Analysis of anatomical connectivity networks in patients with epilepsy embedded in Euclidean space.

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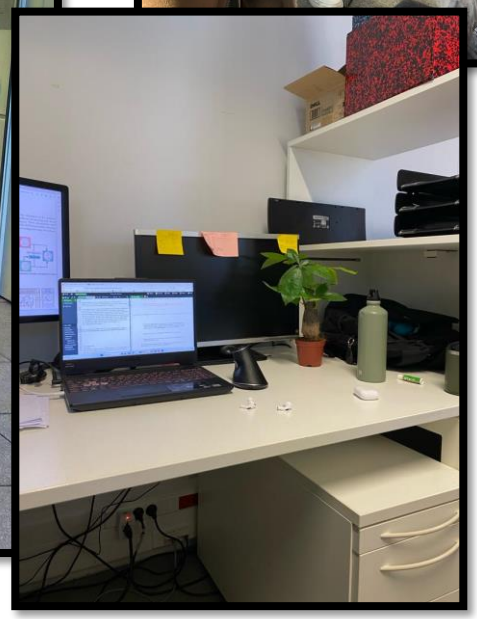
CNRS

Latin American alliance for Capacity buildiNG in Advanced physics
LA-CoNGA physics

Cofinanciado por el programa Erasmus+ de la Unión Europea

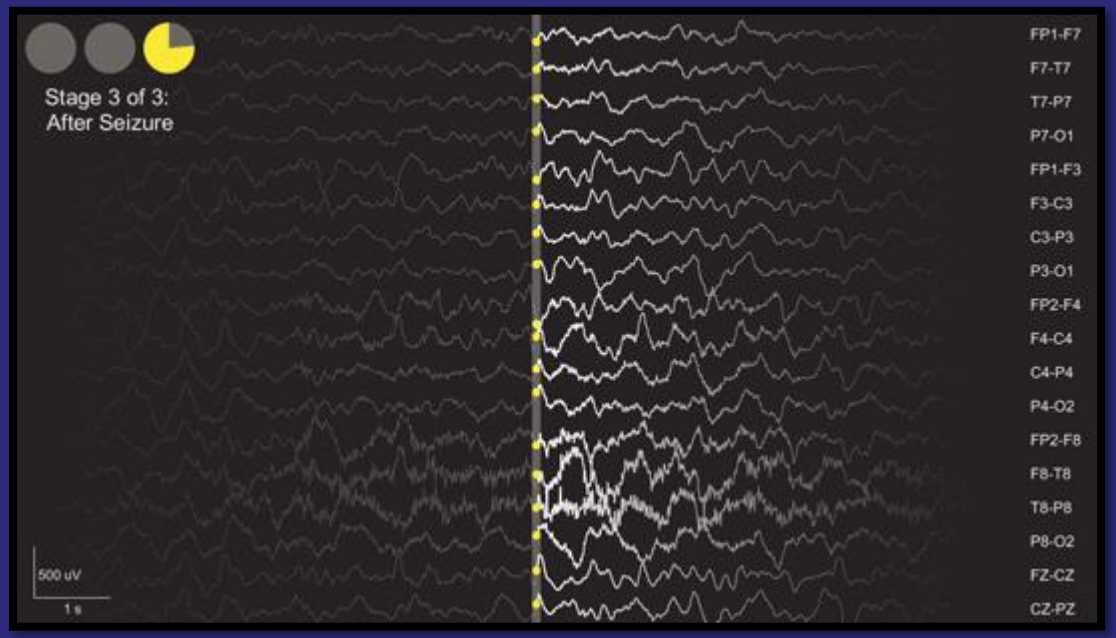
Paris Brain Institute



Data

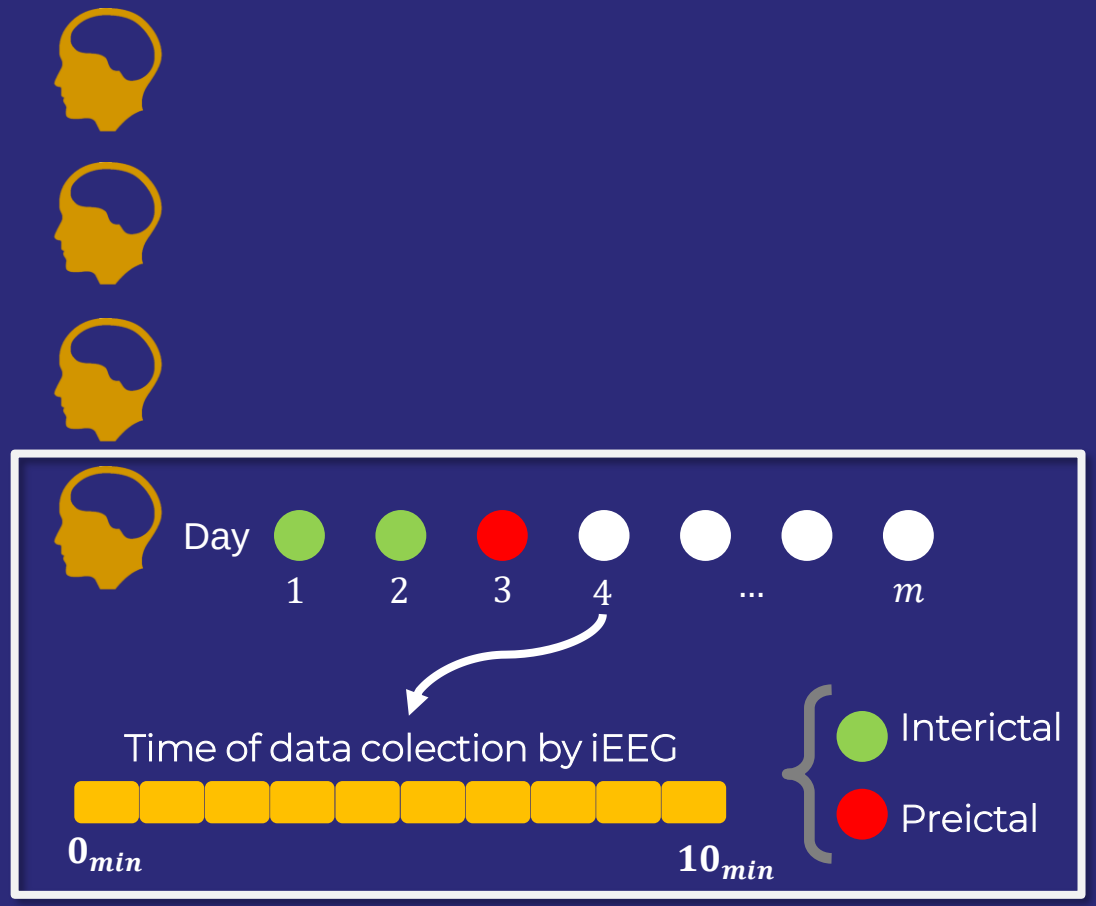
ASSISTANCE PUBLIQUE HÔPITAUX DE PARIS

intracranial electroencephalography (iEEG)

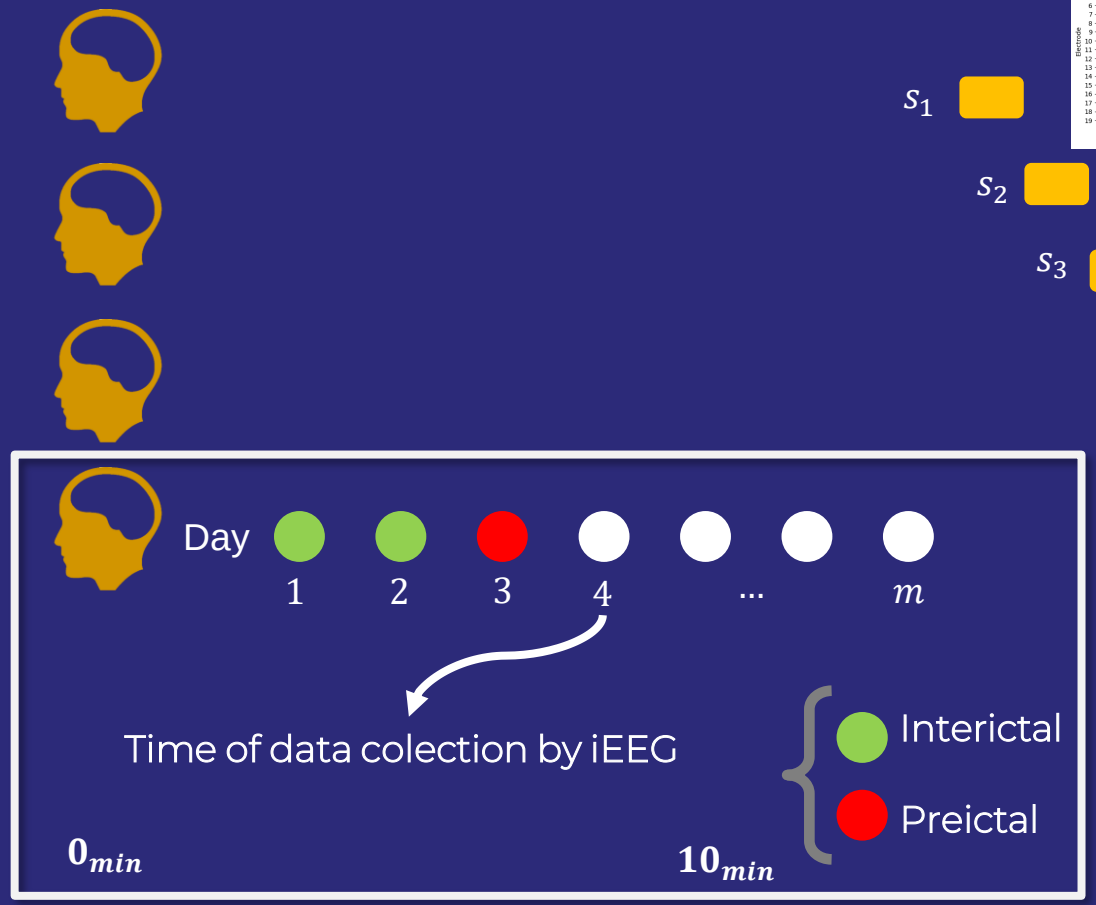


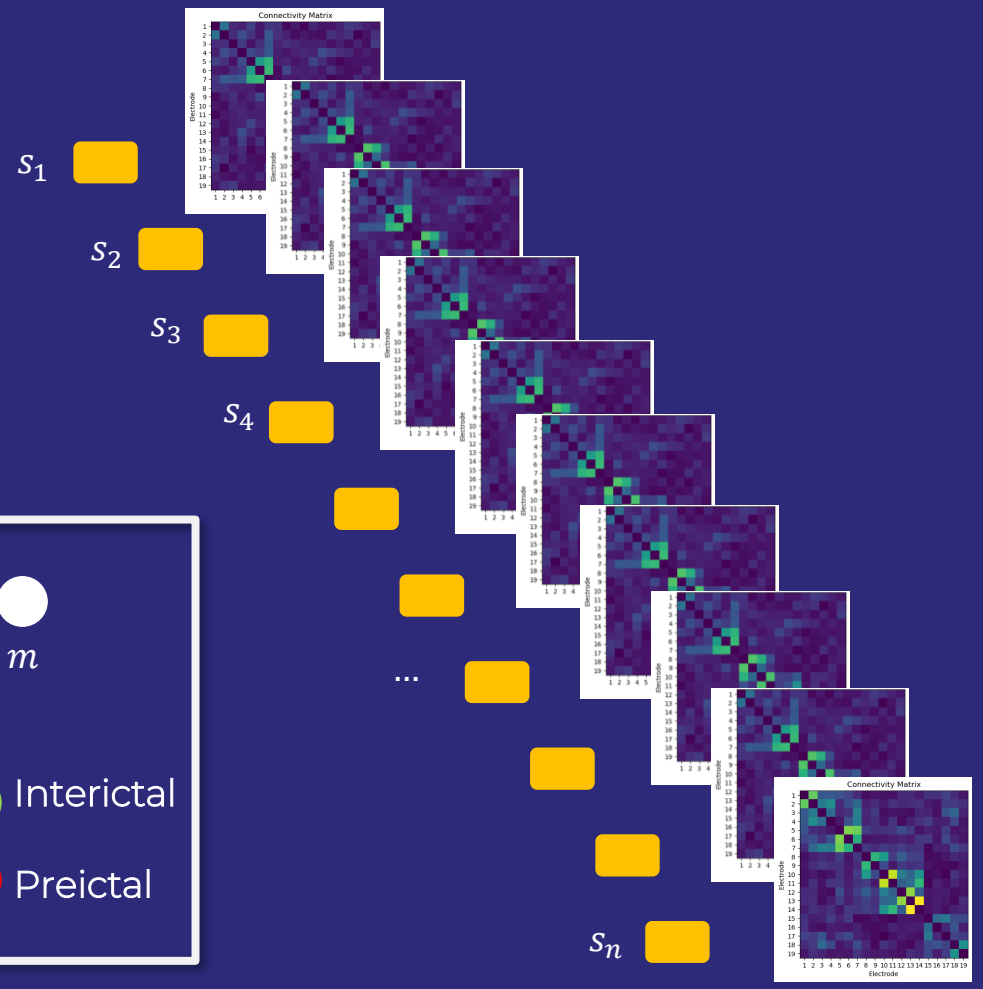
Delta	< 4 Hz
Theta	4 – 7 Hz
Alpha	8 – 12 Hz
Beta	13 – 30 Hz
Low Gamma	> 30 Hz
High Gamma	

Data

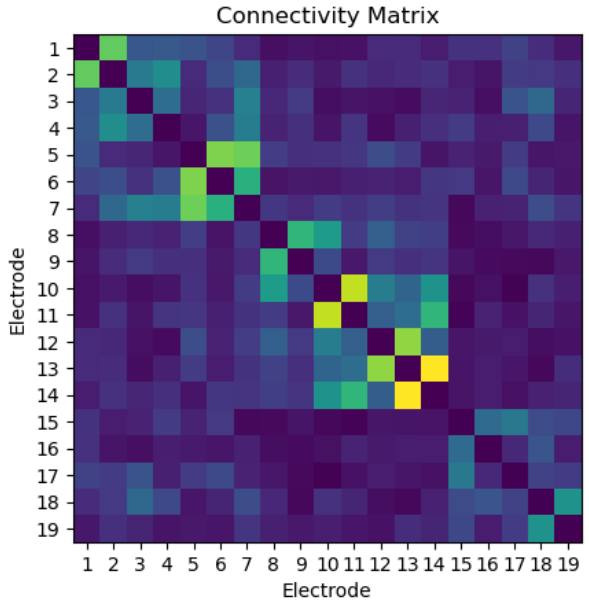

Day
1
2
3
4
...
m
Time of data colection by iEEG
0min
10min
Interictal
Preictal

Data

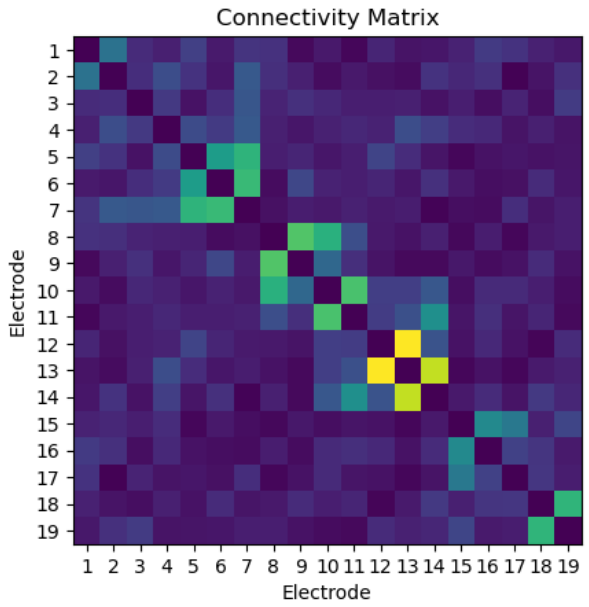

Day
1
2
3
4
...
m
Time of data colection by iEEG
0 min
10 min
Interictal
Preictal


