Topological analysis and deep learning of human speech data

Some of the most active areas of research in machine learning today are explainable AI and interpretable AI. In explainable AI, methods are developed to open up black boxes such as neural networks, while interpretable AI creates white box methods with possibly lower accuracy. Most progress in these areas has been empirical and rooted in computer science, but there is a growing body of literature that suggests fresh insights. They come from fields that are traditionally considered to be pure mathematics, including algebra, geometry, and topology. In this talk, we give an overview of topological approaches to analyzing time-dependent data, with applications to speech recognition as one of the essential components of AI. Leveraging a reciprocity between explainable and interpretable aspects, we further discuss work in progress towards designing topologically enhanced convolutional layers for deep learning speech and audio signals.

http://8.137.126.94/

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Yifei Zhu

Southern University of Science and Technology

2024.7.7

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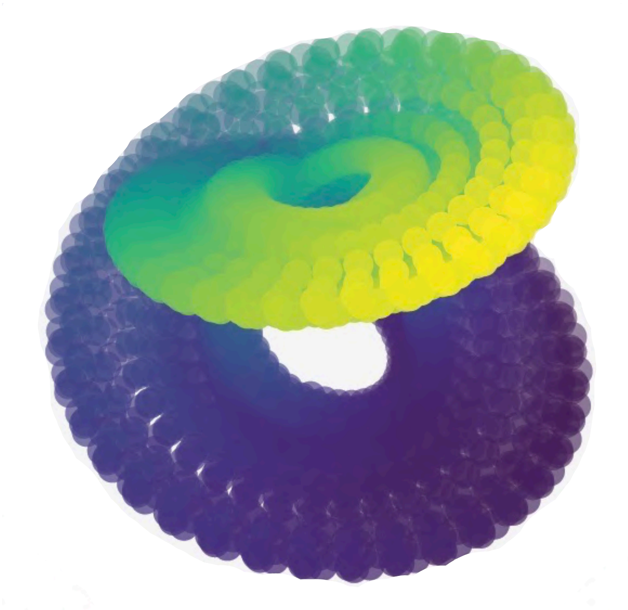

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Periodic phenomena: a motivating example

Let $\mathbb{T}^2 = (\mathbb{R}/\mathbb{Z})^2$ be the 2D torus. Consider the dynamical system given by

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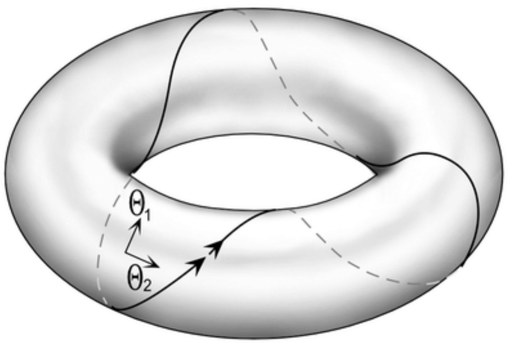

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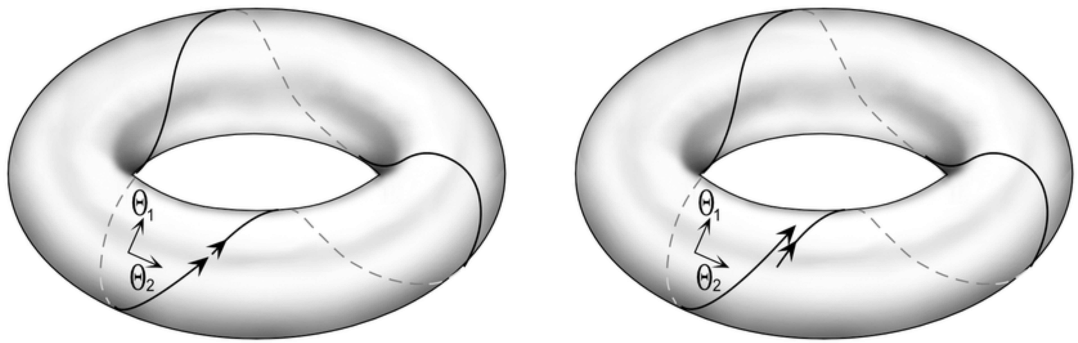

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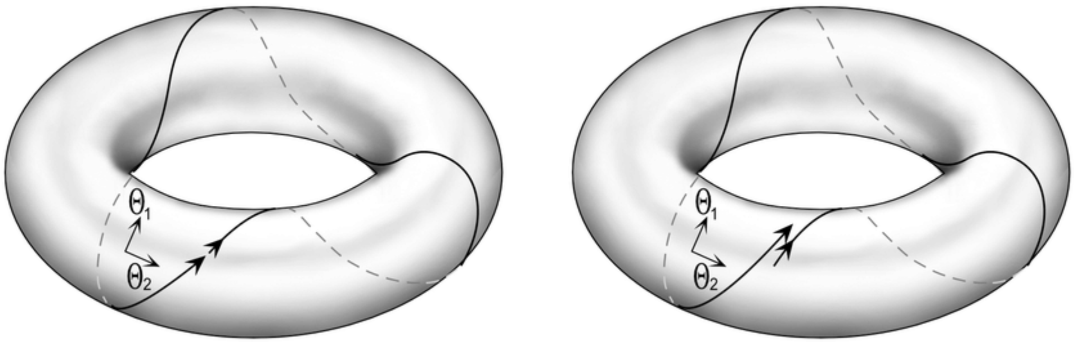

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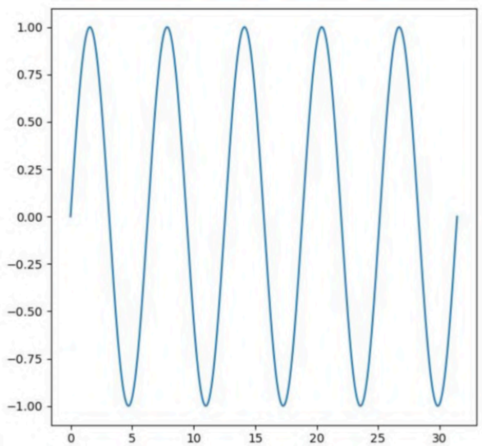
From time series to topological shapes

Most periodic time series can be realized by a topological circle S^1 embedded in a Euclidean space of higher dimension.

Ideas of topological data analysis (TDA)

The topological type (more precisely, homotopy type) is robust against perturbations.



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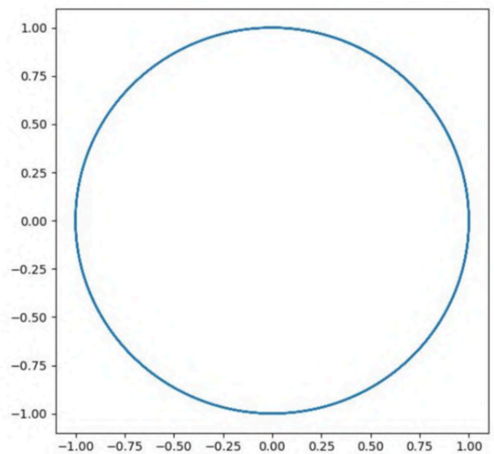

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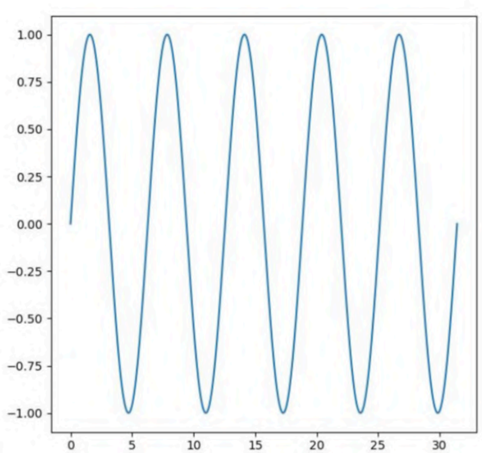

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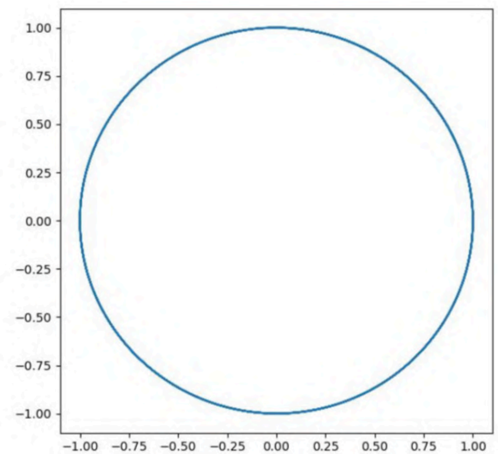
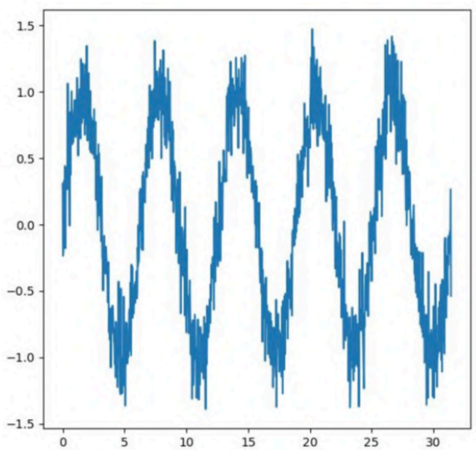
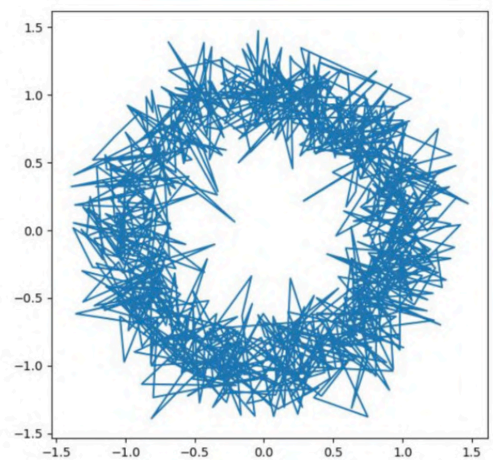




$y = \sin x + \epsilon(x)$



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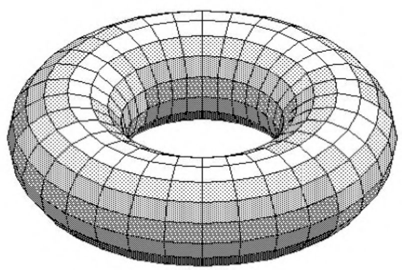

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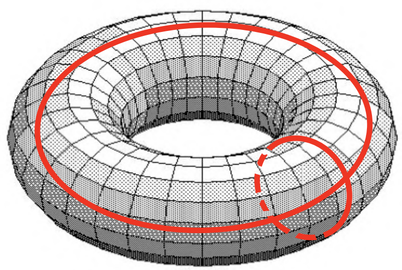

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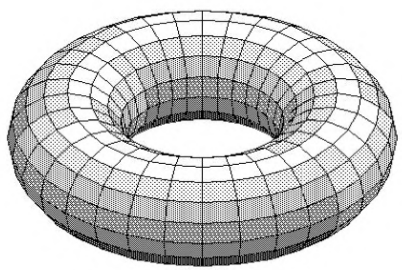

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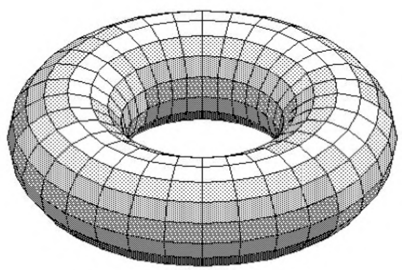

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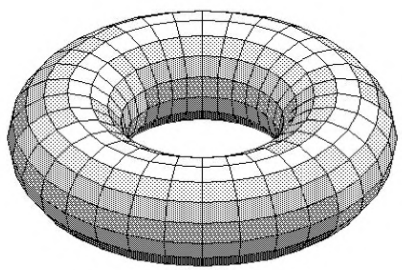

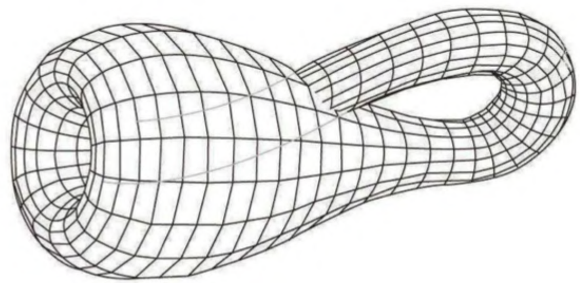

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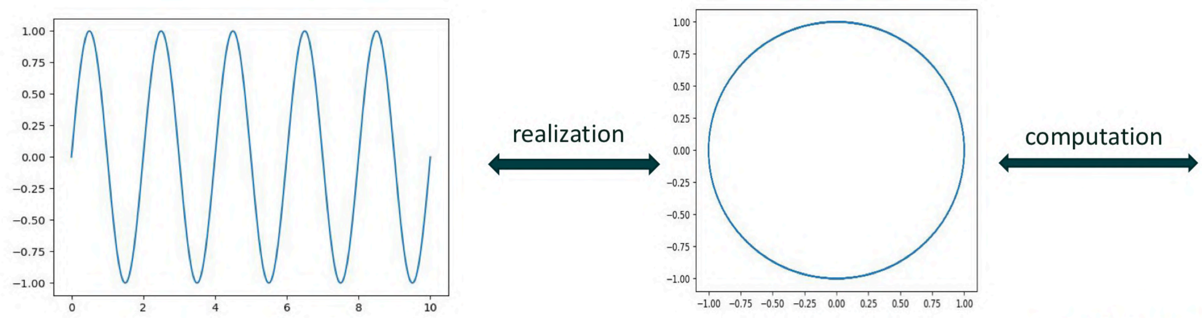

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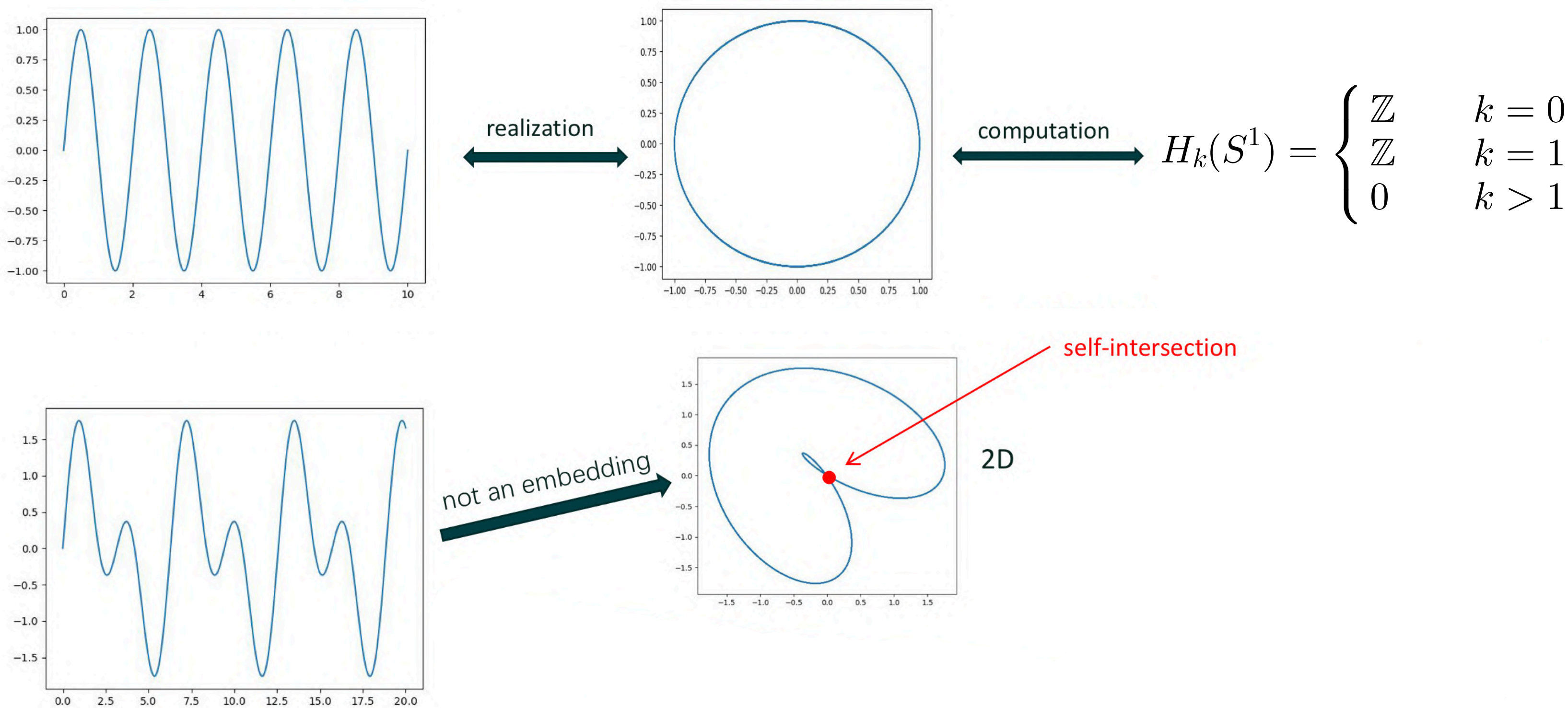

