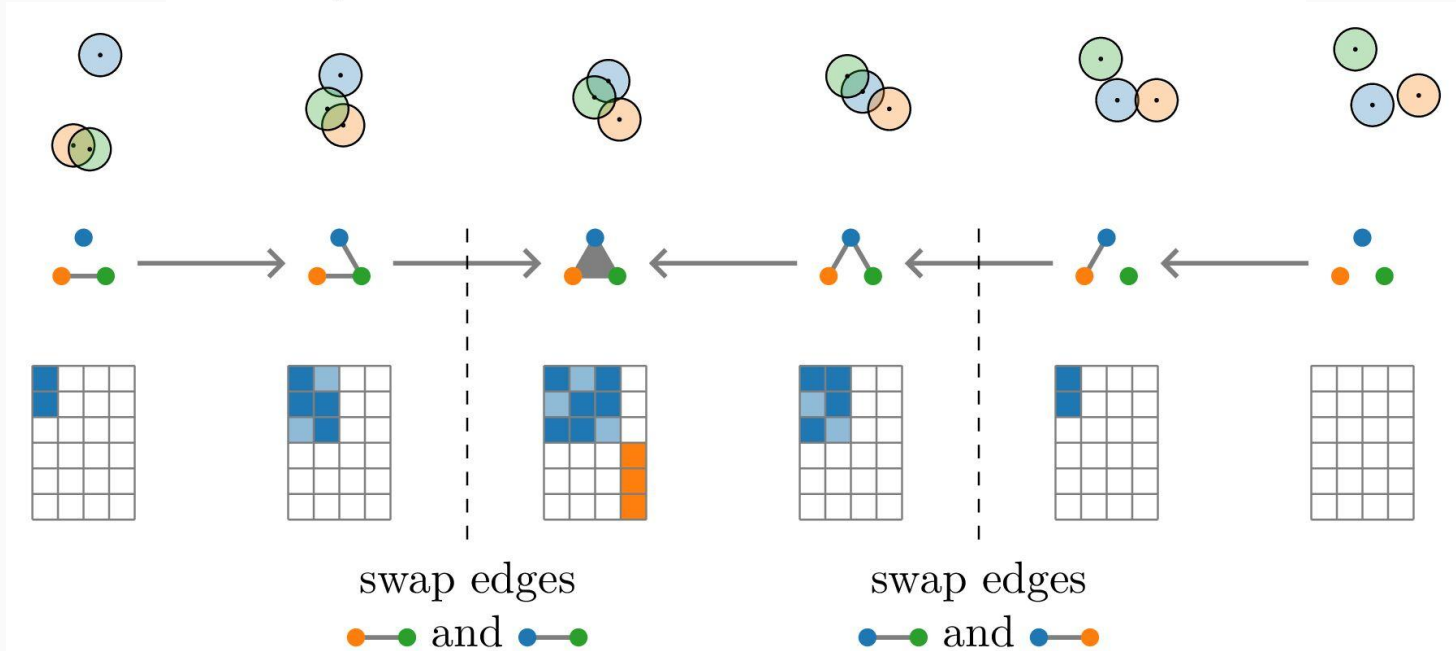
Recover later homology from earlier homology, without recomputing everything



The (un)reduced boundary matrix

The matrix B has one row for each simplex, arranged in increasing dimension and increasing entrance time:

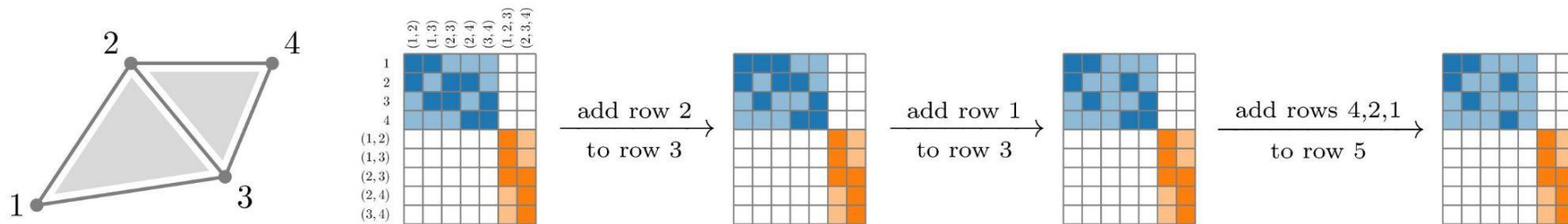
$$B_{i,j} = \begin{cases} 1 & \text{simplex of row } i \text{ is a face of simplex of column } j \\ 0 & \text{else} \end{cases}$$



* terminology

The reduction algorithm

Add earlier columns (in modulo 2) to later columns to ensure one pivot per row:



Gives a decomposition $R = BU$

- B is the (unreduced) boundary matrix
- U is an upper triangular matrix recording the column operations
- R is the reduced boundary matrix

Approach: Add / remove columns from R , use U to ensure removal keeps R reduced

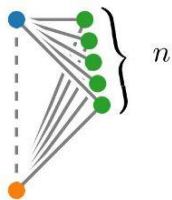
Adding a new edge

Adding a single edge can may have different consequences for:

- number of n -simplices
- number of classes in H_n

$|K_2|$ increases by n
 $|K_3|$ increases by $\binom{n}{2}$
 $|K_4|$ increases by $\binom{n}{3}$

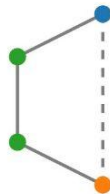
⋮



realized in \mathbf{R}^3

β_1 increases by 1
 β_2 unchanged
 β_3 unchanged

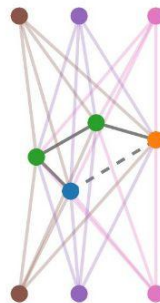
⋮



realized in \mathbf{R}^2

β_1 unchanged
 β_2 increases by n
 β_3 unchanged

⋮

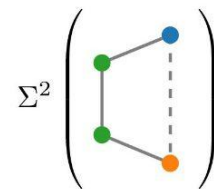


realized in $\mathbf{R}^{n \geq 4}$

β_1 unchanged
 β_2 unchanged
 β_3 increases by n

⋮

n copies of



identified at the equator

realized in $\mathbf{R}^{n \geq 5}$

Removing an existing edge

Removing a **positive** edge

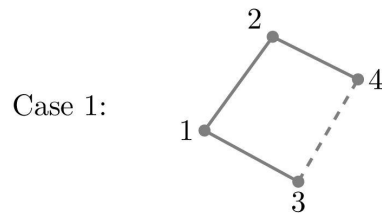
- its column is 0
- pivots in R won't change if this column is removed

Remove

- Row and column of edge
- Rows and columns of all cofaces

Clear:

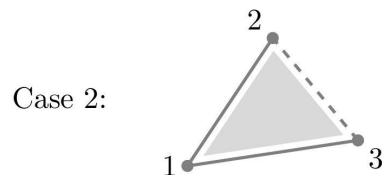
- **R after is still reduced**



R before



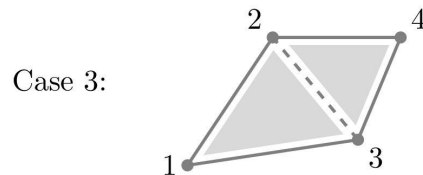
R after



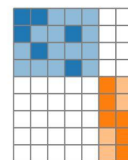
R before



R after



R before



R after



Removing an existing edge

Removing a **negative** edge

- its column is not 0
- pivots in R **may** change if this column is removed

Remove

- Row and column of edge
- Rows and columns of all cofaces

Almost clear:

- **R after is still reduced**

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