s_1
s_2
s_3
s_4
...
s_n
Connectivity Matrix
Electrode

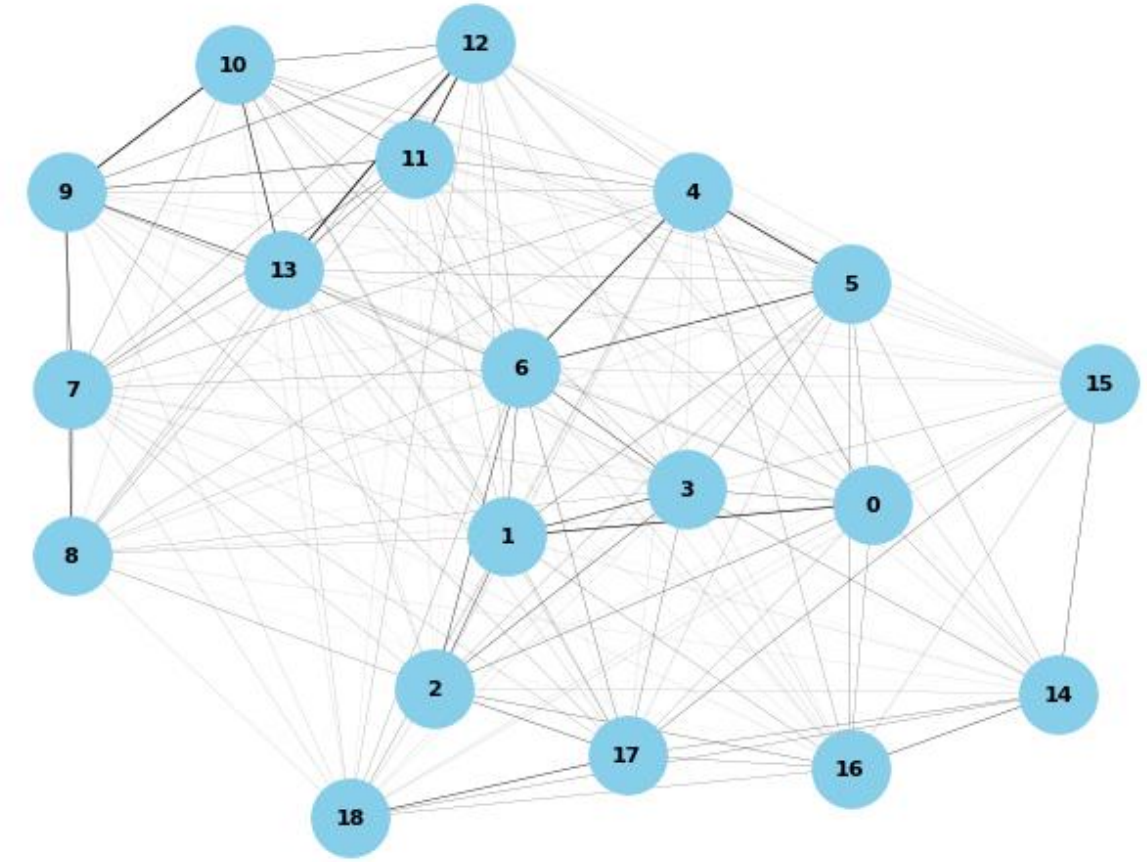
INTERICTAL



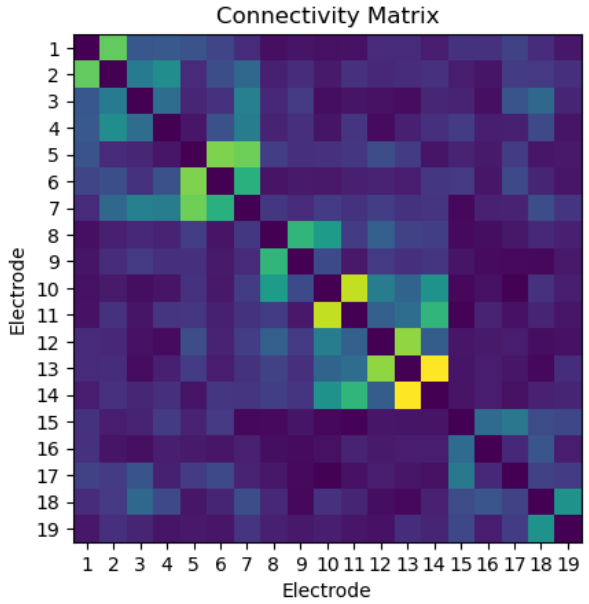
PREICTAL



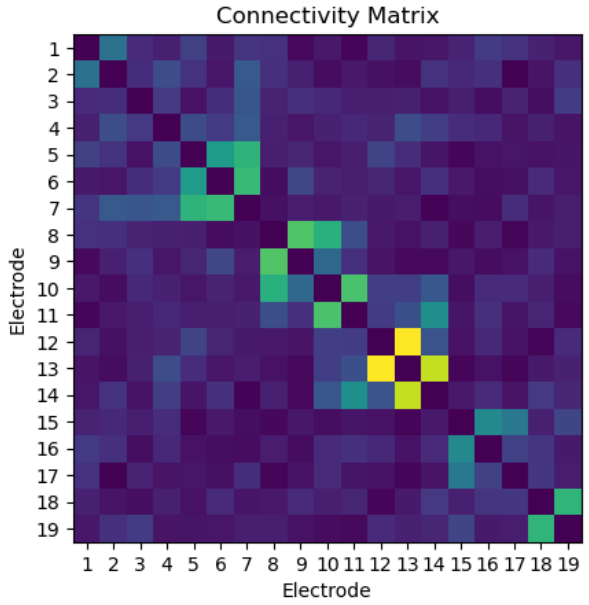
Creation of graphs



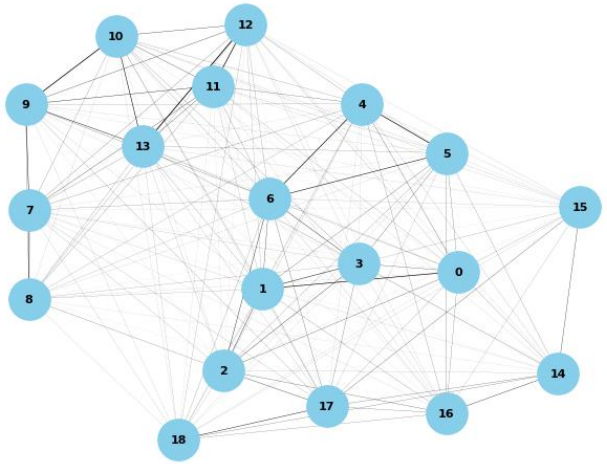
INTERICTAL



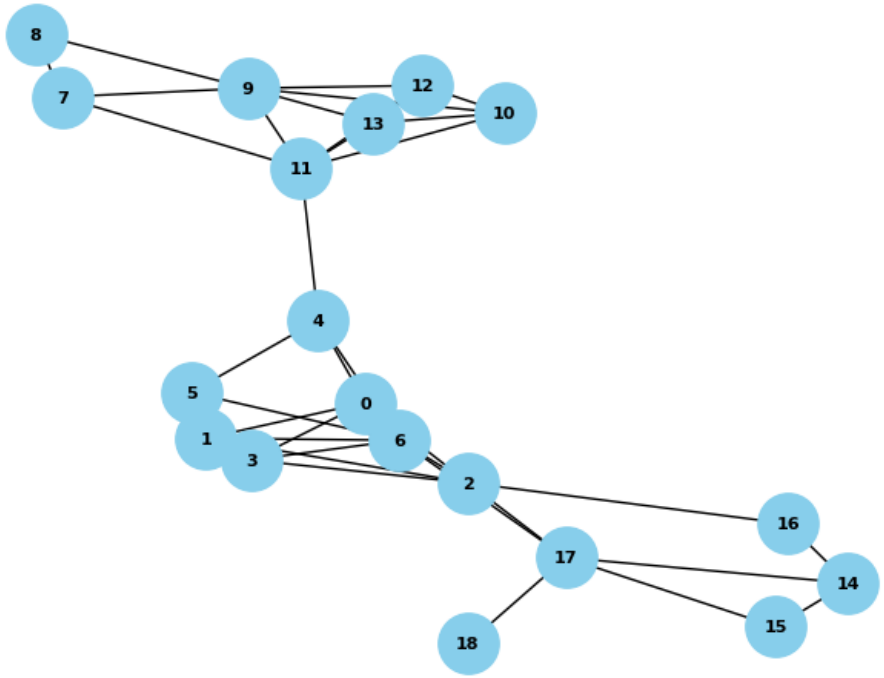
PREICTAL



Creation of graphs



and filtering by spanning tree with mean degree 3



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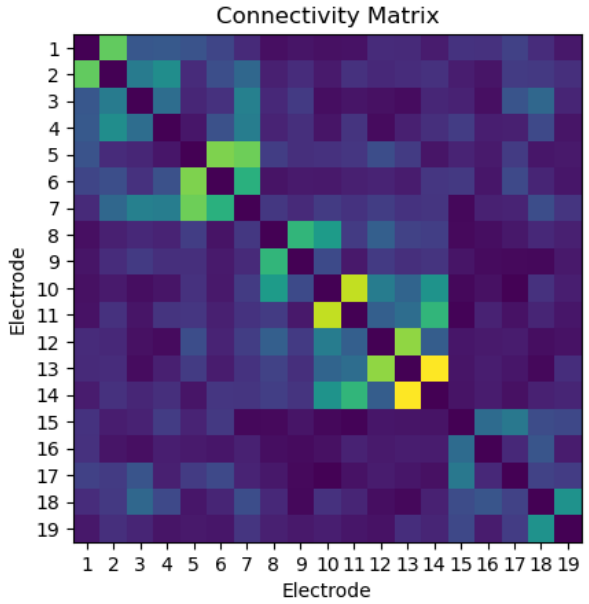

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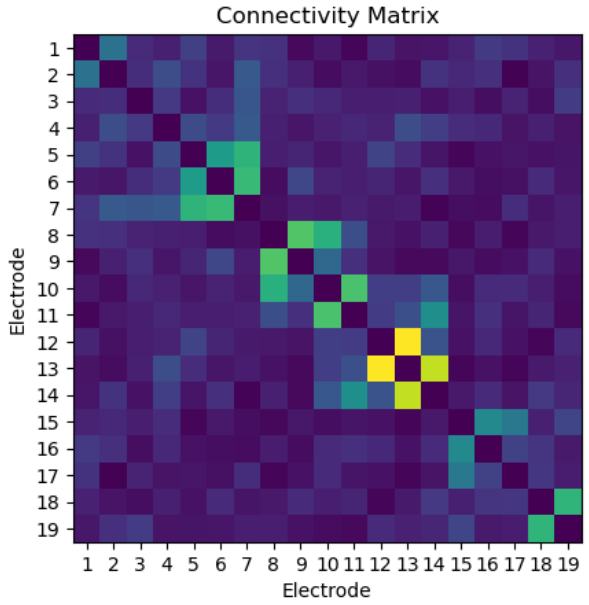
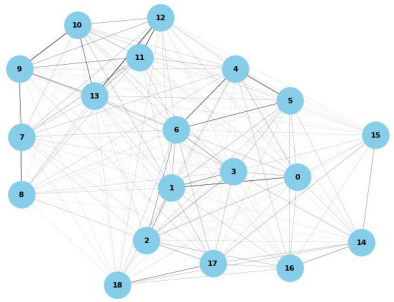
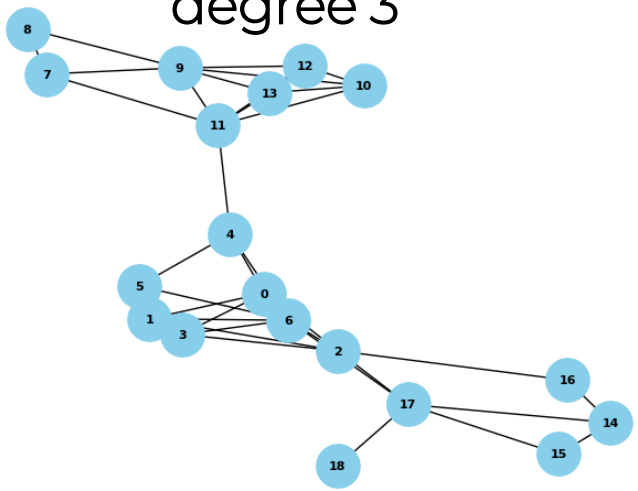


Creation of graphs

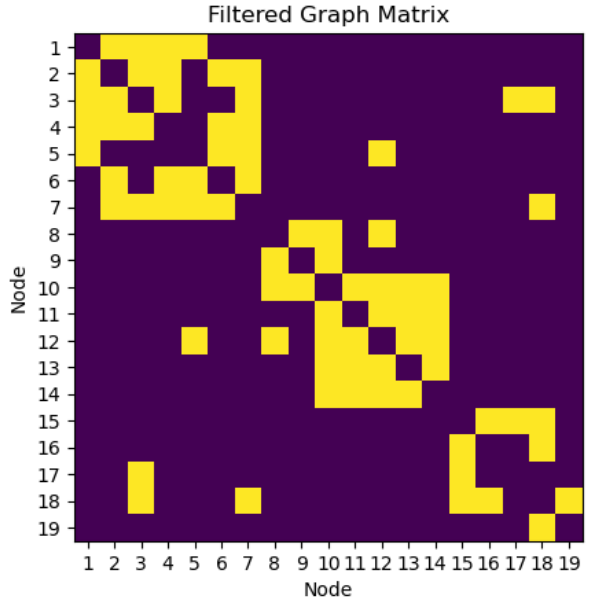


and filtraiting by spanning tree with mean degree 3

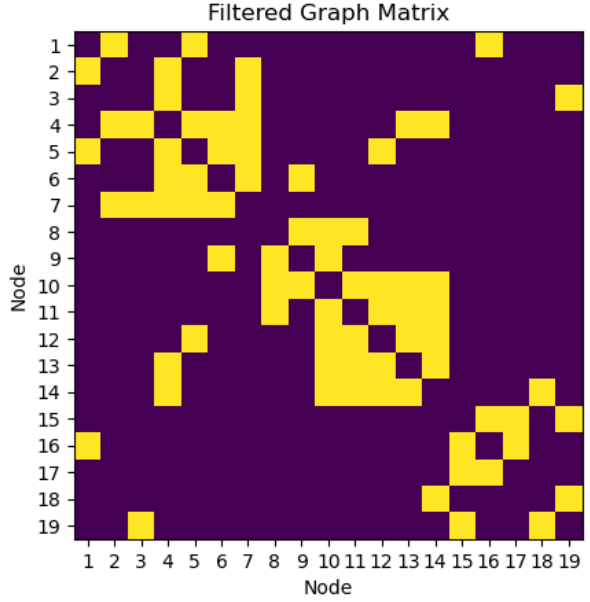


and Binarization

INTERICTAL



PREICTAL

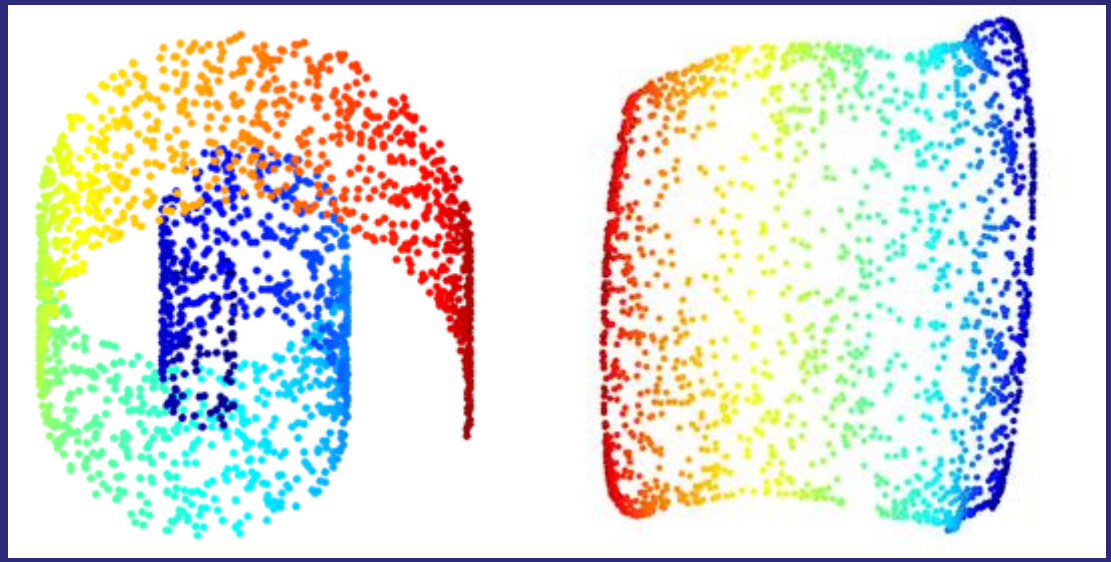


Diffusion Map

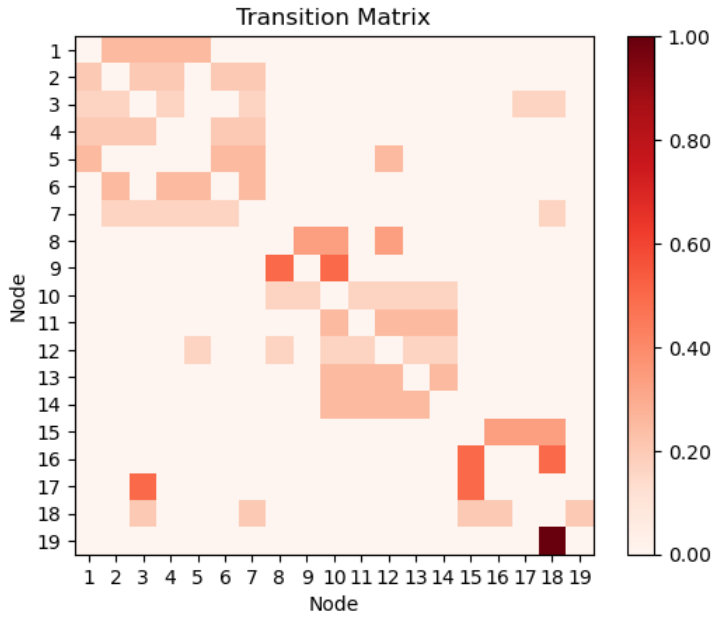
Nonlinear dimensionality reduction technique of a data set in Euclidean space whose coordinates can be computed from the eigenvectors and eigenvalues of a diffusion operator on the data.

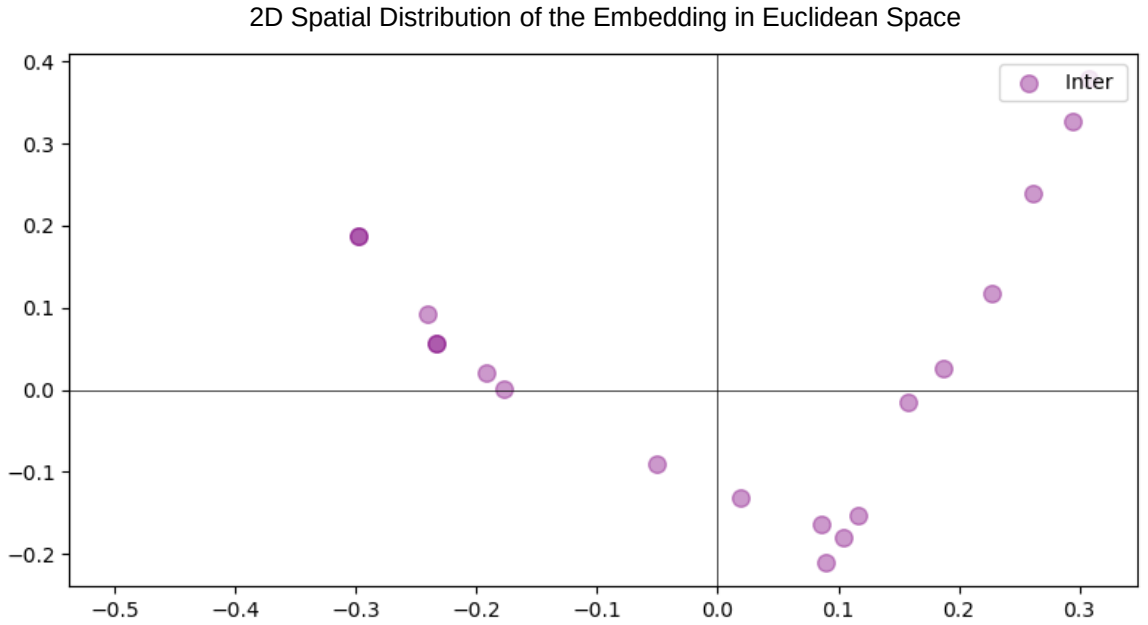
This reduction technique works by using the degree of the graph to find the probability of transition between all the data.

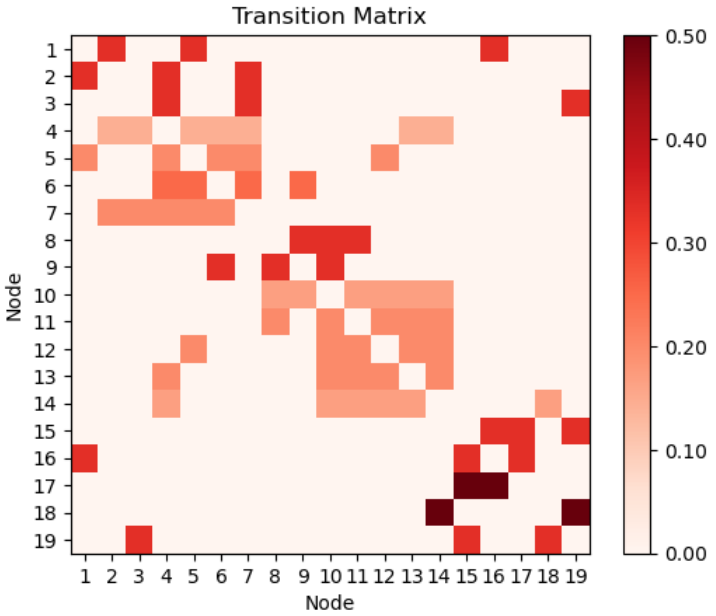
The eigenvalues and eigenvectors of the transition matrix provide the representation of the initial graph as a cloud of points in a lower dimensional space.

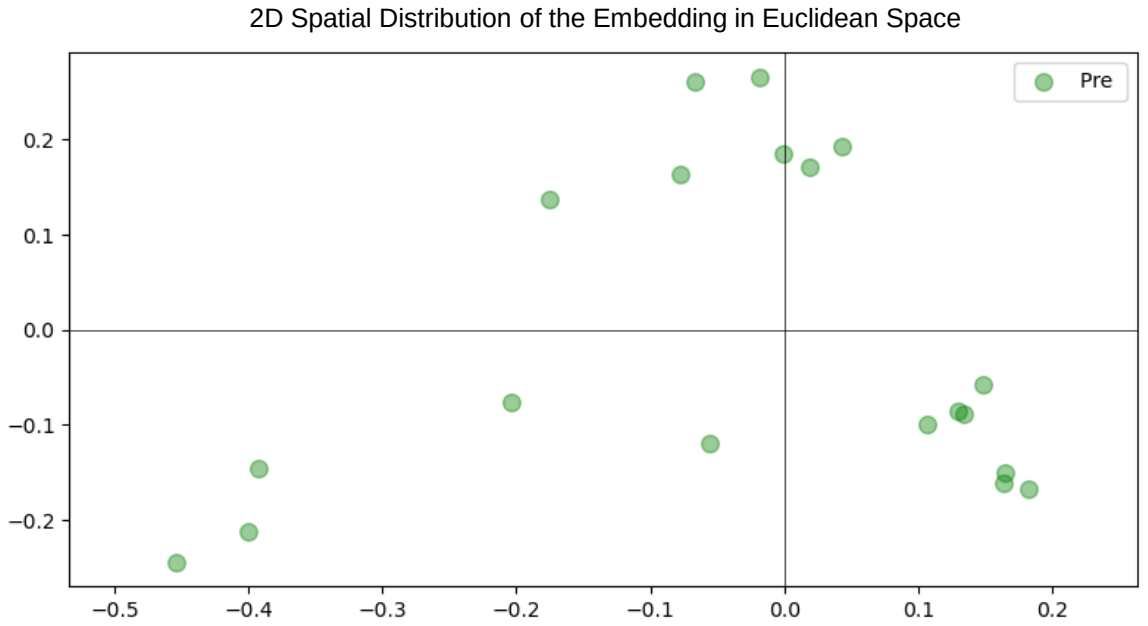


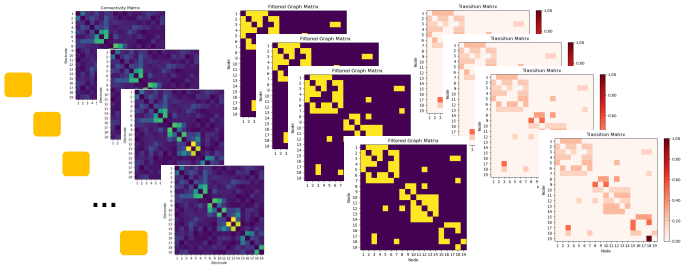
Shan, S., & Daubechies, I. (2022). Diffusion maps: Using the semigroup property for parameter tuning