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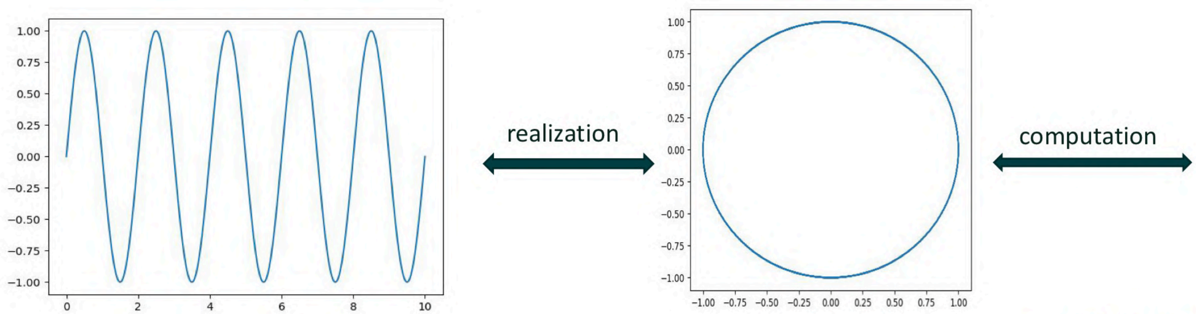

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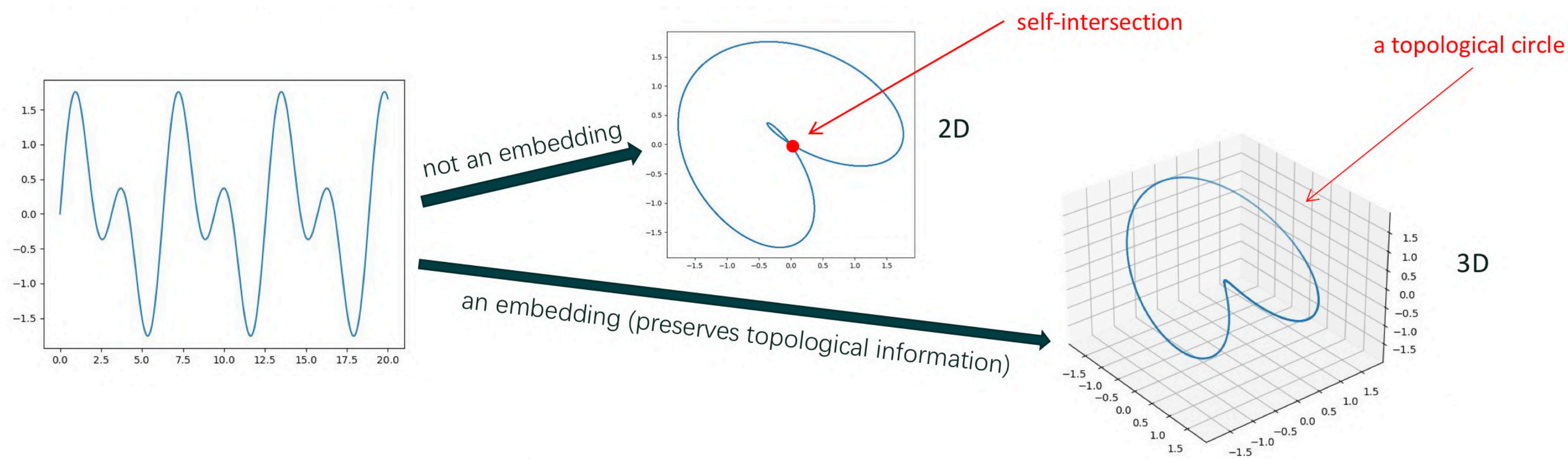

An application: detection of wheeze in medical science (pulmonology)

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As a warm-up, our research group (Siheng Yi) has reproduced their results using the original data and open-source TDA programming package.

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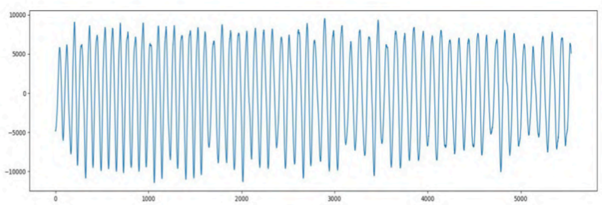
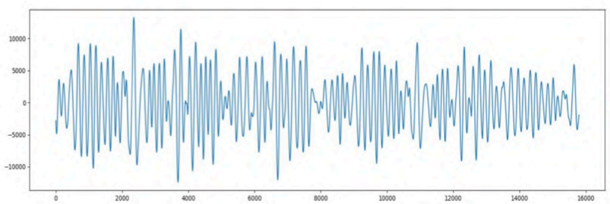
wheeze



normal



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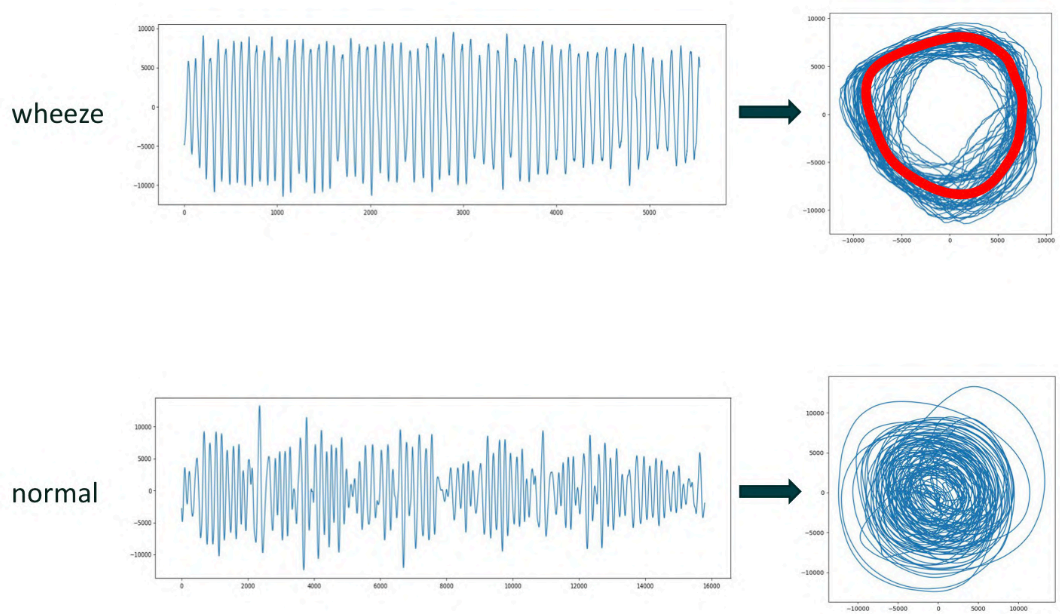

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Realized topological shapes embedded in 2D Euclidean space

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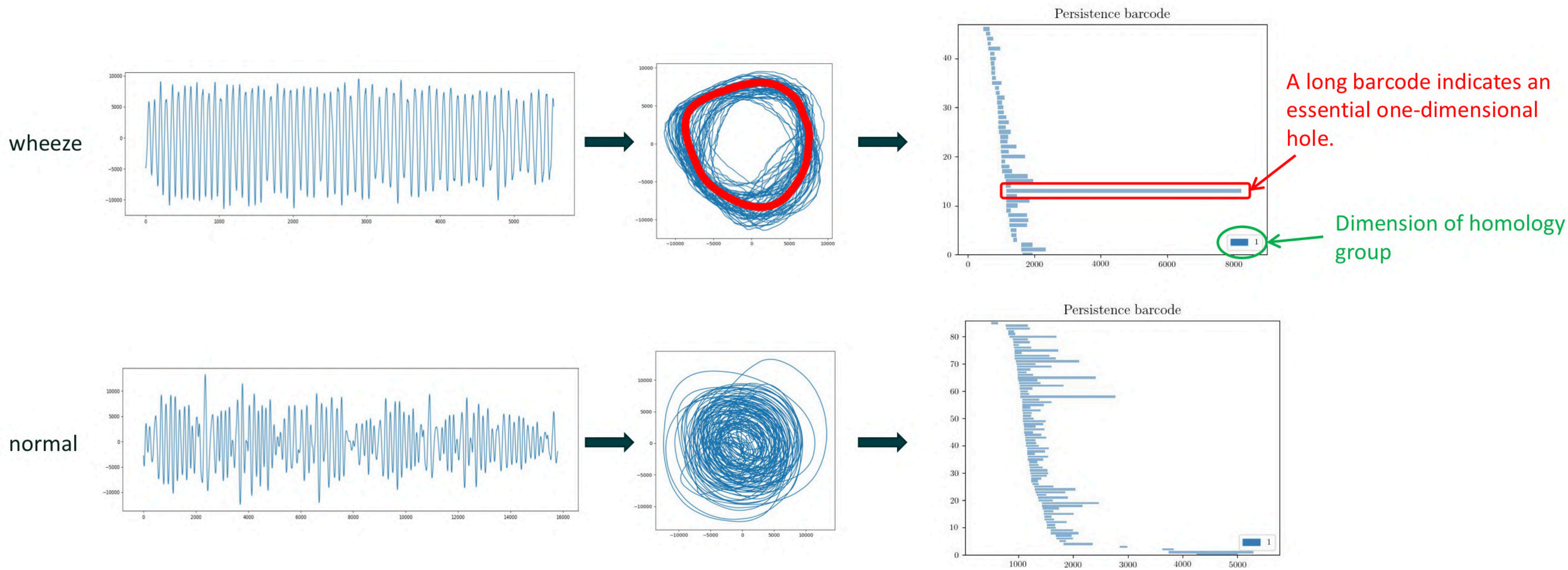

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Realized topological shapes embedded in 2D Euclidean space

“Persistence barcodes” as representations of the algebraic invariant (1D homology group)

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Time series data: $x_1, x_2, x_3, x_4, \ldots$

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Topological feature extraction → Persistent homology

Algebraic invariants: homology groups, persistence barcodes, ...

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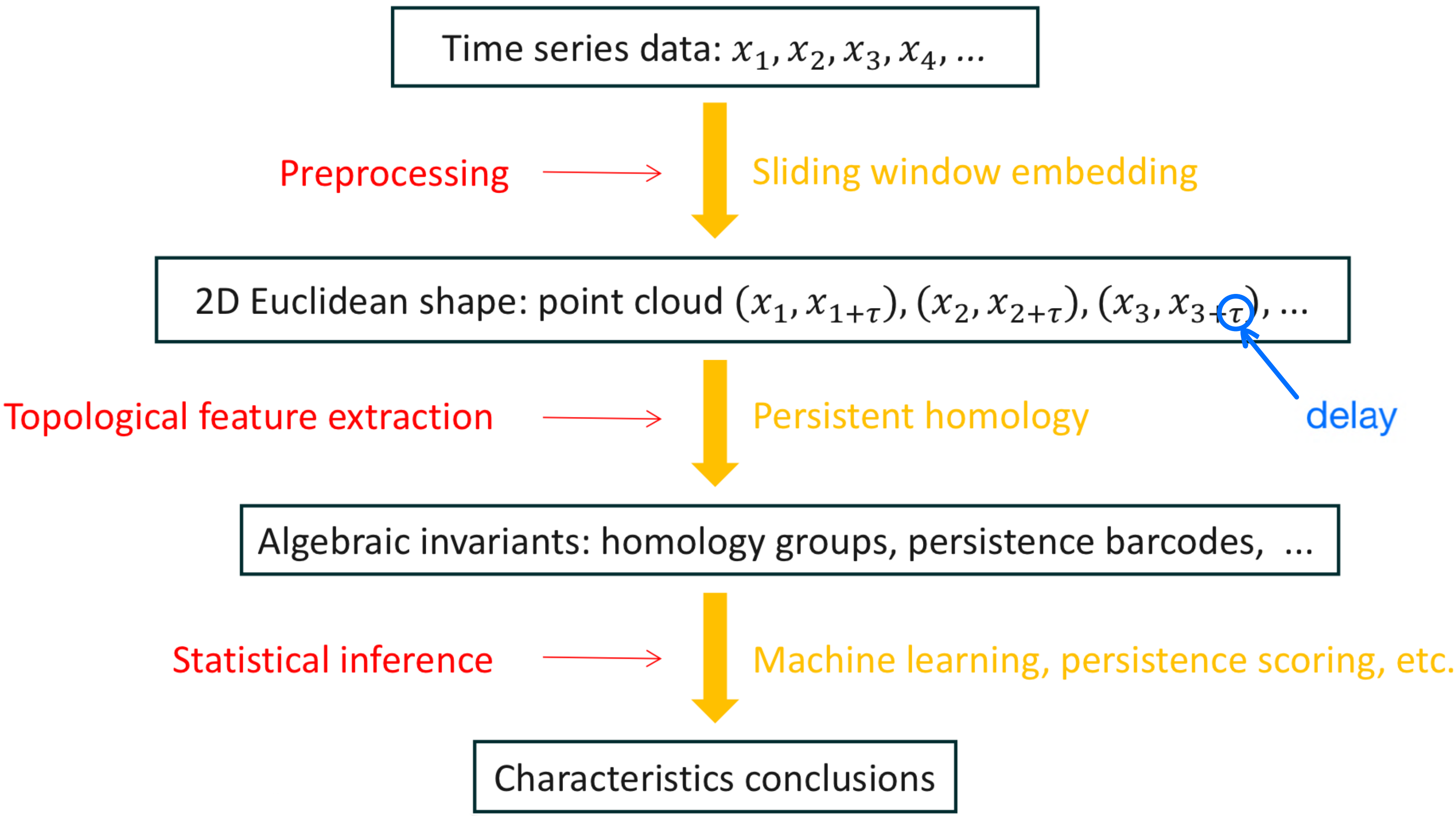

Application I: detection of mouse scratching behavior

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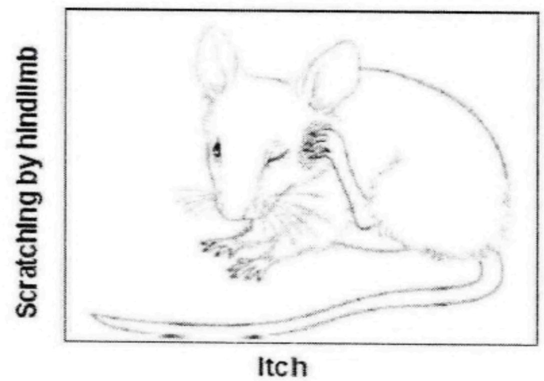