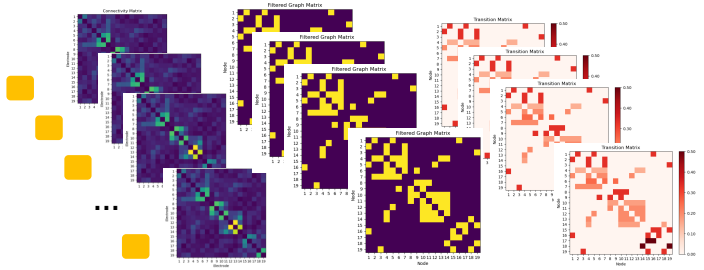

Transition Matrix
Node
Node
1.00
0.80
0.60
0.40
0.20
0.00

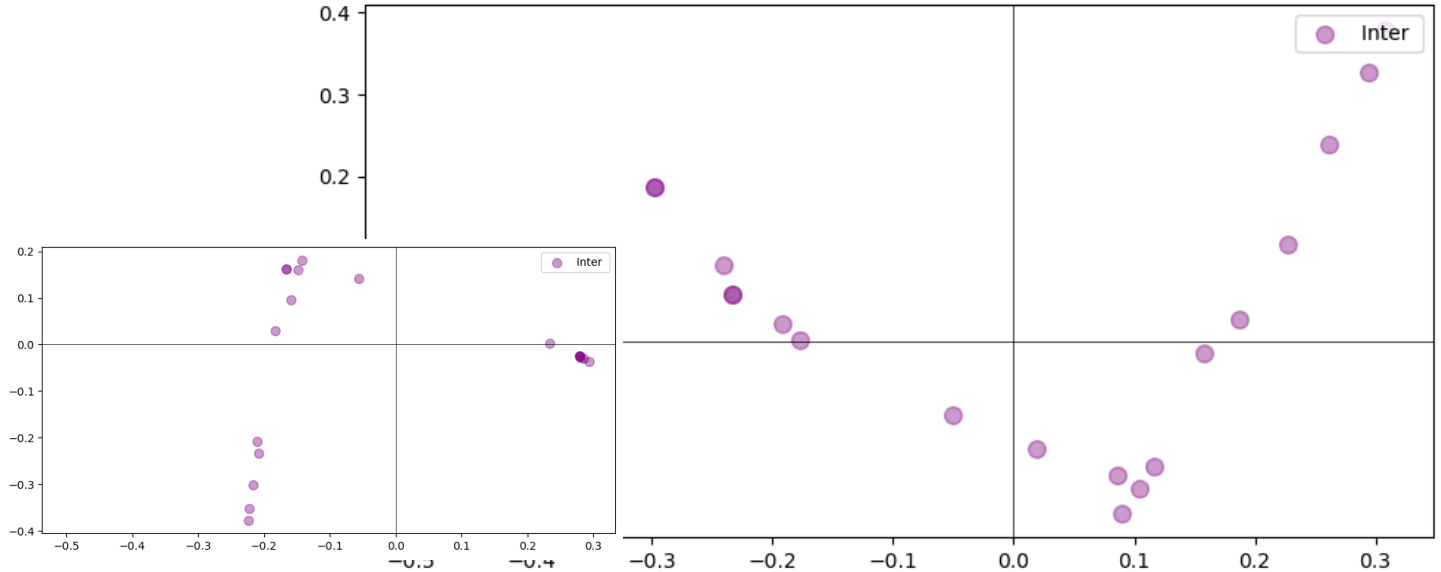

2D Spatial Distribution of the Embedding in Euclidean Space
Inter

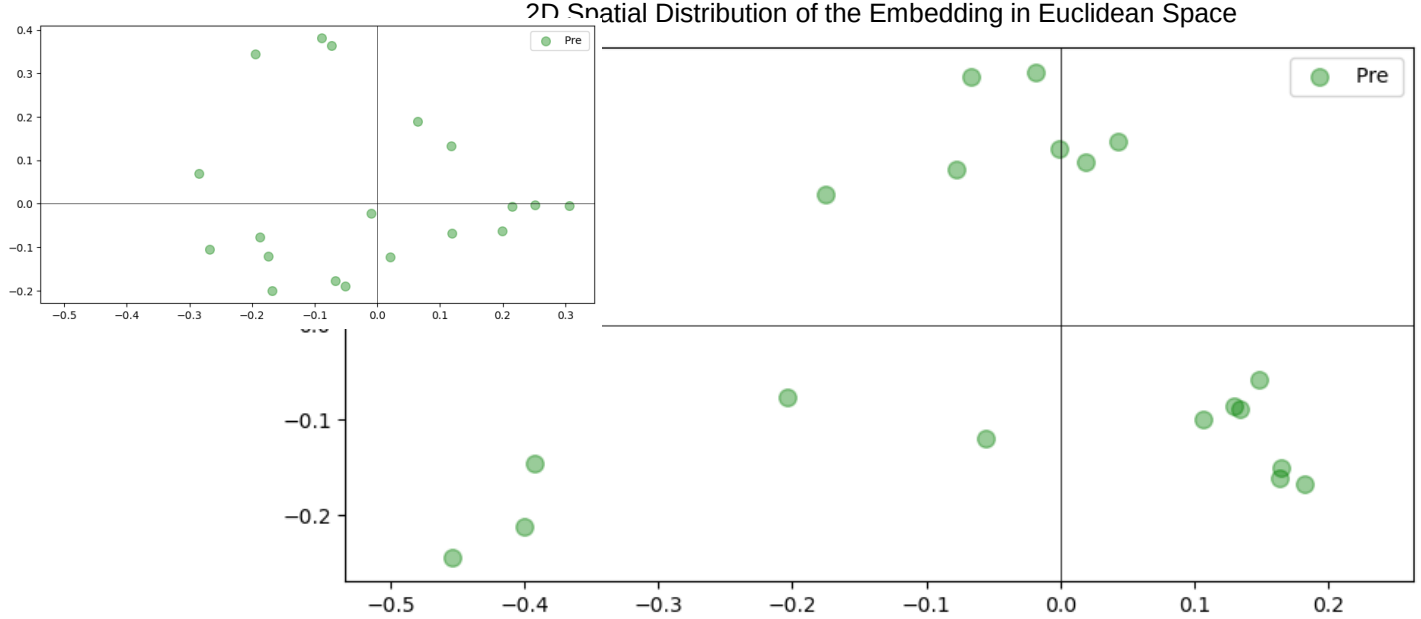

Transition Matrix
Node
Node
0.50
0.40
0.30
0.20
0.10
0.00


2D Spatial Distribution of the Embedding in Euclidean Space
Pre

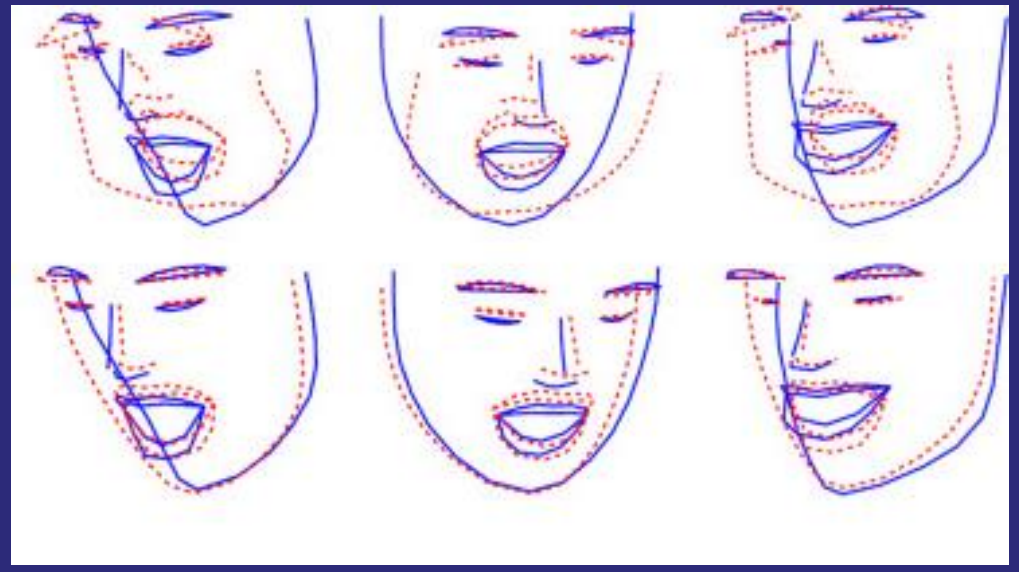




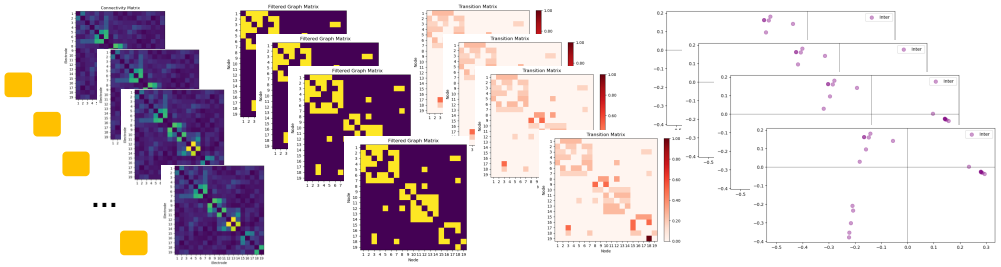

2D Spatial Distribution of the Embedding in Euclidean Space
Inter

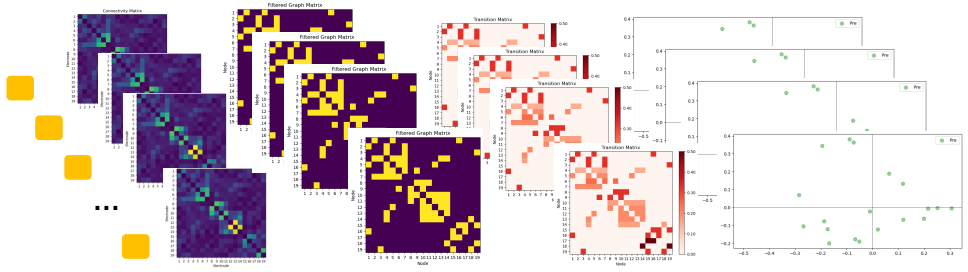

2D Spatial Distribution of the Embedding in Euclidean Space
Pre

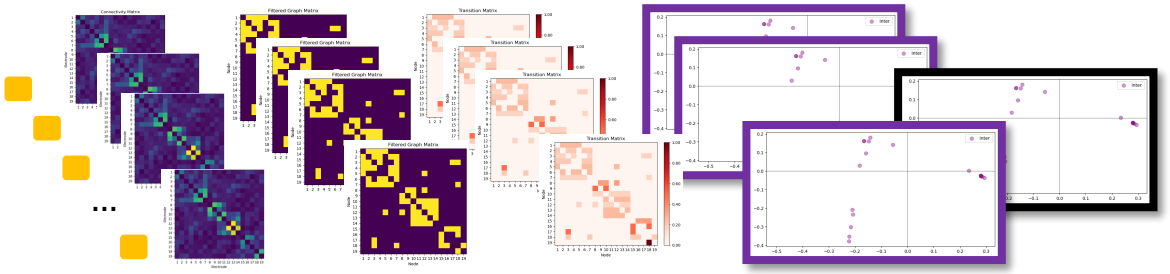
Procrustes

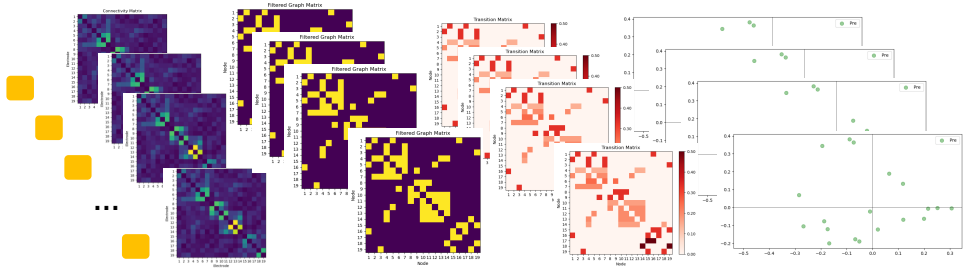


Generalized Procrustes Analysis (GPA) is a multivariate exploratory technique that involves transformations (i.e., translation, rotation, reflection and isotropic rescaling) of individual data matrices to provide optimal comparability.

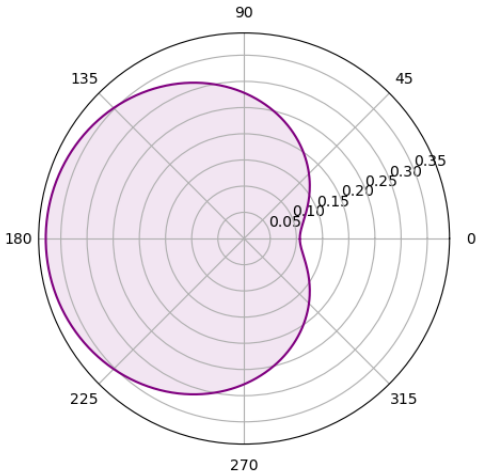




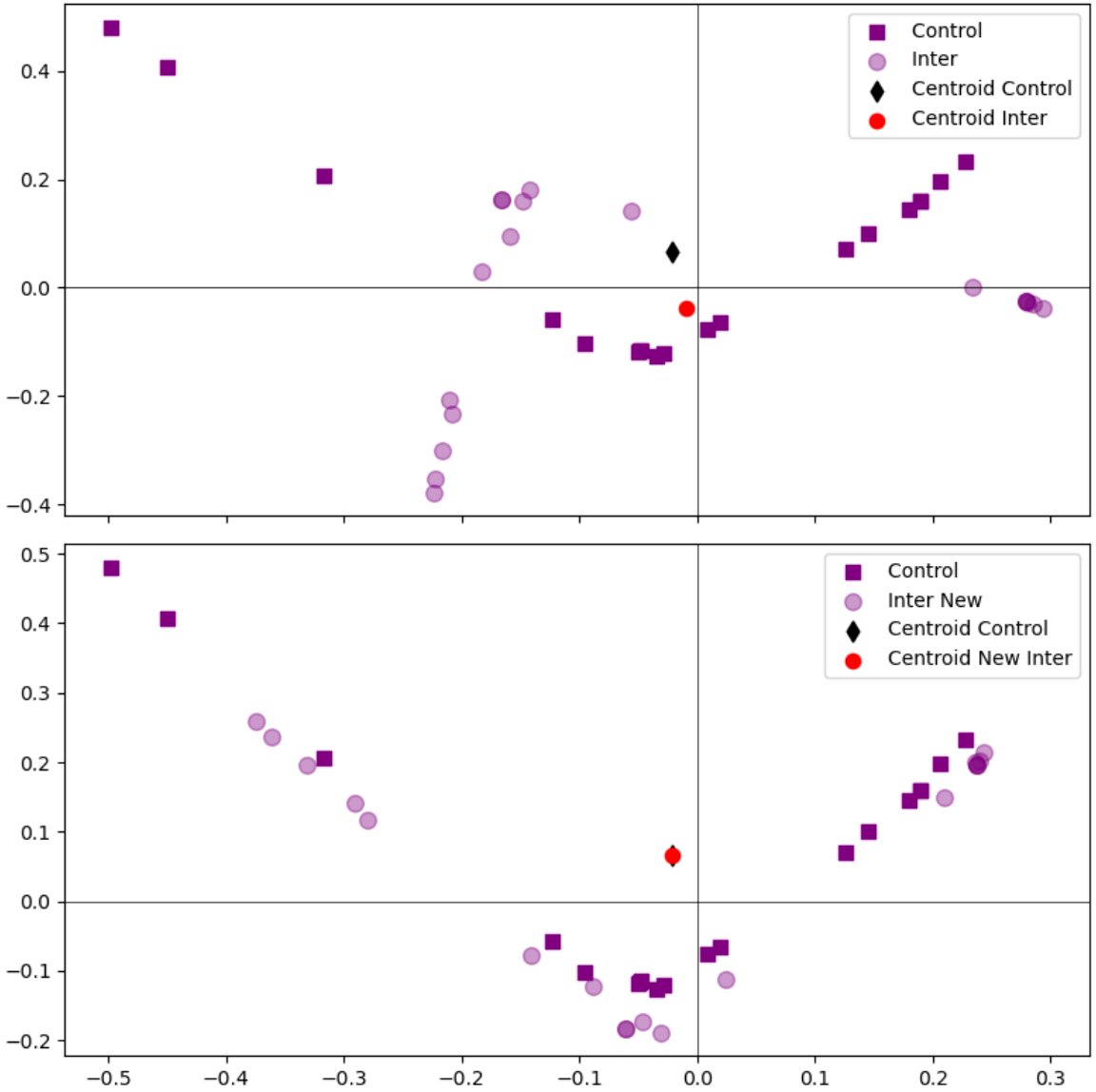


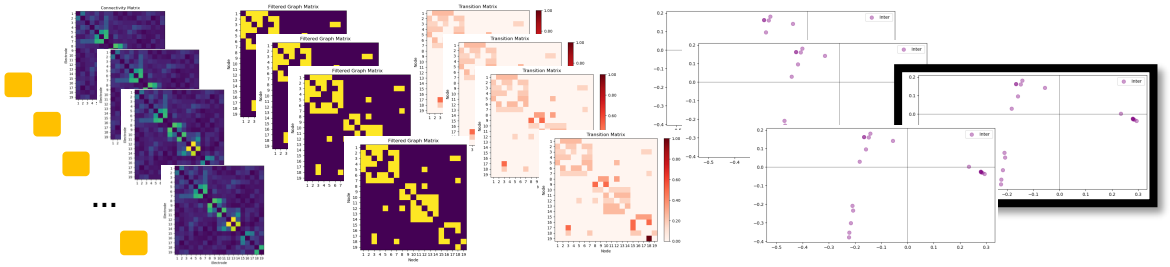


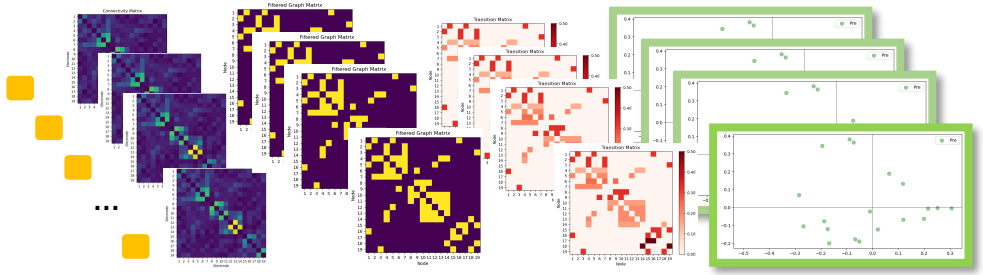
Final aligment's RMS values on rotation



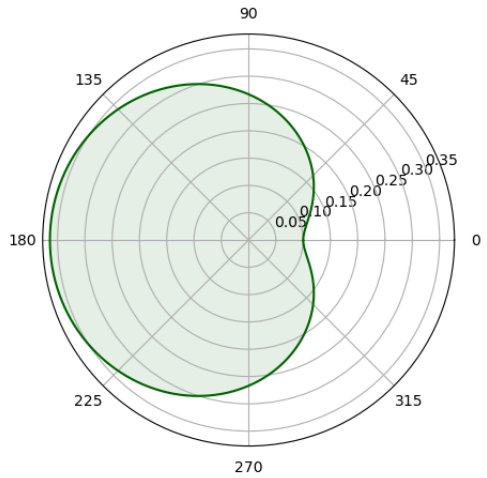
2D Spatial Distribution of the Embedding in Euclidean Space



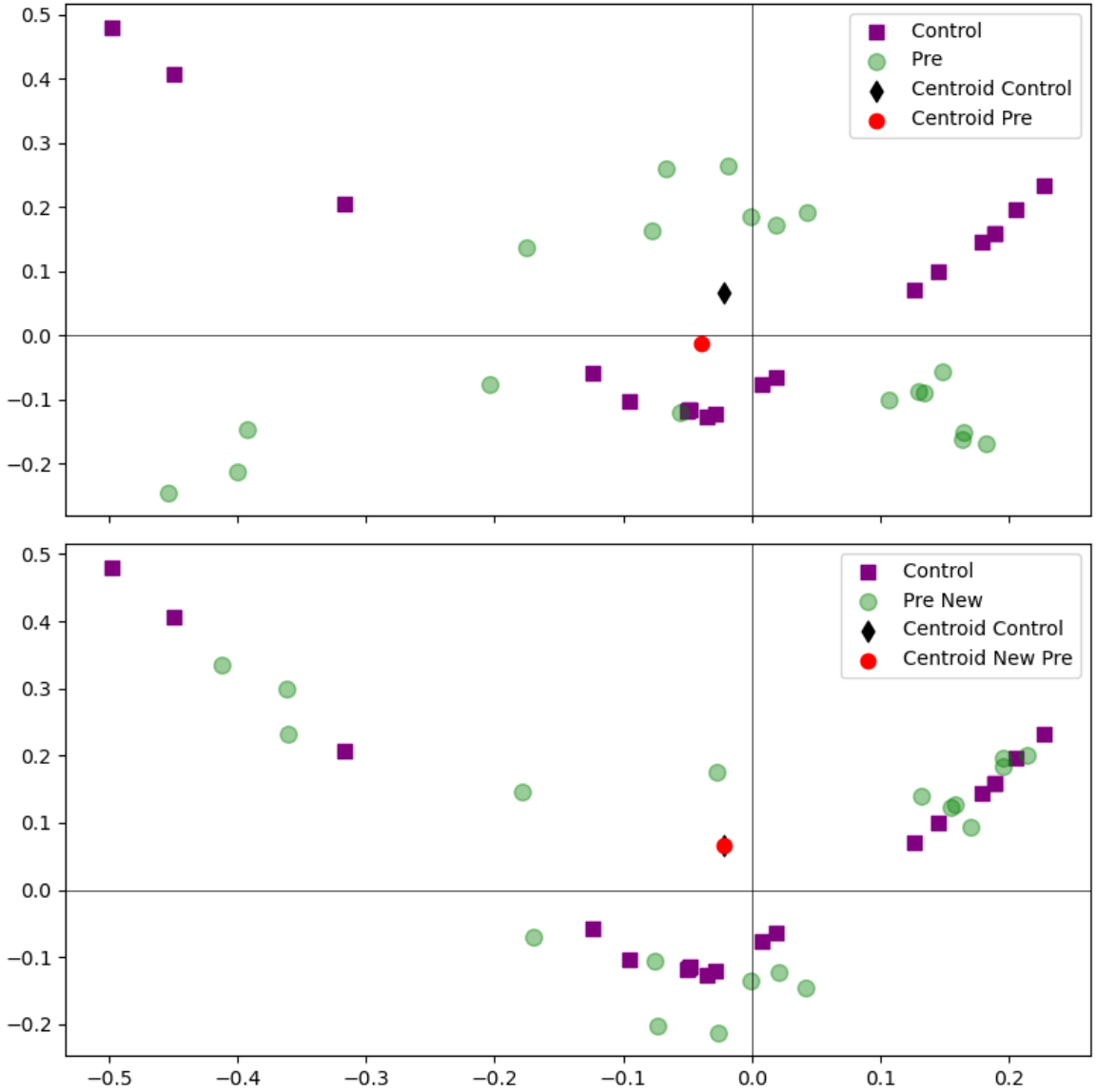




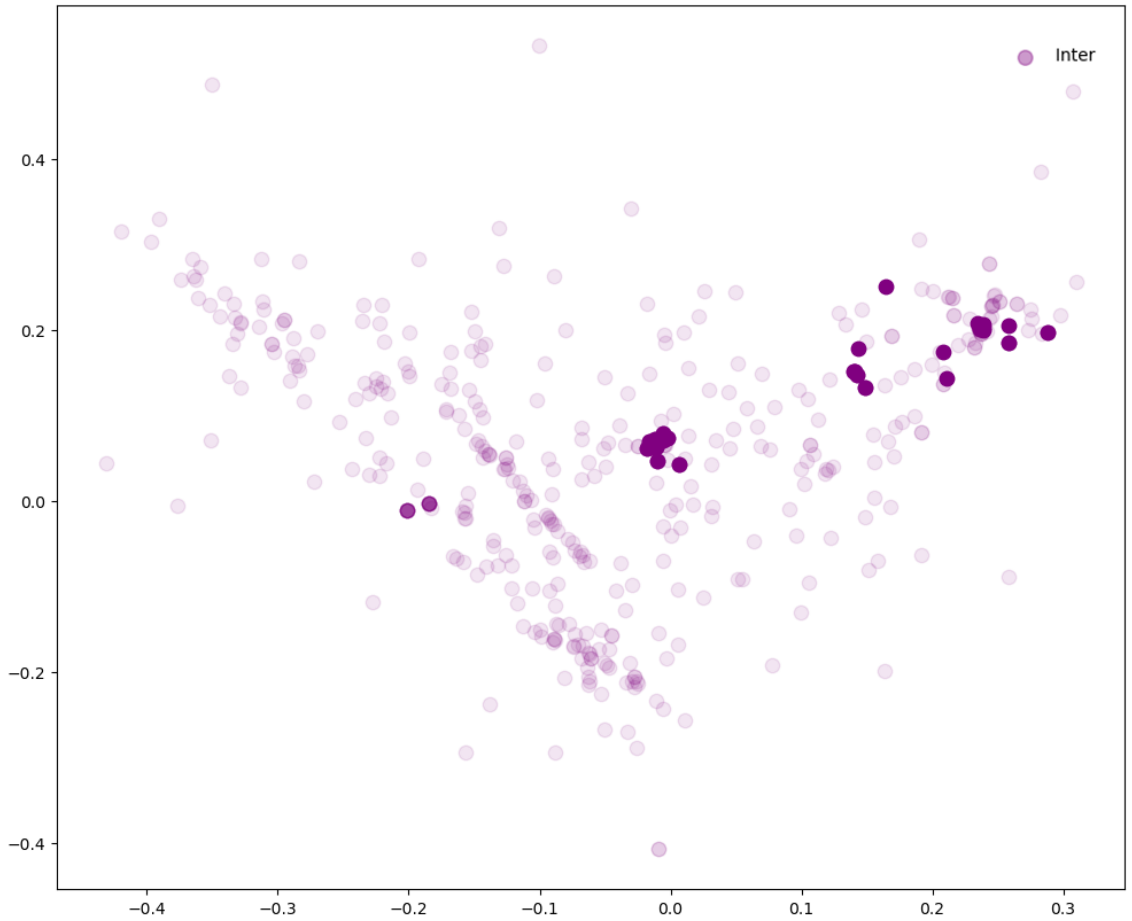
Final aligment's RMS values on rotation



2D Spatial Distribution of the Embedding in Euclidean Space



Spatial Distribution of the Complete data Embedding



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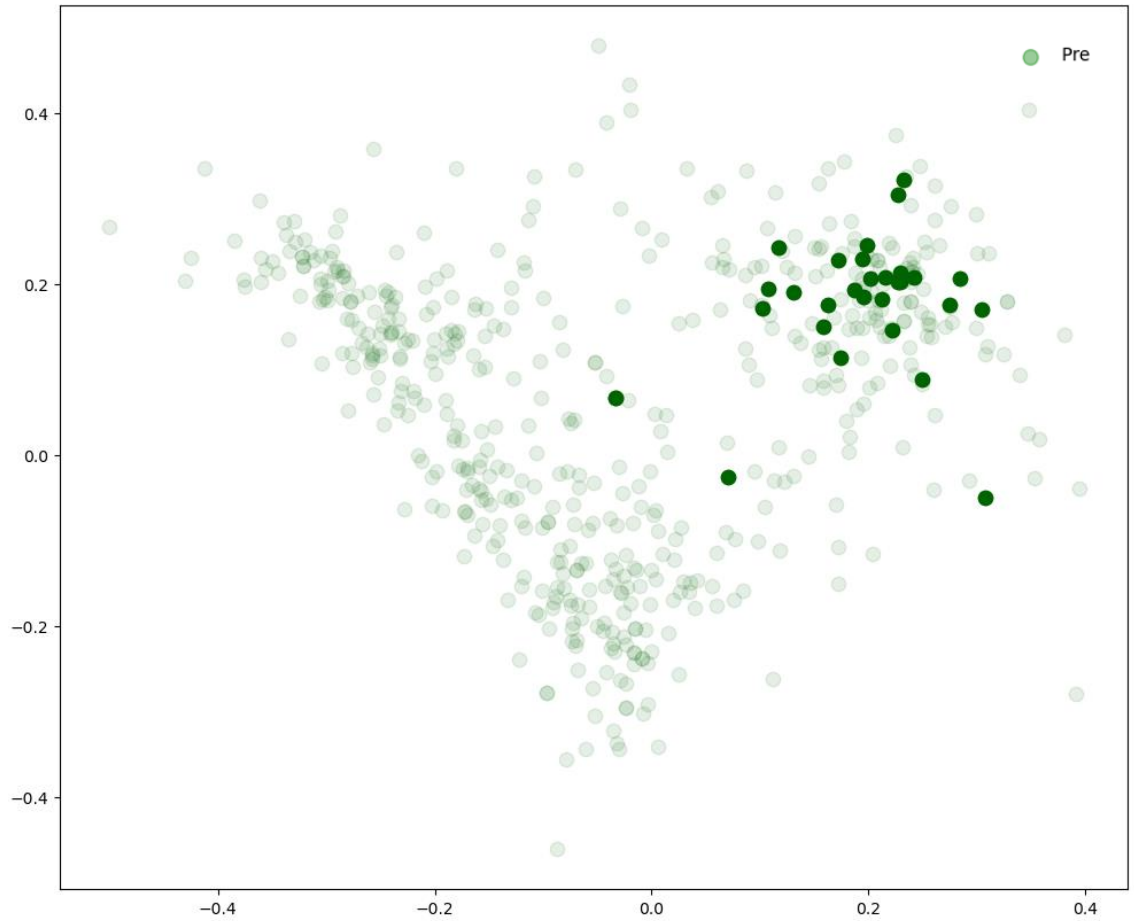
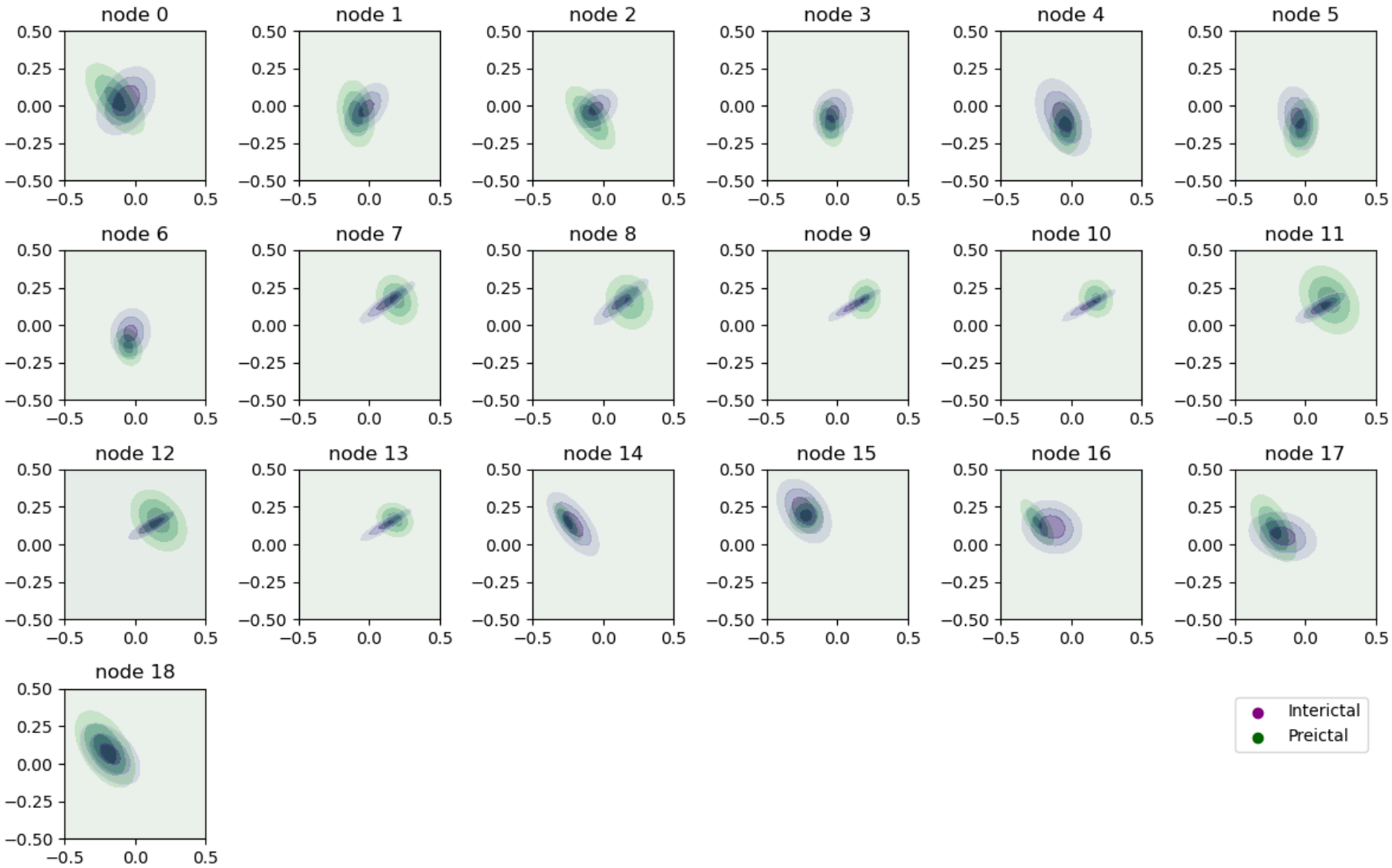


Distribution of the Spatial Position of the Data Node by Node

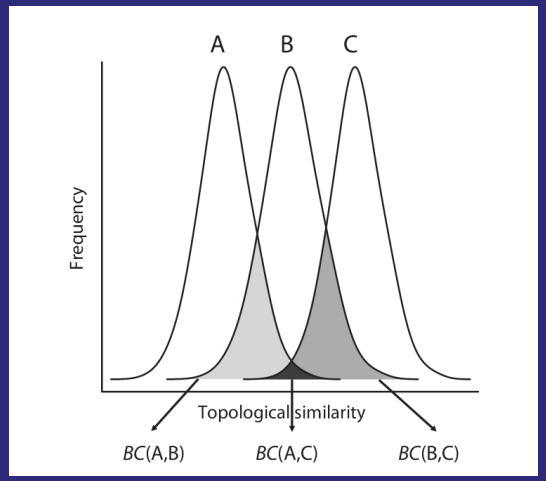


Distances

Metrics to measure the distance between two probability distributions

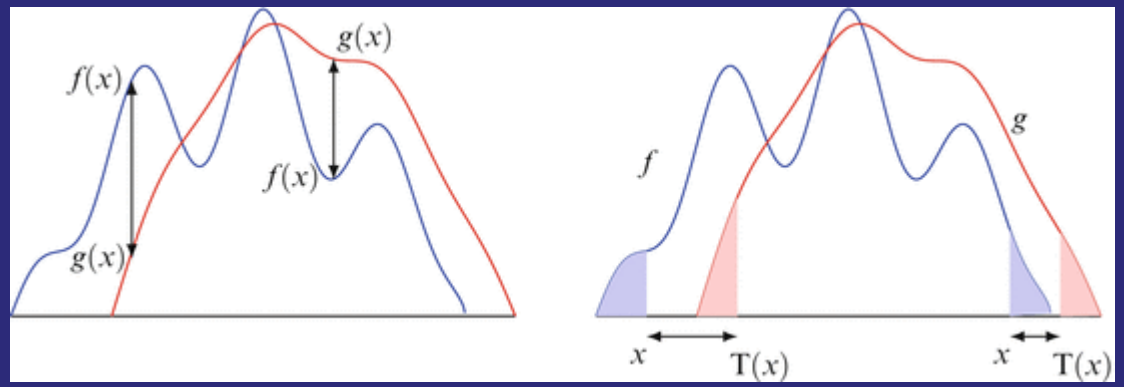
Bhattacharyya

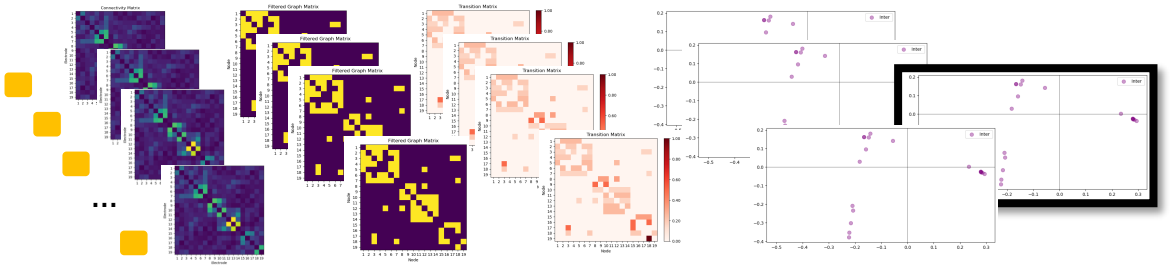
$$D_B(p_1, p_2) = \frac{1}{8}(\mu_1 - \mu_2)^T \Sigma^{-1}(\mu_1 - \mu_2) + \frac{1}{2}\ln\left(\frac{det\Sigma}{\sqrt{det\Sigma_1 det\Sigma_2}}\right)$$

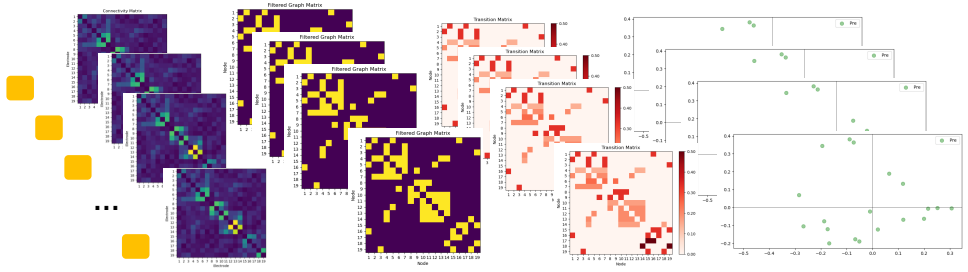


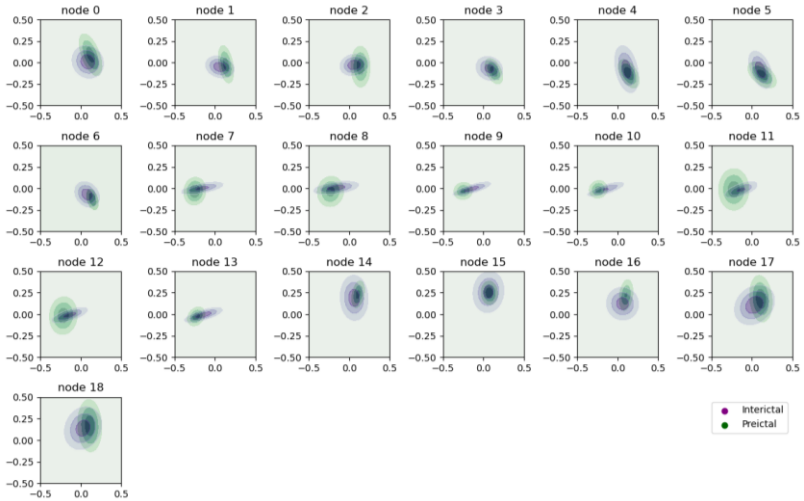
Wasserstein

$$D_W = ||m_1 - m_2||^2 + trace\left(C_1 + C_2 - 2\left(C_2^{\frac{1}{2}} C_1 C_2^{\frac{1}{2}}\right)^{\frac{1}{2}}\right)$$