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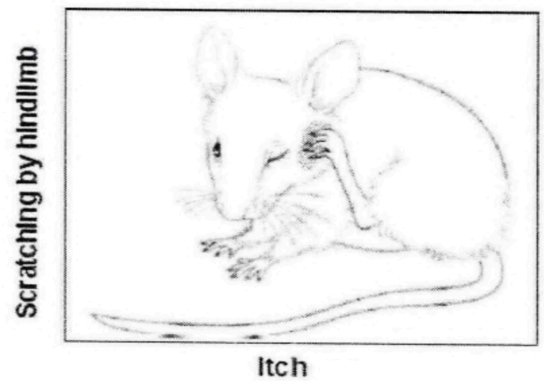

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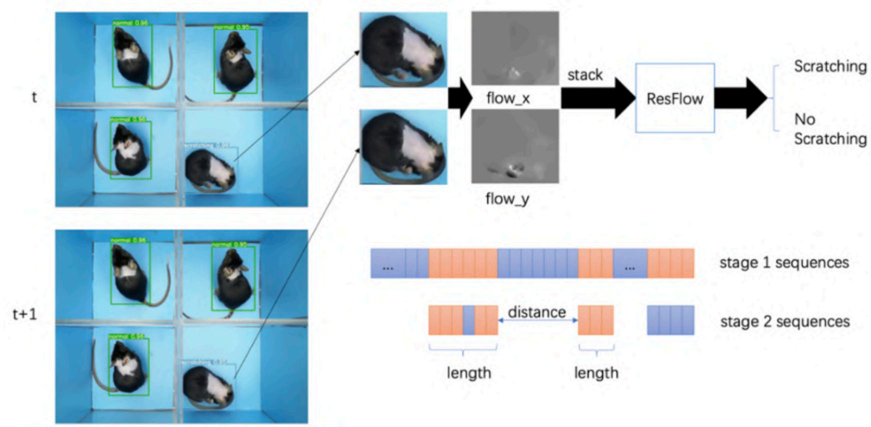

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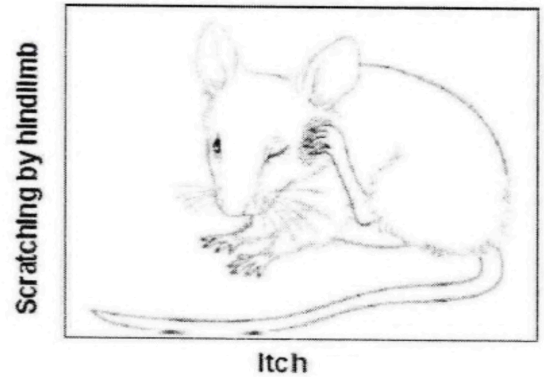

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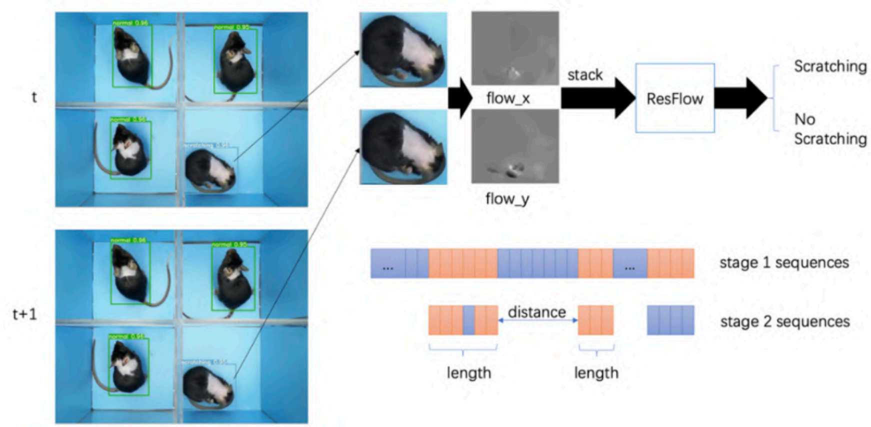

However, the learning process was time consuming, which is impractical for time-sensitive purposes and lab efficiency.

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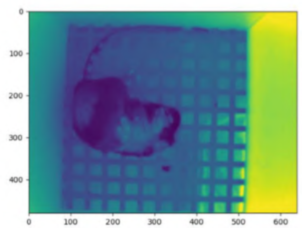
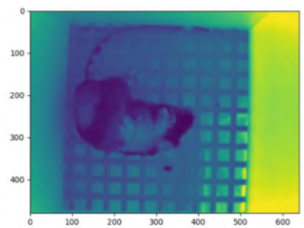
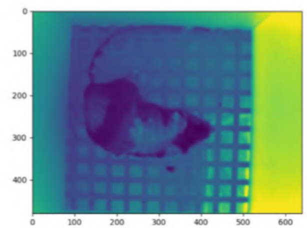
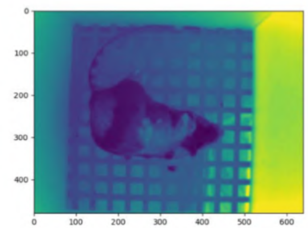

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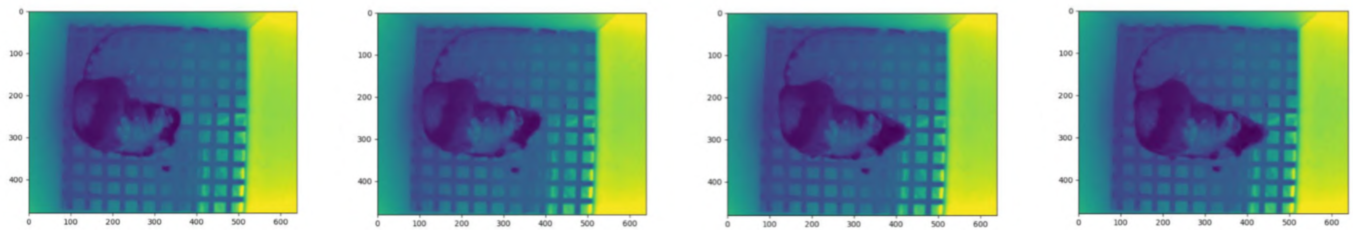

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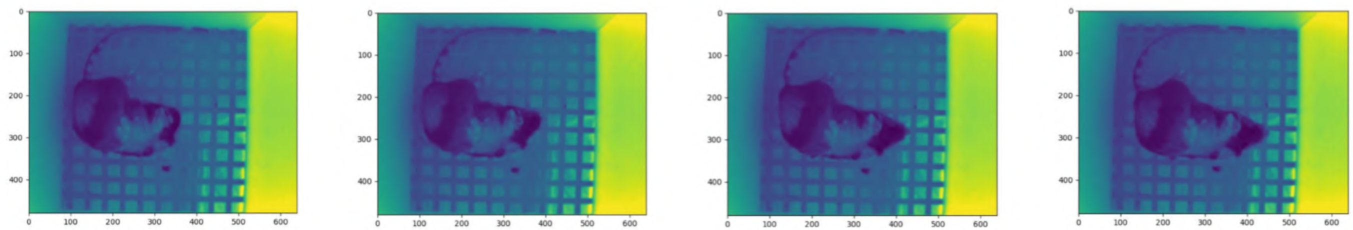
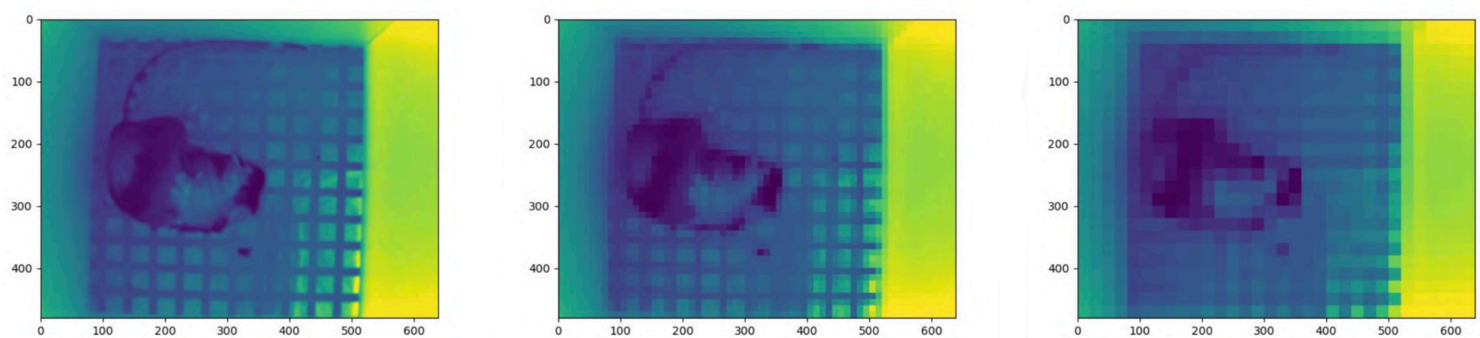


To resolve this issue, we adopted the following approaches:

Approach 1 Sum up all 460 x 640 pixels to extract a series of 1D data which ignores differences caused by global movements. Too coarse?

Approach 2 Blur the images by pooling, and feed the topological pipeline with reduced 100-dimensional data. Still too refined?



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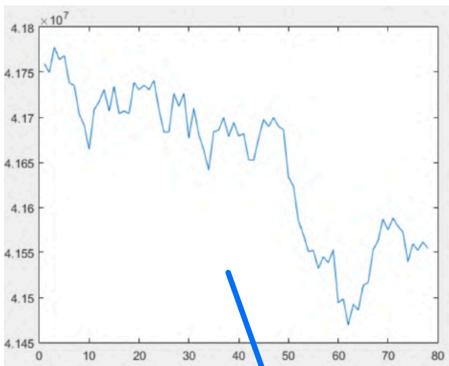
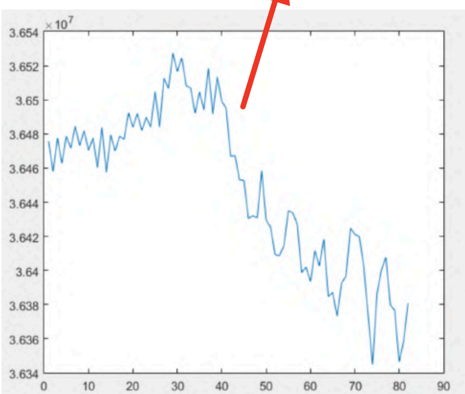


2 filtrations:

$$f' = f * K_3$$
$$f'' = f' - f' * K_7$$



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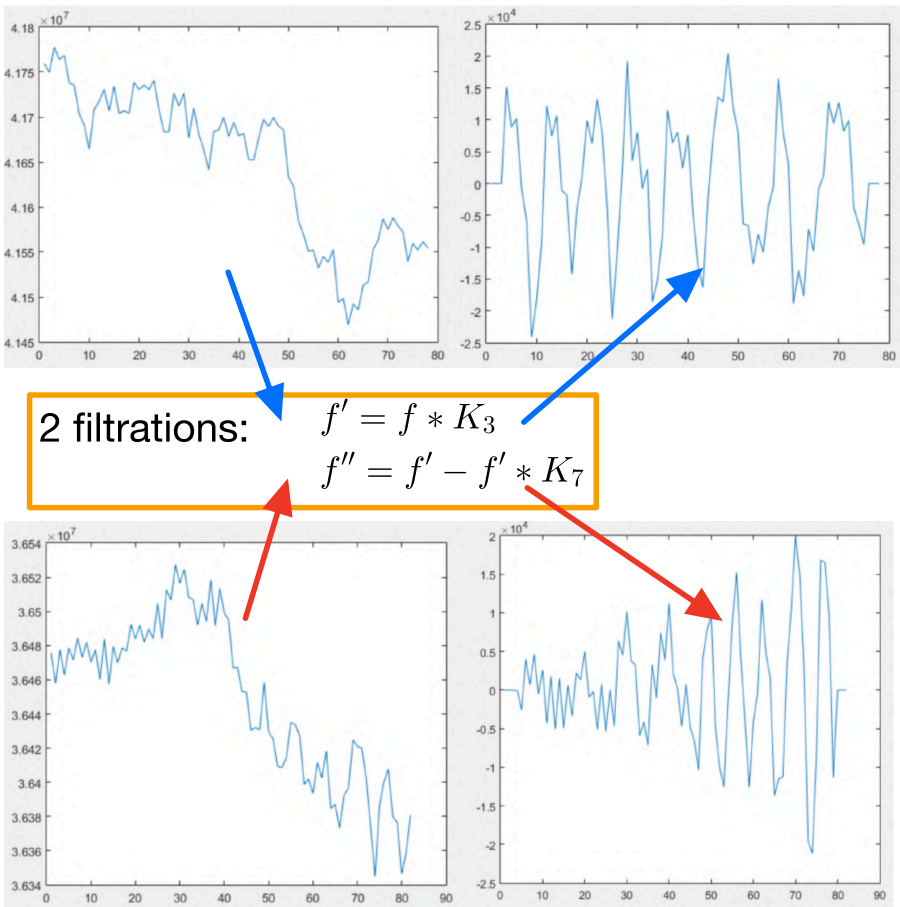

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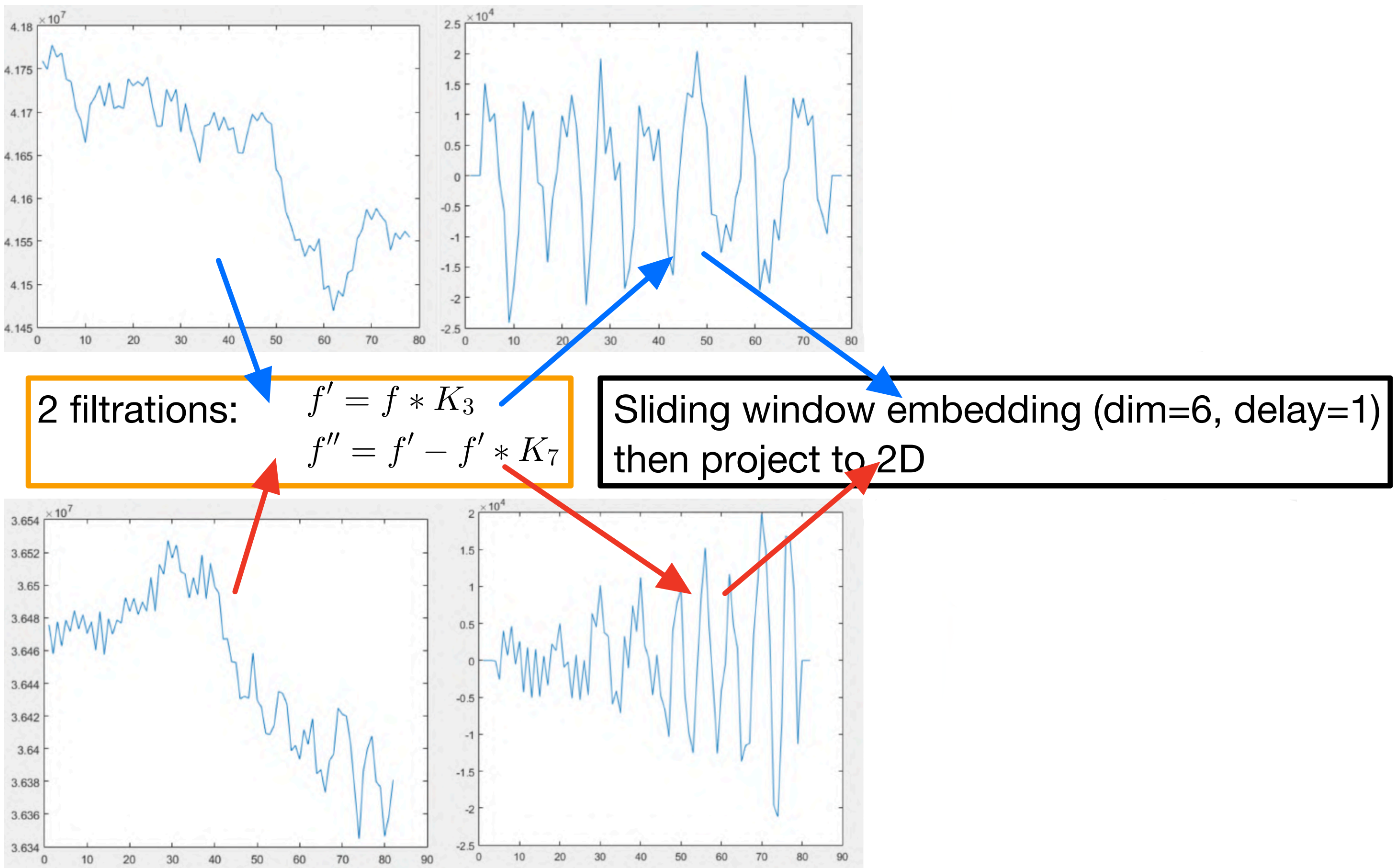