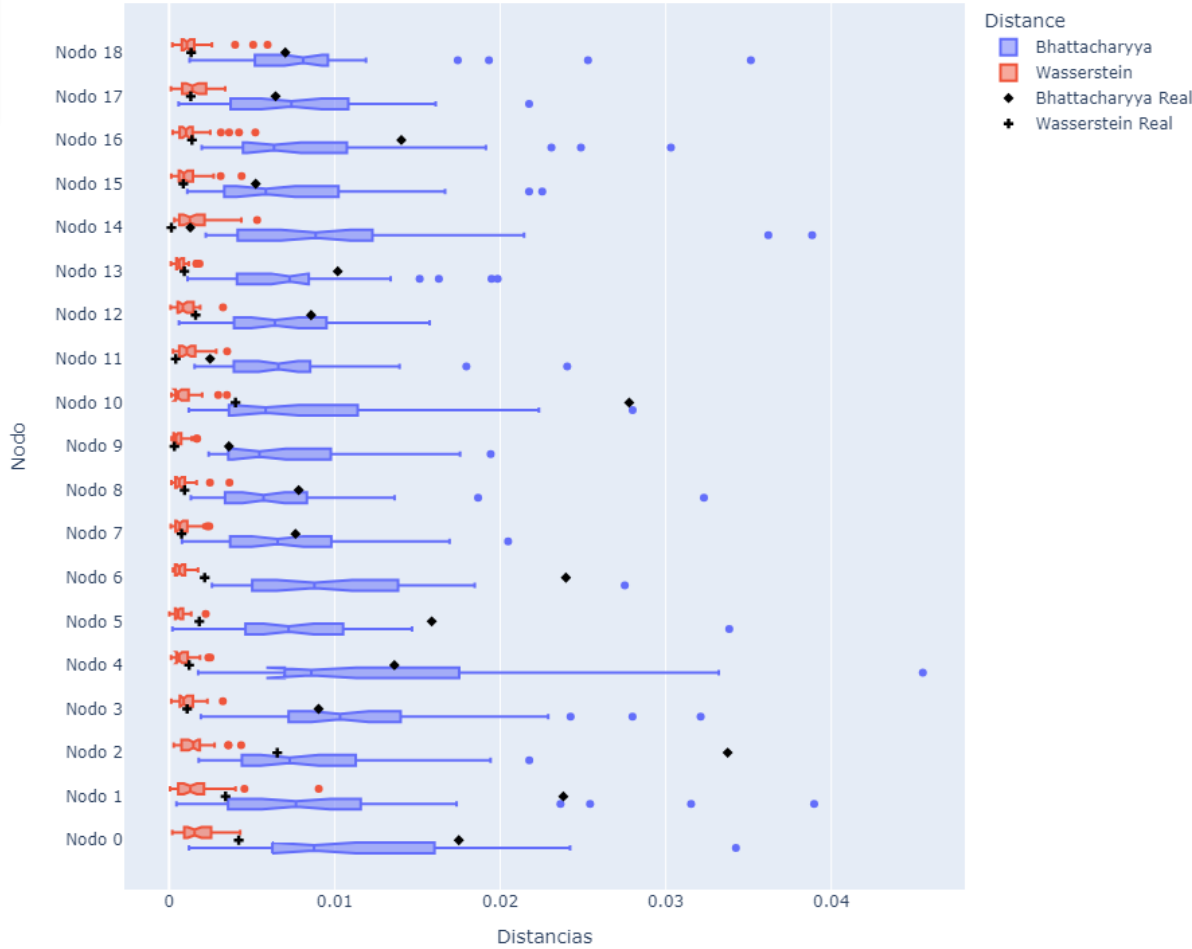








Distance between distribution Node by Node



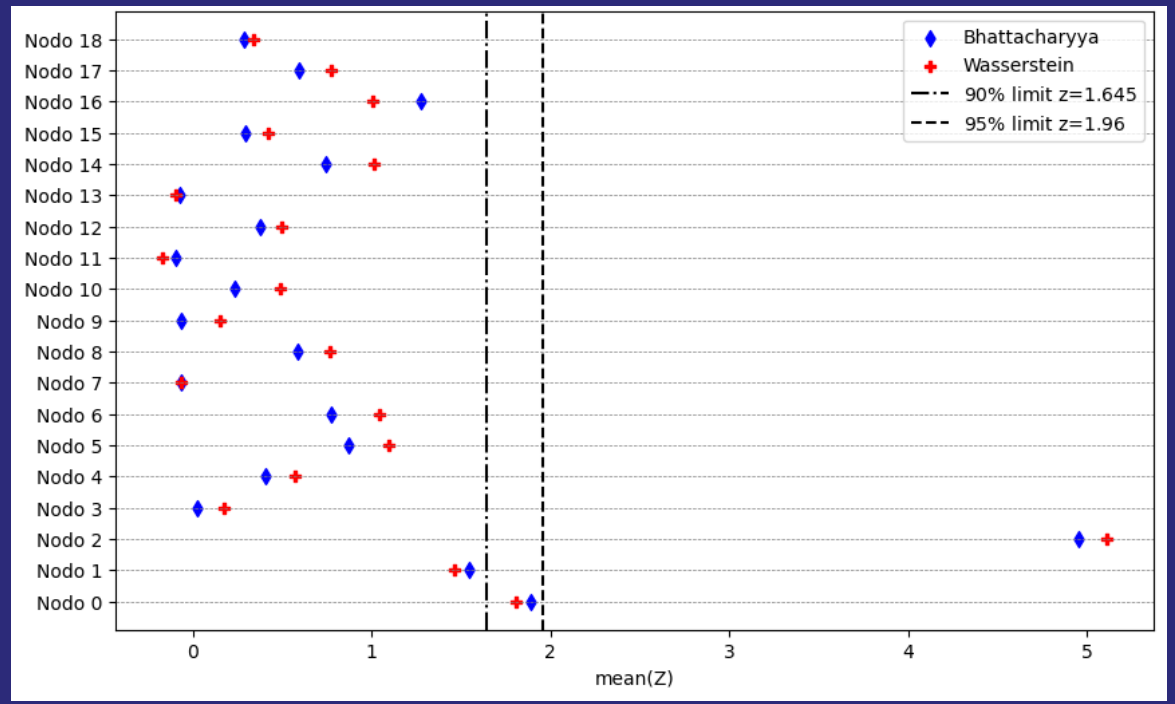
The random test (shuffling) is to defined the base line

Nodes

Measurements normalized by z scores

$$Z = \frac{x - \mu}{\sigma}$$

Z scores for each node



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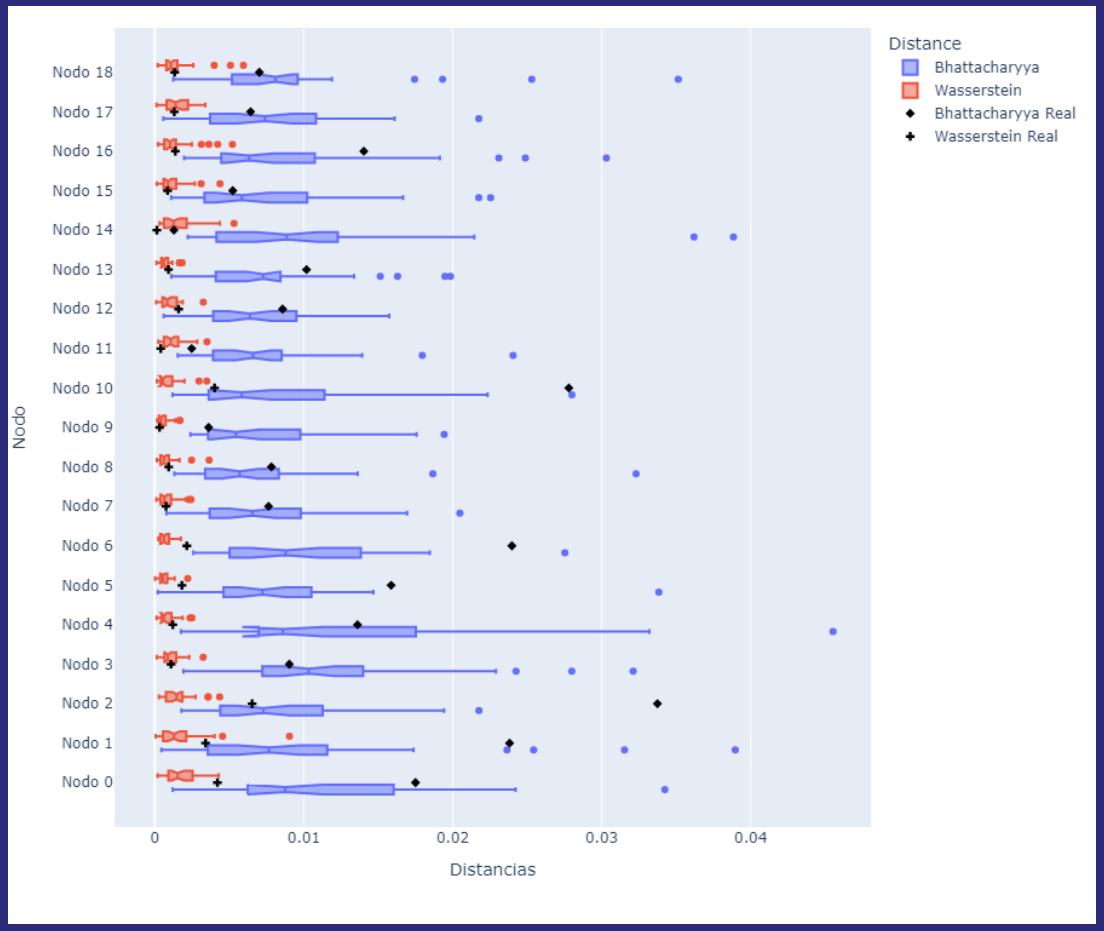
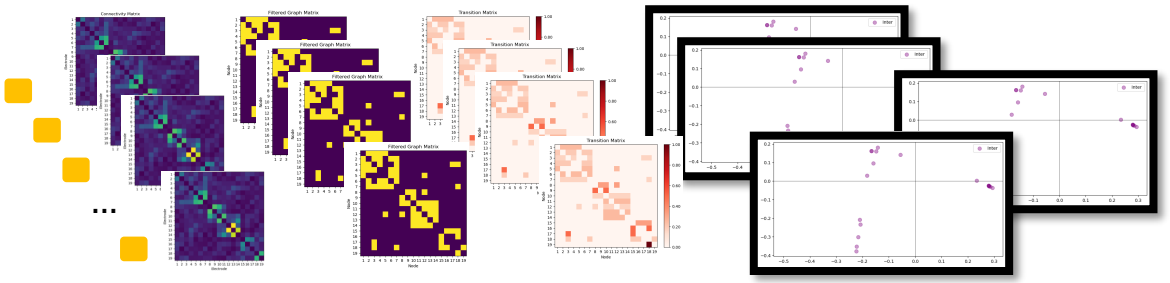
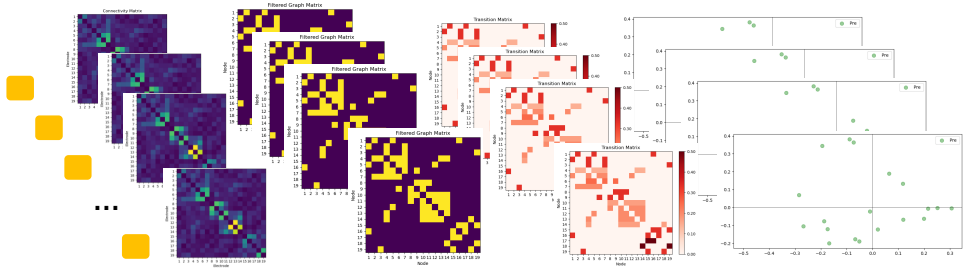
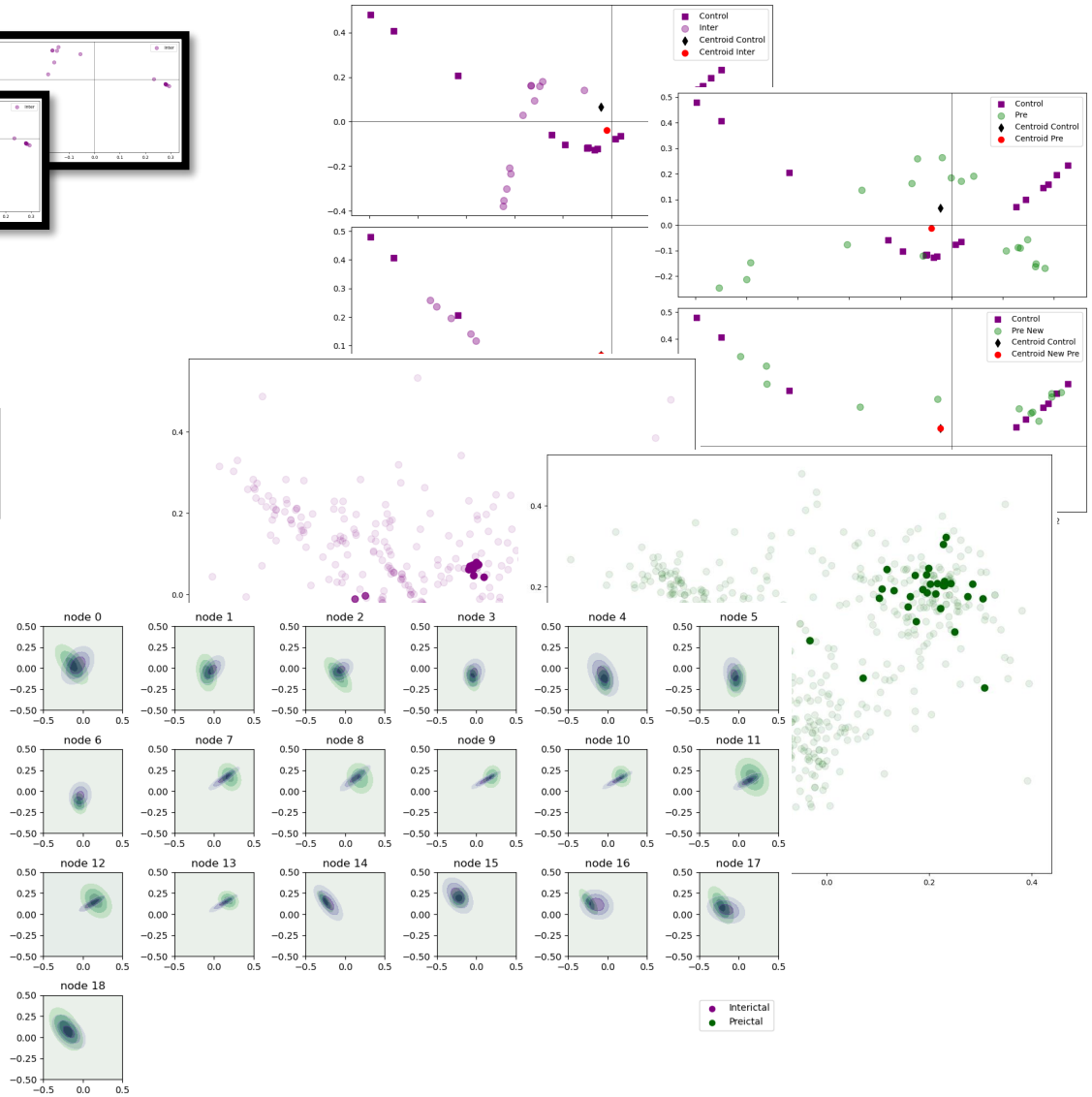
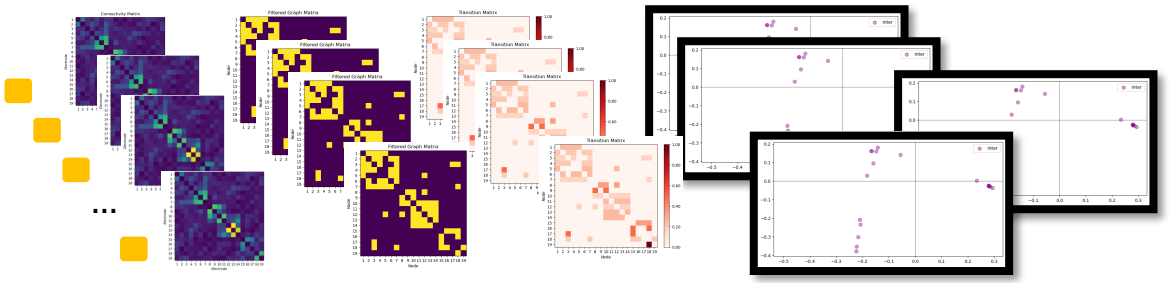
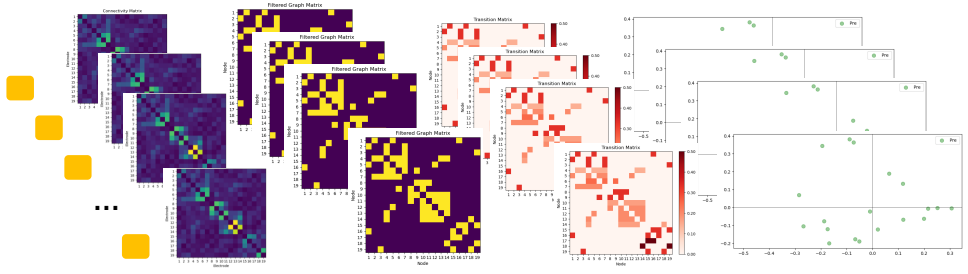