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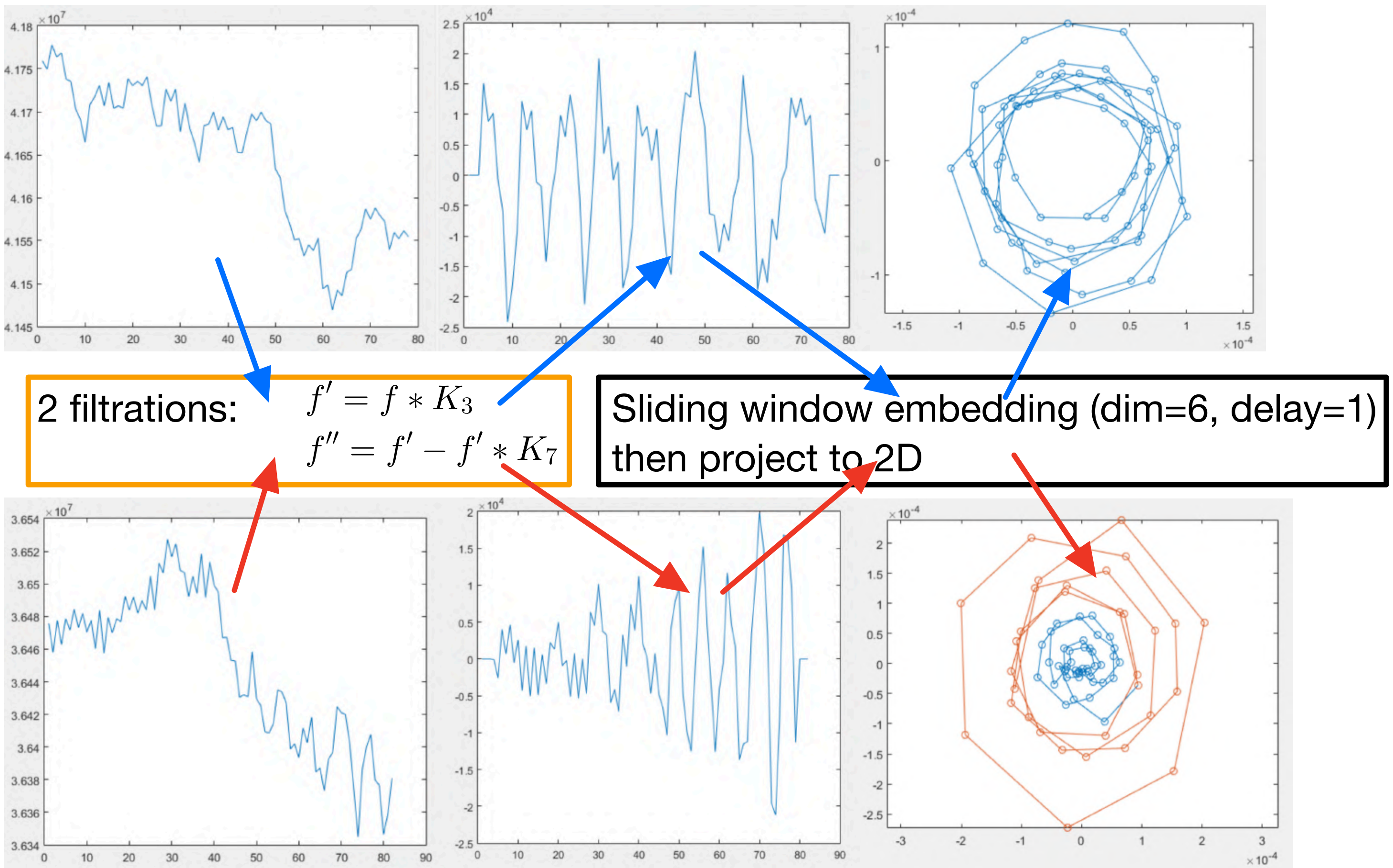

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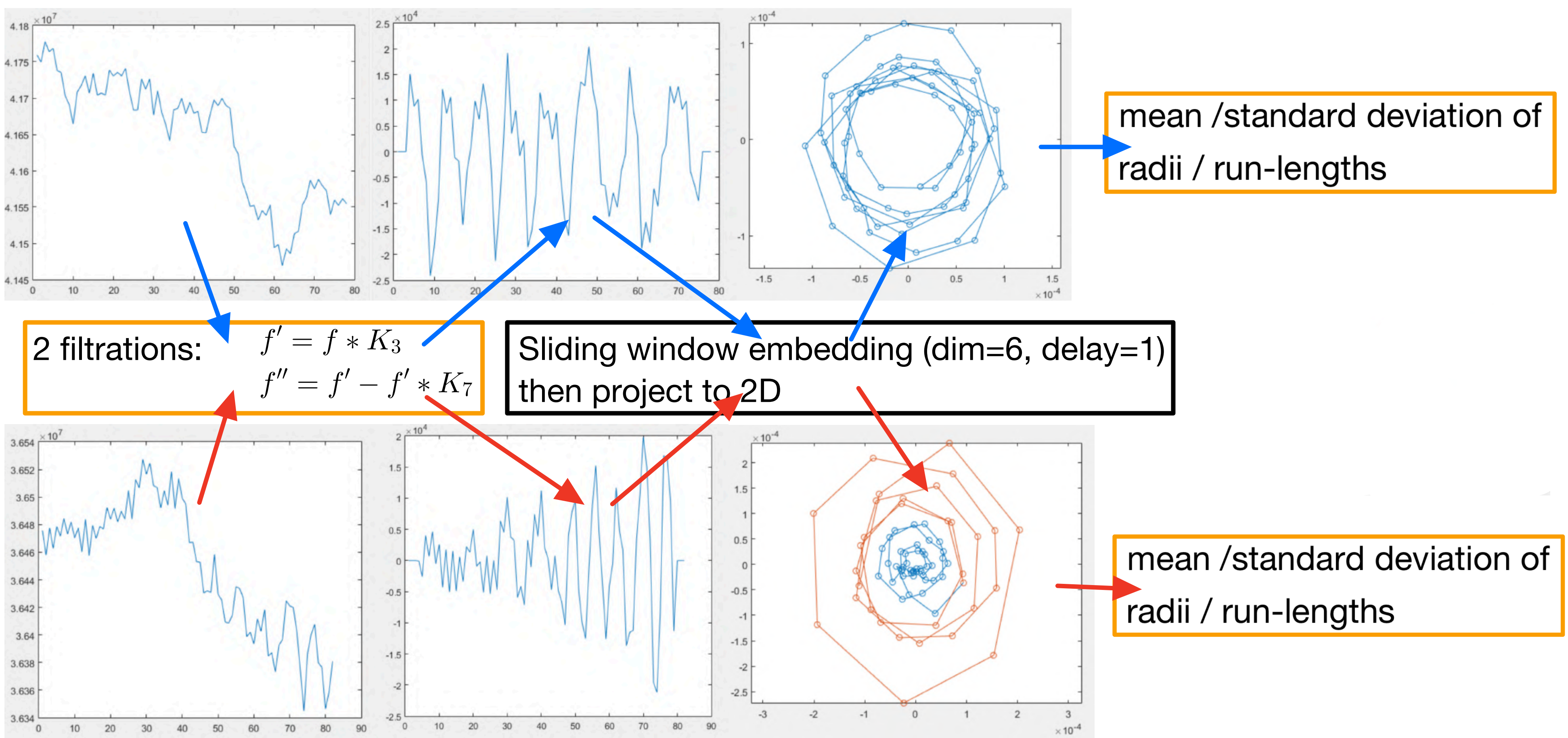

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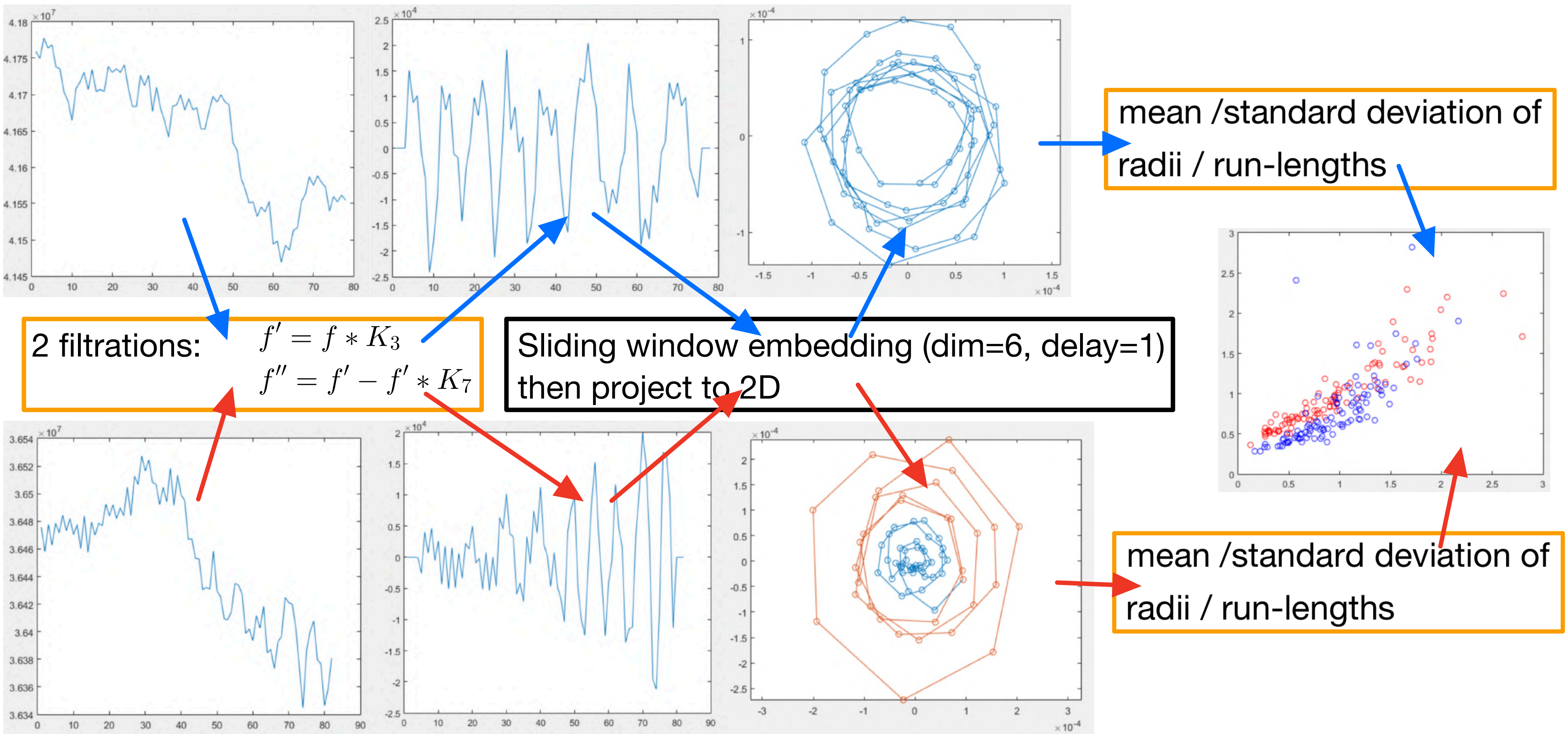

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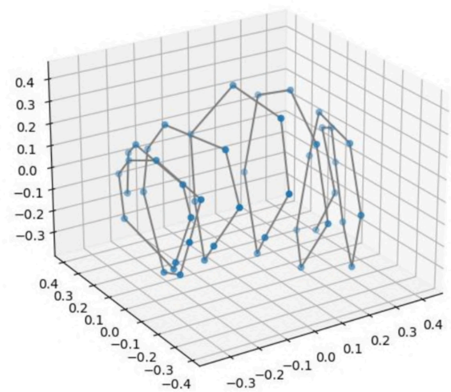
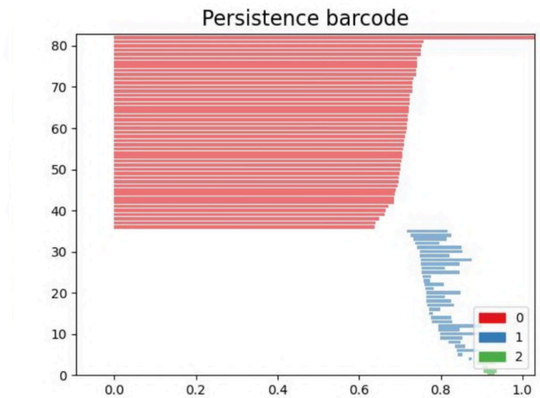
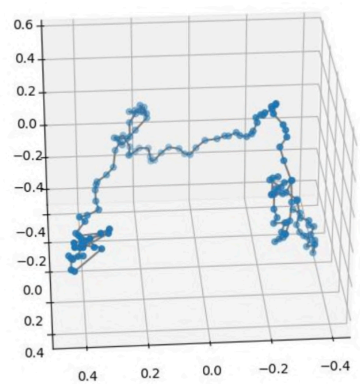
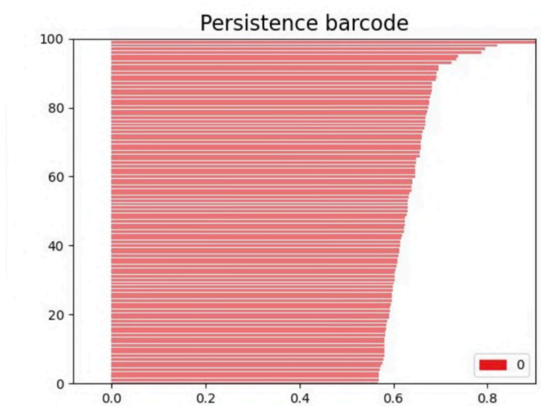
Approach 2 (multi-dimensional data, Siheng Yi), combined with persistent homology and its representations, yielded recognizable characteristics but required considerable computational time.









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Display of speech signals

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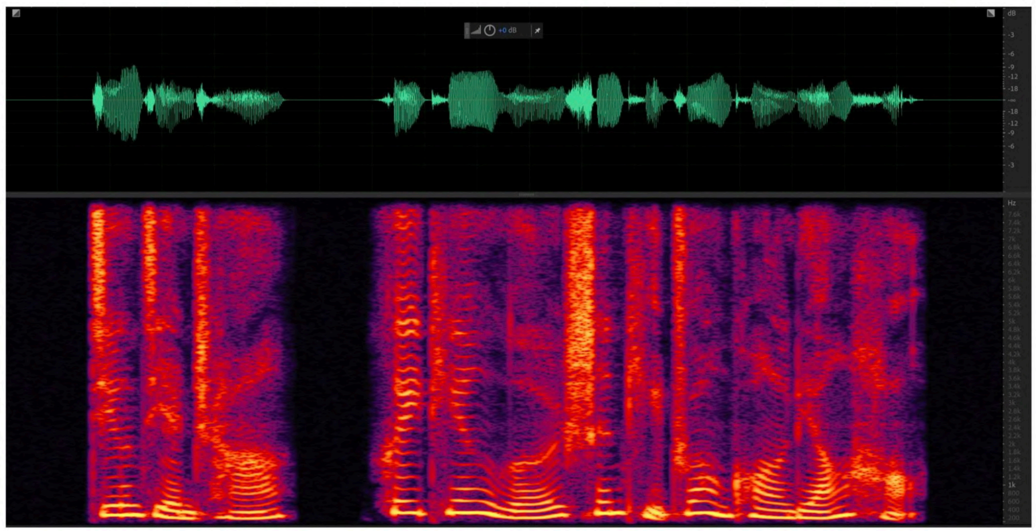

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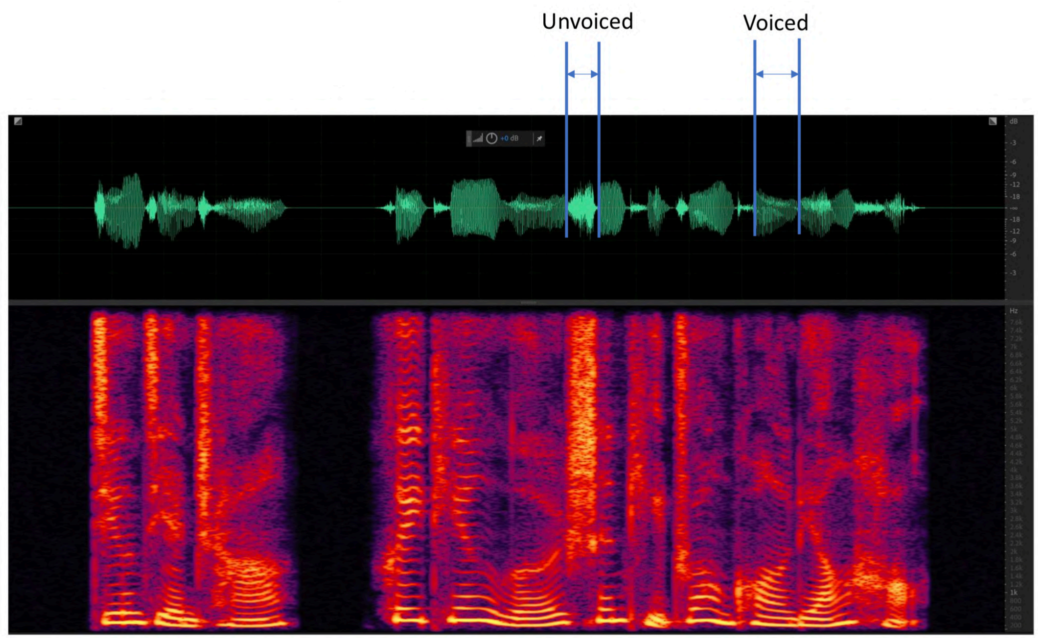

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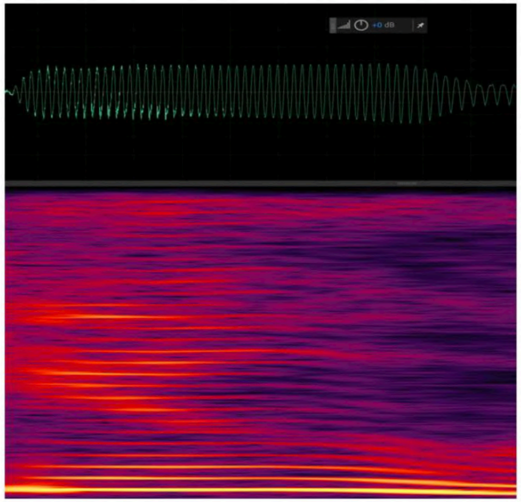
Voiced

Sinusoid in time domain

Harmonics in frequency domain



Time and Time-Frequency domain

Frequency response

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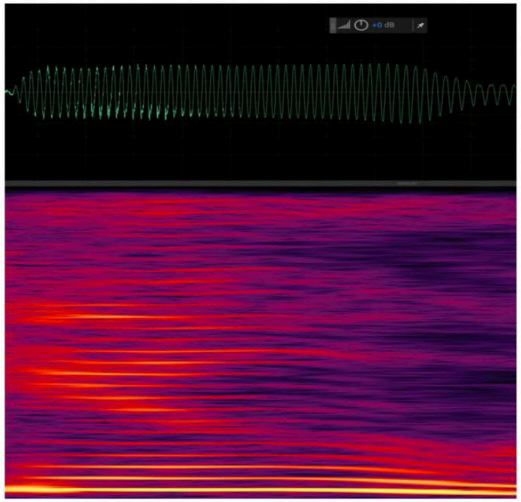
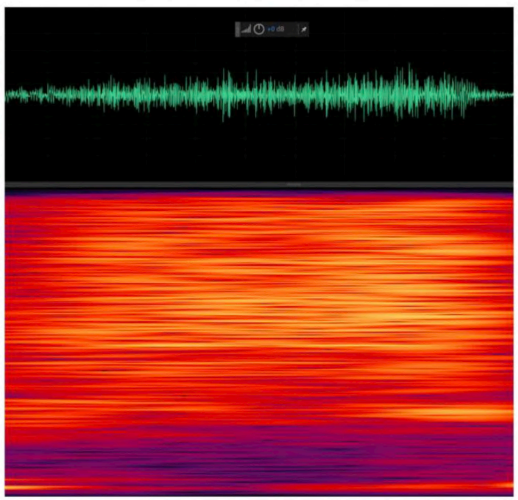


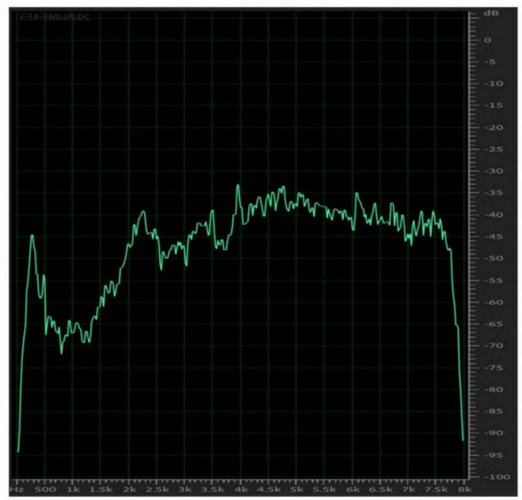
Time and Time-Frequency domain

Frequency response

Voiceless

Like a white noise





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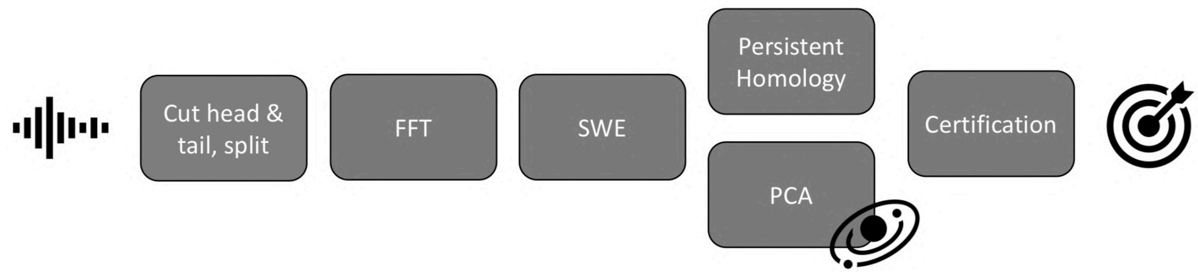
Here is a flowchart for our topological approach:



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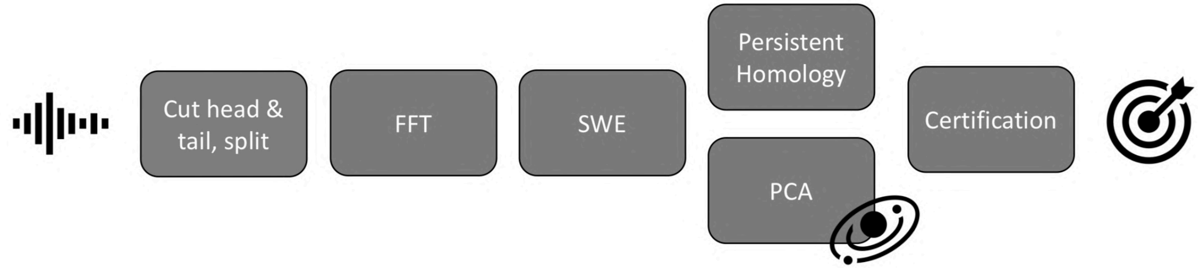
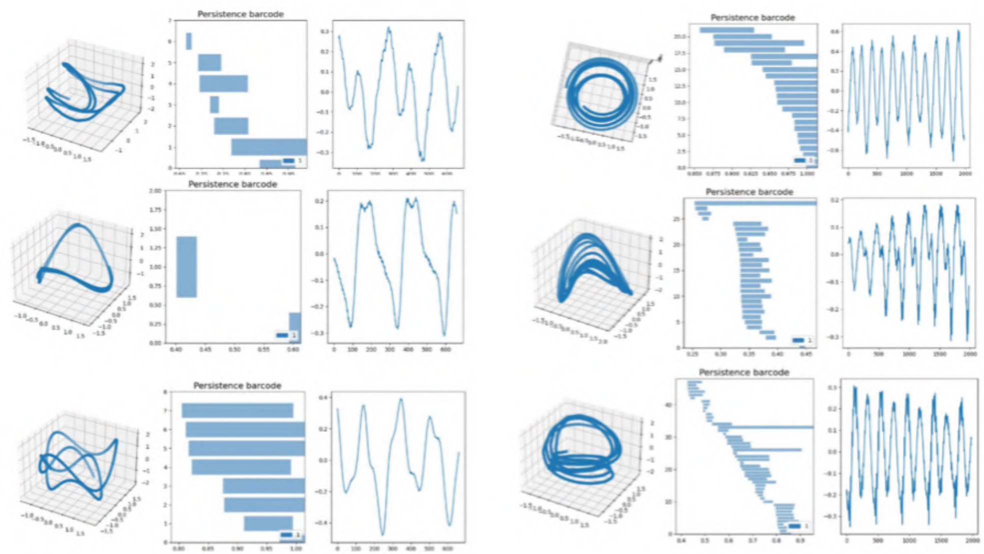


Topological profiles for vowels and consonants (Pingyao Feng)



Features for vowels

Left: frame size: 15ms, frame shift: 5ms; Right: frame size: 45ms, frame shift: 22.5ms

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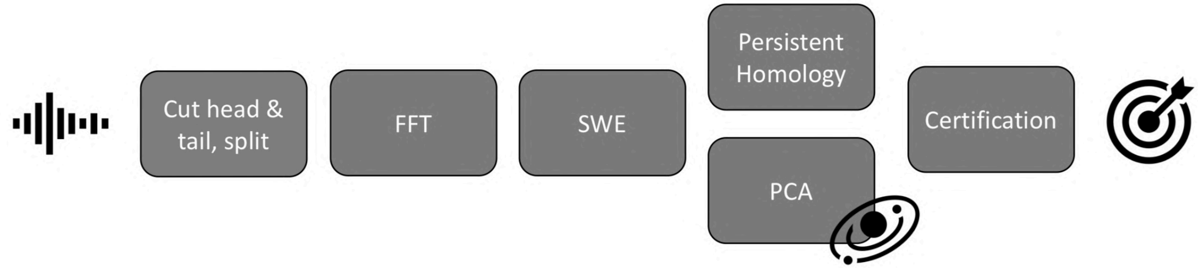

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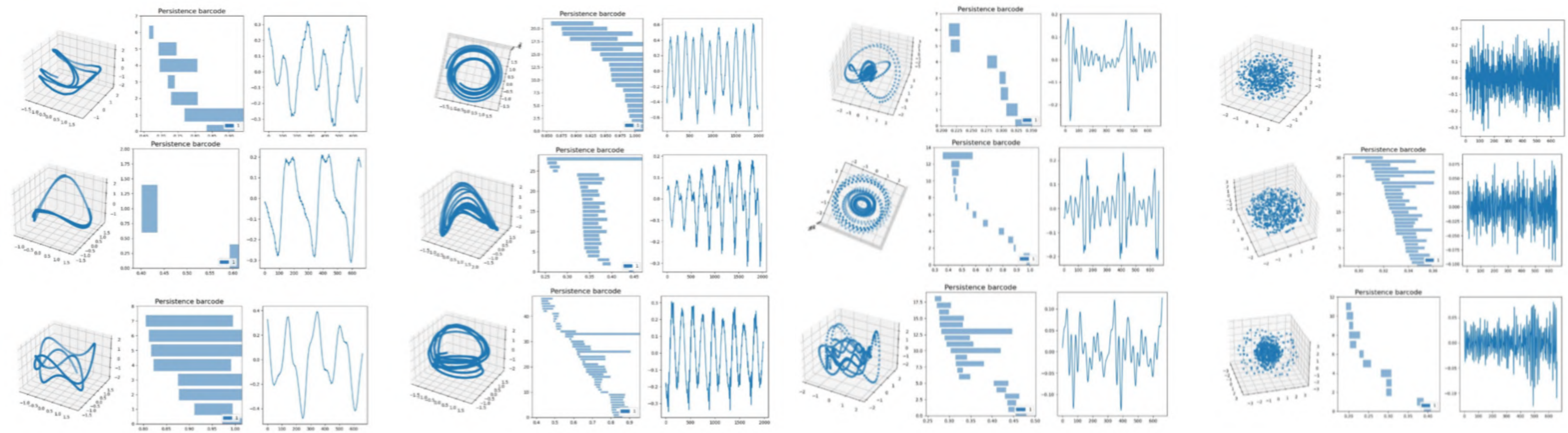

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Features for consonants

Left: pulmonic consonant; Right: non-pulmonic consonant

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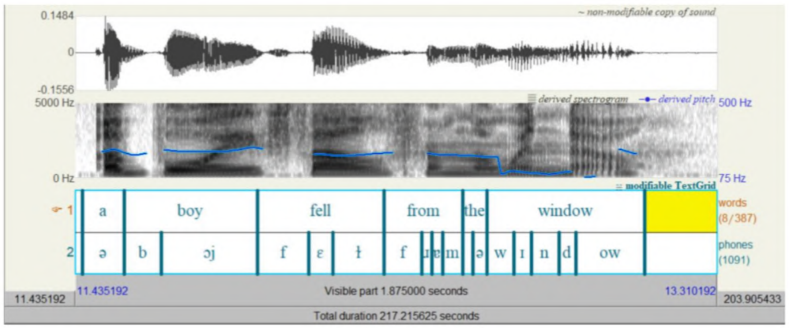


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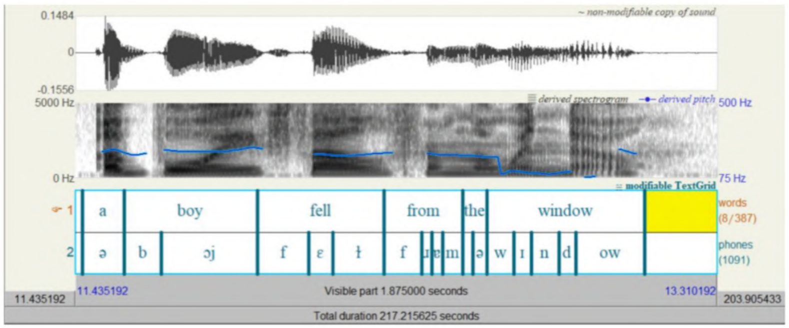