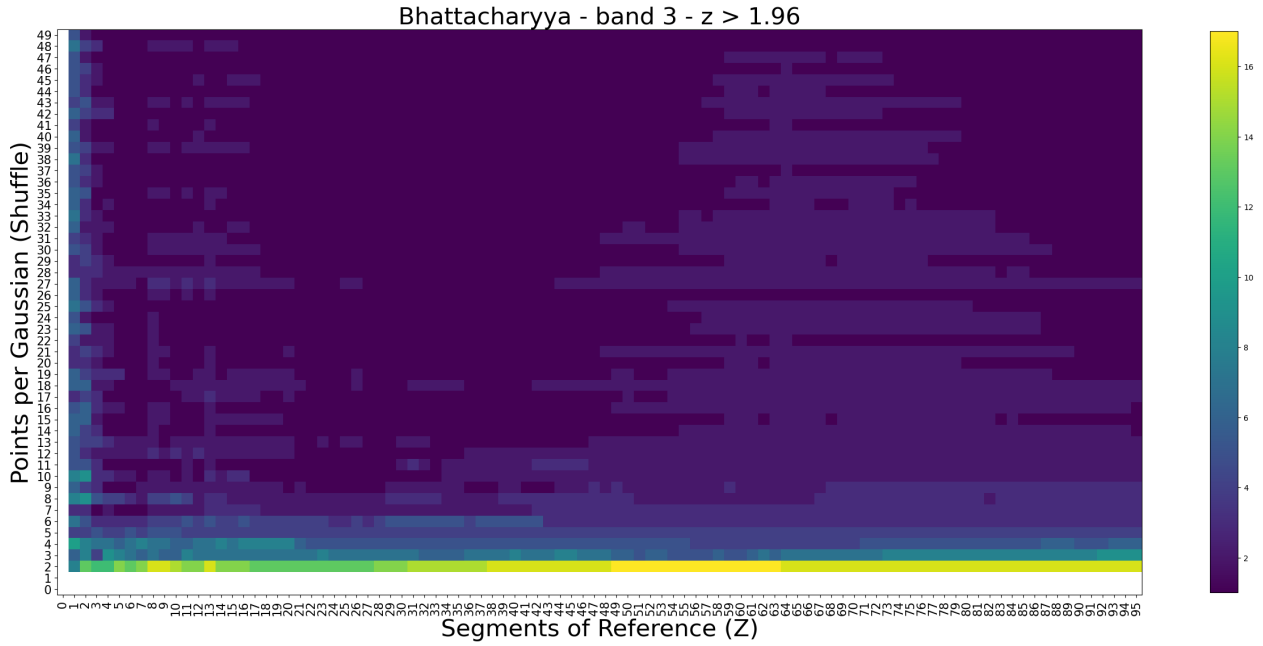


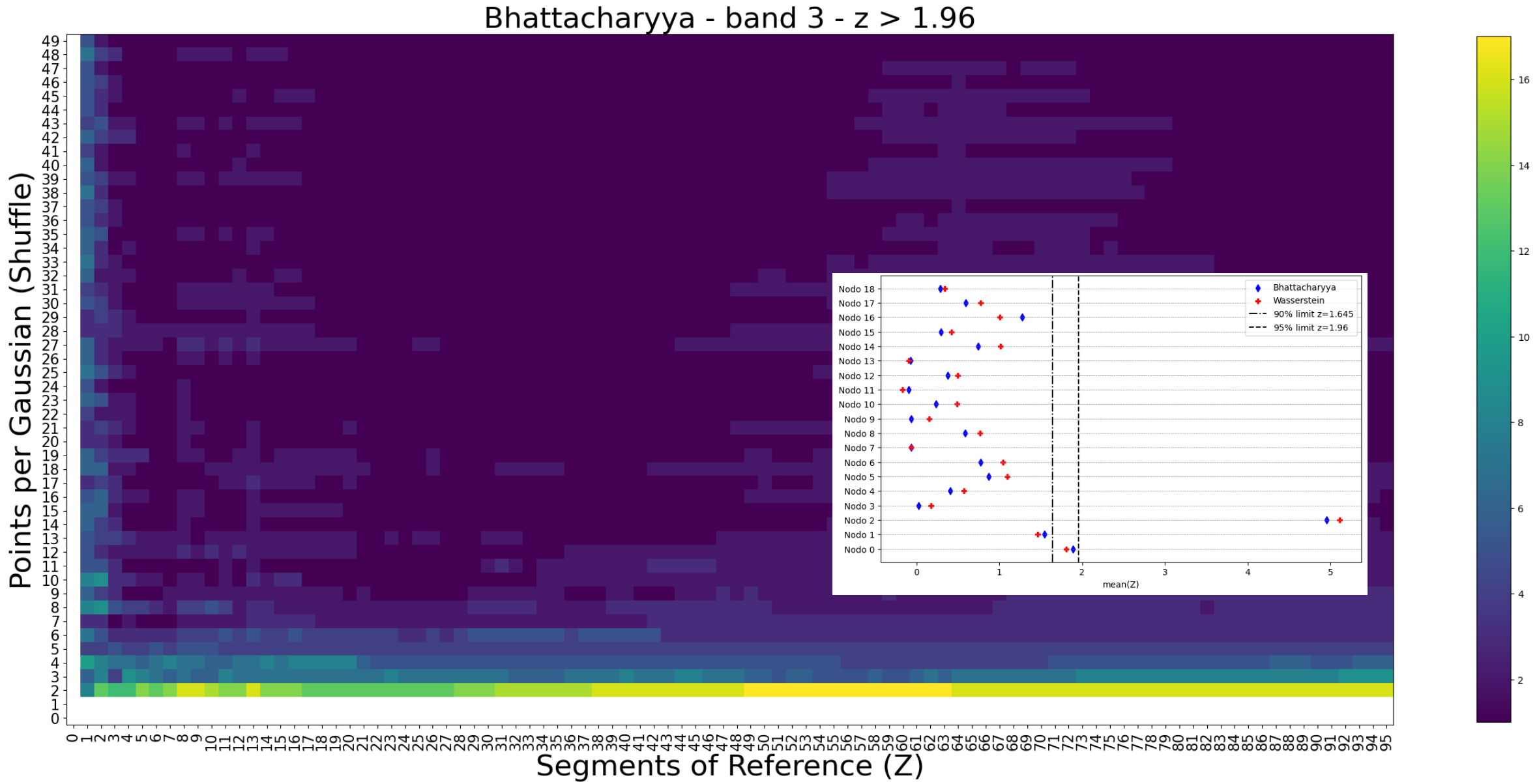


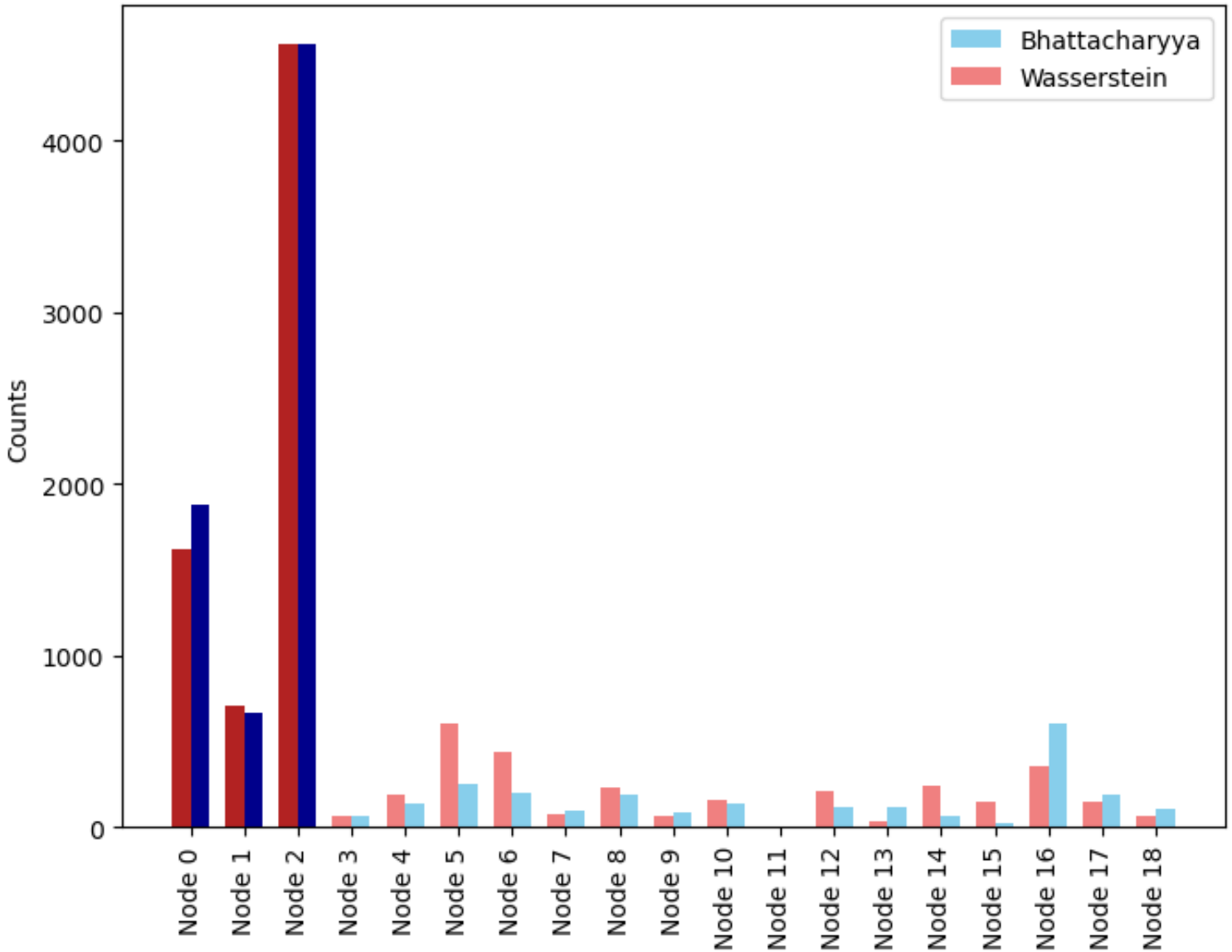

Control
Inter
Centroid Control
Centroid Inter
Control
Pre
Centroid Control
Centroid Pre
Control
Pre New
Centroid Control
Centroid New Pre
node 0
node 1
node 2
node 3
node 4
node 5
node 6
node 7
node 8
node 9
node 10
node 11
node 12
node 13
node 14
node 15
node 16
node 17
node 18
Interictal
Preictal






Bhattacharyya - band 3 - z > 1.96
Points per Gaussian (Shuffle)
Segments of Reference (Z)


Bhattacharyya - band 3 - z > 1.96
Points per Gaussian (Shuffle)
Segments of Reference (Z)
Nodo 18
Nodo 17
Nodo 16
Nodo 15
Nodo 14
Nodo 13
Nodo 12
Nodo 11
Nodo 10
Nodo 9
Nodo 8
Nodo 7
Nodo 6
Nodo 5
Nodo 4
Nodo 3
Nodo 2
Nodo 1
Nodo 0
Bhattacharyya
Wasserstein
90% limit z=1.645
95% limit z=1.96
mean(Z)



Conclusion

In a first approach, embedding iEEG data in the Euclidean space of diffusion maps allows us to identify local connectivity patterns in the network nodes, highlighting those with potential to differentiate seizure states in epilepsy patients.

Impact

This is information that is of interest to clinical staff. We can go back to the brain and point out the region of interest where something is happening. We can also correlate if our node corresponds to the center of the seizure event.

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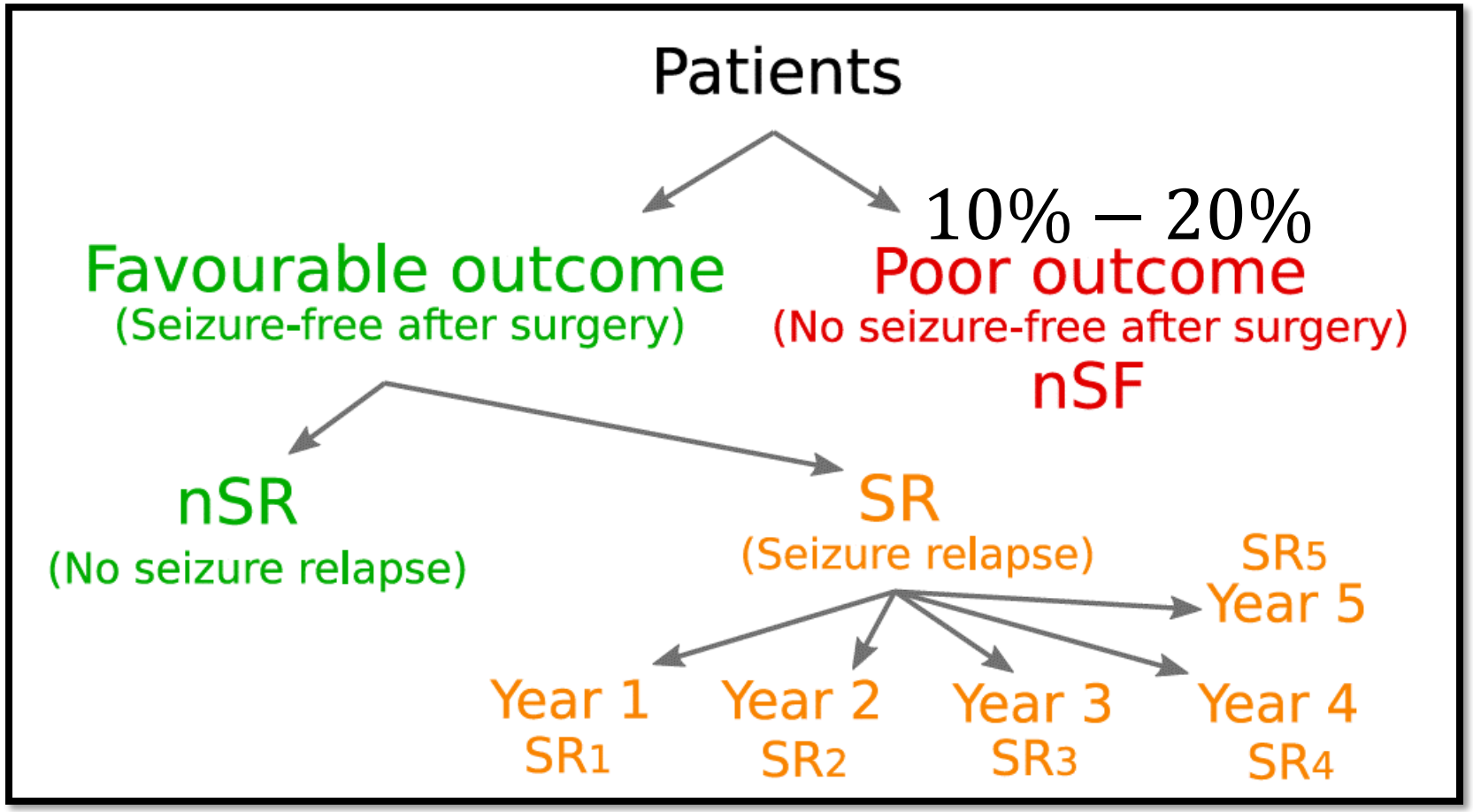
EPILEPSIA:
TODO LO QUE NECESITAS SABER SOBRE ESTA CONDICIÓN
¿QUÉ ES?
UNA ALTERACIÓN DE LA ACTIVIDAD ELÉCTRICA DEL CEREBRO QUE PUEDE SER GENERALIZADA O SOLO EN UNA REGIÓN.
SUS CAUSAS SON VARIADAS: FACTORES GENÉTICOS, INFECCIONES, TUMORES, HEMORRAGIAS O LESIONES.
Y ES TAN COMÚN QUE SI EN UNA HABITACIÓN HAY 20 PERSONAS, ES MUY PROBABLE QUE AL MENOS 1 LA PADEZCA.
FUENTE: Entrevista con Dr. Joseph Sirven y Dr. Jamie Van Gompel, Mayo Clinic.
PICTOLINE


SÍNTOMAS
SUELE MANIFESTARSE EN FORMA DE CONVULSIONES
PERO TAMBIÉN COMO ESPASMOS EN UNA PARTE DEL CUERPO
CRISIS DE AUSENCIA
(LUCE COMO SI ESTUVIERA MIRANDO A LA NADA POR UNOS SEGUNDOS)
MOVIMIENTOS REPETITIVOS (TICS)
SENSACIONES INUSUALES (COMO PERCIBIR LUCES, OLORES, ETC.)
PÉRDIDA DE CONSCIENCIA
PICTOLINE


¿Y QUÉ HACER SI SOSPECHAS QUE LA TIENES?
TÍPICAMENTE LA DIAGNOSTICA UN ESPECIALISTA EN NEUROLOGÍA.
VE A LA CONSULTA CON ALGUIEN QUE TE HAYA VISTO CON LOS SÍNTOMAS, YA QUE ES PROBABLE QUE NO RECUERDES LO QUE PASÓ.
PARA LA MAYORÍA DE LAS PERSONAS EXISTE ALGUNA SOLUCIÓN:
DESDE MEDICAMENTOS, DIETAS O USO DE MARCAPASOS HASTA CIRUGÍA
PICTOLINE



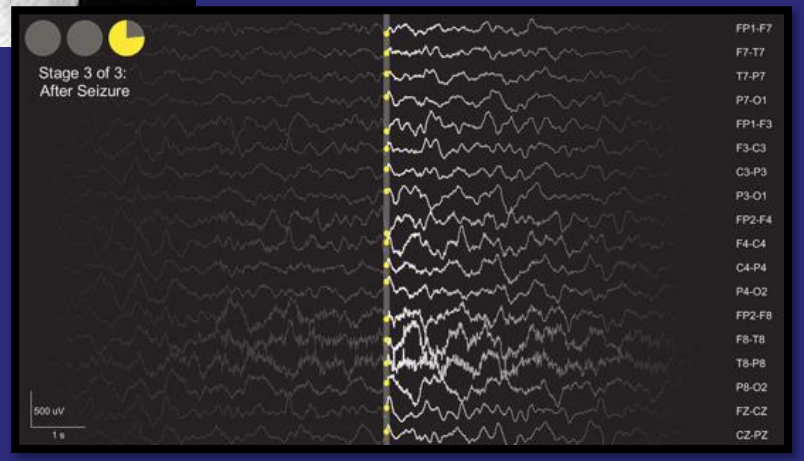
Martin Guillemaud et al. Epileptic seizure forecasting with hyperbolic embedding of brain networks. Article submitted, 2023.

Data

intracranial electroencephalography (iEEG)

ASSISTANCE PUBLIQUE HÔPITAUX DE PARIS

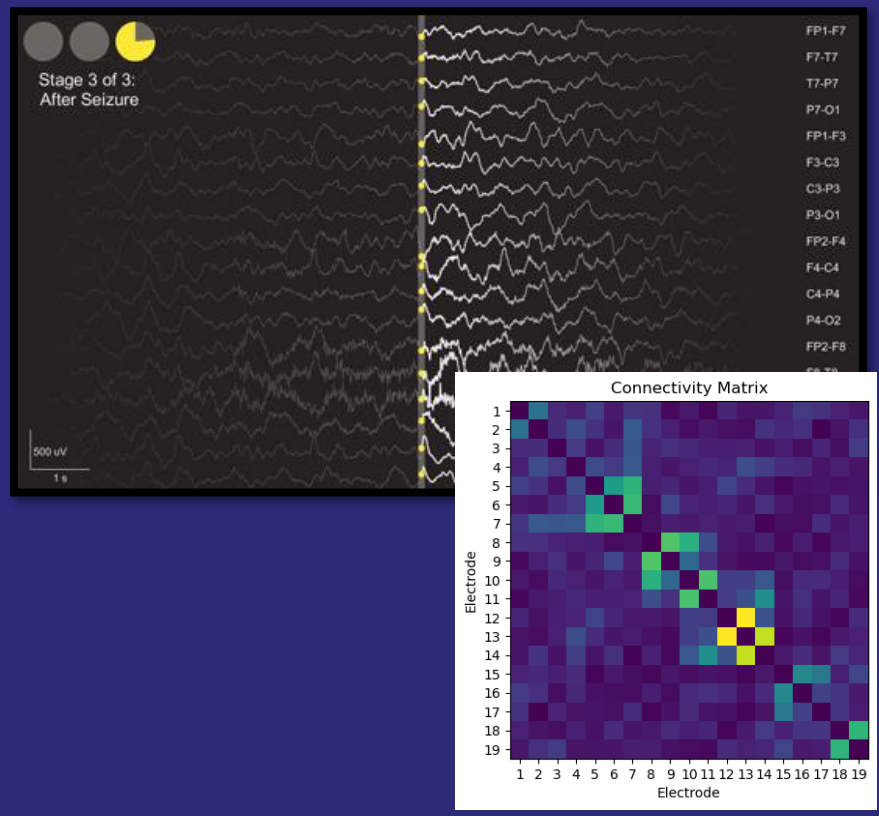
method to record an electrogram of the spontaneous electrical activity of the brain. EEG is the gold standard diagnostic procedure to confirm epilepsy. The sensitivity of a routine EEG to detect interictal epileptiform discharges at epilepsy centers has been reported to be in the range of 29–55%



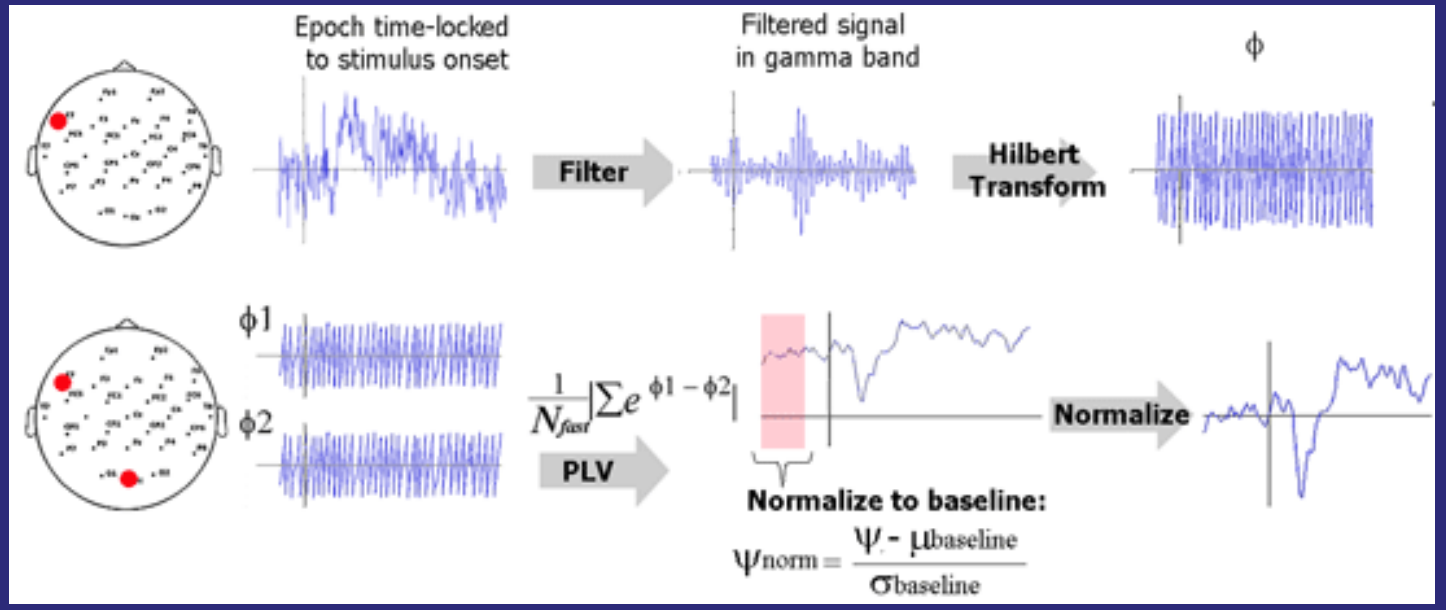
Delta	< 4 Hz
Theta	4 – 7 Hz
Alpha	8 – 12 Hz
Beta	13 – 30 Hz
Low Gamma	> 30 Hz
High Gamma	

Data

intracranial electroencephalography (iEEG)



Use of the **Phase Locking Value Method (PLV)** to construct the conectivitty matrixes with the iEEG signals



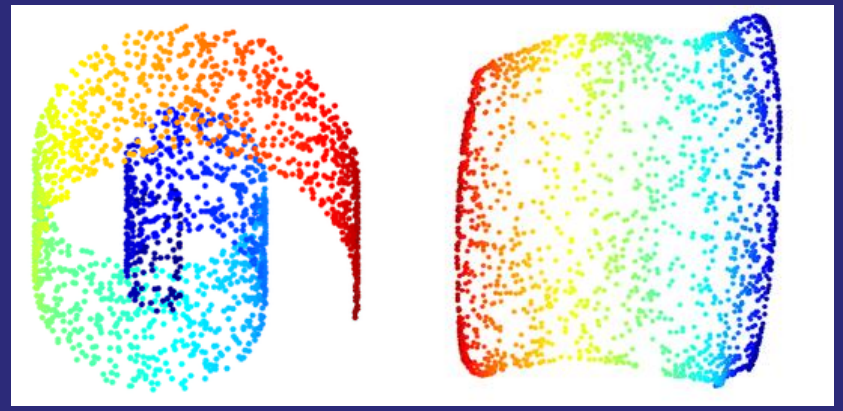
Data

Band Beta	Interictal 8 days	Preictal 3 days
Band Alpha	Interictal 10 days	Preictal 2 days
Band High Gamma	Interictal 2 days	Preictal 2 days

Band Low Gamma
Interictal 9 days
Preictal 3 days

Diffusion Map

Nonlinear dimensionality reduction technique of a data set in Euclidean space whose coordinates can be computed from the eigenvectors and eigenvalues of a diffusion operator on the data.



Shan, S., & Daubechies, I. (2022). Diffusion maps: Using the semigroup property for parameter tuning

This reduction technique works by using the degree of the graph to find the probability of transition between all the data, creating a connection with the spectral theory of random walk.

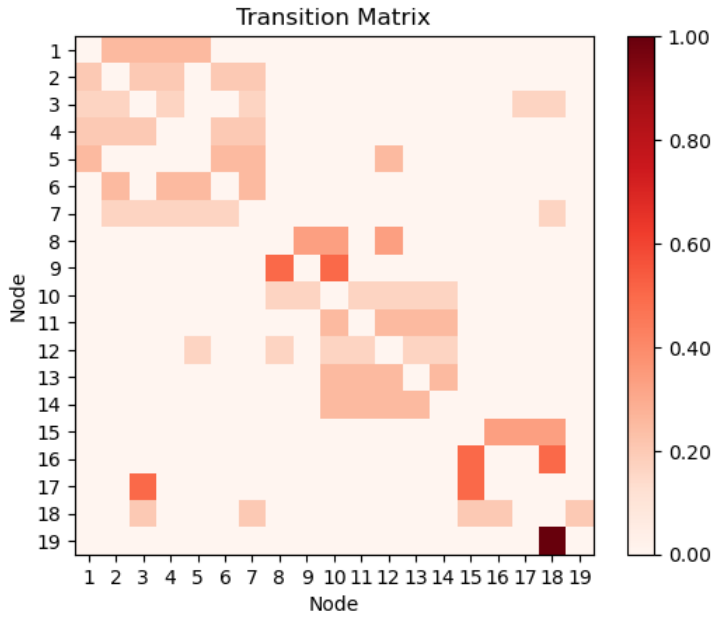
$$p(x,y) = \frac{w(x,y)}{\sum_{z\in\Omega} w(x,z)}$$

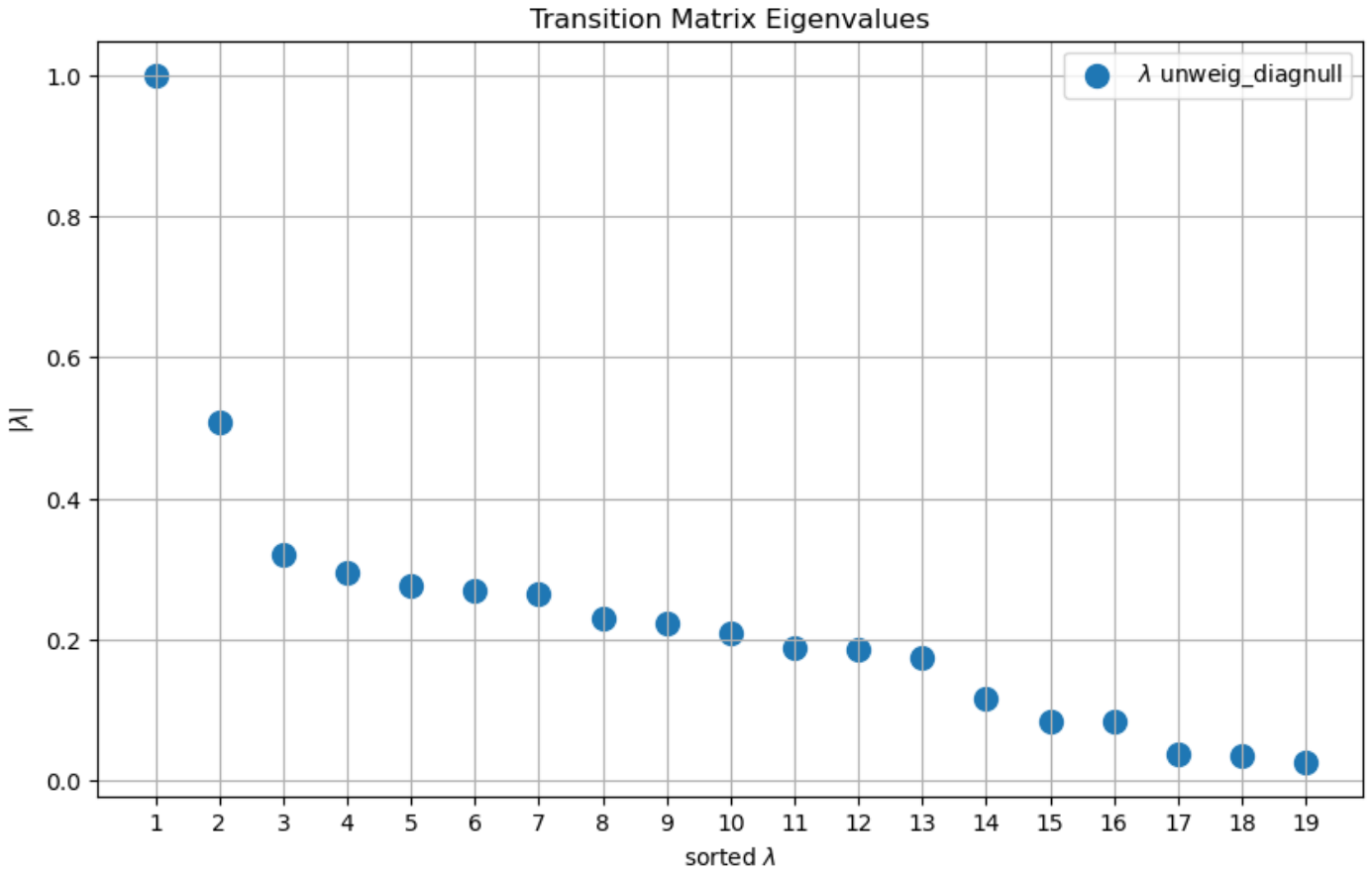
$$\phi_j^T P = \lambda_j \phi_j^T \; and \; P\,\psi_j = \lambda_j \psi_j$$

The eigenvalues and eigenvectors of the transition matrix (P) provide the representation of the initial graph as a cloud of points in a lower dimensional space.

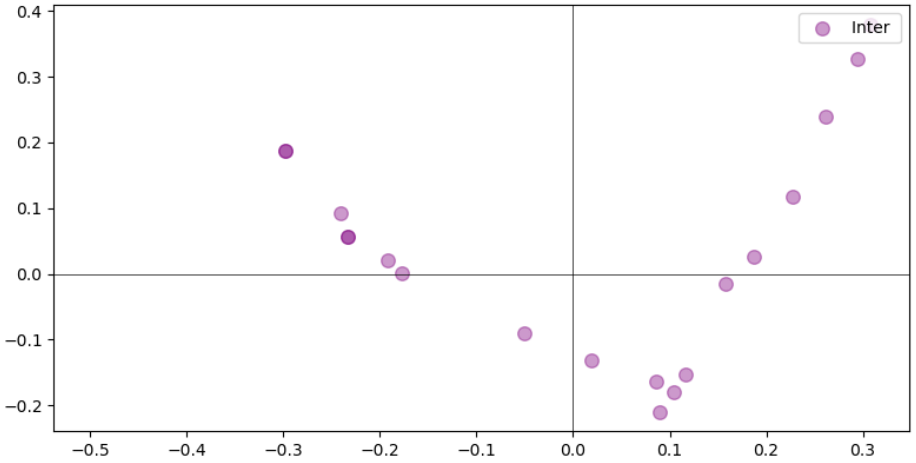
$$\Psi_t: x \rightarrow \begin{pmatrix} \lambda_1^t \psi_1(x) \\ \lambda_2^t \psi_2(x) \\ \vdots \\ \lambda_{q(t)}^t \psi_{q(t)}(x) \end{pmatrix}$$

Lafon, S., & Lee, A. B. (2006). Diffusion maps and coarse-graining: A unified framework for dimensionality reduction, graph partitioning, and data set parameterization



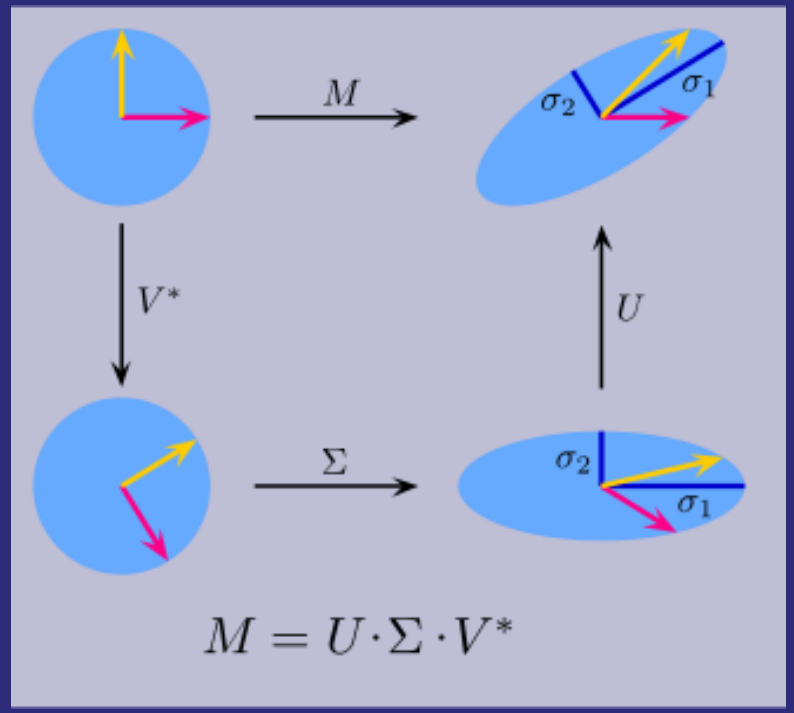


2D Spatial Distribution of the Embedding in Euclidean Space



Procrustes

Generalized Procrustes Analysis (GPA) is a multivariate exploratory technique that involves transformations (i.e., translation, rotation, reflection and isotropic rescaling) of individual data matrices to provide optimal comparability.



First, it is necessary to compute the baricenter of the two dataset and translate the to the origin of the space.

This problem is equivalent to finding the nearest orthogonal matrix to a given matrix $M = BA^T$ using the singular value decomposition

$$M = U\Sigma V^T$$

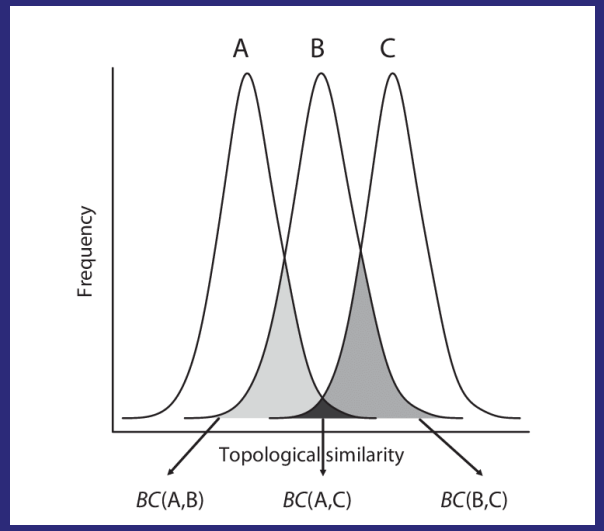
Where the transformation matrix is

$$R = UV^T$$

Distances

Bhattacharyya

$$D_B(p_1, p_2) = \frac{1}{8}(\mu_1 - \mu_2)^T \Sigma^{-1}(\mu_1 - \mu_2) + \frac{1}{2}\ln\left(\frac{det\Sigma}{\sqrt{det\Sigma_1 det\Sigma_2}}\right)$$

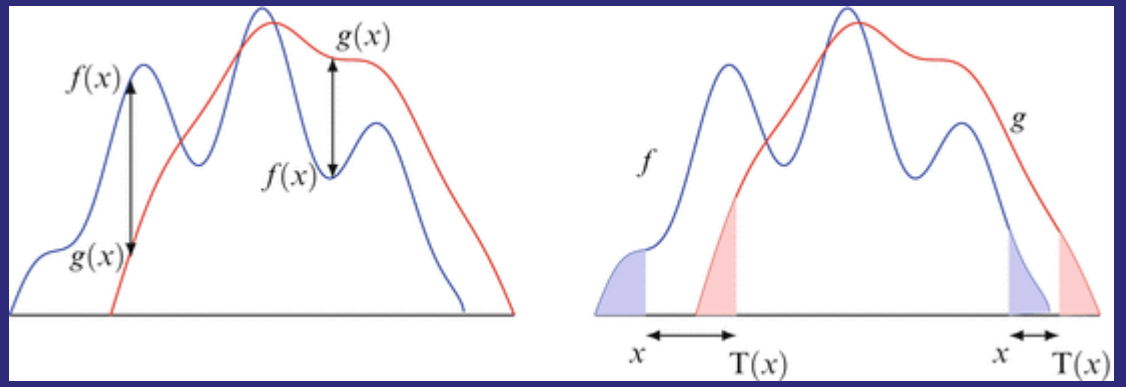


$$\Sigma = \frac{\Sigma_1 + \Sigma_2}{2}$$

It is based on the measure of overlapping areas under the probability curves of the two distributions.

Wasserstein

$$D_W = ||m_1 - m_2||^2 + trace\left(C_1 + C_2 - 2\left(C_2^{\frac{1}{2}} C_1 C_2^{\frac{1}{2}}\right)^{\frac{1}{2}}\right)$$

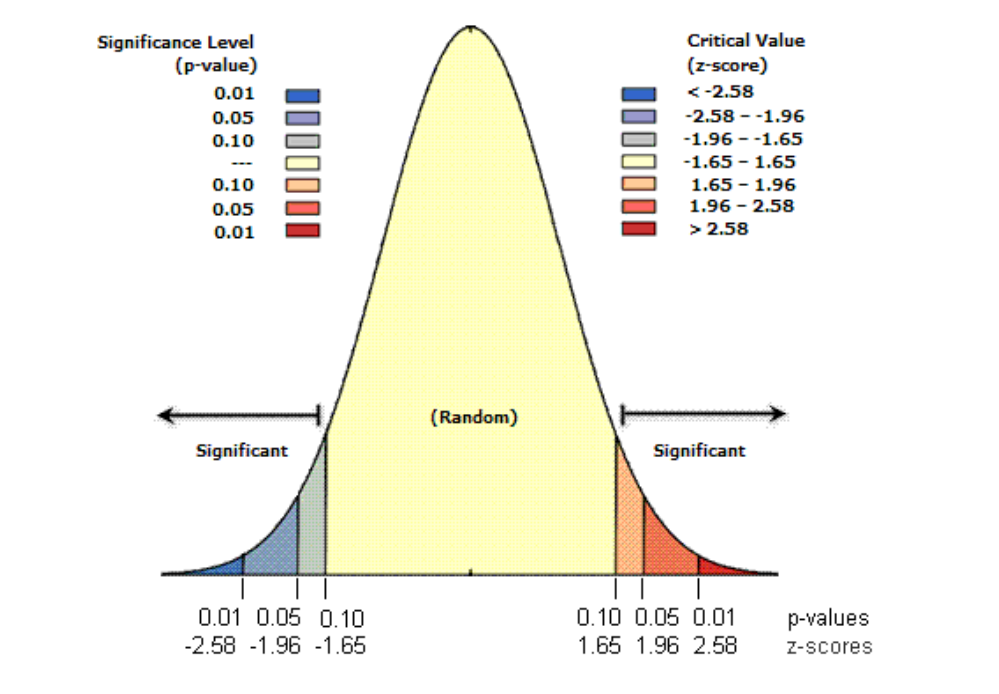


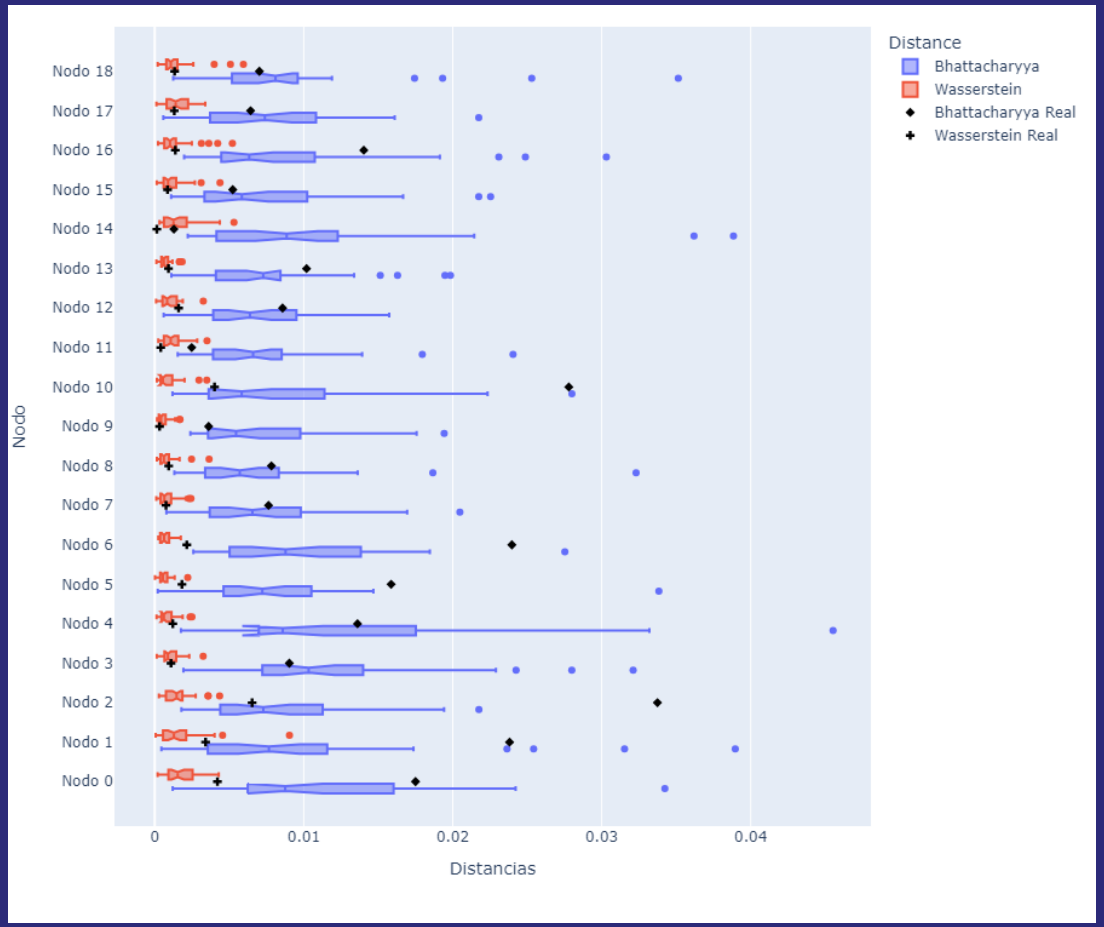
It measures the minimum "cost" necessary to transform one probability distribution into another.