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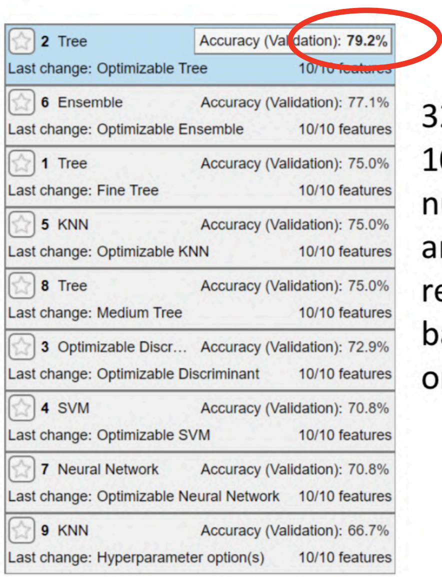

32 vowels, 16 consonants. 10 features: 5 are barcodes number of 5 diag, other 5 are number of barcodes that reaches inf(both consider barcode of 1 dimension for only)

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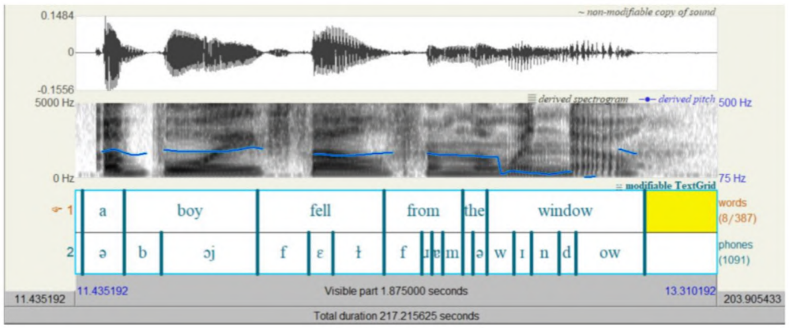


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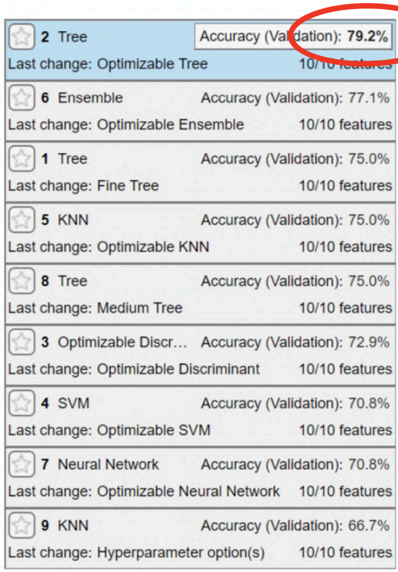

Model	Accuracy (Validation)	Last change	Features
2 Tree	79.2%	Optimizable Tree	10/10 features
6 Ensemble	77.1%	Optimizable Ensemble	10/10 features
1 Tree	75.0%	Fine Tree	10/10 features
5 KNN	75.0%	Optimizable KNN	10/10 features
8 Tree	75.0%	Medium Tree	10/10 features
3 Optimizable Discr…	72.9%	Optimizable Discriminant	10/10 features
4 SVM	70.8%	Optimizable SVM	10/10 features
7 Neural Network	70.8%	Optimizable Neural Network	10/10 features
9 KNN	66.7%	Hyperparameter option(s)	10/10 features

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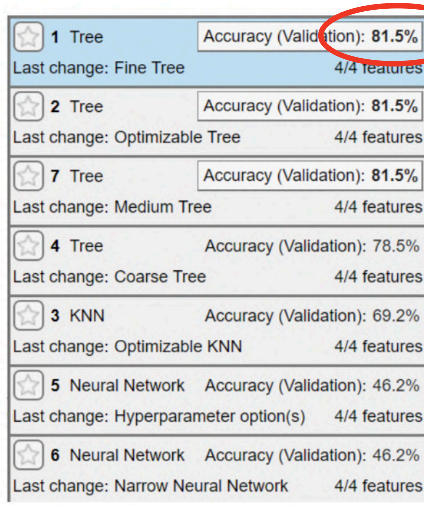

Model	Accuracy (Validation)	Last change	Features
1 Tree	81.5%	Fine Tree	4/4 features
2 Tree	81.5%	Optimizable Tree	4/4 features
7 Tree	81.5%	Medium Tree	4/4 features
4 Tree	78.5%	Coarse Tree	4/4 features
3 KNN	69.2%	Optimizable KNN	4/4 features
5 Neural Network	46.2%	Hyperparameter option(s)	4/4 features
6 Neural Network	46.2%	Narrow Neural Network	4/4 features

32 vowels, 33 consonants. 4 features: bottleneck distance between neighborhood barcode(currently the best result)

A formal recap of the topological methods applied

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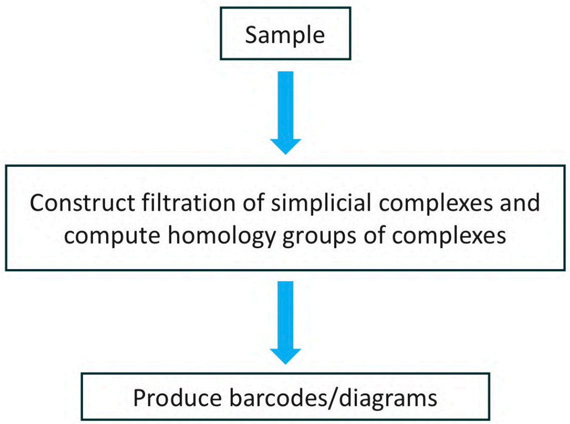
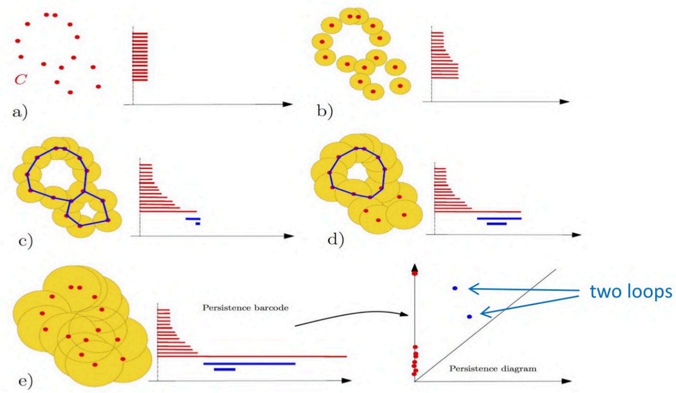
- Persistent homology



How filtration through varying distance measure reveals essential topological features



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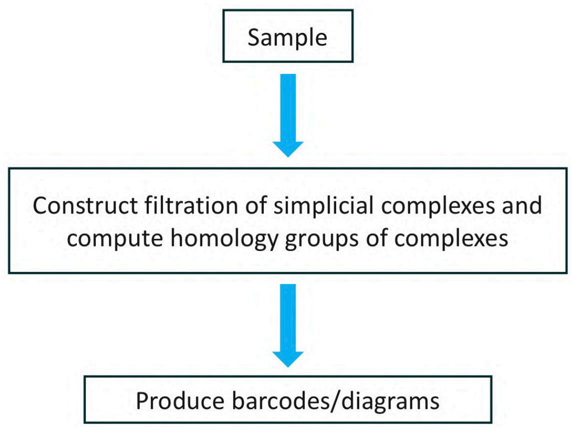

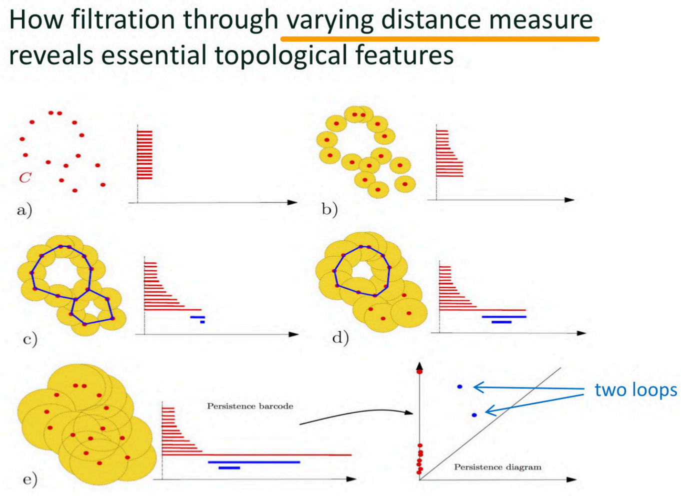

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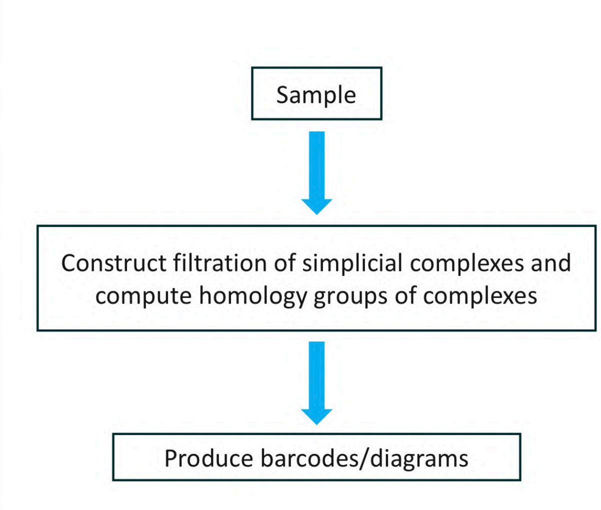

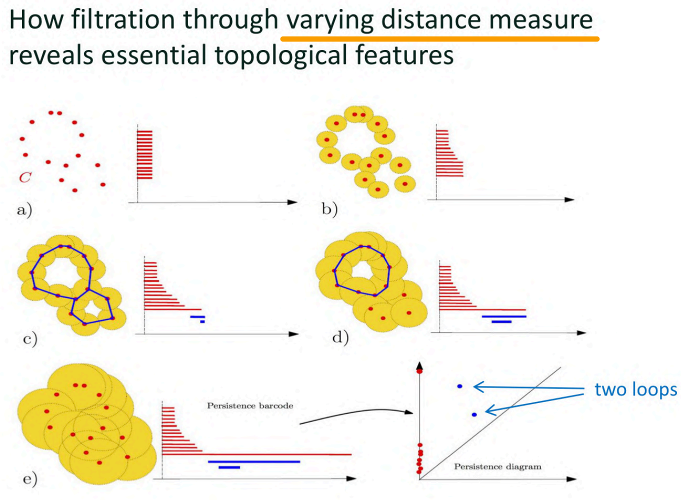

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Theorem (Takens 1981). Let M be a compact manifold of dimension n. Given pairs (ϕ, y) with $\phi : M \to M$ a smooth diffeomorphism and $y : M \to \mathbb{R}$ a smooth function, it is a generic property that the map $\Phi_{(\phi,\, y)} : M \to \mathbb{R}^{2n+1}$ defined by

$$\Phi_{(\varphi,y)}(x) = \left(y\left(x\right), y\big(\varphi(x)\big), \ldots, y\big(\varphi^{2n}(x)\big)\right)$$

is an embedding.

From topological data analysis to topological deep learning

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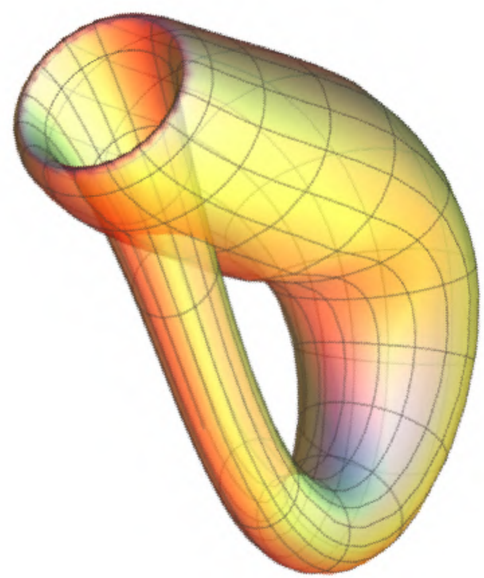

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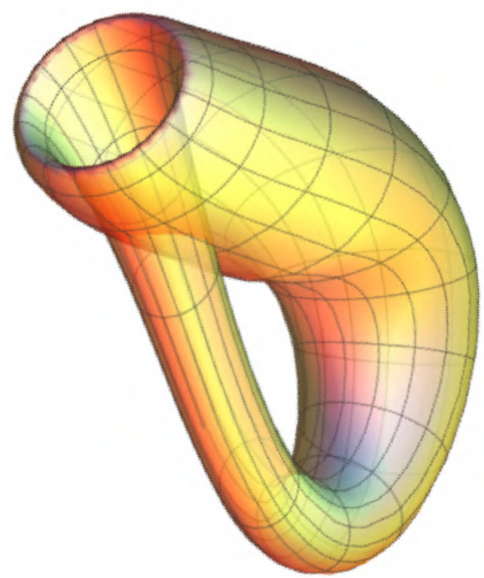
*Gunnar Carlsson et al., On the local behavior of spaces of natural images, **International Journal of Computer Vision**, 2008.*

*Carlsson, Topology and data, **Bulletin of the American Mathematical Society**, 2009.*



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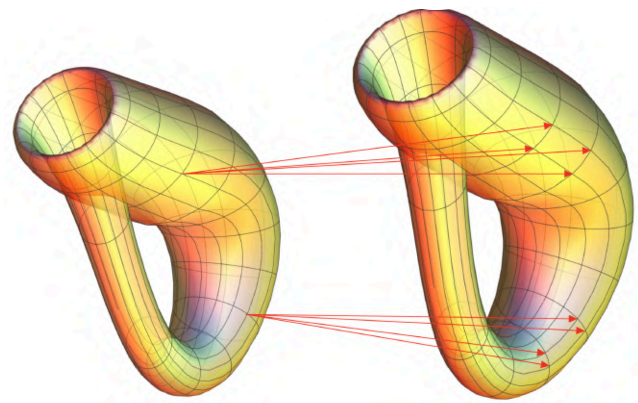

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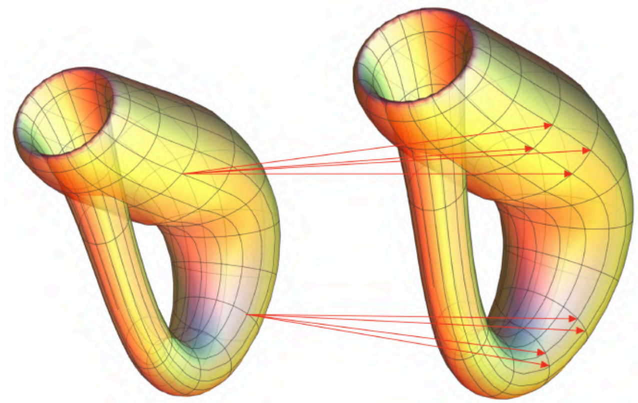

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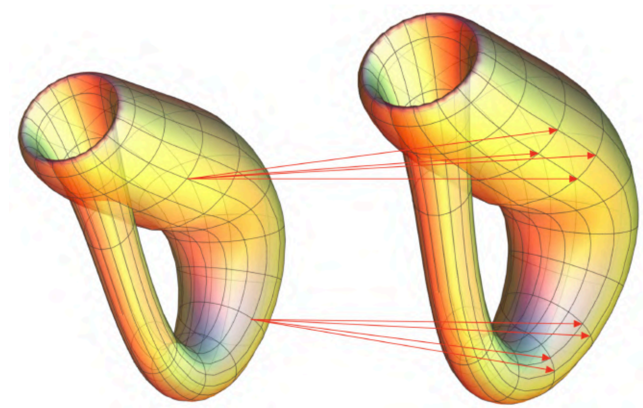

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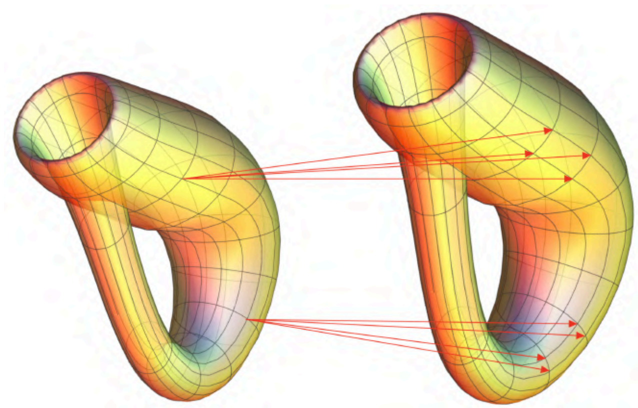

Ephy R. Love et al., Topological convolutional layers for deep learning, ***Journal of Machine Learning Research****, 2023.*

Gunnar Carlsson and Rickard Brüel Gabrielsson, Topological approaches to deep learning, ***Topological Data Analysis: The Abel Symposium****, 2018.*

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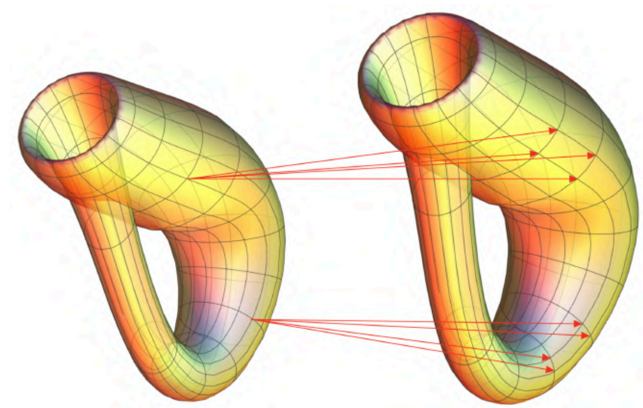

As a second warm-up, our research group (Zhiwang Yu, Haiyu Zhang) have reproduced some of their results.

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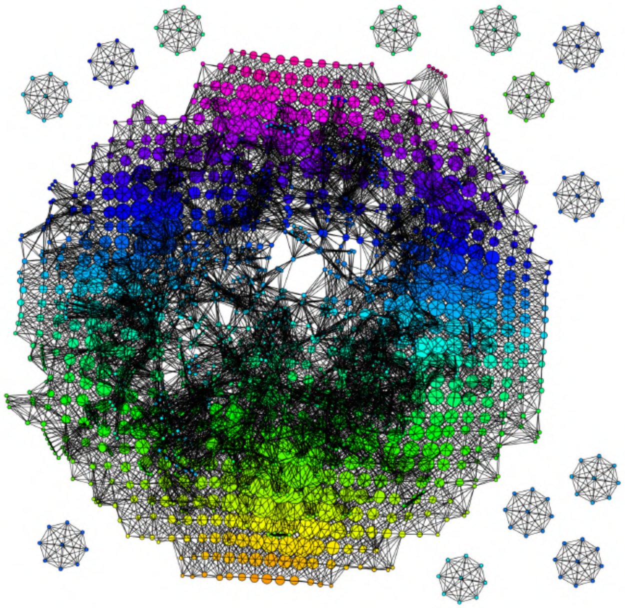
Topology of convolutional neural networks: Emergence of cycles during a training process



Untrained

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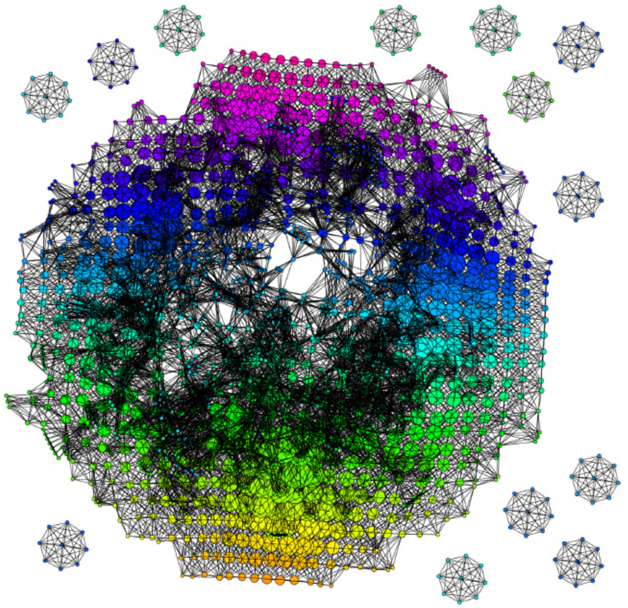

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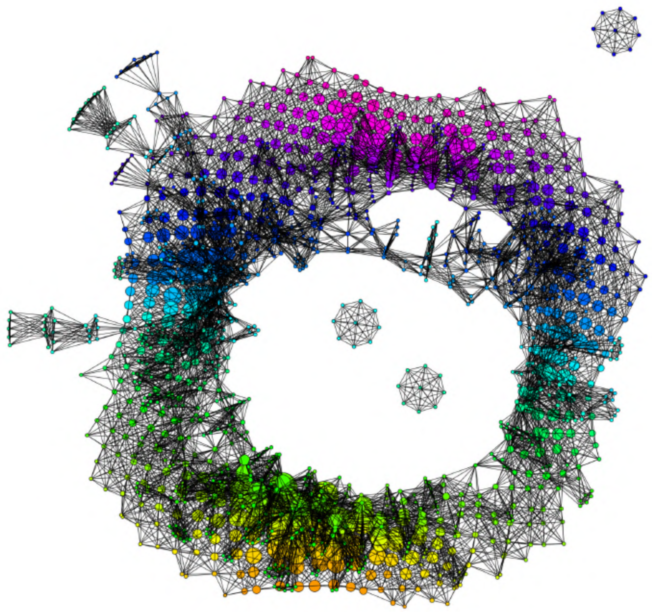
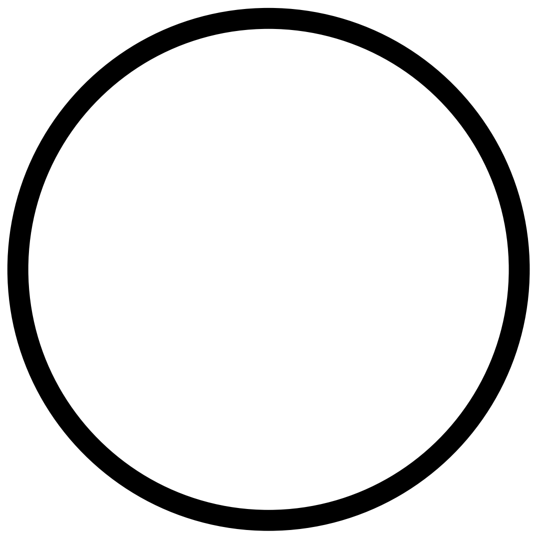


After 5 epochs



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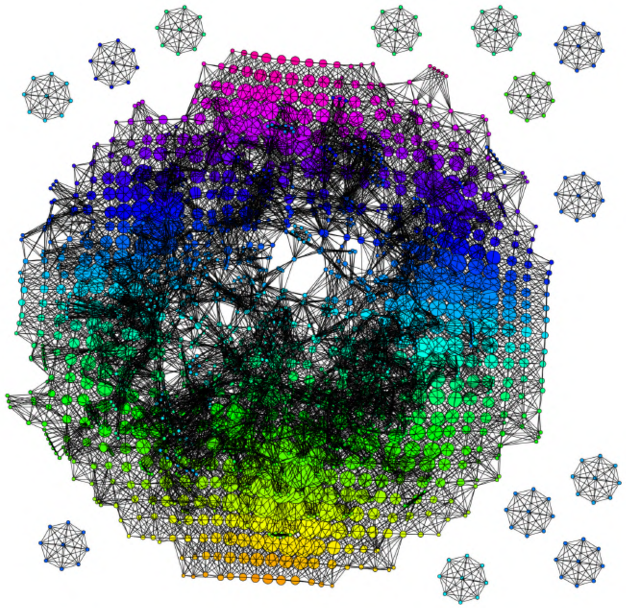

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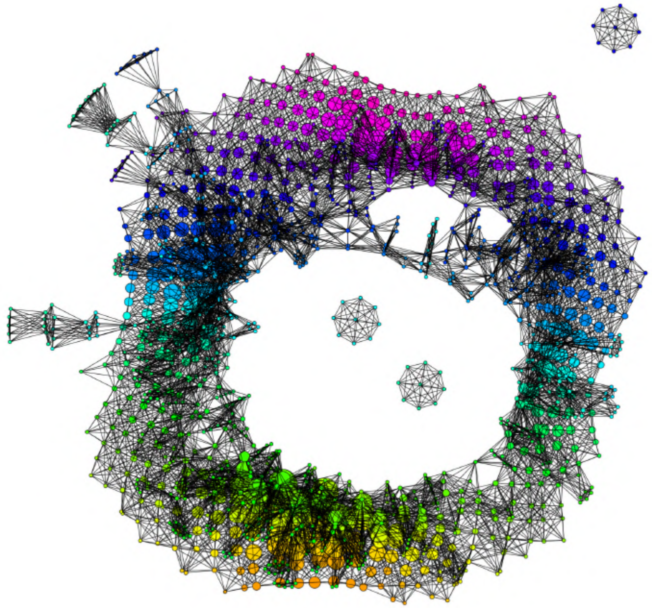

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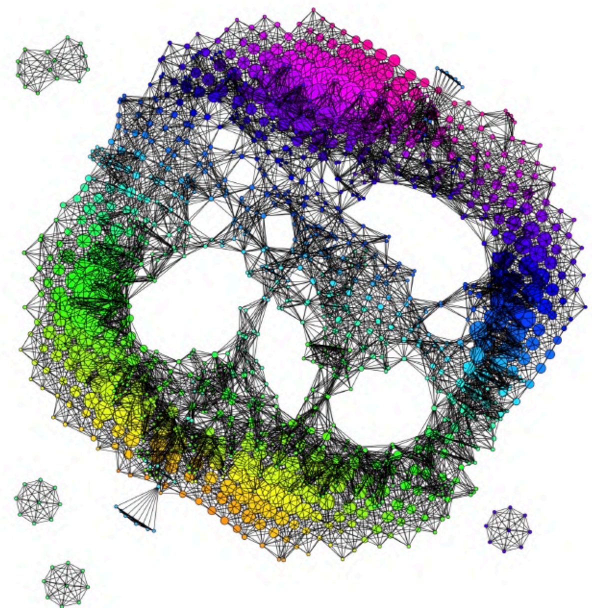
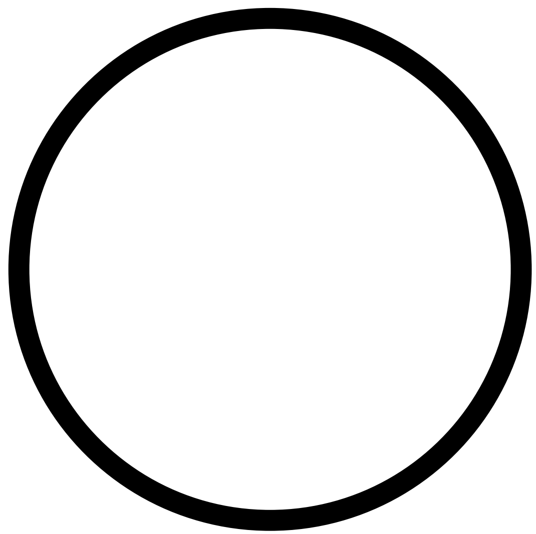
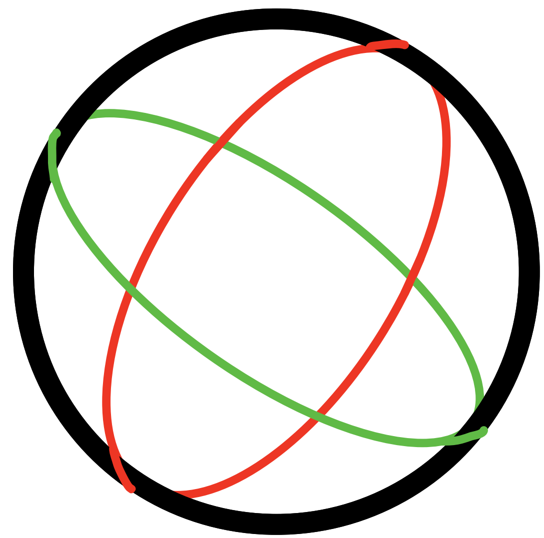


After 20 epochs





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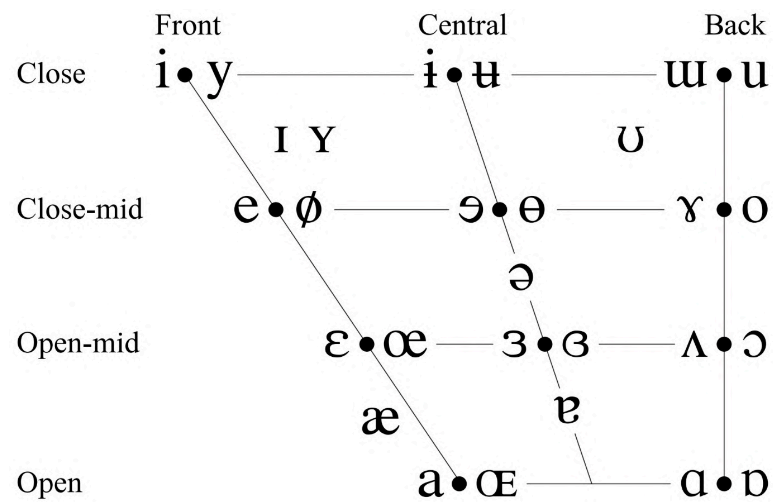

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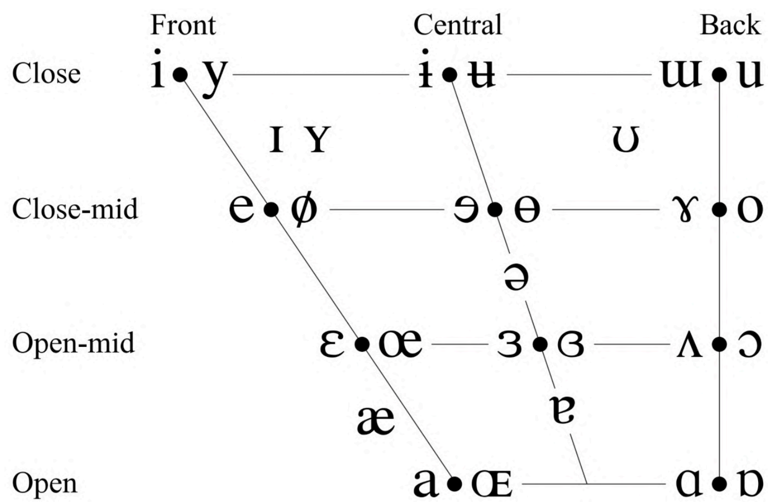
The vertical axis of the chart denotes vowel height. Vowels pronounced with the tongue lowered are at the bottom and raised are at the top. The horizontal axis of the chart denotes vowel backness. Vowels with the tongue moved towards the front of the mouth are in the left of the chart, while those with the tongue moved to the back are placed in right. The last parameter is whether the lips are rounded. At each given spot, vowels on the right and left are rounded and unrounded, respectively.