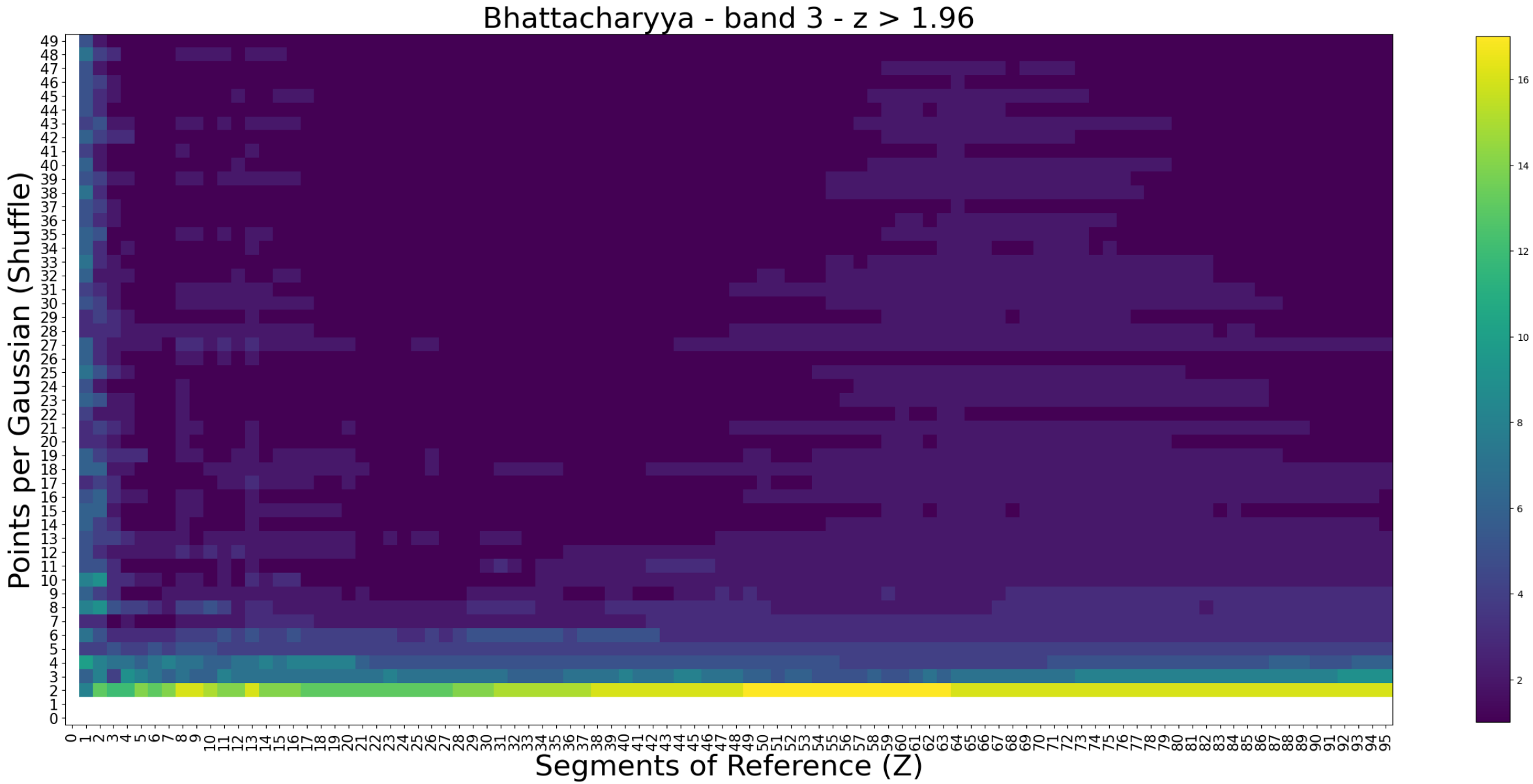
Nodes

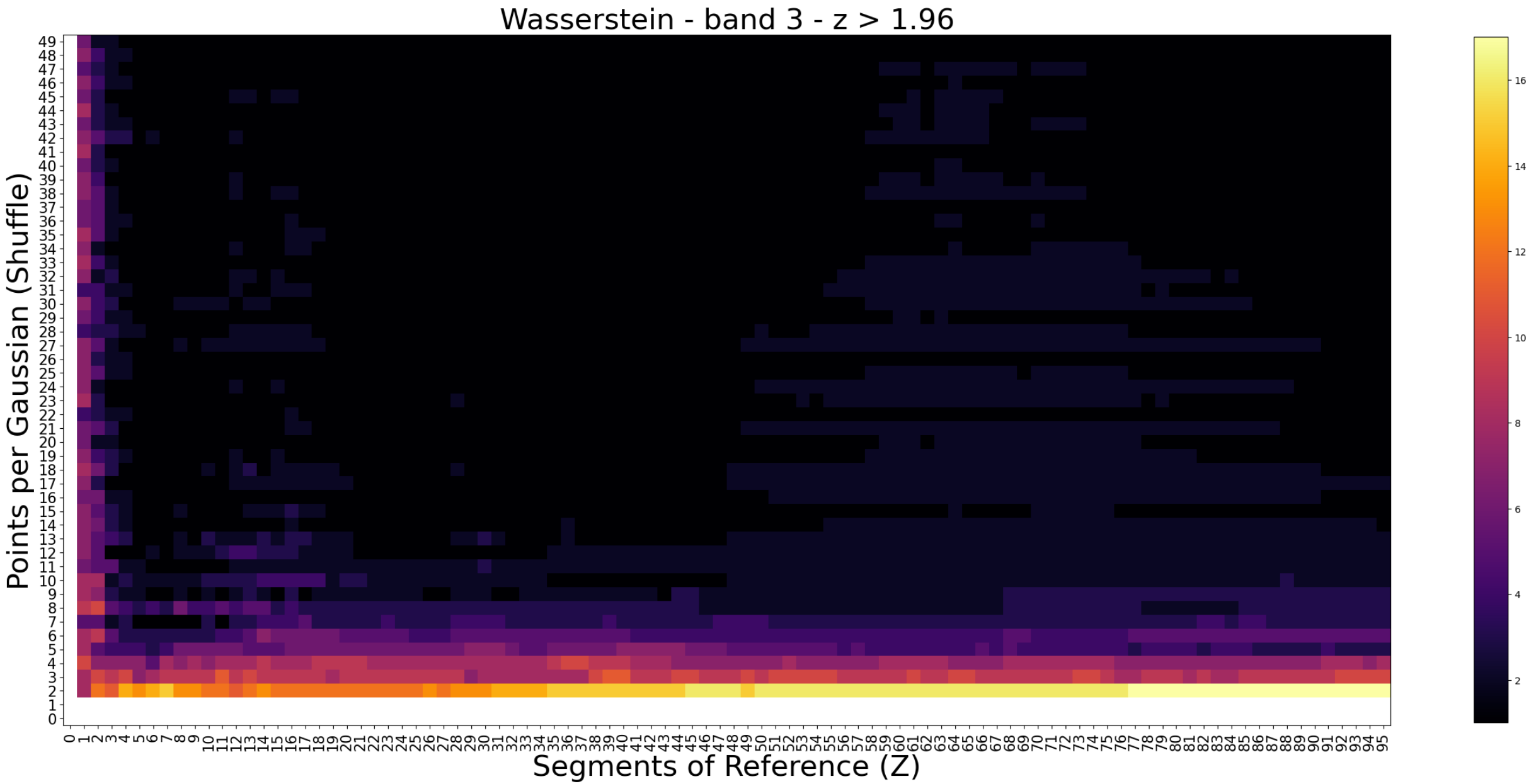
Measurements normalized by z scores

$$Z = \frac{x - \mu}{\sigma}$$






Bhattacharyya - band 3 - z > 1.96
Points per Gaussian (Shuffle)
Segments of Reference (Z)


Wasserstein - band 3 - z > 1.96
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Segments of Reference (Z)

Martin Guillemaud et al. Epileptic seizure forecasting with **hyperbolic embedding** of brain networks. Article submitted, 2023.

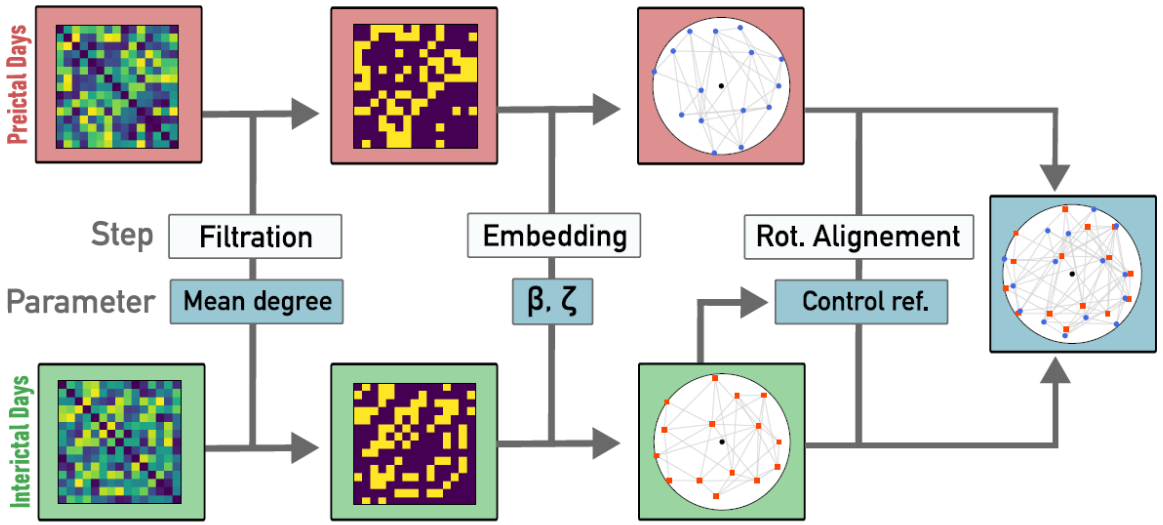
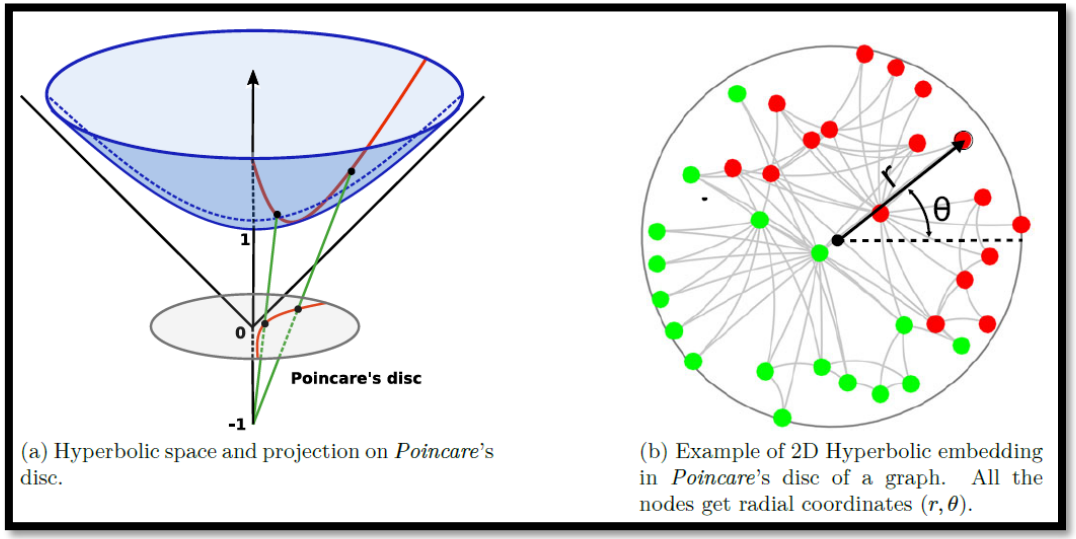


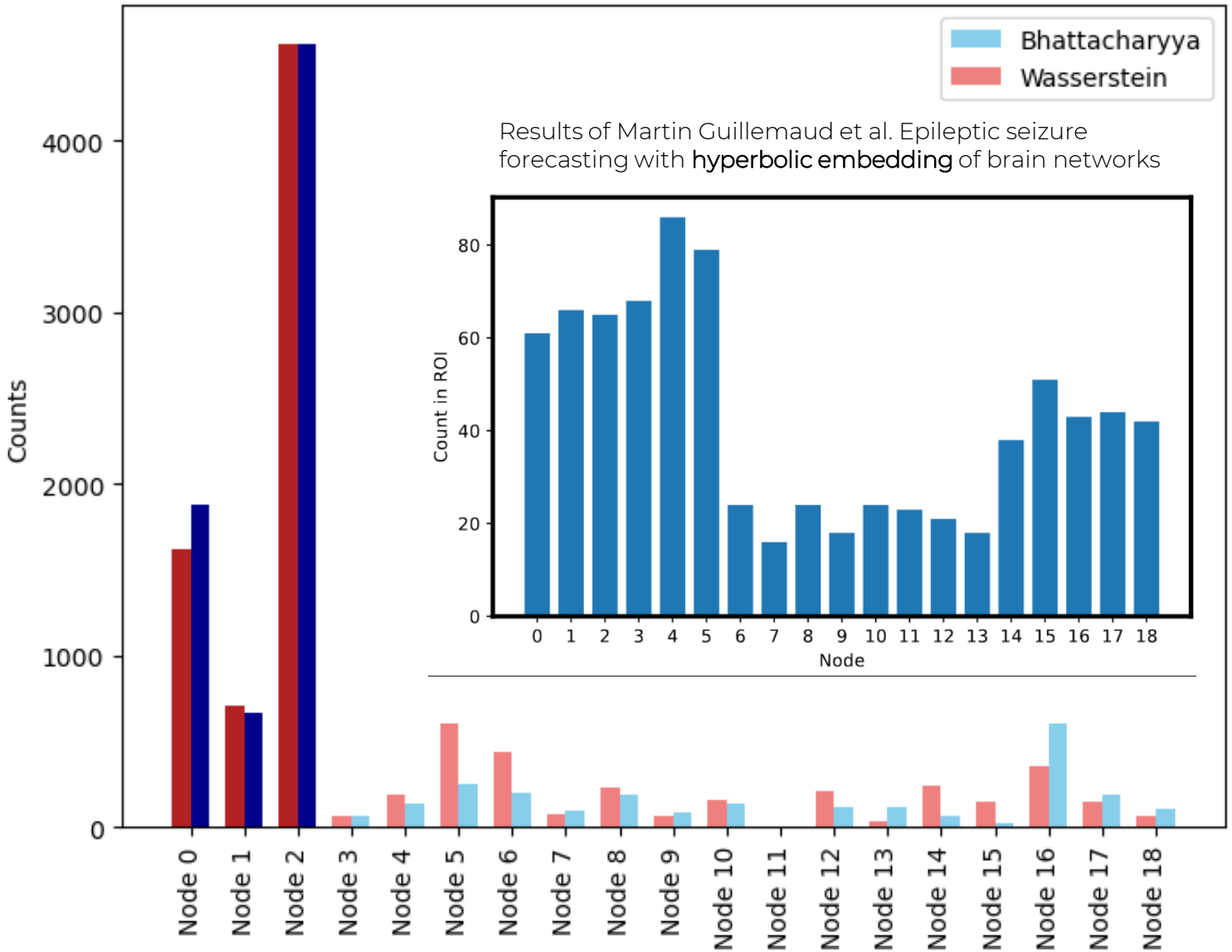
Figure 1: Hyperbolic embedding and re-alignement of brain connectivity networks.



(a) Hyperbolic space and projection on *Poincare*'s disc.

(b) Example of 2D Hyperbolic embedding in *Poincare*'s disc of a graph. All the nodes get radial coordinates (r, θ).

Embedding these networks in hyperbolic geometry has high likelihood of identifying pre-seizure brain connectivity patterns and give light under the success prediction of the epilepsy surgery outcome.



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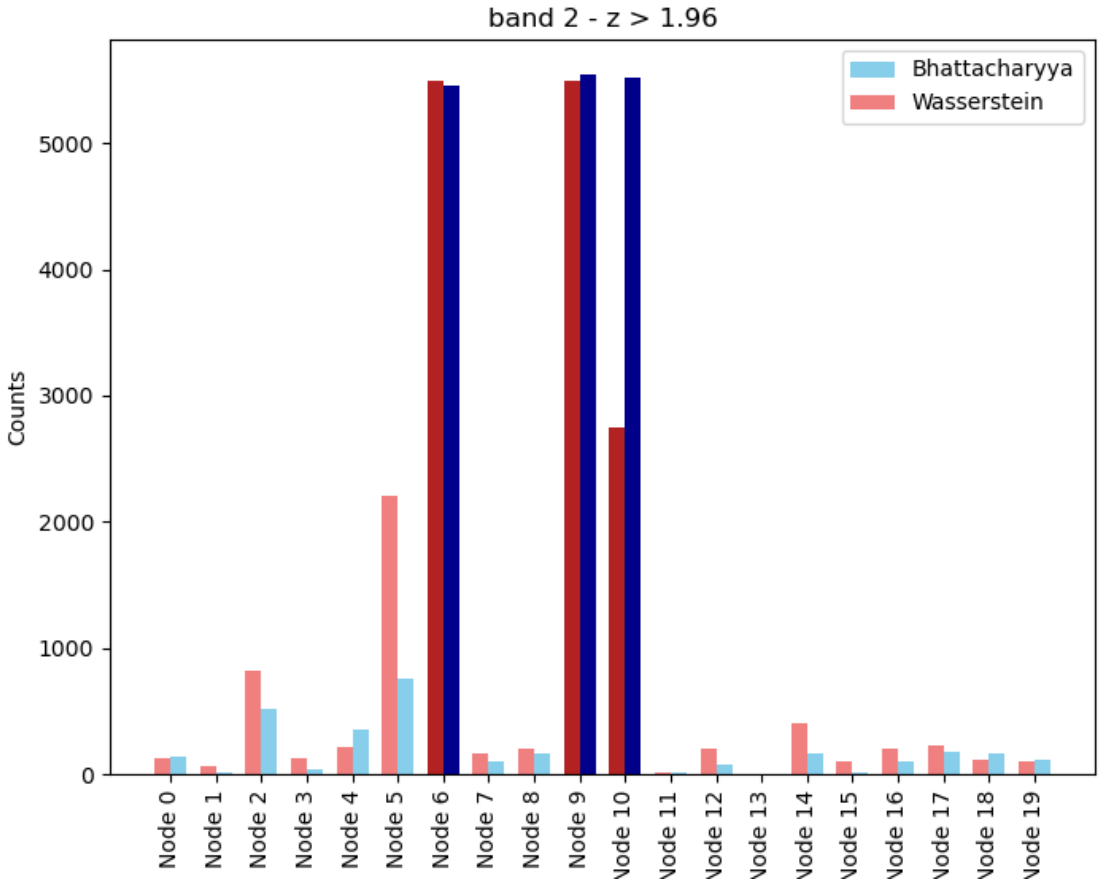
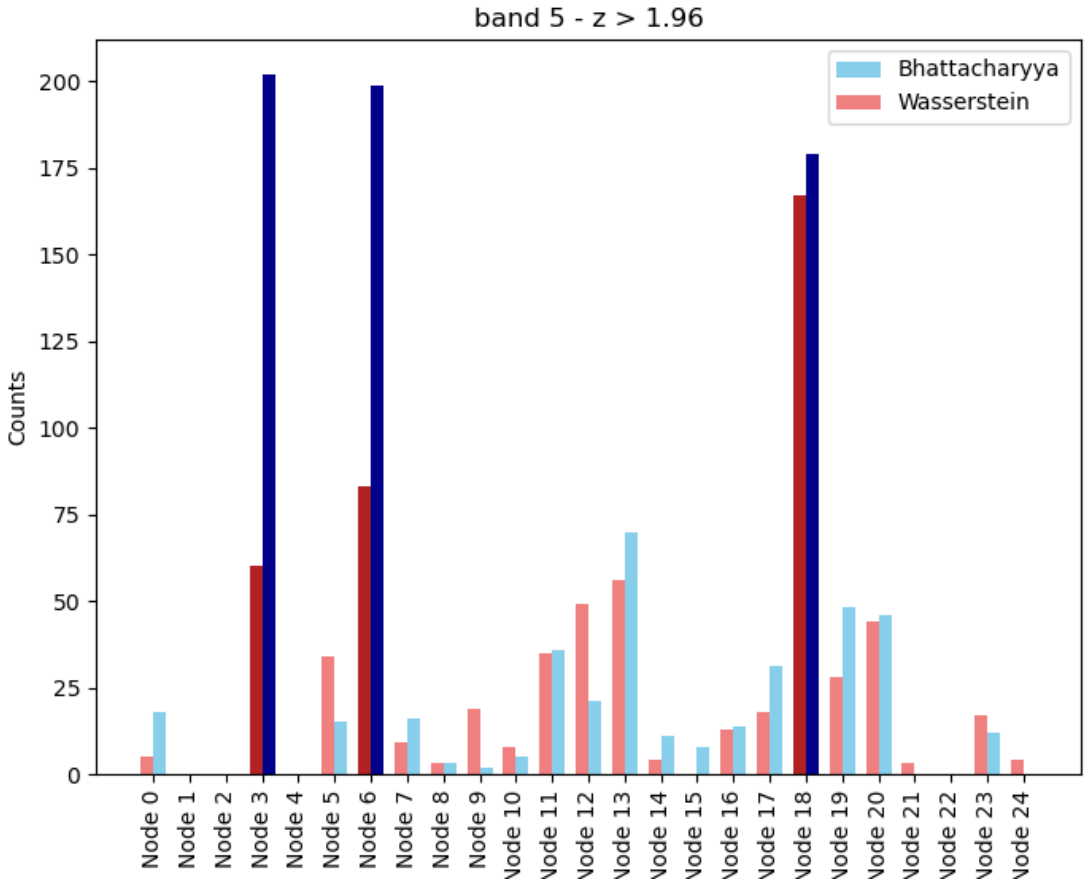

band 2 - z > 1.96
Bhattacharyya
Wasserstein
Counts
0
1000
2000
3000
4000
5000
Node 0
Node 1
Node 2
Node 3
Node 4
Node 5
Node 6
Node 7
Node 8
Node 9
Node 10
Node 11
Node 12
Node 13
Node 14
Node 15
Node 16
Node 17
Node 18
Node 19


band 5 - z > 1.96
Bhattacharyya
Wasserstein
Counts
0
25
50
75
100
125
150
175
200
Node 0
Node 1
Node 2
Node 3
Node 4
Node 5
Node 6
Node 7
Node 8
Node 9
Node 10
Node 11
Node 12
Node 13
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Node 16
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Node 23
Node 24

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