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Topology-enhanced machine learning for consonant recognition

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Conceptually, TDA is an approach that examines data structure through the lens of topology. This discipline was originally formulated to investigate the *shape* of data, particularly point-cloud data in high-dimensional spaces [11]. Characterised by a unique insensitivity to metrics, robustness against noise, invariance under continuous deformation, and coordinate-free computation [1], TDA has been combined with machine learning algorithms to uncover intricate and concealed information within datasets [12, 3, 13, 14, 15, 16]. In these contexts, topological methods have been employed to extract structural information from the dataset, thereby enhancing the efficiency of the original algorithms. Notably, TDA excels in identifying patterns such as clusters, loops, and voids in data, establishing it as a burgeoning tool in the realm of data analysis [17]. Despite being a nascent field of study, with its distinctive emphasis on the shape of data, TDA has led to novel applications in various far-reaching fields, as evidenced in the literature. These include image recognition [18, 19, 20], time series forecasting [21] and classification [22], brain activity monitoring [23, 24], protein structural analysis [25, 26], speech recognition [27], signal processing [28, 29], neural networks [30, 31, 32, 2], among others. It is anticipated that further development of TDA will pave a new direction to enhance numerous aspects of daily life.

The task of extracting features that pertain to structural information is both intriguing and formidable. This process is integral to a multitude of practical applications [33, 34, 35, 36], as scholars strive to identify the most effective representatives and descriptors of shape within a given dataset. Despite the fact that TDA is specifically designed for shape capture, there are several hurdles that persist in this newly developed field of study. These include (1) the nature and sensitivity of descriptors obtained by methods in TDA, (2) the dimensionality of the data and other parameter

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1 Introduction

In 1966, Mark Kac asked the famous question: "Can you hear the shape of a drum?" To hear the shape of a drum is to infer information about the shape of the drumhead from the sound it makes, using mathematical theory. In this article, we venture to flip and mirror the question across senses and address instead: "Can we see the sound of a human speech?"

The artificial intelligence (AI) advancements have led to a widespread adoption of voice recognition technologies, encompassing applications such as speech-to-text conversion and music generation. The rise of topological data analysis (TDA) [1] has integrated topological methods into many areas including AI [2, 3], which makes neural networks more interpretable and efficient, with a focus on structural information. In the field of voice recognition [4, 5], more specifically consonant recognition [6, 7, 8, 9, 10], prevalent methodologies frequently revolve around the analysis of energy and spectral information. While topological approaches are still rare in this area, we combine TDA and machine learning to obtain a classification for speech data, based on geometric patterns hidden within phonetic segments. The method we propose, TopCap (referring to capturing topological structures of data), is not only applicable to audio data but also to general-purpose time series data that require extraction of structural information for machine learning algorithms. Initially, we endow phonetic time series with point-cloud structure in a high-dimensional Euclidean space via time-delay embedding (TDE, see Fig. 1a) with appropriate choices of parameters. Subsequently, 1-dimensional persistence diagrams are computed using persistent homology (see Sec. S.2.2 for an explanation of the terminologies). We then conduct evaluations with nine machine learning algorithms, in comparison with a convolutional neural network (CNN) without topological inputs, to demonstrate the significant capabilities of TopCap in the desired classification.

Conceptually, TDA is an approach that examines data structure through the lens of topology. This discipline was originally formulated to investigate the *shape* of data, particularly point-cloud data in high-dimensional spaces [11]. Characterised by a unique insensitivity to metrics, robustness against noise, invariance under continuous deformation, and coordinate-free computation [1], TDA has been combined with machine learning algorithms to uncover intricate and concealed information within datasets [12, 3, 13, 14, 15, 16]. In these contexts, topological methods have been employed to extract structural information from the dataset, thereby enhancing the efficiency of the original algorithms. Notably, TDA excels in identifying patterns such as clusters, loops, and voids in data, establishing it as a burgeoning tool in the realm of data analysis [17]. Despite being a nascent field of study, with its distinctive emphasis on the shape of data, TDA has led to novel applications in various far-reaching fields, as evidenced in the literature. These include image recognition [18, 19, 20], time series forecasting [21] and classification [22], brain activity monitoring [23, 24], protein structural analysis [25, 26], speech recognition [27], signal processing [28, 29], neural networks [30, 31, 32, 2], among others. It is anticipated that further development of TDA will pave a new direction to enhance numerous aspects of daily life.

The task of extracting features that pertain to structural information is both intriguing and formidable. This process is integral to a multitude of practical applications [33, 34, 35, 36], as scholars strive to identify the most effective representatives and descriptors of shape within a given dataset. Despite the fact that TDA is specifically designed for shape capture, there are several hurdles that persist in this newly developed field of study. These include (1) the nature and sensitivity of descriptors obtained by methods in TDA, (2) the dimensionality of the data and other parameter

From topological data analysis to topological deep learning

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dimension = 10, desired delay = 40			dimension = 50, desired delay = 8			dimension = 100, desired delay = 4		
delay	skip	MP	delay	skip	MP	delay	skip	MP
1	1	0.0610	1	1	0.2834	1	1	0.4270
10	1	0.1299	3	1	0.3021	2	1	0.4337
20	1	0.1312	4	1	0.3054	2	5	0.4146
30	1	0.1281	5	1	0.3058	3	1	0.4357
39	1	0.1229	6	1	0.3042	3	5	0.4120
39	5	0.1134	7	1	0.3052	4	1	0.4381
40	1	0.1290	7	5	0.2886	4	5	0.4139
40	5	0.1195	8	1	0.3093	5	1	0.4375
41	1	0.1200	8	5	0.2928	5	5	0.4105
41	5	0.1153	9	1	0.3091	6	1	0.4347
45	1	0.0940	9	5	0.2913	6	5	0.4114
50	1	0.1226	10	1	0.3069	7	1	0.4380
60	1	0.1315	15	1	0.3070	8	1	0.4378
94	1	empty	18	1	empty	9	1	empty

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Increase dimension for smoothness?

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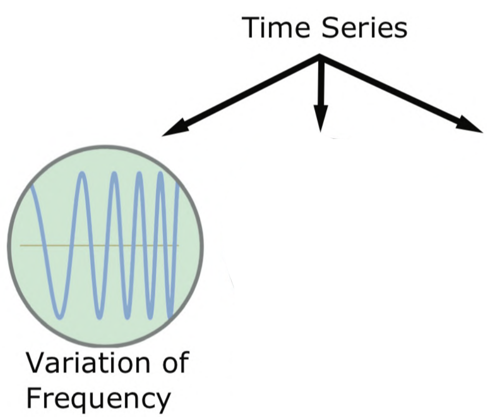

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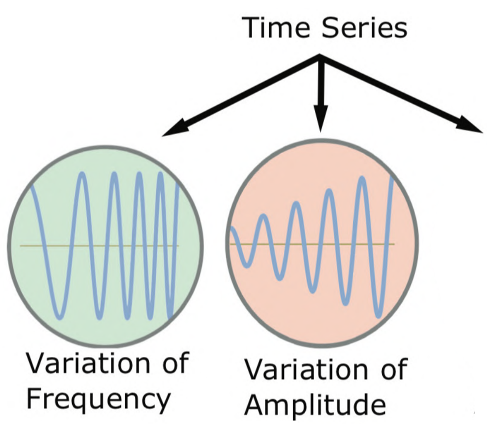

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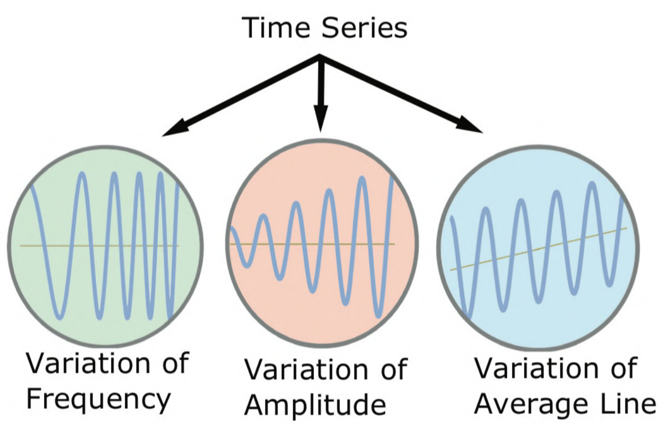

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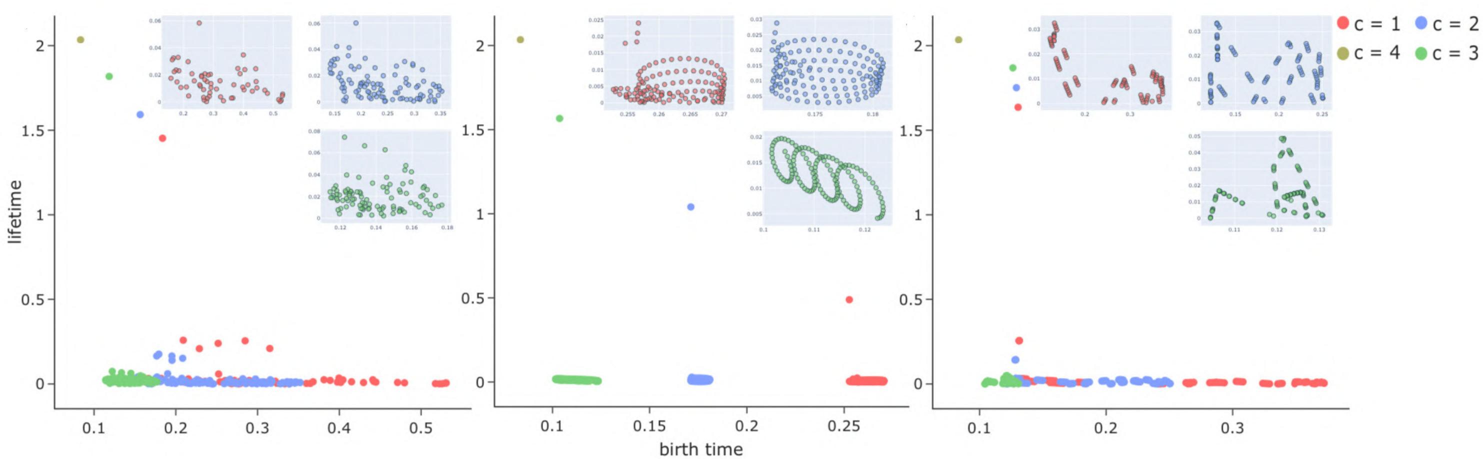

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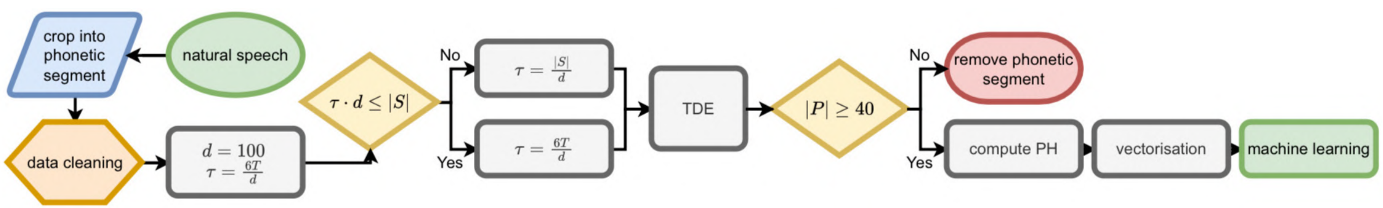

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Question. Is there a computational approach through persistent homology for temporal Gestalt perception of audio signals?

*Cf. Lin Chen, Topological structure in visual perception, **Science**, 1982 and Hongwei Lin's recent work on computational Gestalt models based on persistent homology.*

From topological data analysis to topological deep learning

Reservoir networks and photonic circuits have been applied to vowel recognition, too.

nature photonics

ARTICLES

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Deep learning with coherent nanophotonic circuits

Yichen Shen[1*†], Nicholas C. Harris[1*†], Scott Skirlo[1], Mihika Prabhu[1], Tom Baehr-Jones[2], Michael Hochberg[2], Xin Sun[3], Shijie Zhao[4], Hugo Larochelle[5], Dirk Englund[1] and Marin Soljačić[1]

Artificial neural networks are computational network models inspired by signal processing in the brain. These models have dramatically improved performance for many machine-learning tasks, including speech and image recognition. However, today's computing hardware is inefficient at implementing neural networks, in large part because much of it was designed for von Neumann computing schemes. Significant effort has been made towards developing electronic architectures tuned to implement artificial neural networks that exhibit improved computational speed and accuracy. Here, we propose a new architecture for a fully optical neural network that, in principle, could offer an enhancement in computational speed and power efficiency over state-of-the-art electronics for conventional inference tasks. We experimentally demonstrate the essential part of the concept using a programmable nanophotonic processor featuring a cascaded array of 56 programmable Mach–Zehnder interferometers in a silicon photonic integrated circuit and show its utility for vowel recognition.

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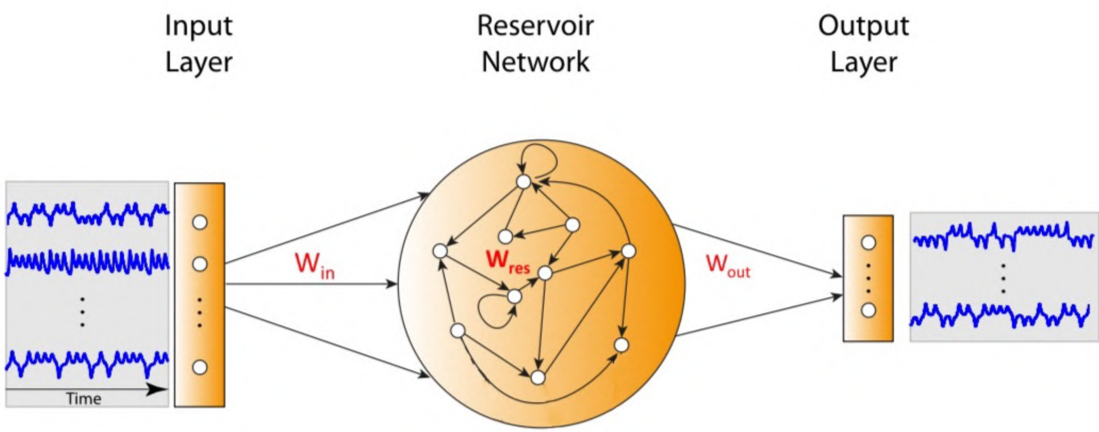

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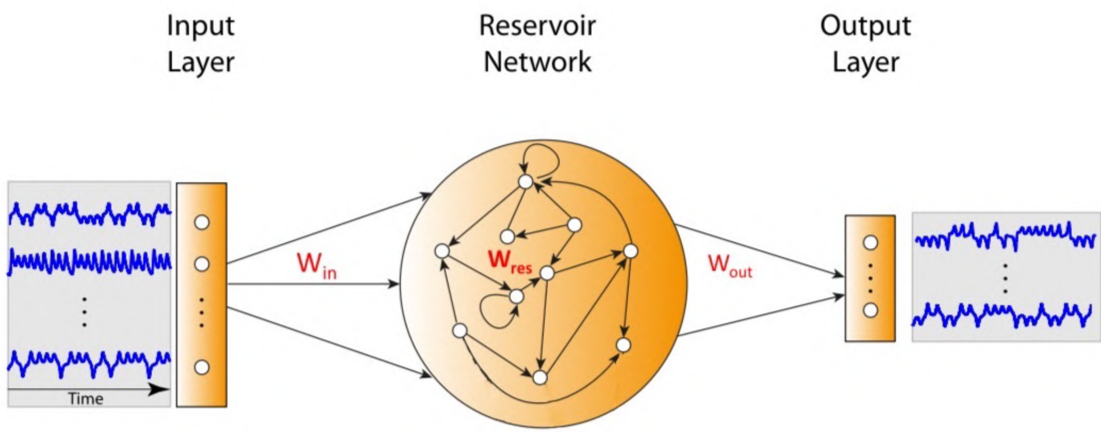

Duan et al. ’23

It will be useful to design and fine-tune them topologically (joint with Huan Li of optical science and engineering at Zhejiang University and Xinxiang Niu of Huawei).

Thank you.